

Stock Management Optimization as a Sales Forecasting Strategy in Ayam Geprek SMEs

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ARTICLE INFO

Keywords: Forecasting, Ayam
Geprek, MAD, MSE, MAPE,
ETS, Production, Stock

Received : 5 October

Revised : 19 November

Accepted: 19 December

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ABSTRACT

Forecasting predicts future sales volumes and is essential for efficient stock management in businesses like ayam geprek, which relies on fresh ingredients. Discrepancies between production and demand can lead to excess inventory, increased costs, and losses. This study employs a quantitative approach, analyzing September 2024 sales data using judgment sampling and methods like Moving Averages and Exponential Smoothing (ETS). Data processing includes error evaluation (MAD, MSE, MAPE) to identify the best forecasting method. Results show ETS with $\alpha = 0.5$ is optimal, achieving the lowest error rates (MAD: 6, MSE: 73, MAPE: 15%). These findings help entrepreneurs improve inventory strategies, reducing risks of shortages or surpluses

INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) play a vital role in supporting economies, particularly in developing countries like Indonesia, where they contribute over 60% of GDP and create numerous job opportunities (Kementerian Koperasi dan UMKM, 2023). Despite their significant contribution, MSMEs often face operational challenges, especially in stock management. Poor inventory management can lead to overstocking or shortages, affecting profitability and customer satisfaction.

The ayam geprek MSME sector has rapidly grown, driven by rising demand for convenient and flavorful fast food. Ayam geprek, a popular Indonesian dish of crispy fried chicken served with spicy sambal, appeals especially to younger demographics. Accurate sales forecasting is critical for addressing stock management issues, helping MSMEs avoid inventory risks, reduce storage costs, and improve cash flow (Dewantara & Jonathan, 2023).

However, many MSMEs still rely on intuition or limited sales data for inventory decisions due to constraints in technical expertise and technological resources. This study examines sales forecasting approaches tailored for MSMEs, aiming to enhance stock management efficiency and competitiveness. By adopting accurate forecasting methods, MSMEs can optimize inventory levels, manage cash flow effectively, and adapt to demand (Puspitawati L & Namara, 2024).

LITERATURE REVIEW

Forecasting

Forecasting is the science of predicting future events. This can be done by involving historical data and projecting it into the future using a systematic model. Additionally, forecasting can also utilize a combination of mathematical models adjusted with sound judgment from a manager (Render & Heizer, 2009).

The Usefulness of Forecasting

The usefulness of forecasting becomes evident when making decisions. A good decision is one that is based on an understanding of what is likely to happen at the time the decision is implemented. If the forecast is inaccurate, forecasting itself becomes a challenge that we must constantly address (Hartini, 2011)

Types of Forecasting Patterns

An important step before determining the forecasting method is identifying the data pattern. Data patterns can be classified into four types, as follows (Ginting, 2007):

- a. Seasonal Pattern (S)
Occurs when a time series is influenced by seasonal factors (such as specific quarters of the year, months, or certain days of the week).
- b. Horizontal Pattern (H)
Occurs when data values fluctuate around a constant or stationary average value.
- c. Trend Pattern (T)
Occurs when there is a long-term increase or decrease in the data.

- d. Cyclical Pattern (C)
Occurs when the data is influenced by long-term economic fluctuations, such as those related to business cycles.

Forecasting Methods

To address various situations that arise, several forecasting methods or techniques have been developed. However, fundamentally, quantitative forecasting methods can be classified as (Gasperz and Vincent, 2004):

- a. Forecasting methods based on analyzing the relationship patterns between the variable to be predicted and other influencing variables that are not time-related, referred to as correlation or causal methods.
- b. Forecasting methods based on analyzing the relationship patterns between the variable to be predicted and the time variable, known as time-series analysis.
- c. Forecasting methods using analysis of the relationship patterns between the variable to be predicted and the time variable.
- d. Smoothing methods, including past data methods, cumulative average methods, moving averages, and exponential smoothing methods.
- e. Box-Jenkins methods, which use time-series data with mathematical models to minimize errors as much as possible.
- f. Trend projection and regression methods, which use trend lines for mathematical equations, allowing for projections based on the derived equation for future predictions.

Time Series Methods

The time series method is a forecasting technique that uses the analysis of the relationship between the variable to be predicted and the time variable. Forecasting a time series data requires attention to the type or pattern of the data. Generally, there are four types of time series data patterns: horizontal, trend, seasonal, and cyclical (Hanke, J.E. and Wichers, D.W., 2005).

Some methods in time series analysis include:

a. Moving Average

Moving Average is one of the time series forecasting models that uses time as the basis for forecasting. Moving Average uses a set of actual data to generate forecast values for the future. The larger the sample size of the data used, the better the estimation of the Moving Average method (Agustian & Wibowo, 2019). Uses the most recent n data points in a periodic series to forecast future periods. Averages changes or movements as new observations. Types include simple average, simple moving average, double moving average, weighted moving average, and moving average with linear trend

b. Exponential Smoothing

- This is a special case of the Weighted Moving Average method where the weights are assigned only to the most recent observation.
- The weight given to the most recent observation is the smoothing constant value, α .
- Types include single exponential smoothing, double exponential smoothing, triple exponential smoothing, and Brown's one-parameter quadratic method.

- Weights for other data values are calculated automatically and decrease as the observation period gets older.

Forecast Error Calculation Methods

The total forecast error is not an accurate measure to determine how effective the forecasting method is, but rather an indicator of bias or the difference generated by the bias. The total error will approach zero in regression forecasting methods. To avoid the issue where positive forecast errors neutralize negative forecast errors, several alternative forecasting error calculation methods are commonly used as follows (Hartini, 2011):

1. Mean Square Error (MSE)

Mean Squared Error is a method that can be used to evaluate the error level of a forecasting method (Andalia & Moulita, 2023). MSE calculates the average of the squared differences between the actual value and the forecasted value. MSE is calculated by summing the squares of all forecast errors for each period and dividing by the number of forecast periods. The advantage of MSE is its simplicity in calculation. However, its weakness lies in the accuracy of the forecast, as it does not consider whether the forecast is greater or smaller than the actual values.

2. Mean Absolute Deviation (MAD)

According to Pratama et al. (2020), Mean Absolute Deviation (MAD) is a key indicator of the accuracy of forecasts across various forecasting models. It is determined by calculating the average of the absolute errors across all periods. MAD is the average of the absolute errors over a specified period, without considering whether the forecast is higher or lower than the actual value. The advantage of MAD is that it provides a simpler error measure by only using the average absolute errors over the period. The downside of MAD is similar to MSE, as it does not account for whether the forecast is over or under the actual values, resulting in a limited accuracy in the forecast.

3. Mean Forecast Error (MFE)

MFE is particularly useful for determining if a forecast is consistently too high or too low over a period. MFE is calculated by summing all forecast errors over the forecasting period and dividing by the number of periods.

4. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error is a method used to evaluate and measure prediction error in percentage form (Andalia & Moulita, 2023). MAPE is a relative error measure, and it is often more meaningful than MAD because MAPE expresses the percentage error of the forecast relative to the actual demand over a period. This provides valuable information regarding whether the forecast errors are consistently too high or too low. A forecast is said to be very accurate if it has a MAPE value of less than 10%. The criteria for MAPE accuracy in forecasting can be seen in Table 1 below (Chicco et al., 2021).

Table 1. MAPE Value Range

Range	Description
<10%	Very good
10-20%	Good
20-50%	Passable
>50%	Not Good

METHODOLOGY

This study was conducted at an Ayam Geprek MSME located in the Cilibende area of Bogor, from early to late September 2024. A quantitative approach was employed, including subject selection and data collection through direct observation.

The population refers to all subjects with specific characteristics and qualities determined by the researcher (Safitri & Fahreza, 2023), while the sample is a subset with similar traits (Widiyanti et al., 2023). In this study, the population comprised sales data for ayam geprek during September 2024. A saturated sampling technique was used, involving all population members as the sample. Non-probability sampling with judgment sampling was applied, focusing on data from the specified period.

Primary data were gathered directly through interviews at the ayam geprek stall. This internal data pertained to production information and was categorized as discrete, represented by whole numbers. Additionally, the data were cross-sectional, reflecting ayam geprek demand during September 2024.

Data analysis was conducted using forecasting methods, including moving averages and exponential smoothing. The process was carried out in Microsoft Excel, following several stages (Pic 1).



Pic 1. Research Flow

Moving Average

The company uses this forecasting method to estimate data over short time periods (Ardiansah et al., 2021). The moving average method is particularly useful when market demand is assumed to remain relatively stable over time. This technique involves summing the historical demand data and dividing it by the number of periods (n). The formula can be systematically expressed as follows (Satmoko et al., 2020):

$$\text{Moving Average} = \frac{\sum \text{Histori Data Permintaan}}{n}$$

Exponential Smoothing

Exponential smoothing is a forecasting method that uses a moving average technique, incorporating past data with weights ranging between $0 \leq \alpha \leq 1$. The formula for this method is as follows (Satmoko et al., 2020):

$$F_t = F_{t-1} + \alpha (A_{t-1} - F_{t-1})$$

Where:

F_t = New forecast

F_{t-1} = Historical data or forecast from period $t-1$

A_{t-1} = Actual data

α = Smoothing constant or weight ($0 \leq \alpha \leq 1$)

During forecasting testing, once the forecast values are determined, the forecasting error is calculated, and the method with the least error is selected. The general formula for calculating forecasting error is (Adawiyah et al., 2022):

$$\text{Forecasting Error} = \text{Actual} - \text{Forecast} = A_t - F_t$$

According to Adawiyah et al. (2022), three popular metrics are used to evaluate forecasting error: Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE).

1. Mean Absolute Deviation (MAD)

MAD is a measure of the overall forecasting error. It is calculated by taking the sum of the absolute individual forecasting errors and dividing it by the total number of data periods (n), with the formula (Kristiani & Andrian, 2023):

$$\text{MAD} = \frac{\sum |\text{Actual} - \text{forecasting}|}{n}$$

2. Mean Square Error (MSE)

MSE is a forecasting error calculation that determines the average of squared differences between actual and forecasted values. The formula is as follows (Kristiani & Andrian, 2023):

$$\text{MSE} = \frac{\sum (\text{Forecasting Error})^2}{n}$$

3. Mean Absolute Percentage Error (MAPE)

MAPE is a metric used to identify the percentage of forecasting errors relative to the actual values in a data series. The formula is as follows (Kristiani & Andrian, 2023):

$$\text{MAPE} = \frac{\sum \left| \frac{A_t - F_t}{A_t} \right|}{n}$$

RESULT

Table 2. Initial Data on Production, Demand, and Surplus of Ayam Geprek in September 2024

Date	Production (pcs)	Demand (pcs)	Surplus (pcs)
1	0	0	0
2	0	0	0
3	0	0	0
4	40	34	6
5	40	40	0
6	40	37	3
7	40	40	0
8	0	0	0
9	40	40	0
10	40	40	0
11	40	38	2
12	40	49	1
13	30	28	0
14	60	58	2
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	40	40	0
20	40	40	0
21	30	29	1
22	0	0	0
23	40	36	4
24	40	40	0
25	40	37	3
26	50	50	0
27	50	47	3
28	0	0	0
29	0	0	0
30	50	46	4
Total	790	769	29
Average	26	26	1

In Table 2, daily production and demand data for ayam geprek in September 2024 reveal variations in operational activities. On some days, production or demand is absent, indicated by a "0" value. These instances, occurring on dates such as September 1-3, 8, 15-18, and 28-29, likely reflect holidays or other conditions disrupting operations.

Efficient production planning is evident on September 5, 7, 9, 10, and 20, where production precisely meets demand, leaving no surplus. On other days, minimal surpluses (1-4 units) appear, such as September 4, 6, 11, 23, and 30, possibly due to slight discrepancies between forecasted and actual demand. On September 12 and 14, demand exceeded production (49 vs. 40 units and 58 vs. 60 units, respectively), reflecting heightened customer interest. Although production almost met demand, these instances suggest opportunities to refine forecasting accuracy for high-demand periods.

Increased production on specific days, like September 14 (60 units) and September 26-27 (50 units), aligns with anticipated demand spikes. Minimal surpluses (0-3 units) on these dates underscore the responsiveness of production planning to demand fluctuations. Overall, the data indicate a flexible production system adapting effectively to daily variations in demand.

Table 3. Forecasting and Forecasting Errors Using Simple Moving Average Method (3-Day and Weekly)

We ek	Da te	Demand (pcs)	Simple moving average s	3-Day Moving Average Forecast	Weekly Moving Average Forecast
	1	34			
	2	40	37		
	3	37	39		
1	4	40	39	37	
	5	40	40	39	
	6	40	40	39	
	7	38	39	40	
	8	49	44	39	38
	9	28	39	42	41
	10	58	43	38	39
2	11	40	49	45	42
	12	40	40	42	42
	13	29	35	46	42
	14	36	33	36	40
	15	40	38	35	40
	16	37	39	35	39
3	17	50	44	38	40
	18	47	49	42	39
	19	46	47	45	40
		Total	654	639	481
		Average	41	40	40
		Next periode	46	48	39

The simple moving average (Table 3) is a forecasting method used to estimate demand values based on the average demand data from previous periods. In this dataset, the simple moving average is calculated by averaging the demand from the preceding days. For instance, on the second day, the demand is forecasted to be 37 units, which is the average of previous demand values. This method is generally applied to stable demand data and is suitable for short-term demand forecasting (Rangkuti, 2019). The average value derived from the simple moving average indicates a stable demand trend of around 40 units, facilitating daily production planning.

The 3-day moving average (Table 3.) smooths out daily demand fluctuations by averaging the demand from the previous three days. This method is effective in identifying short-term trends and reducing the impact of minor, insignificant demand changes. In this dataset, the 3-day moving average yields an average demand of 40 units. According to research by Pratama et al. (2021), the 3-day moving average benefits businesses with daily demand variations as it provides estimates closer to reality compared to long-term forecasts.

The weekly moving average (Table 3.) groups daily demand data into weekly segments and calculates the average to provide a weekly demand outlook. This method is highly relevant for medium-term forecasting, especially for businesses with seasonal or weekly demand patterns. In this dataset, the weekly moving average yields an average demand of 40 units, aligning closely with the simple and 3-day moving averages. This weekly approach enables SMEs to manage stock more effectively and avoid overproduction or shortages (Fadhilah & Santoso, 2022).

Based on the total average calculations of the three methods, the average demand is approximately 40 units, indicating consistency in daily demand. For the next period, the forecast results are 46 units for simple Moving Average, 48 units for 3-Day Moving Average and 39 units for Weekly Moving Average. The close alignment among these methods reflects a stable demand pattern, supporting reliable production and inventory planning.

Forecasting Errors

Table 4. Comparison of Moving Average Error Values

Forecasting Method	Production (pcs)	MAD	MSE	MAPE (%)
<i>Simple Moving</i>	46	5	45	13
<i>3-Day Moving average</i>	40	6	76	16
<i>Weekly Moving average</i>	39	7	86	18

In this data ((Table 4.), the simple moving average method predicts the number of ayam geprek to be 46 units. Based on the calculations, this method has a MAD value of 5, an MSE of 45, and a MAPE of 13%. The low error values indicate that the simple moving average method is quite effective for predicting stable ayam geprek demand (Rangkuti, 2019). The low MAD value suggests that this method has a good accuracy in reducing the absolute prediction error compared to the actual data.

The 3-day moving average considers the average of the last three days to predict the demand for the next day. This method results in a demand prediction of 40 units, with a MAD value of 6, an MSE of 76, and a MAPE of 16%. The error values for the 3-day moving average are slightly higher than the simple moving average, but it still provides fairly accurate estimates (Pratama et al., 2021). A MAPE of 16% indicates that the method has a deviation of about 16% from the actual value, which is still acceptable under fluctuating demand conditions.

The weekly moving average takes the average of weekly demand data to forecast the next period. With a prediction of 39 units, this method has a MAD value of 7, an MSE of 86, and a MAPE of 18%. Although this method has higher errors compared to the others (with higher MAD, MSE, and MAPE values), it remains relevant for observing long-term trends or weekly patterns that might not be captured by daily data (Fadhilah & Santoso, 2022). The higher MAPE of 18% indicates that this method is less accurate for fluctuating daily demand data.

Among the three methods used, the simple moving average has the lowest MAD, MSE, and MAPE values, making it the most accurate prediction for this ayam geprek demand data. While the 3-day and weekly moving averages result in slightly higher errors, the simple moving average is more suitable for short-term predictions and stable demand conditions.

Forecasting Method: Exponential Smoothing

Table 5. Exponential Smoothing Forecasting Results with $\alpha = 0.5$ and 0.9

Week	Day	Demand (pcs)	ETS ($\alpha 0,5$)	ETS ($\alpha 0,9$)
1	1	34		
	2	40	34	34
	3	37	37	39
	4	40	37	37
	5	40	39	40
	6	40	39	40
	7	38	40	40
2	8	49	39	38
	9	28	44	48
	10	58	36	30
	11	40	47	55
	12	40	43	42
	13	29	42	40
	14	36	35	30
3	15	40	36	35
	16	37	38	40
	17	50	37	37
	18	47	44	49

Week	Day	Demand (pcs)	ETS (α 0,5)	ETS (α 0,9)
	19	46	45	47
Total			107	129
Average			6	7
Next Periode			46	46

Table 5 shows the forecasting results using the Exponential Smoothing (ETS) method with $\alpha = 0.5$ for 19 days of demand. Exponential Smoothing is a forecasting method commonly used in time series data analysis, particularly when the data shows stable patterns without seasonality. In Exponential Smoothing forecasting, the forecast value is calculated by combining the actual value and the previous forecast value with a weight α (alpha), where α is a smoothing parameter ranging from 0 to 1. In this table, the α parameter used is 0.5.

The table shows the actual demand and the forecasting results for 19 days using the ETS method. In the first week, the forecast starts with the actual demand on day 1, which is 34 units. On the second day, the forecast is 34 units, reflecting the actual data from day 1. In the following days, the forecast adjusts based on actual data with a weight of $\alpha = 0.5$.

In the first week, the forecast is fairly stable, reflecting a consistent demand pattern around 37 to 40 units. In the second week, there is a larger variation in demand, especially on days 8 and 10, where the demand increases drastically to 49 and 58 units. The ETS model tends to be slow in responding to these large changes due to the moderate α value (0.5). The advantage of this method is its ease of application and effectiveness for data without trends or seasonality. However, the limitation of the ETS method is its lack of responsiveness to large fluctuations in the data, such as on day 10 (58 units). This is because the exponential smoothing method with a fixed α gives equal weight to the most recent data and the previous forecast. The latest forecast for the upcoming period is 45 units (for day 19), indicating that future demand is expected to remain within this range.

Table 6. The Results of Forecasting Errors Using the ETS Method

Metode peramalan	Jumlah ayam geprek (pcs)	MAD	MSE	MAPE (%)
ETS (α 0,5)	46	6	73	15
ETS (α 0,9)	46	7	108	18

In Table 6, there is a comparison of the performance of the ETS model. In the ETS model (α 0.5), the MAD value of 6 indicates the average absolute deviation between actual demand and forecast results. This shows that the ETS with α 0.5 gives smaller forecasting errors compared to the α 0.9 model. The MSE value of 73 indicates a relatively low level of error variability. MSE provides information about the magnitude of squared errors produced by the model, and this result is smaller compared to the MSE of the α 0.9 model. The MAPE value of 15% shows that the ETS model with α 0.5 has a moderate error

rate relative to the actual data, meaning the model performs reasonably well in predicting fried chicken demand.

In the ETS model (α 0.9), the MAD value of 7 indicates that the model with α 0.9 has a greater absolute deviation than the α 0.5 model. This model tends to give more weight to the most recent data, which can cause the model to be more sensitive to sudden fluctuations. The MSE value of 108 indicates a larger mean squared error, reflecting increased sensitivity to outliers or sudden changes in the data. The MAPE value of 18% shows that this model has a higher error rate compared to the α 0.5 model, indicating that the model is less stable in forecasting than the more moderate model.

From the comparison results above, ETS with α 0.5 is better at predicting fried chicken demand with lower error levels across all metrics compared to ETS with α 0.9. This suggests that models with more moderate weights are better suited for data with moderate fluctuations or when the model needs to be more stable against small changes. Conversely, ETS with α 0.9 is more sensitive and responds quickly to changes, which might be suitable for data that shows large fluctuations or sudden changes. However, this increased sensitivity can lead to more errors if applied to relatively stable data.

Research by Gardner (2006) states that the ETS method is highly dependent on selecting the appropriate α parameter. For stable data or slight fluctuations, smaller to moderate α values (0.2 to 0.5) are recommended to maintain forecast stability. Hyndman and Athanasopoulos (2021) emphasize that in many practical applications, moderate smoothing parameters tend to provide more stable and accurate results for periods that are not too volatile. In contrast, for data showing frequent and significant trends or fluctuations, using a higher α (e.g., 0.9) can improve the model's ability to track changes quickly, but with the risk of increased error if the data suddenly stabilizes.

CONCLUSION

The analysis shows that the simple moving average method performs the best with the lowest MAD, MSE, and MAPE values, indicating minimal forecasting errors. Therefore, this method is recommended for use in planning fried chicken stock. Using the right forecasting method will help SMEs reduce the risk of overstocking or understocking and improve inventory management efficiency.

FURTHER STUDY

It is recommended to explore the application of more advanced forecasting methods, such as Exponential Smoothing or ARIMA, to determine if they offer improvements in accuracy, especially in the case of fluctuating or seasonal demand patterns. Additionally, conducting sensitivity analysis by adjusting different parameters like the smoothing constant (α) could provide insights into the method's performance in various scenarios. Lastly, expanding the research to include a larger dataset or applying the forecasting methods to other SMEs in the food industry would help validate the results and assess the generalizability of the findings.

ACKNOWLEDGMENT

My sincere gratitude to the Vocational School for providing the opportunity to use the practical sessions as a platform for conducting this research.

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