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Optimization of Stock Forecasting in Bali Retail Businesses to Support the Digital Economy Using Weighted Moving Average (WMA) Approach

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Abstract:
The development of the digital economy provides new challenges for the retail sector, especially in stock management. Accurate stock management is a key factor in improving operational efficiency and minimizing the risk of overstock and understock. This research aims to optimize stock forecasting in retail businesses in Bali using the Weighted Moving Average (WMA) method. WMA gives greater weight to the most recent data in order to forecast future demand for goods. Sales data from 2017 to 2021 was collected and used as the basis for forecasting. The forecasting process was conducted for several products, including Dolphin and Dua Kelinci. The results show that WMA is able to provide accurate predictions, especially for products with stable demand patterns. For Dolphin products, the WMA forecast for January 2024 predicted a demand of 14.8 units, with a Mean Absolute Deviation (MAD) of 3.64. Dua Kelinci products, however, experienced more fluctuations in demand, with a forecasted January 2024 demand of 7.6 units and a MAD of 4.3. Despite some variations, WMA proved to be more accurate compared to simpler methods like Simple Moving Average (SMA). By using WMA, retailers can more efficiently manage stock, improve customer satisfaction, and reduce the risk of overstocking or understocking. This research confirms the importance of integrating advanced forecasting methods in supporting the competitiveness of the retail sector in the digital economy era.

Keyword : *Forecasting; Sales; Weighted Moving Average (WMA) method; Retail stock management optimization ; Digital economy in Bali*

INTRODUCTION

The digital economy has a big impact on the retail sector, with technology-based retail sector to help in business operations. The retail sector in Bali continues to grow along with the need for businesses to adjust to market trends and changes in consumer demand. One of the main challenges faced by retailers is accurate stock inventory management, which often leads to an imbalance between inventory and market demand when managed manually. Inefficient stock management can bring two major risks, namely the accumulation of unnecessary stock (overstock) which causes capital stagnation, as well as understock which can result in lost sales opportunities because the items consumers are looking for are not available. Therefore, a method is needed that can improve the accuracy of stock forecasting so that inventory can be adjusted to market needs in a timely manner.

One relevant approach to overcome this problem is the Weighted Moving Average (WMA) method, which uses previous sales data by giving greater weight to the most recent data. Moving Average is a point analysis method that is done by averaging a set of count data within a period range (Prado et al., 2020). By adding weights to each period, the WMA method provides a more up-to-date forecasting model when compared to the simple moving average (Wulandari, 2020). WMA can provide an overview of current market demand trends by taking into account the level of data novelty as material in providing consideration.

Research using WMA has been done a lot before, such as being used for Research on forecasting in procurement and on the WMA method has been done a lot before. On the topic of procurement forecasting, procurement forecasting has been conducted for sales predictions using an Artificial Neural Network method (Atmaja et al., 2022), drug supply forecasting (Nuryani et al., 2022) , as well as in inventory management (Saputra et al., 2022). Research on moving averages has also been conducted on the procurement process in

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minimarkets with a single moving average method (Silvya et al., 2020), as well as forecasting on pharmaceutical products (Merkuryeva et al., 2019). By adding weights to the moving average, it is hoped that it can provide an overview of trends in accordance with market needs, while still paying attention to the history of the data that has passed. This research aims to help boost the economy by preventing stock outs and understocks that can provide obstacles to the rotation of the economy that is starting to stretch, by giving consideration to business people through a computerized inventory forecasting method. This approach is expected to improve forecasting accuracy and operational efficiency of retail businesses (Dewantara & Giovanni, 2023; Dewi et al., 2024; Suryawan et al., 2024). By applying the WMA method, retailers in Bali can manage stock more effectively, improve customer satisfaction by ensuring proper product availability, and reduce the risk of losses due to mismatches between stock and market demand.

This research aims to optimize stock forecasting in retail businesses in Bali through the WMA method. The main objectives of this research are to increase the operational efficiency of retail businesses by improving stock forecasting accuracy, reducing the risk of financial losses due to overstock and understock, and supporting the growth of retail businesses in Bali in facing the challenges of the digital economy. This research also aims to improve the competitiveness of retail businesses by helping them respond to market demand more quickly and precisely.

The main implication of this research, especially from a method development perspective, lies in the refinement of stock forecasting approaches in the retail sector. In particular, this research offers a contribution in solving forecasting problems that are more accurate and relevant to current market dynamics. The use of the WMA method not only improves forecasting accuracy compared to conventional methods such as the Simple Moving Average (SMA), but also offers a more adaptive solution to demand fluctuations. This research shows how the WMA method can be integrated into retail operational strategies to improve forecasting accuracy in a broader context, such as stock management with heterogeneous data. Practically, this research provides solutions that can be applied directly by retail businesses to reduce potential risks and improve operational efficiency. On the other hand, in terms of method development, this research is an important basis for further research aimed at creating more complex and sophisticated forecasting models, which are suitable for the needs of the retail industry in the future.

LITERATURE REVIEW

The optimization of stock forecasting in retail businesses is crucial for enhancing operational efficiency and supporting the digital economy. One effective approach to achieving this is through the Weighted Moving Average (WMA) method, which offers a systematic way to predict future inventory needs based on historical sales data. This method allows retailers to assign different weights to past observations, thereby emphasizing more recent data, which is often more indicative of future trends.

The WMA approach has been shown to significantly improve forecasting accuracy in various retail contexts. For example, (Solikin & Hardini, 2019) demonstrate that implementing a WMA-based forecasting information system can streamline decision-making processes regarding stock levels, ultimately leading to enhanced sales performance. Similarly in reaseach (Puspitasari et al., 2023) provide a quantitative analysis of inventory forecasting using WMA, highlighting its effectiveness in predicting inventory needs for trading companies. Their findings indicate that the WMA method can yield more accurate forecasts compared to simpler methods, thereby reducing the risks of overstock and stockouts.

Moreover, the integration of WMA with other forecasting techniques can further enhance its effectiveness. For example, (Taparia, 2023) discusses a hybrid model that combines machine learning algorithms with traditional forecasting methods, achieving a lower mean absolute percentage error (MAPE) and improved inventory management. This suggests that while WMA is a robust method on its own, its performance can be augmented when used in conjunction with advanced analytical techniques.

In the context of the broader retail landscape, accurate demand forecasting is essential for minimizing costs and maximizing customer satisfaction. Retail sales forecasts can lead to improved predictions for individual retailers, which is vital in a competitive market (Pradnyani et al., 2024; Radhitya et al., 2024; Suryadana & Sarasvananda, 2024). This is particularly important as e-commerce continues to grow, necessitating more sophisticated forecasting methods to handle the complexities of online demand. Furthermore, the impact of forecasting accuracy on the bullwhip effect, a phenomenon where small fluctuations in demand at the retail level lead to larger fluctuations up the supply chain, cannot be overlooked. By employing WMA, retailers can mitigate these fluctuations, leading to a more stable inventory flow and better service levels. The Weighted Moving Average method stands out as a valuable tool for stock forecasting in retail businesses, particularly in the context of the digital economy. Its ability to provide accurate, data-driven insights into inventory needs can help retailers optimize their operations, reduce costs, and enhance customer satisfaction. As the retail landscape continues to evolve, integrating WMA with advanced forecasting techniques will be essential for maintaining a competitive edge.

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Weighted Moving Average (WMA)

The Weighted Moving Average method is a forecasting method that gives different weights to each historical data (Anbarasu & Prakash, 2020). This method is used to forecast future demand or inventory of goods based on existing historical data. In forecasting the company's inventory of goods, the Weighted Moving Average method can be used to forecast future inventory of goods based on historical data of existing inventory of goods. The weight given to each historical data can be adjusted according to the importance and characteristics of the data. The closer the historical data is to the forecasting period, the greater the weight given. The Weighted Moving Average method can help companies optimize inventory and avoid excess or shortage of inventory that can affect company performance.
Based on the data that has been processed, the data is then analyzed using the Moving Average method (Chong et al., 2021) which is shown in equation below:

$$S_{t+1} = \frac{X_y + X_{t-1} + X_{t-2} + \cdots + X_{t-n}}{n} \quad (1)$$

Description:
S_{t+1} = Prediction for period t+1
n = Number of periods used to calculate the moving average
X_t = Data for period i

To forecast the supply of goods for the coming period, namely December 2021, a test was carried out using the Moving Average Method with a moving period of 3 months. The following is the calculation for forecasting Moving Average goods inventory:

$$MA = \frac{(n1.1 + n2.2 + n3.3 + \cdots)}{n} \quad (2)$$

Description:
MA = Moving Average
n1 = first period data
n2 = second period data
n3 = third period data
n = number of moving average periods

Testing Using the Mean Absolute Deviation (MAD) Method

Mean Absolute Deviation (MAD) is a calculation used to calculate the average absolute error (Karunasingha, 2022). MAD is used when an analyst wants to measure the forecasting error in the same unit of measure as the original data. MAD measures the accuracy of the forecast by averaging the forecast errors (the absolute value of each error) (Hu et al., 2021). MAD is useful when measuring the forecast error in the same units as the original series. MAD is the first measure of overall forecasting error for a model. Testing the error value in the forecasting process of this study is by using the average absolute deviation MAD (Mean Absolute Deviation), which is the value calculated by taking the sum of the absolute values of each forecasting error divided by the number of data periods (n) (Karunasingha, 2022). By testing the error value in the inventory forecasting process, namely by using the average absolute deviation (MAD), which is the value calculated by taking the sum of the absolute values of each forecasting error divided by the number of data periods (n). The following is the calculation of the MAD (Mean Absolute Deviation) error value(Prado et al., 2020):

$$\text{Mean Absolute Deviation} = \frac{\sum(Actual - Forecast)}{n} \quad (3)$$

Desciption:
MAD = Mean Absolute Deviation
$\sum$ actual = actual value of inventory
$\sum$ forecast = the value of forecasting results of goods
n = number of moving average periods

METHOD

The method used in this study uses an experimental approach to test several forecasting methods in conducting sales forecasting. The stages in this study are divided into 6 stages, 1) Literature study, 2) Data Collection, 3) Data Processing, 4) Implementation of WMA Method, 5) Model Validation, 6) Analysis and Interpretation.

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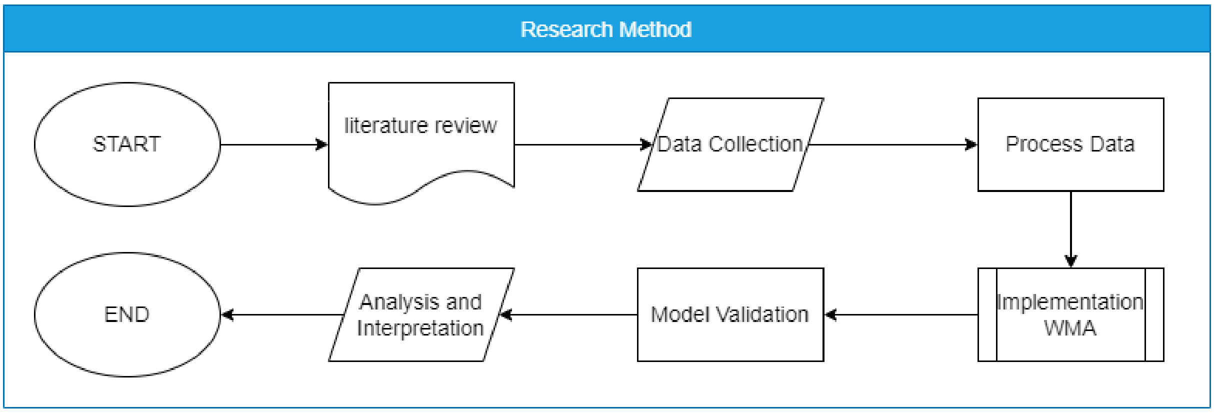

Fig.1 Research Stages

Based on figure 2, each stage can be explained starting from the literature study, which will involve a literature study to understand existing stock forecasting methods, including traditional and current approaches such as Weighted Moving Average (WMA). This literature study will help in gaining a deep understanding of the theoretical and practical frameworks relevant to the research. Next, the process of collecting historical stock data from a number of retail businesses in Bali will be collected. This data includes information on historical sales, inventory, external information such as market trends, weather, and local events that may affect the demand for goods.

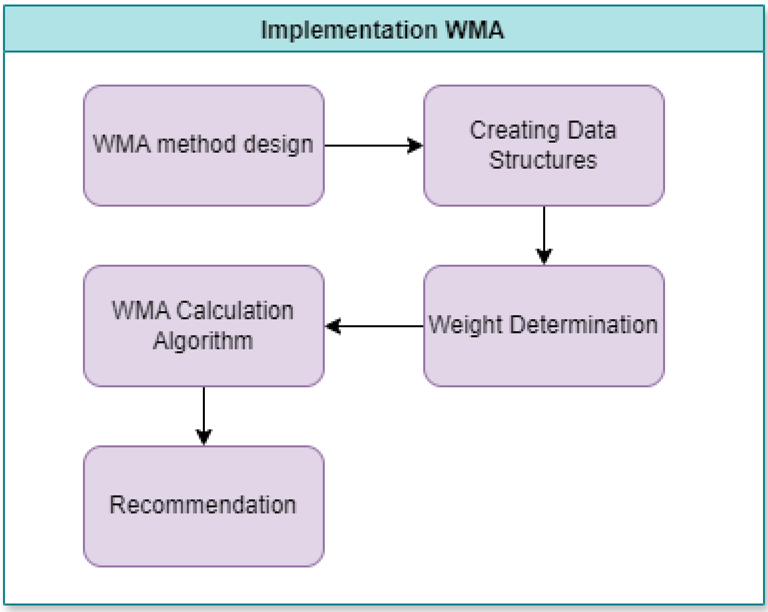

Fig.2 Implementation stages of the WMA method

Figure 2 illustrates the data processing workflow, which includes steps to prepare the collected data for further analysis. This process involves data cleaning, handling missing values, normalizing the data, and making other necessary adjustments to meet the requirements of the analysis. In the implementation stage, the WMA method is applied to the processed stock data. This involves calculating a moving average with appropriate weights to forecast trends and patterns effectively.

RESULTS

Data Analysis

There is sales data for goods in 2017-2021 which are collected and united by month from a total of 557 data on products or goods sold, namely Sos P.Lantai Orange 750ml Reff, Dua Kelinci Kcg.Grg 10*1000gr, Dolpin Garam 1000gr*12, Sos P.Lantai Orange 800ml Reff. Then the data is processed by sorting or checking the data in the form of Microsoft Excel to avoid duplication or redundancy of data. Sales data of goods at Parta trading companies is a research dataset used in the process of forecasting goods.

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Product Forecasting

In this process there is data from dolpin products with a data period of 1 year, namely from January - December 2023 as much as 198 data. The forecasting process is carried out to determine the amount of product data in January 2024.

Table 1. Dolpin Product Data

Month	Time Index (t)	Actual Demand	Forecast based on WMA (4)
January	1	23	-
February	2	11	-
March	3	19	-
April	4	17	-
May	5	16	17
June	6	16	16,4
July	7	17	16,5
August	8	19	16,5
September	9	15	17,5
October	10	16	16,7
November	11	15	16,4
December	12	14	15,7
Jan-24	13	?	14,8

Based on table 1, there are then the results of the actual value of the product, the results of forecasting the WMA method based on the month period. Furthermore, there is a process of calculating the percentage error of each analysis method used, where the error rate is a comparison in testing which analysis tool is most appropriate to use. The following are the results of the WMA analysis method error test for each period of Dolpin products.

Table 2. Dolpin Product Percentage Error Test

Period-n	F	A	E= A-F	RSFE	Absolute Error	Absolute Cumulative	MAD	Tracking Signal
1	17	16	-1	-1	4,8	4,8	4,80	-0,21
2	16,4	16	-0,4	-1,4	1,4	6,2	3,10	-0,45
3	16,5	17	0,5	-0,9	2,7	8,9	2,97	-0,30
4	16,5	19	2,5	1,6	0,5	9,4	2,35	0,68
5	17,5	15	-2,5	-0,9	6,2	15,6	3,12	-0,29
6	16,7	16	-0,7	-1,6	7,5	23,1	3,85	-0,42
7	16,4	15	-1,4	-3	2,7	25,8	3,69	-0,81
8	15,7	14	-1,7	-4,7	3,3	29,1	3,64	-1,29

Table 2 presents the percentage error test for Dolpin products using the WMA method. The table shows the forecasted values (F), actual demand (A), and errors (E = A - F) over various periods. The results indicate how closely the WMA method aligns with actual sales data. Tracking signals and Mean Absolute Deviation (MAD) provide insight into the method's accuracy. A relatively low MAD suggests that the WMA method effectively forecasts demand for most months, maintaining a low error rate. The tracking signal helps monitor the forecast bias, indicating periods when the forecast consistently over or underestimates actual demand.

Table 3.Comparison of Calculation Results for Dolphin Products

Month	Actual data	WMA
5	16	17
6	16	16,4
7	17	16,5
8	19	16,5
9	15	17,5

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10	16	16,7
11	15	16,4
12	14	15,7

Table 3 highlights the comparison between actual sales data and WMA forecasts for Dolpin products from May to December. The table shows a slight deviation between the actual demand and the forecasted values, but overall, the WMA method produces reliable results with minimal variance. This reinforces the method's suitability for predicting demand trends, especially in months with stable sales patterns.

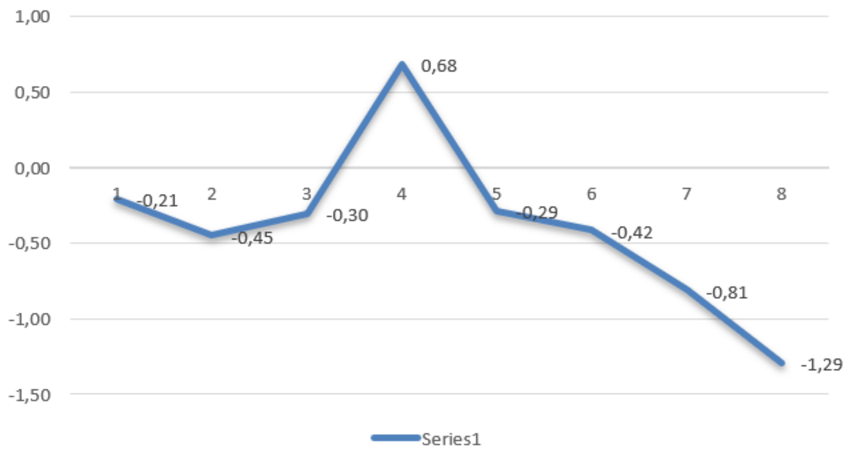

Fig. 3 Data Tracking Signal of Dolpin Product

Figure 3 illustrates the tracking signal for Dolpin product forecasts. It shows the cumulative error over time, which helps determine if the forecasting model is unbiased. The fluctuations within acceptable limits reflect accurate predictions with only minor deviations.

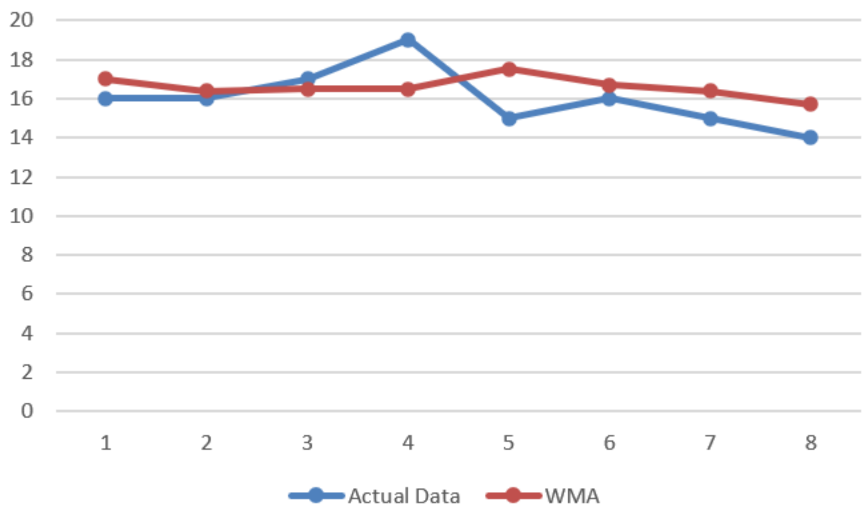

Fig. 4 Comparison of Actual Data and WMA Forecasting Results for Dolpin Products

Figure 4 compares actual demand and WMA forecasted values. The graph shows a close alignment between actual and predicted sales, further validating the effectiveness of WMA in forecasting Dolpin products.

Furthermore, there is this process there is data from Dua Kelinci products with a data period of 1 year, namely from January - December 2023 as much as 100 data. The forecasting process is carried out to determine the amount of product data in January 2024.

Table 4. Dua Kelinci Product Data

Month	Time Index (t)	Actual Demand	Forecast based on WMA (4)
January	1	8	-
February	2	4	-

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March	3	21	-
April	4	7	-
May	5	12	10,7
June	6	13	11,5
July	7	3	12,3
August	8	9	8,2
September	9	2	8,3
October	10	2	5,4
November	11	6	3,5
December	12	13	4,3
Jan-24	13	???	7,6

Based on table 4, there are then the results of the actual value of the product, the results of forecasting the WMA method based on the month period. Furthermore, there is a process of calculating the percentage error of each analysis method used, where the error rate is a comparison in testing which analysis tool is most appropriate to use. The following are the results of the WMA analysis method error test for each period of Dua Kelinci products.

Table 5. Dua Kelinci Product Percentage Error Test

Period-n	F	A	E= A-F	RSFE	Absolute Error	Absolute Cumulative	MAD	Tracking Signal
1	10,7	12	1,3	1,3	4,8	4,8	4,80	0,27
2	11,5	13	1,5	2,8	1,4	6,2	3,10	0,90
3	12,3	3	-9,3	-6,5	2,7	8,9	2,97	-2,19
4	8,2	9	0,8	-5,7	0,5	9,4	2,35	-2,43
5	8,3	2	-6,3	-12	6,2	15,6	3,12	-3,85
6	5,4	2	-3,4	-15,4	7,5	23,1	3,85	-4,00
7	3,5	6	2,5	-12,9	2,7	25,8	3,69	-3,50
8	4,3	13	8,7	-4,2	3,3	29,1	3,64	-1,15

Table 5 presents the percentage error test for Dua Kelinci products, following a similar format to Dolpin's error analysis. The table shows larger variations in demand, especially in periods where actual sales were much lower or higher than the forecasted values. The MAD and tracking signals demonstrate a more fluctuating forecast performance, reflecting the higher volatility in the product's demand pattern compared to Dolpin.

Table 6. Comparison of Calculation Results for Dua Kelinci Products

Month	Actual data	WMA
5	12	10,7
6	13	11,5
7	3	12,3
8	9	8,2
9	2	8,3
10	2	5,4
11	6	3,5
12	13	4,3

Table 6 shows the comparison between actual sales and WMA forecasts for Dua Kelinci products from May to December 2023. The results reveal more substantial discrepancies between forecasted and actual demand, particularly in July and September, where demand was lower than expected. These differences suggest that the WMA method is less accurate for products with high variability in demand but still provides useful estimates for overall trends.

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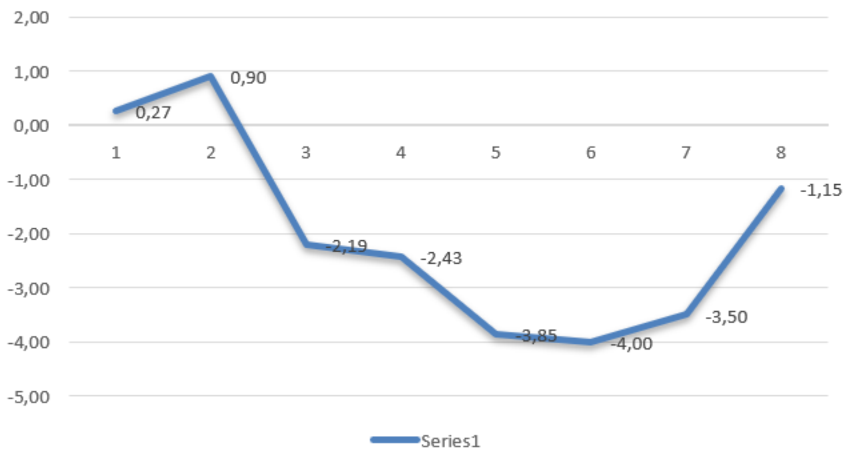

Fig. 5 Tracking Signal Data of Dua Kelinci Products

Figure 5 depicts the tracking signal for Dua Kelinci products. The tracking signal shows greater variability, reflecting fluctuations in demand and the need for close monitoring of forecast bias.

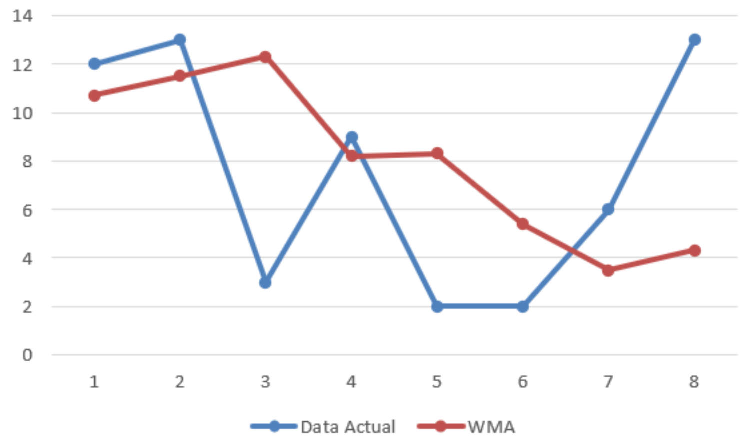

Fig. 6 Comparison of Actual Data and WMA Forecasting Results for Dua Kelinci Products

Figure 6 compares actual and forecasted data for Dua Kelinci products. The greater variance in the graph indicates a more challenging forecasting process due to irregular demand patterns, particularly in certain months where demand dropped sharply.

Forecasting Calculation for Overall Data

There is data on sales of goods in 2017-2021 which is collected and united by month from a total of 557 data on products or goods sold, then the data is processed by sorting or checking the data in Microsoft Excel to avoid duplication or redundancy of data. The sales data of goods at Parta trading companies is a research dataset used in the process of forecasting goods.

Table 7. Overall Product Data for 2023-2024

Month	Time Index (t)	Actual Demand	Forecast based on WMA (4)
January 2023	1	53	-
February 2023	2	32	-
March 2023	3	65	-
April 2023	4	40	-
May 2023	5	47	47,2
June 2023	6	54	47
July 2023	7	37	50,2

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August 2023	8	38	44,4
September 2023	9	56	41,8
October 2023	10	45	46,6
November 2023	11	50	46,1
December 2023	12	40	48,5
January 2024	13	?	45,6

Table 7 aggregates sales data from 2017 to 2021 and applies the WMA method for forecasting sales from May to January 2024. The forecasted results closely match actual demand for most months, particularly in May and November, demonstrating the effectiveness of WMA in forecasting for stable demand patterns. However, the method shows some underperformance in periods with higher variation, as reflected in June and September.

Furthermore, there is a process of calculating the percentage error of each analysis method used, where the error rate is a comparison in testing which analysis tool is most appropriate to use. The following are the results of the WMA analysis method error test for each period of the overall product data.

Table 8. Overall Product Percentage Error Test

Period-n	F	A	E= A-F	RSFE	Absolute Error	Absolute Cumulative	MAD	Tracking Signal
1	47,2	47	-0,2	-0,2	4,8	4,8	4,80	-0,04
2	47	54	7	6,8	1,4	6,2	3,10	2,19
3	50,2	37	-13,2	-6,4	2,7	8,9	2,97	-2,16
4	44,4	38	-6,4	-12,8	0,5	9,4	2,35	-5,45
5	41,8	56	14,2	1,4	6,2	15,6	3,12	0,45
6	46,6	45	-1,6	-0,2	7,5	23,1	3,85	-0,05
7	46,1	50	3,9	3,7	2,7	25,8	3,69	1,00
8	48,5	40	-8,5	-4,8	3,3	29,1	3,64	-1,32

Table 8 analyzes the error rates for overall product data using WMA. The table includes forecasted and actual demand, along with error metrics like RSFE, Absolute Error, and MAD. The MAD remains relatively low, suggesting that the WMA method performs well for products with consistent demand, though the tracking signal indicates slight deviations, particularly in months with sharp changes in sales.

Table 9. Comparison of Calculation Results for Overall Products

Month	Actual data	WMA
5	47	47,2
6	54	47
7	37	50,2
8	38	44,4
9	56	41,8
10	45	46,6
11	50	46,1
12	40	48,5

Table 9 compares actual sales data against WMA forecasts for all products from May to December. The results show consistent accuracy for products with stable demand trends. The forecasts closely follow actual data, especially in months with steady sales, while deviations occur in periods with higher volatility, such as September and October. This further supports the notion that WMA works best for products with stable demand but may require adjustments for more volatile patterns.

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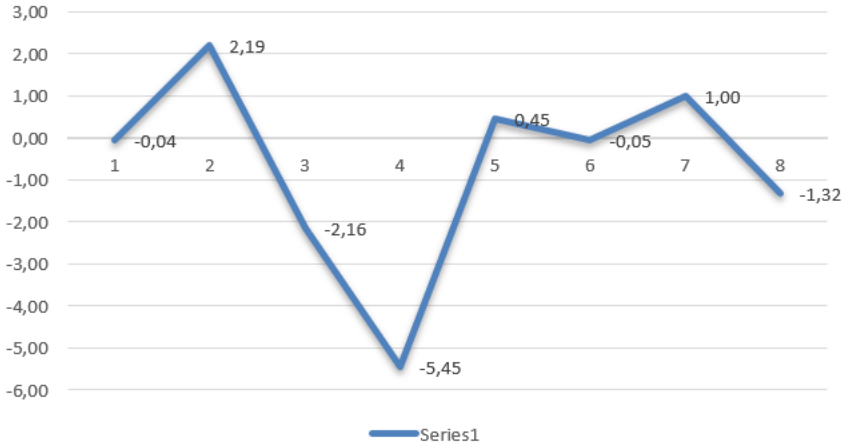

Fig. 7 Overall Product Signal Tracking Data

Figure 7 displays the tracking signal for all products, showing the cumulative error across various periods. The signal highlights periods of deviation but generally remains within acceptable limits, indicating overall forecasting stability.

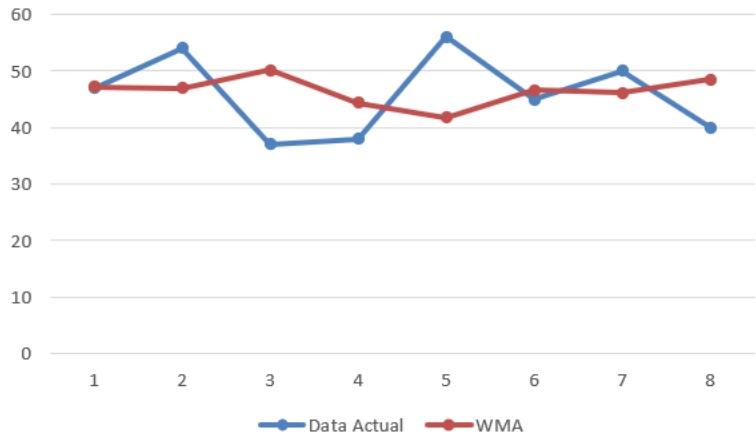

Fig. 8 Comparison of Actual Data and WMA Forecasting Results for all products

Figure 8 illustrates the comparison between actual and forecasted sales data for all products. The graph shows consistent accuracy in the WMA forecasts, particularly in periods with steady demand, affirming the model's ability to handle aggregated product data.

DISCUSSIONS

In the stock forecasting process, the Weighted Moving Average (WMA) method is applied for Dolphin and Dua Kelinci products. Forecasting for Dolphin products uses sales data from January to December 2023. The table shows the forecast results for January 2024 with a predicted demand of 148 units. By comparing actual demand and WMA forecasting results, it can be seen that this forecasting provides fairly accurate predictions, although there are slight differences measured through absolute error and tracking signal. The error test results show that this method is able to maintain accuracy in stock forecasting with low Mean Absolute Deviation (MAD) values, especially in months with stable demand patterns.

For the Dua Kelinci product, the WMA method was also used with a data period from January to December 2023. The forecast for January 2024 shows significantly different values compared to the Dolphin product. The forecast for this product is more variable due to more volatile demand, as seen in September and October, where there was a drastic drop in demand. Nevertheless, the WMA method is still able to provide estimates that are close to the actual values.

When the overall product data from 2017 to 2021 is analyzed, the results show that WMA is very effective in forecasting demand with patterns that tend to be more consistent, especially in months with relatively stable sales volumes. However, in months with higher variations in demand, there is an increase in prediction error.

Nonetheless, this method still provides the advantage of being able to adjust the weights based on recent trends, providing better flexibility in dealing with changes in demand.

CONCLUSION

This research proves that the Weighted Moving Average (WMA) method can be effectively implemented to forecast stock requirements in retail businesses, particularly in Bali. The results show that WMA provides accurate predictions, especially in products with stable demand patterns. For example, Dolphin products exhibited a low Mean Absolute Deviation (MAD) of 3.64, reflecting the method's precision in predicting stock levels. Even for products with volatile demand, such as Dua Kelinci, where fluctuations were more significant, WMA still managed to forecast reasonably accurate values, with a MAD of 4.3, demonstrating its robustness.The WMA method addressed the core challenge of balancing stock levels by offering a data-driven approach that helps reduce the risk of overstocking and understocking, which are common issues in the retail sector. This research contributes by demonstrating that WMA can be a reliable tool in optimizing stock forecasting and enhancing operational efficiency, particularly in the context of the digital economy.For future research, it is suggested to explore the integration of WMA with other advanced forecasting methods, such as machine learning or AI, to further improve accuracy in predicting highly volatile demand patterns. Additionally, applying the WMA method to a broader range of product categories can offer more insights into its adaptability and performance across different retail sectors.

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