Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 9, No. 4, November, Pp. 307-316

Performance comparison between double exponential smoothing and double moving average methods in seasonal beef demand

Bain Khusnul Khotimah[1*], Setiani[2], Ana Yuniasti Retno Wulandari[3], Devie Rosa Anamisa[1]
Department of Informatics Engineering, Faculty of Engineering, Universitas Trunojoyo Madura, Bangkalan, Indonesia[1]
Faculty of Agriculture, Universitas Trunojoyo Madura, Bangkalan, Indonesia[2]
Department of Science Education, Faculty of Education, Universitas Trunojoyo Madura, Bangkalan, Indonesia[3]

Article Info

Keywords:
Double Exponential Smoothing, Double Moving Average, Madura Cattle, Forecasting, MAPE, Seasional Data

Article history:
Received: December 18, 2023
Accepted: July 15, 2024
Published: November 30, 2024

Cite:
B. Khusnul Khotimah, Setiani, A. Y. R. Wulandari, and D. R. Anamisa, "Performance Comparison between Double Exponential Smoothing and Double Moving Average Methods in Seasonal Beef Demand", *KINETIK*, vol. 9, no. 4, Nov. 2024. https://doi.org/10.22219/kinetik.v9i4.1934

*Corresponding author.
Bain Khusnul Khotimah
E-mail address:
bain@trunojoyo.ac.id

Abstract
Beef demand relies on seasonal patterns because it depends on feed supplies, especially in the rural areas, that still rely on natural feeds. Beef supply is regulated by the government as it is one of the highly demanded commodities. It is a livestock product containing nutritional value to meet the protein needs of the community. The supply is influenced by several factors such as beef production, beef consumption, and the people's income level. In order to anticipate the increasing demand for beef, it is necessary to conduct a forecast to estimate the demand for meat in the future. In forecasting, various methods were examined to choose the method with the lowest error rate. This research compared the Mean Absolute Percentage Error (MAPE) resulted from Double Exponential Smoothing (DES) and Double Moving Average (DMA) methods. Based on the test results and analysis on beef supplies in Madura, it can be concluded that the method with the lowest MAPE value is Double Exponential Smoothing, i.e. 9.50% with an alpha parameter of 0.5. Meanwhile, the test using the Double Moving Average method to determine the best MAPE value, resulted the best time order of 2 with a MAPE value of 29.8408%. After finding the parameter with the lowest MAPE value, that parameter was used for the data testing. In the measurement, the data used for the testing were the data of 1-year, 2-year, 3-year, and 4-year period. Each method has a level of error value that increases the same; the number of data entered can affect the MAPE value. Therefore, the more data entered, the lower the error value.

1. Introduction

Beef is a livestock product with nutritional value to fulfill society's protein needs, a commodity whose demand will continue to increase along with the increase in income of the Indonesian population. The Indonesian population consumption trend continues to grow yearly [1]. However, the rise of beef demand in Indonesia has not been fulfilled by the production, both in terms of quality and quantity [2]. So far, the demand for beef supplies in Indonesia can only be met by 70% of production, while the other 30% is fulfilled by beef imports [3]. Forecasting plays an important part in decision making of business management to find trends and seasonal patterns in the form of models that can be used for future forecasting [4]. The seasonal time series is often available over long, continuous periods containing records of many seasonal cycles. For example, accurate forecasts and prediction intervals are required to determine meat demands for seasonal products corresponding to each period in the seasonal cycle [5].

In addition, food prices often fluctuate due to various factors, including natural phenomena (climate), market failures, and distribution problems. Seasonal price fluctuations are the risks faced by producers and consumers [5][6]. The higher level of demand, the lower the price; conversely, the price will increase if the level of demand is lower. Accurate forecasting will produce an effective company management system [7]. The Brown's model is a forecasting method developed to overcome problems that arose in previous forecasting methods, namely overcoming the problem of trends and seasonality [8].

The technique, among others, was based on averaging time series data using exponential weighting of longer analysis values. Single Exponential Smoothing, Double Exponential Smoothing, and triple exponential smoothing are three examples of Exponential Smoothing techniques. The two-parameter Holt method and Brown's one-parameter linear method are two methods of double exponential smoothing that carry out the smoothing process twice the double exponential smoothing method developed by Brown [9][10]. There are three general approaches to measure the degree of forecasting error: MAD (Mean Absolute Deviation), MSE (Mean Square Error), and MAPE (Mean Absolute Percentage Error). MAD calculates the average absolute difference, MSE is the average rank difference, and MAPE is the average percentage of fundamental differences [11][12].

The findings of a study comparing the forecast using Single Exponential Smoothing method and Double Exponential Smoothing method to predict the demand for LPG gas cylinders at PT Petrogas Prima Services show that

Double Exponential Smoothing method has appropriate MAPE, MAD, and MSE values [13]. Data on demand for LPG gas cylinders has a trend data type because demand for LPG gas cylinders' shows increases and decreases in certain months; this is shown from the results of the previous data plot testing experiments [14].

Another method for analyzing trends and seasonality is moving average method, which uses a moving average model. Data that experiences significant changes or irregular data can be considered unstable [15]. The research uses Double Moving Average method to overcome the weakness of Single Moving Average method, which only depends on the trend pattern [16]. If the basic everyday strategy of the Single Moving Average technique cannot beat when a pattern occurs, then the Double Moving Average technique can handle it better. The time order parameters used in the Double Moving Average method in previous research are very diverse, starting from using time order parameters 2, 4, 6, 8, 10, 20, 30, ... etc. Meanwhile, the Double Moving Average method calculation is suitable for unstable data with errancy up and down [17][18].

The demand for meat aimed to support the public consumption and as a scheduled supply of raw materials for SMEs [19]. This amount of meat stock is determined by the overall development of the cattle population in Madura Island, apart from the supply of meat from outside the region, such as from Java. The data is dominated by populations spread across the area, and the data depends on seasonal patterns that are prone to natural disasters that geopolitical factors cannot predict [20][21]. In certain months, there is a lot of demand, for example, the fertile season or the rainy season, because feedstocks are abundant, even MSMEs will compete to reproduce in making shredded meat, beef jerky, etc., for an average duration of 2 to 6 months [22]. However, the complexity of DEA forecasting is higher than that of DMA forecasting because it is sensitive to other indicators of time movement due to its instability, non-stationary nature, unpredictable extreme shocks, and poor ACF and PACF values [23][24][25]. It sets the task of estimating the time series {xt} to compare data from 4 regions of meat demand per month. The research aimed to find the best model that could be used to predict seasonal patterns in dry and rainy seasons.

This research aims to use forecasting methods, such as Double Moving Average and Double Exponential Smoothing algorithm models, on seasonal beef demand data in the Madura. This research compares the Double Moving Average and Double Exponential Smoothing techniques for data forecasting in 4 districts, namely Bangkalan, Sampang, Pamekasan, and Sumenep. The measure of the method's effectiveness is based on the MAD, MSE, and MAPE values in forecasting.

2. Methodology

Improvement in this research has many problems, thus we propose to compare two methods, namely DES and DMA, to determine which performance is the best. The reason for using DES is because this method has three main variants. Exponential smoothing has generally been applied in several studies, namely simple Brownian exponential smoothing [7]; exponential smoothing with Holt trend correction [10]; and the Holt-Winters Method [17]. Furthermore, numerous improvements on this method were carried out by Brown and Meyer [18], Trigg [14], Trigg and Leach [19], and other researchers to know the following variations of exponential smoothing methodology [21].

Figure 1 estimates the future values in a time series using changes due to ever-changing movements by using the moving average method [24,25]. Recent time series forecasting research has focused on developing sophisticated methods for forecasting of incoming call arrivals. However, there is a lot of evidence [12][18][26] such that the simple Seasonal Moving Average outperforms this method (SMA), while its development was analyzed, trends and seasonality with Double Moving Average (DMA) were used for longer estimates. The capacity planning decisions were made for forecast per period, a time series consisting of the trend, the level of smoothness, and how much the seasonal value as the characteristic of the market at that time so predictions could be made [8][16].

© 2024 The Authors. Published by Universitas Muhammadiyah Malang
This is an open access article under the CC BY NC SA license (https://creativecommons.org/licenses/by-nc-sa/4.0/)

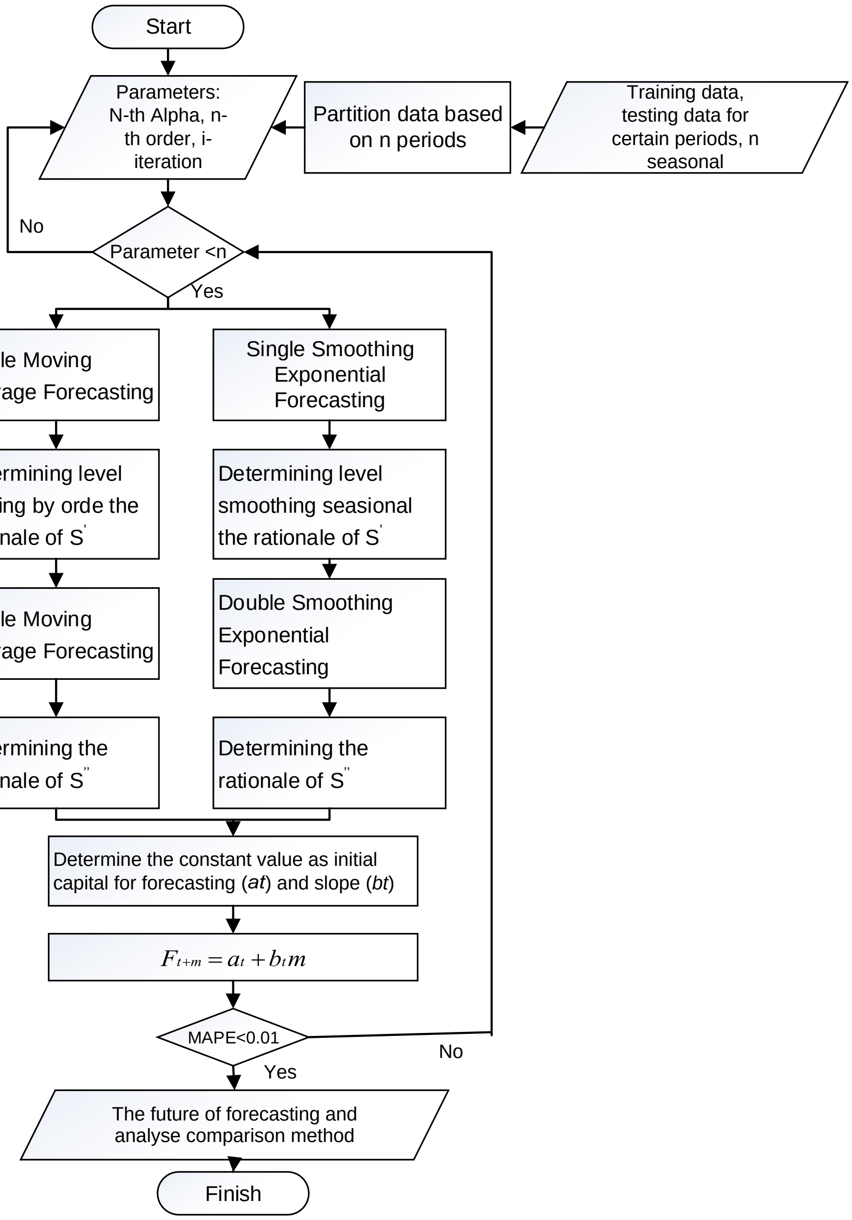

Figure 1. Comparison Steps of the Proposed Forecasting Method

2.1 Double Exponential Smoothing Method

Brown developed linear trend-based forecasting known as Brown's Double Exponential Smoothing [8]. Pujiati's study regarding Brown's Double Exponential Smoothing Method for Forecasting (Case Study: Consumer Price Index (CPI) shows that this approach is used when the data in the graph shows a trend [15]. The pattern is a smooth measure of general developments towards the end of the year of each period. The purpose of this smoothing is like a typical straight movement where the top of the information is smoothed and multiplied by a single average. The difference between single and double smoothing values is adjusted according to the trend, if any. The Brown's Equation 1, Equation 2, Equation 3, and Equation 4 for determining forecasting with double exponential smoothing are described as follows:

1. Determine the results of the first smoothing (S'_t)

$$S'_t = \alpha X_t + (1-\alpha)S'_{t-1} \tag{1}$$

2. Define the second smoothing value (S''_t)

$$S''_t = \alpha S'_t + (1-\alpha)S''_{t-1} \tag{2}$$

3. Determine the constant value as initial capital for forecasting (a_t)

$$a_t = 2S'_t - S''_t \tag{3}$$

4. Determine the slope value as the point of significant value change (b_t)

$$b_t = \frac{\alpha}{1-\alpha}(S'_t - S''_t) \tag{4}$$

Description:
S'_t : Smoothing value Single Exponential Smoothing
S''_t : Smoothing value Double Exponential Smoothing
α : Smoothing parameters

The values of S'_{t-1} and S''_{t-1} must be determined by choosing the default value as the initial value when t = 1, which must be selected at the beginning of the cycle and then used to determine the values of a and b. This value of S'_1 and S''_1 will be used as a parameter for forecasting using the same actual data [15].

2.2 Metode Double Moving Average

Moving Average methods that use seasonal moving average length values are assessed to determine their impact on forecast accuracy. For a forecasting series that uses moving average length values, n periods start from 2, 3, 4, ... n periods with the same seasonality to model weekly and daily seasonality, respectively [9]. The series of seasonals is set to represent seasonality at a particular time. The seasonal selection cycle is consistent with the nature of the arrival series, showing evidence of daily, weekly, 3-month, 6-month, and 1-year seasonal cycles, etc. Even better results are obtained using seasonal cycles depending on the total amount of data [17]. The research was conducted by forecasting using a Single Moving Average (SMA), which uses a single S' value [10]. The SMA method has the weakness that it is suitable for short-term data, while it still has a high bias for the long term. So, other research was developed to improve SMA by using a Double Moving Average (DMA), which uses n seasons. The Double Moving Average method uses the equations 5-8 for the future period [19].

1. Determine the first smoothing value (S'_t)

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

2. Determine the second, third,...n-th values for smoothing as (S''_t).

$$S'' = \frac{S'_t + S'_{t-1} + S'_{t-2} + \cdots + S'_{t-n+1}}{n} \tag{6}$$

3. Determine the constant value results (a).

$$a_t = 2S'_t - S''_t \tag{7}$$

4. Determine the resulting slope value as the steepness point (b_t).

$$b_t = \frac{2}{n-1}(S'_t - S''_t) \tag{8}$$

Description:
S' = The first moving average value in period t
S'' = The value of the second moving average in period t
x_t = The value of the second moving average in time period t
n = The number of limits in the moving average (n-th orde)

© 2024 The Authors. Published by Universitas Muhammadiyah Malang
This is an open access article under the CC BY NC SA license (https://creativecommons.org/licenses/by-nc-sa/4.0/)

Forecasting of future periods will occur when the *at* and *bt* values are considered for alpha calculations. The moving average is *n* order, and *s* is the length of the seasonal cycle. This study evaluated different *k* values to determine their impact on forecasting accuracy. Values of *s* representing daily or weekly seasonality were chosen to minimize the mean squared error on the training set. The results of the forecasting value (F_{t+m}) is determined by using Equation 9 as follows:

$$F_{t+m} = a_t + b_t m \tag{9}$$

Description:

F_{t+m} : Forecasting results in the next period
X_t : The actual data value in period t
m : The number of subsequent time periods to be predicted
a_t : The number of period constant values t
b_t : The trend value results in the appropriate data

Forecasting performance is obtained by calculating the value of the difference in actual demand estimated over a specific period. MAPE is a measure of relative error that provides error proportion results, which indicate whether the error proportion is low or high [20]. The formula for MAPE is presented in Equation 10 and Equation 11 as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} |PE_t| \tag{10}$$

With:

$$PE_t = \left(\frac{X_t - F_t}{X_t}\right) 100\% \tag{11}$$

Description:

n = The number of testing data periods
PE_t = The percentage error
X_t = Actual value in period t
F_t = Forecast value in period t

The MAPE score categories for the procedures are shown in Table 1. The technique works well when the MAPE value is below 10%. The method performs better when the MAPE value is lower [21].

Table 1. MAPE value level categories

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

3. Result and Discussion

3.1 Data Preparation

All time series are of the univariate type in the form of total meat demand (tons/month) per district in Madura. Data was taken over five years with an estimated total of 60 records and will be divided into training data and testing data with a percentage distribution of 90:10. Meanwhile, the best model will be used as a fundamental forecast for forecasting future data. Data visualization is shown in Figure 2.

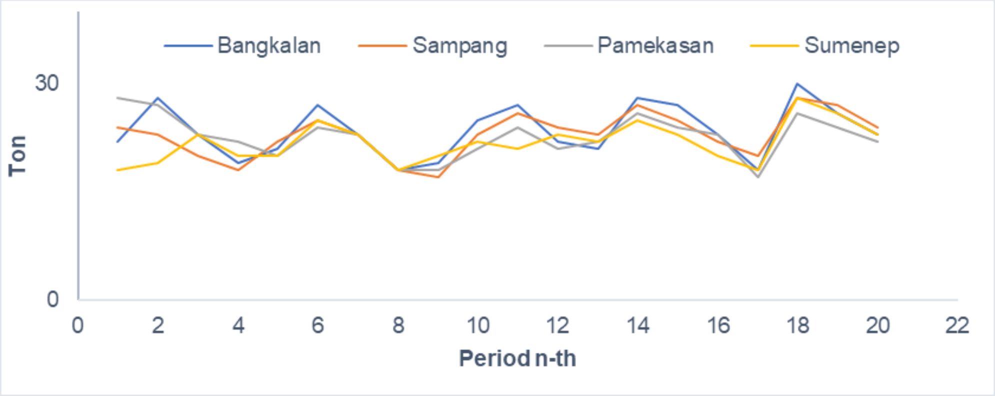

Figure 2. Visualization of Data on Demand for Meat Stocks in Madura

The scenario was used to answer the problems in this research, and the general steps of the method are shown in Figure 3. In the first scenario, the best MAPE value for the DES and DMA methods is determined by testing various parameters. The second scenario compares the MAPE values from the two forecasting methods on several data in certain seasons to assess the influence of time.

Algorithm DES and DMA

```
from statsmodels.tsa.api import ExponentialSmoothing
from statsmodels.tsa.api import MovingAverage

# Create a DMA Function
DMA <- function(data, orde) {
# Define First MA vector
s1=c()
# Calculating the first MA
for (i in orde: length(data)) {
  s1[i] = mean(data[(i-orde+1):i])
}
#Defining the Second MA vector
s2=c()
# Calculating the second MA
for (j in (2*orde-1): length(data)) {
  s2[j] = mean(s1[(j-orde+1):j])
}
# Defining Slope Constants and Coefficients
a= c()
b= c()
# Calculating Constants and Slope Coefficients
for (k in (2*orde-1):length(data)) {
  a[k] = s1[k] + (s1[k]-s2[k])
  b[k] = 2/(orde-1)*(s1[k]-s2[k])
}
f =c()
# Defining Forecast
f[2*orde-1] = a[2*orde-1]
for (l in (2*orde):(length(data)+1)) {
  f[l] = a[l-1]+b[l-1]
}
PE = c()
#Calculation PE
for (m in (2*orde-1):length(data))
{
  PE[m] = abs(data[m]-f[m])/data[m]*100
}

# Create an instance of ExponentialSmoothing class
model_Double = ExponentialSmoothing (data,
seasonal_periods=12, trend='add', seasonal='add') # Fit the
model to the data model_double_fit = model_double.fit ()

#Calculation MAPE
MAPE = mean(PE, na.rm = TRUE)
```

© 2024 The Authors. Published by Universitas Muhammadiyah Malang
This is an open access article under the CC BY NC SA license (https://creativecommons.org/licenses/by-nc-sa/4.0/)

```
Result Calculation = data.frame(Data = data, S1 = s1, S2 =
s2, a = a, b = b, Ft= f[-length(f)], PE = PE)
list (Result_Calculation = Result_Calculation, MAPE = MAPE,
Forecasting_1_Period_next time = f[length(f)])
}
```

Figure 3. Algorithm Comparison DES dan DMA

Figure 3 shows the steps of several proposed methods in systematic relationships, patterns and trends for forecasting future data. The explanation of the method steps to be carried out is as follows:

1. Change the use of the alpha parameter in the calculation of the Double Exponential Smoothing method in specific ranges 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9. to find the MAPE value of each alpha parameter to conclude the best result in the form of the smallest MAPE. The Alpha parameter greatly influences the smoothness and trend patterns in the prediction results.
2. Change the time order parameter value in the Double Moving Average method to the values 2, 4, 6, and 8 to find the best results in the form of the smallest MAPE in each Order. The Order value will be used to determine the seasonal value in the data so that predictive data analysis will be easy to carry out.

3.2 Experimental results

This DES process is a step for the second smoothing after using the alpha results from the single exponential smoothing process to continue the calculations for the double smoothing to produce a trend. The next step is to use the alpha (***α***) value range of 0.1 to 1.0 to continue calculating the *bt* coefficient value as a slope index for the slope to produce the *ft* function and then to find out the PE and MAPE error values for each parameter. Table 3 shows that A compares the SES and DES test results using the best alpha parameter to control the influence of past values on the smoothing results.

Table 3. Determination of the Model Based on Changes in Alpha Parameters in SES and DES

Parameter	SEA			DEA		
Alpha	at	bt	|PE|	at	bt	|PE|
0.1	27.4886	-0.4854	0.0116	17.7364	-5.9492	0.5011
0.2	39.2762	0.7279	0.0080	29.2768	1.9022	0.4080
0.3	81.1136	1.8929	0.0026	61.7630	6.2709	0.0070
0.4	47.5843	2.4145	0.0041	17.5216	5.4959	0.5400
0.5	65.5980	14.5980	0.0987	25.5987	14.5097	0
0.6	21.6884	-0.6839	0.0217	87.9865	-0.6839	0.4218
0.7	30.1065	0.8936	0.0009	78.9540	3.7931	0.6569
0.8	49.2811	0.7159	0.0062	89.2817	2.9071	0.0987
0.9	32.0468	-0.0512	0.0132	54.0665	-0.3051	0.0132
1	22.0468	-0.2565	0.1130	25.9807	-0.2305	0.2102
	MAPE alpha = 0.3		9.2306%	MAPE alpha = 0.5		3.9948%

Table 4 shows that the result SES with using alpha parameter 0.3 is the parameter with the lowest PE (Percentage Error). This model was used for testing when *at* = 81.1136 and *bt* = 1.8929, with the lowest PE value resulting in the model F = at + bt. Meanwhile, the result using DES shows the best *at* alpha = 0.5, then showing the best model that can be used for testing future data.

Table 4. Determination of the Model Based on Changes in Alpha Parameters in SMA and DMA

Parameter	SMA			DMA		
Order n-th	at	bt	|PE|	at	bt	|PE|
2	13.7543	0	0	20.6586	49.1877	0.2052
3	16.3120	0.2311	0.6441	10.6586	30.0065	0.2052
4	53.1875	4.7916	0.0359	13.7675	22.7780	0.0359
5	11.9065	0.9887	0.8280	20.6586	49.1097	0.2052
6	77.1944	-0.1222	0.9137	21.1944	-3.1097	0.0935
7	13.5332	-0.3913	1.8272	10.6586	21.1877	0.2052
8	18.4218	0.4151	0.3037	17.4218	0	0
	MAPE order 2nd time		29.8408%	MAPE order 8th time		12.9010%

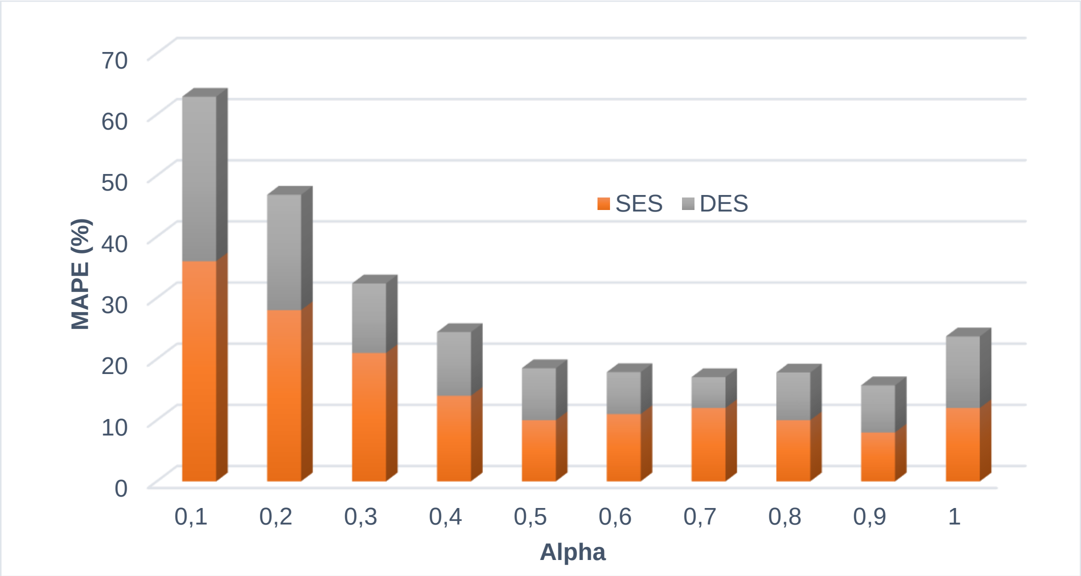

Figure 4. Results of Comparison of MAPE Values for Each Change in Alpha parameter (α)

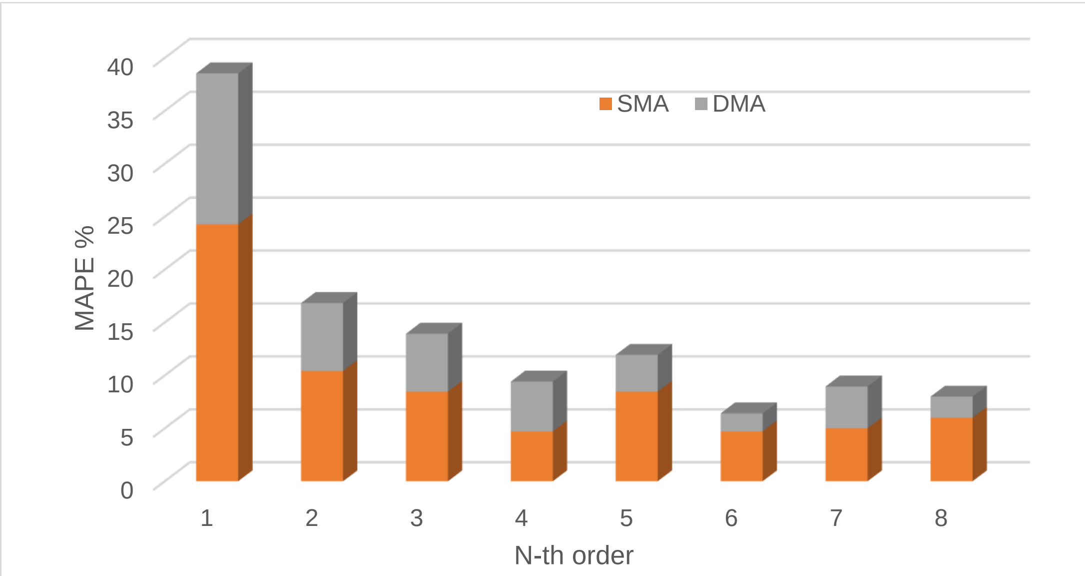

Figure 5. Results of Comparison of MAPE Values for Each Parameter N-th order

Figure 4 explains that the exponential process is a method that models these trends, depending on the Exponential Trend parameter **(α)**, to produce the lowest MAPE. Figure 5 shows the MAPE value results from parameter changes starting with time order = 2. If time order < *n* is specified, then repetition continues to add time order values until MAPE <01 is obtained. If the time order is equal to *n* and the MAPE value limit is determined, then the repetition process has been completed. The results show that the SMA method outperforms the length of the seasonal moving average, which considers lengths 2 and 5, especially for short-term data. DMA exceeds the SMA of both methods in the long run at the 8th-order point. While these results provide a good summary, it could be more consistent to consider the impact of moving average length on the accuracy of both approaches.

3.3 Discussion

The results of the MAPE values from comparing the SES, DES, SMA, and DMA methods in this research using data on sales demand for meat in Madura were predicted and divided into several periods. Based on the performance comparison results, the one with the smallest MAPE value is the DMA method with the smallest MAPE value of 0.96% at time order parameter 10. The following are the results of the MAPE value of each method, which is very varied, in

© 2024 The Authors. Published by Universitas Muhammadiyah Malang
This is an open access article under the CC BY NC SA license (https://creativecommons.org/licenses/by-nc-sa/4.0/)

which the SES method depends on the higher the alpha, the higher the yield since the better the value, the lower the error rate. Meanwhile, SMA depends on higher-order values, which is different from DMA, which relies on the diversity of data. The comparison of the order values is in the order of values below 10, which produces good grades with the lowest error because the data values fluctuate in each period, which is constantly changing. Table 5 shows the results of testing several methods using each of the best models, namely SES alpha = 0.9, DES alpha = 0.5, while SMA is in the 10th order, DMA is in the 6th order.

Table 5. Test Results Comparing the Best MAPE Values for Several Methods According to the Time Period

Forecasting Methode (MAPE %)	Short (6 month/rainy)	Short (6 month/dry)	Medium	Long
SES	3.3952	4.7320	5.3952	12.5328
DES	4.8551	6.7895	2.8000	9.9805
SMA	4.2598	2.858	8.0958	10.7058
DMA	13.3975	10.3139	3.5221	1.3975

The impact of the moving average length on the influence of seasonal data has been evaluated for the proposed SES, DES, SMA, and DMA methods, and the results are presented in Table 5. MAPE was used to measure the error directly in each time series. The value of each method is determined by changing the alpha parameters, and moving average length produces the best DES on short-term data. Meanwhile, using the seasonal moving average for the next five years has the best value with a MAPE of 100.81. The results in the last column of Table 5 show that the best method depends on the length of the data period and the diversity of the data. The result testing depended on the correct choice of alpha and the average order size. Likewise, the entire averages containing up-to-date information tend to have the best accuracy in short to medium time frames. The usage of the model was intuitive and understandable because with shorter lead times, shorter averages will give greater significance to recent and recent changes in incoming call demand. Meanwhile, the further the forecast, the more critical the long-term historical trend in demand.

4. Conclusion

Based on the results of trials and analysis regarding the comparison between Double Exponential Smoothing and Double Moving Average methods for beef demand, it can be concluded that the best method for forecasting this data shows that the DES method outperformed the DMA method. Test result with the best MAPE on DES using the parameter alpha = 0.5 was 9.50%. Meanwhile, the test results using the DMA method, by determining the best MAPE value, show that the best time order in the DMA method is in the 2nd time order parameter with a MAPE value of 29.8408%. In data testing for seasonal data in the rainy season period of six months, one-year, two-year, and three-year of dry season. Each method has a level of error value that increases almost the same. The amount of data training that was entered can greatly influence the small MAPE values. So. the more training data used, the smaller the error value.

DES and DMA have shortcomings that need to be fixed because they require selecting appropriate parameters, thus requiring an optimization method. Hyperparameter methods with Grid Search or the like and computational-based methods are needed for parameter searches to determine the best alpha, beta, and gamma. In addition, for future input, the author needs to refine the adaptive combined model by modifying its seasonal level into certain segment forms, testing stationarity, and performing data normalization so that a stable and measurable data pattern can be found.

Acknowledgment

Gratitude is expressed to LPPM Trunojoyo University Madura, UNISMA Malang in the field of animal husbandry, DKPP in the Madura region for the cooperation program in the field of research and the implementation of the 2024 BIMA Fundamental research grant. Therefore, we would like to thank all parties, both the community and students who have participated in the MBKM program and several cattle slaughtering centers as meat stocks Madura, for their assistance in providing data and willingness to be interviewed for this study.

References

[1] M. Shahbandeh, "Cattle population worldwide 2012-2023," *Agriculture*, Sep 19, 2023.
[2] K. Kozicka, J. Žukovskis, and W. Gront, E. Explaining Global Trends in Cattle Population Changes between 1961 and 2020 Directly Affecting Methane Emissions, *Sustainability*, Vol. 15, 10533, 2023. https://doi.org/10.3390/su151310533
[3] M. Hwan Na, W. Cho, S. Kang, and Inseop Na, "Comparative Analysis of Statistical Regression Models for Prediction of Live Weight of Korean Cattle during Growth," *Agriculture*, Vol.13, No.10, 1895, 27 September 2023. Comparative Analysis of Statistical Regression Models for Prediction of Live Weight of Korean Cattle during Growth
[4] B. K. Khotimah, F. Agustina, O. R. Puspitarini, Husni, D. R. Anamisa, N. Prayugo, and A. M. S. Putri, "Random Search Hyperparameter Optimization for BPNN to Forecasting Cattle Population," *E3S Web of Conferences*, Vol. 499, 01017, 2024. https://doi.org/10.1051/e3sconf/202449901017

[5] F. Firdaus, B. A. Atmoko, E. Baliarti, T. S. M. Widi, D. Maharani, and Panjono, “The meta-analysis of beef cattle body weight prediction using body measurement approach with breed, sex, and age categories,” *J Adv Vet Anim Res*., Vol. 10, No. 4, Pp. 630–638, Dec. 2023. https://doi.org/10.5455/javar.2023.j718

[6] T. C. Lwin, T. T. Zin and P. Tin, "Predicting Calving Time of Dairy Cows by Exponential Smoothing Models," *2020 IEEE 9th Global Conference on Consumer Electronics (GCCE)*, Kobe, Japan, Pp. 322-323, 2020. https://doi.org/10.1109/GCCE50665.2020.9291903

[7] V. Tenrisanna, and S. N. Kasim, “Trends and forecasting of meat production and consumption inIndonesia: Livestock development strategies,” in *IOP Conf. Series: Earth and Environmental Science*, Vol. 492, 012156, 2020. https://doi.org/10.1088/1755-1315/492/1/012156

[8] D. Effrosynidis, E. Spiliotis, G. Sylaios, and A. Arampatzis, “Time series and regression methods for univariate environmental forecasting: An empirical evaluation,” *in Science of The Total Environment*, Vol. 875, 162580, 2023. https://doi.org/10.1016/j.scitotenv.2023.162580

[9] A. A. Dewi, and D. Idayani, “The Comparison of Simple Moving Average and Double Exponential Smoothing Methods in Predicting New Debtors,” *JURTEKSI (Jurnal Teknologi dan Sistem Informasi)*, Vol. 9, No. 3, Pp.369-376, June 2023. DOI: https://doi.org/10.33330/jurteksi.v9i3.2254

[10] M. A. C. Lascorz, P. J. Herrera. A. Troncoso, and G. A. Cortés, “A new hybrid method for predicting univariate and multivariate time series based on pattern forecasting,” *Information Sciences*, Vol. 586, Pp. 611-627, 2022. https://doi.org/10.1016/j.scitotenv.2023.162580

[11] I. Svetunkova. H. Chenb, and J. E. Boylan, “A new taxonomy for vector exponential smoothing and its application to seasonal time series,” European Journal of Operational Research, Vol. 304, No. 3 Pp. 964-980, 1 February 2023. https://doi.org/10.1016/j.ejor.2022.04.040

[12] N. A. Atussaliha and P. H. Darwis, "Metode Double Exponential Smoothing pada Sistem Peramalan," *ILKOM Jurnal Ilmiah*, Vol. 3, Pp.183-190, Desember 2020. https://doi.org/10.33096/ilkom.v12i3.607.183-190

[13] G. Moiseev, “Forecasting oil tanker shipping market in crisis periods: Exponential smoothing model application,” *The Asian Journal of Shipping and Logistics*, Vol.37, No. 3, Pp. 239-244, September 2021. https://doi.org/10.1016/j.ajsl.2021.06.002

[14] J. F. R. Sanchez and L. M. Menezes, “Structural combination of seasonal exponential smoothing forecasts applied to load forecasting,” *European Journal of Operational Research*, Vol. 275, No.3, Pp. 916–924, 2019. https://doi.org/10.1016/j.ejor.2018.12.013

[15] D. Febrian, S. I. A. Idrus, and D. A. J. Nainggolan, “The Comparison of Double Moving Average and Double Exponential Smoothing Methods in Forecasting the Number of Foreign Tourists Coming to North Sumatera,” *J. Phys.: Conf. Ser,* Vol,1462, 2020. https://doi.org/10.1088/1742-6596/1462/1/012046

[16] D. Guleryuz, “Forecasting outbreak of COVID-19 in Turkey; Comparison of Box–Jenkins, Brown’s exponential smoothing and long short-term memory models,” *Process Safety and Environmental Protection*, Vol.149, Pp. 927-935, 2021. https://doi.org/10.1016/j.psep.2021.03.032

[17] K. Talordphop, S. Sukparungsee, and Y. Areepong, “On designing new mixed modified exponentially weighted moving average - exponentially weighted moving average control chart,” *Results in Engineering*,18,101152, 2023. https://doi.org/10.1016/j.rineng.2023.

[18] Q. Shao, A. Aldhafeeri, S. Qiu, and S. Khuder, “A multiplicative Holt–Winters model and autoregressive moving-average for hyponatremia mortality rates,” *Healthcare Analytics*, Vol. 4,100262, 2023. https://doi.org/10.1016/j.health.2023.

[19] R. Taboran, S. Sukparungsee, and Y. Areepong, “Mixed moving average-exponentially weighted moving average control charts for monitoring of parameter change,” *in: Proceeding of the International MultiConference of Engineers and Computer Scientists*, Pp.13–15. 2019.

[20] M. Melikoglu, and Z. K. Menekse, “Forecasting Turkey's cattle and sheep manure based biomethane potentials till 2026,” *Biomass and Bioenergy*, Vol.132, 105440, 2020. https://doi.org/10.1016/j.biombioe.2019.105440

[21] M. Ordu, and Y. Zengin, “A comparative forecasting approach to forecast animal production: A case of Turkey*,” Livestock Studies*, Vol. 60, No.1, Pp. 25-32, 2020. https://doi.org/10.46897/lahaed.719095

[22] S. Gokulakrishnan, G. Senthil Kumar, A. Serma Saravana Pandian, J. Ramesh, P. Thilakar, L. Radhakrishnan, and A. R. Nanthini, “Time Series Modelling and Forecasting of Prices of Cattle Feed In Tamil Nadu,” *IJVASR*, Vol. 53, No.2, March - April 2024.

[23] G. A. Ryu, A. Nasridinov, H. Rah, and K. Yoo, “Forecasts of the Amount Purchase Pork Meat by Using Structured and Unstructured Big Data,” *Agriculture*, Vol.10, No.1, 2020. https://doi.org/10.3390/agriculture10010021

[24] P. Guerra, Uri, L. Mamani, Natalio, P. Durand, Manuel, Pierr, Manrique, Condori, E. G. Herreros, and Manuel, “Seasonal autoregressive integrated moving average (SARIMA) time-series model for milk production forecasting in pasture-based dairy cows in the Andean highlands,” *PLoS ONE*, Vol.18, 2023. https://doi./10.1371/journal.pone.0288849

[25] E. Kasatkina, D. Vavilova, and R. Faizullin, “Development of econometric models to forecast indicators of the livestock industry,” *E3S Web of Conferences*, Vol.548, 03002, 2024. https://doi.org/10.1051/e3sconf/202454803002

© 2024 The Authors. Published by Universitas Muhammadiyah Malang
This is an open access article under the CC BY NC SA license (https://creativecommons.org/licenses/by-nc-sa/4.0/)