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MODELING COOKING OIL PRODUCTION WITH CRUDE PALM OIL (CPO) PRICE USING TRANSFER FUNCTION

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ABSTRACT

Indonesia is the largest palm oil producer in the world. However, Indonesia is currently experiencing a significant scarcity of cooking oil for the basic needs of the community. One of the causes of this problem is the high price of crude palm oil (CPO). The price of CPO affects the production of cooking oil produced by the cooking oil industry. CPO prices are released in the form of daily prices in the market which form a time series pattern that affects the production of cooking oil which is also produced daily in the industry. To forecast cooking oil production from CPO prices can be done with a transfer function model. The stages of analysis are forming an ARIMA model, processing input time series whitening, and output time series whitening. Checking white noise by plotting ACF αt, ACF βt. Make a CCF graph and determine the order (r,s,b). Estimate the first parameter of the disturbance series (nt) and identify the disturbance series (nt) in the ARIMA model. Next, perform a diagnostic check of the transfer function model by checking the cross-correlation between Xt & Yt and checking the autocorrelation of Xt and Yt for model feasibility testing. Then make an ACF graph of the transfer function model's residuals to test the model's suitability. The final stage is to select the best model based on the smallest AIC value, ensuring the accuracy of the selected model using MAPE value, and making predictions. As a result, the model for CPO price is an input series variable, and cooking oil production is an output series variable. However, the MAPE result was 100%, indicating that the model is not very accurate for this data. Nevertheless, by ignoring the result and continuing with the forecasting, this model shows that the forecasted values for cooking oil based on CPO price have increased from the form of the model obtained for the time data from 2013 to 2022.

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1. INTRODUCTION

Cooking oil was once a hot topic of discussion in Indonesia in early 2022. This was due to the scarcity and high price of cooking oil in the hands of the community. But at present, it is still an object of concern, because the price is still expensive for 1 liter of purchase [1]. Cooking oil is included in the basic needs of the community. Cooking oil is an item that must be present in the kitchen of Indonesian households. Following the decision of the Minister of Industry and Trade of the Republic of Indonesia No.115 of 1988 concerning the types of goods for the basic needs of the community, it is stated that cooking oil is in the 3rd place of the Nine Basic Materials.

Cooking oil on the market is currently made from crude palm oil (CPO). According to data from the Central Statistics Agency (BPS), Indonesia's palm oil plantation area in 2019 amounted to 14.45 million ha, this area ranked first in the world through the publication of the United States Department of Agriculture (USDA) in 2020. Meanwhile, Indonesia's palm oil production is in the range of 47.12 million tons [2]. The high area and production of palm oil in Indonesia can provide information that the production of cooking oil will also be high to meet the needs of the community, but this is contrary to reality. People still have difficulties to fulfill this need, both regarding the availability of cooking oil and the high price as well. The incidence of cooking oil cases reported by [3] is due to the high world price of crude oil or CPO. The high price of CPO affects the production of cooking oil, which ultimately results in the fulfillment of the basic needs of the community.

The world CPO price is always changing in units of days, changing depending on time which forms a pattern, so this will also affect the production of cooking oil. Likewise, cooking oil production also changes according to the time-dependent price of CPO as well. An event that depends on time and forms a pattern of events is called a time series event. Time series events that occur in previous events will have the opportunity to determine future events, usually called event prediction. So that by predicting events that will occur in the future, it will be able to provide an overview in determining decisions. Events that occur in a time series pattern usually occur in univariate time, but not always so. Sometimes some cases use time series with more than one time series event.

Time series events in the case of CPO prices affect the occurrence of cooking oil production which follows a time series pattern. When existing cooking oil production data is used to predict and estimate future cooking oil production, in the realm of statistics, it can be analyzed with a transfer function model.

Box and Jenkins in 1970 presented an improved statistical method for modeling the relationship between inputs and outputs to a system. This technique was called the Box-Jenkins transfer function modeling technique [4], [5]. A transfer function model is a model for forecasting the future state of a time series (called the output time series or Y_t) regarding past values of the series itself (Y_t) and is also based on one or more periodic series associated (called the input time series or X_t) with the output time series. Transfer function models are flexible between the input series and the output series at the time $t, t-1, t-2, \dots, t-k$. In a transfer function, this relationship can result in a delay between the input variable and the output variable [5].

The relationship between the output time series (Y_t) influenced by the input time series (X_t) is a causal relationship between time series data. Research on causal relationships with transfer functions has been conducted by Zhang [6] conveying that the generative model of network structure captures variations in causal networks over time, which is observed in fMRI brain connectivity data for subjects in various stages of Alzheimer's disease development. In addition, Perwita [7] also produced research on hotel tax revenues as outputs and variables of the number of guests staying, and the average length of stay of guests, which conveyed that 98.9% of input variables could be carried out in forecasting hotel tax revenues in Malang city. Then Zaki's research [8], used a transfer function to model rainfall. The results show that the rainy season ends in the fifth month and the dry season begins in the sixth month, while the next rainy season or the end of the dry season will occur in the eleventh month. Furthermore, Huang's research [9] used transfer functions to forecast student learning achievement. The result is that the function model shows a "good" level of accuracy and the transfer function model will be good for predicting students' academic performance on the college entrance examination.

Research was also conducted by Ye & Dai [10] who connected electrochemical impedance spectroscopy as an input with the electrochemical dynamic output voltage response of the power system. In this research, it is conveyed that the transfer function simulates the frequency impedance of the Warburg impedance spectrum (FLW) of limited length, and the dynamic potential response of the FLW in the time domain has been established. Furthermore, Rinjani [11] conveyed that the transfer function model provides good forecasting results compared to the backpropagation neural network model in forecasting gold prices.

The transfer function contains the output time series (Y_t) that is expected to be influenced by the input time series (X_t) and other inputs that combine into a group called noise N_t. In other words, the input time series X_t affects the output time series Y_t which is related to a transfer function. Transfer function analysis is used as an alternative for solving problems that involve more than one time series. These events in statistics are known as multivariate time series [12].

The output series is influenced by the input series through a transfer function that dynamically distributes the influence over several future periods by a certain percentage referred to as impulse response weights or transfer function weights [13]. The case of cooking oil production is the output at the event at the time t and the price of CPO is the input that affects the event at the time t as well. So, from the description above, it becomes the basis of this research on modeling cooking oil production influenced by CPO prices with a transfer function model.

2. RESEARCH METHODS

The data used in this study are CPO prices in monthly periods obtained from data from the Commodity Futures Trading Supervisory Agency taken from the Central Statistics Agency (BPS). Then the national cooking oil production data was taken from the Ministry of Industry and Trade in 2013-2022.

2.1 Definition Research Variables

This research consists of input variables and output variables. The definition of research variables can be seen in **Table 1** below:

Table 1. Definition of Research

No	Research Variable	Definition	Data scale
1	Cooking oil production (Y_t) in tons	Output variables as cooking oil production at time $t = 1, 2, .., n$	Ratio
2	CPO price (X_t) in USD	Input variables as CPO price at time $t = 1, 2, .., n$	Ratio

Likewise, the data structure can be seen in the **Table 2** below:

Table 2. Data Structure of Total Cooking Oil Production and CPO Price

t	Y_t	X_t
1	Y_1	X_1
2	Y_2	X_2
⋮	⋮	.
n	Y_n	X_n

2.2 Research Procedure

This research uses R software [14] with procedures were carried out according to the following stages:

1. Forming the ARIMA model
    a. Create a time series graph of the data
    b. Checking for variance stationarity in the input time series (X_t) and output time series (Y_t) [15].
    c. Perform Box-Cox transformation if the data is not stationary on variance.
    d. Average stationarity check on the input time series (X_t) and output time series (Y_t).
    e. Performing differencing process if the data is not stationary.
    f. Perform identification based on PACF and ACF plots for the ARIMA (p, d, q) model.
    g. Form a temporary ARIMA(p, d, q) model.
    h. Estimate the parameters of the ARIMA model.
    i. Perform feasibility test of ARIMA (p, d, q) model L-Jung Box Q test.

j. Selecting the best model of the ARIMA (p, d, q) model based on the smallest AIC value [16]. ARIMA(p, d, q) [17] is a combination of AR(p), MA(q) and ARMA(p, q) classes. AR(p) [17] is an autoregressive model of order p.

2. The process of bleaching the time series is carried out input to obtain the α_t series and bleaching the output time series to obtain the β_t series and then checking for white noise by making ACF α_t, ACF β_t plots [18].

3. Make a CCF (Cross-correlation Function) graph. Determine the value of (r, s, b) based on the CCF graph between the input time series (X_t) and the output time series (Y_t) to obtain a temporary transfer function model [18], [19].

4. Estimate the first parameter of the disturbance series (n_t) and identify for the disturbance series (n_t) in the ARIMA model [20].

5. Diagnostic checks of transfer function models are performed by;
   a. Checking the cross-correlation between X_t & Y_t as well as checking the autocorrelation of X_t and Y_t for model feasibility test
   b. Creating an ACF graph of the transfer function model's residuals for the model fit test

6. Selecting the best model based on the smallest AIC value for the transfer function,

7. Perform prediction.

3. RESULTS AND DISCUSSION

Research on palm oil production with input variables, namely CPO prices, has the form of an event pattern as below:

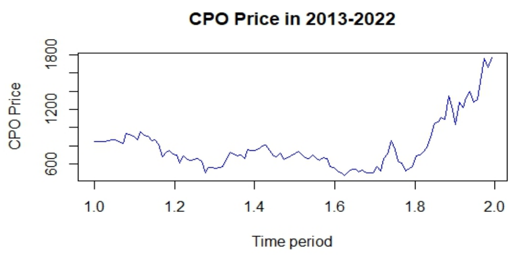

Figure 1. The price of CPO

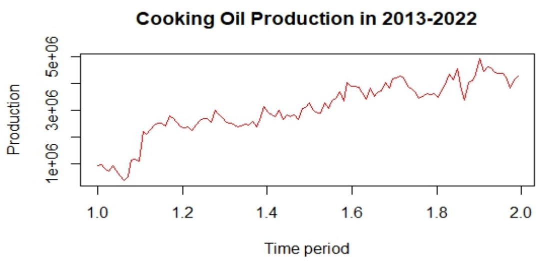

Figure 2. The cooking oil production

The graph above presents the price of CPO from 2013 to 2022, it is conveyed that the price of CPO often changes either increasing or decreasing, but in the last 1 year it was found that the price of CPO always increased, although there were prices that fell within a certain period but this situation was only temporary, after which it increased again.

1) Modeling input series and output series

Data on cooking oil production as output data and CPO price data as input data were modeled for each variable. Modeling the input series and output series starts with identifying the CPO price series variables and the cooking oil production series variables. In this modeling process, the data is divided into training data and testing data [21], [22]. Training data is used for modeling and testing data is used for forecasting cooking oil production.

The initial identification is done on the input series variable, CPO price. Modeling of the CPO input series must meet the data stationarity requirements, both stationary to variance and stationary to average. The process of checking data stationarity and overcoming non-stationarity to variance and average is presented in the graph below.

Figure 3. **Graph of CPO price training data**

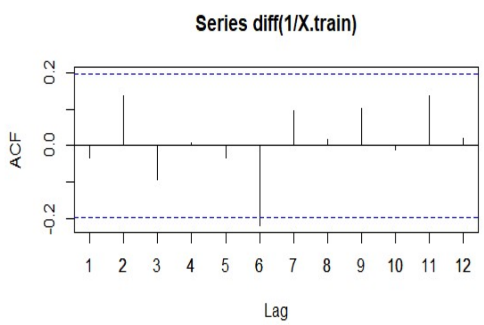

Figure 4. **ACF plot of CPO price**

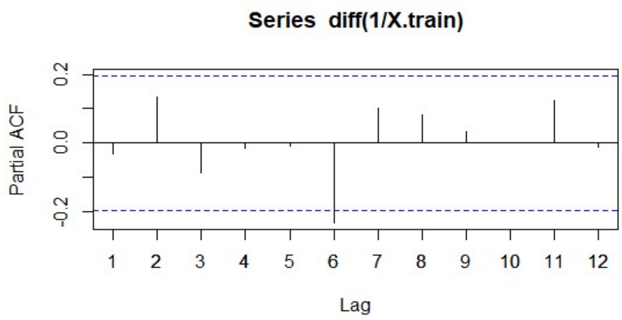

Figure 5. **PACF Plot of CPO Price**

In Figure 3 of the training data graph above, it is stated that the data is not stationary in variance and average, so the CPO price data needs to be transformed and differenced twice. The results of the transformation and differencing produce stationary data and have been shown in Figure 4 and Figure 5. These results are also expressed through the following statistical analysis:

Hypothesis:
H_0: Input series data is not stationary.
H_1: Input series data is stationary.

Table 3. **Augmented Dickey-Fuller Test for Training Data**

Augmented Dickey-Fuller Test
data: diff(1/X.train) Dickey-Fuller = -4.5238, Lag order = 4, *p*-value = 0.01 alternative hypothesis: stationary

Decision criteria: If P-value $< \alpha$ (0.05) then reject H_0.

Then from the calculation using the ADF test, it is obtained that the p-value is $0.01 < 0.05$ (α) which means that the input series data is stationary at 2 times differencing.

Table 4. **ARIMA Model Parameters on Training Input Data**

Model	**Parameter**	**Estimation**	**Standard error**	**T statistic**	***P*-Value**	**Decision**
ARIMA (0,2,6)	MA1	0.0767	0.1081	0.7095	0.4797	Rejected
	MA2	0.1683	0.1026	1.6404	0.1041	Rejected
	MA3	-0.0870	0.1097	-0.7931	0.4296	Rejected
	MA4	0.1561	0.1021	1.5289	0.1295	Rejected
	MA5	0.1995	0.1018	1.9597	0.0528	Rejected
	MA6	-0.1947	0.1188	-1.6389	0.1044	Rejected
ARIMA (6,2,0)	AR1	-0.0251	0.0979	-0.2564	0.7982	Rejected
	AR2	0.1265	0.0974	1.2988	0.1970	Rejected
	AR3	-0.1064	0.0986	-1.0791	0.2832	Rejected
	AR4	0.0152	0.0973	0.1562	0.8762	Rejected
	AR5	-0.0178	0.0970	-0.1835	0.8548	Rejected
	AR6	-0.2327	0.0975	-2.3867	0.0189	Accepted
ARIMA (1,2,1)	AR1	-0.6298	0.3028	-2.0799	0.0401	Accepted
	MA1	0.5532	0.3160	1.7506	0.0831	Rejected
	AR1	-0.7021	0.0987	-7.1135	0.000	Accepted

Model	Parameter	Estimation	Standard error	T statistic	*P*-Value	Decision
ARIMA (2,2,0)	AR2	-0.2136	0.0982	-2.1752	0.032	Accepted
ARIMA (2,2,2)	AR1	-0.3135	0.3782	-0.8289	0.4092	Rejected
	AR2	0.1377	0.1086	1.2680	0.2078	Rejected
	MA1	-0.6825	0.3752	-1.8190	0.0720	Rejected
	MA2	-0.2896	0.3589	-0.8069	0.4217	Rejected
ARIMA (2,2,1)	AR1	-0.0228	0.1044	-0.2184	0.8276	Rejected
	AR2	0.1399	0.1039	1.3465	0.1813	Rejected
	MA1	-0.9810	0.0479	-20.4802	0.0000	Accepted
ARIMA (0,2,2)	MA1	-0.9971	0.0934	-10.6756	0.0000	Accepted
	MA2	0.0292	0.0906	0.3223	0.7479	Rejected

The model that can be used for the CPO price input series is the ARIMA (1,2,1) model. However, by considering the significance of the parameters, it can be concluded that the ARIMA (2,2,0) model is a suitable model for the input series because it has met the "parameter significance" and sufficient conditions of the model, namely the residuals have met the white noise process. Thus, the "pre-whitening" of the input and output series can be done through the equation.

$$\alpha_t = \frac{(1-\hat{\varphi}_1 B)}{(1-\hat{\theta}_1 B)} x_t = \frac{(1+0.7021B)}{(1+0.78424B)} x_t$$

2) Model with one output series (Cooking Oil Production data)

Initial identification is carried out on the output series variable, namely cooking oil production data. Modeling of the output series of cooking oil production must meet the requirements of data stationarity, both stationary to variance and stationary to average. The process of checking data stationarity and overcoming non-stationarity concerning variance and average is presented in the graph below.

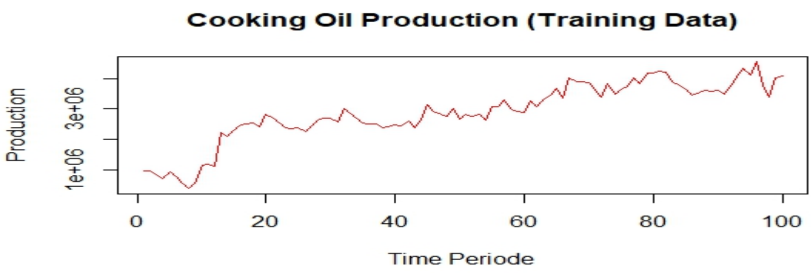

Figure 6. Graph of Cooking Oil Production Training Data

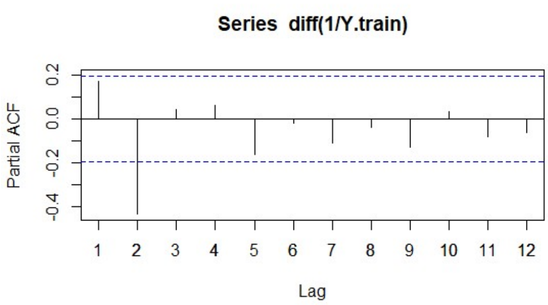

Figure 7. ACF plot of Cooking Oil Production

Figure 8. PACF plot of Cooking Oil Production

The output series data of cooking oil production has met stationarity so that further ARIMA modeling is carried out. The form of the ARIMA model obtained from the output series data of cooking oil production is as follows:

Table 5. ARIMA Model Parameters on Training Output Data

Model	Parameter	Estimation	Standard error	t statistic	p-value	Decision
ARIMA (2,2,0)	AR1	-0.2436	0.0854	-2.8525	0.0053	Accepted
	AR2	-0.5284	0.0842	-6.2755	0.0000	Accepted
ARIMA (2,2,2)	AR1	0.1891	0.1783	1.0606	0.2915	Rejected
	AR2	-0.4165	0.0965	-4.3161	0.0000	Accepted
	MA1	-0.9252	0.1914	-4.8339	0.0000	Accepted
	MA2	-0.0748	0.1886	-0.3966	0.6925	Rejected
ARIMA (0,2,2)	MA1	-0.5848	0.0998	-5.8597	0	Accepted
	MA2	-0.4152	0.0968	-4.2893	0	Accepted
ARIMA (2,2,1)	AR1	0.2495	0.0907	2.7508	0.0071	Accepted
	AR2	-0.4274	0.0901	-4.7436	0.0000	Accepted
	MA1	-1.0000	0.0341	-29.3255	0.0000	Accepted

3). Calculation of the Cros-Correlation Function (CCF) between α_t values and β_t values for transfer model identification

Based on the CCF plot below, it appears that there is 1 crossing the line, meaning that the function that satisfies is (0,1,0). However, to find the best model, the following models will be tried:

Table 6. Estimated Transfer Model

			Coefficient	Standard error	var
Model 1	ARIMA (1,0,1)	AR1	-0.230	0.138	
		MA1	0.5687	0.0442	
	Transfer (0,1,0)	Constant	-8.49e-09	NaN	
		Omega1	-2.96e-05	1.73e-04	
		Delta1	-1.80e-06	1.69e-04	
Model 2	ARIMA (1,0,2)	AR1	0.1	NaN	
		MA1	0.01	NaN	
		MA2	0.01	NaN	
	Transfer (1,0,0)	Constant	4.92e-07	NaN	
		Omega1	0.1	NaN	
		Delta1	0.1000	NaN	
Model 3	ARIMA (1,0,2)	AR1	0.5791	0.0983	
		MA1	-0.3822	0.0896	
		MA2	-0.4732	0.0808	
	Transfer (0,1,0)	Constant	-9.61e-09	NaN	
		Omega1	-7.59e-05	1.49e-04	
		Delta1	-2.68e-05	1.44e-04	
Model 4	ARIMA (1,0,0)	AR1	0.1	NaN	
	Transfer (1,0,2)	Constant	4.91e-07	NaN	
		Omega1	0.1000	0.0113	
		Omega2	0.1	NaN	
		Delta1	0.1000	0.0114	
		Delta2	0.1	NaN	
Model 5	ARIMA (0,0,0)	-	-	-	-
	Transfer (2,1,0)	Constant	4.91e-07	7.33e-07	0.6698
		Omega1	0.1000	0.0217	4.6083
		Omega2	0.1000	0.023	4.3478
		Delta1	0.1000	0.362	0.2762
		Delta2	0.1000	0.217	0.4608
Model 6	ARIMA (0,0,0)	-	-	-	-
	Transfer (0,1,0)	Constant	-8.01e-09	4.53e-05	-0.00002
		Omega1	4.53e-05	1.79e-04	0.25307
		Delta1	-4.53e-05	1.80e-04	0.2517

The model obtained from the analysis results for the cooking oil production model with the transfer function is:

$$y_t = \frac{-8.01 \times 10^{-9}(1 - 4.53 \times 10^{-5}B)}{(1 - 4.53 \times 10^{-5}B)} x_{t-2} + a_t$$

4. CONCLUSIONS

The model performed on CPO price and cooking oil production variables performance with $y_t = \frac{-8.01\times10^{-9}(1-4.53\times10^{-5}B)}{(1-4.53\times10^{-5}B)} x_{t-2} + a_t$. This model obtained a MAPE value of 100, indicating that the model is not very accurate. So, the transfer function model for predicting CPO price results from 2013-2022 will have a very small percentage compared to the actual values. It is recommended to use another model that can provide more accurate predictions.

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