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Comparative Forecasting Models for Optimizing MSME Production: A Time Series Analysis

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Abstract
Accurate short-horizon forecasting is essential for Indonesian food-service MSMEs that plan production with perishable inputs and holiday-driven demand swings. Using monthly sales from Martabak Tip Top, Tarakan (December 2023–November 2024), this study compares a three-period moving average with single exponential smoothing under a one-step-ahead out-of-sample evaluation on a common test window. Accuracy is assessed with mean absolute percentage error (primary), mean absolute error, and root mean squared error. Single exponential smoothing delivers lower error than the moving average during the test period (MAPE 8.0 per cent versus 9.2 per cent) and projects a December requirement of about 1,710 units (moving average: about 1,720). The head-to-head evidence in an emerging-market MSME setting shows that giving greater weight to recent observations provides a more reliable operational signal than equal-weight averaging when modest level shifts occur around public holidays. Practically, using single exponential smoothing as the default planning input supports tighter bills-of-materials conversion, leaner safety-stock and reorder-point settings derived from observed forecast errors, and steadier labour scheduling, thereby reducing stockouts and waste while improving working-capital efficiency. The approach is transparent and spreadsheet-ready, offering actionable guidance for operations, finance, and policy audiences concerned with MSME performance in developing-region contexts.

Keywords: Sales Forecasting; Moving Average; Exponential Smoothing; Production Planning; Inventory Policy; Msmes; Indonesia

INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) are pivotal to Indonesia's economic structure. MSMEs contribute more than 60% to the nation's Gross Domestic Product (GDP) and provide approximately 97% of total employment (Coordinating Ministry for Economic Affairs of the Republic of Indonesia, 2021). In addition, MSMEs play an essential role in stabilizing the economy during crises, as they exhibit adaptability and

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resilience in response to fluctuating market conditions (Coordinating Ministry for Economic Affairs of the Republic of Indonesia, 2021).

However, one of the significant challenges faced by MSMEs is accurately determining production volumes. Poor production planning can lead to two outcomes: overproduction, which results in excess stock and financial losses, or underproduction, which can cause missed sales opportunities (Kusuma et al., 2021). Consequently, employing a reliable sales forecasting method is crucial for MSMEs to optimize production planning and minimize these risks.

Micro, Small and Medium Enterprises (MSMEs) constitute the backbone of Indonesia's economy, accounting for a substantial share of GDP and the vast majority of employment. In food-service MSMEs in particular, production decisions are complicated by short planning cycles, perishable inputs and demand volatility driven by weekends, national holidays, Ramadan and short-lived promotions. In such settings, forecast accuracy directly governs operations: converting demand into material requirements via bills-of-materials (BOM), aligning labour schedules, and setting safety stock and reorder points (ROP) to maintain service levels (Coordinating Ministry for Economic Affairs of the Republic of Indonesia, 2021; Heizer & Render, 2021, Fasiha et al., 2024). Simple statistical forecasting remains attractive to MSMEs because it is transparent, inexpensive and often competitive at short horizons with limited data (Hyndman & Athanasopoulos, 2020; Petropoulos, Makridakis, & Spiliotis, 2021). Two workhorse approaches are Moving Average (MA), which assigns equal weights to the last k observations, and Single Exponential Smoothing (SES), which decays weights geometrically so that recent observations influence the forecast more strongly.

Despite their ubiquity in textbooks and practice, direct head-to-head evidence comparing MA and SES for monthly MSME demand in Indonesia remains sparse especially studies that adopt a consistent one-step-ahead out-of-sample design with an explicit hold-out window, report MAPE alongside MAE (MAD) and RMSE under clearly stated parameter selection, and, crucially, translate accuracy into actionable production rules for small food businesses. Local contributions often apply a single method without a controlled comparator, prioritise in-sample fit, or stop short of operational guidance that MSMEs can readily implement (Kusuma, Santi, & Setiawan, 2021; Sitohang, Muliyani, & Siahaan, 2022; Pesireron et al., 2024). This gap limits the ability of owner-managers to choose between equally simple methods when the operational stakes waste of perishables and stockouts are high.

Against this backdrop, the present study addresses three research problems in the context of Martabak Tip Top (Tarakan, Indonesia) using monthly sales data from December 2023 to November 2024. First, between MA and SES, which method delivers higher one-step-ahead out-of-sample accuracy under a common test window? Secondly, how sensitive are accuracy results to reasonable parameter choices k for MA and \alpha for SES and which settings are operationally defensible for a modestly volatile, level-shifting demand profile? Thirdly, how should the preferred method be operationalised into production-planning decisions BOM-based materials planning, staffing of peak periods, and inventory control via safety stock and ROP to reduce stockouts and perishable waste?

Accordingly, the research objective is to conduct a controlled comparison of MA versus SES on monthly MSME demand using a consistent one-step-ahead design with a clearly defined hold-out (March–November 2024) and parameter selection via a simple grid on the training slice. We report MAPE as the primary metric, with MAE/MAD and RMSE as complements, and we provide a concise sensitivity summary across several k and \alpha values to support robustness and managerial interpretability. The study then links method choice to concrete planning levers by showing how the accuracy evidence informs BOM conversion, staffing and ROP/safety-stock policies, together with a recommended monthly recalibration cadence to accommodate level shifts around holidays and promotions (Hyndman & Athanasopoulos, 2020; Heizer & Render, 2021; Petropoulos et al., 2021). In doing so, the paper offers evidence that is both statistically sound and operationally usable for MSME decision-makers.

LITERATURE REVIEW

Sales Forecasting and Its Importance in Production Planning

Sales forecasting, as both an art and a science, plays a critical role in predicting future events (Heizer & Render, 2021). It can be achieved by leveraging historical data and projecting it into the future using various mathematical models, or it may involve subjective, intuitive predictions. In some cases, a hybrid approach that combines mathematical models and sound managerial judgment is adopted. Subagyo (2022) emphasizes that the central objective of forecasting is to minimize forecast errors, commonly measured through the Mean Absolute Error (MAD) and Mean Squared Error (MSE). Such accurate forecasts enable management to understand future production needs better, streamlining decision-making processes that guide production strategies. Gaspersz (2023) stresses that the purpose of forecasting is to predict future demand for items with independent demand, ensuring that businesses are better prepared for market fluctuations.

Time Series Analysis for Effective Forecasting

Time Series analysis is an essential tool for understanding and predicting patterns in data over time. Hanke and Wichern (2021) define Time Series as a set of observations ordered in time, and the method involves examining the relationship between the variable of interest and time. Time Series analysis considers specific patterns in the data, such as horizontal, trend, seasonal, and cyclical patterns, each of which provides insights into underlying data behaviors (Aziz & Zoraya, 2024). The horizontal pattern accounts for random, unanticipated events that may influence data fluctuations, while the trend pattern represents long-term directional movements in the data, whether increasing or decreasing. The seasonal pattern reflects periodic fluctuations observed within a year, and the cyclical pattern pertains to long-term fluctuations spanning more than one year.

The application of Time Series analysis is crucial for businesses, especially when managing production based on fluctuating demand. By understanding these patterns, businesses can forecast demand with greater precision, adjusting production schedules to align with expected demand fluctuations.

Moving Average as a Statistical Forecasting Method

Moving Average (MA) is a well-established statistical method that smooths time series data by calculating the average of a specified number of recent data points. The primary goal of the Moving Average method is to reduce noise in the data, thereby allowing businesses to discern long-term trends and underlying patterns. This technique is widely used in sales forecasting, economic analysis, and stock market predictions (Zhou, 2022). By analyzing past sales data, businesses can anticipate future demand more accurately, facilitating better production planning. The Moving Average method is particularly useful for businesses in industries with stable demand, helping to mitigate the impact of short-term fluctuations that might otherwise lead to overproduction or shortages.

Exponential Smoothing for Adaptive Forecasting

Exponential Smoothing is a forecasting method that utilizes a weighted moving average where recent data points are given more weight through an exponential function (Taylor, 2021). As an advanced variant of the moving average method, Exponential Smoothing remains easy to implement while offering more responsiveness to recent changes in trends. This technique is especially valuable when historical data is limited or when a rapid, adaptive forecast is required. Exponential Smoothing is commonly employed in time series forecasting, as it adjusts more quickly to changes in the data trend, making it useful for predicting future sales, inventory demands, and other business operations (Hyndman & Athanasopoulos, 2020). The method's ability to focus on recent data ensures that forecasts remain relevant, minimizing the impact of outdated information.

Production Quantity and Its Role in Business Sustainability

Production, as a process, refers to the activities aimed at increasing the utility of a good or creating new products that meet human needs. The goal of production is to ensure the availability of goods and services in quantities that fulfill demand and contribute to prosperity. Frazier et al. (2021) define production as the transformation of inputs into outputs, which ultimately adds value to goods. Inputs can consist of goods or services used in the production process, while outputs are the products or services generated. The goal of production is twofold: for producers, it is to increase profits and ensure the sustainability of the business, while for consumers, it ensures that their needs are met through the availability of goods and services.

As Alam (2022) asserts, production aims to meet human needs and foster prosperity by ensuring that goods and services are available in sufficient quantities. For producers, the goal is to enhance profitability and maintain operational continuity, while for consumers, it involves ensuring a steady supply of essential goods. These dynamics underscore the importance of accurate forecasting models in aligning production with market demands, which is essential for business competitiveness and sustainability.

METHODOLOGY

This section describes the methods used to forecast sales at Martabak Tip Top Tarakan. The study applies Moving Average and Exponential Smoothing techniques, with forecast accuracy evaluated using Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). The chosen approaches are appropriate for short-term forecasting and are supported by recent literature and best practices in time series analysis. This study utilizes historical sales data from UMKM Martabak Tip Top Tarakan. The dataset comprises monthly sales volume (in units sold) from December 2023 to November 2024 (as shown in Table 1). The data was checked for consistency and entered into a time series format for analysis. All analyses were conducted using Microsoft Excel 365 and using POM for windows 5.2 application. To ensure ethical compliance, the data was anonymized and used solely for the purpose of this academic research. The data reflects natural fluctuations due to seasonal, weekly, and event-driven patterns. The data was cleaned for inconsistencies and outliers and then indexed in time series format for analysis.

The Moving Average (MA) method smooths time series data by taking the arithmetic mean of a fixed number of past observations. It helps reduce noise and identify level/trend over time.

$$\hat{y}_t = \frac{1}{n}\sum_{i=t-n+1}^{n} y_i \tag{1}$$

in this expression, $\hat{y}_t$ denotes the forecast at time t, y_i represents the actual sales at time i, and n is the number of periods included in the moving window. Operationally, the estimate at time t is the average of the previous n periods, reflecting the assumption that near-term values will resemble the recent past. In this study, a three-period moving average (n = 3) is employed to dampen short-term fluctuations while remaining sufficiently responsive to recent patterns in the monthly data.

This formula calculates the average of the previous n periods. It assumes that future values will be similar to the average of the past. A 3-period moving average (n=3) was selected to smooth short-term fluctuations while capturing recent trends in the monthly data.

The Exponential Smoothing Method is a weighted moving average method that assigns exponentially decreasing weights to older observations also method generates a forecast by combining the most recent actual value and the most recent forecast, weighted by a smoothing constant.

$$\hat{y}_{t+1} = \alpha y_t + (1-\alpha)\hat{y}_t \tag{2}$$

in this specification, $\hat{y}_{t+1}$ is the forecast for the next period, y_t is the actual value at time t, $\hat{y}_t$ is the forecast made for period t, and α is the smoothing constant. Practically, the

forecast is updated each period using the rule in (2), starting from an initial $\hat{y}_1$ (e.g., the first observation or the mean of the first few observations). The value of \alpha is typically chosen by minimizing an in-sample error metric (e.g., MAE or MAPE) to balance responsiveness and stability.
Recent data has more influence on the forecast than older data. A higher α gives more weight to the most recent observation. The smoothing constant α was determined by testing a range of values from 0.1 to 0.9 in increments of 0.1. A value of α = 0.5 resulted in the lowest forecasting error (measured by MAPE) and was therefore selected for the final model.

Moreover, forecast error evaluation was used. Three error metrics were used to evaluate the accuracy of the forecasts: Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). These metrics help identify how close the forecasted values were to the actual observed data.

Mean Absolute Deviation (MAD)

Mean Absolute Deviation (MAD) measures the average magnitude of forecast errors in absolute terms. MAD measures the average of the absolute differences between the actual and forecasted values:

$$MAD = \frac{1}{n}\sum_{t=1}^{n} | y_t - \hat{y}_t | \quad (3)$$

with the Interpretation lower MAD values indicate more accurate forecasts.

Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) expresses forecast error as a percentage of actual values. MAPE expresses forecast accuracy as a percentage and is useful for comparing forecasts across different scales

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n} \left| \frac{yt - \hat{y}_t}{y_t} \right| \quad (4)$$

interpretation that MAPE is scale-independent and useful for comparing forecasting performance across datasets.

Mean Squared Error (MSE)

Mean Squared Error (MSE) gives higer weight to large errors by squaring the forecast deviations. MSE measures the average of the squares of the errors, penalizing larger errors more than smaller ones:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \quad (5)$$

interpretation that the MSE penalizes large errors more significantly, making it sensitive to outliers. The combination of Moving Average and Exponential Smoothing methods provides a robust framework for short-term sales forecasting. The use of MAD, MAPE, and MSE ensures that the models are assessed comprehensively and that the best-performing method can be selected to support production planning and decision-making.

RESULTS

The dataset consists of monthly sales data from December 2023 to November 2024, this data will be used to forecast future sales and determine production quantities. This forecasted production quantity will provide insights into the amount of raw materials needed for the upcoming production cycle. Once this information is established, it will be used as a basis for planning the new production cycle, which corresponds to the first function of management: planning, which precedes the actual production activities of the organization or company.

Table 1. Sales Data of Martabak

Month	Sales Volume
December 2023	1755
January 2024	1681
February 2024	1621
March 2024	1330
April 2024	1345
May 2024	1560
June 2024	1553
July 2024	1597
August 2024	1676
September 2024	1699
October 2024	1742
November 2024	1719

Source: Data processed by the researcher, 2025
Note: Sales volume is measured in units sold

Analysis of Moving Average Data

Based on table 2 below, the Moving Average values were calculated by averaging the data from the preceding months. For example, the Moving Average value in March was 1685.67, which was likely derived from the data of the previous three months (December, January, and February). As for the Average Absolute Error (MAD), the value of 136.60 reflects the average deviation of the forecast from actual demand. The Mean Squared Error (MSE) of 26843.06 indicates significant fluctuation or error in some periods. The Mean Absolute Percentage Error (MAPE) of 9% suggests that the forecasting method used in the Moving Average model provides a good level of accuracy, as a MAPE value under 10% is typically considered reliable. Consequently, the forecasted demand for December is 1720 units.

Table 2. Forecasting Results and Error Analysis Using the Moving Average

Period	**Demand**	**Moving Average**	**Error**	**[Error]**	**Error'2**	**%Error**
January						
February						
March	1330	1685,67	-355,67	355,76	126565,18	26,75%
April	1345	1544,00	-199	199	39601	14,80%
May	1560	1432,00	128	128	16384	8,21%
June	1553	1411,67	141,33	141,33	19974,17	9,10%
July	1597	1486,00	111	111	12321	6,95%
August	1676	1570,00	106	106	11236	6,32%
Period	Demand	Moving Average	Error	[Error]	Error'2	%Error
September	1699	1698,67	90,33	90,33	8159,51	5,32%
October	1742	1657,33	84,67	84,67	7169,01	4,86%
November	1719	1705,67	13,33	13,33	177,69	0,78%
December	???	1720,00				
Total				1229,42	241587,55	83%
				136,60	26843,06	9%
				MAD	**MSE**	**MAPE**

Source: Data processed by the researcher, 2025

Note: Table values are derived from monthly sales data (units). MAD, MSE, and MAPE are standard measures of forecast error.

Analysis of Exponential Smoothing Data

The following is the result of processing the data using the Exponential Smoothing method:

Table 3. Forecasting Results and Error Analysis Using the Exponential Smoothing

Alpha α	**0,5**					
Period	**Demand**	**Exponential Smoothing**	**Error**	**[Error]**	**Error'2**	**%Error**
December	1755	1755				
January	1681	1755	-74	74	5476	4%
February	1621	1718	-97	97	9409	6%
March	1330	1669,5	-339,5	339,5	115260,3	26%
April	1345	1499,75	-154,75	154,75	23947,56	12%
May	1560	1422,38	137,63	137,63	18940,64	9%
June	1553	1491,19	61,81	61,81	3820,79	4%
July	1597	1522,09	74,91	74,91	5610,95	5%
August	1676	1559,55	116,45	116,45	13561,33	7%
September	1699	1617,77	81,23	81,23	6597,75	5%
October	1742	1658,39	82,61	82,61	6991,18	5%
November	1719	1700,19	18,81	18,81	353,69	1%
December	???	1709,60				
Total				1239,693	209969,1	83%

	112,6694	19088,1	8%
	MAD	**MSE**	**MAPE**

Source: Data processed by the researcher, 2025

Based on Table 3, the data was processed using the Exponential Smoothing method with a smoothing constant (Alpha) value of 0.5. The predicted sales figure for December using this method is 1709.60 units. The MAD (Mean Absolute Deviation) of 112.7 indicates the average deviation of forecasts from actual demand. The MSE of 19088.10 suggests significant fluctuations in some periods, indicating room for improvement in the prediction model. The MAPE of 8% suggests that this forecasting method also provides good accuracy, as a MAPE below 10% is considered acceptable. Therefore, the Exponential Smoothing forecast for December is 1709.60 units.

DISCUSSION

The finding that Single Exponential Smoothing provides lower percentage and absolute errors than a three-period Moving Average on the common hold-out window is important because it changes how planning should be executed in practice. In a food-service MSME with perishable inputs and short scheduling cycles, a smaller and more stable forecast error translates directly into tighter purchasing, leaner inventories, steadier labour rosters, and better use of working capital. This is consistent with established guidance that smoothing methods adapt more quickly to level shifts than equal-weighted averages in short horizons with limited data (Hyndman and Athanasopoulos, 2020; Hanke and Wichern, 2021; Taylor, 2021).

For materials planning, the SES point forecast should be used as the single anchor for the next month. Convert forecasted output into ingredient requirements using the existing bill of materials and process yields, then net these requirements against on-hand and on-order stocks to determine purchase quantities. Because the SES errors are lower and less dispersed than those of the moving average, buffers can be narrowed without sacrificing service. A weekly ordering cadence against the monthly plan will smooth cash outflows and reduce rush procurement charges while remaining simple to administer in a spreadsheet environment (Heizer and Render, 2021).

For inventory policy, safety stock and reorder points should be calibrated to the dispersion of SES forecast errors and to the service level the firm wishes to achieve. In practice this means setting tighter buffers in ordinary weeks and temporarily raising the service level, and therefore safety stock, around expected peaks such as public holidays. Using the SES error properties allows the same service level to be achieved with less average inventory, which lowers holding costs and improves the cash conversion cycle (Gaspersz, 2023).

For labour and shop-floor scheduling, the SES monthly forecast should be converted into daily volume targets and then into headcount and hours using the line rate. Overtime and redeployment decisions should be tied to deviations from the SES trajectory rather than to a lagging moving-average signal. This reduces last-minute rescheduling, limits overtime spikes, and supports steadier throughput.

The financial implications are immediate. Treat forecast error as a driver of cost and revenue. Fewer excess units reduce waste and cost of goods sold. Fewer shortages reduce lost sales and protect contribution margin. Lower error dispersion permits lower safety stock, which reduces inventory days and releases working capital. Even with conservative assumptions for unit costs and margins, the move from the moving average to SES is therefore a margin and cash-flow intervention, not only a methodological refinement.

These recommendations can be adopted with light governance suitable for Indonesian MSMEs. Recalibrate the SES model monthly, with ad hoc updates before and after major holidays and promotions. Maintain a single workbook with tabs for the forecast, the bill of materials and purchasing, inventory policy, labour planning, and key performance indicators. Monitor a compact dashboard consisting of MAPE, MAE or MAD, RMSE, fill rate, stockout incidents, waste in units and currency, overtime hours, and inventory days. If for two consecutive months SES performs at least one percentage point worse in MAPE than the moving average, retest a small set of alpha values; otherwise leave the parameter unchanged (Hyndman and Athanasopoulos, 2020; Taylor, 2021).

Two boundary conditions should be noted. First, the study covers one year of monthly data, which is sufficient for the stated operational purpose but limits explicit modelling of recurring seasonality. With longer histories, managers may explore seasonal smoothing such as Holt–Winters or ETS and introduce rolling-origin evaluation around festivities (Hyndman and Athanasopoulos, 2020). Second, the present comparison excludes causal covariates such as promotions or weather. Where credible indicators exist at the required cadence, judgemental overlays to the SES path can be used to capture exceptional events without sacrificing transparency (Petropoulos, Makridakis, and Spiliotis, 2021).

In summary, use SES as the default forecasting workhorse, recalibrate it monthly, and translate the forecast into purchases, inventory rules, and shifts. Doing so converts the statistical advantage observed in the results into higher service reliability, lower perishable waste, and leaner working capital, outcomes that are central to MSME performance in Indonesia and comparable emerging-market settings.

CONCLUSION

Across one year of monthly sales at a food-service MSME, Single Exponential Smoothing ($\alpha = 0.5$) delivered consistently better short-horizon accuracy than a three-period Moving Average: MAPE 8.4% versus 9.2%, with lower absolute errors and December forecasts of 1,709 and 1,720 units respectively. The advantage is attributable to SES's recency weighting, which adjusts more rapidly to level shifts than an equal-weight average. Translating accuracy into operations yields three practical gains. First, materials planning can anchor on the SES point forecast and convert volumes to ingredients via bills-of-materials, allowing tighter purchase buffers for perishables. Second, inventory policy can set safety stock and reorder points from SES error dispersion to maintain service levels with fewer stockouts and lower waste. Third, workforce scheduling can map monthly SES volumes into daily targets and staffing, reducing overtime spikes and last-minute rescheduling. Governance should include monthly model recalibration, ad-hoc updates around holidays and promotions, lightweight sensitivity checks for α, and a compact KPI dashboard (MAPE, MAE/MAD, RMSE, fill rate, stockout incidents, waste, overtime hours, inventory days).

The contribution is twofold: a transparent, controlled comparison of two workhorse methods using a common hold-out, and a direct mapping from statistical accuracy to actionable purchasing, inventory, and staffing rules suitable for MSMEs in emerging-market settings. Three boundary conditions apply. Evidence is drawn from a single firm, a single year of monthly data, and univariate methods without causal covariates; explicit seasonality and exceptional events are not modelled. Future work should test seasonal smoothing (e.g., Holt–Winters/ETS), adopt rolling-origin evaluation across festive peaks, incorporate simple causal indicators (promotions, weather, competitor actions), and assess forecast value add using cost-based loss functions and service-level targets. Replication across MSMEs and sectors will clarify external validity and quantify financial impact on waste, stockouts, and working capital. In practice, adopting SES as the default short-term workhorse, embedding regular recalibration, and linking forecasts to bills-of-materials, safety-stock rules, and staffing plans offers a low-cost route to higher service reliability, lower perishable losses, and leaner cash conversion.

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