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Cheng Fuzzy Time Series Model to Forecast the Price of Crude Oil in Malaysia

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HIGHLIGHTS

- Cheng Fuzzy Time Series Model is suitable for forecasting the price of crude oil price in Malaysia because it is able to deal with the inconsistency pattern of historical data and the method produces lower MAPE and RMSE.
- The numbers intervals used in the model representing the linguistic variables for price of Crude oil, from the highest price to the lowest price, have an influence on the output forecast.
- The study finds that the use of eight intervals in the model produces more accurate forecast of price of crude oil in Malaysia.
- The finding of the study may assist the related sectors such as governments, investors and others to do better management planning for improving the economy.

ABSTRACT

Crude oil is one of the important commodities to Malaysia. As a producer and exporter of oil and gas, Malaysia has gained high Gross Revenue from this sector. Crude oil is the global commodity and highly demanded. Therefore, major price changes on the commodity have a significant influence on world economy. Market sentiment, demand, and supply are some elements directly influencing the oil prices. Since crude oil is the backbone of businesses and is extremely important to the economy, it is essential to study the price of crude oil for future planning purposes. For that reason, this study proposes the use of the Cheng Fuzzy Time Series to predict crude oil price in Malaysia. In this study, Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used to evaluate the forecast performance. The finding shows that Cheng Fuzzy Time Series Model using eight intervals representing linguistic prices is able to produce a good result in forecasting since the analyses shows low values of RMSE and MAPE (less than 10 percent). Although this is the fundamental study but the finding may assist many sectors in Malaysia, such as governments, enterprises, investors, and businesses to produce a better economic planning in the future especially after the pandemic covid-19 phase.

Keywords: *Crude oil price, Fuzzy Time Series, Cheng Fuzzy Time Series, Linguistic Variables, RMSE, MAPE*

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INTRODUCTION

Malaysia was the second largest oil and natural gas producer in Southeast Asia, and the world's fifth largest exporter of oil and liquefied natural gas in 2019 (U.S. Energy Information Administration, 2021). It produced about 1.7 million barrels of oil per day on average in 2018 and 596,000 barrels of oil per day in 2020. Oil and gas industries have contributed higher percentage in Malaysia Gross Revenue (Zakaria & Shamsuddin, 2017). As an oil and gas exporter, Malaysia gain more gross revenues from higher world oil price and vice versa (Jalil et al., 2009).

The term "Oil Price" refers to the current spot price for a barrel of benchmark crude oil. The price of oil is determined by the grade, locality, and sulphur content. Besides, the price of oil may be affected by the balance between its demand and supply. Oil storage trade is a technique in which major oil corporations acquire oil at low prices for immediate storage and delivery. These huge oil firms then hold the oil in store till the price of oil rises. Because oil is a global commodity in high demand, major price changes have the potential to have a significant influence on the global economy. Market sentiment, demand, and supply are the three primary elements directly influencing oil prices. When supply falls, demand rises, and the price of oil rises, and vice versa. The supply of oil is determined by taxes, the legal framework, geological discoveries, the political status of oil-producing firms, and the cost of extracting the oil. Global macroeconomic circumstances influence oil demand. High oil prices contribute to greater inflation, which harms the economy of countries that import oil. Conversely, low oil prices may cause economic collapse and political instability in oil-producing countries by disrupting economic growth.

Another factor affecting the fluctuation of crude oil price is a natural disaster, such as COVID_19. Since 2020, the disease has spread globally, resulting in a pandemic. This disease has a significant influence on the economy of the entire world, including Malaysia. Demand shocks in the oil market have been caused by the Movement Control Act (MCO) and international travel control. As compared to 2020, the global oil demand fell to 19.9 million barrels per day in April 2020 (IEA, 2020). However, global oil consumption is gradually rebound beginning in the second quarter of 2020. As the majority of the economy's operations had paused during the pandemic, demand for oil decreased while supply surged. As a result, BRENT oil prices have fallen from $50 USD to $20 USD since mid-March, while WTI oil prices have fallen to negative $37.63 USD for the first time in history on 20 April 2020. This makes the oil investors tremble and loss of confidence (Mensi et al., 2020). Besides, Malaysia's economic growth decreased severely by 3.1% in 2020 due to the impact of the policy responses implemented to prevent the spread of COVID-19 (World Bank, 2021).

Predicting the price of crude oil is essential in providing information for policy makers to the government and investors. Many researchers have put some effort into developing various mathematical forecasting models to predict oil price with minimal error such as Variational Mode Decomposition (VMD) (Huang and Deng, 2021; Li,2019) and New Text-Based and Big Driven Models (Wu, 2021), Autoregressive Model Moving Average (ARIMA) (Jain and Gupta, 2018) and many more.

Although there are many forecasting models, Fuzzy Time Series (FTS) is one of the suitable methods for forecasting. This method is capable of dealing with fluctuation data, imprecise environment, uncertainty and subjectivity in the data, as compared to the classical statistics (Song and Chissom, 1993). FTS has been implemented in many studies such as in students' enrolment prediction (Song and Chissom,1993), oil price prediction (Zhang et al., 2010), stock market prediction (Cai, et al.,2013) and many more.

Fuzzy time series (FTS) using fuzzy relations equations and approximate reasoning introduced by Chong and Chissom to predict the number of student enrolments has been extended for more accurate

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prediction by Chen in utilizing arithmetic operations and the result is better in predicting the students' enrolment (Chen,1996). The Chen's Model has weaknesses since it does not emphasize repetition and does not have a smaller weight on more extended observations. Then, Cheng's model was developed to improve the Chen's model by implying the weight in each group fuzzy relation (Cheng, 2008).

Cheng FTS has been widely used in forecasting problems and produces good forecasting result with minimal error. The model has been used to predict the total population of Indonesia (Bettiza et al., 2020) and the forecast result shows a very high accuracy with Mean Average Percentage Error (MAPE) of 0.0535%. Besides that, the model has been applied to forecast the number of tourists visiting the Province of West Sumatra (Rahmawati, et al., 2019). The finding also shows that the model is considered good for prediction with MAPE's value of 14.6 percent (10-20 percent is considered good) and the prediction accuracy is 85.39 percent. Wirawan et al. (2021) have compared Chen and Cheng Fuzzy Time Series Models in predicting chili prices in Indonesia. The forecast result shows that the Cheng's is more accurate in prediction than the Chen's because the Cheng's produced smaller value of MAPE as compared to the Chen's.

In this study, Cheng FTS Method will be implemented to predict Malaysian crude oil price. The model performance will be tested using Root Mean Square Error (RMSE) and Mean Average Percentage Error (MAPE).

METHODOLOGY

Data Collection Method

The monthly data of crude oil price in Malaysia from September 2011 to September 2021 as stated in Table 1 were collected from the IndexMundi Website Page. The maximum price was RM358.59 per barrel on March 2012 and the minimum price is RM91.64 per barrel on April 2020.

Table 1: Price of Crude Oil in Malaysia

Month	Price of crude oil per barrel (RM)	Month	Price of crude oil per barrel (RM)	Month	Price of crude oil per barrel (RM)
Sep-11	311.68	Apr-20	91.64	Feb-2	244.62
Oct-11	313.55	May-20	131.98	Mac-21	262.31
Nov-11	331.98	Jun-20	168.71	Apr-21	259.61
Dec-11	329.66	Jul-20	179.38	May-21	273.99
Jan-12	333.18	Aug-20	182.04	Jun-21	296.88
Feb-12	340.88	Sep-20	168.53	Jul-21	307.68
Mar-12	358.59	Oct-20	165.72	Aug-21	290.7
Apr-12	348.05	Nov-20	174.18	Sep-21	303.58

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⋮	⋮	Dec-20	177.99	Aug-21	290.7
Mac-20	138.34	Jan-21	216.38	Sep-21	303.58

Implementation of Cheng Fuzzy Time Series Model to Forecast Crude Oil Price in Malaysia

The definitions of FTS of Song and Chissom (1993) are still relevant in Cheng Fuzzy Time Series Model and they are as stated below:

Definition 1: Let $Y(t)$ with $t = 1,2,3,...$, a subset of R be the universe of discourse in which fuzzy set $f_i(t)$ are defined. If $F(t)$ consists of $f_i(t)$ with $i = 1,2,3,...$ then $F(t)$ is called a Fuzzy time series defined on $Y(t)$.

Definition 2: If $F(t-1) = A_i$ and $F(t) = A_j$, the relationship between 2 consecutive observation, $F(t-1)$ and $F(t)$ written as $A_i \rightarrow A_j$ is called Fuzzy Logical Relationship (FLR) and A_i is the known as Left Hand Side (LHS) and A_j is the Right Hand Side (RHS).

Definition 3: All FLRs of the same LHS are grouped together into a Fuzzy Logical Relationship Group (FLRG). For example, the two FLS $A_i \rightarrow A_{j1}$ and $A_i \rightarrow A_{j2}$ are grouped as $A_i \rightarrow A_{j1}, A_{j1}$.

The followings are the details of Cheng's algorithms:

Step 1: Define the universe of discourse and establish fuzzy intervals.

The universe is defined as

$$U = [U_{\min} - D_1, U_{\max} + D_2] \tag{1}$$

where $U_{\min}$ and $U_{\max}$ represent the minimum and maximum actual oil prices. Both D_1 and D_2 are positive numbers. D_1 and D_2 are any positive numbers chosen to divide the interval evenly.

$$\begin{aligned} U &= [(U_{\min} - D_1), (U_{\max} + D_2)] \\ &= [(91.64 - 1.64), (358.59 + 1.41)] \\ &= [90, 360] \end{aligned}$$

The number of linguistic intervals can be calculated by using this Sturges formula:

$$\begin{aligned} k &= 1 + 3.322 \log n \\ &= 1 + 3.322 \log 121 \approx 8 \end{aligned} \tag{2}$$

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where k is the number of interval and n is the number of historical data of crude oil price.

The calculated number of the intervals is 8 and the intervals are denoted as $A1$, $A2$, $A3$, $A4$, $A5$, $A6$, $A7$ and $A8$ as in Table 2.

Table 2: Linguistic Description

Fuzzy Value	Linguistic Variable
$A1$	Lowest price
$A2$	Very low price
$A3$	Little low price
$A4$	Regular price
$A5$	Little high price
$A6$	Moderate high price
$A7$	Very high price
$A8$	Highest price

The length of linguistic intervals, l can be calculated using the formula

$$\begin{aligned} l &= \frac{(U_{\max} + D_2) - (U_{\min} - D_1)}{k} \\ &= \frac{(358.59 + 1.41) - (91.64 - 1.6)}{8} \\ &= 33.75 \end{aligned} \tag{3}$$

Step 2: Fuzzify the crude oil prices into linguistic values and define the fuzzy set based on the universe of discourse and intervals.

By referring to the value of l, the result for grouping up the intervals is shown in Table 3.

Table 3: Fuzzy Sets Intervals and Midpoints

Fuzzification	Interval			Midpoint, M_i
A_1	90	-	123.75	106.875
A_2	123.75	-	157.50	140.625

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A_3	157.50	-	191.25	174.375
A_4	191.25	-	225.00	208.125
A_5	225.00	-	258.75	241.875
A_6	258.75	-	292.50	275.625
A_7	292.50	-	326.25	309.375
A_8	326.25	-	360.00	343.125

Fuzzy sets, $A_1, A_2, \ldots, A_k$ on the universe of discourse is defined according to (4), where a_{ij} represents the membership of u_j in the fuzzy set A_i. In fuzzy sets theory also has $a_{ij} \in [0,1](0 \le i \le k, 0 \le j \le n)$. In this study, the fuzzy sets A_1 $until$ A_n are defined as represented in Equation (4).

$$A_1 = \frac{1}{u_1}, \frac{0.5}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}, \frac{0}{u_8}$$
$$A_2 = \frac{0.5}{u_1}, \frac{1}{u_2}, \frac{0.5}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}, \frac{0}{u_8}$$
$$A_3 = \frac{0}{u_1}, \frac{0.5}{u_2}, \frac{1}{u_3}, \frac{0.5}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}, \frac{0}{u_8}$$
$$\vdots$$
$$A_8 = \frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0.5}{u_7}, \frac{1}{u_8} \tag{4}$$

Then find each crude oil price's membership belongs to $A_i(1 \le i \le k)$. If the maximum membership of one crude oil price is in A_n, then we fuzzy this price as A_n.

Step 3: Create fuzzy logical relationship (FLR). If there are two consecutives $A_i(t-1)$ and $A_j(t)$, then they are written as fuzzy logic relationship, $A_i(t-1) \rightarrow A_j(t)$.

Table 4: Fuzzification and Fuzzy Logical Relationship (FLR)

Month/year	Price	Fuzzification	FLR		
Sep-11	311.68	A7	N/A	→	A7
Oct-11	313.55	A7	A7	→	A7
Nov-11	331.98	A8	A7	→	A8
Dec-11	329.66	A8	A8	→	A8

Jan-12	333.18	A8	A8	→	A8
Feb-12	340.88	A8	A8	→	A8
⋮	⋮	⋮	⋮	⋮	⋮
Apr-21	259.61	A6	A6	→	A6
May-21	273.99	A6	A6	→	A6
Jun-21	296.88	A7	A6	→	A7
Jul-21	307.68	A7	A7	→	A7
Aug-21	290.7	A6	A7	→	A6
Sep-21	303.58	A7	A6	→	A7
Aug-21	290.7	A6	A7	→	A6
Sep-21	303.58	A7	A6	→	A7

Step 4: Create Fuzzy Logical Relationship Group (FLRG) based on the FLR's Left-Hand Side(LHS).

For example, if there are 4 FLRs with the same LHS, let say $A_1 \to A_2, A_1 \to A_2, A_1 \to A_3$ *and* $A_1 \to A_4$ we can group them as FLRG $A_1 \to A_1, A_2, A_3, A_4$.
To easily view the relationship of each LHS to RHS, the frequency of FLGS in Matrix form is created as in in Table 5.

Table 5: Fuzzy Logical Relationship (FLR) Frequency Matrix

	A1	A2	A3	A4	A5	A6	A7	A8	Total
A1	0	1	0	0	0	0	0	0	1
A2	1	3	2	0	0	0	0	0	6
A3	0	1	8	5	0	0	0	0	14
A4	0	1	4	9	4	0	0	0	18
A5	0	0	0	4	15	5	0	0	24
A6	0	0	0	0	5	6	5	0	16
A7	0	0	0	0	0	5	10	4	19
A8	0	0	0	0	0	0	4	18	22

Step 5: Find the normalized weighting matrix by

$$W(t)^T = \left[\frac{c_1}{\sum_{q=1}^{p} c_q}, \frac{c_2}{\sum_{q=1}^{p} c_q}, \ldots, \frac{c_q}{\sum_{q=1}^{p} c_q} \right] \tag{5}$$

where $c_1, c_2, c_3, \ldots c_q$ are the fuzzy relationship's occurrences.

Using the Equation (5), the normalized weighting matrix in Table 6 is obtained.

Table 6: Weighting Matrix

	A1	A2	A3	A4	A5	A6	A7	A8	Total
A1	0	1/1	0	0	0	0	0	0	1
A2	1/6	3/6	2/6	0	0	0	0	0	6
A3	0	1/14	8/14	5/14	0	0	0	0	14
A4	0	1/18	4/18	9/18	4/18	0	0	0	18
A5	0	0	0	4/24	15/24	5/24	0	0	24
A6	0	0	0	0	5/16	6/16	5/16	0	16
A7	0	0	0	0	0	5/19	10/19	4/19	19
A8	0	0	0	0	0	0	4/22	18/22	22

Step 6: Calculate the forecast price of crude oil by using the formula

$$F(t+1) = B_{df}(t) \times W^T(t) \tag{6}$$

where

$B_{df}(t) = \left[m_{11}, m_{12}, \ldots, m_{1p} \right]$ is the midpoint of each interval A_i (Refer to Table 1) and it is called as the defuzzified matrix .

For example

$$F(t+1) = B_{df}(t) \times W^T(t)$$
$$= [M_6, M_7, M_8] \times \left[\frac{5}{19}, \frac{10}{19}, \frac{4}{19} \right]$$
$$= [275.625, 309.375, 343.125] \times \left[\frac{5}{19}, \frac{10}{19}, \frac{4}{19} \right] = 307.5987$$

The calculated forecasted values of the crude oil price are shown in Table 7.

Table 7: The Defuzzified Matrix for Each Interval

Variables	$B_{df}(t)$	$W^T(t)$	$Bdf \times W^T(t)$

A1	0	0	0
	106.875	0	0
	140.625	1	140.625
			140.625
A2	106.875	0.166667	17.8125
	140.625	0.5	70.3125
	174.375	0.333333	58.125
			146.25
⋮	⋮	⋮	⋮
A7	275.625	0.263158	72.53289
	309.375	0.526316	162.8289
	343.125	0.210526	72.23684
			307.5987
A8	309.375	0.181818	56.25
	343.125	0.818182	280.7386
	0	0	0
			336.9886

Step 7: Use an adaptive forecasting model to control our forecast outcome because of the crude oil market's clustering phenomenon. One period error is used to update the forecast. Otherwise, a cumulative variance will produce a poor forecast result. If the current fuzzy price is *P(t),* the following period's price is calculated as

$$F\left(t+1\right)=P(t)+\varepsilon_{t-1} \tag{8}$$

where ε_{t-1} denotes forecasting errors of period $t-1$.

The forecast price of crude oil after defuzzification and forecast error are listed in Table 8.

Table 8: The Forecast Price of Crude Oil and Forecast Error

Month	Original Price RM	Defuzzified Forecast Price Per Barrel RM	Forecast error
Sep-11	311.68	0	0
Oct-11	313.55	307.5986842	-5.951315789
Nov-11	331.98	336.9886364	5.008636364
Dec-11	329.66	336.9886364	7.328636364
Jan-12	333.18	336.9886364	3.808636364

Feb-12	340.88	336.9886364	-3.891363636
⋮	⋮	⋮	⋮
Apr-21	259.61	275.625	16.015
May-21	273.99	275.625	1.635
Jun-21	296.88	307.5986842	10.71868421
Jul-21	307.68	307.5986842	-0.081315789
Aug-21	290.7	275.625	-15.075
Sep-21	303.58	307.5986842	4.018684211

This study also uses several different number of intervals with different class widths since the midpoint gives the influence on the defuzzified forecast result.

Model Evaluation Method

To determine the accuracy of the crude oil price prediction, the evaluation of the result obtained from the FTS Cheng method is analyzed by using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

$$RMSE = \frac{1}{n}\sqrt{\sum_{t=1}^{n}\left(P(t) - F(t)\right)^2} \tag{9}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P(t) - F(t)}{P(t)}\right| * 100 \tag{10}$$

where

$P(t)$ and $F(t)$ are the actual and forecasting price of crude oil, respectively and

n is the number of observations.

RMSE is a good measure of how accurately the model predicts the response, and it is the most important criterion to fit the original data for prediction purposes. Lower values of RMSE indicates a better fit. For MAPE, the assessment results are indicated as excellent significance if the result is less than 10 percent, good significance if the result is 10 percent to 20 percent, moderate significance if the result is 20 percent to 50 percent and low significance if the result is greater than 50 percent. In conclusion, the smaller values in MAPE indicates the more accurate the prediction is.

FINDINGS AND DISCUSSIONS

Figure 1 shows the actual historical price of crude oil in Malaysia. There is no such regular fluctuation pattern. For the period of 10 years, the highest price of crude oil per barrel was RM358.59 in March 2012 while the lowest price was RM91.64 in April 2020 due to Covid-19 pandemic. Luckily, the price starts to increase beginning May 2020 onwards though the small fluctuation is still there.

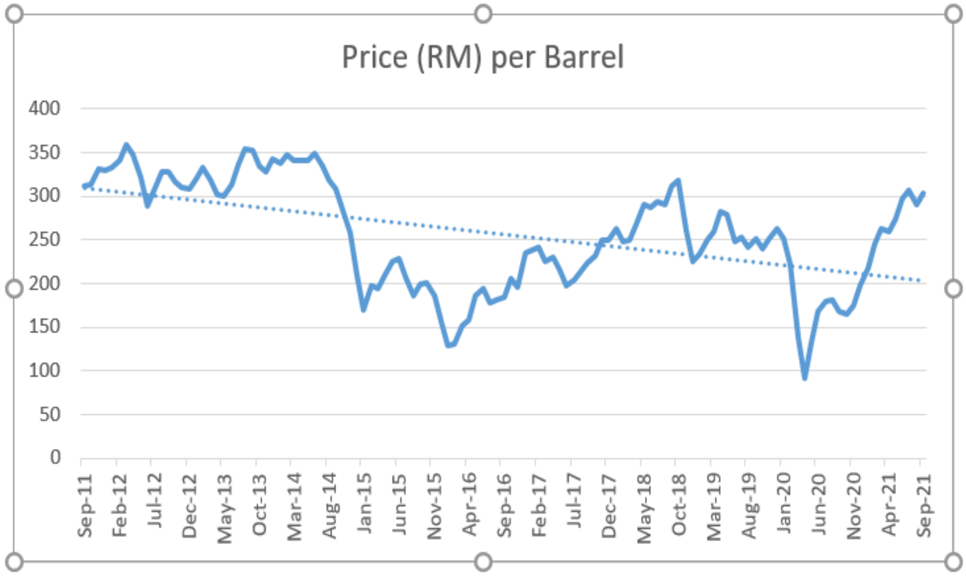

Figure 1: Price of Crude Oil in Malaysia

Several intervals are being tested in the model but majority show a very high MAPE and RMSE. The ability to predict are categorized as very poor. Only the FTS Cheng model with 7, 8 and 10 intervals of crude oil price shows more accurate output as shown in Table 9 and Figure 2.

Table 9: Forecast Result for 7, 8 and 10 Intervals

Month/year	Price	Forecast value 7 intervals	Forecast value 8 intervals	Forecast value 10 intervals
Sep-11	311.68	0	0	0
Oct-11	313.55	301.673956	305.7286842	301.655
Nov-11	331.98	285.113956	318.5586364	285.095
Dec-11	329.66	305.863956	339.3086364	305.845
Jan-12	333.18	300.023956	333.4686364	336.6270588
Feb-12	340.88	295.843956	329.2886364	332.4470588
⋮	⋮	⋮	⋮	⋮
Apr-21	259.61	244.1002747	278.325	266.7789474
May-21	273.99	286.0714286	261.245	249.6989474
Jun-21	296.88	286.0714286	284.7086842	274.5190909

Jul-21	307.68	303.543956	296.7986842	292.725
Aug-21	290.7	286.0714286	292.605	314.3890909
Sep-21	303.58	303.543956	294.7186842	284.5290909

Figure 2 shows the comparison of monthly forecast results crude oil price in Malaysia using 7, 8 and 10 intervals. There is slightly small difference between the actual price and forecast results using 8 intervals compared to forecast results using 7 and 10 intervals. Moreover, the forecast result using 8 intervals had accurate line with actual crude oil price intervals compare to forecast result using 7 and 10 intervals.

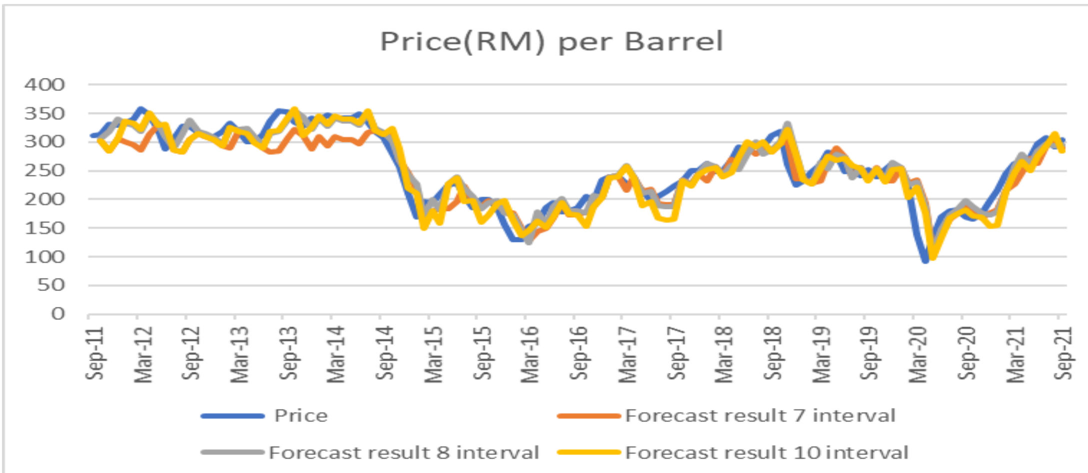

Figure 2: Forecast Results of Crude Oil Price in Malaysia Using 7,8 And 10 Intervals

Table 10 shows the value of RMSE and MAPE for 7, 8 and 10 intervals. The forecast 8 intervals have the smallest value of RMSE and MAPE with 23.44669 and 8.09% respectively. However, the forecast 7 intervals have the highest value of RMSE and MAPE with 29.1195617 and 9.90% respectively. To conclude, the forecast using 8 intervals in FTS Cheng is the best fit model because its RMSE is the smallest and its percentage error is also the smallest.

Table 10: RMSE and MAPE for 7, 8 and 10 intervals

Fuzzy Time Series	RMSE	MAPE
7 intervals	29.1195617	9.90%
8 intervals	23.44669	8.09%
10 intervals	26.41379	9.16%

CONCLUSION AND RECOMMENDATIONS

Cheng FTS model has been proposed and implemented to predict the price of crude oil in Malaysia. The actual data are partitioned into several number of intervals and class widths are being tested in the same model. The finding shows that only 7, 8 and 10 intervals are fit the original data and the model shows good performance since their MAPE < 10%. Among these three, Cheng FTS with 8 intervals is the best performance for crude oil price prediction.

The finding of this study shows that the number of intervals used would give great influence on the prediction and this may cause higher percentage error in forecasting. More variations in linguistic values affects the forecast output and need to further studied. It is advisable to do the right partitioning of the universe in order to improve the forecasting result. On some cases, better accuracy can be achieved with a shorter interval length (Huarng, 2001).

This preliminary study is only focusing on Cheng FTS method where there is no comparison made with other forecasting models. To find a better prediction model, there is a need to use and compare with other models of forecasting techniques not only other fuzzy time series models but also to use econometric models, artificial intelligence models and statistical models as well.

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CONFLICT OF INTEREST DISCLOSURE

All authors declare that they have no conflicts of interest to disclose

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