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Forecasting Rice Sales Using Weighted Moving Average Method: Case Study at KAKANG MART GROSIR Bandung

Nenden Siti Nurkholipah[1], Tubagus Robbi Megantara[2*], Rizki Apriva Hidayana[3]

[1,2,3] *Department of Mathematics, Faculty of Mathematics and Natural Sciences, The National University of the Republic of Indonesia, Bandung, Indonesia*

**Corresponding author email:* nendensitinurkholipah@mipa.ukri.ac.id

Abstract

Effective inventory management is critical for retail businesses, and accurate sales forecasting is its cornerstone, especially for staple products like rice. This study aims to forecast the sales of packaged rice at KAKANG MART GROSIR, a major retailer in Bandung, by analyzing its daily sales data. The research utilizes the Weighted Moving Average (WMA) method on primary sales data for six top-selling rice brands collected over a three-month period from March 1 to May 31, 2025. The WMA model, which assigns greater importance to recent observations, was employed to smooth short-term fluctuations and identify underlying sales trends. The analysis revealed highly dynamic and distinct sales patterns: the JM Cianjur brand showed the highest average sales but with significant weekly volatility, the Setrawangi RS brand demonstrated strong and consistent growth to become a market leader, while the Setrawangi DI brand experienced a sharp decline. Furthermore, the BMW brand was found to have remarkably stable and predictable sales, whereas the Lahap and Sedap Wangi brands consistently remained at the lowest sales tier. The findings confirm that the WMA is a valuable tool for identifying diverse sales trajectories, providing actionable insights for developing tailored inventory strategies for each product.

Keywords: Sales Forecasting, Weighted Moving Average, Time Series Analysis, Inventory Management, Retail

1. Introduction

The background of rice sales in Indonesia is deeply intertwined with the country's agricultural policies, consumer preferences, and technological advancements. Rice is a staple food for nearly all of Indonesia's 220 million people, making it a critical component of both the rural economy and national food security strategies (McCulloch & Timmer, 2008). Despite its importance, the Indonesian rice market faces challenges such as discrepancies in production and consumption data, which complicate the understanding of whether the country is a net importer or exporter of rice (Rosner & McCulloch, 2008). Historically, Indonesia achieved self-sufficiency in rice production in the 1980s, but this was short-lived due to declining growth rates and the high costs associated with maintaining self-sufficiency (Simatupang & Timmer, 2008). Government interventions, including price policies, have played a significant role in shaping the rice market, impacting both private profitability and economic opportunities across regions (Ali, 1987). Technological innovations have been pivotal in increasing rice yields, with advancements in rice varieties, integrated crop management, and agricultural machinery contributing to sustainable food security (Sutardi et al., 2022). However, the irrigation infrastructure, crucial for rice production, is in dire need of modernization, as a significant portion is damaged, affecting water management and contributing to climate change through greenhouse gas emissions (Tirtalistyani et al., 2022). Consumer preferences also influence the rice market, with a strong inclination towards local rice varieties, although there is a lack of awareness about the different types available (Antriyandarti et al., 2023). The transformation of the Indonesian agrifood system reflects a broader shift beyond rice, as urban and rural consumers diversify their food budgets to include more fruits, vegetables, and animal proteins (Reardon et al., 2015). This diversification, coupled with the need for improved irrigation and technological innovation, underscores the complexity of the rice sales landscape in Indonesia, necessitating a multifaceted approach to policy and market development.

Inventory management in the retail sector is a multifaceted challenge that significantly impacts business performance and profitability. Retailers must balance the dual objectives of avoiding stockouts, which lead to lost sales, and minimizing overstock, which ties up capital and incurs additional costs (Abernathy et al., 1999; Mohamed, 2024). The complexity of retail inventory management is heightened by the need to manage a vast number of SKUs across multiple locations, often with delayed and inaccurate demand data, which complicates accurate inventory positioning and demand forecasting (Nahmias & Smith, 1993). Small and Medium-sized Enterprises (SMEs) in the retail sector often rely on basic systems like Excel or simple ERP solutions due to resource constraints, which limits their ability to adopt advanced inventory management systems (Macas et al., 2021). However, the adoption of sophisticated systems, such as Vendor-Managed Inventory (VMI) and Just-in-Time (JIT), can enhance supply chain performance by reducing inventory levels and improving material flow, though these systems also present their own challenges (Mohamed, 2024). The integration of technology, such as Inventory Management Systems, is crucial for overcoming traditional inventory management obstacles, enabling data-driven decision-making, and enhancing operational efficiency (Putra et al., 2024). Moreover, strategic decisions in inventory management, such as those observed in case studies of successful retailers, highlight the importance of aligning inventory strategies with broader supply chain and human resource considerations to ensure financial well-being (Damron et al., 2016). The evolution of retail supply chain management, driven by advancements in e-commerce and mobile technologies, further underscores the need for innovative inventory management practices to meet dynamic and stochastic demands (Ge et al., 2019; Minner & Sachs, 2023). Overall, effective inventory management in retail requires a comprehensive approach that incorporates accurate demand forecasting, strategic use of technology, and alignment with supply chain management practices to optimize costs and enhance customer satisfaction.

Effective inventory management for staple goods like rice is crucial for retailers such as KAKANG MART GROSIR, as it directly influences profitability and customer satisfaction. Accurate demand forecasting is essential to avoid stockouts, which can lead to lost sales, and overstocking, which incurs higher holding costs and spoilage risks. Traditional forecasting methods often struggle with the complexities of modern retail environments, where factors like seasonality and consumer behavior play significant roles. The Weighted Moving Average (WMA) method, chosen for its emphasis on recent sales data, can effectively model sales patterns and adapt to emerging trends. Additionally, advanced machine learning techniques, such as Long Short-Term Memory (LSTM) networks, have shown superior performance in capturing complex demand patterns, significantly improving forecasting accuracy. By applying these methodologies, KAKANG MART GROSIR can enhance its inventory control and purchasing strategies, ultimately maintaining a competitive edge in the market. The integration of machine learning and business intelligence in demand forecasting has been shown to improve accuracy significantly, with some models achieving up to 92.38% accuracy in real-time applications, which is crucial for effective decision-making in inventory management (Khan et al., 2020). Moreover, the use of advanced models like Transformers and Particle Swarm Optimization (PSO) has demonstrated substantial improvements in forecast accuracy and operational cost reductions, highlighting the potential for these technologies to optimize inventory management further (Bo & Jie, 2024). The adoption of robust demand estimators and hybrid statistical-genetic models also contributes to more accurate demand forecasts, which are essential for balancing the risks of over-stocking and stockouts (Jacobs & Wagner, 1989; Sayed et al., 2009). Furthermore, addressing issues such as inventory record inaccuracy and demand estimation from censored observations can reduce biases in demand forecasts, thereby enhancing inventory management strategies (Mersereau, 2015; Trapero et al., 2023). Overall, leveraging these advanced forecasting techniques and addressing common challenges in demand estimation can significantly improve inventory management for retailers like KAKANG MART GROSIR, ensuring better alignment with market demands and operational efficiency.

This study addresses the challenge of sales forecasting by analyzing the daily sales data of six best-selling packaged rice brands at KAKANG MART GROSIR. The research employs the Weighted Moving Average (WMA) method to model and predict sales patterns. The WMA method was chosen for its ability to assign greater importance to more recent sales data, making it particularly effective for identifying and adapting to emerging trends. The primary objective of this research is to apply the WMA model to the collected sales data to generate reliable forecasts. The findings are intended to provide actionable insights for KAKANG MART GROSIR's management, enabling more strategic inventory control and purchasing decisions.

2. Literature Review

The weighted moving average (WMA) is a forecasting method that assigns different weights to past observations, giving more importance to recent data points, which enhances its responsiveness to changes in trends and patterns. This method has been applied across various domains, demonstrating its versatility and effectiveness. For instance, in the fashion industry, the WMA method was used to predict the demand for robes, helping to manage inventory levels more efficiently by reducing excess stock and avoiding shortages, with a mean absolute percentage error (MAPE) of 5% for adult robes and 12% for children's robes (Chan et al., 2024). In the financial sector, the WMA method was applied to predict Bitcoin prices using high-frequency data, achieving a MAPE of 0.72%, indicating high reliability for investors making portfolio decisions (Bakar & Rosbi, 2018). These examples illustrate the WMA method's adaptability and precision in various forecasting scenarios, making it a valuable tool for decision-makers across different industries.

3. Materials and Methods

3.1. Materials

The data utilized in this research is primary quantitative data. It was obtained through a collaboration with the management of KAKANG MART GROSIR, a prominent retail and wholesale store in Bandung City known for its significant sales volume of staple goods. Official permission to access and use the sales data for academic purposes was granted by the store's management. Data acquisition was performed by exporting raw transaction records from the store's Point of Sale (POS) system. The raw data was provided in a .csv (Comma-Separated Values) format, encompassing the complete transaction history for the relevant products during the specified period. The object of this research is the daily sales data of six (6) brands of packaged rice. The selection of these six brands was based on the following inclusion criteria:

a) Highest Sales Volume: The brands represent the top six best-selling rice products at KAKANG MART GROSIR consistently over the last year prior to the research period. This ensures that the data obtained is significant and representative for analysis.
b) Stock Availability: These brands have a record of relatively stable stock availability, minimizing the potential for zero-sales days caused by stockouts.

The rice brands that met the criteria and were used in this study are: Setrawangi RS, Setrawangi DI, JM Cianjur, BMW, Lahap, and Sedap Wangi. The data observation period was set for three months, commencing on March 1, 2025, and concluding on May 31, 2025. This timeframe was chosen to capture short-term sales dynamics without being affected by extreme long-term seasonal fluctuations (e.g., non-holiday periods). A total of 92 data points (days) were collected for each rice brand. The raw data from the POS system underwent several pre-processing stages to ensure its quality and readiness for analysis.

a) Data Cleaning: The aggregated daily data was verified for completeness. A check for missing values or anomalies was performed. During the observation period, no missing daily data points were found, indicating that KAKANG MART GROSIR was in continuous operation for all 92 days.
b) Data Aggregation: Individual transaction records were aggregated into total daily sales for each brand.
c) Variable Definition: The primary unit of measurement used in the analysis is sacks per day. The dependent variable (Sales_Volume) is an integer representing the total number of sacks sold for a specific brand on a given day.

After pre-processing, the final dataset was structured into a tabular (panel data) format as follows:

Table 1: Dataset structure

Date (YYYY-MM-DD)	Brand_ID	Brand_Name	Sales_Volume (sacks)
2025-03-01	B01	Setrawangi RS	10
2025-03-01	B02	Setrawangi DI	45
…	…	…	…
2025-05-31	B06	Sedap Wangi	17

The entire process of data pre-processing, descriptive statistical analysis, and implementation of forecasting models was conducted using statistical software and programming languages. Microsoft Excel was used for the initial data inspection, while further data cleaning, transformation, and analysis were performed using the Python programming language with its primary libraries Pandas for data manipulation and NumPy for numerical operations.

3.2. Methods

The Weighted Moving Average (WMA) is a statistical method used for forecasting and smoothing time series data. Unlike the Simple Moving Average (SMA), which assigns equal importance to all data points in the specified period, the WMA assigns a greater weight to more recent data points. The underlying assumption is that recent observations are more relevant for predicting future values. This method is particularly useful in scenarios where the underlying trend of the data is believed to be evolving.

The calculation of the WMA involves multiplying each data point within the look-back period by a predetermined weight and then summing the results. The weights are typically assigned in a linearly decreasing manner, with the most recent data point receiving the highest weight and the oldest data point receiving the lowest.

The formula for the Weighted Moving Average is derived from the principle of assigning linearly decreasing weights to the data points in the time series. Let the time series data be represented by $p_1, p_2, \dots, p_n$, where p_n is the most recent data point. For a WMA of period n, the weight assigned to each data point p_i is proportional to its position in the sequence. The most recent price, p_n, receives a weight of n. The second most recent price, p_{n-1}, receives a weight of $n-1$, and so on, until the first price in the period, p_1, which receives a weight of 1. The Weighted Moving Average (WMA_n) is then the sum of the weighted prices divided by the sum of the weights. The numerator is the sum of the price multiplied by its weight:

$$Numerator = n \cdot p_n + (n-1) \cdot p_{n-1} + \cdots + 2 \cdot p_2 + 1 \cdot p_1. \tag{1}$$

This can be expressed in summation notation as:

$$\sum_{i=1}^{n} i \cdot p_i. \tag{2}$$

The denominator is the sum of the weights. This is the sum of the first n integers, which is a well-known arithmetic series:

$$Denominator = n + (n-1) + \cdots + 2 + 1. \tag{3}$$

The formula for the sum of the first n integers is:

$$\sum_{i=1}^{n} i = \frac{n(n+1)}{2}. \tag{4}$$

By combining the numerator and the denominator, we arrive at the general formula for the Weighted Moving Average:

$$WMA_n = \frac{\sum_{i=1}^{n} i \cdot p_i}{\sum_{i=1}^{n} i}. \tag{5}$$

Substituting the formula for the sum of the weights, the final expression for the WMA is:

$$WMA_n = \frac{n \cdot p_n + (n-1) \cdot p_{n-1} + \cdots + 1 \cdot p_1}{\frac{n(n+1)}{2}}. \tag{6}$$

This formula provides a smoothed value for the time series at the most recent time point, with a greater emphasis placed on the more recent observations. The selection of the period n is a critical parameter that depends on the characteristics of the data and the desired sensitivity of the moving average to recent changes. A shorter period will result in a more responsive moving average, while a longer period will produce a smoother, less volatile result.

4. Results and Discussion

This chapter presents the results of the quantitative analysis of the sales data for six rice brands from KAKANG MART GROSIR for the period of March 1 to May 31, 2025. The chapter begins with a descriptive statistical analysis to characterize the fundamental properties of the sales data. This is followed by a discussion of the findings and their managerial implications, particularly in the context of inventory management and sales forecasting.

Descriptive statistics were employed to provide a quantitative summary of the sales data. This analysis includes measures of central tendency (mean, median) and measures of dispersion (minimum, maximum, standard deviation). The objective is to outline the sales volume and volatility for each of the six rice brands. The results of the descriptive statistical analysis are presented in Table 1.

Table 2: Descriptive Statistics of Daily Rice Sales (Unit: Sacks)

Statistical Measure	Sestrawangi RS	Sestrawangi DI	JM Cianjur	BMW	Lahap	Sedap Wangi
Mean	75.39	53.32	99.57	69.70	30.62	27.90
Min	10	18	50	60	10	10
Median	79.5	54	86	69	31	30
Mode	109	48	85	67	23	26
Max	131	85	152	80	50	40
Standard Deviation	34.04	17.82	30.63	6.08	12.20	8.90

The JM Cianjur brand recorded the highest mean daily sales at 99.57 sacks, establishing it as the best-selling product among the six brands during the observation period. It was followed by Setrawangi RS (75.39 sacks) and BMW (69.70 sacks). Conversely, the Sedap Wangi (27.90 sacks) and Lahap (30.62 sacks) brands demonstrated the lowest average sales volumes.

The standard deviation metric highlights significant differences in sales consistency across the brands. Setrawangi RS exhibited the highest volatility with a standard deviation of 34.04, closely followed by JM Cianjur at 30.63. These high values indicate substantial day-to-day fluctuations in sales, implying a lower degree of predictability. In stark contrast, the BMW brand displayed remarkable stability, with the lowest standard deviation of 6.08. This suggests a highly consistent and predictable sales pattern.

The range between the minimum and maximum daily sales further corroborates the findings on volatility. JM Cianjur not only had the highest average sales but also the widest sales range (102 sacks), confirming its fluctuating demand. The BMW brand had the narrowest range (20 sacks), reinforcing the observation of its stable demand.

For the JM Cianjur brand, the mean (99.57) is notably higher than the median (86.00). This indicates a positively skewed (right-skewed) data distribution, where a few days of exceptionally high sales influence the average. For brands like BMW, Lahap, and Sedap Wangi, the proximity of the mean to the median suggests a more symmetric data distribution.

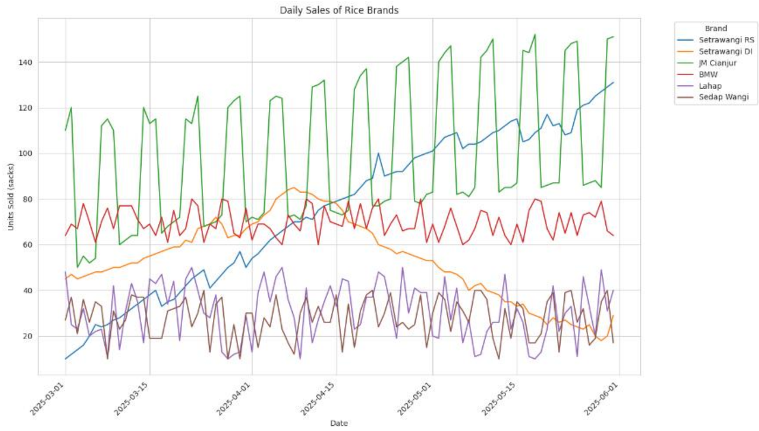

Figure 1: Daily Sales of Rice Brands

Figure 1 presents a comparison of daily sales, in sacks, for six different rice brands during the period from March to early June 2025. Overall, the JM Cianjur brand (green line) consistently dominates the market as the top-selling brand, characterized by a very clear cyclical sales pattern with regular peaks and troughs, most likely reflecting a weekly sales trend.

The two most prominent trends are the strong growth of the Setrawangi RS brand (blue line) and the significant decline of Setrawangi DI (orange line). Setrawangi RS shows a stable positive trend, starting as one of the lowest-selling brands and gradually rising to become the second-strongest competitor by the end of the period. In contrast, the initially strong Setrawangi DI experienced a drastic sales decline after reaching its peak in mid-April. Meanwhile, the BMW brand (red line) shows fluctuating yet relatively stable sales in the middle tier, while the Lahap (purple) and Sedap Wangi (brown) brands are consistently at the lowest sales level.

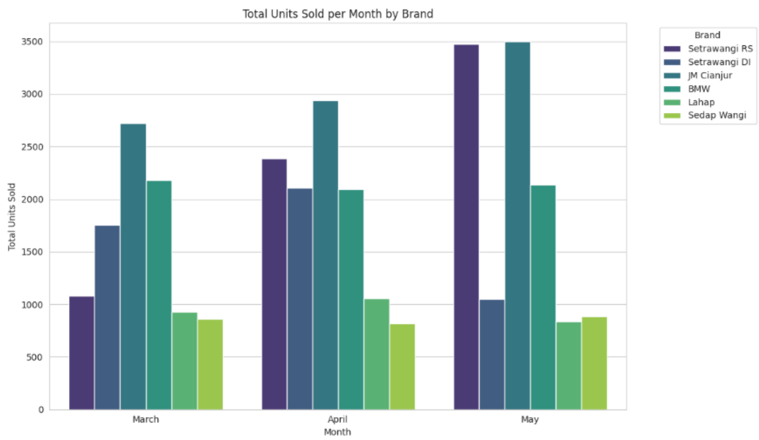

Figure 2: Total Units Sold per Month by Brand

Figure 2 illustrates the total monthly sales for six different rice brands over a three-month period: March, April, and May. The most striking trend is the remarkable growth of the Setrawangi RS brand (dark purple). It began in March with modest sales but grew exponentially each month, culminating in May where it tied with JM Cianjur (dark teal) as the top-selling brand, with both reaching 3,500 units sold. While JM Cianjur started as the clear market leader, its top position was matched by the rapid ascent of Setrawangi RS.

Conversely, the Setrawangi DI brand (light blue) shows a downward trajectory. After an increase in sales from March to April, its performance dropped sharply in May, moving it from a strong competitor to one of the lower-selling brands. The BMW brand (green) maintained relatively stable, mid-range sales throughout the three months. Meanwhile, Lahap and Sedap Wangi (lighter greens) consistently remained the brands with the lowest sales volumes in this period.

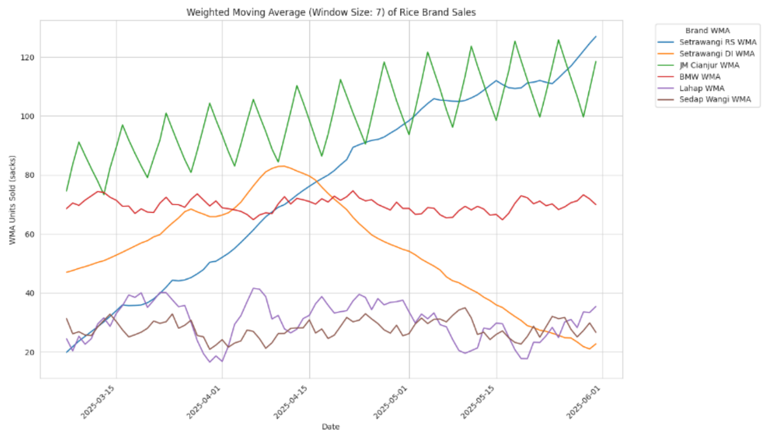

Figure 3: Weighted Moving Average (Window Size: 7) of Rice Brand Sales

Figure 3 presents a sales trend analysis for the six rice brands using a 7-day Weighted Moving Average (WMA). This method serves to smooth out daily sales fluctuations, making the fundamental trend for each brand more clearly visible.

With this method, the main trends observed previously become even more pronounced. JM Cianjur (green) clearly shows a strong weekly cyclical pattern, appearing as a consistent wave. The exponential growth trend of Setrawangi RS (blue) is visible as a smooth upward curve, confirming its strong positive momentum. Conversely, the downward trend of Setrawangi DI (orange) after reaching its mid-April peak appears very sharp and uninterrupted.

Furthermore, this WMA chart reveals that sales for the BMW brand (red) are fundamentally very stable, with a trend line that moves relatively flat in the mid-tier. This indicates that the high fluctuations in its daily data were simply short-term noise. Meanwhile, the Lahap (purple) and Sedap Wangi (brown) brands consistently show the lowest sales trends.

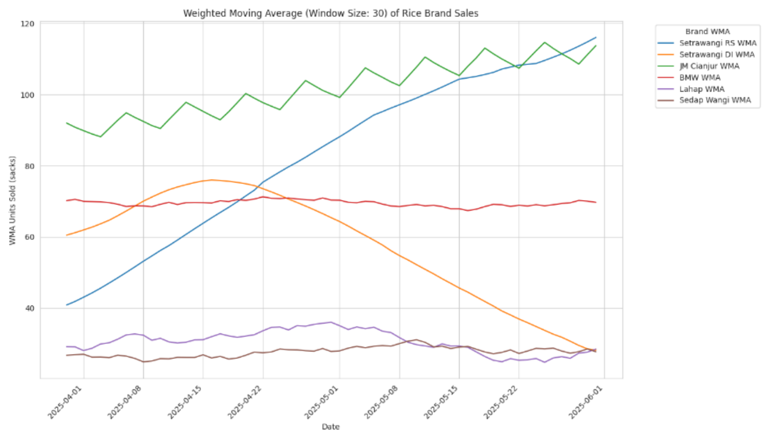

Figure 4: Weighted Moving Average (Window Size: 30) of Rice Brand Sales

Figure 4 displays a long-term sales trend analysis using a wider 30-day Weighted Moving Average (WMA). Using this 30-day window removes nearly all short-term fluctuations, including the weekly cycles seen in the previous chart, leaving only the core, multi-month trends.

This long-term analysis dramatically highlights a shift in market leadership. Setrawangi RS (blue) shows a very strong and smooth growth trajectory, culminating in it overtaking JM Cianjur (green) in late May to become the top-selling brand. Although JM Cianjur also shows a slight positive long-term growth trend (its wavy line is now a straight upward slope), its rate of growth is not as rapid as that of Setrawangi RS.

Meanwhile, the drastic downward trend of the Setrawangi DI brand (orange) is even more apparent as a smooth arc, confirming its market collapse. The chart also confirms the remarkable stability of the BMW brand (red), whose long-term trend is almost completely flat. The Lahap (purple) and Sedap Wangi (brown) brands are shown to have stagnant market positions at the lowest tier.

5. Conclusion

This research was conducted to analyze and forecast the sales of six main rice brands at KAKANG MART GROSIR using the Weighted Moving Average (WMA) method. The analysis of daily sales data from March 1, 2025, to May 31, 2025, revealed distinct and dynamic sales patterns for each brand. The study successfully demonstrated that the WMA method is an effective tool for smoothing short-term volatility and highlighting underlying sales trends, which are critical for informed inventory management.

The key findings indicate a significant shift in market leadership during the observation period. While the JM Cianjur brand had the highest average daily sales, it also exhibited high volatility with a strong weekly cyclical pattern. The most notable trend was the strong, consistent growth of the Setrawangi RS brand, which evolved from a low-volume seller to a market co-leader by the end of May. Conversely, the Setrawangi DI brand experienced a sharp and continuous decline after peaking in mid-April. Meanwhile, the BMW brand demonstrated remarkable sales stability, making it the most predictable, whereas the Lahap and Sedap Wangi brands consistently registered the lowest sales volumes. The application of 7-day and 30-day WMA models effectively visualized these diverse trajectories, confirming the momentum of each brand.

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