International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 07 Issue 11 November 2024
DOI: 10.47191/ijcsrr/V7-i11-04, Impact Factor: 7.943
IJCSRR @ 2024
www.ijcsrr.org

Crude Oil Price Forecasting Using Hybrid Heuristic Model and Fuzzy C-Means on Type 2 Fuzzy Time Series

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ABSTRACT: Forecasting world crude oil prices needs to be done because it has an essential role in Indonesia's economy, so an accurate and efficient forecasting approach is needed. This research combines heuristic and Fuzzy C-Means (FCM) models on Type 2 Fuzzy Time Series (T2FTS) to forecast crude oil prices. T2FTS, an extension of Fuzzy Time Series (FTS) by adding observations, is used to enrich the fuzzy relationship of the Type 1 model and can improve forecasting performance. FCM is used to determine unequal interval lengths and heuristic models to optimize fuzzy relations by identifying crude oil price movements using up and down trends. The data used in this study is the price of Brent crude oil as one of the benchmarks for world crude oil prices from 1 January 2023 - 31 May 2024. Mean Absolute Percentage Error (MAPE) measures accuracy in assessing forecasting results. The results showed that the combination of heuristic and FCM models in T2FTS gave accurate results, as evidenced by the MAPE value obtained, which was 1.50%, so it fell into the excellent category.

KEYWORDS: Type 2 Fuzzy Time Series, Fuzzy C-Means, heuristic model, forecast, crude oil

INTRODUCTION

One of the essential energy sources for the global economy is crude oil. Many countries rely heavily on the import of crude oil for power generation, transportation, heating, and others [1]. Therefore, crude oil as an energy source has become one of the main components of daily life and will continue to be an alternative source for the world. The price of crude oil is also essential as its rise and fall have high consequences on the global economy. Forecasting the price of crude oil is complicated because many things affect it. Some main factors are changes in supply and demand, world economic conditions, political tensions between countries, and prevailing rules and policies [2]. Forecasting world crude oil prices needs to be done because it has an essential role in the economy of Indonesia, such as having an impact on domestic inflation, the amount of money circulating in Indonesia, the Indonesia Stock Exchange (IDX), and the actual rupiah exchange rate[3]. There are two benchmark crude oil prices, namely the price of West Texas Intermediate (WTI) and Brent crude oil.

Fuzzy Time Series (FTS) has several models that have been developed, such as the Song, Chen, Cheng, and Markov-Chain models. Based on research [4] compared the four models, showing that the Chen model provides the best forecasting results. Chen's model improves the limitations contained in the Song and Chrissom model [5], [6] in determining the interval length of each fuzzy relation matrix to be larger, so [7] uses more straightforward arithmetic calculations than the max-min operation in Song and Chrissom. In addition to developments in the model, many methods have been combined with FTS. FTS combination with Particle Swarm Optimization (PSO) and Fuzzy C-Means (FCM) [8], FCM and neural network [9], heuristic model [10], firefly clustering [11], and others.

In general, determining forecasting performance requires four factors [12], such as (1) determining the universe of discourse especially in the number of intervals and interval length, (2) rules in fuzzification, (3) setting rules in forming Fuzzy Logic Rule (FLR), (4) defuzzification. The effectiveness of FTS lies in determining its internal length [13]. [14] applied FCM to solve the interval division problem so that the distribution of historical data can be considered and intervals of unequal size can be derived. [8] combined FCM with FCM to obtain optimal interval division. [13] used FCM to determine the length of unequal intervals.

This heuristic model helps understand oil price movements by observing patterns. It captures the trend of the time series more accurately and thus improves forecasting results. The study of [10], assumes that the heuristic model shows a decrease or increase in the next period. implemented FTS with a heuristic model and significantly improved results compared to other FTS.

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www.ijcsrr.org

Type 2 Fuzzy Time Series (T2FTS) is a development of Fuzzy Time Series, where additional observations are made to improve forecasting performance and extend the fuzzy relationships acquired from Type 1 models [15]. [16] applied T2FTS to forecast the price of the Indonesia Composite Index (IDX), which showed that the proposed method gave good results.

Therefore, this study aims to combine heuristic and Fuzzy C-Means models on T2FTS to forecast crude oil prices. FCM is used to determine intervals that are not equal in length, and the heuristic model optimizes fuzzy relations by understanding the movement of oil prices using up-and-down trends.

METHOD

A. Type 2 Fuzzy Time Series (T2FTS)

Type 2 Fuzzy Time Series (T2FTS) model is an improved version of the Type 1 model. This Type 2 model uses the fuzzy relationships created by the Type 1 model based on the Type 1 observations. It uses operators to add or subtract fuzzy relationships from Type 1 and Type 2 observations and then forecasts using those relationships [15]. Operasi yang digunakan adalah union dan intersection, dimana union is used for combining fuzzy relationships and intersection is intended for filtering them out.

Definition 1 [15]

The union ($\vee$) and intersection ($\wedge$) operators are defined to determine the relationships between two Fuzzy Logical Relationship Groups (FLRGs):

$$\vee(LHS_d, LHS_e) = RHS_d \cup RHS_e \quad (1)$$

$$\wedge(LHS_d, LHS_e) = RHS_d \cap RHS_e \quad (2)$$

$\vee$ represents the union operator and $\wedge$ denotes the intersection operator in set theory. RHS_d and LHS_d are RHS and LHS indicate Right Hand Side (RHS) and Left Hand Side (LHS) of the FLRG ,d, respectively.

Since multiple Fuzzy Logical Relationship Groups (FLRGs) may arise from Type 2 observations, the operator $\vee$ and $\wedge$ extended to accommodate several FLRGs, defined as $\vee_m$ and $\wedge_m$

Definition 2 [15]

Union ($\vee$) and intersection ($\wedge$) operators for some $\vee_m$ and $\wedge_m$ are defined as follows:

$$\vee_m(LHS_c, LHS_d, LHS_e, \dots) = \vee \dots (\vee(\vee(LHS_c, LHS_d), LHS_e), \dots), \quad (3)$$

$$\wedge_m(LHS_c, LHS_d, LHS_e, \dots) = \wedge \dots (\wedge(\wedge(LHS_c, LHS_d), LHS_e), \dots) \quad (4)$$

where $LHS_c, LHS_d, LHS_e, \dots$ and $RHS_c, RHS_d, RHS_e, \dots$ represent the LHS and RHS of FLRG $c, d, e, \dots$

Definition 3 [15]

If $\vee_m(LHS_c, LHS_d, LHS_e, \dots) = \emptyset$, given $\vee_m(LHS_c, LHS_d, LHS_e, \dots) = LHS_x$.

where LHS_x is obtained from the FLRG built from Type 1.

a) If $\wedge_m(LHS_c, LHS_d, LHS_e, \dots) = \emptyset$, given $\wedge_m(LHS_c, LHS_d, LHS_e, \dots) = LHS_x$.

where LHS_x is obtained from the FLRG built from Type 1.

B. Fuzzy C-Means

The fundamental concept of Fuzzy C-Means clustering by Bezdek [17] can be summarized as follows: Given a raw input vector data set $X = \{x_1, x_2, x_3, \dots, x_n\}$, FCM uses fuzzy partitioning, which allows data to fit into several clusters with different degrees of membership, ranging from 0 to 1. The objective of FCM is to minimize the following function [9]:

$$J_m(X, V, U) = \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m d^2(x_k, v_i) \quad (5)$$

where,

c = number of clusters; $2 \leq c \leq n$,

m = fuzziness parameter; $1 \leq m \leq \infty$,

U = fuzzy c-partition of X

$d(x_k, v_i)$ = distance between object (x_k) and cluster center r (v_i)

$v = (v_1, v_2, \dots, v_c)$ = center vector

$v_i = (v_{i1}, v_{i2}, \dots, v_{in})$ =cluster center of i

u_{ik} = membership value of the kth data to cluster i.

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C. Heuristic Model

The Heuristic Model is applied in FLRG to identify trends, which is divided into two categories: increase (↑) and decrease (↓). Heuristic increase (↑) indicates that the stock price data for the following period has risen, while the heuristic decrease (↓) signals that the stock price for the next period has dropped. The heuristic function is represented as $h(x; A_q, A_r, \dots)$, where x acts as an indicator for forecasting stock prices. Members of the FLRG are classified under the increase heuristic when $A_j \geq A_i$ (the fuzzy value in period j is greater than or equal to that of the previous period). otherwise, it becomes part of the decrease heuristic $A_j \leq A_i$ [10].

D. Data Source

This study uses data on Brent crude oil prices, which is known as one of the indicators of global oil prices. The data is obtained from the *investing.com* Website and covers the daily price of Brent crude oil in USD from 1 January 2023 to 31 May 2024. Furthermore, the data is separated into two sets for training and testing.

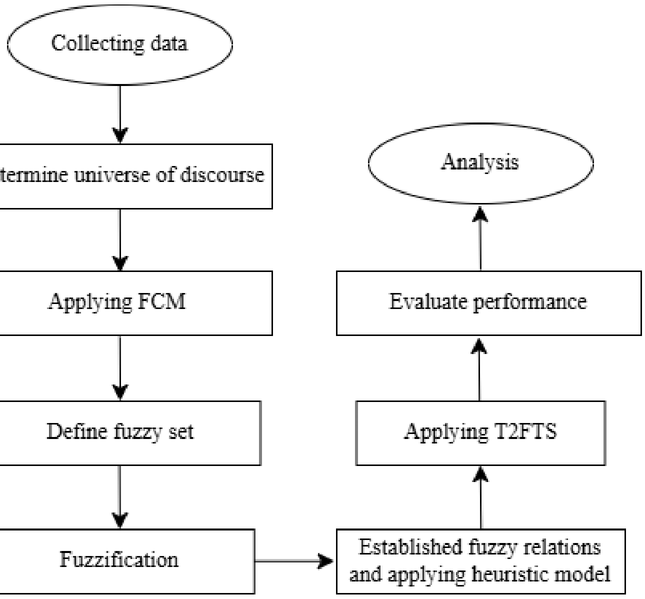

Figure 1 Flowchart hybrid heuristic model and Fuzzy C-Means on Type 2 Fuzzy Time Series (T2FTS)

Figure 1, a flow chart of the combination, shows the steps of the combination of heuristic model and Fuzzy C-Means on Type 2 Fuzzy Time Series (T2FTS) for Brent crude oil price forecasting.

RESULT AND DISCUSSION

A. Hybrid Heuristic Model and Fuzzy C-Means (FCM) on Type 2 Fuzzy Time Series (T2FTS)

Collecting data: This study uses daily data from the world crude oil price of Brent. Daily price data from 1 January 2023 to 31 May 2024 are obtained from the investing.com Website. Training and testing data is formed from the division of all of them. The training data includes 257 data from 1 January - 29 December 2023, and testing data with 109 data from 2 January - 31 May 2024.

Determine Universe of Discourse (U): The Universe of Discourse step is important in the fuzzy model-building process. The universe of speech is a range of values that includes all historical data to be processed. The training data is shown in the Table 1. In calculating the Universe of Discourse, it is necessary to find the minimum, maximum, D_1, and D_2. Thus, $D_{max} = 96.55$, $D_{min} = 71.84$, $D_1 = 16.74$, and $D_2 = 16.32$ are obtained.

$U = [D_{min} - D_1, D_{max} + D_2] = [55.100 , 112.87]$. Then, the universe of speech obtained is $[55.100 , 112.87]$.

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Table 1. Training Data (Close Data)

No	*Date*	*Close Data*
1	03/01/2023	82.10
2	04/01/2023	77.84
3	05/01/2023	78.69
…	…	…
255	27/12/2023	79.65
256	28/12/2023	78.39
257	29/12/2023	77.04

Applying Fuzzy C-Means (FCM): In this step, several steps are performed based on [17]:

1) Determine parameters
   Number of cluster (c) using 10, $m = 2, \in= 0{,}01$, and max iterations = 100.
2) Initialization of membership matrix
   At this initialization step, determine a random value as a membership value with the value being at 0 and 1 with a total of each data is 1. The initialization matrix at iteration 1 is as follows

$$U(0) = \begin{bmatrix} 0.049994 & \dots & 0.031808 \\ 0.087673 & \dots & 0.117405 \\ \vdots & \ddots & \vdots \\ 0.0856 & \dots & 0.119773 \\ 0.089813 & \dots & 0.114793 \end{bmatrix}$$

3) Determining thcluster center
   In determining the cluster center using equation (6), the results of cluster center iteration 1 are shown in Table 2.

$$v_i = \frac{\sum_{k=1}^{N} (u_{ik})^m x_k}{\sum_{k=1}^{N} (u_{ik})^m} \tag{6}$$

Table 2. Cluster Center Iteration 1

Cluster	*Value*
C_1	81.3307
C_2	81.75742
…	…
C_9	82.57634
C_{10}	82.66546

Then, the calculation is done again by calculating the membership matrix and calculating the cluster center until $\{|u_{ij}(t+1) - u_{ij}| < \epsilon\}$ is obtained using Python programming, which is instrumental in this process. Iteration stops at the 55th

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iteration with a value of $\epsilon = 0.008810$ where the value is already less than the predetermined ϵ, which is $\in= 0{,}01$. At the 55th iteration, the cluster center is obtained, which will be used to determine the interval at the next stage. The 55th iteration cluster center is shown in Table 3.

Table 3. Cluster Center 55

Cluster	*Value*
C_1	73.72168
C_2	76.13523
…	…
C_9	92.19355
C_{10}	94.4102

Next, interval formation is carried out, where the interval is formed from the cluster center determined using FCM. Intervals are formed using the middle value of each cluster center, and the results of the middle value are used for the boundaries of each interval. So that the intervals and middle values are shown in Table 4.

Table 4. Interval and Middle Value

u	*Interval*	*Middle Value Interval*
u_1	[55.100, 74.9285]	65.0142275
u_2	[74.9285, 77.09984]	76.014145
u_3	[77.09984, 79.007085]	78.05346
u_4	[79.007085, 81.282435]	80.14476
u_5	[81.282435, 83.691645]	82.48704
u_6	[83.691645, 85.68366]	84.6876525
u_7	[85.68366, 88.359355]	87.0215075
u_8	[88.359355, 91.156545]	89.75795
u_9	[91.15655, 93.30188]	92.22921
u_{10}	[93.30188, 112.87]	103.085938

Define fuzzy set: Furthermore, the degree of membership of the fuzzy set

$$A_1 = \frac{1}{u_1} + \frac{0{,}5}{u_2} + \cdots + \frac{0}{u_8} + \frac{0}{u_9}$$
$$A_2 = \frac{0{,}5}{u_1} + \frac{1}{u_2} + \cdots + \frac{0}{u_8} + \frac{0}{u_9}$$
$$\dots$$

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$$A_8 = \frac{0}{u_1} + \frac{0}{u_2} + \cdots + \frac{1}{u_8} + \frac{0,5}{u_9}$$
$$A_9 = \frac{0}{u_1} + \frac{0}{u_2} + \cdots + \frac{0,5}{u_8} + \frac{1}{u_9}$$

Fuzzification: Converting data into fuzzy sets is fuzzification. The fuzzification results are presented in Table 5.

Table 5. Fuzzification Data Training

No	*Date*	*Close Data*	*Fuzzification*
1	03/01/2023	82.10	A_5
2	30/06/2023	77.84	A_3
3	03/07/2023	78.69	A_3
…	…	…	…
256	28/12/2023	78.39	A_3
257	29/12/2023	77.04	A_2

Established fuzzy relations and applying heuristic model: Fuzzy Logical Relationship (FLR) describes the relationship between fuzzy sets. Fuzzy Logical Relationship Group (FLRG) is a collection of several FLRs. The FLR and FLRG results are shown in Table 6 and 7.

Table 6. Fuzzy Logical Relationship (FLR)

No	*Date*	*Close Data*	*Fuzzification*	*FLR*
1	03/01/2023	82.10	A_5	−
2	30/06/2023	77.84	A_3	$A_5 \to A_3$
3	03/07/2023	78.69	A_3	$A_3 \to A_3$
…	…	…	…	…
256	28/12/2023	78.39	A_3	$A_4 \to A_3$
257	29/12/2023	77.04	A_2	$A_3 \to A_2$

Table 7. Fuzzy Logical Relationship Group (FLRG)

FLRG		
A_1	$\to$	A_1, A_2
A_2	$\to$	A_1, A_2, A_3
A_3	$\to$	A_1, A_2, A_3, A_4
A_4	$\to$	A_2, A_3, A_4, A_5, A_6

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A_5	$\rightarrow$	A_3, A_4, A_5
A_6	$\rightarrow$	A_5, A_6, A_7
A_7	$\rightarrow$	A_5, A_6, A_7, A_8
A_8	$\rightarrow$	A_7, A_8, A_9
A_9	$\rightarrow$	A_8, A_9, A_{10}
A_{10}	$\rightarrow$	A_8, A_9, A_{10}

In FLRG, the Heuristic Model is used to determine the trend. *T*hen divided into two parts: increase (↑) and decrease (↓). Heuristic increase (↑) represents an increase in stock price data for the following period, and heuristic decrease (↓) represents a decrease in stock price data for the following period. The heuristic function is represented as $h(x; A_q, A_r, \ldots)$, where x acts as an indicator for forecasting stock prices. Members of the FLRG are classified under the increase heuristic when $A_j \geq A_i$ (the fuzzy value in period j is greater than or equal to that of the previous period). otherwise, it becomes part of the decrease heuristic $A_j \leq A_i$ [10]. The results of the FLRG heuristic are shown in Table 8.

Table 8. FLRG Heuristic

FLRG			***Trend***	***FLRG Heuristic***
A_1	$\rightarrow$	A_1, A_2	↑	$A_1 \rightarrow A_1, A_2$
			↓	$A_1 \rightarrow A_1$
A_2	$\rightarrow$	A_1, A_2, A_3	↑	$A_2 \rightarrow A_2, A_3$
			↓	$A_2 \rightarrow A_1, A_2$
A_3	$\rightarrow$	A_1, A_2, A_3, A_4	↑	$A_3 \rightarrow A_3, A_4$
			↓	$A_3 \rightarrow A_1, A_2, A_3$
…	…	…	…	…
A_9	$\rightarrow$	A_8, A_9, A_{10}	↑	$A_9 \rightarrow A_9, A_{10}$
			↓	$A_9 \rightarrow A_8, A_9$
A_{10}	$\rightarrow$	A_8, A_9, A_{10}	↑	$A_{10} \rightarrow A_{10}$
			↓	$A_{10} \rightarrow A_8, A_9, A_{10}$

Applying Type 2 Fuzzy Time Series (T2FTS): Pick Type 2 observations

The data in Type 2 used crude oil prices from 2 January to 31 May 2024, called the testing data. Each observation is notated with close (P), high (Q), and low (R) prices.

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Table 9. Data Testing

t	*Date*	*Close Price (P)*	*High Price (Q)*	*Low Price (R)*
258	02/01/2024	75.89	79.06	75.60
259	03/01/2024	85.42	85.69	83.98
260	04/01/2024	85.34	85.55	84.6
…	…	…	…	…
363	29/05/2024	83.60	85.02	83.29
364	30/05/2024	81.86	83.77	81.80
365	31/05/2024	81.62	82.18	81.17

Categorizing obsevations into FLRG Heuristic

Applying to close (P), high (Q), and low (R) price

Applying the heuristic model for close price (P). Suppose on 2 January 2024: The data used is the data in the previous period (t-1), 29 December 2023 where the close price (P) is 77.04 (A_2). Therefore, the FLRG for A_2 is $A_2 \to A_1, A_2, A_3$. Assumed that the heuristic value shows an decrease in the expected closing price. Therefore, based on Table 8, $h(\downarrow; A_1, A_2, A_3) = A_1, A_2$. So, for 2 January 2024, the heuristic FLRG is $A_2 \to A_1, A_2$.

This is also done on all close (P), high (Q), and low (R) prices to determine the trend price for each period. The FLRG Heuristic categorization results on the close (P), high (Q), and low (R) prices testing data information are shown in Tables 10, 11, and 12.

Table 10. Fuzzification and FLRG Heuristic Close Price (P)

t	*Date*	*Close Price (P)*	*P Fuzzification*	*Trend*	*P FLRG Heuristic*
256	28/12/2023	78.39	A_3	-	-
257	29/12/2023	77.04	A_2	↓	$A_3 \to A_1, A_2, A_3$
258	02/01/2024	75.89	A_2	↓	$A_2 \to A_1, A_2$
259	03/01/2024	85.42	A_3	↑	$A_2 \to A_2, A_3$
260	04/01/2024	85.34	A_3	↓	$A_6 \to A_5, A_6$
…	…	…	…	…	…
363	29/05/2024	83.60	A_5	↓	$A_6 \to A_5, A_6$
364	30/05/2024	81.86	A_5	↓	$A_5 \to A_3, A_4, A_5$
365	31/05/2024	81.62	A_5	↓	$A_5 \to A_3, A_4, A_5$

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Table 11. Fuzzification and FLRG Heuristic High Price (Q)

t	*Date*	*High Price (Q)*	*Q Fuzzification*	*Trend*	*Q FLRG Heuristic*
256	28/12/2023	79.95	A_4	-	-
257	29/12/2023	77.98	A_3	↓	$A_4 \rightarrow A_2, A_3, A_4$
258	02/01/2024	79.06	A_4	↑	$A_3 \rightarrow A_3, A_4$
259	03/01/2024	85.69	A_3	↓	$A_4 \rightarrow A_2, A_3, A_4$
260	04/01/2024	85.55	A_4	↑	$A_3 \rightarrow A_3, A_4$
…	…	…	…	…	…
363	29/05/2024	85.02	A_6	↑	$A_6 \rightarrow A_6, A_7$
364	30/05/2024	83.77	A_6	↓	$A_6 \rightarrow A_6, A_5$
365	31/05/2024	82.18	A_5	↓	$A_6 \rightarrow A_6, A_5$

Table 12. Fuzzification and FLRG Heuristic Low Price (R)

t	*Date*	*Low Price (R)*	*R Fuzzification*	*Trend*	*R FLRG Heuristic*
256	28/12/2023	78.25	A_3	-	-
257	29/12/2023	76.73	A_2	↓	$A_3 \rightarrow A_1, A_2, A_3$
258	02/01/2024	75.60	A_2	↓	$A_2 \rightarrow A_1, A_2$
259	03/01/2024	83.98	A_1	↓	$A_2 \rightarrow A_1, A_2$
260	04/01/2024	84.6	A_2	↑	$A_1 \rightarrow A_1, A_2$
…	…	…	…	…	…
363	29/05/2024	83.29	A_5	↑	$A_5 \rightarrow A_6, A_5$
364	30/05/2024	81.80	A_5	↓	$A_5 \rightarrow A_3, A_4, A_5$
365	31/05/2024	81.17	A_4	↓	$A_5 \rightarrow A_3, A_4, A_5$

Applying Type 2 operators to all observations

Illustrate for example forecasting for 2 January 2024 ($t = 258$) using $\vee_m$ and $\wedge_m$ operators on the FLRG heuristics close (X), high (Y), and low (Z), then calculating the forecast using the result of fuzzification when 29 December 2023 ($t = 257$).

$P_{257}: A_3 \rightarrow A_1, A_2, A_3$

$Q_{257}: A_4 \rightarrow A_2, A_3, A_4$

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$R_{257}: A_3 \rightarrow A_1, A_2, A_3$
Forecasting for $t = 258$ with $\vee_m$
$\vee_m(LHS_c, LHS_d, LHS_e, \dots) = (RHS_c \cup RHS_d \cup RHS_e \cup \dots)$
$\vee_m(A_3, A_4, A_3) = \{A_1, A_2, A_3\} \cup \{A_2, A_3, A_4\} \cup \{A_1, A_2, A_3\}$
$\vee_m(A_3, A_4, A_3) = \{A_1, A_2, A_3, A_4\}$
Forecasting for $t = 258$ with $\wedge_m$
$\wedge_m(LHS_c, LHS_d, LHS_e, \dots) = (RHS_c \cap RHS_d \cap RHS_e \cap \dots)$
$\wedge_m(A_3, A_4, A_3) = \{A_1, A_2, A_3\} \cap \{A_2, A_3, A_4\} \cap \{A_1, A_2, A_3\}$
$\wedge_m(A_3, A_4, A_3) = \{A_2, A_3\}$

Table 13. Result Operators

t	*Date*	*Variable*	*FLRG Heuristic*	$\wedge_m$	$\vee_m$
258	02/01/2024	Close (P)	$A_3 \rightarrow A_1, A_2, A_3$	A_2, A_3	A_1, A_2, A_3, A_4
		High (Q)	$A_4 \rightarrow A_2, A_3, A_4$		
		Low (R)	$A_3 \rightarrow A_1, A_2, A_3$		
259	03/01/2024	Close (P)	$A_2 \rightarrow A_1, A_2$	A_2	A_1, A_2, A_3, A_4
		High (Q)	$A_3 \rightarrow A_3, A_4$		
		Low (R)	$A_2 \rightarrow A_1, A_2$		
…	…		…	…	…
365	31/05/2024	Close (P)	$A_5 \rightarrow A_3, A_4, A_5$	A_5	A_3, A_4, A_5, A_6
		High (Q)	$A_6 \rightarrow A_6, A_5$		
		Low (R)	$A_5 \rightarrow A_3, A_4, A_5$		

Defuzzification

Furthermore, the results of the application of the operators are defuzzified, as shown in the formula (Huarng & Yu, 2005),

$$defuzzification_k\ (t) = \frac{\sum_{z=1}^{j} m_{qz}}{j} \quad (7)$$

$defuzzification_k(t)$ is the defuzzification forecasting union and intersection Type 2 observations, m_{qz} is the midpoint and there are j total observations.

Suppose at $t = 258$. Then, the defuzzification result

$\text{Defuzzification}_{union\ (258)} = \frac{m_1+m_2+m_3+m_4}{4} = \frac{65.0142275+76.014145+78.05346+80.144769}{4} = 74.806648$

$\text{Defuzzification}_{intersection\ (258)} = \frac{m_2+m_3}{2} = \frac{76.014145+78.05346}{2} = 77.033803$

The defuzzification results are shown in Table 14.

Type 2 Forecasting

The intersection and union forecasting results are then averaged to produce the Type 2 forecasting outcomes. In Type 2 forecasting, the following equation is applied.

International Journal of Current Science Research and Review
ISSN: 2581-8341
Volume 07 Issue 11 November 2024
DOI: 10.47191/ijcsrr/V7-i11-04, Impact Factor: 7.943
IJCSRR @ 2024
www.ijcsrr.org

$$\hat{X}_t = \frac{\text{Defuzzification}_{union\,(t)} + \text{Defuzzification}_{intersection\,(t)}}{2} \quad (8)$$

where $\hat{X}_t$ is Type 2 forecasting.

Suppose that based on the calculation results at $t = 258$, result $\text{Defuzzification}_{union\,(258)}$ and $\text{Defuzzification}_{intersection\,(258)}$ are known, then Type 2 forecasting is performed

$$\hat{X}_{258} = \frac{\text{Defuzzification}_{union\,(258)} + \text{Defuzzification}_{intersection\,(258)}}{2} = \frac{77.033803 + 74.806648}{2} = 75.920225$$

So, the forecasting result on 15 March 2024 is 84.70985958. The forecasting results are shown in Table 14.

Table 14. Defuzzification and Type 2 Forecast

t	*Date*	*Variable*	$\text{Defuzzification}_{intersection}$	$\text{Defuzzification}_{union}$	$\hat{X}_t$
258	15/03/2024	Close (P) High (Q) Low (R)	77.033803	74.806648	75.920225
259	18/03/2024	Close (P) High (Q) Low (R)	76.014145	74.806648	75.410397
…	…	…	…	…	…
313	19/03/2024	Close (P) High (Q) Low (R)	82.487040	81.343228	81.915134

B. Method performance evaluation

After the forecasting results are obtained, it is necessary to test the accuracy of the proposed model. Accuracy testing uses MAPE which is formulated as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{X_t - \hat{X}_t}{X_t}\right| \times 100\% \quad (9)$$

MAPE (Mean Absolute Percentage Error) calculates accuracy, measuring how close the prediction results are to the actual data. The criteria for MAPE values are presented in Table 15 [18].

Table 15. MAPE Criterion

No	*Date*	*Criterion*
1	<10%	Very good
2	10% - 20%	Good
3	20% - 50%	Fair
4	>50%	Poor

The MAPE value obtained is 1.50%. Based on Table 15 where the MAPE value is <10%, the value is in the excellent category. The plot of forecasting comparison results with actual data is presented in Figure 2.

C. Analysis

This model combines heuristic and FCM approaches in FTS Type 2 to forecast crude oil prices. FCM is used to form intervals, while the heuristic approach is applied to improve the performance of FLRG by recognizing up and down trends. The forecasting results show a trend following the actual crude oil price pattern. Using historical data of the closing, high, and low prices, the model successfully forecasts the prices very well with the MAPE value is 1.50%, as shown by the MAPE value <10%.

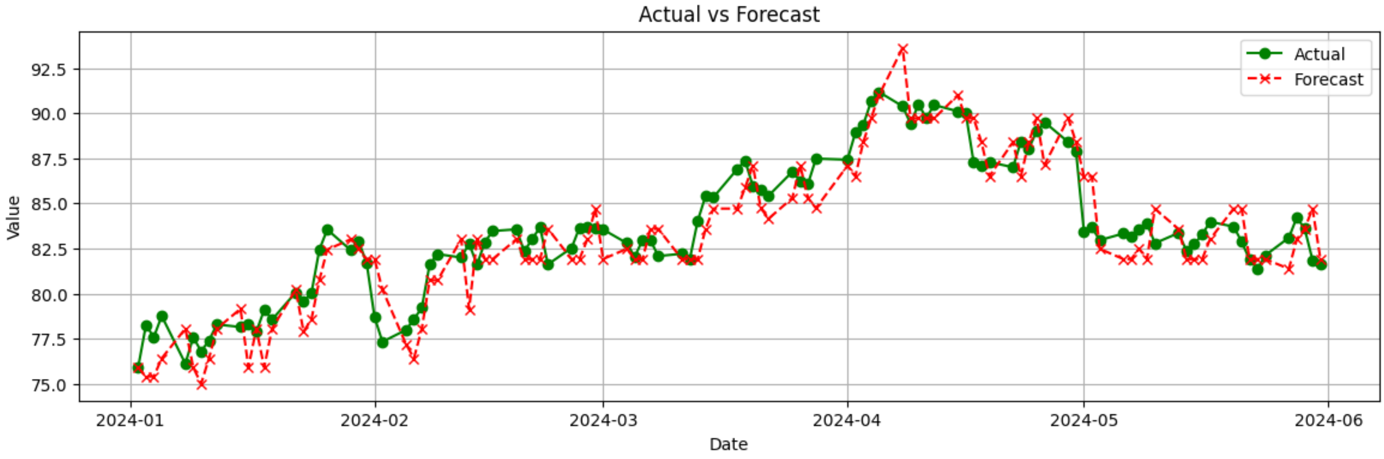

Figure 2. Actual Data and Forecast Data

Figure 2 shows that the actual and forecasting data have slight differences. The actual data is shown with a green line, and the forecasting data is shown with a red x-dashed line. Therefore, based on the MAPE results and plots obtained, the proposed model provides excellent results.

CONCLUSION

This study establishes a combination of heuristic models and Fuzzy C-Means (FCM) on Type 2 Fuzzy Time Series (T2FTS) for crude oil price forecasting. FCM is applied to determine intervals of unequal length so that it is possible to adapt to dynamic pattern changes. The heuristic model is able to improve the effectiveness of the FLRG in the context of T2FTS to predict stock prices and identify pattern trends from up-and-down data to understand price movements in depth. This combination provides accurate results, as evidenced by the MAPE value of 1.50%, indicating excellent accuracy because the MAPE value is less than 10%. So, it can be concluded that the proposed model provides excellent accuracy and is suitable for forecasting, especially in crude oil forecasting which can be utilized for other energy price calculations.

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