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Research Paper

Accuracy Evaluation of Weighted Moving Average and Quadratic Trend for Production and Inventory Planning of Retread Rubber

Imam Husni Al Amin[1]*, Fatkhul Amin[2], Fendy Widianto[3], Muhammad Rafi Haidar Arsyad[4], Ratih Milati Ilham[5], Fithri Widyanita Yarisma[6]
[1,3]*Faculty of Information Technology, Universitas Stikubank, Semarang, Indonesia*
[2,5,6]*Faculty of Economic and Business, Universitas PGRI, Semarang, Indonesia*
[3]*Faculty of Sain and Technology, Universitas USTEDI Semarang, Indonesia*
**Corresponding author*

Abstract*—Unvalidated forecasts may cause stockouts, lost sales, or excess production. This study evaluates a three-period Weighted Moving Average (WMA) and a quadratic trend model as inputs for the production and inventory planning of retread rubber at PT Bernike Semarang. Monthly sales data from January to December 2025 were assessed using one-step-ahead rolling-origin validation for July–December 2025, with the naïve method as a baseline. Performance was measured using mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), bias, and tracking signal. A sensitivity analysis of four WMA weighting schemes was also conducted. The naïve method achieved the lowest MAPE of 4.55%, followed by the quadratic trend at 6.14% and WMA 1:2:3 at 7.00%. The quadratic trend outperformed WMA but tended to over-forecast with a bias of −IDR 45.13 million, whereas WMA consistently under-forecast with a bias of IDR 91.18 million. Assigning greater weights to recent observations reduced WMA MAPE to 6.27%, but it still did not outperform the naïve benchmark. The 2027 extrapolation produced widely divergent annual scenarios, indicating that long-horizon forecasts should not be used without actual observations and periodic model updating. Managerially, the company is advised to use the naïve baseline for short-term operational planning, the quadratic trend as an upper scenario, and monthly forecast reviews linked to safety stock, lead time, capacity, and service-level targets.*

Keywords*—forecast accuracy, production planning, quadratic trend, retread rubber, weighted moving average*

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I. INTRODUCTION

Demand forecasting is an initial stage of operations planning because it affects material purchasing, capacity determination, production scheduling, inventory, distribution, and service targets. Forecasts that are too low increase the risks of stockouts, lost sales, and delayed order fulfillment, whereas forecasts that are too high may increase holding costs and working capital. Forecast quality should therefore be assessed not only by its fit to historical data but also by its ability to support consistent operational decisions (Petropoulos et al., 2022; Fildes et al., 2022).

Industrial forecasting practice does not always require complex models. With short datasets, simple models are often more stable, easier to audit, and easier to translate into production policies. Large-scale forecasting competitions have also shown that sophisticated models do not consistently outperform simpler alternatives across all series; therefore, simple benchmarks remain necessary for assessing the added value of a method (Makridakis et al., 2022). In this context, moving average, weighted moving average, exponential smoothing, trend regression, and the naïve method remain relevant operational decision-support tools.

Weighted Moving Average (WMA) assigns greater weights to the most recent observations and is therefore intuitively more responsive to changes in demand. However, the model still smooths the data and may lag when a series is continuously increasing or decreasing. A quadratic trend can follow nonlinear changes, but its extrapolation may grow too rapidly outside the observed data range. These characteristics indicate that model selection should be based on out-of-sample evaluation rather than solely on in-sample fit or graphical appearance (Hyndman & Athanasopoulos, 2021; Hewamalage et al., 2023).

Several Indonesian industrial engineering studies have applied simple methods to inventory and production problems. Albani and Wahyudin (2024) obtained a MAPE of 13.70% for exponential smoothing in forecasting packaging requirements, whereas Sigit and Herwanto (2024) found that a three-month moving average produced a lower MSE than double exponential smoothing for oil-filter inventory. In bulk cement production, Single Exponential Smoothing yielded the lowest MSE compared with Moving Average and WMA (Erlangga& Pulansari, 2025). These varying results confirm that forecasting performance is data-dependent and must be tested against the specific characteristics of each case.

Other studies also demonstrate the importance of comparing more than one model. Aryadinata and Waluyo (2025) selected Single Exponential Smoothing because it produced the lowest MAPE for towel products, whereas Nasution et al. (2026) reported that linear regression outperformed moving average and double exponential smoothing for packaging-item demand. Juanda and Debora (2026) showed that moving average provides stable forecasts, while linear regression provides more explicit trend information. Awwaluddin and Wahyudin (2026) framed forecasting-method selection as an effort to reduce the risk of raw-material overstock. Although practically relevant, some studies still rely on a single data split, a single error measure, or omit a very simple baseline.

PT Bernike Semarang produces and sells rubber for tire-retreading applications. The sales data show a decline at the beginning of 2025 and a relatively consistent increase from the middle of the year. This condition makes it difficult for the company to determine production and inventory levels when decisions rely only on managerial intuition. The original article on this case focused primarily on application development, use-case, activity, and sequence diagrams, and interface displays, while model-accuracy evaluation and production implications were not the main emphasis. For an industrial engineering and management article, the more important aspects are forecast validity, error patterns, bias risk, and the linkage between results and operational decisions.

The research gap concerns the absence of an evaluation of WMA and quadratic trend using rolling-origin validation, a naïve baseline, multiple accuracy measures, bias analysis, and weight sensitivity. This study offers four contributions: transparently recalculating both models; testing one-step-ahead performance at multiple forecast origins; examining whether more aggressive weights improve WMA; and translating statistical results into production and inventory recommendations. This focus distinguishes the study from research that reports only a final forecast value or application output.

TABLE I
COMPARISON OF PREVIOUS STUDIES AND THE POSITION OF THIS RESEARCH

Study	Methods, findings, and research gap
Albani & Wahyudin (2024)	MA and exponential smoothing evaluated with MAPE; exponential smoothing performed best, but rolling-origin validation and bias were not discussed.
Sigit & Herwanto (2024)	DES and three-month MA evaluated with MSE; MA performed better for oil-filter inventory, but the focus was on final inventory outcomes.
Erlangga & Pulansari (2025)	MA, WMA, and SES evaluated with MSE; SES performed best, showing that WMA is not always superior for short datasets.
Nasution et al. (2026)	DES, MA, and linear regression evaluated using MSE and tracking signal; linear regression performed best for data with a trend.
This study	Naïve, WMA, and quadratic trend; rolling-origin validation, MAE, RMSE, MAPE, bias, tracking signal, weight sensitivity, and production implications.

2. METHODOLOGY

2.1 Research Design

This research employs a quantitative case-study design with univariate time-series analysis. The unit of analysis is the monthly sales value of retread rubber in Indonesian rupiah. The research stages include data checking, descriptive analysis, model development, rolling-origin validation, calculation of error measures, weight-sensitivity analysis, scenario development, and managerial interpretation, as shown in Figure 1. The method is not selected from a single future forecast but from error patterns across several periods for which actual values are already available.

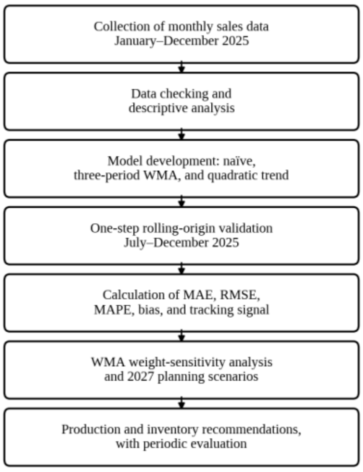

Figure 1. Research and model-evaluation workflow

2.2 Data and Preprocessing

Secondary data were obtained from PT Bernike Semarang's monthly sales records for January–December 2025. The original values were expressed in rupiah and converted to IDR million to improve table readability. Initial checks covered the completeness of the 12 periods, chronological order, zero values, and unit consistency. No imputation was performed because all months were available. The use of sales value rather than unit volume was retained to remain consistent with the source data; however, its implications are discussed as a limitation because price changes may affect the observed sales value.

TABLE II
RETREAD RUBBER SALES DATA FOR 2025

Mo.	Sales	Mo.	Sales
Jan	1,131.72	Jul	1,222.05
Feb	1,112.76	Aug	1,199.55
Mar	1,135.68	Sep	1,314.03
Apr	1,035.48	Oct	1,344.72
May	1,012.95	Nov	1,384.71
Jun	1,117.86	Dec	1,427.49

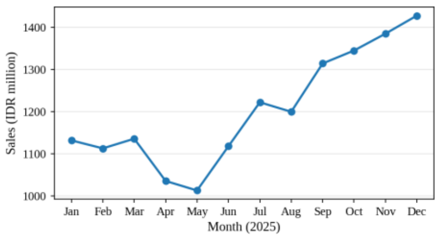

Figure 2. Monthly sales trend in 2025

2.3 Weighted Moving Average Model

The three-period WMA uses the three most recent observations and assigns larger weights to periods closer to the forecast origin. The main formulation uses a 1:2:3 ratio, resulting in normalized weights of 1/6, 2/6, and 3/6. This approach is simple and can be implemented easily in a spreadsheet or information system, but theoretically it still exhibits lag when a trend changes rapidly (Hyndman & Athanasopoulos, 2021).

$$F_t = (Y_{t-3} + 2Y_{t-2} + 3Y_{t-1}) / 6 \qquad (1)$$

where F_t is the forecast for period t and Y is the actual value. To evaluate the dependence of the results on weight selection, a sensitivity analysis was conducted for the 1:1:1, 1:2:3, 1:3:5, and 1:4:7 schemes. All schemes use a three-period window so that performance differences arise from weighting intensity rather than a change in window length.

2.4 Quadratic Trend Model

The quadratic trend assumes that the relationship between time and sales value follows a parabola. Parameters a, b, and c are estimated using least squares. When all 2025 data are modeled, time is coded as $t = -11, -9, ..., 11$ so that the midpoint of the series is close to zero and numerical correlation among parameters is reduced.

$$F_t = a + bt + ct^2 \qquad (2)$$

Estimation using all 2025 observations produced a = IDR 1,144.70 million, b = IDR 16.12 million, and c = IDR 1.23 million. The positive value of c indicates an accelerating increase at the end of the series. However, the quadratic coefficient may also cause forecasts to rise rapidly when the horizon is extended; therefore, one-step validation and horizon restrictions are essential.

2.5 Baseline and Rolling-Origin Validation

The naïve method is used as a baseline by setting the forecast for period t equal to the actual value in period t−1. A baseline is required because a more complex model should be selected only when it provides a consistent improvement over the simplest rule (Hewamalage et al., 2023). Validation was conducted for July–December 2025. At each origin, a model used only data available up to the preceding month and generated a one-step-ahead forecast. The quadratic trend model was re-estimated at each origin. This procedure preserves chronological order and prevents future observations from entering model training, consistent with out-of-sample time-series evaluation principles (Tashman, 2000).

2.6 Accuracy Measures and Bias Diagnostics

Performance was assessed using MAE, RMSE, MAPE, bias, cumulative forecast error (CFE), and tracking signal. MAE represents the average absolute error, RMSE assigns a greater penalty to extreme errors, and MAPE facilitates percentage-based interpretation. No single measure is universally superior; therefore, model selection should consider several measures simultaneously (Hyndman & Koehler, 2006).

$$MAE = (1/n)\ \Sigma\ |Y_t - F_t| \qquad (3)$$
$$RMSE = \sqrt{[(1/n)\ \Sigma\ (Y_t - F_t)^2]} \qquad (4)$$
$$MAPE = (100/n)\ \Sigma\ |(Y_t - F_t)/Y_t| \qquad (5)$$
$$Bias = (1/n)\ \Sigma\ (Y_t - F_t) \qquad (6)$$
$$Tracking\ signal = CFE / MAD \qquad (7)$$

A positive bias means that the model tends to under-forecast, whereas a negative bias indicates over-forecasting. Because all actual values are far from zero, MAPE remains applicable in this study. The tracking signal is used as an additional indicator of accumulated error direction rather than as the sole decision criterion. The results are then translated into production risks: under-forecasting is associated with stock shortages and service loss, whereas over-forecasting is associated with excess production and holding costs.

III. RESULTS AND DISCUSSION

3.1 Characteristics of the Sales Data

Sales in 2025 averaged IDR 1,203.25 million with a standard deviation of IDR 136.64 million, resulting in a coefficient of variation of 11.36%. The minimum value occurred in May at IDR 1,012.95 million, while the maximum occurred in December at IDR 1,427.49 million. December sales were 26.13% higher than January sales, equivalent to compound growth of approximately 2.13% per month over eleven intervals. The pattern in Figure 2 shows two phases: weakening through May and a strong recovery beginning in June. This phase change explains why moving-average-based models may lag during the second half of the year.

TABLE III
DESCRIPTIVE STATISTICS OF 2025 SALES

Measure	Value
Number of observations	12 months
Mean	IDR 1,203.25 million
Standard deviation	IDR 136.64 million
Coefficient of variation	11.36%
Minimum	IDR 1,012.95 million (May)
Maximum	IDR 1,427.49 million (December)
Jan–Dec growth	26.13%

The increase was not uninterrupted. August sales decreased by 1.84% from July, but September sales grew again by 9.54%. Such local fluctuations may cause the quadratic trend to react too strongly, while WMA may over-smooth the change. With only 12 observations, seasonality cannot be identified reliably because more than one annual cycle is required. Accordingly, this research limits its interpretation to short-term trends and validation-error patterns.

3.2 Rolling-Origin Validation Results

TABLE IV
ONE-STEP-AHEAD FORECASTS FOR JULY–DECEMBER 2025

Period	Actual	Naïve	WMA	Quadratic
Jul	1,222.0	1,117.9	1,069.2	1,117.1
Aug	1,199.5	1,222.0	1,152.5	1,301.1
Sep	1,314.0	1,199.5	1,193.4	1,319.1
Oct	1,344.7	1,314.0	1,260.5	1,423.6
Nov	1,384.7	1,344.7	1,310.3	1,479.8
Dec	1,427.5	1,384.7	1,359.6	1,522.7

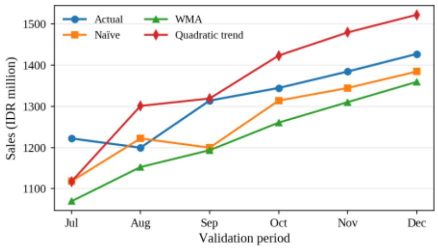

Figure 3. Comparison of actual values and forecasts during the validation period

In July, all models produced forecasts below the actual value because the sales increase had not yet been reflected in previous data. After July, the naïve method immediately adjusted to the higher level and over-forecast only in August. WMA remained below the actual value throughout the validation period. The quadratic trend was close to the actual value in September but moved above the actual values in October–December. These different patterns confirm that average error measures should be interpreted together with error direction.

3.3 Comparison of Accuracy and Bias

TABLE V
ACCURACY MEASURES AND ERROR DIAGNOSTICS

Method	MAE	RMSE	MAPE	Bias	CFE	TS
Naïve	59.11	69.33	4.55%	51.61	309.63	5.24
Quadratic	80.11	87.25	6.14%	−45.13	−270.79	−3.38
WMA 1:2:3	91.17	97.78	7.00%	91.17	547.05	6.00

Table V shows that the naïve method produced the lowest MAE, RMSE, and MAPE. A MAPE of 4.55% means that, on average across the six periods, the absolute deviation was approximately 4.55% of the actual value. The quadratic trend ranked second with a MAPE of 6.14%, followed by WMA 1:2:3 at 7.00%. This finding is consistent with the principle that simple models should be used as benchmarks because additional complexity does not automatically improve accuracy (Hewamalage et al., 2023; Makridakis et al., 2022).

Between the two main methods, the quadratic trend was more accurate than WMA. However, its bias was −IDR 45.13 million, indicating a tendency to over-forecast. WMA had a bias of IDR 91.18 million and all its residuals were positive, meaning that it systematically under-forecast during the growth phase. The WMA tracking signal of 6.00 and naïve tracking signal of 5.24 indicate the accumulation of errors in the same direction, whereas the quadratic trend value of −3.38 indicates a tendency in the opposite direction. These values should be interpreted cautiously because the validation sample contains only six periods.

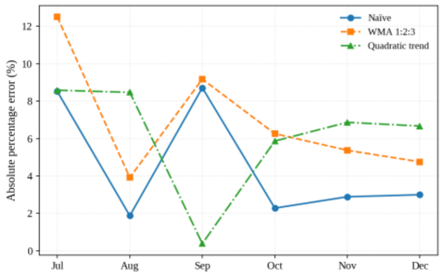

Figure 4. Monthly absolute percentage error during the validation period

Figure 4 shows that the advantage of the naïve method does not arise from being the best model in every month. In August, WMA error was lower than those of the naïve and quadratic-trend models. In September, the quadratic trend was nearly equal to the actual value. Nevertheless, the naïve method was more consistent in October–December and did not generate an extreme error. Model selection is therefore based on stability across forecast origins rather than on one period that happens to be highly accurate.

3.4 Sensitivity Analysis of WMA Weights

WMA weights are often selected subjectively. To determine whether the weakness of WMA 1:2:3 resulted from insufficient responsiveness, four schemes were tested using the same three-month window. Table VI and Figure 5 show that greater emphasis on the most recent observation reduced the error. MAPE decreased from 8.46% with equal weights to 6.27% with the 1:4:7 scheme.

TABLE VI
SENSITIVITY OF WMA WEIGHTING SCHEMES

Scheme	MAE	RMSE	MAPE	Bias
SMA 1:1:1	110.09	114.35	8.46%	110.09
WMA 1:2:3	91.17	97.78	7.00%	91.17
WMA 1:3:5	84.87	92.62	6.51%	84.87
WMA 1:4:7	81.72	90.12	6.27%	81.72

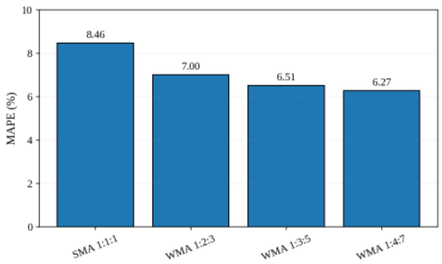

Figure 5. Changes in MAPE under different WMA weighting schemes

This improvement indicates that the latest observations were indeed more informative during the growth phase. Nevertheless, WMA 1:4:7 still produced a MAPE of 6.27%, higher than the naïve method's 4.55%, and retained a positive bias of IDR 81.72 million. Thus, changing the weights reduces lag but does not eliminate the structural limitation of a moving average. This result also explains why different studies may identify different best-performing methods: model and parameter selection should be determined through validation rather than habit or general assumption (Rini & Ananda, 2022; Septiansyah & Wahyudin, 2023).

3.5 Forecast Scenarios for 2027 and Extrapolation Risk

After estimating the parameters from all 2025 data, WMA 1:2:3 and the quadratic trend were used to develop scenarios for January–December 2027. These values are not validated results because actual 2027 observations are unavailable. Their purpose is to demonstrate the consequences of each model form when the horizon is extended. WMA was calculated recursively, meaning that previous forecasts were used as inputs when actual values were unavailable.

TABLE VII
SALES FORECAST SCENARIOS FOR 2027

Mo.	WMA (IDR million)	Quadratic (IDR million)
Jan	1,399.43	1,561.85
Feb	1,406.33	1,662.88
Mar	1,407.56	1,773.74
Apr	1,405.80	1,894.42
May	1,406.47	2,024.92
Jun	1,406.43	2,165.25
Jul	1,406.34	2,315.41
Aug	1,406.39	2,475.40
Sep	1,406.38	2,645.21
Oct	1,406.38	2,824.85
Nov	1,406.38	3,014.32
Dec	1,406.38	3,213.61

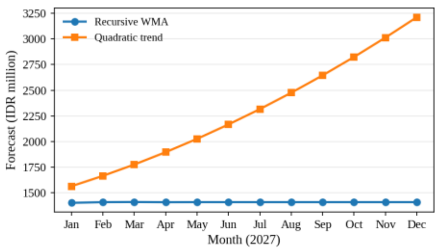

Figure 6. Divergence of the 2027 forecast scenarios

The total WMA scenario was IDR 16.87 billion, whereas the quadratic-trend scenario reached IDR 27.57 billion. The 63.43% annual difference indicates that production decisions would differ substantially if the company selected a model without evaluating the forecast horizon. By December 2027, the quadratic scenario was more than twice the WMA value. WMA tended to converge near IDR 1,406 million per month because forecasts were used recursively, whereas the t^2 component caused the quadratic trend to continue accelerating.

This difference does not prove that either scenario is correct. Instead, it demonstrates the danger of long-horizon extrapolation from a series of only 12 months. Forecasting literature emphasizes that uncertainty increases with the horizon and that structural changes may invalidate historical relationships (Fildes et al., 2022; Zellner et al., 2021). Therefore, the 2027 scenarios should be used only as an exploratory range and replaced by a rolling forecast as soon as the actual January observation becomes available.

3.6 Implications for Production and Inventory Planning

The validation results suggest that models should be used according to their decision function. The naïve method is the most appropriate one-month operational baseline because it is the most accurate and can be updated easily. The quadratic trend can be used as an upper scenario for testing capacity adequacy, but it should not serve as the sole plan. WMA can function as a smoothing indicator, particularly when the company seeks to reduce the influence of a single observation; however, its weights must be calibrated and its bias monitored.

TABLE VIII
TRANSLATING FORECAST RESULTS INTO OPERATIONAL DECISIONS

Finding and risk	Recommended action
The naïve model is the most accurate but depends on the most recent month.	Use it as the baseline for monthly production planning and compare it with actual orders.
WMA under-forecasts, creating risks of stockouts, overtime, and lost sales.	Apply a bias correction or safety stock; change weights only after validation.

The quadratic trend over-forecasts, creating risks of overproduction and holding costs.	Use it as an upper scenario rather than a direct production target.
The 12-month scenarios diverge, creating a risk of excessive material and capacity commitments.	Apply a monthly rolling forecast and limit the horizon for irreversible decisions.
Rupiah-based data combine volume and price changes.	Collect unit volume, price, orders, lead time, and stockout data separately.

Forecasts must be integrated with inventory parameters. Safety stock should be determined from demand variability during lead time and the target service level, rather than by adding the same percentage every month. Forecasts should also be compared with regular capacity, overtime capacity, material availability, and delivery schedules. In practice, an improvement in statistical accuracy does not necessarily produce an immediate cost improvement if lot size, lead time, or ordering policies remain unchanged. Future evaluation should therefore link forecast errors with holding cost, stockout, service-level, and capacity-utilization indicators.

3.7 Comparison with Previous Studies

The results differ from those of Sigit and Herwanto (2024), who identified moving average as the method with the lowest MSE, and from Erlangga and Pulansari (2025), who found Single Exponential Smoothing to be the best method. These differences are reasonable because demand patterns, data length, horizons, and error measures differ. In the PT Bernike dataset, growth during the second half of the year caused WMA to lag. The results are closer to those of Nasution et al. (2026) and Juanda and Debora (2026), who showed that trend models can outperform moving averages when directional change is dominant.

Although the quadratic trend outperformed WMA, the naïve method remained the best model. This finding reinforces modern forecast-evaluation recommendations to always include a simple benchmark and avoid selecting a model solely from goodness-of-fit (Hewamalage et al., 2023). This study also extends industrial forecasting research that typically reports only MSE or MAPE by adding bias, tracking signal, weight sensitivity, and operational-risk interpretation. Thus, the main contribution is not a new algorithm but improved evaluation validity and managerial relevance for a limited company dataset.

3.8 Limitations and Future Research

This study has four limitations. First, the data cover only 12 months, so seasonality cannot be identified and the results are sensitive to changes in a single observation. Second, the variable is sales value rather than unit volume, so the effect of price cannot be separated. Third, actual 2027 data are unavailable, and the long-horizon scenarios cannot be verified. Fourth, the models do not include backorders, promotions, capacity, lead time, or raw-material price changes. These limitations mean that the results are more appropriately viewed as a methodological evaluation and a design for a forecast-control system.

Future research should use at least 24–36 months of sales-volume data for each rubber type. Comparison models can be expanded to Holt, Holt–Winters when seasonality is confirmed, ARIMA/ETS, and causal models incorporating prices and customer orders. Evaluation should continue to use time-series cross-validation, a naïve benchmark, and multiple accuracy measures. In addition, model selection should be tested according to its impact on inventory cost and service level rather than ending with the MAPE value.

IV. CONCLUSION

Rolling-origin validation showed that the naïve method provided the highest accuracy for one-month-ahead forecasting of PT Bernike Semarang's retread-rubber sales, with a MAPE of 4.55%, followed by the quadratic trend at 6.14% and WMA 1:2:3 at 7.00%. The quadratic trend was more accurate than WMA but tended to over-forecast, with a bias of −IDR 45.13 million. In contrast, WMA under-forecast throughout the validation period, with a bias of IDR 91.18 million, because it lagged when sales increased. Sensitivity analysis showed that assigning greater weight to the latest data could reduce WMA MAPE to 6.27%, but it still did not outperform the naïve method. The 2027 extrapolation generated widely divergent scenarios; therefore, neither the quadratic model nor WMA should be used as a fixed annual plan without actual-data updates. The research objectives were achieved through model re-evaluation, out-of-sample testing, bias analysis, and translation of results into industrial decisions. The company is advised to use the naïve method as the baseline for monthly plans, the quadratic trend as an upper scenario, and rolling forecasts as a control mechanism. Future implementation should use longer sales-volume series and integrate forecasts with safety stock, lead time, capacity, cost, and service-level targets.

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