

Original Article

Analysis Shifting of Cooking Oil Prices Using Forecasting Production Volumes of Crude Prime Oil (CPO) and Biodiesel

¹Fastha Aulia Pradhani, ²Juwita Sari

¹Sekolah Tinggi Ilmu Ekonomi Indonesia, Indonesia, Surabaya.

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Abstract: *(The increase in the price of cooking oil was one of the problems in Indonesia. One of the reasons is the reduction of raw material of cooking oil, Crude Prime Oil (CPO), which happened from the beginning of 2020, at the same time as the first pandemic covid 19 at Indonesia. Mandatori B30 program is one of another; 30% of biodiesel must be produced from palm oil and 70% from solar energy. In this study, the shifting of the price of cooking oil is analyzed with the estimation of the forecast model from CPO and the biodiesel variable. The method that was used was Neural Networks. The best model for forecast was determined from the minimum of MAPE. The results showed that the best model for forecasting CPO was Neural Networks with architecture MLP (3-3-1) and MLP (1-7-1) for biodiesel. 5 years later, the CPO and biodiesel production will be increased, so the government should make regulations that can be cooking oil prices to be much more stable, even though the raw material would be reduced.*

Keywords: Biodiesel, CPO, Forecasting, Neural Networks, MLP Architecture.

I. INTRODUCTION

The increased cooking oil prices in recent times have impacted several sectors. The community certainly feels the direct impact, considering that cooking oil is one of the leading companion ingredients in daily food processing. According to data compiled from the Market Monitoring System and Basic Needs of the Ministry of Trade, the cooking oil price has skyrocketed from the end of 2021 until April 2022, reaching Rp18,300 per liter for bulk cooking oil and Rp 23,600 per liter for simple packaged cooking oil. Even when compared to the same period in the previous year, the percentage increase reached 50.3% for bulk cooking oil and 73.02% for simple packaged cooking oil [1].

The increase in cooking oil prices is influenced by several factors, one of which is the high demand for Crude Prime Oil (CPO), which is not matched by its production capacity. The longer this condition lasts, the more CPOs will be needed. In fact, since the beginning of 2020, along with the beginning of the COVID-19 pandemic in Indonesia, there has been a 5.01% decline in CPO production compared to 2019 to 44.76 million tons [2]. Increased demand for CPO in various parts of the world due to the economic recovery after the second wave of the COVID-19 pandemic has also exacerbated the condition of CPO scarcity, which has had an impact on the increase in cooking oil prices in Indonesia. Other factors, such as the increase in biodiesel production made from palm oil, also trigger the increase in cooking oil prices. In recent times, the President of the Republic of Indonesia, Joko Widodo, has announced that Indonesia will implement the mandatory B30 program (a mixture of 30% biodiesel and 70% diesel fuel), which previously was the B20 program (a mixture of 20% biodiesel and 80% diesel fuel) [3]. Implementing the B30 program tends to increase demand for CPO, considering that the raw material for biodiesel production in Indonesia also comes from palm oil [4].

Some of the conditions discussed above indicate that the increase in CPO and biodiesel production, which is not accompanied by the supply of production volume, can directly influence the increase in cooking oil prices. Therefore, predictions from these two things are fundamental to do. In this study, predictions were made by creating a forecasting model. The modelling is done using the Neural Networks method. It is more flexible and has the characteristics of capabilities that resemble human biological tissue [5]. The neural network method is one of the statistical methods that can be predicted for a future period with some factor. Indeed, it is more than structural equation modeling, which can know the relation between factors without making a prediction [6]. Using MAPE and RMSE criteria, one of the best models was chosen to forecast for the subsequent three periods. After knowing the predictions for the next five years, it is hoped that this can be additional information for strategic policies such as exports and imports of CPO and the implementation of the B30 program.



II. LITERATURE REVIEW

These are some of the literature used in this research.

A) Cooking Oil Price Fluctuation

According to [2], the instability of cooking oil prices, which currently tend to rise, is undoubtedly caused by several factors. The factors included the declining supply of CPO, followed by an increase in demand for oil in various parts of the world following the economic recovery after the COVID-19 pandemic wave, which also affected the economy in Indonesia. The increasing world demand for biofuels derived from palm oil [7] is also one of the causes of the increase in cooking oil prices in Indonesia.

B) Crude Prime Oil

Crude Prime Oil or Palm oil is one of the products of the oil palm plant. This type of plantation plant has the form of a straight-trunk tree that comes from the Palmae family. The growing time of oil palm plants is 20-25 years. CPO is produced from processed palm meat, with a yield of 20% CPO extraction [8]

C) Biodiesel

Biodiesel is an alternative fuel for diesel engines/motors derived from chemical compounds such as alkyl esters, which are taken from vegetable oils and animal fats and even used in cooking oil. Vegetable oils are used as consumption materials and raw materials for making biodiesel, including palm oil, corn oil, coconut oil, sunflower seed oil, etc. Meanwhile, sources of biodiesel derived from non-consumable oils include *Pongamia pinata*, Sea mango, *Jatropha curcas*, etc. [9]

D) Neural Networks

Neural Networks are information-processing systems with capability characteristics similar to biological neural networks [5]. Between neurons are connected through a direct link in which each has a weight. Weights describe the information the network uses to solve a problem [10] used with the same interval.

III. RESULTS AND DISCUSSION

A) Characteristics of CPO and Biodiesel

Two kinds of different data are used for modeling. The first data is the volume of CPO production in 1980-2023 from the Plantation Statistics Book published by the Directorate General of Plantations, Ministry of Agriculture of the Republic of Indonesia. Otherwise, another data is biodiesel production volume, which comes from the Indonesian Biofuel Producers Association for the last 16 years, 2008-2023. In this study, the type of neural network used is Feed Forward Neural Network, with a backpropagation learning method and Multi-Layer Perceptron architecture.

The first step of analysis described the characteristics of the data. A description was performed through the time series plots as follows.

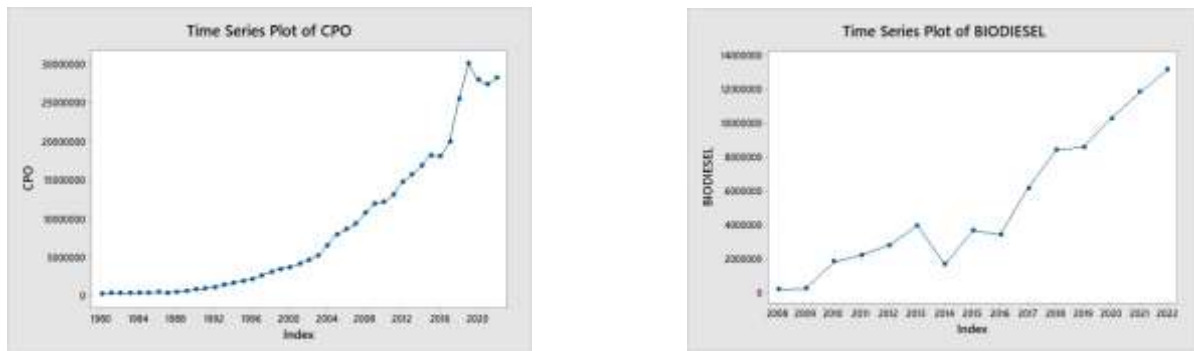


Fig. 1 Time Series Plot CPO and Biodiesel

Based on the two figures above, it can be seen that both variables tend to have an upward trend pattern. In the CPO variable, a sharp increase occurred in 2019, although in the following year, there was another decrease in production, which was 2124197 tons. Meanwhile, in the biodiesel variable, a sharp decline in production occurred in 2014. However, for the next year (2015), there was another increase with almost the same production volume as in the previous year, which was 2003558 kL (2013). The characteristics of the data are also described through the values of the size of the concentration and distribution of the data presented in Table 1. Table 1 shows the diversity of data on the CPO variable tends to be higher than the biodiesel variable, meaning that the annual CPO production volume tends to be more diverse compared to the biodiesel variable.

Table 1: Descriptive Statistics of CPO and Biodiesel

Variable	Minimum	Maximum	Mean	Std. Deviation
CPO	221544	30060003	8416989.698	9235598.982
BIO	190000	13151000	5222736.482	4231521.407

B) Neural Network Modelling of CPO and Biodiesel

The following step was modelled using the neural network's method on both variables. It begins with dividing the data into training and testing. Training data is used to estimate the model; testing data is used to validate before forecasting is carried out, namely the last five periods, and the rest is training data. Furthermore, the training data is carried out by a learning process using the backpropagation learning method with the Levenberg Marquart algorithm. In this research, the chosen model architecture uses a Multi-Layer Perceptron, so there is one additional hidden layer. The activation function used for the hidden layer is logistic sigmoid, while the output layer is pure. The number of input units is determined based on the significant lags in the autocorrelation plot in Figure 2. At the same time, the number of units in the hidden layer is determined based on the best learning results. These results were obtained by the training set with 1000 maximum iterations, initial weight initialization randomly, performance goal of 0.001, the maximum number of epochs of 1000, epochs between displays of 20, momentum constant of 0.95, and learning rate of 0.1. Next, the best number of hidden layer units is selected using the minor RMSE and MAPE testing criteria, considering the purpose of modelling is to do forecasting. In contrast, the number of output units is 1.

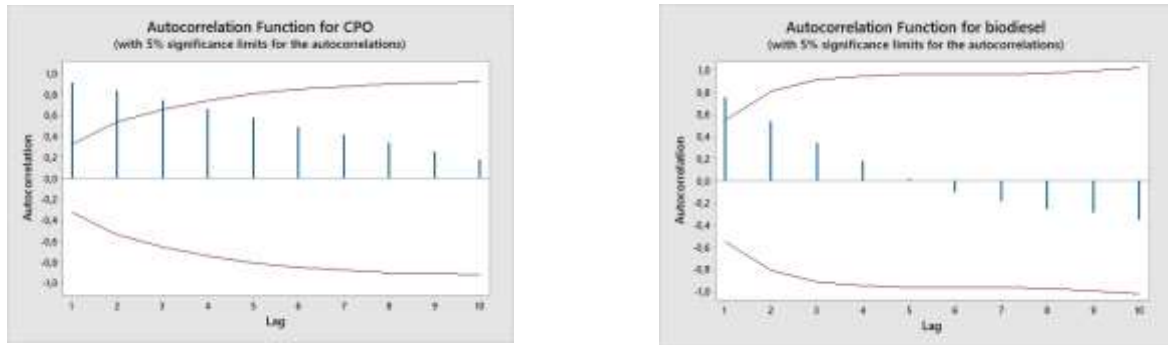


Fig. 2 Autocorrelation Plot CPO and Biodiesel

Figure 2 can be seen that the significant lag is the lag to 1, 2, and 3. So, the number of input units for the CPO production variable is 3, while for the 1st biodiesel lag variable, it is a significant step, so the input unit for the biodiesel variable is 1. Furthermore, the data was standardized through Matlab function press, and neural networks were modeled. The number of hidden units is determined using trial and error, and the one that best produces the model with optimal RMSE and MAPE values is selected.

Table 2: Results of the Best Modeling Criteria in Data Training and Testing

Variable	Hidden unit	Iteration	Training		Testing	
			RMSE	MAPE	RMSE	MAPE
CPO	1	17	1.0775	117.9862	0.9154	78.5997
	2	6	0.9402	177.0888	1.6167	417.708
	3	9	1.7489	114.3536	0.3783	20.6864
	4	6	0.9516	67.3622	2.8854	323.6639
	5	7	1.5875	128.9126	1.3874	180.7054
	6	2	1.1622	32.7346	0.7940	63.4426
	7	3	1.0996	176.3886	3.1582	269.881
	8	5	0.5483	19.8736	1.5908	325.4652
	9	6	2.2162	87.157	4.5183	78.6429
	10	1	0.4280	28.4885	1.1343	49.5553
Biodiesel	1	6	0.3612	33.2726	1.4208	758.4510
	2	8	0.5295	126.4313	1.8719	281.3223
	3	7	0.643	10.9996	1.2151	2784.4
	4	12	1.0682	257.2387	1.3738	1010
	5	3	0.6860	17.0851	1.3015	2369.8
	6	4	0.7494	34.6296	1.4047	828.4911
	7	5	2.0677	137.3431	0.5412	20.9749
	8	4	0.8733	59.0533	2.1746	222.5133

	9	3	0.5528	37.6267	1.4568	643.6133
	10	4	0.9507	70.6181	2.5566	187.1022

Based on the table above, it can be seen that by using several variations in the number of hidden units, different training and testing criteria values are obtained. In the CPO variable, the lowest RMSE criteria are found in the 10th hidden unit for training data and the 8th hidden unit for the MAPE criteria, while in the testing data, the lowest RMSE and MAPE criteria are found in the 3rd hidden unit. For the biodiesel variable, in the training data, the lowest RMSE is found in the hidden unit, which is 1, while for 7MAPE, it is in the 5th hidden unit. As for data testing, the number of hidden units 7 is the unit with the minimum RMSE and MAPE criteria. The number of hidden units is selected based on the minimum criteria in data testing because the purpose of this study is to get prediction results. The model architecture formed is MLP (3 – 3 – 1) for the CPO variable and the biodiesel variable; the model architecture formed is MLP (1 – 7 – 1). The shape of both network architectures is shown in Figure 3.

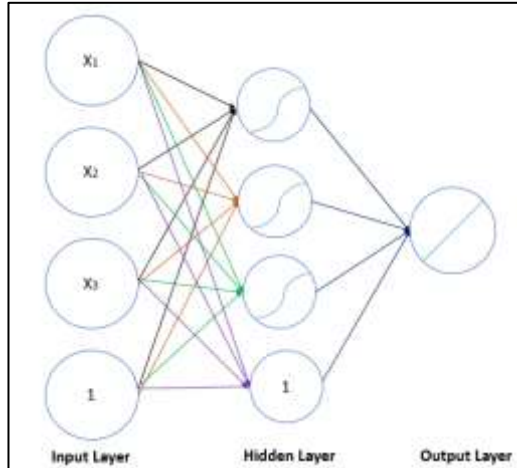


Fig. 3(a) MLP Architecture (3-3-1)

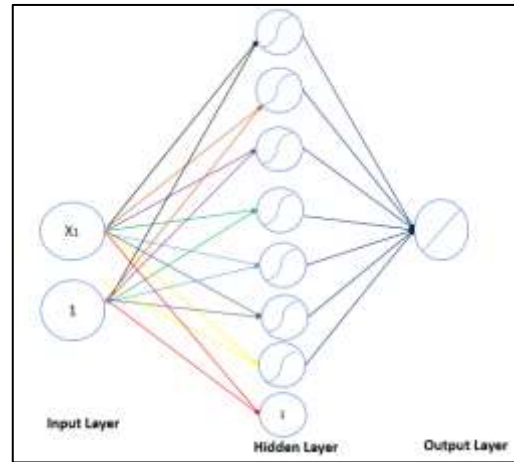


Fig. 3(b) MLP Architecture (1-7-1)

Furthermore, using the two architectural network models above, forecasting is carried out for the next 5 periods. The data used to forecast is a combination of *training* and testing data. The results of the forecast are presented in the following Table 3.

Table 3: CPO and Biodiesel Forecast Results for the Next 5 Periods

Variables	Years	Forecast
CPO	2024	169264181.6
	2025	918123489.4
	2026	4893808726
	2027	26000643455.54
	2028	138056442970.6
Biodiesel	2024	274150749.6
	2025	6804319389
	2026	170189016839.7
	2027	4258071096652.8
	2028	106536804412819.0

Based on Table 3, it can be seen that over the next 5 periods, the production of CPO and biodiesel will continue to increase. The skyrocketing price of CPO from year to year can encourage business actors to continue to increase CPO production, one of which is by routinely fertilizing [11]. Data from the Ministry of Agriculture also shows that in the vulnerable time between 2017 and 2020, there was an expansion of 540 thousand hectares of land, which is expected to continue to add areas in the following year. Another factor that is suspected to have affected the increase in CPO production, namely the El Nino storm, which only hit most of Southern Indonesia, did not have a significant effect on CPO production. The increase in biodiesel can also be caused by the impact of several government programs to increase biodiesel production, ranging from the mandatory B20 program to the mandatory B30 program.

The forecast results that show an increase in CPO production are favorable conditions. However, the increase in biodiesel production volume also shows that one of the results of CPO production is also mostly allocated to the biodiesel

manufacturing process. The demand for CPO also continues to increase for other allocations, one of which is in the export sector. Based on data from the Ministry of Trade, there is an increase in demand for CPO, especially from China and India [12]. Even over the past few years, the number of exports for CPO commodities has continued to decline compared to other commodities. CPO exports in 2019 reached 36.17 million tons, but in the next 4 years, soybean oil exports are much higher and can surpass CPO exports. This condition can cause an increase in CPO prices, which will have an impact on the increase in cooking oil prices. This is in line with the statement that the projected CPO price in 2025 can still skyrocket [13]. If this condition continues to occur over the next few periods, it is feared that it will also have an impact on other aspects, such as the increase in the burden of fuel subsidies and electricity subsidies in the state budget, which can further trigger an increase in the budget deficit and fiscal balance. Therefore, the government is expected to implement several potential long-term policies so that the increase in cooking oil prices does not continue, considering that some of the policies that have been implemented by the government today are still in the form of short-term policies, including Domestic *Market Obligation* (DMO) and Domestic *Price Obligation* (DPO), as well as cooking oil subsidies.

IV. CONCLUSION

The results of forecasting using the Neural Networks method, the results show that the amount of CPO and biodiesel production continues to increase over the next 5 periods. However, the increase in production that occurs in biodiesel indicates that most of the production from CPO will be allocated for biodiesel production, so it is feared that it can have an impact on the condition of rising cooking oil prices in Indonesia; therefore the government is expected to determine potential long-term policies that in addition to being able to overcome the problem of rising cooking oil prices as well as several other impacts.

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