Indonesian Journal of Electrical Engineering and Computer Science
Vol. 37, No. 1, January 2025, pp. 625~633
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v37.i1.pp625-633

Seasonal meat stock demand used comparison of performance smoothing-average forecasting

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Article Info

Article history:

Received May 20, 2024
Revised Sep 12, 2024
Accepted Sep 29, 2024

Keywords:

Double exponential smoothing
Double moving average
Forecasting
Seasonal meat stock demand
Single exponential smoothing

ABSTRACT

Seasonal patterns significantly influence the demand for beef stock, especially in rural areas that rely on natural feed. Accurate forecasting is essential for managing this demand due to beef's status as a government-regulated nutritional commodity. Food production, consumption, and income levels affect the demand for beef stocks. This research aims to identify the most precise forecasting method for predicting future beef stock needs. We evaluated multiple techniques, including single exponential smoothing (SES), double exponential smoothing (DES), single moving average (SMA), and double moving average (DMA), using the mean absolute percentage error (MAPE) metric, focusing specifically on beef supplies in Pemalang. The results indicated that the DMA method achieved the highest accuracy with a MAPE value of 5.993% at the 4^{th}-order parameter. Additionally, increasing the data volume improved forecasting accuracy, demonstrating the effectiveness of the DMA method for beef stock prediction.

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1. INTRODUCTION

The demand for beef, a staple of the Indonesian diet and a critical source of protein is steadily increasing as the country's income levels rise [1]. This growth in demand underscores the importance of effective beef stock management to ensure that nutritional needs are met. Despite this increasing demand, local beef production still needs to be improved [2], fulfilling only 70% of the national requirement. The remaining 30% is met through imports, highlighting a significant gap that needs to be addressed through improved forecasting and management practices [3]. Accurate forecasting of beef stock requirements is essential for several reasons. It helps understand and predict trends and seasonal patterns, vital for effective business management and decision-making [4]. Seasonal time series data, often spanning long periods and capturing multiple cycles, are crucial for precise forecasts [1]. These forecasts are necessary to determine meat stock requirements for seasonal products, which vary significantly throughout the year. The volatility in food prices, driven by climate conditions, market failures, and distribution challenges, further complicates the task [5]. These fluctuations pose substantial risks for producers and consumers, making robust forecasting systems indispensable for stabilizing inventory levels and pricing [6].

Several forecasting techniques have been developed to tackle these challenges, with notable contributions from crucial researchers. Brown's model, for instance, was designed to address issues related to trends and seasonal fluctuations [7]. This model and others have been widely studied and applied, like single exponential smoothing (SES), double exponential smoothing (DES), and triple exponential smoothing. The two-parameter Holt method and the one-parameter brown linear method, both variations of DES, perform a two-fold smoothing process to enhance forecast accuracy [8], [9]. These methods aim to minimize forecasting errors, measured through metrics such as mean absolute deviation (MAD), mean square error (MSE), and mean absolute percentage error (MAPE) [10], [11]. Additionally, moving average techniques like single moving average (SMA) and double moving average (DMA) are used to predict future production needs, adding another layer of methodological rigor.

However, despite the advancements in these techniques, problems still need to be solved and areas for improvement [12]. Existing methods often struggle to capture the complexity of various seasonal patterns and the external factors affecting beef stock levels [13]. More refined approaches are needed that can reduce error rates and improve forecasting accuracy, ensuring more reliable predictions [14]. This study seeks to address these gaps by comparing the performance of DES and DMA techniques in forecasting beef stock requirements. By evaluating these methods using MAD, MSE, and MAPE metrics, the research aims to identify the most accurate forecasting approach. The focus is on a case study in Pemalang, where beef stock levels are influenced by local cattle populations and external supplies, such as those from Madura Island. The data from this region, characterized by seasonal patterns and vulnerabilities to natural and geopolitical disruptions, provides a robust basis for testing and validating the forecasting models [15].

In Pemalang, the size of the beef stock is closely linked to the development of the local cattle population and the supply of meat from other areas. The region experiences significant seasonal variations that affect beef stock levels [11]. For instance, when raw materials are more abundant, there is a higher demand for beef products during the fertile season or the rainy season. This demand drives increased production activities, especially among micro, small, and medium enterprises (MSMEs) that produce items like shredded meat and beef jerky. These seasonal patterns necessitate accurate forecasting to manage stock levels effectively. This research compares the DES and DMA techniques, starting with SES values for DES and SMA values for DMA, to determine the method with the lowest error rates. The study spans four districts: Pemalang, Petarukan, Ampelgading, and Comal, providing a comprehensive view of beef stock demand across the region. The effectiveness of each method is measured using MAD, MSE, and MAPE metrics, ensuring a thorough evaluation of their performance.

This paper is structured as follows: section 2 outlines the methodologies employed, detailing the DES and DMA techniques and their respective starting points from SES and SMA values. Section 3 presents the results of our comparative analysis, discussing the performance of each method based on MAD, MSE, and MAPE metrics. Finally, section 4 provides the conclusion, summarizing the findings and their implications for beef stock forecasting and management in the studied regions.

2. METHOD

This section details the methodologies employed in this study, providing a comprehensive description of the experimental setup, data collection, and the theoretical basis of the forecasting techniques used. This research compares the performance of DES and DMA techniques in forecasting beef stock requirements. The study evaluates these methods using the MAD, MSE, and MAPE metrics.

2.1. Dataset description

The dataset used in this study comprises univariate time series data representing the total meat stock requirements per district in Pemalang, measured in tons per month. The data spans six years, from January 2015 to December 2020, providing 72 monthly records. These records are divided into training and test datasets, with 64 records used for training and 8 for testing, following a 90%:10% ratio. The training set is utilized to develop the forecasting models, while the test set is employed to evaluate their performance. The dataset includes monthly meat stock requirements for four districts: Pemalang, Petarukan, Ampelgading, and Comal, as shown in Figure 1. Temporal patterns in the dataset reflect seasonal variations influenced by natural and geopolitical factors, such as the rainy season and festive periods. As illustrated in Figure 1, the monthly meat stock demand in Pemalang shows significant seasonal variations and trends. This visual representation aids in understanding the underlying data characteristics and informs the selection of appropriate forecasting models.

2.2. Theoretical basis of forecasting methods

Forecasting techniques are essential for predicting future values based on historical data. This study compares two primary methods: DES and DMA [16], [17]. DES is an extension of SES designed to address linear trends in the data [18]. It involves two stages of smoothing: first, applying exponential smoothing to the raw data to generate a smoothed value, and second, applying exponential smoothing to the smoothed values obtained in the first stage. The DES method is defined by calculating (1)-(8).

The first smoothing value is calculated by (1). S_t' is the smoothed value at time *t*, α is the smoothing parameter (where $0 < \alpha < 10$), X_t is the actual value at time *t*, and S_{t-1}' is the smoothed value at time $t-1$. This equation applies exponential smoothing to the raw data to generate a smoothed value. Next, the second smoothing value is calculated by (2). S_t'' is the twice smoothed value at time *t* and S_{t-1}'. This second smoothing stage further refines the smoothed values to capture trends more accurately.

$$S_t' = \alpha X_t + (1-\alpha)S_{t-1}' \tag{1}$$

$$S_t'' = \alpha S_t' + (1-\alpha)S_{t-1}'' \tag{2}$$

The constant value (a_t) is determined as (3) by adjusting the smoothed values obtained from the first and second stages, providing a baseline for the forecast. Additionally, the slope value (b_t) is calculated as (3) by the difference between the first and second smoothed values, scaled by the smoothing parameter. This value represents the trend component of the forecast.

$$\mathrm{b}_t = \frac{a}{1-a}(S_t' - S_t'') \tag{3}$$

The DMA method extends the SMA by incorporating multiple smoothing stages to better capture trends and seasonality [19]. The first moving average is calculated by (4). S_t' is the first moving average at time *t*, and *n* is the number of periods in the moving average. This method averages the values over nnn periods to smooth short-term fluctuations and highlight longer-term trends. Additionally, the second moving average is calculated by (5). S_t'' is the second moving average at time *t*, obtained by averaging the first moving averages over *n* periods. This second averaging stage further smooths the data, making the forecast more robust to short-term variability.

$$S' = \frac{X_t + X_{t-1} + X_{t-2} + \cdots + X_{t-n+1}}{n} \tag{4}$$

$$S'' = \frac{S'_t + S'_{t-1} + S'_{t-2} + \cdots + S'_{t-n+1}}{n} \tag{5}$$

The constant value is determined by (6). This formula calculates the constant value (a_t) for the DMA method, similar to the DES method, by adjusting the first and second moving averages. Moving to slope value (b_t), it is derived from the difference between the first and second moving averages, scaled by the factor $\frac{2}{n-1}$, representing the trend component of the forecast in the DMA method and is calculated by (7). The DMA method benefits datasets with vital seasonal components, allowing for more accurate long-term forecasts.

$$a_t = 2S'_t - S''_t \tag{6}$$

$$b_t = \frac{2}{n-1}(S'_t - S''_t) \tag{7}$$

In this study, forecasting future meat stock requirements was conducted using two primary methods: DES and DMA. The forecast for future periods relies on these methods' calculated constant (a_t) and slope (b_t) values. The forecast value (F_{t+m}) for a future period mmm is given by (8), where *m* represents the number of subsequent periods to be predicted. This formula combines the constant and slope values to project the forecast into the future.

$$F_{t+m} = a_t + b_t m \tag{8}$$

The MAPE was used to evaluate the accuracy of these forecasting models. MAPE measures forecast accuracy as a percentage [20], indicating the proportionate error of the forecast relative to the actual values [21]. MAPE is calculated using (9).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_t - F_t}{X_t}\right| x100\% \tag{9}$$

Here, n represents the number of testing data periods, X_t is the actual value in period ttt, and F_t is the forecast value in period *t*. MAPE provides a percentage-based measure of forecast accuracy, with lower MAPE values indicating better forecasting performance. The MAPE score categories are shown in Table 1. The technique is considered excellent when the MAPE value is below 10%, with the method performing better as the MAPE value decreases [22]. This categorization helps in interpreting the effectiveness of the forecasting models, where a lower MAPE value corresponds to higher forecasting accuracy.

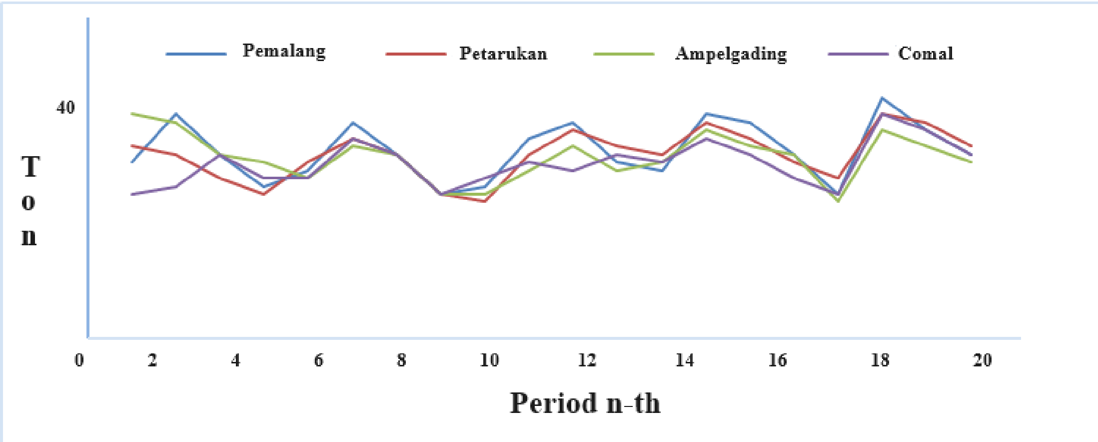


Figure 1. Visualization of data on demand for meat stocks in Pemalang

Table 1. MAPE value level categories

MAPE value	Categories
<10%	Excellent
10%-20%	Good
20%-50%	Enough
>50%	Poor

2.3. Proposed methods

The proposed methods focus on developing and evaluating accurate forecasting models for meat stock requirements using DES and DMA. The process begins with data preparation, where the dataset, consisting of monthly meat stock data from four districts in Pemalang over six years, is cleaned to handle missing values and outliers. The data is then partitioned into training (90%) and test (10%) sets and divided based on seasonal patterns to facilitate robust analysis.

Figure 2 illustrates the systematic process employed to compare DES and DMA methods to minimize the MAPE. The procedure begins by initializing key parameters, including the alpha (α) for DES, the order (n) for DMA, and the number of iterations (i). The dataset is then partitioned to create a structured foundation for the analysis.

The DES method involves calculating the first and second smoothing values using the selected α, followed by determining the constant (a_t) and slope (b_t) values that form the basis for future forecasts. The DMA method similarly calculates the first and second moving averages, which are then used to derive the corresponding constant and slope values [23].

Forecasts for future periods (F_(t+m)) are generated using the (8), where m represents the number of periods into the future being forecasted. The accuracy of these forecasts is evaluated using MAPE, which measures the percentage error relative to actual values [24], [25]. The flowchart in Figure 2 outlines two critical scenarios:

i) Parameter optimization: various parameters within DES and DMA are tested to identify the configuration that yields the lowest MAPE value.
ii) Temporal stability: MAPE values from both methods are compared across different seasons to assess the impact of time on forecast accuracy.

Iteratively adjusts parameters, calculating MAPE after each iteration to ensure the best forecast accuracy. A MAPE value below 10% is considered excellent, and the method producing the lowest MAPE is deemed optimal for future forecasting and analysis. This concise approach ensures that the most reliable forecasting model is selected, providing a solid basis for decision-making in meat stock management.

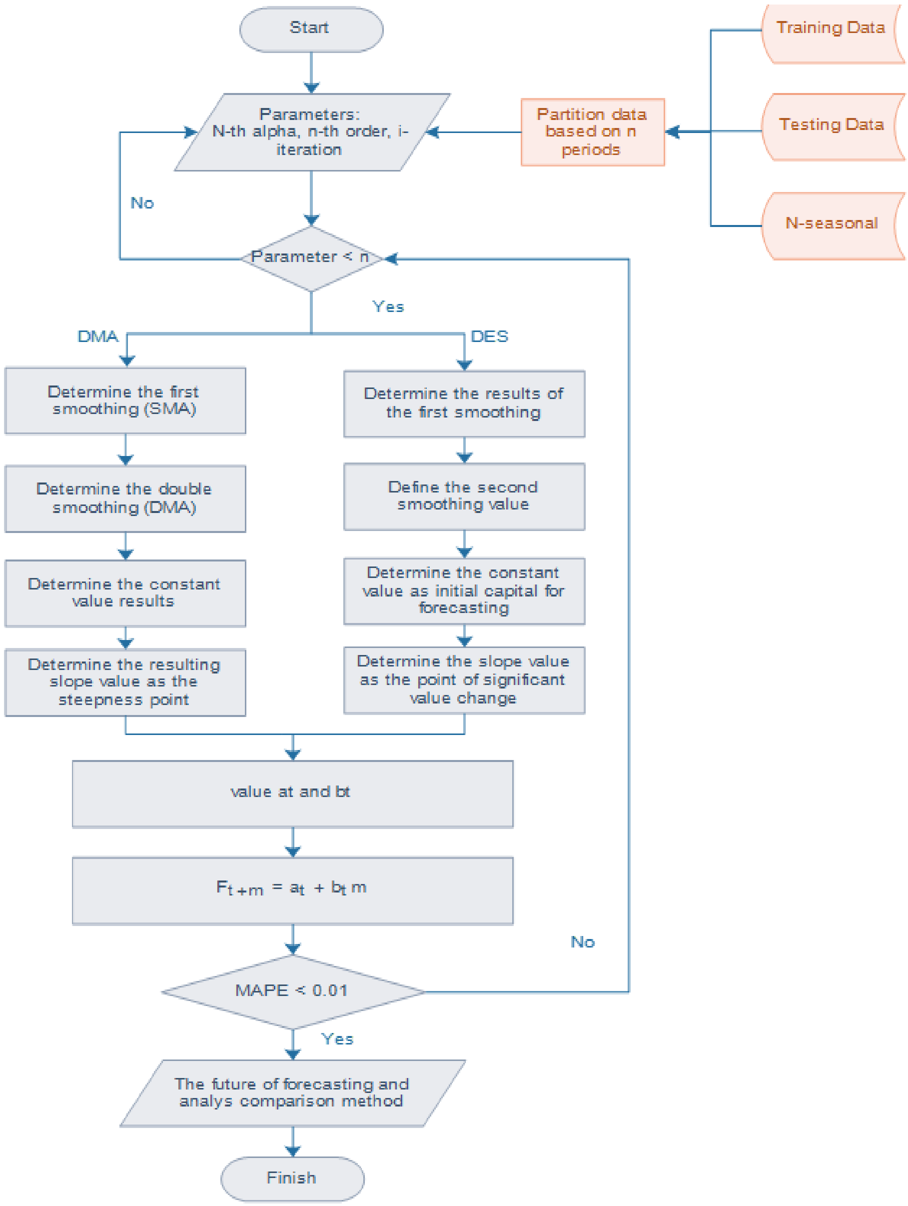


Figure 2. Comparison steps of the proposed forecasting method

3. RESULTS AND DISCUSSION

This section presents a detailed analysis of the experimental results obtained from the application of DES and DMA methods, compared with SE and SMA methods. The primary objective is identifying which method yields the lowest MAPE, thereby indicating superior forecasting accuracy for meat stock demand in Pemalang.

3.1. DES vs. SES: alpha parameter impact

The DES process begins with the initial application of the alpha parameter (α) obtained from the SES method. The experiment involves varying the alpha parameter between 0.1 and 0.9 to explore its impact on the slope coefficient (b_t)), which is integral to constructing the forecast function (F_t). By calculating the percentage error (PE) and MAPE for each alpha value, the goal is to determine which parameter setting provides the most accurate forecast.

The results from this comparative analysis, presented in Table 2, indicate that the SES method, with an alpha value of 0.9, achieved a MAPE of 6.52%. In contrast, with an optimal alpha value of 0.4, the DES method produced a MAPE of 8.21%. These findings are visually represented in Figure 3 which is precisely in figure 3(a), where the MAPE values corresponding to each alpha parameter are plotted for both SES and DES. The visual comparison demonstrates that SES consistently outperforms DES across the range of tested alpha values. Specifically, the SES method exhibits lower MAPE values as the alpha parameter increases, suggesting that SES is more responsive to recent data trends, which enhances its predictive accuracy. Conversely, the DES method, which involves an additional smoothing step, appears less stable, with MAPE values fluctuating significantly depending on the alpha setting. This variability indicates that DES may be more sensitive to the chosen parameters, which could limit its reliability in specific forecasting contexts.

Table 2. MAPE comparison of SES and DES based on varying alpha parameters

Parameter		SES			DES	
Alpha	at	bt	|PE|	at	bt	|PE|
0.1	33.63899	0.9	0.04058	35.93782	0.15542	0.04268
0.2	33.90132	0.8	0.03607	37.09227	0.38511	0.04303
0.3	34.16366	0.7	0.03156	37.10898	0.43264	0.04282
0.4	34.42599	0.6	0.02705	36.44938	0.11652	0.04032
0.5	34.68832	0.5	0.02254	35.79896	-0.44217	0.06776
0.6	34.95066	0.4	0.01803	35.41831	-1.06961	0.04586
0.7	35.21299	0.3	0.01352	35.35396	-1.55682	0.06119
0.8	35.47533	0.2	0.00901	35.60039	-1.39835	0.04994
0.9	35.73766	0.1	0.00450	36.15000	1.90006	0.05694
	MAPE alpha=0.9		6.52%	MAPE alpha=0.4		8.21%

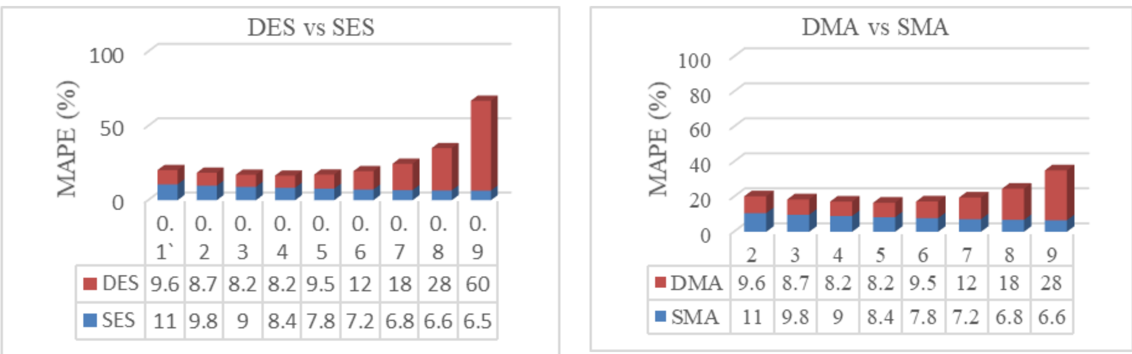
3.2. DMA vs. SMA: time order parameter analysis

The experiment adjusted the time order parameter from 2 to 9 to compare the DMA and SMA methods. The objective was to determine the time order yielding the lowest MAPE and offering the most accurate forecast. As shown in Table 3, when applied with a time order of 2, the SMA method resulted in an MAPE of 6.123%. The DMA method, optimized at a time order of 4, achieved a significantly lower MAPE of 5.993%.

These findings are visually represented in Figure 3 which is precisely in the representation of Figure 3(b) graphically illustrates these results, highlighting the superior performance of the DMA method over SMA as the time order increases. The data suggests that the DMA method's enhanced ability to model cyclical patterns and seasonal variations inherent in the dataset is likely responsible for its improved forecasting accuracy. The gradual reduction in MAPE as the time order parameter increases indicates that DMA can effectively capture and smooth out the fluctuations in the data, leading to more precise long-term forecasts.

Table 3. MAPE comparison of SMA and DMA based on varying time order parameters

Parameter		SMA			DMA	
Order n-th	at	bt	|PE|	at	bt	|PE|
2	35.5	0.5	0.01389	36.25	0.5	0.02083
3	36.1	0.4	0.01852	34.7778	-0.8889	0.058641
4	36.5	0.3	0.02778	35.9375	-0.375	0.012152
5	36.8	0.03	0.02778	36.88	0.04	0.025556
6	36	0.7142	0.02315	37.7222	0.3556	0.057716
7	36.2	0.3	0.01587	38.4489	0.5782	0.084089
8	36	0.11	0.14145	39.0312	0.7232	0.104290
9	35.3	0.2	0.02469	38.9506	0.7098	0.101680
	MAPE order 2nd time		6.123%	MAPE order 4th time		5.993%



(a) (b)

Figure 3. Comparison of MAPE Values for (a) DES vs. SES and (b) DMA vs. SMA Methods

3.3. Discussion of results

The more profound implications of these findings are manifold. The comparison between SES and DES reveals that while DES theoretically offers a more sophisticated approach by incorporating an additional smoothing stage, more is needed to translate into better forecasting accuracy for this specific dataset. The higher MAPE values associated with DES and its sensitivity to parameter changes suggest that its complexity might introduce unnecessary variability, particularly in datasets where the trend is not pronounced or the data points are relatively stable. In contrast, with its more straightforward model structure, SES proves more robust and consistent, especially when the alpha parameter is tuned to higher values that emphasize recent trends.

On the other hand, the comparison between SMA and DMA underscores the effectiveness of the DMA method in handling datasets with seasonal solid components. The lower MAPE values achieved by DMA, especially at the 4^{th} time order, highlight its ability to integrate both the immediate and extended past data points, thereby providing a more comprehensive smoothing mechanism that effectively captures the underlying patterns. This is particularly important in scenarios where the data exhibits complex seasonal and trend behaviors, as seen in the meat stock demand data from Pemalang.

Furthermore, the graphical representations in Figures 3(a) and 3(b) visually affirm the superiority of DMA over SMA and SES over DES, making it evident that the choice of method can significantly impact the accuracy of the forecast. The consistent performance of DMA, particularly at higher time orders, suggests that it is better suited for datasets with pronounced seasonal fluctuations, where capturing long-term trends is crucial. Conversely, SES's performance relative to DES suggests that simplicity in model structure can sometimes outweigh the benefits of additional complexity, particularly in datasets where the trend component is less dominant.

3.4. Findings

The experimental results indicate that the DMA method, particularly with a 4th time order, offers the best forecasting accuracy for meat stock requirements in Pemalang, as evidenced by its lowest MAPE value of 5.993%. This method's superior performance is likely due to its ability to capture and smooth the intricate seasonal patterns in the data, making it the most reliable choice for long-term forecasts. The SES method also shows strong performance, particularly at higher alpha values, indicating its robustness in scenarios where the focus is on recent data trends. Overall, the findings underscore the importance of selecting the appropriate forecasting method based on the specific characteristics of the dataset, with DMA emerging as the most effective approach for this particular case.

4. CONCLUSION

This study has demonstrated that among the forecasting methods analyzed SES, DES, SMA, and DMA, the DMA method with a 4^{th}-order time parameter offers the highest accuracy, achieving a MAPE of 5.993%, making it superior to the SMA method at 6.123%, SES at 6.52% (α=0.9), and DES at 8.21% (α=0.4). All methods are classified as excellent, with MAPE values below 10%, underscoring their reliability in forecasting meat stock demand. However, the sensitivity of DES and DMA to parameter settings, such as alpha and time order, suggests that further refinement is needed. Future research should explore optimization techniques, like hyperparameter tuning, to enhance these methods' robustness and accuracy, ensuring they can adapt to various time series data with greater precision.

ACKNOWLEDGEMENTS

The authors express their gratitude to STIKOM CKI (Indonesia), AGH University of Krakow (Poland), UPN Veteran Yogyakarta (Indonesia), Universitas Jember (Indonesia), and Universitas Krisnadwipayana for their support and contributions to this research.

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