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Application of Cheng's Fuzzy Time Series in World Crude Oil Price Prediction

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Abstract. Fuzzy time series is a new concept that can be used to predict an event using historical data. Historical data is processed using the principles and logic of fuzzy sets. The aim of this study is to predict world oil prices. The historical data used was from 3 January 2022 to 30 June 2023. This article discusses Cheng's Fuzzy Time Series application. Determining the number of fuzzy class intervals uses 3 approaches, namely using the Sturges formula, Average-based and Partial Frequency Density. The 3 approaches used will be compared. Fuzzy Time Series with the Sturges formula produces a MAPE of 10.54% and a MSE of 9.13. Average-based Fuzzy Time Series produces a MAPE of 7.64% and a MSE of 5.15. Partial Frequency Density Fuzzy Time Series produces a MAPE of 8.09% and a MSE of 5.99. The results of this study state that Cheng's Average based Fuzzy Time Series has the best accuracy in predicting world oil prices.

1 Introduction

Oil is one of the energy sources for human life. Crude oil is useful as an industrial raw material, vehicle fuel, household furniture making material, and as an ingredient in beauty and health products. Because crude oil is very useful in life, all people in the world need crude oil and including all its derivative products. Limited crude oil and the movement of world oil demand according to the seasons affect the movement of world oil prices, and cause oil prices to fluctuate every day. World oil prices refer to the price of West Texas Intermediate (WTI) oil, also known as Texas light sweet. WTI prices are frequently mentioned in oil price news, in addition to the price of Brent crude oil from the North Sea. Movements in crude oil prices affect the burden of fuel subsidies, electricity subsidies, electricity compensation, transportation costs and costs for industries that use non-subsidized fuel, as well as affecting investors related to world energy. Nizar [9], researchers from the Ministry of Finance conducted research on the influence of oil prices on the Indonesian economy. The research results show that the oil price shocks in the world market have a positive impact on quarterly economic growth. The price of oil also influences domestic inflation, domestic money supply, Indonesia Stock Exchange (IDX) and affect the real exchange rate of Rupiah. Based on that article, the government must think of various ways to reduce the need for petroleum,

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by starting to use fuel that is vegetable-based or based on wind power or solar power. The government must start providing education to the public about energy saving and promote alternative energy development. If world crude oil prices continue to rise and contribute to pushing up Indonesian crude oil prices, inflation will rise, especially in terms of inflation in the transportation sector.

World oil prices are important in the nation's economic life, so researchers predict world oil prices using various methods. Setiyowati [11] uses the ARIMA Combination model. The result of that research showed that ARIMA (1,1,0) model produces the best accuracy for predicting the next thirty-six months. Fauzanissa [3] uses a Radial Basis Function Neural Network. The model of Radial Basis Function Neural network is suitable for large scale data processing, because this model uses only a part of data input and has a total processing time of a rapid system. This model has a neural network architecture consisting of an input layer, hidden layer and output layer. This research states that the proposed method has good accuracy. Hussein [6] uses Deep Learning methods. The Deep learning LSTM (Long Short-Term Memory) model is used to predict the oil price in a certain period. This method is used because the architecture can modify to non-linear learning from complex time series data. The models that were built had a good accuracy to predict oil prices well. Herawati [5] uses Ensemble Empirical Mode Decomposition and Resilient Backpropagation. The use of the resilient method produces better forecasting and fewer epochs compared to the gradient Descent method. Zainal et all [12] uses the generalized Autoregressive Conditional Heteroscedasticity method. The accuracy values of that research had very good for forecasting world crude oil prices.

Setiyono et all [10] stated that world crude oil prices have reached a point of stability, after two years when the world was hit by the Covid-19 pandemic which caused world crude oil prices to fall. Therefore, a tool for predicting world crude oil prices using data mining techniques is needed. In this world crude oil price prediction research, we carry out predictions using a forecasting algorithm using the Prophet method. Nathanael et all [8] studied about Autoregressive Fractionally Integrated Moving Average (ARFIMA). This model is a development of the ARIMA model. This article shows that non integer differentiation can be solved with ARFIMA. ARFIMA can be used for modeling high changes in the long term. That model can provide solution of simple parameters for data with long term and short term. Data of world oil price contain long memory effect, then used ARFIMA method to get the best model. Febryo et all [4] stated that the price of crude oil per barrel is determined by factors US Dollar (USD) exchange rate, inventory (supply) world crude oil, demand (demand), and related commodity market sentiment. There is an Artificial Neural Network (ANN) method Backpropagation (BP) that can be used to carry out price forecasting definitely by studying patterns that have been formed. Each feedforward process attributes and weight improvements with backpropagation produces price classification oil falls drastically, down, steady, up, or up drastic.

Fuzzy Time Series (FTS) is often used by researchers in various studies. Chen [1] stated that FTS is a forecasting method founded by Song and Chissom. Forecasting using the Fuzzy Time Series method uses historical data, various properties, definition, and logic in fuzzy sets. Muhammad et all [7] used FTS Lee to predict the exchange rate for farmers in the livestock subsector of East Kalimantan province. Fauzi et al [2] evaluated the use of the FTS Cheng and Ruey Chyn Tsaur methods in predicting exchange rates for farmers in Central Java province. In this article, world oil price movements are predicted using FTS Cheng. Determining the number of fuzzy classes is carried out using 3 methods, namely using the Sturges formula, using average based and using Partial Frequency Density (PFD). The aim of this research is to find out the method that has the best accuracy in predicting world crude oil prices.

2 Materials and methods

As explained in the introductory chapter, in this article we discuss the application of Cheng FTS to predict world crude oil prices. Crude oil prices are taken from the page at https://id.investing.com/commodities/crude-oil-historical-data.

The data used was from 3 January 2022 to 30 June 2023. The length of the interval and the choice of method used greatly influence the MAPE value. This research aims to find out the method that provides the highest accuracy. In more detail, we use 3 methods of Cheng FTS, where the calculation of fuzzy class intervals uses the Sturges formula, Average Based and Partial Frequency Density FTS.

Explanation of Cheng's Fuzzy Time Series calculation scheme:

1. Historical data of crude oil price is used for Cheng's Fuzzy Time Series method.
2. Determine Xmax, Xmin, D1, D2, the middle value (midpoint) where Xmin = Minimum data and Xmax = Maximum data. D1 and D2 are arbitrary positive numbers and are chosen by the researcher to make the calculation easier.
3. Find U. U is universe of discourse of historical data universes. U can be written as:

$$U = \{X_{\min} - D_1, X_{\max} + D_2] \qquad (1)$$

4. The length of the interval is calculated using 3 methods.
   a. For 1st method, we use Sturges formula. The number of interval will be find with the Struges formula:

   $$k = 1+3{,}32 \log n \qquad (2)$$

   where k is the number of intervals, n is the amount of data. After that, we calculate the number of intervals.

   a. For 2nd method, we use average based method (Virginia, [13]). The calculation is as follows:
      1) Calculate sum of the absolute of the difference between X_{t+1} and X_t where t = 1, 2, …., n-1. The absolute values are added up and we use the formula for the average absolute difference value as follows.

      $$\text{mean}= \frac{\sum_{i=1}^{n} |X_{t+1}\text{-}X_t|}{n} \qquad (3)$$

      Where:
      Mean = average value
      N = amount of data
      X_t = data at time t

      2) We calculate the length of the interval obtained from the mean value in equation (2) using the following equation:

      $$I = \frac{Mean}{2} \qquad (4)$$

      The length of the interval is then rounded to the basis of the interval. In general, the range length and its basis are shown in Table 1.

Table 1. Range and base

Range	Base
0.1 - 1	0.1
1.1 - 10	1
11 - 100	10
101 - 1000	100
1001- 10000	1000

We determine the basis of the interval length according to the basis tabulation. The length of the interval is then rounded according to the basis of the interval.

3) The number of intervals /fuzzy numbers (p) is determined by the following equation:

$$p = \frac{(X_{max} + D_2 + X_{min} + D_1)}{l} \quad (5)$$

c. For 3rd method, we use frequency density-based partitioning. The interval with the first densest frequency is divided into k subintervals. The number of k is form 1st method. The interval with the second densest frequency is divided into k-1 subintervals. The interval with the third densest frequency is divided into k-2 subintervals and so on. We will have a new number of intervals.

5. We define the fuzzy set depending on the number of classes after obtaining the number of intervals. For instance, if a set is fuzzy and has linguistic value, its definition in the universal set *U* is as follows.

$$\begin{aligned} A_1 &= 1/u_1 + 0,5/u_2 + 0/u_3 + \ldots + 0/u_p \\ A_2 &= 0,5/u_1 + 1/u_2 + 0,5/u_3 + \ldots + 0/u_p \\ A_3 &= 0/u_1 + 0,5/u_2 + 1/u_3 + 0,5/u_4 \ldots + 0/u_p \\ &\ldots \\ A_p &= 0/u_1 + 0/u_2 + 0/u_3 + \ldots 0,5/u_{p-1} + 1/u_p \end{aligned} \quad (6)$$

Where $u_i(i = 1,2,3,\ldots, p)$ is the number of the universal set *u* and the number marked with the symbol "/" informs the degree of membership $\mu_{Ai}(\mu_i)$ to $A_i(i = 1,2,3,\ldots, p)$ which the value is 0, 0.5 or 1.

6. The historical data is entered into one class using the fuzzy set-in step 5.
7. We create the FLR after obtaining the fuzzy set. Data from month *i* and j are related in a fuzzy way by the FLR. When $j.\ (t-1) = A_i$ and $F(t) = A_j\ j.\ (t-1) = A_i$ and $F(t) = A_j\ j.\ (t-1) = A_i$ and $F(t) = A_j\ j.\ (t-1) = A_i$ and $F(t) = A_j$. The group Fuzzy Logical Relationship Group (FLRG) was created from FLR and shares the same left side.
8. After calculating FLRG, defuzzification is carried out. At Cheng's Fuzzy Time Series [2].

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We can use the formula Mean Absolute Percentages Error (MAPE) to calculate the prediction error rate. We can also use Mean Squared Error (MSE) to calculate the prediction error rate where x_i = actual data in the day i; p_i = forecast value in the day I; n = number of data.

$$\text{MAPE}=\sum_{i=1}^{n}\left|\frac{x_i-p_i}{x_i}\right| \text{x}100\% \tag{7}$$

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(x_i-p_i\right)^2 \text{x}100\% \tag{8}$$

3 Results and discussion

The graphic of the historical data taken from https://id.investing.com/commodities/crude-oil-historical-data at Figure 1.

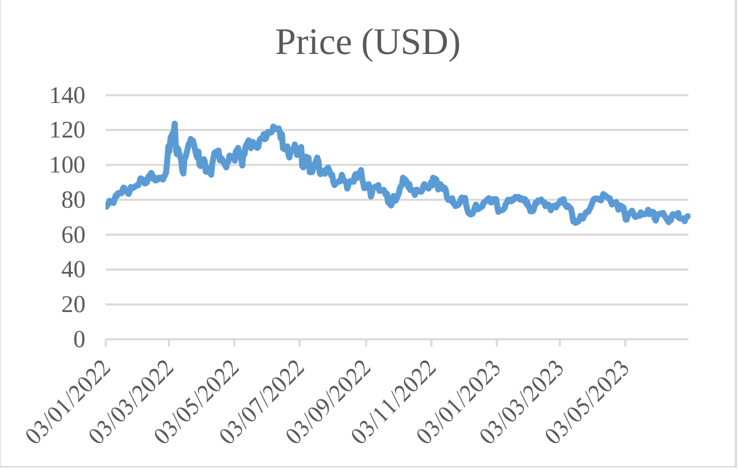

Fig 1. Historical data of crude oil price

From the historical data and using the logic and rule of fuzzy time series, we can calculate prediction value of price of crude oil. Determining the number of fuzzy class intervals uses 3 approaches, namely using the Sturges formula, Average-based and Partial Frequency Density.

3.1 Using Sturges Formula

Considering the historical data, we had the number of data is 406, and using the Sturges formula that we discussed above, k= 1+3,32 log n. The number n is 406 so the variable k is 9,665523 and rounded to 10. The minimum value of this historical data is 66.74 and the maximum value of this data historical is 123.7. We can choose D1 = 1.74 and D2 = 1.3 and we have the universe set is [65,125]. The interval that just created is [65,71], [71,77], …, [113,119], [119,125].

After we know the interval, the historical data classes to fuzzy classes. Fuzzification of this historical data stated the Table 2 as follow.

Table 2. Fuzzification of the historical data

No	Date	Price	Fuzzification
1	03/01/2022	76,08	A2
2	04/01/2022	76,99	A2
3	05/01/2022	77,85	A3
…	…	…	…
101	20/05/2022	113,23	A9
102	23/05/2022	110,29	A8
103	24/05/2022	109,77	A8
…	…	…	…
401	23/06/2023	69,16	A1
402	26/06/2023	69,37	A1
403	27/06/2023	67,7	A1
404	28/06/2023	69,56	A1
405	29/06/2023	69,86	A1
406	30/06/2023	70,64	A1

From Table 2, we can create the fuzzy logic relation (FLR). Fuzzy logic relation is the relationship of two consecutive historical data. For example, FLR of 03/01/2022 → 04/01/2022 is A2 → A2. FLR of 04/01/2022 → 05/01/2022 is A2 → A3 and so on and can be described as the Table 3 as follow.

Table 3. Fuzzy Logic Relation (FLR)

No	Date	Price	Fuzzification	FLR
1	03/01/2022	76,08	A2	
2	04/01/2022	76,99	A2	A2 → A2
3	05/01/2022	77,85	A3	A2 → A3
…	…	…	…	…
101	20/05/2022	113,23	A9	A8 → A9

No	Date	Price	Fuzzification	FLR
102	23/05/2022	110,29	A8	A9 → A8
103	24/05/2022	109,77	A8	A8 → A8
…	…	…	…	…
401	23/06/2023	69,16	A1	A1 → A1
402	26/06/2023	69,37	A1	A1 → A1
403	27/06/2023	67,7	A1	A1 → A1
404	28/06/2023	69,56	A1	A1 → A1
405	29/06/2023	69,86	A1	A1 → A1
406	30/06/2023	70,64	A1	A1 → A1

After all historical data are classified into FLR at the Table 3, we can create Fuzzy Logic Relation Group (FLRG). FLRG is a group obtained from FLR which has the same left side. Doing pivot at the Table 3 we have the Table 4.

Table 4. Pivot Table

Row Labels	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	21	8								
A2	7	55	10							
A3		10	72	6						
A4			6	44	8					
A5				8	33	6				
A6					6	10	6	2		
A7						8	18	6	1	
A8							9	16	4	1
A9								6	10	1
A10									2	5

Based on Table 4, we can state FLRG at the Table 5 as follows:

Table 5. Fuzzy Logic Relation Group (FLRG)

No	FLRG
1	A1 → 21A1, 8A2
2	A2 → 7A1, 55A2, 10A3
3	A3 → 10A2, 72A3, 6A4
4	A4 → 6A3, 44A4, 5A5
5	A5 → 8A4, 33A5, 6A6
6	A6 → 6A5, 10A6, 6A7, 2A8
7	A7 → 8A6, 18A7, 6A8, A9
8	A8 → 9A7, 16A8, 4A9, A10
9	A9 → 6A8, 10A9, A10
10	A10 → 2A9, 510

From Table 5, we have prediction of each fuzzy class that be shown at the Table 6.

Table 6. Defuzzification of each Fuzzy Classes

No	Fuzzy Classes	Defuzzification
1	A1	69,65517
2	A2	74,25
3	A3	79,72727
4	A4	86,2069
5	A5	91,74468
6	A6	99
7	A7	104
8	A8	109,4
9	A9	114,2353
10	A10	120,2857

Table 7. Prediction using Sturges formula

No	Date	Price	Prediction
1	03/01/2022	76,08	
2	04/01/2022	76,99	74,25
3	05/01/2022	77,85	74,25
…	…	…	…
101	20/05/2022	113,23	109,4
102	23/05/2022	110,29	114,2352941
103	24/05/2022	109,77	109,4
…	…	…	…
401	23/06/2023	69,16	69,65517241
402	26/06/2023	69,37	69,65517241
403	27/06/2023	67,7	69,65517241
404	28/06/2023	69,56	69,65517241
405	29/06/2023	69,86	69,65517241
406	30/06/2023	70,64	69,65517241

3.2 Using Average Based

The average begins by calculating all the absolute values of the difference between X_{t+1} and X_t where t = 1,2,…, n-1. The absolute values are added up and we use the formula for the average absolute difference value. From the historical data, we have minimum value of price is 66.74 and maximum value of the price is 123.7. To make calculation easier, we choose D1 = 0.74 and D2 = 0.3 so we have the universe set as [66,124]. Based on the total of differences and using the formula of average based above, we have the length of interval is 0,941765432 and rounded to 1. With this length of interval, we have 58 fuzzy classes that [66,67], [67,68], …, [122,123], [123,124].

The result of Fuzzy Classes and Fuzzy Logic Relation (FLR) described at the Table 8 as follows.

Table 8. Fuzzy Classes and Fuzzy Logic Relation (FLR)

No	Date	Price	Difference	Fuzzy Classes	FLR
1	03/01/2022	76,08			

No	Date	Price	Difference	Fuzzy Classes	FLR
2	04/01/2022	76,99	0,91	A11	A11 → A11
3	05/01/2022	77,85	0,86	A12	A11 → A12
…	…	…	…	…	…
101	20/05/2022	113,23	1,02	A48	A47 → A48
102	23/05/2022	110,29	2,94	A45	A48 → A45
103	24/05/2022	109,77	0,52	A44	A45 → A44
…	…	…	…	…	…
401	23/06/2023	69,16	0,35	A4	A4 → A4
402	26/06/2023	69,37	0,21	A4	A4 → A4
403	27/06/2023	67,7	1,67	A2	A4 → A2
404	28/06/2023	69,56	1,86	A4	A2 → A4
405	29/06/2023	69,86	0,3	A4	A4 → A4
406	30/06/2023	70,64	0,78	A5	A4 → A5

Using the pivot table, we have the FLRG as follows.

Table 9. Fuzzy Logic Relation Group (FLRG)

No	FLRG
1	A1 → A2
2	A2 → A3, 3A4
3	A3 → A1, A3, 2A5, A6
4	A4 → A2, A3, 4A4, 2A5, A7
…	…
55	A55 → A53, A55
56	A56 → A55
57	A57 → A56

No	FLRG
58	A58 → A43

From Table 9, we have prediction of each fuzzy class that be shown at the Table 10.

Table 10. Defuzzification using AVG

No	Fuzzy Classes	Defuzzification
1	A1	67,5
2	A2	69,25
3	A3	69,5
4	A4	69,6
…	…	…
54	A54	123
55	A55	119,5
56	A56	120,5
57	A57	121,5
58	A58	108,5

3.3 Using Partial Frequency Density

The idea of this method is to pay attention to historical data that often appears at a certain interval. Interval that has a high frequency are divided into smaller intervals, so we have a precise interval. Using the Sturges formula we have 10 intervals. A3 is a fuzzy class that have the most event (88) and we will divide with 10. A2 have 72 events and will divide with 9 and so on so the calculation shows this table.

Table 11. Fuzzy Classes, Total Event and Divider

Fuzzy Classes	Total event	Divider
A1	29	4
A2	72	9
A3	88	10
A4	58	8

A5	47	7
A6	24	3
A7	33	6
A8	30	5
A9	17	2
A10	7	1

For A1, the interval [65,71] divided by 4 so we have a new interval [65,66.5], [66.5,68], [68,69.5], [69.5,71]. For A2, the interval [71,77] divided by 9 and we found a new interval [71,71.666], [71.666,72.332], …, [75.632,76.292], [76.292,77]. All fuzzy classes are divided and finally we have 55 new classes. The fuzzy classes. FLR described at the table 12.

Table 12. Fuzzy classes and FLR using partial frequency density.

No	Date	Price	Fuzzy Classes	FLR
1	03/01/2022	76,08	A12	
2	04/01/2022	76,99	A13	A12 → A13
3	05/01/2022	77,85	A14	A13 → A14
…	…	…	…	…
101	20/05/2022	113,23	A53	A52 → A53
102	23/05/2022	110,29	A50	A53 → A50
103	24/05/2022	109,77	A50	A50 → A50
…	…	…	…	…
401	23/06/2023	69,16	A3	A4 → A3
402	26/06/2023	69,37	A3	A3 → A3
403	27/06/2023	67,7	A2	A3 → A2
404	28/06/2023	69,56	A4	A2 → A4
405	29/06/2023	69,86	A4	A4 → A4
406	30/06/2023	70,64	A4	A4 → A4

Using 55 intervals we have FLRG as follows.

Table 13. Fuzzy Logic Relation Group (FLRG)

No	FLRG
1	A2 → A2, 3A3, A4
2	A3 → 2A2, 4A3, 3A4, A5, A7
3	A4 → A2, 2A3, 4A4, A5, 2A6, 2A7
4	A5 → A2, A3, 3A4, A5, 2A6, A8
…	…
49	A52 → A50, A51, 2A53
50	A53 → A46, A50, 2A52, 3A53, 3A54, A55
51	A54 → A50, 2A53, 2A54, A55
52	A55 → A49, A54, 5A55

From Table 13, we have prediction of each fuzzy class that be shown at the Table 14.

Table 14. Defuzzification using Partial Frequency Density (PFD)

No	Fuzzy Classes	Defuzzification
1	A2	68,75
2	A3	69,47682
3	A4	70,53375
4	A5	70,60033
5	A6	72,145
…	…	…
48	A51	110,3333
49	A52	112,55
50	A53	114,3909
51	A54	116
52	A55	119,4714

Finally, we have completed 3 methods for predicting oil prices. From these 3 methods, we get the following prediction that seen at the Table 15.

Table 15. Prediction using Sturges, AVG and PFD

No	Date	Price	Using Sturges	Using AVG	Using PFD
1	03/01/2022	76,08			
2	04/01/2022	76,99	74,25	76,24	76,16
3	05/01/2022	77,85	74,25	76,24	76,55
…	…	…	…	…	…
101	20/05/2022	113,23	109,4	112	112,55
102	23/05/2022	110,29	114,2352941	108	114,4
103	24/05/2022	109,77	109,4	108,67	108,91
…	…	…	…	…	…
401	23/06/2023	69,16	69,65517241	69,6	70,54
402	26/06/2023	69,37	69,65517241	69,6	69,48
403	27/06/2023	67,7	69,65517241	69,6	69,48
404	28/06/2023	69,56	69,65517241	69,25	68,75
405	29/06/2023	69,86	69,65517241	69,6	70,54
406	30/06/2023	70,64	69,65517241	69,6	70,54

From all methods, we found this figure as follows:

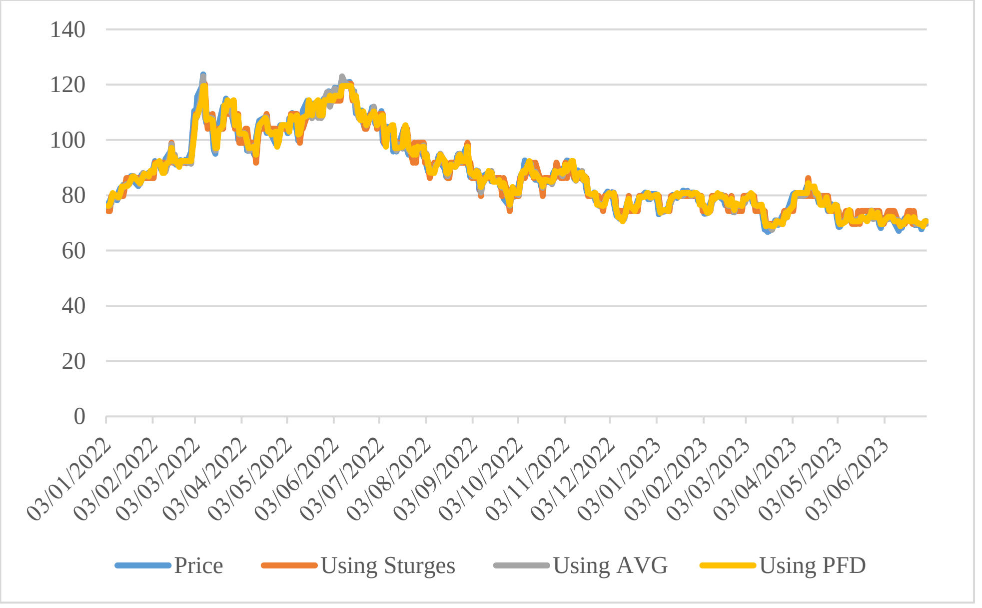

Fig 2. Prediction of Crude Oil Price

4 Conclusion

In this research, we found that Fuzzy Time Series with the Sturges formula produces a MAPE of 10.54% and a MSE of 9.13%. Average-based Fuzzy Time Series produces a MAPE of 7.64% and a MSE of 5.15. Partial Frequency Density Fuzzy Time Series produces a MAPE of 8.09 and a MSE of 5.99. The results of this study state that Cheng's Average based Fuzzy Time Series has the best accuracy in predicting world oil prices. This research can be developed using other methods.

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