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Brent Crude Oil Price Forecasting using the Cascade Forward Neural Network

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Abstract

Crude oil is one of the most traded non-food products or commodities in the world. In Indonesia, crude oil will still be a contributor to the Gross Domestic Product in 2021. Excessive consumption of fuel oil (BBM) in Indonesia has resulted in a scarcity of crude oil, especially diesel. Forecasting the price of Brent crude oil is an important effort to anticipate fluctuations in the price of fuel oil. The Cascade Forward Neural Network (CFNN) method is proposed to forecast fuel prices because of its superiority in fluctuating data types. The data used in this research is the price of Brent crude oil in the period January 2008 to December 2022. The CFNN method will be evaluated using the Mean Absolute Percentage Error (MAPE) to choose the best architectural model. The best Architectural Model is used to predict the next 12 months. After 10 architectural model trials, 2-6-1 became the best model with a MAPE data training value of 6.3473% and MAPE data testing of 9.4689%. Forecasting results for Brent crude oil for the next 12 months tend to experience a downward trend until December 2023.

Keywords: *artificial neural networks; cascade forwards; brent; crude oil; MAPE*

1. Introduction

Crude oil is still one of the most traded non-food products or commodities in the world today. The ever-increasing need for crude oil has made it the most influential commodity product in the world's largest commodity market. Many countries continue to attempt to replace their reliance on crude oil with renewable energy sources. Without a doubt, the worldwide demand for crude oil remains the greatest. The demand for crude oil in Indonesia is extremely strong. The volume of crude oil shipments from 2013 to 2022 demonstrates this. More crude oil is exported from Indonesia [1]-[3].

By injecting subsidies, the government has tried to keep the price of fuel oil (BBM) from rising. However, it has yet to be able to manage fuel prices in Indonesia due to the effects of the subsidies that continue to swell the budget [4]. This must be studied carefully when dealing with volatile and often changing world crude oil prices. Brent is a type of crude oil trade that is used as a reference for world oil prices. Although its quality is lower than West Texas Intermediate (WTI), it is still suitable for refining into diesel fuel. Diesel fuel has been restricted recently as our society's usage has increased [5]. In Indonesia, the demand for Brent crude oil is very high, so price forecasting is necessary to determine subsidy policies and the purchase or sale of crude oil. Brent crude oil price data is a time series where past Brent crude oil price data is needed to anticipate future Brent crude oil prices.

The Autoregressive Moving Average (ARIMA) method is used in several forecasting systems, particularly short-term and accurate forecasts [6]. However, this method has significant flaws because several assumptions must be met to generate reliable analytical results especially if applied to financial data that does not fit the method's assumptions [7]. The Neural Network approach is one of many that can avoid the assumptions of the ARIMA method while still providing acceptable estimation results.

The Neural Network method may recognize patterns in input data by employing learning methods for additional training. It can be determined by learning from prior data patterns and attempting to find a function that relates past data patterns with the desired output at this time [8]. A neural network (NN) is an information processing system with properties comparable to those found in living things [9]. There are numerous models within the Neural Network, one of which is the Cascade Forward Neural Network.

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(CFNN). The Cascade Forward Neural Network (CFNN) network design is nearly identical to the Feed Forward Neural Network (FFNN) network architecture.

In FFNN, the input and output relationships are not direct, but in CFNN, the input and output relationships are direct [10]. The Cascade Forward Neural Network approach has the advantage of assisting the nonlinear link between input and output without removing the linear relationship between the two. As a result, the CFNN network is well-suited for analyzing crude oil prices, which are volatile, linear, and non-stationary [11]. So crude oil forecasting using the CFNN method produces very good accuracy.

With the Backpropagation algorithm, the Cascade Forward Neural Network method was utilized to predict the rupiah exchange rate against the US dollar, yielding a training Mean Percentages Absolute Error (MAPE) value of 0.2995% and a MAPE testing value of 0.1504 [11]. Meanwhile, the CFNN approach was utilized to anticipate the daily stock price of PT. XL Axiata, Tbk, with a MAPE training value of 1.8248% and a MAPE testing value of 2.3136%. Furthermore, the Cascade Forward Neural Network method was used to compared with several methods such as Feedforward Neural Network and Generalized Regression Neural Network. The best method was obtained, namely the Cascade Forward Neural Network method with results close to the actual value and obtained a MAPE value of 7.6%, which is smaller than the MAPE value in other methods [12]. Several other studies related to CFNN [13]–[16].

The objective of this research is to employ the Cascade Forward Neural Network method to obtain accurate Brent crude oil price prediction results. The introduction section of this paper contains the motivation for writing. The Cascade Forward Neural Network approach is presented in full in the second section. The third section discusses the results and analysis of data processing using both methods. The last section contains the acquired findings.

2. Research Methods

The data used in this study is secondary data sourced from the investment.com website. This data is Brent crude oil price data for the period January 2008 to December 2022 with a total of 180 data.

This research flow can be seen in Figure 1 begins by identifying input values based on Partial Autocorrelation Function (PACF). The next step is to divide the data for training (75%) and testing (25%). Normalization is applied to equalize the scale of the data. After the data is normalized, the next step is CFNN modeling. After the model is obtained, the model evaluation is applied. The best model is used for forecasting.

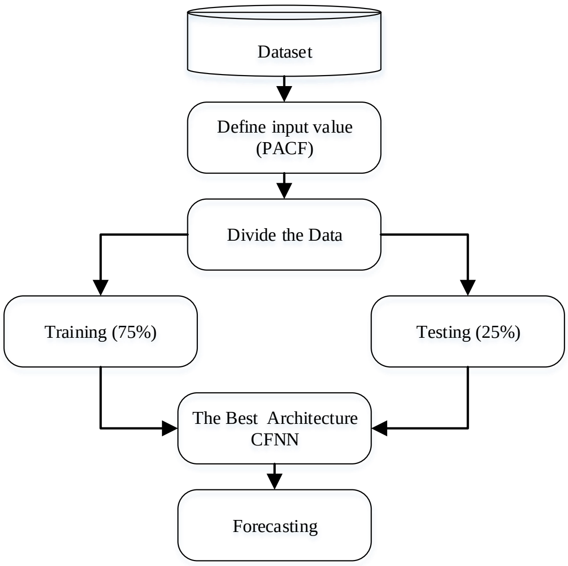

Figure 1. Research flow

2.1 Time Series analysis

Time series analysis aims to predict data or conditions for the future, see the relationship between variables and find out whether the process is under control or not. The types of data patterns are also things that need to be considered to get the right method. Time Series data is a data pattern that is determined by quantitative forecasting where the data is obtained from the past which is based on time [17]. The Autocorrelation function (ACF) describes how data points in a time series are connected to preceding data points on average. In other words, it assesses the self-similarity of signals with varying temporal delays. As a result, ACF is a function of the delay/lag, which affects the time shift taken from the past to estimate the similarity of data points [18]. ACF also describes how the correlation between two signal levels varies with distance. It is a stochastic process memory time domain measure. Furthermore, it does not give information regarding the process's frequency content. In general, ACF is defined as Equation 1 for things like error signals [19].

$$\rho_k = \frac{Cov(X_t, X_{t+k})}{\sqrt{Var(X_t)}\sqrt{Var(X_{t+k})}} = \frac{\gamma_k}{\gamma_0} \quad (1)$$

In general, the Partial Autocorrelation Function PACF is a conditional correlation. This is a correlation between two variables when the values of multiple other sets of variables are assumed to be known and taken into consideration. The partial autocorrelation function can be seen in Equation 2 [19].

$$\rho_k = \frac{Cov[(Z_t - \hat{Z}_t),(Z_{t+k} - \hat{Z}_{t+k})]}{\sqrt{Var((Z_t - \hat{Z}_t)}\sqrt{Var(Z_{t+k} - \hat{Z}_{t+k})}} \quad (2)$$

2.2 Pre-processing

Before further testing is carried out, the input data and target data must be normalized first so that the data enters the range that corresponds to the activation

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function that will be used later. The pre-processing process on this artificial neural network is done by data normalization using Equation 3 as the formula [20]:

$$x = \frac{0{,}8(x_p - \min(x_p))}{(\max(x_p) - \min(x_p))} + 0{,}1 \quad (3)$$

After forming the network and obtaining the output of each method, the data must be returned in its original form so that it can be compared to the findings of the real data being studied. Equation 4 is a post-processing formula [20].

$$X = \frac{(\hat{y} - 0{,}1)(a - b)}{0{,}8} + b \quad (4)$$

2.3 Artificial Neural Network

Artificial Neural Networks, also known as artificial neural networks (ANN), function similarly to the human brain. The key feature of ANN is its capacity to learn; this may be seen as a process of altering weighted parameters because the intended output is dependent on the value of the set's interconnectivity weights. If the error value is deemed minimal enough for all pairs of training data, the procedure will be terminated. Networks that are learning are often in the training stage; only after completion will there be an object-testing phase [21].

An artificial neural network is shown in Figure 2 made up of three layers: the Input Layer, the Hidden Layer, and the Output Layer. Each layer is accountable for the same function, which is to complete the system [22]: The pattern of connections between neurons is commonly referred to as network architecture; The method for determining the weight is commonly called the learning method; and Activation Function, namely the function to be used.

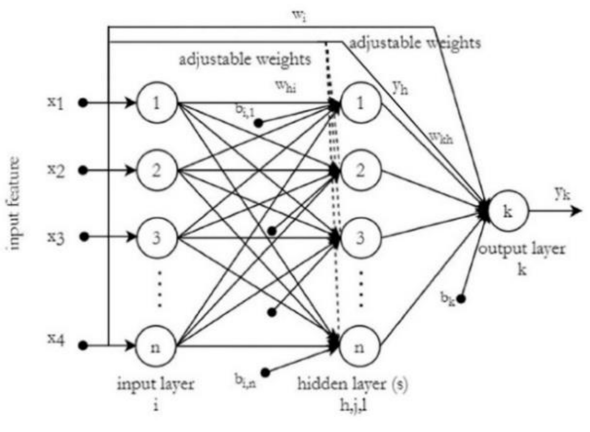

Figure 2. Network Architecture

2.4 Cascade Forward Neural Network

The network design of the Cascade Forward Neural Network is essentially the same as that of the Feedforward Neural Network. The link made between input and output in the perceptron is a direct relationship, whereas the connection formed between input and output in the FFNN is an indirect relationship. Through the activation function of the buried layer, the link is nonlinear. When the perceptron and multilayer networks are merged, a network with a direct connection between the input and output layers, as well as an indirect connection, is generated. A Cascade Forward Neural Network (CFNN) is a network built using this connection arrangement [10]. The equation resulting from the CFNN model with one output layer unit can be seen in Equation 5.

$$y = \sum_{i=1}^{I} f^i u_{ik} x_i + \left(w_{ok} + \sum_{j=1}^{J} w_{jk} f^j \left(v_{oj} + \sum_{j=1}^{I} \sum_{i=1}^{I} v_{ij} x_i\right)\right) \quad (5)$$

2.5 Backpropagation

The most prevalent supervised learning algorithm is the backpropagation algorithm. The concept behind this algorithm is to use a function based on the delta rule to select the weights that minimize the error between the ANN's actual output and anticipated output. Working backwards from the output layer, the weights are adjusted to lower the average error across all layers. This procedure is done until the output error is minimized as possible [23]

Network training consists of three stages utilizing the Backpropagation algorithm. The first stage is the advanced stage. Using the provided activation function, the input pattern is computed forward from the input layer to the output layer. The reverse phase is the second phase. An error occurs when the network output differs from the anticipated target. The error is transmitted backwards, beginning with the line directly connected to the output layer units. The third phase is weight modification, which is used to eliminate errors [24].

2.6 Best Model Criteria

To produce accurate forecasts, an evaluation is carried out using the Mean Absolute Percentage Error (MAPE) method. MAPE shows how big the error in predicting is compared to the actual value [25]. Equation 6 is used to compute MAPE:

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \frac{|X_t - \hat{X}_t|}{X_t} \times 100\% \quad (6)$$

3. Results and Discussions

This section describes the results of testing and analysis of the Cascade Forward Neural Network(CFNN) method in forecasting the price of Brent crude oil. Based on Figure 3, the price of crude oil is very volatile, this shows that the CFNN method is very appropriate for forecasting it.

In network modelling, data will be divided into two parts: training data and testing data, with a composition of 75% for training data and 25% for testing data. Meanwhile, a Partial Autocorrelation Function (PACF) plot is used to determine network input. This is because data from the preceding period influences the relationship between the data to be looked for. The network inputs utilized have considerable delays in the PACF figure, as shown by the line passing across the confidence interval (dashed line).

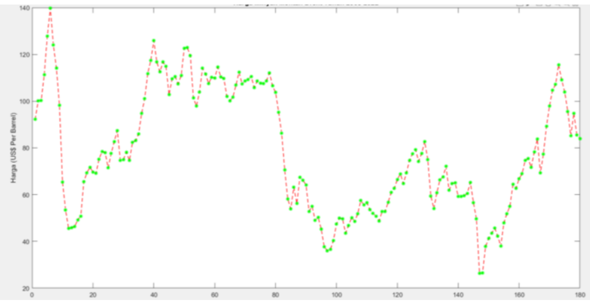

Figure 3. Time Series Plot for Crude Oil

The lines that notably pass through the confidence interval based on the PACF Plot are lag 1 and lag 2 (Figure 4). This demonstrates that one variable, lag 1 and lag2, is collected and will be utilized as the input component. The network is made up of $x_t$impacted by x_{t-1} and x_{t-2}, hence the data utilized for network input is 178. Ten trials are performed to determine the ideal network design for a Cascade Forward Neural Network network, as shown in Table 2.

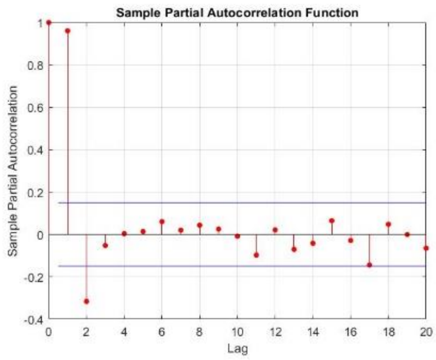

Figure 4. Partial Autocorrelation Function (PACF) Plots

The results of the training and testing process are shown in the network architecture in Table 2 with the architecture experiments being carried out 10 times and the best network architecture is found in the 6th number of neurons. To produce a display of the network training process as shown in Table 3 and a display of network architecture 2-6-1 as shown in Figure 3.

Table 2. Experimental CFNN Network Architecture

Architecture	MAPE Training	MAPE Testing
2-1-1	6,4841	9,7257
2-2-1	6,4178	10,1114
2-3-1	6,5152	10,2697
2-4-1	6,3656	9,7713
2-5-1	8,8400	11,5692
2-6-1*	6,2471	9,7165
2-7-1	6,3745	10,4431
2-8-1	6,4714	12,5273
2-9-1	6,4953	10,3047
2-10-1	6,4157	9,7203

*) The best

Table 3. Network Training Process 2-6-1

Performance Parameter	Value
Epoch	197 Iteration
Time	0:00:01
Performance	0,00175
Gradient	0,000107
Step Size	0,00

The results of the training with the 2-6-1 architecture can be explained that the epoch (number of iterations) carried out was 197 iterations with a very fast time of even less than 1 second. Then for performance or show it is 0,00175, while the gradient (slope) is 0,000107. Figure 5 is the result of the best network architecture 2-6-1. The values of the architectural parameters are listed in Table 4.

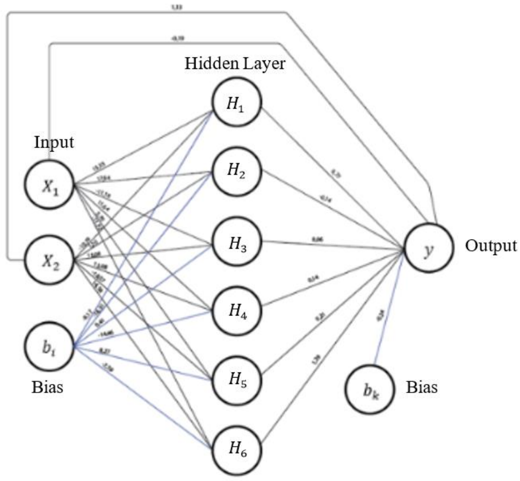

Figure 5. Network Architecture 2-6-1

Table 4. Network Architecture Value 2-6-1

Parameters	Value
$X_1 \rightarrow y$	1,13
$X_2 \rightarrow y$	-0,19
$X_1 \rightarrow H_1$	15,35
$X_1 \rightarrow H_2$	17,64
$X_1 \rightarrow H_3$	-11,18
$X_1 \rightarrow H_4$	11,64
$X_1 \rightarrow H_5$	5,70
$X_1 \rightarrow H_6$	-11,92
$X_2 \rightarrow H_1$	-10,79
$X_2 \rightarrow H_2$	1,20
$X_2 \rightarrow H_3$	15,08
$X_2 \rightarrow H_4$	13,08
$X_2 \rightarrow H_5$	-18,57
$X_2 \rightarrow H_6$	14,58
$b_1 \rightarrow H_1$	-9,17
$b_2 \rightarrow H_2$	-16,51
$b_3 \rightarrow H_3$	0,41
$b_4 \rightarrow H_4$	-14,46
$b_5 \rightarrow H_5$	8,27
$b_6 \rightarrow H_6$	-7,59
$b_k \rightarrow y$	-0,24
$H_1 \rightarrow y$	0,77
$H_2 \rightarrow y$	-0,14
$H_3 \rightarrow y$	0,06
$H_4 \rightarrow y$	0,14
$H_5 \rightarrow y$	0,21
$H_6 \rightarrow y$	1,29

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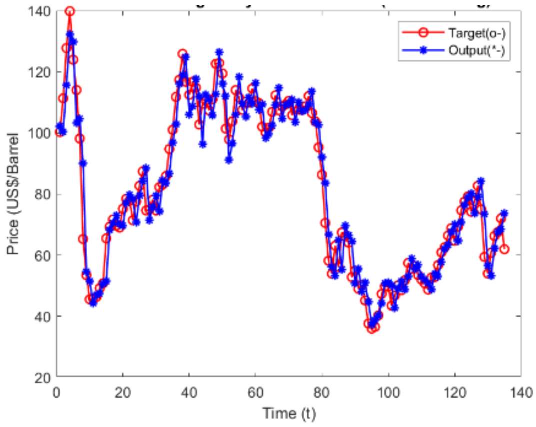
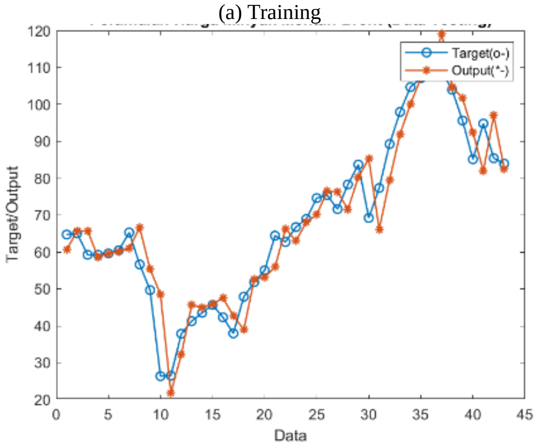
From the network architecture that has been formed, a plot is obtained from the output of training and testing results are presented as shown in Figure 6 (a) and Figure 6 (b). The figure above shows that the targeted value and the resultant output are not much different; in fact, the target value and output are very near, where 6,2471% is the obtained MAPE training value.



(a) Training



(b) Testing

Figure 6. Comparison of Targets (predictions) and Outputs (observed)

Figure 7 plot shows that the target value and the resultant output are not significantly different and that the target value and output are close together. When the concluding MAPE testing number is 9,7165%, which equals <10%, it may be stated that the testing process's predicting accuracy is very good.

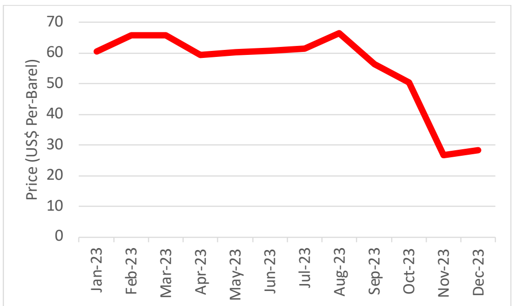


Figure 7. The plot of Forecasting Results for Brent Crude Oil in 2023

The results of projecting the price of Brent crude oil for the following 12 periods, namely from January 2023 to December 2023, were obtained from the previous training and testing procedure using the Backpropagation algorithm. The dataset utilized is 135 data of monthly Brent crude oil price data as training data and 43 data of testing data. Forecasting results are presented in Table 5.

Table 5. Forecasting Results for Brent Crude Oil in 2023

Period	Month	Forecast Result
1	January 2023	60,44
2	February 2023	65.72
3	March 2023	65,69
4	April 2023	59,33
5	May 2023	60,25
6	June 2023	60,64
7	July 2023	61,51
8	August 2023	66,44
9	September 2023	56,39
10	October 2023	50,45
11	November 2023	26,78
12	December 2023	28,23

4. Conclusion

The Cascade Forward Neural Network (CFNN) method has been utilized for predicting Brent crude oil prices. Based on a 75% distribution of training data and a 25% distribution of testing data, the best network architecture model is 2-6-1, the activation function is traincgf, the learning rate is 0.1, the error tolerance is 0.011, and the epoch is 1000, the MAPE training value is 6.2471% and MAPE testing is 9.7165%, and both are <10%, indicating that the accuracy of Brent crude oil price forecasting using the Cascade Forward Neural Network method is very good. By using the Backpropagation algorithm to forecast the price of Brent crude oil over 12 periods, from January 2023 to December 2023, it is feasible to conclude that the price of rice is highest in the eighth month, August, at US$66.59 per barrel, and lowest in the eleventh month, November, at US$24.15 per barrel.

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