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Implementation of Simple and Weighted Moving Average for Forecasting Tela-Tela Production in MSME X

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Abstract

Accurate production forecasting is essential for micro, small, and medium enterprises (MSMEs) to support effective production planning, inventory control, and decision-making. This study evaluates the performance of the Simple Moving Average (SMA) and Weighted Moving Average (WMA) methods in forecasting tela-tela production demand at MSME X using different historical period lengths. Production data from November 2023 to October 2024 were analyzed, and forecasting accuracy was assessed using the Mean Absolute Percentage Error (MAPE). The results indicate that forecasting accuracy varies depending on both the length of the moving average period and the weighting scheme applied. The WMA model with a 4-period window (n = 4) achieved the highest accuracy, producing the lowest MAPE value of 8.36%, which is classified as highly accurate. The SMA model with n = 4 also demonstrated good performance, with a MAPE value of 14.40%. Meanwhile, models employing longer historical periods (n = 8) yielded MAPE values of 16.20% for WMA and 19.82% for SMA, both falling within the good forecasting performance category but exhibiting lower responsiveness to recent demand changes. These findings highlight that shorter historical periods, when combined with appropriate weighting, can more effectively capture recent demand patterns in dynamic production environments. Accordingly, the WMA method with a 4-period window is recommended for MSME X as a reliable and accurate approach to support production planning, optimize resource allocation, and reduce the risk of overproduction or stock shortages.

Keywords: *Tela-Tela, Forecasting, Simple Moving Average, Weighted Moving Average, MAPE*

1. Introduction

Cassava (*Manihot esculenta*) is an important food commodity in Indonesia and ranks as the third major source of carbohydrates after rice and maize. This crop is easy to cultivate, capable of growing year-round in tropical regions, and exhibits high adaptability to various soil conditions, including dry and less fertile lands. Its relatively high productivity, moderate resistance to diseases, and flexible harvesting period make cassava a promising "living granary" for local communities. In addition to the tubers, cassava leaves can also be processed into a variety of food products, either as staple foods or snacks [1]. Cassava possesses a fairly complete nutritional profile. In 100 g of cassava tuber, there are approximately 34.7 g of carbohydrates, 1.2 g of protein, 33 mg of calcium, and 30 mg of vitamin C. By comparison, 100 g of cooked rice contains 79.34 g of carbohydrates, 6.6 g of protein, and 0.58 g of fat, while 100 g of maize contains 63.6 g of carbohydrates, 7.9 g of protein, and 3.4 g of fat. Based on this composition, cassava has considerable potential as an alternative carbohydrate source and is worthy of further development in efforts to promote national food diversification [2].

One form of diversification that can be pursued is the processing of cassava into *tela-tela*, a snack that is widely popular among consumers [3]. In its production process, cassava undergoes a series of stages, including cutting, frying, and seasoning, resulting in a product with a crispy exterior and a soft interior. Due to the high consumer demand for *tela-tela*, particularly in the city of Pontianak, MSME X (Figure 1) takes advantage of this opportunity to generate economic benefits. Nevertheless, the price of cassava as the main raw material tends to fluctuate, especially during certain seasons. When cassava supply declines, raw material prices increase significantly, leading to higher production costs. Therefore, the ability to conduct demand forecasting becomes crucial for MSME X.

By accurately predicting demand levels, the enterprise can plan raw material requirements, schedule cassava procurement before price surges, and adjust production capacity more efficiently. Demand forecasting also helps prevent stock shortages during periods of high demand as well as overproduction during periods of low demand, thereby supporting more stable operations and enhancing business competitiveness.

Figure 1. Tela-tela slices prepared to be fried (left) and documentation of interview session (right)

Moving Averages are among the most widely used forecasting methods in production and demand planning. This approach relies on historical data to predict future values, aiming to smooth out fluctuations and identify underlying trends over time. Several Moving Average methods have been developed, including the Simple Moving Average (SMA) and Weighted Moving Average (WMA) [4][5][6][7], Double Moving Average (DMA) [8][9], and Autoregressive Integrated Moving Average (ARIMA) [10][11][12][13][14]. DMA is an extension of the Simple Moving Average (SMA) that calculates the average of previous averages. This approach allows DMA to capture medium-term trends more effectively and is commonly applied in forecasting production or inventory based on historical data. Previously, Arsy et al. [8] implemented DMA by calculating the average of previous averages to forecast production at UMKM Biohart Yoghurt, whereas Pujiharta et al. [9] applied DMA for inventory forecasting in an automotive company, showing how historical data can be processed using the DMA method to generate more stable forecasts compared to a simple SMA.

ARIMA is a time series forecasting method that combines autoregressive (AR), integration (I), and moving average (MA) components to capture long-term and seasonal patterns. Previously, Wibowo et al. [10] implemented the ARIMA model for forecasting gold prices, including parameter identification (p, d, q), stationarity testing, and model construction using historical data. Saputra and Febrianti [11] applied ARIMA to inflation data, performing model identification and validation steps for time series prediction. Ajunu et al. [12] used ARIMA to forecast import values, following the standard procedure of parameter estimation and model fitting. Zahara et al. [13] implemented ARIMA in forecasting outpatient visits, processing historical records to build the predictive model. Santosa et al. [14] applied ARIMA to stock price data (LQ45), including model selection, parameter estimation, and construction of the forecast model.

Among moving average methods, the Simple Moving Average (SMA) and Weighted Moving Average (WMA) are the most commonly applied because of their simplicity and ease of use. SMA is a forecasting method that calculates predicted values by taking the average of a certain number of data points from previous periods without assigning different weights to each observation; all data points are assumed to contribute equally to the forecast. In contrast, WMA is a forecasting method that estimates future values by assigning specific weights to each data point within n previous periods according to their relative importance. The forecasted value is obtained by dividing the total weighted sum by the sum of the applied weights [4].

Various studies have demonstrated that the Simple Moving Average (SMA) and Weighted Moving Average (WMA) methods are effective for forecasting applications. Wulan and Riani [5] conducted a comparative analysis of several forecasting techniques, including SMA and WMA, to predict the sales volume of JNE logistics services at the Student Cooperative of Universitas Negeri Yogyakarta (UNY). Tamtama and Riantisari [6] also applied these methods to forecast service demand at Exist Auto Detailing. In addition, Darwati and Hayuningtyas [7] utilized SMA and WMA to estimate rice production in East Java Province. Meanwhile, Sariati et al. [4] implemented both methods in forecasting the production of yellow pumpkin chips in an MSME in Pontianak City. Based on the success of these previous studies, the present research adopts SMA and WMA to forecast *tela-tela*

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production demand at MSME X and evaluates forecasting accuracy using the Mean Absolute Percentage Error (MAPE).

2. Research Methods

This study adopts the forecasting methods proposed by Sariati et al. [4] and Aji et al. [15], with slight modifications tailored to the specific context of MSME X. The research procedure consists of three main stages designed to ensure a systematic and comprehensive approach. The first stage involves the collection of production demand data, which was conducted through direct observation of the production process and in-depth interviews with the owner of MSME X to obtain detailed insights into production patterns and constraints. The second stage focuses on performing forecasting calculations using two widely recognized methods, namely the Simple Moving Average (SMA) and the Weighted Moving Average (WMA), with variations in the historical period length to assess their impact on forecast accuracy. Finally, the third stage entails measuring and evaluating the forecasting accuracy of each method using the Mean Absolute Percentage Error (MAPE) to determine their reliability in predicting future production demand. Through these procedures, complete production data for tela-tela covering the period from November 2023 to October 2024 were successfully obtained as presented in Table 1.

Table 1. Tela-tela Production History by MSME X

Month	Year	Tela-tela Production (kg)
November	2023	300
December	2023	220
January	2024	260
February	2024	300
March	2024	100
April	2024	80
May	2024	300
June	2024	300
July	2024	300
August	2024	300
September	2024	290
October	2024	300

Based on production data up to October 2024, forecasts were generated for November 2024 (X_{t+1}) using SMA and WMA. The calculation for the SMA method is presented as follows [4][15]:

$$SMA_{t+1} = \frac{X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-n+1}}{n} \tag{1}$$

where:

- SMA_{t+1} = the forecasted value using the SMA method for the period following t
- X_t = the actual observed data in period t
- n = the number of periods used in the SMA calculation

In this study, the values of n were set to 4 and 8; therefore, SMA forecasting for the subsequent period was performed using production data from the previous four and eight months. Furthermore, the calculation for the WMA method is expressed as follows [4][15]:

$$WMA_{t+1} = \frac{(w_1 * X_t) + (w_2 * X_{t-1}) + \cdots + (w_n * X_{t-n+1})}{w_1 + w_2 + \cdots + w_n} \tag{2}$$

where:

- WMA_{t+1} = the forecasted value using the WMA method for the period following t
- X_t = the actual observed data in period t
- n = the number of periods used in the WMA calculation
- $w_1, w_2, \ldots, w_n$ = the weights assigned to each data point, where w_1 represents the weight of the most recent data and w_n represents the oldest data

Similar to the SMA method, the WMA approach in this study utilized n values of 4 and 8. Consequently, forecasts for the subsequent period were also derived from production data of the preceding four and eight months. In contrast to SMA, which assigns equal importance to all observations within the selected window, the WMA

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method allocates different weights to each period. Specifically, more recent production data are given higher weights, while older data receive progressively smaller weights. This weighting scheme reflects the assumption that recent production levels have a stronger influence on near-future outcomes than past observations. The specific weights applied to each period are summarized in Table 2.

Table 2. Weight Assignment for Weighted Moving Average (WMA)

Period	Weight Assignment for WMA	
	n = 4	n = 8
X_{t-7}	-	1
X_{t-6}	-	2
X_{t-5}	-	3
X_{t-4}	-	4
X_{t-3}	1	5
X_{t-2}	2	6
X_{t-1}	3	7
X_t	4	8
Σ Weight	10	36

The accuracy of the production forecasting results was evaluated using the Mean Absolute Percentage Error (MAPE) calculated in Microsoft Excel. MAPE is a widely used metric for assessing forecasting accuracy by expressing prediction errors as percentages, enabling intuitive interpretation and direct comparison among different forecasting models. One key advantage of MAPE is its scale-independent nature, which allows it to be applied to various datasets without being influenced by the magnitude of the observed values. MAPE is calculated by determining the absolute difference between the actual and forecasted values for each observation period, dividing this difference by the corresponding actual value, and multiplying the result by 100%. The resulting absolute percentage errors are then averaged across all observation periods to obtain a single MAPE value representing overall forecasting accuracy. By using absolute values, MAPE prevents positive and negative errors from offsetting each other, thereby providing a more reliable measure of forecasting deviation. The smaller the resulting MAPE value, the better the performance of the forecasting model. In this study, the MAPE calculation was conducted using production data from July to October 2024 to ensure a fair comparison across all forecasting methods, as this period corresponds to the time range for which actual and forecasts data were available for every model. The MAPE formula is presented as follows: [17]

$$MAPE\ (\%) = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Xt - Ft}{Xt}\right| x\ 100\% \tag{3}$$

where:

- X_t = the actual observed data in period t
- F_t = the forecasted value in period t
- n = the number of data points used in the MAPE calculation

To evaluate the performance level of a forecasting model, MAPE has specific value ranges that serve as evaluation benchmarks. Based on the classification of MAPE values, according to Nabillah and Ranggadara [16], a forecasting model is categorized as highly accurate when the MAPE value is less than 10%, indicating that the model produces very small deviations from actual values and is suitable for precise decision-making. A model is considered good when the MAPE falls within the range of 10–20%, suggesting that the forecasting results are still reliable and useful for most practical applications. When the MAPE value lies between 20–50%, the model performance is regarded as acceptable, meaning that although forecasting errors are relatively larger, the model can still provide a general trend or approximation of future values. However, if the MAPE value exceeds 50%, the forecasting model is classified as poor, as the predictions deviate substantially from the actual data and may lead to misleading conclusions or ineffective decision-making [16].

3. Results and Discussion

The results of the analysis obtained using the Simple Moving Average (SMA) and Weighted Moving Average (WMA) methods with 4-month and 8-month forecasting periods are presented in Tables 3 and 4, respectively, and are further illustrated in graphical form to facilitate interpretation of the forecasting behavior (Figure 2). Forecast values are not available for the initial months (November 2023 to February 2024 for 4-month forecasting period and November 2023 to June 2024 for 8-month forecasting period) because the minimum amount of historical data required to perform the moving average calculations had not yet been met. For the November 2024 forecast (X_{t+1}),

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the SMA method with a 4-month period produced an estimated production requirement of 297.5 kg, while the 8-month period yielded an estimate of 246.25 kg. By using the WMA method, the 4-month period resulted in a projected value of 297 kg, whereas the 8-month period produced a forecast of 280.28 kg. These results demonstrate that both the choice of forecasting method (SMA versus WMA) and the length of the averaging period (4 versus 8 months) significantly affect the forecasted production values.

Table 3. Tela-tela Production Forecasting at MSME X using Simple Moving Average (SMA)

Month	Year	Production Forecasting (kg)	
		SMA (n = 4)	SMA (n = 8)
November	2023	-	-
December	2023	-	-
January	2024	-	-
February	2024	-	-
March	2024	$\frac{(300+220+260+300)}{4} = 270.00$	-
April	2024	$\frac{(220+260+300+100)}{4} = 220.00$	-
May	2024	$\frac{(260+300+100+80)}{4} = 185.00$	-
June	2024	$\frac{(300+100+80+300)}{4} = 195.00$	-
July	2024	$\frac{(100+80+300+300)}{4} = 195.00$	$\frac{(300+220+260+300+100+80+300+300)}{8} = 232.50$
August	2024	$\frac{(80+300+300+300)}{4} = 245.00$	$\frac{(220+260+300+100+80+300+300+300)}{8} = 232.50$
September	2024	$\frac{(300+300+300+300)}{4} = 300.00$	$\frac{(260+300+100+80+300+300+300+300)}{8} = 242.50$
October	2024	$\frac{(300+300+300+290)}{4} = 297.50$	$\frac{(300+100+80+300+300+300+300+290)}{8} = 246.25$
November	2024	$\frac{(300+300+290+300)}{4} = 297.50$	$\frac{(100+80+300+300+300+300+290+300)}{8} = 246.25$

The forecasting performance of the Simple Moving Average (SMA) and Weighted Moving Average (WMA) models varied depending on the length of the historical period used. Based on the MAPE results, the WMA model with n = 4 achieved the lowest MAPE value of 8.36%, indicating the highest forecasting accuracy among all evaluated models. According to the MAPE classification criteria [16], this result falls within the highly accurate category (<10%), suggesting that the WMA method with a shorter historical window is capable of capturing recent demand patterns effectively.

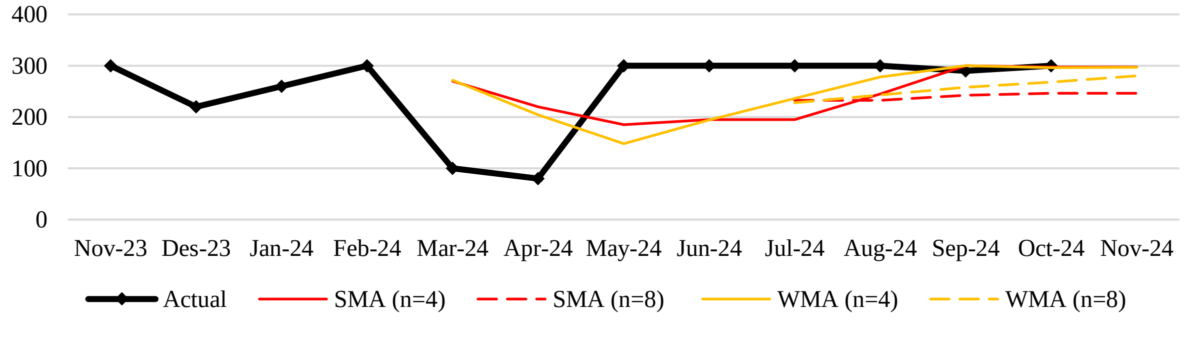

Figure 2. Actual production data and forecasting behavior of SMA and WMA

Table 4. Tela-tela Production Forecasting at MSME X using Weighted Moving Average (WMA)

Month	Year	Production Forecasting (kg)	
		WMA (*n* = 4)	WMA (*n* = 8)
November	2023	-	-
December	2023	-	-
January	2024	-	-
February	2024	-	-
March	2024	$\frac{(1*300)+(2*220)+(3*260)+(4*300)}{10}$ = 272.00	-
April	2024	$\frac{(1*220)+(2*260)+(3*300)+(4*100)}{10}$ = 204.00	-
May	2024	$\frac{(1*260)+(2*300)+(3*100)+(4*80)}{10}$ = 148.00	-
June	2024	$\frac{(1*300)+(2*100)+(3*80)+(4*300)}{10}$ = 194.00	-
July	2024	$\frac{(1*100)+(2*80)+(3*300)+(4*300)}{10}$ = 236.00	$\frac{(1*300)+(2*220)+(3*260)+(4*300)+(5*100)+(6*80)+(7*300)+(8*300)}{36}$ = 227.78
August	2024	$\frac{(1*80)+(2*300)+(3*300)+(4*300)}{10}$ = 278.00	$\frac{(1*220)+(2*260)+(3*300)+(4*100)+(5*80)+(6*300)+(7*300)+(8*300)}{36}$ = 242.78
September	2024	$\frac{(1*300)+(2*300)+(3*300)+(4*300)}{10}$ = 300.00	$\frac{(1*260)+(2*300)+(3*100)+(4*80)+(5*300)+(6*300)+(7*300)+(8*300)}{36}$ = 257.78
October	2024	$\frac{(1*300)+(2*300)+(3*300)+(4*290)}{10}$ = 296.00	$\frac{(1*300)+(2*100)+(3*80)+(4*300)+(5*300)+(6*300)+(7*300)+(8*290)}{36}$ = 268.33
November	**2024**	$\frac{(1*300)+(2*300)+(3*290)+(4*300)}{10}$ = 297.00	$\frac{(1*100)+(2*80)+(3*300)+(4*300)+(5*300)+(6*300)+(7*290)+(8*300)}{36}$ = 280.28

The SMA model with n = 4 also demonstrated good forecasting performance, yielding a MAPE value of 14.40%, which is classified as good accuracy (10–20%). This indicates that even with a relatively short averaging period, the SMA method can still provide acceptable forecasts, although it is less accurate than its weighted counterpart due to the equal weighting assigned to all observations. For models employing a longer historical window, the WMA model with n = 8 produced a MAPE value of 16.20%, while the SMA model with n = 8 resulted in a slightly higher MAPE value of 19.82%. Both values fall within the good forecasting performance category, indicating that longer-period models remain reliable; however, their accuracy is lower than that of the WMA model with n = 4. This suggests that incorporating older data may reduce responsiveness to recent changes in production demand, particularly in environments with short-term variability.

Table 5. MAPE calculation for each method

Method	MAPE (%)
Simple Moving Average (SMA) model (*n* = 4)	14.40
Simple Moving Average (SMA) model (*n* = 8)	19.82
Weighted Moving Average (WMA) model (*n* = 4)	8.36
Weighted Moving Average (WMA) model (*n* = 8)	16.20

Overall, these results indicate that shorter historical periods can yield superior forecasting accuracy when combined with appropriate weighting schemes, as demonstrated by the WMA model with n = 4. The weighting mechanism allows recent observations to exert greater influence on the forecast, making the model more responsive to current demand conditions. In contrast, longer historical periods provide a stronger smoothing effect but may dilute the impact of recent demand shifts. From a practical perspective, these findings highlight the importance of selecting an appropriate period length based on the characteristics of the production system. For MSMEs operating in dynamic or fluctuating markets, the WMA method with a shorter historical window (n = 4)

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is recommended, as it offers high accuracy while remaining responsive to recent changes. Nevertheless, longer-period models may still be useful in more stable demand environments where smoothing short-term fluctuations is prioritized. Selecting the optimal period length is therefore essential to improve forecasting accuracy, minimize the risk of overproduction or stock shortages, and support effective production planning and decision-making.

4. Conclusion

This study concludes that forecasting accuracy is influenced by both the length of the moving average period and the weighting scheme applied in the SMA and WMA methods. The results indicate that shorter historical periods can provide higher forecasting accuracy when combined with appropriate weighting, as demonstrated by the Weighted Moving Average (WMA) model with n = 4, which achieved the lowest MAPE value of 8.36% and was classified as highly accurate. The Simple Moving Average (SMA) model with n = 4 also produced acceptable forecasting performance, with a MAPE value of 14.40%, although its accuracy was lower than that of the weighted model due to the equal contribution of all observations. Meanwhile, models employing longer historical periods (n = 8) yielded MAPE values of 16.20% for WMA and 19.82% for SMA, both of which fall within the good performance category, indicating reliable but less responsive forecasting outcomes. These findings suggest that while longer periods enhance smoothing and stability, they may reduce sensitivity to recent demand changes. Therefore, for MSME X, which operates in a dynamic production environment, the WMA method with a 4-period window is recommended as the most suitable approach for supporting accurate production planning and effective decision-making.

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