Jurnal Matematika Integratif. p-ISSN:1412-6184, e-ISSN:2549-903
Vol. 19 No.1 (2023), pp. 41–54. doi:10.24198/jmi.v19.n1.44573.41-54

Forecasting the Indonesian Coffee Production and Consumption Using the Exponential Smoothing Methods with Modified Golden Section Search to Estimate the Smoothing Parameters

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Abstract
The Double Exponential Smoothing (DES) and Triple Exponential Smoothing (TES) are forecasting methods that require two and three smoothing parameters, respectively. Smoothing parameters are often determined through a trial and error process that is not really efficient since many experiments need to be done. Therefore, in this study, a smoothing parameter estimation algorithm is conducted in the form of the modified Golden Section Search (GSS) to obtain the optimal smoothing parameters from the DES and TES methods. Forecasting is carried out on production, domestic consumption, and export consumption data of Indonesian coffee, which is one of the leading agricultural sub-sector commodities. The data is obtained from the Ministry of Agriculture of the Republic of Indonesia. The smoothing parameters obtained by applying the modified GSS are used to forecast production and domestic consumption data using the DES method, while the forecasting of the export consumption data is done with the TES method. All of the MAPE values are less than 20% which indicates that the smoothing parameters obtained by using the modified GSS are able to perform good forecasting. The results show that coffee production in Indonesia cannot meet its demand until 2024 since the total coffee consumption exceeds the production.

Keywords: double exponential smoothing, triple exponential smoothing, golden section search, Indonesian coffee forecast

1. Introduction

Forecasting is the process of predicting the future as accurately as possible [1]. One of the most popular forecasting methods is the Exponential Smoothing (ES) method, which consists of Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Triple Exponential Smoothing (TES). The SES method can be applied to stationary data series, while the DES method is suitable to data containing the trend component. However, the TES method is applicable for data not only with the trend component but also with seasonality. The SES has a single smoothing parameter, whereas the DES and TES methods have two and

2000 Mathematics Subject Classification: 49M37, 90C30
Received: 2023-01-16, Accepted: 2023-03-31, Published: 2023-06-01 .

three smoothing parameters, respectively. The smoothing parameters in the DES method are α and β, while the TES method has an additional smoothing parameter, namely γ. All of the smoothing parameters values are between zero and one.

Many studies have used the DES and TES methods to forecast various real-life problems. For instance, the aforementioned methods were used to predict coffee and rubber production in Aceh Province, Indonesia [2]. The smoothing parameters were estimated by calculating the forecasting errors from ten different combinations of the smoothing parameters for each method. Another research that implements those methods was carried out by [3] in which both of them were compared by applying five different smoothing parameters for each method. Furthermore, a research was conducted by [4] using the trial and error process to acquire the optimal smoothing parameters. The trial and error process was done by checking the forecasting errors from 81 pairs of the smoothing parameter combinations.

Even though the smoothing parameters value can be estimated through the trial and error process, this method is inefficient since it requires a lot of experiments. According to [5, 6, 7, 8], the smoothing parameters can be determined through a non-linear optimization algorithm to find the optimal value. An optimal smoothing parameter is able to minimize the forecasting error measurement such as Mean Squared Error (MSE) or Mean Absolute Percentage Error (MAPE). Therefore, a more efficient algorithm to obtain the optimal smoothing parameters is necessary, such as the Golden Section Search (GSS). The Golden Section Search method is a one-variable non-linear optimization algorithm based on the elimination of a search area containing the optimum point. However, the estimation of the optimal smoothing parameters by minimizing the forecasting error for the DES and TES methods can be done by using the modified Golden Section Search method. The GSS is modified to be a multi-variable non-linear optimization algorithm to meet the needs of the two smoothing parameters for the DES method and the three smoothing parameters for the TES method.

In this study, the DES and TES methods are applied to forecast Indonesian coffee production and consumption. The methods are chosen based on the pattern of the data, which shows the trend and seasonal elements. Indonesian coffee is one of the most important agricultural commodities for domestic and export consumption. Coffee is one of the leading commodities contributing to Indonesias foreign exchange [9]. Coffee is consumed by 3040% of the world's population, with Indonesia as one of the largest coffee-producing countries. Indonesian coffee, which is produced from plantations in Indonesia, is one of the leading commodities for domestic and foreign markets. Export consumption of Indonesian coffee exceeded 359 tons in 2019, with domestic consumption of 1,692 kg/capita/year [10]. Almost all provinces in Indonesia are coffee producers, except Jakarta province [11]. This commodity's total production area is estimated to be 1.2 million hectares [12]. In addition, 12.1% of total agricultural exports in 2014 were coffee commodities [13].

This research extends the conventional procedure of estimating smoothing parameters. The work presented in this research aims to reduce the inefficiency of numerous trial and error to obtain the optimal smoothing parameters in exponential smoothing methods by implementing a non-linear programming algorithm. We choose MAPE as the forecast error measurement. This error measurement is chosen due to the relative error, as it can be easily interpreted because it provides information about the forecast accuracy in percentage form. MAPE as the objective function is difficult to express in an explicit form. Thus, in terms of the optimal smoothing parameters selection, we use the modified GSS method because it is one of the most efficient derivative-free interval elimination algorithms [14, 15, 16, 17, 18]. It is also known for its fast performance and precision [19, 20, 21]. In general, a forecast is classified as a good forecast if the value of the MAPE is less than 20% [22, 23, 24].

This paper is organized as follows: In Section 2, the research methods are discussed, such as the DES method, the TES method, and the modified GSS as well. The results of this study are presented in Section 3. First, we identified the pattern of the data and followed by estimating the smoothing parameters using the modified GSS algorithm. In addition, the optimal smoothing parameters are used to forecast the production and consumption of Indonesian coffee until 2024. Finally, we present the remarks of this study in Section 4.

2. Research methods

In the current research, the forecasting methods being used are the DES and TES methods. Moreover, a modified Golden Section Search algorithm is used to estimate the smoothing parameters. The data is obtained from the Center for Agricultural Data and Information Systems at the Secretariat General of the Ministry of Agriculture of the Republic of Indonesia [10]. Three data sets are being used, namely production, domestic consumption, and export consumption with the time span from 19932019. We exclude the data series from 20202022 since they are not applicable due to the COVID-19 pandemic. The following sub-sections briefly explain the aforementioned methods.

2.1. **Forecasting.** Forecasting is predicting the future as accurately as possible with available information, such as historical data and knowledge of future events that can affect the forecast results [1], [25]. Forecasting takes past and current data into account to estimate future value [26, 27]. In order to perform a proper forecasting analysis, the pattern of data plays an important role. Generally, the pattern of data might exhibit one of the following patterns, such as horizontal, seasonal, cyclic, or trend [28, 29]. However, it is also possible that there is more than one pattern existing in the data, such as the combination of the trend and seasonal elements [30, 31].

2.2. **Dickey-Fuller unit root test.** As mentioned in the previous section, the DES and TES methods are suitable for data that contains the trend and trend-seasonal patterns, respectively. Therefore, we need to check the stationarity of the data. If the data is not stationary, then it most likely contains other data patterns such as trends and seasonality. In stationary data, fluctuations are time-independent and gravitate toward a certain constant average value [32]. One of the statistical tests that can provide information about the stationarity of the data is the Dickey-Fuller unit root test. According to [33, 34], the calculation of the Dickey-Fuller unit root test is given by the following equation

$$\Delta Y_t = \delta Y_{t-1} + u_t \tag{1}$$

in which

t : Time ($t = 1, 2, 3, \ldots$),
Y_{t-1} : Variable being observed at time $t-1$,
ΔY_t : Difference of variables at time t,
δ : Autoregressive coefficient,
u_t : White noise variable.

White noise is a random and uncorrelated error, with a constant variance and zero mean [33]. The Dickey-Fuller unit root test is calculated by solving the τ statistic as follows

$$\tau = \frac{\delta}{SE(\delta)} \tag{2}$$

The hypotheses being tested are as follows

H_0 : $\delta = 0$ (data contains unit root, thus it is not stationary),
H_1 : $\delta < 0$ (data does not contains unit root, thus it is stationary).

The criteria in this test are accept H_0 if $|\tau| < |\tau_{table}|$, which means that the data is not stationary, and reject H_0 if $|\tau| > |\tau_{table}|$, which implies that the data is stationary. The table consisting of τ values are presented as such in Table 1 [35], with the critical value being considered in this paper is 5%.

TABLE 1. Values of τ_{table}.

Critical value	τ_{table}
1%	-1.61
5%	-1.95
10%	-2.60

2.3. **Double Exponential Smoothing (DES).** The DES method is a forecasting method suitable for data containing trend elements. This method possesses two smoothing parameters, namely and whose values range between zero (0) and one (1). The α parameter is used to smooth the level component, while the β parameter smooths the trend component [36, 37]. Forecasting steps with this method are as follows [5]:

(1) Initializing level and trend components

$$L_1 = Y_1, \tag{3}$$

$$b_1 = Y_2 - Y_1. \tag{4}$$

(2) Smoothing level and trend components

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + b_{t-1}), \tag{5}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}. \tag{6}$$

(3) Calculating the forecast at $t + m$

$$F_{t+m} = L_t + b_t m. \tag{7}$$

2.4. **Triple Exponential Smoothing (TES).** The TES is a forecasting method which deals with data containing both the trend and seasonal elements. Usually, the length of the seasonality is denoted by s. In terms of the smoothing parameters, this method has α, β, and γ parameters that serve as smoothing factors for different components of the data. The α and β smooth the same components as explained in the DES method, while γ smooths the seasonal component [37, 38]. Forecasting steps with this method are as follows [5]:

(1) Initializing level, trend, and seasonal components

$$L_s = \frac{1}{s}(Y_1 + Y_2 + \ldots + Y_s), \tag{8}$$

$$b_s = \frac{1}{s}[\frac{Y_{s+1} - Y_1}{s} + \frac{Y_{s+2} - Y_2}{s} + \ldots + \frac{Y_{s+s} - Y_s}{s}], \tag{9}$$

$$S_1 = Y_1 - L_s, S_2 = Y_2 - L_s, \ldots, S_s = Y_s - L_s. \tag{10}$$

(2) Smoothing level and trend components

$$L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}), \tag{11}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}, \tag{12}$$

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s}. \tag{13}$$

(3) Calculating the forecast at $t + m$

$$F_{t+m} = L_t + b_t m + S_{t-s+m}. \tag{14}$$

2.5. **Mean Absolute Percentage Error (MAPE).** Measuring the accuracy of the forecasting model is possible by calculating the MAPE [39, 40]. The MAPE is the average of absolute percentage error of forecasting results. A smaller MAPE value indicates a better forecasting process [41, 42]. The MAPE is calculated with the following equation [43]

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_t - \hat{X}_t}{X_t} \times 100\right|. \tag{15}$$

According to [44, 45], the interpretation of the MAPE value which shows the accuracy of the forecasting method are shown in Table 2.

Table 2. Forecast accuracy according to MAPE criteria.

MAPE value	**Forecast accuracy**
MAPE $<$ 10%	Very good forecast
10% $\leq$ MAPE $<$ 20%	Good forecast
20% $\leq$ MAPE $<$ 50%	Okay forecast
MAPE $\geq$ 50%	Bad forecast

2.6. **Golden Section Search (GSS).** The GSS is a method of solving non-linear programming problems with the principle of reducing the boundary area that can produce the optimum value of the objective function (maximum or minimum) [46, 47]. The GSS method is used to solve problems with the general form of the objective function $f(x)$ with $a \leq x \leq d$ constraint using the golden ratio [48, 49]. This method reduces the search area iteratively for one-variable non-linear programming problems [50, 51]. The GSS method is one of the most efficient, precise, and fast interval elimination algorithms that does not involve any derivatives [14, 15, 16, 17, 18, 19, 20, 21].

The steps of the GSS method follow the algorithm below:

Step 1 Input the objective function, stopping criteria (error tolerance), upper bound (u_b), and lower bound (l_b).

Step 2 Calculate the golden ratio
$r = \frac{-1+sqrt5}{2} = 0.61803389$.

Step 3 Determine new evaluation points
$x_1 = r \cdot l_b + (1-r) \cdot u_b$
$x_2 = u_b + l_b - x_1$.

Step 4 Evaluate the function values using new points.

Step 5 Compare the function values to obtain a new reduced interval containing the optimum point.

Step 6 Evaluate the stopping criteria. If the new interval is bigger than the error tolerance or the iterations carried out are less than the maximum number of iterations, repeat Step 3 until either one of the stopping criteria is met.

2.7. **Modified Golden Section Search.** The GSS method is capable of optimizing one-variable non-linear optimization problems only. The modified GSS method is present as a solution to yield the optimum points from multi-variable non-linear optimization problems. This research implements the modified GSS to estimate the smoothing parameters for the DES and TES forecasting methods. The objective function is to minimize the value of the MAPE so that the forecasting process has better accuracy. The general form of the modified GSS can be written as [52]

maximize or minimize

$$f(x_1, x_2, x_3, \ldots, x_n), \tag{16}$$

subject to

$$\begin{cases} a_1 \leq x_1 \leq d_1 \\ a_2 \leq x_2 \leq d_2 \\ a_3 \leq x_3 \leq d_3 \\ \quad\vdots \\ a_n \leq x_n \leq d_n. \end{cases} \tag{17}$$

The algorithm for this modified version of GSS is similar to the previously mentioned algorithm for GSS. The difference lies in the number of evaluated variables. Based on the chosen forecasting methods, in this research, the modified GSS is applied to determine the optimal values of the objective function containing two and three variables for the DES and TES methods, consecutively.

3. Results and discussion

3.1. Analyzing Data Patterns and Seasonality. The data sets analyzed in this research are the data sets of production, domestic consumption, and export consumption of Indonesian coffee that are shown in Figure 1, Figure 2, and Figure 3, respectively.

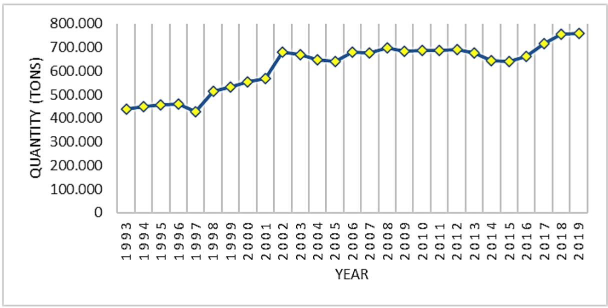

Figure 1. Production data.

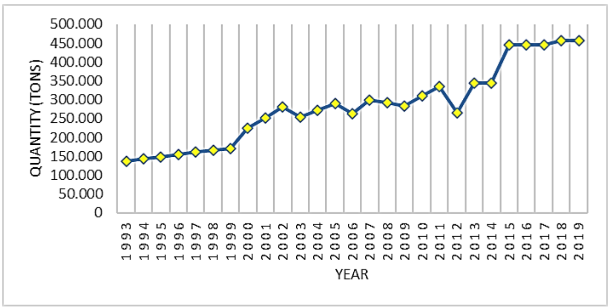

Figure 2. Domestic consumption data.

In Figure 1 and Figure 2, it can be seen that the production and domestic consumption are categorized as data with the trend patterns, while the export consumption data shown in Figure 3 has a combination of the trend and seasonal patterns. It is in accordance with the results of the Dickey-Fuller unit root test of those data. The parameter of the Dickey-Fuller unit root test τ is calculated by using Equation 2 and the results are shown in Table 3.

According to the statistical hypothesis of the Dickey-Fuller test in Subsection 2.2, the absolute values of the Dickey-Fuller statistic $|\tau|$ for these three data sets are less than the critical value $|\tau_{table}|$ with a statistical significance of 5% (see Table 3). Thus, H_0 is accepted which

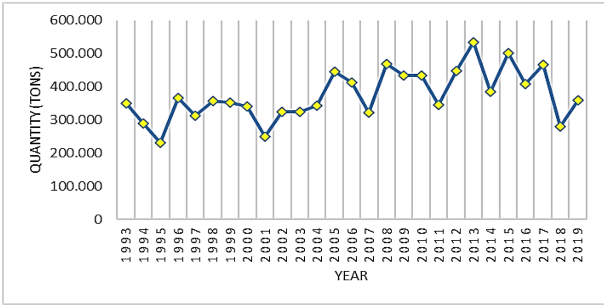

FIGURE 3. Export consumption data.

TABLE 3. Dickey-Fuller unit root test results.

Data	$\lvert\tau\rvert$	$\lvert\tau_{table}\rvert$
Production	1.653	
Domestic consumption	1.577	1.95
Export consumption	0.563	

implies that all data sets are not stationary. Since the production and domestic consumption data are both not stationary because of the existence of the trend element, these data sets will be forecasted by using the DES method.

From Figure 3, we can observe that there are some peaks that repeat periodically which indicates the existence of seasonal elements. This notion is supported by Table 4 where the peaks are visible by comparing data points that are grouped in a certain period, which is 4. Hence, the export consumption data contains not only the trend but also seasonal elements with the length of seasonality $s = 4$. In this case, since the data set has a combination of the trend and seasonal data pattern, the TES method is suitable to apply.

TABLE 4. Checking the seasonality of export consumption data.

Period	**Season 1**	**Season 2**	**Season 3**	**Season 4**	**Season 5**	**Season 6**
1	349916	313430	250818	445829	433600	534023
2	289288	357550	325009	413500	433595	384816
3	230201	352967	323520	321404	346493	502021
4	366602	340887	344077	468749	448591	408838
Mean	309002	341209	310856	412371	415570	457425

3.2. **Estimating the Smoothing Parameters using the Modified Golden Section Search.** In this section, we perform the estimation of the smoothing parameters using the modified GSS algorithm, since the data sets are forecasted by using the DES and TES methods so that each of them involves more than one smoothing parameter. The estimation of the smoothing parameters using the modified GSS algorithm follows the steps in Subsection 2.6. In this study, the objective function is to minimize the MAPE value which can be stated as a function of the smoothing parameters. The objective function and constraints to perform the modified GSS algorithm for the DES method that refer to Equation 16 and Equation 17 are written as follows

$$\text{minimize} \quad : \quad MAPE = f(\alpha, \beta), \tag{18}$$

$$\text{subject to} \quad : \quad \begin{cases} 0 < \alpha < 1 \\ 0 < \beta < 1 \end{cases} \tag{19}$$

Meanwhile, the objective function and constraints for the TES method are

$$\text{minimize} \quad : \quad MAPE = f(\alpha, \beta, \gamma), \tag{20}$$

$$\text{subject to} \quad : \quad \begin{cases} 0 < \alpha < 1 \\ 0 < \beta < 1 \\ 0 < \gamma < 1 \end{cases} \tag{21}$$

The stopping criteria in this algorithm refers to the error tolerance ε. The error tolerance is set to $\varepsilon = 1 \times 10^{-8}$ as it can generate the smoothing parameters with sufficient accuracy [51]. The upper bound and lower bound are determined by the smoothing parameter interval, namely $l_b = 0$ and $u_b = 1$. The results of the smoothing parameter estimation for production, domestic consumption, and export consumption data are shown in Table 5, Table 6, and Table 7, respectively.

Table 5. Parameter estimation for production data.

Iteration	α_1	α_2	β_1	β_2
1	0.38196601	1.00000000	0.38196601	1.00000000
2	0.61803399	1.00000000	0.38196601	0.76393202
3	0.76393202	1.00000000	0.38196601	0.61803398
4	0.76393202	0.90983006	0.38196601	0.52786404
⋮	⋮	⋮	⋮	⋮
36	0.90983003	0.90983006	0.38196601	0.38196604
37	0.90983004	0.90983006	0.38196601	0.38196603
38	0.90983005	0.90983006	0.38196601	0.38196602
38	0.90983005	0.90983006	0.38196601	0.38196602
39	0.90983005	0.90983005	0.38196601	0.38196601

Table 5 shows the iteration process to estimate the optimal smoothing parameters α and β to be used to forecast the production data using the DES method. From Table 5, it can be observed that as the iteration goes on the error of both α_1, α_2 and β_1, β_2 decrease and get smaller than the error tolerance at the 39th iteration. Thus, each α and β converges to a certain value, i.e., $\alpha = 0.90983005$ and $\beta = 0.38196601$, which implies the optimal smoothing parameters.

Table 6. Parameter estimation for domestic consumption data.

Iteration	α_1	α_2	β_1	β_2
1	0.38196601	1.00000000	0.00000000	0.61803399
2	0.38196601	0.76393202	0.00000000	0.38196601
3	0.52786405	0.76393202	0.00000000	0.23606798
4	0.61803399	0.76393202	0.00000000	0.14589803
⋮	⋮	⋮	⋮	⋮
36	0.72949017	0.72949020	0.02203416	0.02203419
37	0.72949017	0.72949019	0.02203416	0.02203418
38	0.72949017	0.72949018	0.02203417	0.02203418
39	0.72949017	0.72949017	0.02203417	0.02203417

The modified GSS iteration process to estimate the optimal smoothing parameters α and β to be used to forecast the domestic consumption data using the DES method in Table 6 stopped at the same iteration. The optimal smoothing parameters obtained from this iteration process are $\alpha = 0.72949017$ and $\beta = 0.02203417$. By the same procedure, we obtain the optimal value for the three smoothing parameters that are involved in the TES method in order to forecast the export consumption data. As seen in the iteration process to estimate α, β, and γ in Table 7, the optimal smoothing parameters are $\alpha = 0.00181241$, $\beta = 0.05572809$, and $\gamma = 0.23606798$.

TABLE 7. Parameter estimation for export consumption data.

Iteration	α_1	α_2	β_1	β_2	γ_1	γ_2
1	0.00000000	0.61803399	0.00000000	0.61803399	0,00000000	0.61803399
2	0.00000000	0.38196601	0.00000000	0.38196601	0,23606798	0.61803399
3	0.00000000	0.23606798	0.00000000	0.23606798	0,23606798	0.47213595
4	0.00000000	0.14589803	0.00000000	0.14589803	0,23606798	0.38196601
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
36	0.00181239	0.00181242	0.05572806	0.05572809	0.23606798	0.23606801
37	0.00181240	0.00181242	0.05572807	0.05572809	0.23606798	0.23606800
38	0.00181240	0.00181241	0.05572808	0.05572809	0.23606798	0.23606799
39	0.00181241	0.00181241	0.05572809	0.05572809	0.23606798	0.23606798

3.3. **Forecasting of The Production, Domestic Consumption, and Export Consumption Data.** The optimal smoothing parameters obtained by the modified GSS method in the previous section are used to forecast the production, domestic, and export consumption data of Indonesian coffee for the next five years. The forecasting process for the production data by applying the DES method starts with the initialization of the level component using Equation 3 and the trend component using Equation 4,
$L_1 = 438868$,
$b_1 = 450191 - 438868 = 11323$.

Next, we smooth the level and trend components in the next period by using Equation 5 and Equation 6 with the smoothing parameters obtained from the previous subsection. Meanwhile, the forecast is evaluated using Equation 7. The calculations are as below and this process is repeated for the remaining data points.
$L_2 = 0.90983005(450191) + (1 - 0.90983005)(438868 + 11323) = 450191$,
$b_2 = 0.38196601(450191 - 438868) + (1 - 0.38196601)11323 = 11323$,
$F_2 = 438868 + 11323(1) = 450191$.

The forecasting process for the domestic consumption data is done in the same manner as both data sets have the trend component as their element. For the export consumption data that contains the trend and seasonal components, the forecasting initialization uses Equation 8-10.
$L_4 = \frac{1}{4}(349916 + 289288 + 230201 + 366602) = 309001.8$,
$b_4 = \frac{1}{4}[\frac{-36486}{4} + \frac{68262}{4} + \frac{122766}{4} + \frac{-25715}{4}] = 8051.688$,
$S_1 = 349916 - 309001.8 = 40914, S_2 = 289288 - 309001.8 = -19714$,
$S_3 = 230201 - 309001.8 = -78801, S_4 = 366602 - 309001.8 = 57600$.

Subsequently, Equation 11-13 successively smooth the level, trend, and seasonal components while Equation 14 calculates the forecast, yield
$L_5 = 0.00181241(313430 - 40914) + (1 - 0.00181241)(309001.8 + 8051.688) = 316972.8$,
$b_5 = 0.05572809(316972.8 - 309001.8) + (1 - 0.05572809)8051.688 = 8047, .95$,
$S_5 = 0.23606798(313430 - 316972.8) + (1 - 0.23606798)40914 = 30419.27$,
$F_5 = 316972.8 + 8047.195(1) + 40914 = 357968$.

The forecasting results from the above process for the production, domestic consumption, and export consumption data are shown in Figure 4, Figure 5, and Figure 6, respectively.

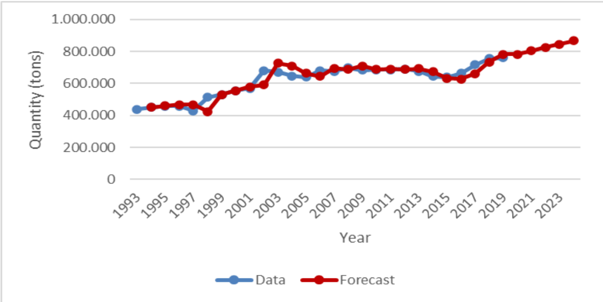

FIGURE 4. Production forecast.

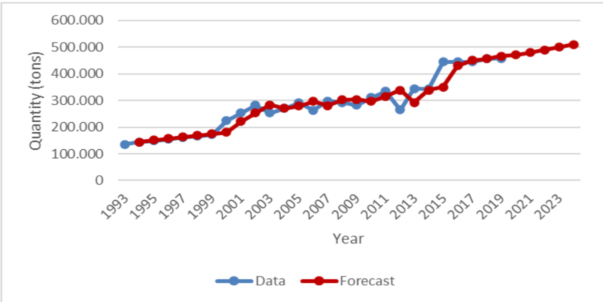

FIGURE 5. Domestic consumption forecast.

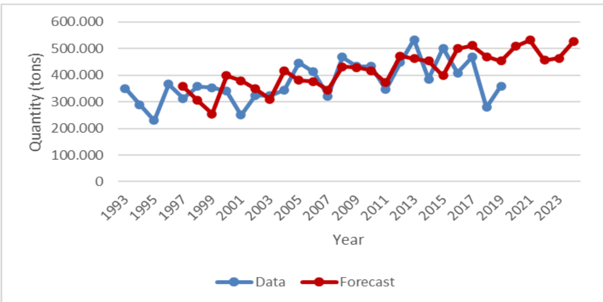

FIGURE 6. Export consumption forecast.

Performing accurate forecasting is important because it affects the decision-making process. Here, the forecasting accuracy uses the MAPE in Equation 15 and the results are presented in Table 8. The interpretation of forecasting error measurement also plays a significant role. From Table 2, the forecasting accuracy is distinguished by various MAPE value intervals. Accordingly, from the MAPE values in Table 8, the forecasting process of the production and consumption data are below 10% and they fall under the very accurate forecasting category, whereas the MAPE of the export consumption forecast is categorized as accurate forecasting.

The total production and consumption of Indonesian coffee in the next five years and their difference based on the forecasting results are shown in Table 9. These results are presented to provide insight about the Indonesian coffee production and consumption in the next five years.

Table 8. The recapitulation of the forecasting process.

Data	**Method**	α	β	γ	**MAPE**
Production	Double Exponential Smoothing	0.90983005	0.38196601	–	4.164564%
Domestic consumption	Double Exponential Smoothing	0.72949017	0.02203417	–	6.904378%
Export consumption	Triple Exponential Smoothing	0.00181241	0.05572809	0.23606798	17.05853%

Table 9. Difference between total production and total consumption.

Period	**Year**	**Total production (tons)**	**Total consumption (tons)**	**Difference (tons)**
28	2020	783912	980051	-196139
29	2021	804917	1013022	-208105
30	2022	825922	946684	-120762
31	2023	846927	964263	-117336
32	2024	867932	1037537	-169605

Based on Table 9, it can be seen that the difference is always negative. Thus, Indonesia's coffee production activities are not sufficient to meet the needs of coffee consumption in the next five years.

4. Conclusions

Indonesian coffee is one of the most profitable agricultural commodities; thus, it is important to predict the behavior of its production and consumption activity in the future to maximize its full potential. In this research, the production and consumption of Indonesian coffee have been forecasted by using the DES and TES methods, since the data pattern shows the existence of the trend and the combination of the trend and seasonal elements. Estimating the smoothing parameters might be feasible through a trial and error process, but it can be inefficient and time-consuming. Therefore, this research performed the estimation of the smoothing parameters by using a non-linear programming algorithm, namely modified Golden Section Search as an alternative. The implementation of this method has generated an efficient process for obtaining the smoothing parameters.

Essentially, when performing the trial and error process, numerous smoothing parameter combinations have to be calculated to single out the ones that bring in the lowest MAPE value. The complexity escalates as a result of increasing the possible parameter combinations when an additional smoothing parameter is introduced in the TES method. Moreover, enhancing accuracy by augmenting more decimal digits of the smoothing parameters also demands greater effort.

Based on the MAPE values, the TES method delivers a good forecasting result for the export consumption data, while the DES method yields a very good forecasting result. The results of the forecast for production, domestic consumption, and export consumption of Indonesian coffee until 2024 show that coffee production is unable to meet the demand for coffee consumption every year. Hopefully, the results and methods in this study provide information to enrich the mathematical tools in forecasting and as a quantitative basis for decision-makers in Indonesia to minimize the loss of profit from the coffee commodity that could happen in the future.

References

[1] Hyndman, R.J., and Athanasopoulos, G., 2018., *Forecasting: Principles and Practice*, OTexts.

[2] Amelia, Nurviana, Muliani, F., Nuri, B., 2019, Forecasting annual coffee and rubber production in Aceh using exponential smoothing, *Regular Proceeding 3rd ISIMMED*, Pages 3 - 10.

[3] Khairina, D.M., Daniel, Y., Widagdo, P.P, 2121, Comparison of double exponential smoothing and triple exponential smoothing methods in predicting income of local water company, *Journal of Physics: Conference Series*, Volume 1943, Issue 1.

[4] Rahmawati, A., Desviona, N., Sari, T.P., 2022, Estimation of the open unemployment rate on Province Jambi using the double exponential smoothing, *Nucleus*, Volume 3, Issue 1, Pages 10 - 19.

[5] Makridakis, S, Wheelwright, S.C., Hyndman, R.J., 1998., *Forecasting: Methods and Applications*, Wiley, New Jersey.

[6] Zhu, X., Xu, Q., Tang, M., Nie, W., Ma, S., and Xu, Z., 2017, Comparison of two optimized machine learning models for predicting displacement of rainfall-induced landslide: A case study in Sichuan Province, China, *Engineering Geology*, Volume 218, Pages 213 - 222.

[7] Jiang, W., Wu, X., Gong, Y., Yu, W., and Zhong, X., 2020, HoltWinters smoothing enhanced by fruit fly optimization algorithm to forecast monthly electricity consumption, *Energy*, Volume 193.

[8] Chusyairi, A., Saputra, P.R.N., and Handayani, E., 2018, Optimization of exponential smoothing method using genetic algorithm to predict e-report service, *Proceedings - 2018 3rd International Conference on Information Technology, Information Systems and Electrical Engineering, ICITISEE 2018*, Pages 292 - 297.

[9] Irmeilyana, Ngudiantoro, and Rodiah, D., 2021, Correspondence analysis pada hubungan faktor-faktor yang mempengaruhi pendapatan petani kopi Pagaralam, *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, Volume 15, Issue 1, Pages 179 - 192.

[10] Kementerian Pertanian Republik Indonesia, 2020, *Buku Outlook Komoditas Perkebunan Kopi*, Kementerian Pertanian Republik Indonesia, Jakarta.

[11] Kusmiati, A., Windiarti, R., 2011, Analisis wilayah komoditas kopi di Indonesia, *Jurnal Sosial Ekonomi Pertanian*, Volume 5, Issue 2, Pages 47 - 58.

[12] Badan Pusat Statistik, 2014, *Buletin Statistik Perdagangan Luar Negeri Ekspor Menurut Kelompok Komoditi dan Negara Desember 2014*, Badan Pusat Statistik, Jakarta.

[13] Ginting, C.P., Kartiasih, F., 2019, Analisis ekspor kopi Indonesia ke negara-negara ASEAN, *Jurnal Ilmiah Ekonomi Dan Bisnis*, Volume 16, Issue 2, Pages 143 - 157.

[14] Cai, J., Han, D., Chen, C., and Chen, S., 2010, Application of the golden section search algorithm in the nonlinear isoconversional calculations to the determination of the activation energy from nonisothermal kinetic conversion data, *Solid State Sciences*, Volume 12, Issue 5, Pages 829 - 833.

[15] Vieira, D.A.G., Takahashi, R.H.C., and Saldanha, R.R., 2012, Multicriteria optimization with a multiobjective golden section line search, *Mathematical Programming*, Volume 13, Pages 131 - 161.

[16] Pejic, D., and Arsic, M., 2019., Minimization and Maximization of Functions: Golden-Section Search in One Dimension, *Exploring the DataFlow Supercomputing Paradigm*, Springer International Publishing, Pages 55 - 90.

[17] Koupaei, J.A., Hosseini, S.M.M., and Ghaini, F.M.M., 2016, A new optimization algorithm based on chaotic maps and golden section search method, *Engineering Applications of Artificial Intelligence*, Volume 50, Pages 201 - 214.

[18] Singh, S., 2018, Maximum power point tracking technique for PV system by using golden section search method, *Advances in Systems Science and Applications*, Volume 18, Issue 3, Pages 111 - 122.

[19] Scherrer, T., Kim, S.Y., and Yi, C., 2013, Low complexity, real-time adjusted power management policy using Golden Section Search, *ISOCC 2013 - 2013 International SoC Design Conference*, Pages 229 - 232.

[20] Shao, R., Wei, R., and Chang, L., 2014, A multi-stage MPPT algorithm for PV systems based on golden section search method, *Conference Proceedings - IEEE Applied Power Electronics Conference and Exposition - APEC*, Pages 676 - 683.

[21] Ding, X., Guo, H., and Guo, S., 2017, Efficiency Enhancement of traction system based on loss models and golden section search in electric vehicle, *Energy Procedia*, Volume 105, Pages 2923 - 2928.

[22] Alias, A.R., Zainun, N.Y., and Rahman, I.A., 2016, Comparison between ARIMA and DES methods of forecasting population for housing demand in Johor, *MATEC Web of Conferences*, Volume 81, Pages 1 - 5.

[23] Anggrainingsih, R., Aprianto, G.R., and Sihwi, S.W., 2016, Time series forecasting using exponential smoothing to predict the number of website visitor of Sebelas Maret University, *ICITACEE 2015 - 2nd International Conference on Information Technology, Computer, and Electrical Engineering: Green Technology Strengthening in Information Technology, Electrical and Computer Engineering Implementation, Proceedings*, Pages 14 - 19.

[24] Da Veiga, C.P., Da Veiga, C.R., Catapan, A., Tortato, U., and Da Silva, W.V., 2014, Demand forecasting in food retail: A comparison between the Holt-Winters and ARIMA models, *WSEAS Transactions on Business and Economics*, Volume 11, Issue 1, Pages 608 - 614.

[25] Taylor, S.J., and Letham, B., 2018, Forecasting at Scale, *American Statistician*, Volume 72, Issue 1, Pages 37 - 45.

[26] Habsari, H.D.P., Purnamasari, I., Yuniarti, D., 2020, Forecasting Uses Double Exponential Smoothing Method and Forecasting Verification Uses Tracking Signal Control Chart (Case Study: Ihk Data of East Kalimantan Province), *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, Volume 14, Issue 1, Pages 13 - 22.

[27] Tsai, S.B., Xue, Y., Zhang, J., Chen, Q., Liu, Y., Zhou, J., and Dong, W., 2017, Models for forecasting growth trends in renewable energy, *Renewable and Sustainable Energy Reviews*, Volume 77, Pages 1169 - 1178.

[28] Dwiguna, W.E., 2017, Peramalan Material Polyster Textured 75D pada Periode November 2016 sampai dengan Mei 2017 PT Tiga Manunggal Synthetic dengan Metode Time Series, *Portal E-Journal Karya Ilmiah Undip*.

[29] Fahlevi, A., Bachtiar, F.A., and Setiawan, B.D., 2018, Perbandingan Holt's dan Winter's Exponential Smoothing untuk Peramalan Indeks Harga Konsumen Kelompok Transportasi, Komunikasi, dan Jasa Keuangan, *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, Volume 2, Issue 12, Pages 6136 - 6145.

[30] Yapar, G., Yavuz, I., and Selamlar, H.T., 2017, Why and how does exponential smoothing fail? An in depth comparison of ATA-simple and simple exponential smoothing, *Turkish Journal of Forecasting*, Volume 1, Issue 1, Pages 30 - 29.

[31] deLivera, A.M., Hyndman, R.J., and Snyder, R.D., 2011, Forecasting time series with complex seasonal patterns using exponential smoothing, *Journal of the American Statistical Association*, Volume 106, Issue 496, Pages 1513 - 1527.

[32] Ilmayasinta, N., 2021, Forecasting Arrival of Foreign Tourists Using Seasonal Arima Box-Jenkins, *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, Volume 15, Issue 2, Pages 223 - 230.

[33] Gujarati, D.N., and Porter, D.C., 2009., *Basic Econometrics*, McGraw Hill Inc., New York.

[34] Paparoditis, E., and Politis, D.N., 2021, The asymptotic size and power of the augmented DickeyFuller test for a unit root, *Econometric Reviews*, Volume 37, Issue 9, Pages 955 - 973.

[35] Floyd, J.E., 2009., *STATISTICS AND ECONOMETRICS USING XLISPSTAT*, University of Toronto, Toronto.

[36] Omer, A.W., Blbas, H.T.A., and Kadir, D.H., 2021, A Comparison between Browns and Holts Double Exponential Smoothing for Forecasting Applied Generation Electrical Energies in Kurdistan Region, *Cihan University-Erbil Scientific Journal*, Volume 5, Issue 2, Pages 56 - 63.

[37] Crevits, R., and Croux, C., 2018, Forecasting Using Robust Exponential Smoothing with Damped Trend and Seasonal Components, *SSRN Electronic Journal*, Volume 19, Issue 3, Pages 275 - 294.

[38] Oral, I.O., 2019, Comparison of The Winters Seasonality Exponential Smoothing Method With The Pegels Classification: Forecasting of Turkeys Economic Growth Rates, *Anadolu Universitesi Sosyal Bil-imler Dergisi*, Volume 19, Issue 3, Pages 275 - 294.

[39] Prianda, B. G., and Widodo, E., 2021, Perbandingan Metode Seasonal Arima Dan Extreme Learning Machine Pada Peramalan Jumlah Wisatawan Mancanegara Ke Bali, *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, Volume 15, Issue 4, Pages 639 - 650.

[40] Khoojine, A.S., Shadabfar, M., and Tabriz, Y.E., 2022, A Mutual Information-Based Network Autoregressive Model for Crude Oil Price Forecasting Using Open-High-Low-Close Prices, *Mathematics*, Volume 10, Issue 17.

[41] Swamidass, P.M., 2000., *Encyclopedia of Production and Manufacturing Management*, Kluwer Academic Publishers, Boston.

[42] Maruddani, D.A.I, and Trimono, 2018, Modeling stock prices in a portfolio using multidimensional geometric brownian motion, *Journal of Physics: Conference Series*, Volume 1025, Issue 1.

[43] Kartikasari, M.D., 2022, FORECASTING OF CURRENCY CIRCULATION IN INDONESIA, *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, Volume 16, Issue 2, Pages 635 - 642.

[44] Moreno, J.J.M., Pol A.P., Abad, A.S., and Blasco, B.C., 2013, El índice R-MAPE como medida resistente del ajuste en la previsiońn, *Psicothema*, Volume 25, Issue 4, Pages 500 - 506.

[45] Lewis, C.D., 1989., *Industrial and Business Forecasting Methods: A Practical Guide to Exponential Smoothing and Curve Fitting*, Butterworth-Heinemann, Oxford.

[46] Saputra, N.D., Aziz, A., and Harjito, B., 2021, Parameter optimization of Browns and Holts double exponential smoothing using golden section method for predicting Indonesian Crude Oil Price (ICP), *Proceedings - 2016 3rd International Conference on Information Technology, Computer, and Electrical Engineering, ICITACEE 2016*, Pages 356 - 360.

[47] Andrean, V., Chang, P.C., and Lian, K.L., 2018, A review and new problems discovery of four simple decentralized maximum power point tracking algorithms-perturb and observe, incremental conductance, golden section search, and Newtons quadratic interpolation, *Energies*, Volume 11, Issue 11.

[48] Prihatmono, M.W., and Utami, E., 2017, Analysis of moving average and holt-winters optimization by using golden section for ritase forecasting, *Journal of Theoretical and Applied Information Technology*, Volume 95, Issue 32, Pages 6575 - 6584.

[49] Hughes, E.J., 2021, Many-objective directed evolutionary line search, *Genetic and Evolutionary Computation Conference, GECCO11*, Pages 761 - 768.

[50] Akbari, F., Setyanto, A., and Wibowo, F.W., 2018, Optimasi parameter pemulusan algoritma Brown menggunakan metode golden section untuk prediksi data tren positif dan negatif, *Jurnal Resti*, Volume 2, Issue 1, Pages 307 - 314.

[51] Rani, G.S., Jayan, S. and Nagaraja, K.V., 2019, An extension of golden section algorithm for n-variable functions with MATLAB code, *IOP Conference Series: Materials Science and Engineering*, Volume 577, Issue 1.

[52] Saputra, N.D., Aziz, A., and Harjito, B., 2022, Perhitungan Kompleksitas Metode Golden Section dalam Optimasi Parameter Pemulusan Eksponensial Ganda Brown dan Holt, *Jurnal Algoritma*, Volume 18, Issue 2, Pages 330 - 341.