
ACCURACY COMPARISON OF MOVING AVERAGE AND WEIGHTED MOVING AVERAGE METHODS FOR SALES FORECASTING

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Abstract: Sales forecasting supports production and raw-material planning in culinary businesses, yet small outlets often lack the long, multi-variable records that machine-learning models require. This study compares two simple and transparent methods, the 3-month Simple Moving Average (SMA) and Weighted Moving Average (WMA, weights 1-2-3), using monthly sales of ten burger products at Shizuka Burger Tower from January to December 2025. Accuracy was evaluated with the Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) over nine test months per product. Both methods were highly accurate, with MAPE below 10% for every product. The average MAPE was 3.46% for WMA and 3.58% for SMA, and WMA was more accurate for seven of the ten products, whereas SMA was better for Double Nugget, Single Patty, and Beef Patty. The advantage of WMA is therefore small and depends on the sales pattern: it appears for steadily growing products but not for products that fluctuate around a level. The results are compared with eight previous studies, and forecasts for January 2026 are reported. WMA is recommended as the default method for the outlet, with SMA as an alternative for irregular products.

Keyword: forecasting; moving average; sales prediction; SMA; WMA

Abstrak: Peramalan penjualan membantu perencanaan produksi dan bahan baku pada usaha kuliner, tetapi usaha kecil sering tidak memiliki data yang panjang dan multivariabel seperti yang dibutuhkan model pembelajaran mesin. Penelitian ini membandingkan dua metode sederhana, yaitu Simple Moving Average (SMA) 3 bulan dan Weighted Moving Average (WMA, bobot 1-2-3), menggunakan data penjualan bulanan sepuluh produk burger pada Shizuka Burger Tower dari Januari hingga Desember 2025. Akurasi dievaluasi dengan Mean Absolute Deviation (MAD), Mean Squared Error (MSE), dan Mean Absolute Percentage Error (MAPE) pada sembilan bulan pengujian untuk setiap produk. Kedua metode sangat akurat, dengan MAPE di bawah 10% untuk semua produk. Rata-rata MAPE sebesar 3,46% untuk WMA dan 3,58% untuk SMA, dan WMA lebih akurat pada tujuh dari sepuluh produk, sedangkan SMA lebih baik pada Double Nugget, Single Patty, dan Beef Patty. Keunggulan WMA dengan demikian kecil dan bergantung pada pola penjualan: tampak pada produk yang meningkat secara bertahap, tetapi tidak pada produk yang berfluktuasi di sekitar suatu level. Hasil dibandingkan dengan delapan penelitian terdahulu dan peramalan Januari 2026 dilaporkan. WMA direkomendasikan sebagai metode utama bagi usaha tersebut, dengan SMA sebagai alternatif untuk produk yang tidak beraturan.

Kata kunci: forecasting; moving average; prediksi penjualan; SMA; WMA

INTRODUCTION

Micro, small, and medium enterprises (MSMEs) play an important role in the Indonesian economy, including in the culinary sector. A recent systematic review found that MSMEs contribute significantly to gross domestic product and absorb a large share of the workforce, although they remain constrained by limited capital, uneven access to technology, and the quality of human resources (Zevender et al., 2026). Changing lifestyles have created good opportunities for burger businesses, but strong competition requires owners to manage operations effectively. An outlet such as Shizuka Burger Tower must know how many portions of each product it is likely to sell in the next period in order to decide production volumes and raw-material purchases. Over-estimating demand leaves unsold stock, whereas under-estimating it causes shortages and lost sales.

Forecast accuracy therefore has direct operational value. In retail, accurate sales forecasts affect supply-chain and storage costs, stock availability, and promotion planning (Eglite & Birzniece, 2022), and in restaurants, more accurate demand forecasts are argued to support purchase planning and to reduce food waste (Olivos et al., 2025). Forecasting is thus a basic tool for data-based decisions in culinary MSMEs.

The state of the art in demand forecasting is moving toward data-driven and hybrid models. Reviews classify forecasting approaches into qualitative, statistical, artificial-intelligence, and hybrid groups (Swaminathan & Venkitasubramony, 2024), and broad syntheses of forecasting theory and practice are available (Petropoulos et al., 2022). Deep learning has been reviewed extensively for retail sales (Eglite & Birzniece, 2022), and a review of hybrid statistical–neural models found ARIMA in about 80% and LSTM in about 60% of the studies examined, with ARIMA–LSTM the most frequent combination in several domains (Xhabafti & Sinaj, 2025). In food demand forecasting, LSTM and CNN-LSTM models reached about 92% accuracy against about 75% for ARIMA in a study whose data combined sales history with weather, holiday, and promotion variables (Jayamma et al., 2025), and gradient boosting gave the lowest error among six machine-learning models for predicting

restaurant food inputs, validated on one year of records from a single restaurant (Olivos et al., 2025). Large benchmarks such as the M5 competition work with 42,840 hierarchical Walmart unit-sales series (Makridakis et al., 2022), a scale far from that of a single outlet.

However, such models assume long histories, several explanatory variables, and the technical capacity to tune and maintain them. A small outlet like Shizuka Burger Tower typically has only monthly sales totals. For this reason, moving-average methods remain widely used in Indonesian MSME studies because they are easy to compute and to explain. The Simple Moving Average (SMA) averages the most recent observations with equal weights, whereas the Weighted Moving Average (WMA) gives larger weights to more recent data. Recent studies have applied them to stock planning (Robby & Santi, 2022; Febrianti et al., 2025), courier services (Wulan & Riani, 2024), small food producers (Riandi et al., 2024; Wiyanti et al., 2026), a coffee shop (Ramdani & Nawindah, 2025), a bakery (Juarsa et al., 2026), and a grocery store (Tako & Ilmananda, 2026).

Their conclusions are not consistent. Some report that WMA is slightly better than SMA (Tako & Ilmananda, 2026), others that SMA is better (Wulan & Riani, 2024), and others that exponential smoothing outperforms the moving-average family (Robby & Santi, 2022; Juarsa et al., 2026). Moreover, most of these studies analyse one product or one aggregated series, apply a single method, or concern non-food retail, and the reported error levels vary widely (roughly 2% to 23% MAPE). Evidence for a burger outlet with several menu items, evaluated product by product with several error measures, is limited; none of the studies reviewed here addresses this setting.

This study therefore (1) forecasts the monthly sales of ten burger products at Shizuka Burger Tower with 3-month SMA and WMA; (2) compares their accuracy using the Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE), both per product and on average; (3) reports the forecasts for January 2026; and (4) positions the findings against previous studies. Its contribution is a product-level comparison that shows when weighting recent data helps and when it does not, offering a

practical and low-cost basis for production and stock decisions.

METHOD

Research Framework

The research followed the framework shown in Image 1. It consisted of the collection of monthly sales data, tabulation of the data for ten products, forecasting with SMA and WMA, error measurement with MAD, MSE, and MAPE, classification of the accuracy level, comparison of the two methods, and forecasting of January 2026 sales.

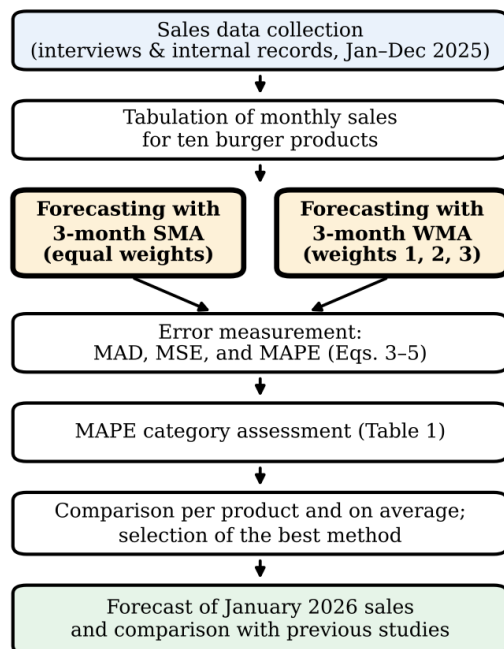


Image 1. Research framework

Data Collection

The data were obtained from Shizuka Burger Tower (Latsitarda Kisaran outlet) through interviews and internal sales records. They are monthly sales volumes, in portions, from January to December 2025 for ten products: Double Nugget, Nugget Egg, Nugget Cheese, Nugget Jumbo, Single Patty, Beef Patty, Shizuka Burger Tower, Burger 1M, Burger 2M, and Sostel. Each product therefore has 12 observations (Table 2).

Table 2. Monthly sales data of Shizuka Burger Tower, 2025 (portions)

Month	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Jan	125	102	97	88	124	111	76	92	81	105
Feb	120	100	99	90	122	122	78	94	83	107
Mar	122	104	102	91	126	119	75	94	84	108
Apr	125	110	103	90	131	131	81	97	86	110
May	125	105	100	93	137	128	83	99	85	112
Jun	120	112	102	94	125	122	84	100	88	114
Jul	118	108	106	96	129	123	86	99	91	116
Aug	122	100	104	99	137		85	103	90	117
Sep	126	104	106	97	133	117	89	105	94	119
Oct	120	110	108	100	135	126	90	106	95	121
Nov	125	112	111	102	147	134	87	103	93	123
Dec	130	108	114	105	132	125	94	110	99	125

P1 = Double Nugget; P2 = Nugget Egg; P3 = Nugget Cheese; P4 = Nugget Jumbo; P5 = Single Patty; P6 = Beef Patty; P7 = Shizuka Burger Tower; P8 = Burger 1M; P9 = Burger 2M; P10 = Sostel.

Simple Moving Average (SMA)

SMA forecasts the next period as the arithmetic mean of the n most recent observations (Equation 1):

$$SMA = (X_1 + X_2 + \dots + X_n) / n \quad (1)$$

where X_i is the actual sales in the i -th previous period and n is the number of periods in the average. This study uses $n = 3$, so the forecast for April is the mean of January, February, and March. Because all observations have equal weight, SMA smooths short-term fluctuations but reacts slowly when the sales level changes.

Weighted Moving Average (WMA)

WMA assigns larger weights to more recent observations (Equation 2):

$$WMA = \sum (w_i \cdot X_i) / \sum w_i \quad (2)$$

where w_i is the weight of period i . Weights of 3, 2, and 1 were used for the most recent, second most recent, and third most recent month, respectively ($\sum w_i = 6$). Image 2 illustrates both calculations for the April forecast of Double Nugget.

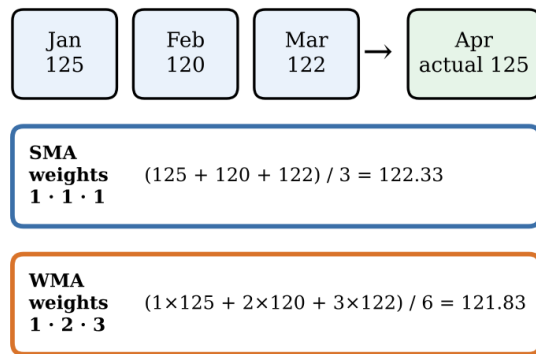


Image 2. Illustration of the 3-month SMA and WMA calculation (Double Nugget, April forecast)

Forecast Accuracy Measures

Forecast accuracy was measured by comparing the forecast F_t with the actual value A_t over the n test periods. Three indicators, also used in recent MSME forecasting studies (Ramdani & Nawindah, 2025; Tako & Ilmananda, 2026; Juarsa et al., 2026), were applied (Equations 3–5):

$$MAD = (1/n) \cdot \sum |A_t - F_t| \quad (3)$$

$$MSE = (1/n) \cdot \sum (A_t - F_t)^2 \quad (4)$$

$$MAPE = (100\% / n) \cdot \sum |A_t - F_t| / A_t \quad (5)$$

Smaller values indicate higher accuracy. MAD expresses the average error in portions, MSE penalises large errors more heavily, and MAPE expresses the error relative to actual sales, which allows comparison between products with different volumes. Because the first forecast requires three previous months, forecasts start in April, so $n = 9$ (April–December) for every product. The MAPE values were classified using Table 1 (Tako & Ilmananda, 2026).

Table 1. MAPE ranges and their forecasting categories

MAPE range	Category
< 10%	Highly accurate forecasting
10–20%	Good forecasting
20–50%	Reasonable forecasting
> 50%	Inaccurate forecasting

The methods were compared at three levels: a worked example for Double Nugget, MAPE for each product, and the average over the ten products together with the number of products for which each method gave the lower MAPE. Finally, the forecasts for January 2026

were computed from the October–December 2025 data.

RESULT AND DISCUSSIONS

Sales Data Pattern

The monthly sales in Table 2 are stable and usually change by only a few portions between consecutive months, but the patterns differ between products. Several products grow gradually: Shizuka Burger Tower rose from 76 to 94 portions (+23.7%) and Sostel from 105 to 125 portions (+19.0%) between January and December. Others, such as Double Nugget (118–130 portions) and Single Patty (122–147 portions), fluctuate around a level without a clear trend. These two patterns matter for how the two methods behave.

Worked Example: Double Nugget

Tables 3 and 4 show the SMA and WMA calculations for Double Nugget. For SMA, MAD = the total absolute error of 32.33 over nine months gives MAD = 3.59 portions, MSE = 16.14, and MAPE = 2.90%. For WMA, the corresponding values are MAD = 3.81, MSE = 16.80, and MAPE = 3.08%.

Table 3. SMA calculation for Double Nugget

Month	Actual	Forecast	Error	Error	Error ²	APE (%)
Jan	125	–	–	–	–	–
Feb	120	–	–	–	–	–
Mar	122	–	–	–	–	–
Apr	125	122.33	2.67	2.67	7.11	2.13
May	125	122.33	2.67	2.67	7.11	2.13
Jun	120	124.00	-4.00	4.00	16.00	3.33
Jul	118	123.33	-5.33	5.33	28.44	4.52
Aug	122	121.00	1.00	1.00	1.00	0.82
Sep	126	120.00	6.00	6.00	36.00	4.76
Oct	120	122.00	-2.00	2.00	4.00	1.67
Nov	125	122.67	2.33	2.33	5.44	1.87
Dec	130	123.67	6.33	6.33	40.11	4.87
Total				32.33	145.22	26.11
Mean				3.59	16.14	2.90

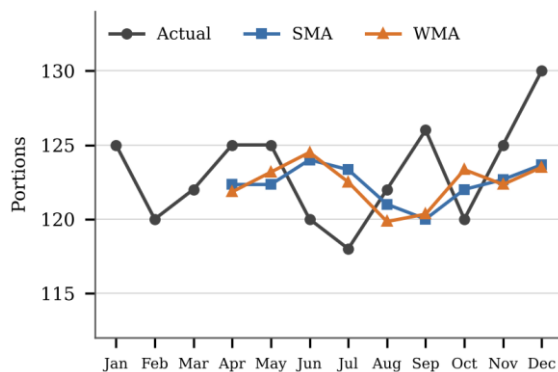
Table 4. WMA calculation for Double Nugget

Month	Actual	Forecast	Error	Error	Error ²	APE (%)
Jan	125	—	—	—	—	—
Feb	120	—	—	—	—	—
Mar	122	—	—	—	—	—
Apr	125	121.83	3.17	3.17	10.03	2.53
May	125	123.17	1.83	1.83	3.36	1.47
Jun	120	124.50	-4.50	4.50	20.25	3.75
Jul	118	122.50	-4.50	4.50	20.25	3.81
Aug	122	119.83	2.17	2.17	4.69	1.78
Sep	126	120.33	5.67	5.67	32.11	4.50
Oct	120	123.33	-3.33	3.33	11.11	2.78
Nov	125	122.33	2.67	2.67	7.11	2.13
Dec	130	123.50	6.50	6.50	42.25	5.00
Total				34.33	151.17	27.75
Mean				3.81	16.80	3.08

Table 5. Accuracy of SMA and WMA for Double Nugget

Method	MAD	MSE	MAPE (%)
Simple Moving Average (SMA)	3.59	16.14	2.90
Weighted Moving Average (WMA)	3.81	16.80	3.08

Both methods are highly accurate for this product, with MAPE below 10%, and SMA is slightly better on all three indicators. Image 3 shows why: the actual series fluctuates around a level of about 122 portions, so the forecasts of both methods stay close to that level, and the heavier weight that WMA gives to the latest month carries some of its short-term noise into the next forecast.

**Image 3. Actual sales and SMA and WMA forecasts for Double Nugget**

Accuracy of SMA and WMA for Each Product

Image 4 shows that the accuracy of SMA varies between products, which indicates that forecast quality depends on the demand pattern of each menu item. Nugget Cheese has the lowest MAPE (2.71%), meaning that its sales were relatively stable and the SMA forecasts were close to the actual values. Beef Patty has the highest MAPE (4.98%), which is still far below the 10% limit of the highly accurate category. All ten products are therefore in the highly accurate category under SMA.

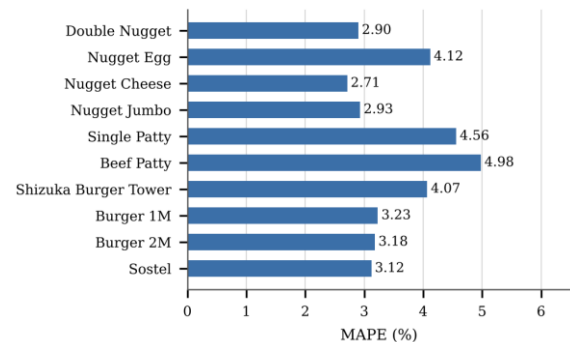
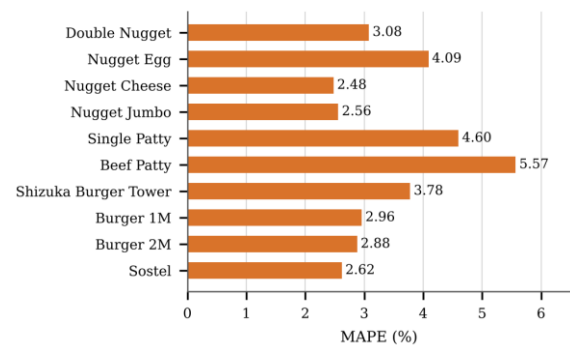
**Image 4. MAPE of SMA for each product**

Image 5 shows the same analysis for WMA. Nugget Cheese again has the lowest MAPE (2.48%) and Beef Patty the highest (5.57%); all products remain below 10%, so all are also in the highly accurate category under WMA.

**Image 5. MAPE of WMA for each product**

Comparison of SMA and WMA

Table 6 and Image 6 compare the two methods. The average MAPE is 3.58% for SMA and 3.46% for WMA, so both are in the highly accurate category and their accuracy is very close. WMA has the lower MAPE in seven of the ten products (Nugget Egg, Nugget Cheese, Nugget Jumbo, Shizuka Burger Tower, Burger 1M, Burger 2M, and Sostel), whereas SMA is better in three (Double Nugget, Single Patty, and

Beef Patty). The three indicators rank the methods identically for every product. The overall difference is small (0.12 percentage points); WMA's largest advantage is for Sostel (0.50 points), while SMA's largest advantage is for Beef Patty (0.59 points).

Table 6. Accuracy of SMA and WMA for the ten products

Product	SMA MAD	SMA MSE	SMA MAPE	WMA MAD	WMA MSE	WMA MAPE
Double Nugget	3.59	16.14	2.90	3.81	16.80	3.08
Nugget Egg	4.44	29.33	4.12	4.41	27.96	4.09
Nugget Cheese	2.93	11.57	2.71	2.67	9.48	2.48
Nugget Jumbo	2.88	10.74	2.93	2.53	8.59	2.56
Single Patty	6.18	49.62	4.56	6.22	54.40	4.60
Beef Patty	6.41	69.97	4.98	7.12	75.24	5.57
Shizuka Burger Tower	3.52	14.85	4.07	3.28	13.21	3.78
Burger 1M	3.33	13.06	3.23	3.06	11.30	2.96
Burger 2M	2.92	11.25	3.18	2.67	9.70	2.88
Sostel	3.67	13.57	3.12	3.07	9.56	2.62
Average	3.99	24.01	3.58	3.88	23.62	3.46

MAD in portions; MSE in portions²; MAPE in %. Bold: lower MAPE of the two methods.

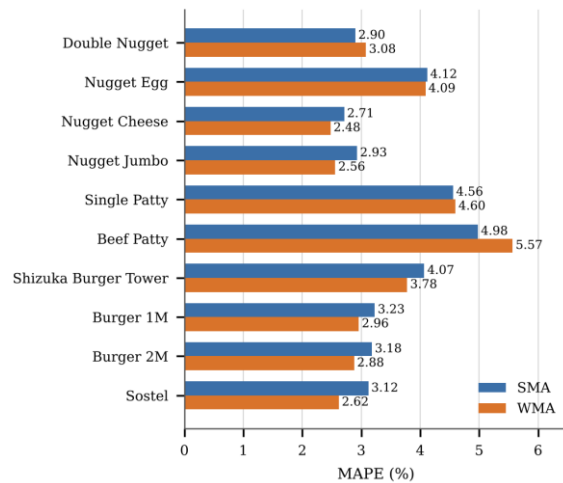


Image 6. Comparison of the MAPE of SMA and WMA for each product

The pattern of the results is consistent with how the two methods work. WMA is better for products with steadily rising sales (Sostel, Burger 1M, Burger 2M, Shizuka Burger Tower, Nugget Cheese, and Nugget Jumbo), where recent months are a better guide to the next month than older ones. SMA is better for products that fluctuate around a level without a clear trend (Double Nugget, Single Patty, and Beef Patty), where a heavy weight on the latest month passes its random deviation into the forecast. This explanation fits the data patterns described above but was not tested statistically.

Forecast for January 2026

Table 7 presents the January 2026 forecasts computed from the October–December 2025 sales. WMA gives higher forecasts than SMA for seven of the ten products, mainly those with rising sales, because it places the largest weight on December sales.

Table 7. Forecast of January 2026 sales (portions)

Product	SMA	WMA
Double Nugget	125.0	126.7
Nugget Egg	110.0	109.7
Nugget Cheese	111.0	112.0
Nugget Jumbo	102.3	103.2
Single Patty	138.0	137.5
Beef Patty	128.3	128.2
Shizuka Burger Tower	90.3	91.0
Burger 1M	106.3	107.0
Burger 2M	95.7	96.3
Sostel	123.0	123.7

Comparison with Previous Studies

Table 8 places the findings among eight recent studies that used moving-average-type methods. First, the accuracy level obtained here (average MAPE 3.46–3.58%) is considerably better than that of the other studies that report MAPE for comparable methods: about 21–22% for grocery products (Tako & Ilmananda, 2026), 23% for coffee sales (Ramdani & Nawindah, 2025), 14.31% for a two-period moving average on bakery sales (Juarsa et al., 2026), 10.73% for salted-egg sales (Wiyanti et al., 2026), and 9.43% for rice stock (Febrianti et al., 2025). Only the nasi bakar study (Riandi et al., 2024) reports a lower MAPE (1.98%), for a single product with sales between about 740 and 805 packs. The smooth series of Shizuka Burger Tower, with month-to-month changes of a few portions in a single outlet, probably explains the low error, so the accuracy should not be generalised to more volatile products.

Table 8. Comparison with previous studies

Study	Object and data	Methods	Best method (reported result)
Robby & Santi (2022)	Printer-ink store; historical sales for stock	WMA, SMA, DES	DES (lowest average MSE)
Wulan & Riani (2024)	Courier service; monthly sales, 2022	Naive, SMA-3, WMA-3	SMA-3 (MPE 12.07% vs 14.27% WMA and 20.26% naive)
Riandi et al. (2024)	Nasi bakar MSME; 19 months	WMA-3 (0.2/0.3/0.5)	WMA only; MAPE 1.98%
Ramdani & Nawindah (2025)	Coffee shop; historical sales	SES, SMA	Mixed: SMA better on MAPE (average 23%); SES better on MAD and MSE for some products
Febrianti et al. (2025)	Rice wholesaler; Jan 2024–Jan 2025	SMA	SMA only; MAD 23.32, MSE 1,203.20, MAPE 9.43%
Tako & Ilmananda (2026)	Grocery store; 10 products, Jan–Sep 2025	SMA-3, WMA-3	WMA (average MAPE 21.07% vs 21.74%), not consistent across products
Juarsa et al. (2026)	Bakery MSME; monthly sales, 2024	MA-2, exponential smoothing	ES, $\alpha = 0.4$ (MAPE 11.47% vs 14.31%)
Wiyanti et al. (2026)	Salted-egg MSME; monthly sales, 2025	SMA-3	SMA only; MAPE 10.73%
This study	Burger outlet; 10 products, Jan–Dec 2025	SMA-3, WMA-3 (weights 1-2-3)	WMA (average MAPE 3.46% vs 3.58%); SMA better for 3 products

SES = single exponential smoothing; DES = double exponential smoothing; MA-2 = two-period moving average; MPE = mean percentage error. Results are as reported by the authors.

Second, the ranking of the methods agrees with part of the literature. The small average advantage of WMA found here is in line with Tako and Ilmananda (2026), who also compared the two methods across ten products and found a small WMA advantage that was not consistent across products, and with the very low error that Riandi et al. (2024) obtained with WMA. In contrast, Wulan and Riani (2024) found 3-month SMA better than WMA for courier sales, while Robby and Santi (2022) and Juarsa et al. (2026) preferred exponential smoothing. The product-level results of this study help to reconcile these findings: SMA was better for products that fluctuate around a level, as in Wulan and Riani (2024), and WMA was better for steadily growing products. The choice of method therefore depends on the demand pattern rather than on a universal ranking. In addition, Ramdani and Nawindah (2025) found that the preferred method changed with the error measure, which supports reporting several indicators, as done here; in our data MAD, MSE, and MAPE agreed for every product.

Third, machine-learning approaches report high accuracy (Jayamma et al., 2025; Olivos et

al., 2025) but use richer data, such as weather, holiday, promotion, and inventory records, and different error measures, so their results cannot be compared directly with those reported here. With only 12 monthly observations per product, such models would likely have too little data to train reliably, so SMA and WMA are a pragmatic baseline for this outlet. As more data accumulate, machine-learning and hybrid models (Xhabafti & Sinaj, 2025) can be tested against these baselines. Moving averages also do not model seasonality; for tuberculosis case data, time-series decomposition outperformed the moving average (Novanda & Hidayati, 2024), which signals that seasonal products will need methods that capture seasonal effects.

Practical Implications and Limitations

For the owner, WMA is a suitable default method for planning production and raw-material stock, with SMA as a reasonable alternative for the products that fluctuate around a stable level (Double Nugget, Single Patty, and Beef Patty). Both methods can be updated each month in a spreadsheet without special software.

Several limitations should be noted. The data come from one outlet and one year, giving nine test months per product; the window length (3 months) and the weights (3-2-1) were fixed and not optimised; the difference between the methods is small and was not tested statistically; seasonal effects cannot be assessed with 12 months; and the data, which came from interviews and internal records, may contain recording errors. External factors such as promotions and holidays were not modelled.

CONCLUSION

This study compared the accuracy of the 3-month SMA and WMA for forecasting the monthly sales of ten burger products at Shizuka Burger Tower in 2025. Both methods were highly accurate for every product (MAPE below 10%). The average MAPE was 3.46% for WMA and 3.58% for SMA, and WMA was better for seven of the ten products, while SMA was better for Double Nugget, Single Patty, and Beef Patty. WMA is therefore recommended as the default method for the outlet, but its advantage is small and depends on the sales pattern: it appears for steadily growing products and not for products that fluctuate around a level. Compared with

previous studies, the error levels here are low, probably because the sales series are smooth. Future research should use longer series to capture seasonality, optimise the window length and weights, include external factors such as promotions and holidays, and test exponential smoothing and machine-learning models against these baselines.

ACKNOWLEDGMENT

The authors thank Shizuka Burger Tower for providing the sales data used in this study.

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