Forecasting Sustainable Oil Palm Production (A Case Study Pt. Ana) In East Petasia District, North Morowali Regency

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DOI: https://doi.org/10.5281/zenodo.8133908

Published Date: 11-July-2023

Abstract: **The objective of the research was to forecast the Fresh Fruit Bunches (FFB) production of oil palm managed by PT. ANA in East Petasia District, North Morowali Regency (Kabupaten Morowali Utara), using the "SARIMA Model" (9, 1, 1) (0, 1, 4)^{12}. The location selection was done through purposive sampling considering that the area is one of the emerging oil palm centers in Central Sulawesi Province. The research approach used the *Box-Jenkins Method* of the SARIMA Model, which is an extension of the ARIMA Box-Jenkins model by incorporating seasonal variables. The results of the model identification indicate that the best model for forecasting the production of FFB of oil palm is managed by PT. ANA is the SARIMA Model (9, 1, 1) (0, 1, 4)^{12}. The forecasting results show that the projected production of FFB of oil palm for the upcoming period is 78.060.472 tons, which is approximately 38,95% lower compared to the previous production in (2019).**

***Keywords*: forecasting, palm oil, industry.**

I. INTRODUCTION

Companies, as a vital component of economic development, consistently strive to maintain their presence and profitability in the national economy[1],[2] However, they are inevitably confronted with various risks and uncertainties[3], [4] One agribusiness sector that is particularly susceptible to such risks and uncertainties is oil palm cultivation. The risks and uncertainties in the palm oil plantation business primarily lie in the production of Fresh Fruit Bunches (FFB), which are influenced by weather and climate conditions [5], [6] with rainfall being a critical determinant. Nevertheless, the cultivation of oil palm continues due to its significant role in the national economy as a major foreign exchange earner[7], [8]

With the increasing global demand for Crude Palm Oil (CPO), companies are driven to expand their production by extending the plantation area[9], [10] Consequently, there is a need to convert forested areas into plantations. On one hand, oil palm plantations contribute to the national economy. On the other hand, they can harm ecosystems and accelerate the depletion of limited forest resources for local communities [11], [12]

The extent of oil palm plantations in Indonesia has significantly increased since 1980, with an average annual growth rate of 12,30%.[10], [13] In 2015, the plantation area covered 11,3 million hectares, but it expanded by approximately 5 million hectares by 2017, reaching a total of 16 million hectares. The management is predominantly dominated by smallholder plantations (53%), while private plantations account for 42% and state-owned enterprises for 5%, with a total CPO production of 42 million tons (Kementerian Pertanian, 2015).

The increase in production has also spurred the rapid development of the palm oil industry[14], [15] making Indonesia the world's largest producer since 2006, with a CPO market share of 53,4% of global production [16], [17]. One of the palm oil development regions in Indonesia is Central Sulawesi Province, which includes five regencies designated for palm oil development, including North Morowali Regency (Kabupaten Morowali Utara or MORUT) .In that region, there are four companies involved in oil palm plantations: PT. Cipta Agro Nusantara in the Lembo District, PT. Karunia Alam Makmur in the Mamosalato District, PT. Sinar Mas in the Mori Atas District, and PT. ANA located in the East Petasia District (Dinas Pertanian dan pangan Kabupaten Morowali Utara, 2019).

PT. ANA is the largest plantation company in MORUT due to its extensive land area and highest production volume. Its plantation area includes the villages of Molino, Bungintimbe, Tompira, and Bunta in the East Petasia District. Since its establishment on November 22, 2006, the company has received support from the local community and surrounding areas. It has contributed to job creation and reduced unemployment, thereby mitigating the rate of rural-to-urban migration among the millennial generation [4], [11].

PT. ANA is faced with risks and uncertainties specifically fluctuating production whose occurrence and extent of losses in each period are unknown. Production uncertainty is often caused by natural factors such as unpredictable weather and climate [18], [19]. This uncertainty arises from the limited information available to PT. ANA managers regarding the timing of heavy rainfall and dry seasons, leading to unpredictable production risks, costs, and revenues [20], [21]Therefore, efforts are needed to eliminate uncertainty in order to estimate the magnitude of the associated risks.

One approach to mitigate this uncertainty is through effective production planning, which enables more informed decision-making and helps achieve targeted profits [22], [23]. Sound planning relies on accurate data and information about future events. Hence, to address the company's challenges, forecasting[21], [24] using the SARIMA (P, D, Q)^{12} model, which is an ARIMA (p, d, q)(P, D, Q)^{12} model incorporating seasonal variables, can be used (Dadang Ruhiat; & Adang Effendi, 2018). The research findings indicate that the required production of Fresh Fruit Bunches (FFB) for the upcoming year is projected to be 78.060.472 tons. With this information, the company can minimize cost and excess FFB production risks while conserving forested areas for expanding oil palm plantations.

II. RESEARCH METHOD

This research was conducted in the Petasia Timur District of North Morowali Utara (MORUT) Regency, Central Sulawesi Province. The reason for choosing this area is that it is one of the new centers for the development of oil palm plantations. In this newly established regency, there are four companies involved in oil palm cultivation, one of which is PT. ANA (is located in the Petasia Timur District. The company began its operations around 2009 and started production in 2014. PT. ANA was selected as the subject of study because it has the largest land area compared to other companies, encompassing: 1) Molino Villages; 2) Bungimtimbe Villages; and 3) Tompira Villages.

The selection of the research location was done *purposively* due to several advantages: 1) its integrated business management model with palm oil processing units (CPO) and palm kernel; and 2) its greater potential for area development. Thus, it can represent the oil palm plantation companies in the region. The research was conducted over a period of approximately three months, starting from March 2019 until May 2019.

The data collected in this research consists of primary data from the company and secondary data from relevant institutions. The primary data includes the company's identity or owner, company employees, and time series data of Fresh Fruit Bunch (FFB) production for a period of 5 years, from 2015 to 2019. The data collection techniques involved observation and interviews with company leaders and employees using a questionnaire. The secondary data were obtained from literature/journals and relevant institutions related to this research.

Data Analysis Methods

The data that has been edited and rationalized is further analyzed using the *Box- Jenkis Autoregressive Integrated Moving Average/*ARIMA method[25], [26] yang bentuk umumnya dapat di formulasikan sebagai berikut:

$$Y_t = \gamma_0 + \partial_1 Y_{t-1} + \partial_2 Y_{t-2} + \ldots + \partial_n Y_{t-p} - \lambda_1 e_{t-1} - \lambda_2 e_{t-2} - \lambda_n e_{t-q}$$

Y_t = stationary time series, e_t = residual at time "t",

γ_t = constant, δ and λ = model coefficients

The ARIMA model consists of three components: the Autoregressive (AR) Model, Moving Average (MA) Model, and the Integrated (I) Model*:*

AR : P = order of the autoregressive process

I : d = degree of differencing

MA : q = order of the moving average process *(moving average)*

Model *Autoregresif (AR)*

AR The AR model describes that the dependent variable is influenced by itself in previous periods (up to 60 periods). The AR model can be formulated as follows [27], [28]

$$Y_t = \theta_0 + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_p Y_{t-p} - e_t$$

Where :

Y_t : stationary time series

θ_0 : constant

$Y_{t-1} \ldots Y_{t-p}$: past values related to time "t"

$\theta_1, \ldots, \theta_p$: coefficients or parameters of the *Autoregressive* model

e_t : residual at time "t"

This model is represented by the order "p" or AR(p), or ARIMA(p,d,0) model.

Model *Moving Average (MA)*

The difference between the Moving Average (MA) model and the Autoregressive (AR) model lies in the type of independent variable. In the AR model, the independent variable is the lagged value of the dependent variable (Y_t) itself, while in the MA model, the independent variable is the residual value from the previous period. The MA model can be formulated as follows [29], [30]

$$\mathrm{Y_t} = \varphi_0 + \varphi_1 \mathrm{e}_{t-1} - \varphi_2 \mathrm{e}_{t-2} - \ldots - \varphi_n \mathrm{e}_{t-q}$$

where :

Y_t : stationary time series

φ_0 : constant

$\varphi_1 \ldots \varphi_n$: coefficients of the moving average model

e_t : residual from the past used by the model

This model is represented by the order q or MA(q), or ARIMA(0,d,q) model. (0,d,q).

Integrated

The general form of the integrated model with order d (I(d)) or ARIMA(0,d,0) model. Integrated here refers to differencing the data. In other words, in constructing an ARIMA model, a prerequisite is that the data needs to be stationary. If the data is stationary at the original level, the order is 0. However, if it is stationary after at the first difference, the order is 1, represented by the ARIMA (0, 1, 0) model, and so on.

III. RESULTS AND DISCUSSION

Basic Forecasting Data

The data used as the basis for forecasting in this study is the actual production data (FFB) of Oil Palm for the period from January 2015 to December 2019, consisting of 60 samples. Based on this data, forecasts are made for the subsequent periods

(January-December, 2020/2021). The data collected during the 3-month study period ending in March 2019, indicates that the data is a time series data influenced by seasons (Graph 1). This is because the production of FFB is influenced by various factors (Hasril Hasan, 1998), including seasons, especially rainfall which has a negative (-) effect, and rainy days which have a positive (+) effect [31], [32], resulting in fluctuating trends in the production of Oil Palm FFB during the observation period (Firdaus, 2006). In order to forecast the production of Oil Palm FFB for the future period (2020/2021), it is necessary to select the best model to ensure that the forecasting results are closer to the actual data.

Determination of the Best Model

The statistical analysis method commonly used to analyze time series data is the ARIMA (*Autoregressive Integrated Moving Average*) model, but this model is less appropriate when the data is influenced by seasonal factors. The best model for analyzing seasonal time series data is the SARIMA (Seasonal Autoregressive Integrated Moving Average) model, which is an extension of the ARIMA model itself. The difference from the ARIMA model lies in the inclusion of seasonal factors. In the ARIMA model, seasonal variables are not included, while the SARIMA model is formulated as follows [33], [34]

$$\text{ARIMA } (p,d,q)\ (P,D,Q)^S$$

With:

(p,d,q) : non-seasonal ARIMA model

(P,D,Q) : seasonal ARIMA model

S : number periods per season

Next, the best SARIMA or ARIMA (p,d,q) $(P,D,Q)^S$ model obtained is used to forecast the value of FFB production for the period of January-December, 2020/2021. This model has also been used by Dadang Ruhiat and Adang Effendi (2018).

Data Analysis with SARIMA Model

Before conducting the forecasting, an analysis is performed to assess whether the collected seasonal time series data of FFB (Fresh Fruit Bunch) production for the period of January-December 2019 is stationary. Stationarity of data can be identified through two methods: visual inspection and statistical tests[34], [35]. This effort can be achieved using commonly used analysis tools such as Microsoft Excel 2019 version 16.37 and Eviews version 10.0 software.

Data Stationary Test

There are several tests for data stationarity commonly used by experts, including: 1) plotting data with graphics; 2) plotting the autocorrelation and partial autocorrelation functions; and 3) unit root test). These tests have been widely utilized by experts and researchers in the field of forecasting, such for forecasting the inflation of primary food commodities in Palu City. If the data is found to be stationary using these models, the next step is to determine the best SARIMA model. However, if the data is still non-stationary, it can be made stationary by using methods like differencing and logarithm transformation[31], [36]

Based on the data plot above, it can be observed that the production of FFB from oil palm is seasonal (Vita Mami Nikmatullah, 2018). Each year, there is a tendency for production to increase from January to May, then decrease from May to August. Conversely, from August to November, there is an increase in production, followed by a decrease in December

The most dominant seasonal factor affecting the production of FFB (Fresh Fruit Bunches) in PT. Ana's oil palm plantation is the monthly rainfall, particularly occurring from the end of December to the middle of the current year. However, the highest rainfall often happens from January to May, followed by a decreasing trend until the end of November or early December (BPS. Kabupaten Morowali Utara, 2018). The influence of rainfall is significant for the growth of oil palm plants, especially in terms of nutrient absorption from the soil, development of female flowers, flower maturity level, and weight of the fruit bunches [37], [38]. As a result, there is a tendency for FFB production to rise or fall in accordance with seasonal patterns. Therefore, data influenced by seasons is non-stationary and needs to be made stationary through appropriate methods.

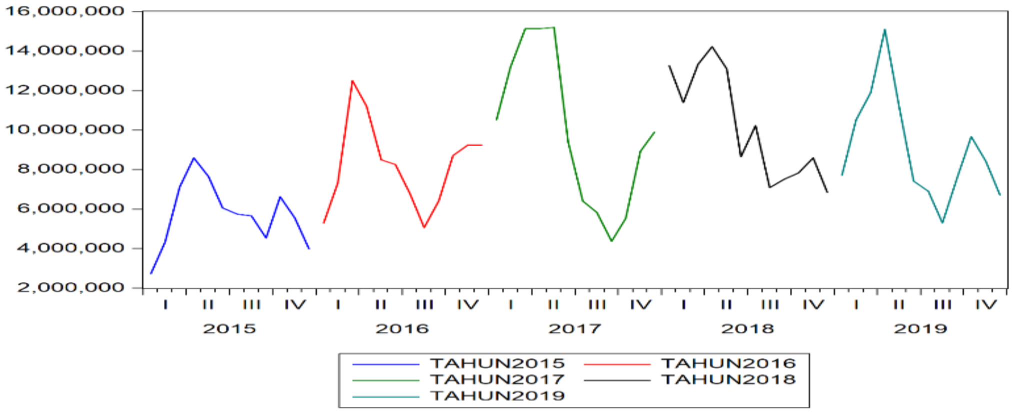


Fig 1. Results of Graphical Stationary Test for PT. ANA Data over 5 periods (2015-2019) in Kabupaten Morowali Utara, Central Sulawesi Province 2019.

Determination of The Best Model

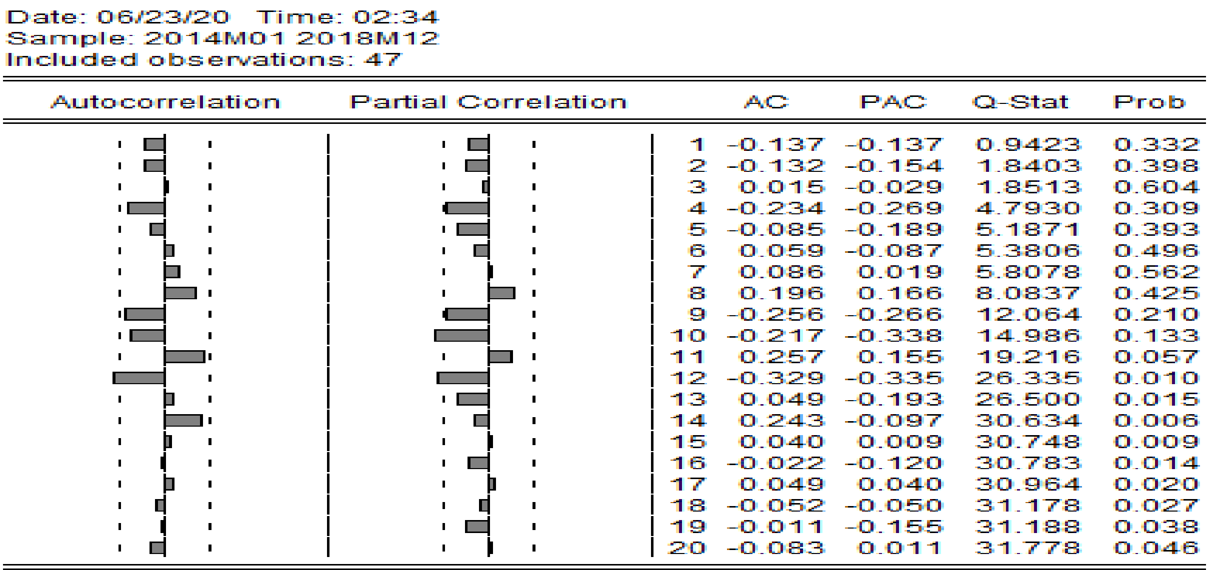
The procedure for testing the best SARIMA (*Seasonal Autoregressive Integrated Moving Average*) model for forecasting is similar to the ARIMA model. The difference lies in the seasonal factor, so the SARIMA model can generally be formulated as follows:

$$\text{ARIMA } (p,d,q)\ (P,D,Q)^{S}$$

where,

(p,d,q)	: non-seasonal ARIMA model
(P,D,Q)	: seasonal ARIMA model
S	: number of periods per season

The determination of the best SARIMA model for forecasting follows the steps of stationary testing, model identification, residual diagnostic testing, and model estimation. The identification stage is crucial in SARIMA modeling because it incorporates seasonal variables/factors. For the SARIMA model, the data differencing process is performed on both the seasonal and non-seasonal components, and the results are combined into one. Based on the unit root tests on the combined data[20], [39] it can be concluded that the data is stationary, as indicated by the t-statistic values of ADF and PP being greater than the 5% significance level (α).Results of ADF and PP Statistical Tests.



Date: 06/23/20 Time: 02:34
Sample: 2014M01 2018M12
Included observations: 47

	AC	PAC	Q-Stat	Prob
1	-0.137	-0.137	0.9423	0.332
2	-0.132	-0.154	1.8403	0.398
3	0.015	-0.029	1.8513	0.604
4	-0.234	-0.269	4.7930	0.309
5	-0.085	-0.189	5.1871	0.393
6	0.059	-0.087	5.3806	0.496
7	0.086	0.019	5.8078	0.562
8	0.196	0.166	8.0837	0.425
9	-0.256	-0.266	12.064	0.210
10	-0.217	-0.338	14.986	0.133
11	0.257	0.155	19.216	0.057
12	-0.329	-0.335	26.335	0.010
13	0.049	-0.193	26.500	0.015
14	0.243	-0.097	30.634	0.006
15	0.040	0.009	30.748	0.009
16	-0.022	-0.120	30.783	0.014
17	0.049	0.040	30.964	0.020
18	-0.052	-0.050	31.178	0.027
19	-0.011	-0.155	31.188	0.038
20	-0.083	0.011	31.778	0.046

Fig 2. Result of Processed Primary Data 2019

Null Hypothesis: DLOGGABUNGTBS has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.729074	0.0000
Test critical values:	1% level	-4.170583	
	5% level	-3.510740	
	10% level	-3.185512	

*MacKinnon (1996) one-sided p-values.

Fig 3. Result of Processed Primary Data 2019

Null Hypothesis: DLOGGABUNGTBS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 20 (Automatic - based on SIC, maxlag=20)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.250716	0.0126
Test critical values:	1% level	-4.356068	
	5% level	-3.595026	
	10% level	-3.233456	

*MacKinnon (1996) one-sided p-values.

Fig 4. Result of Processed Primary Data 2019

Next, based on the above autocorrelation plot, the model that satisfies the criteria for forecasting can be observed in the following table.

TABLE I. Best Model for Forecasting is the SARIMA Model

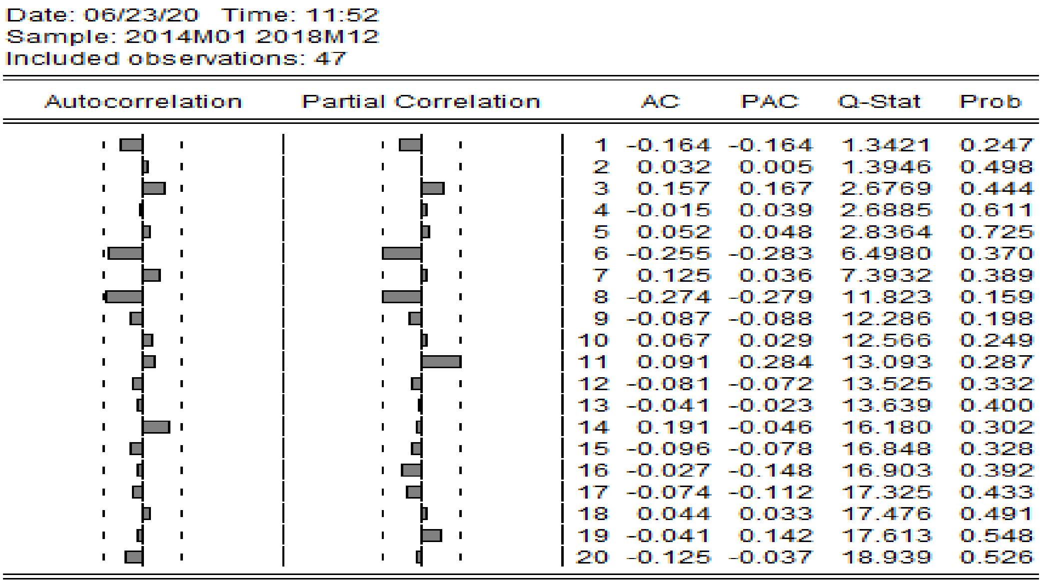
Model	Nilai AIC	Nilai SIC
SARIMA (4,1,5) (0,1,1)^{12}	0,158	0,354
SARIMA (9,1,1) (0,1,4)^{12}	0.143	0,339
SARIMA (12,1,5) (0,1,4)^{12}	0,147	0,343
SARIMA (4,1,1) (0,1,5)^{12}	0,158	0,354

The table above shows that the best model for forecasting is SARIMA (9,1,1) (0,1,4)^{12} and SARIMA (12,1,5) (0,1,4)^{12} as a comparison. This is indicated by the smallest AIC (Akaike Information Criterion) and SIC (Schwarz Information Criterion) values. Furthermore, the results of diagnostic residual tests indicate that both models have random residuals, as the Q-statistic at lag 20 for both models is smaller than the chi-square table value with a probability greater than 0,05, as shown in the following table:

Table II. Residual Test, RMSE, MAE, MAPE, and Bias Proportion of the Selected Model

Model	Statistic Value-Q (lag-20)	Probability
SARIMA (9,1,1) (0,1,4)^{12}	21,066 < 31,41	0,223
SARIMA (12,1,5) (0,1,4)^{12}	17,377 < 31,41	0,429

Similarly, the squared residual values of both models are also random. This is indicated by the non-significant autocorrelation values towards zero, with all lag probabilities exceeding 0.05, as shown in the following table.



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Sample: 2014M01 2018M12
Included observations: 47

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.164	-0.164	1.3421	0.247
		2	0.032	0.005	1.3946	0.498
		3	0.157	0.167	2.6769	0.444
		4	-0.015	0.039	2.6885	0.611
		5	0.052	0.048	2.8364	0.725
		6	-0.255	-0.283	6.4980	0.370
		7	0.125	0.036	7.3932	0.389
		8	-0.274	-0.279	11.823	0.159
		9	-0.087	-0.088	12.286	0.198
		10	0.067	0.029	12.566	0.249
		11	0.091	0.284	13.093	0.287
		12	-0.081	-0.072	13.525	0.332
		13	-0.041	-0.023	13.639	0.400
		14	0.191	-0.046	16.180	0.302
		15	-0.096	-0.078	16.848	0.328
		16	-0.027	-0.148	16.903	0.392
		17	-0.074	-0.112	17.325	0.433
		18	0.044	0.033	17.476	0.491
		19	-0.041	0.142	17.613	0.548
		20	-0.125	-0.037	18.939	0.526

Fig 5. Result of Processed Primary Data 2019

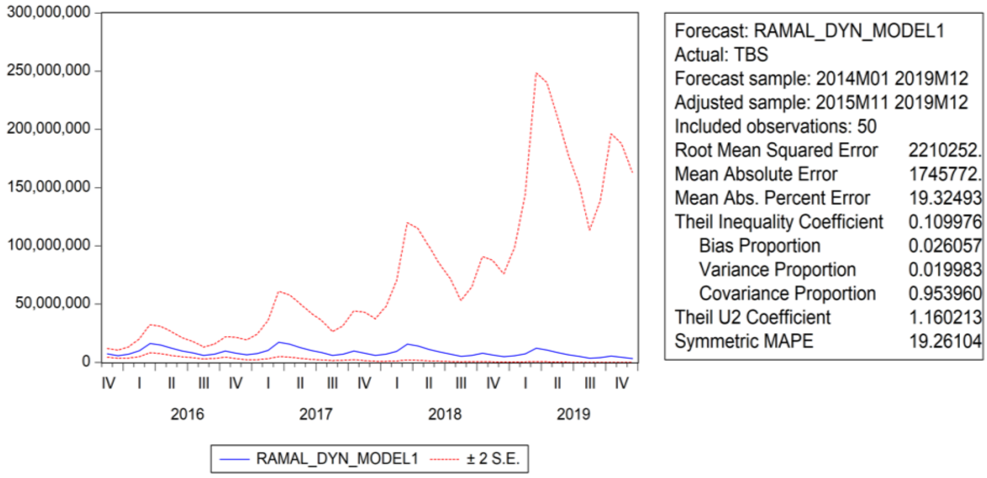

Fig 6. Result of Processed Primary Data 2019

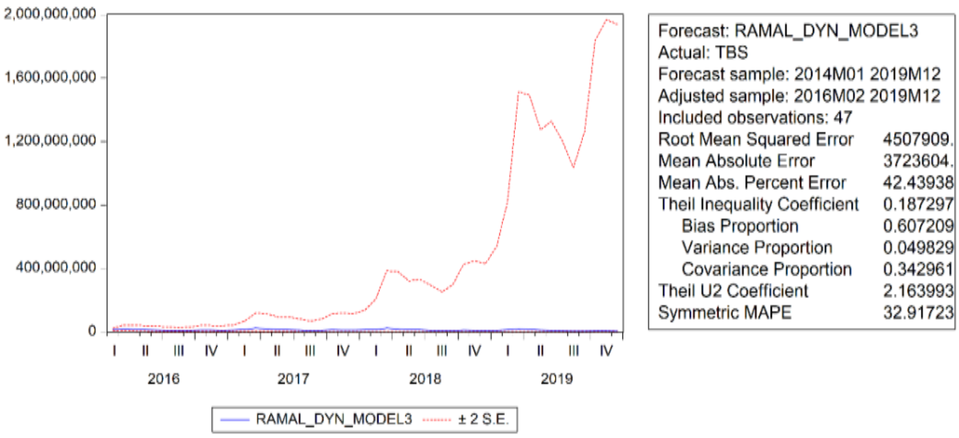

Fig 7. Result of Processed Primary Data 2019

Based on the values of RMSE, MAE, MAPE, and *bias proportion*, the SARIMA (9,1,1) $(0,1,4)^{12}$ model has smaller values compared to the SARIMA (12,1,5) $(0,1,4)^{12}$ model. Therefore, it can be concluded that the SARIMA (9,1,1) $(0,1,4)^{12}$ model is the best model for forecasting the quantity of FFB production at PT. Ana. The forecasted values for the next period, which is the year 2020/2021, are shown in the following table:

TABLE III. Forecasted Results of FFB (Fresh Fruit Bunch) Production at PT. ANA for the Next Period in Petasia Timur Subdistrict, MORUT Regency, 2020/2021

Month	Year
	2019
January	5.686.738
February	7.517.951
March	12.175.476
April	10.787.416
May	8.502.021
June	6.705.801
July	5.258.180
August	3.704.643
September	4.255.410
October	5.639.023
November	4.441.513
December	3.386.300

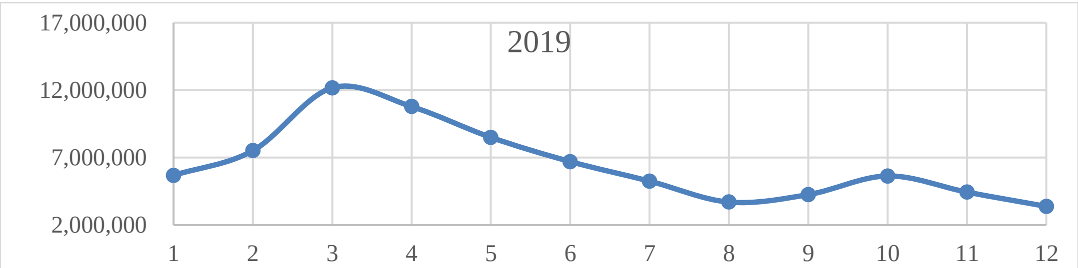

Fig 8. Result of Processed Primary Data 2019

Mathematically, the equation for the SARIMA (9,1,1) $(0,1,4)^{12}$ model can be formulated as follows::

$$Y_t = (1-\theta_9)\beta + \theta_9 Y_{t-9} + \alpha_4 \varepsilon_{t-4} + \Theta \varepsilon_{t-12} + \varepsilon_t$$

Based on the forecasted FFB (Fresh Fruit Bunches) production of oil palm for the year 2020, it shows a similar trend to the actual FFB production pattern. Similarly, the trend in the forecasted production quantity also closely matches the previous year's actual production. In this case, the FFB production experiences an increase from January to June and a declining trend from May to December. This pattern is attributed to the seasonal influence at the research location.

IV. CONCLUSION

The best SARIMA model used to forecast the FFB (Fresh Fruit Bunches) production of PT. ANA for the upcoming period is the SARIMA (9,1,1) $(0,1,4)^{12}$ model. Using this model, the forecasted FFB production is approximately 78.060.472 tons, which is about 38,95% lower than the actual production. The forecasted results serve as valuable information for the company in making production management plans and implementing work programs for the next period (2020/2021).

The availability of FFB forecasts helps to reduce production uncertainty risks for the company. This allows the company to carry out the CPO (Crude Palm Oil) agro-processing accurately, aligning with consumer demand, cost planning, sales, and distribution, as well as negotiating favorable and sustainable CPO product prices due to the certainty of future production quantities.

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