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TIME SERIES METHOD FOR FORECASTING MODEL FOR AMOUNT OF GINGER PLANT PRODUCTION

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Abstract: The ginger plant is a medicinal plant with great potential to be developed as an ingredient in traditional medicine and a raw material for drinks and food. From 2015 to 2021, almost all of the crops in this rhizome group experienced an increase in harvested area, but only ginger plants experienced a decrease in production. This is due to unpredictable weather changes, which can affect crop yields. Good production results can help farmers and industry in processing ginger crops. Therefore, accurate forecasting is needed to determine the quality of decision-making. This research uses primary data from ginger crop harvest from January 2015 to December 2019. Several trials have been carried out using time series forecasting methods: Double Exponential Smoothing (DES) and Triple Exponential Smoothing (TES). The aim is to find the accuracy of several time series methods in predicting the amount of ginger production so that farmers do not fail to carry out scientific forecasting. This research shows that the best forecasting method is to use the TES forecasting model with a Mean Absolute Percentage Error (MAPE) value of 38.10% compared to DES with a MAPE value of 42.49%. This shows that the TES method is better and more capable of forecasting the amount of ginger plant production.

Keywords: time series methods; forecasting model; production of ginger plants; MAPE.

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1. INTRODUCTION

Ginger is a rhizome plant that has many benefits, such as cooking spices, herbal medicine, herbal medicine, and others [1]. The origin of the ginger plant is unknown, but in Tropical Asia, this type has been known for its properties and cultivated since ancient times. Ginger plants are a group of rhizomes that, from 2015 to 2021, almost all regions in Asia experienced an increase in harvested area, but only ginger plants experienced a decrease in production. Therefore, there has been a lot of research on forecasting models for the amount of production, which is proliferating in line with increasing needs, as in research conducted by [2] regarding forecasting the amount of palm oil production for the next period. The results of this research have increased in 2016 by 25905 tons and in 2017 by 33260 tons. This shows that forecasting the amount of oil palm production can be a reference in determining business policies and strategies[3][4]. Apart from that, in research by [5] regarding forecasting for food crop products will also increase in the future. The results of this research are that the amount of rice commodity production has increased by approximately 1000 tonnes in period 23. And in the research [6] regarding analysis of production forecasting, harvest area, and price of soybean crops in Central Java province. This research shows that the development of soybean production and harvest area is very volatile and has a downward trend. This indicates that the process of forecasting production quantities requires a method that has a high level of accuracy and small error[7][8].

Therefore, this research applies the time series method to predict the amount of ginger plant production. This is done because the type of data pattern from the ginger plant consists of several periods. The time series methods used are the DES and TES methods. The DES method is a forecasting method by smoothing the distribution curve over time with a periodic series model[9]. The DES model uses two parameters, namely alpha and beta, to estimate the level and trend components of the time series respectively [10]. There are several studies regarding forecasting using the DES method, such as [11] regarding forecasting car production and produces a MAPE of 46.67% which is at the parameter value α=0.618034 and parameter γ=0.381966 so the forecast results for the Toyota Avanza car in May 2022 are 16263 units. Then developed by [12] regarding applying the exponential smoothing method in predicting the number of new students at Favorite High School with better DES results than SES. This is proven by the MAPE value in the DES method being smaller than in the SES model. Apart from the DES method having a small error rate, the TES method is also an exponential smoothing method using three weightings in the forecasting process[13]. The three weights have a value range of zero to one. The advantages of these two methods can be seen from the relative ease of the forecasting process and better accuracy [14]. However, these two methods need to be compared to improve the method in the future so that it becomes more accurate [15].

Based on the problems above, this research designed a forecast for the amount of ginger plant production by applying several time series methods such as DES and TES to get the best level of accuracy and based on the smallest error so that farmers can carry out all planning well in predicting the amount of ginger plant production in the year. will come.

2. PRELIMINARIES

The data used in this research was obtained from harvest results from various ginger production farming areas in Madura, collected at the Madura Agriculture Service from January 2015 to December 2019, totaling 250 datasets. The stages of this research start from problem formulation, literature study, primary data, data normalization, application of both DES and TES methods, evaluation, and conclusion, as in Figure 1.

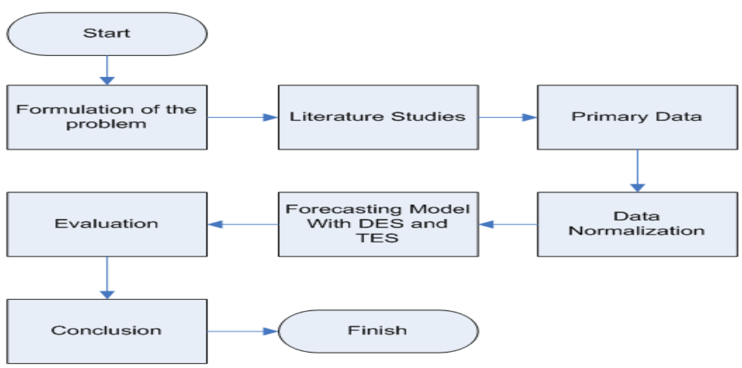

Figure 1. Research stages

Based on Figure 1, the first stage of this research is problem formulation, where the aim is to predict the amount of ginger plant production by applying the time series method, namely DES and TES, and evaluating the error level of the two methods. Then, at the literature study stage, look for and understand relevant information as a source or reference for solving the problems in this research. Then, collect primary data and normalize the data with the binary sigmoid function from 0 to 1. The function formula is as in Equation (1) [16]. The data normalization process aims to ensure that the input data values can be adjusted to the activation function that will be used in this research [17].

$$y' = \frac{x - xmin}{xmax - xmin} * (0.9 - 0.1) + 0.1 \tag{1}$$

Meanwhile, the DES and TES methods are used to apply the time series method for forecasting the amount of ginger plant production. This research proposed this method because the data pattern on the amount of ginger plant production is unstable, so that an exponential smoothing model can be used. DES is a method that repeats calculations continuously using parameters that are different from the parameters used in the original series [18]. The forecasting value from this method is obtained using two smoothing constants with values between 0 and 1, which can be seen in equation (2) [19]. The TES method consists of three elements: smoothing elements, trend elements, and seasonality for each period, using three weightings in the forecasting process. These three weights are alpha (α), beta (β), and gamma (γ). Forecasting calculations using the TES method can be seen in equation (3) [20]. Exponential smoothing is a smoothed estimate of the data values at the end of each period. And trend is a smoothed estimate of the average growth at the end of each period [21]. The stages of the DES and TES method process for predicting the amount of ginger plant production can be seen in Figure 2.

$$S_n = \alpha Y_n + (1 - \alpha)(S_{n-1} + T_{n-1}) \tag{2}$$
$$T_n = \gamma(S_n - S_{n-1}) + (1 + \gamma)T_{n-1}$$
$$Y_{n+m} = S_n + T_{n+m}$$
$$b_n = \gamma(S_n - S_{n-1}) + (1 - \gamma)T_{n-1} \tag{3}$$
$$I_n = \beta \frac{X_t}{S_n} + (1 - \beta)I_{n-1}$$

$$S_n' = \alpha \frac{X_t}{S_n} + (1-\alpha)(S_n + T_{n-1})$$

$$f_{n+m} = (S_n' + T_{n+m})I_{n+m}$$

where S_n directly to the trend of the previous period, i.e T_{n-1} by adding the final smoothing value, i.e S_{n-1}. This helps to eliminate lag and ground the current forecast data. And if there is still a little randomness, then this is eliminated by smoothing with γ (gamma) the trend in the last period $(S_n - S_{n-1})$ and add it to the previous trend estimate multiplied by (1-γ). I_n is trend, S_n' is exponential smoothing, f_{n+m} is the prediction for the n-th period.

The forecast evaluation results are carried out to measure the accuracy of the forecasting process. This approach is practical when the size of the forecast variable is essential in evaluating the accuracy of the forecast, where the correspondence between existing data and forecast data[16]. Several calculations are commonly used to calculate total forecasting error, one of which is MAPE. MAPE is calculated using the absolute error for each period divided by the actual observed value. Then, average the fundamental percentage errors. MAPE is an error measurement that calculates the percentage of deviation between real data and forecast data. The MAPE value can be calculated using equation (4).

$$MAPE = \left(\frac{100\%}{n}\right) \sum_{t=1}^{n} \frac{|x_t - f_t|}{x_t} \quad (4)$$

where x_t is the actual data in period t, f_t is the forecast value in period t, n is the amount of data.

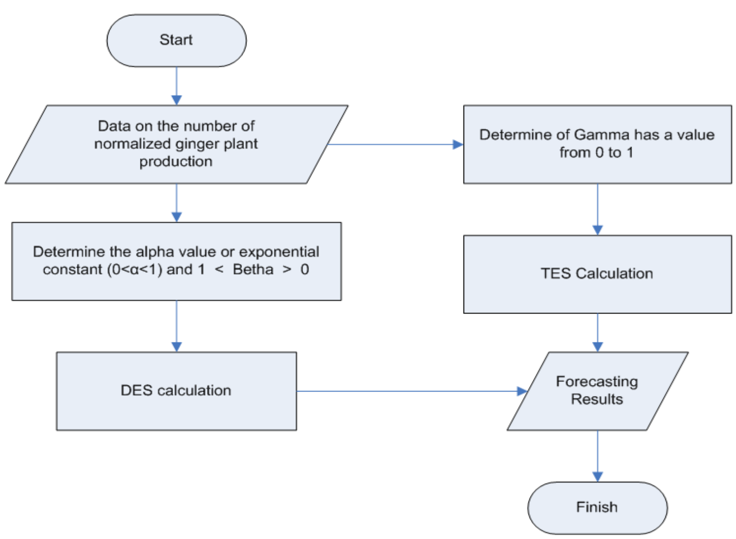

Figure 2. DES And TES process stages for forecasting the amount of ginger plant production

3. MAIN RESULTS

This section discusses the trials and implementation results of DES and TES predictions for forecasting the amount of ginger plant production. The initial stage is to prepare the data that the system will predict. The data pattern used is shown in Figure 3. Based on Figure 3, it can be seen that the data pattern increases with an increase in the number of ginger plants, which means that ginger production has decreased or vice versa. There is a fluctuating data pattern, so it can be said that the data contains trend and seasonal patterns.

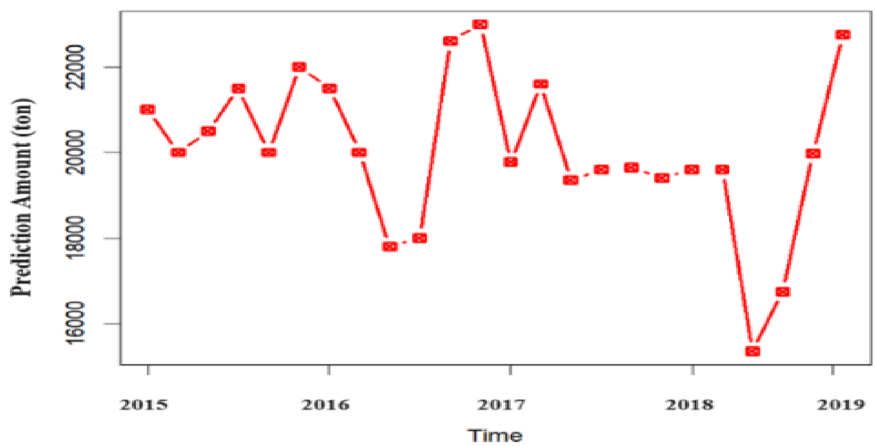

Figure 3. Data Patterns of Ginger Crop Production in Madura

Before the forecasting process is carried out using the DES and TES models, primary data is transformed to eliminate duplicates and reduce complexity. The results of the normalization of data on the amount of ginger plant production can be seen in Table 1. Based on Table 1, the next step is to make predictions using the DES method, so optimum level smoothing (α) and trend smoothing (β) parameter values are needed. In this study, we used experiments by combining several α and β values and then tested them against the test data to obtain an error value in MAPE, as in Table 2. Based on Table 2, the DES model with parameters $\alpha = 0.4$ and $\beta = 0.3$ has shown a MAPE value of 42.49%, so the best DES model can be used as a forecast for several periods into the future. Calculation of the predicted value (fitted value) on the combination of train data and test data (returning the entire data) based on the DES model as in Table 3. Comparison between actual data, fitted value, and the results of forecasting the amount of ginger plant production can be seen in Figure 4. Figure 4 shows that the red line follows the actual data pattern, so the DES method can be stated that the model is suitable for forecasting the amount of ginger plant production.

Table 1. Normalization Data of Ginger Crop Production with Binary Sigmoid

No	Years				
	2019	2018	2017	2016	2015
..	..	..	…	…	…
11	0.5521	0.7354	0.6302	0.4943	0.7329
12	0.5111	0.6733	0.7141	0.3325	0.6254
13	0.3897	0.5747	0.8935	0.2595	0.6140
14	0.4922	0.5866	0.5771	0.1943	0.5742
15	0.4628	0.4742	0.5642	0.3000	0.5595
16	0.5310	0.3140	0.4997	0.4694	0.5325
17	0.5898	0.4315	0.4762	0.4723	0.5222
18	0.6203	0.5699	0.4825	0.4762	0.4935
19	0.6264	0.8742	0.4855	0.5771	0.4412
20	0.6349	0.9483	0.4774	0.6076	0.4095
…	…	…	…	…	…
50	0.5875	0.5674	0.7210	0.5865	0.4131

Table 2. Combination of α and β Parameter Values With the DES Method

Model of DES		MAPE
α	β	(%)
0.8	0.3	50.93
	0.5	47.22
	0.7	49.01
0.7	0.3	45.56
	0.5	50.65
	0.7	43.57
0.6	0.3	45.42
	0.5	48.56
	0.7	51.73
0.5	0.3	47.22
	0.5	49.01
	0.7	52.96
0.4	0.3	42.49
	0.5	44.42
	0.7	45.40
0.3	0.3	48.53
	0.5	43.76
	0.7	43.79

Table 3. Fitted Value on Overall Data With DES Model

No	Level (S_n)	Trend (T_n)	Forecast (Y_{n+m})
..	…	…	…
11	0.195079	-0.025955	0.156129
12	0.236259	-0.012528	0.169124
13	0.343216	0.011369	0.223731
14	0.495048	0.039462	0.354585
15	0.551370	0.042834	0.534510
16	0.468043	0.017601	0.594203
17	0.500827	0.020638	0.485644
18	0.598224	0.035990	0.521465
19	0.449956	-0.000862	0.634214
20	0.491124	0.007544	0.449094
..	…	…	…
240	0.433637	0.003219	0.426225
241	0.443012	0.004450	0.436856
242	0.452369	0.005431	0.447462
243	0.461539	0.006179	0.457801
244	0.470415	0.006718	0.467719
245	0.478939	0.007079	0.477134
246	0.487091	0.007294	0.486018
247	0.494881	0.007393	0.494385
248	0.502336	0.007406	0.502274
249	0.509497	0.007357	0.509742
250	0.433637	0.003219	0.426225

The forecasting process with the TES model is carried out based on the optimum α, β, and γ values and the smallest MAPE, and so the prediction results can be seen in Table 4. Based on table 4 shows that the combination of parameters α and β is the same as the DES model, and γ=0.1 has produced MAPE amounting to 38.10%. This indicates that the measurement error of the TES model is smaller than the DES model because it has the smallest MAPE value, so it can be said that the TES forecasting ability is excellent compared to the DES model. Meanwhile, the comparison plot of actual data, forecasting data using DES and predicting results using TES can be seen in Figure 5. Figure 5 shows that the forecasting results from the TES and DES models have a minor error rate, namely the TES model, so TES is the best model for predicting—the amount of ginger plant production for the next period.

Table 4. Combination of α, β, γ Parameter Values With the TES Method

Model of TES			MAPE
α	**β**	**γ**	**(%)**
0.8	0.3	0.1	44.66
	0.5	0.2	43.50
	0.7	0.3	41.71
0.7	0.3	0.1	40.83
	0.5	0.2	42.16
	0.7	0.3	44.42
0.6	0.3	0.1	45.40
	0.5	0.2	48.53
	0.7	0.3	39.89
0.5	0.3	0.1	45.04
	0.5	0.2	45.56
	0.7	0.3	40.76
0.4	0.3	0.1	38.10
	0.5	0.2	43.79
	0.7	0.3	46.05
0.3	0.3	0.1	44.52
	0.5	0.2	47.21
	0.7	0.3	46.21

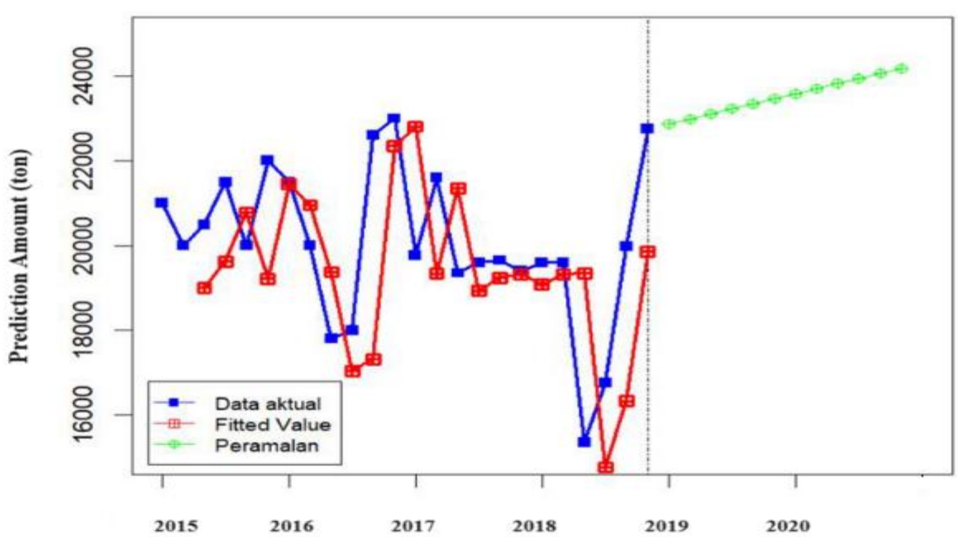

Figure 4. DES Method Forecasting Results

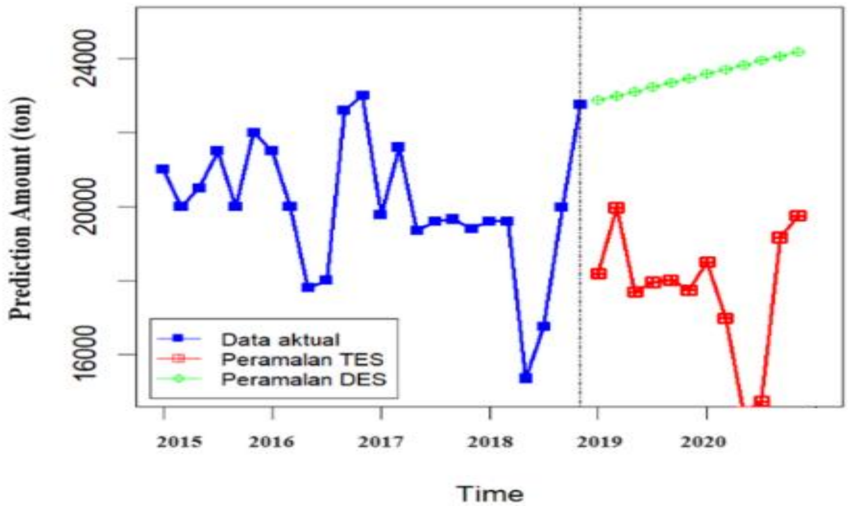

Figure 5. Comparison of Actual Data, DES Forecasting, TES Forecasting

4. CONCLUSION

Based on research that has been carried out on predicting the amount of ginger plant production using the time series method, namely DES and TES, it can be concluded that the best method is the method that produces the smallest MAPE. The MAPE value from the DES model is 42.49% with parameters $\alpha = 0.4$ and $\beta = 0.3$, while the MAPE value from TES is 38.10% with parameters $\gamma=0.1$ so it can be seen that the most suitable model to use for forecasting the amount of ginger plant production is TES. The results of this research can be used by spice farmers in planning production so that they can reduce losses that occur. Meanwhile, development in further research is to carry out forecasting again by optimizing forecasting parameters to produce a smaller error rate, such as using the Particle Swarm Optimization (PSO) method or Genetic Algorithm.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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