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Predicting Malaysian Crude Palm Oil Prices Using Intuitionistic Fuzzy Time Series Forecasting Model

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ABSTRACT

Crude palm oil (CPO) is one of the commodities in Malaysia that highly contributes to economic growth. Since CPO prices fluctuate over years, it is significant to accurately forecast CPO prices in the future to avoid losses. The objective of this paper is to propose an intuitionistic fuzzy time series forecasting model to forecast Malaysian CPO prices. The proposed model uses a defuzzification formula that fully utilizes the main properties of the intuitionistic fuzzy set (IFS), which include the membership and non-membership functions. The proposed formula has the advantage of handling uncertainty in the time series data. Based on the results, the proposed model has reduced the forecasting error compared to the existing IFS-based models. The mean square error, root mean square error, and mean absolute error were reduced from 1.57% to 24.93%, 0.79% to 11.77%, and 1.34% to 10.39%, respectively. It is recommended that the decision-makers from respective parties make the right decision based on the forecasted prices to maintain Malaysia as one of the largest CPO producers.

Keywords: *Crude palm oil prices; intuitionistic fuzzy set; fuzzy time series; forecasting*

1. INTRODUCTION

Palm oil is one of the commodities in Malaysia that highly contributes to economic growth. In fact, Malaysia is ranked as the second country that majorly produces crude palm oil (CPO) worldwide [1]. However, CPO prices have fluctuated over the years [2]. According to [3], there are no clear trends and cyclical patterns in the fluctuation of CPO prices in the past 30 years.

To maintain the country as one of the relevant contributors to the world's exports, it is very significant to accurately forecast CPO prices in the future so that the decision-makers from relevant fields can advise the ways so as to avoid any future losses. Thus, in dealing with uncertainty and vagueness, the fuzzy time series (FTS) forecasting model [4] has been identified as one of the best models for handling fluctuating data in an imprecise environment [5].

Song and Chissom [4] were the first to define the FTS, in which the time series data are described by linguistic values instead of crisp numbers. The classical forecasting methods cannot deal with data in the form of linguistic values. The first FTS forecasting model was implemented to forecast student enrollments at the University of Alabama [6-7]. Since then, extensive work has been delved to improve the FTS model [8-14].

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In 1986, Atanassov [15] extended Zadeh's fuzzy set into an intuitionistic fuzzy set (IFS). The IFS is characterized by membership and non-membership functions. The membership function defines how much a variable belongs to the fuzzy set, while the non-membership function indicates the degree of non-belongingness to the set. Among the applications of IFS are image processing, pattern recognition, and decision making [16]. Furthermore, the IFS has also been applied in the FTS and it has been evidenced that the IFS exhibits a better performance in forecasting compared to the classical fuzzy set [17].

To adopt the advantages of IFS in improving forecasting performance in the FTS forecasting procedure, this paper aims to propose an intuitionistic FTS forecasting model to forecast Malaysian CPO prices. This paper is organized as follows: Section 1 briefly introduces the study; Section 2 reviews some related preliminaries; Section 3 proposes the intuitionistic FTS forecasting model; Section 4 implements the model to forecast the Malaysian CPO prices; Section 5 discusses the results; Section 6 concludes the paper.

2. LITERATURE REVIEW

Fuzzy time series (FTS) was proposed by Song and Chissom [4], which made the forecasting data in the form of linguistic variables possible. The first FTS forecasting model was implemented in [6-7] to forecast student enrollments at the University of Alabama. In their model, the data were fuzzified using seven linguistic variables, namely "not many," "not too many," "many," "many many," "very many," "too many," and "too many many."

However, the max-min composition operation in [6] has led to a high level of computational complexity. Hence, Chen [8] simplified Song and Chissom's [6] model by using simple arithmetic operations considering the midpoints of intervals to calculate the forecasted output. Instead of using fuzzy sets [18], Liu [9] used trapezoidal fuzzy numbers to improve the forecasting procedure. Cheng *et al.* [10] combined the FTS with particle swarm optimization, the *K*-means clustering and similarity measures to improve the forecasting performance.

In improving forecasting performance, much work has also been carried out to investigate the effects of using different interval lengths on the forecasting results. Huarng [11] proposed the average-based partitioning method to divide the universe of discourse into several intervals. The results showed that the forecasting performance using the proposed interval partitioning method was greatly improved. The frequency density-based method was also proposed by Chen and Hsu [12]. In 2011, Tsaur and Kuo [13] proposed a redivide-randomly chosen length method to improve forecasting performance. These three methods were compared in [14] and the findings showed that the average-based length method outperforms the other methods.

Based on the concept of intuitionistic fuzzy set (IFS) [15], Joshi and Kumar [19] proposed an intuitionistic FTS forecasting model in which the hesitancy degree of IFS was utilized to define the intuitionistic fuzzy logical relationships (IFLR). In addition, Kumar and Gangwar [20] established induced fuzzy sets from the IFS to construct the IFLR, while Abhishekh *et al.* [21] constructed higher-order IFLR to perform the intuitionistic FTS forecasting. The score function-based IFLR was further used in [22] where only the maximum degree of score function is considered. Recently, an intuitionistic FTS forecasting model via equal distribution of hesitancy was also proposed in [23] to improve forecasting performance.

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Comparing the performance of the FTS forecasting model based on the fuzzy set and IFS, the model with IFS as its basis exhibits better forecasting performance compared to the classical fuzzy set [17]. Hence, it is crucial to further develop the intuitionistic FTS forecasting model and implement the model when forecasting time series data.

3. PRELIMINARIES

In this section, some definitions related to the intuitionistic fuzzy set and intuitionistic fuzzy time series are reviewed. Briefly, an intuitionistic fuzzy set (IFS) is a generalization of the classical fuzzy set, which is defined as follows:

Definition 1 [15] An IFS, I in the universe of discourse, ζ is of the form

$$I = \{\theta, \mu(\theta), \nu(\theta) \mid \theta \in \zeta\} \tag{1}$$

where $\mu(\theta)$ and $\nu(\theta)$ denote the degree of membership and non-membership, respectively. The hesitation index of the IFS is defined as follows:

$$\pi(\theta) = 1 - \mu(\theta) - \nu(\theta). \tag{2}$$

The intuitionistic FTS concept is defined in the following definition:

Definition 2 [24] Let $X(\tau)\left(\tau = ..., 0, 1, 2, ...\right)$ be ζ and $X(\tau) \subseteq \mathbb{R}$. If $I_j(\tau)\left(j = 1, 2, 3, ...\right)$ is IFS defined in $X(\tau)$, then the collection $\xi(\tau)$ of $I_j(\tau)$ is called intuitionistic FTS on $X(\tau)$. The relation $I_j(\tau - 1) \rightarrow I_k(\tau)$ indicates that $I_k(\tau)$ is caused by $I_j(\tau - 1)$.

In most intuitionistic FTS models, Atanassov's conversion of IFS is commonly used to convert fuzzy sets into IFS. Atanassov's conversion of IFS is given as follows:

Definition 3 [25] Let $A_F \in FS(\zeta)$ where $FS(\zeta)$ is the collection of all fuzzy sets in ζ. Let $\sigma : \zeta \rightarrow [0,1]$ and $\omega : \zeta \rightarrow [0,1]$, then $f : [0,1]^2 \times [0,1] \rightarrow L^*$ where $f\left(\theta, \sigma, \omega\right) = \left(f_\mu\left(\theta, \sigma, \omega\right), f_\nu\left(\theta, \sigma, \omega\right)\right)$ and

$$f_\mu\left(\theta, \sigma, \omega\right) = \theta\left(1 - \sigma\omega\right) \tag{3}$$

$$f_\nu\left(\theta, \sigma, \omega\right) = 1 - \sigma\omega - \theta\left(1 - \sigma\omega\right). \tag{4}$$

To compare between two intuitionistic fuzzy numbers (IFN), Xu and Yager [26] defined the following score function:

Definition 4 [26] Let $\alpha = \left(\mu_\alpha, \nu_\alpha\right)$ and $\beta = \left(\mu_\beta, \nu_\beta\right)$ denote two IFN, where μ_i and ν_i denote the membership and non-membership functions, respectively, for $i = \alpha, \beta$. Finally, the score function is defined by

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$$S(i) = \mu_i - \nu_i \tag{5}$$

where $S(i) \in [-1,1]$. If $S(\alpha) > S(\beta)$, then $\alpha > \beta$.

4. METHODOLOGY

In this section, the forecasting procedure using intuitionistic FTS is proposed. The proposed model consists of three phases. Phase 1 entails the fuzzification process from Step 1 until Step 3, while Phase 2 entails the establishment of IFS from Step 4 until Step 6. Finally, Phase 3 entails the defuzzification process, which covers the last two steps from Step 7 until Step 8.

Step 1: Define the universe of discourse, $\zeta = [D_{\min} - \varepsilon_1, D_{\max} + \varepsilon_2]$ where $D_{\min}$ and $D_{\max}$ are the smallest and largest historical data, respectively. ε_1 and ε_2 are two proper real numbers.

Step 2: Divide ζ into several intervals using the average-based length method [11].

Step 3: Fuzzify the historical data using trapezoidal fuzzy numbers.

Step 4: Convert the fuzzy sets into IFS using Atanassov's conversion method [25].

Step 5: Evaluate the score functions using equation (5) [26].

Step 6: Assign the IFS to each historical data based on the score function values. Next, the intuitionistic fuzzy logical relationships (IFLR) can be formed and grouped.

Step 7: Each IFS is defuzzified using the following formula:

$$\kappa = \frac{\sum |u_\theta - \nu_\theta| \theta}{\sum |u_\theta - \nu_\theta|} \tag{6}$$

where θ denotes the historical data that belong to the IFS as defined in equation (1) and κ is a defuzzified crisp value.

Step 8: Evaluate the forecasted data using the following rules:

1. Let $I_1 \to I_2$ be the relation between year *n* and year $n+1$. Then, the forecasted data of year $n+1$ is given by κ_2, which is the defuzzified value of I_2.

2. Let $I_1 \to I_2, I_3, ..., I_m$ be the relation between year *n* and year $n+1$. Then, the forecasted data of year $n+1$ is given by

$$\frac{\kappa_2 + \kappa_3 + ... + \kappa_m}{m-1}$$

where $\kappa_2, \kappa_3, ..., \kappa_m$ are the defuzzified values of $I_2, I_3, ..., I_m$, respectively.

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3. Let $I_1 \rightarrow \phi$ be the relation between year n and year $n+1$. Then, the forecasted data of year $n+1$ is given by κ_1, which is the defuzzified value of I_1.

5. FORECASTING MALAYSIAN CRUDE PALM OIL PRICES

The monthly average Malaysian CPO prices were extracted from the Malaysian Palm Oil Board website. The data from January 2017 until December 2021 are shown in Figure 1.

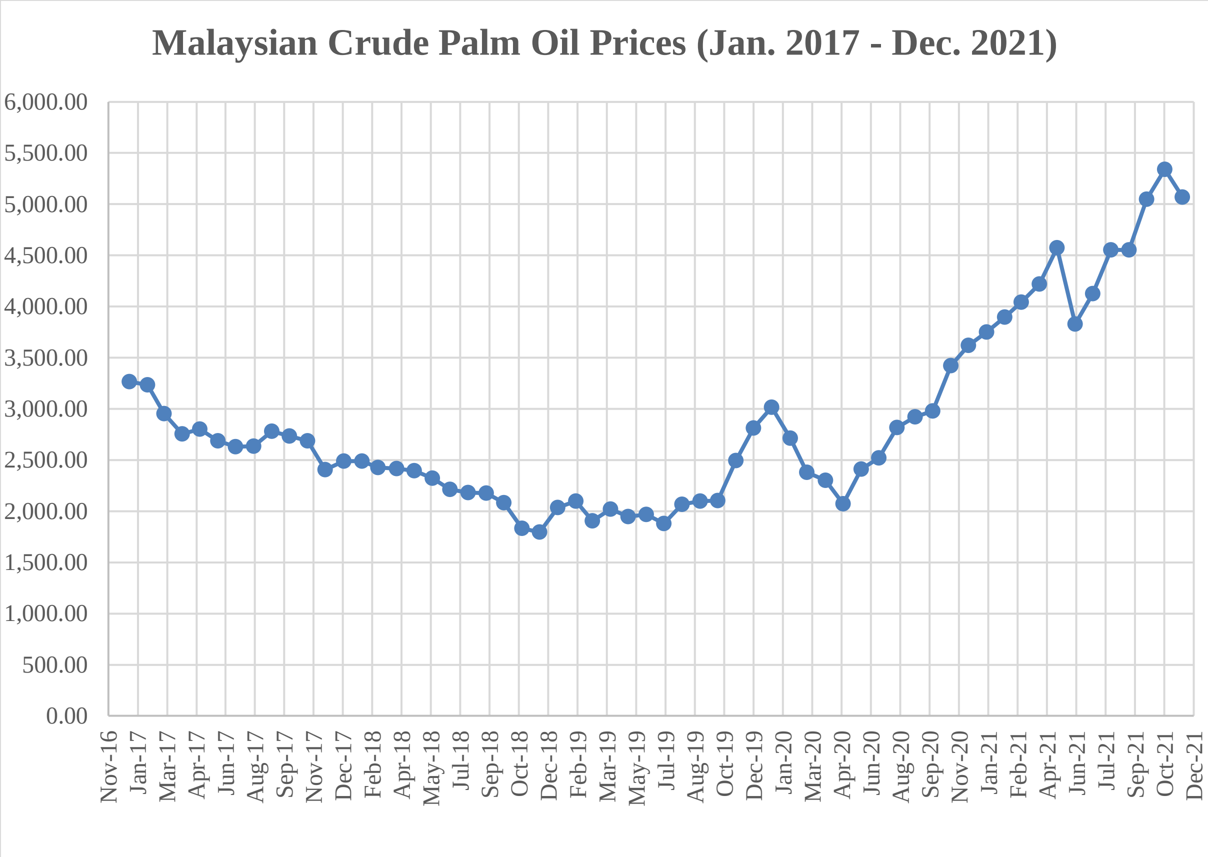

Figure 1: Malaysian Crude Palm Oil Prices (January 2017 – December 2021)

Using the proposed methodology, the forecasting of Malaysian CPO prices is based on the following steps:

Step 1: The historical data were analyzed and the minimum and maximum data were obtained as RM1,794.50 and RM5,341.00, respectively. Hence, $\varepsilon_1 = 44.50$ and $\varepsilon_2 = 9.00$ were chosen such that $\zeta = [1750, 5350]$.

Step 2: Using the average-based length method [11], $\zeta = [1750, 5350]$ was divided into 36 intervals in that $\zeta_1 = [1750, 1850]$, $\zeta_2 = [1850, 1950]$, $\zeta_3 = [1950, 2050]$,..., $\zeta_{36} = [5250, 5350]$. Then, as shown in Table 1, the trapezoidal fuzzy number for each interval is defined.

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Table 1: Intervals with Corresponding Trapezoidal Fuzzy Numbers

Interval	Trapezoidal Fuzzy Number	Interval	Trapezoidal Fuzzy Number
[1750,1850]	(1650,1750,1850,1950)	[3550,3650]	(3450,3550,3650,3750)
[1850,1950]	(1750,1850,1950,2050)	[3650,3750]	(3550,3650,3750,3850)
[1950,2050]	(1850,1950,2050,2150)	[3750,3850]	(3650,3750,3850,3950)
[2050,2150]	(1950,2050,2150,2250)	[3850,3950]	(3750,3850,3950,4050)
[2150,2250]	(2050,2150,2250,2350)	[3950,4050]	(3850,3950,4050,4150)
[2250,2350]	(2150,2250,2350,2450)	[4050,4150]	(3950,4050,4150,4250)
[2350,2450]	(2250,2350,2450,2550)	[4150,4250]	(4050,4150,4250,4350)
[2450,2550]	(2350,2450,2550,2650)	[4250,4350]	(4150,4250,4350,4450)
[2550,2650]	(2450,2550,2650,2750)	[4350,4450]	(4250,4350,4450,4550)
[2650,2750]	(2550,2650,2750,2850)	[4450,4550]	(4350,4450,4550,4650)
[2750,2850]	(2650,2750,2850,2950)	[4550,4650]	(4450,4550,4650,4750)
[2850,2950]	(2750,2850,2950,3050)	[4650,4750]	(4550,4650,4750,4850)
[2950,3050]	(2850,2950,3050,3150)	[4750,4850]	(4650,4750,4850,4950)
[3050,3150]	(2950,3050,3150,3250)	[4850,4950]	(4750,4850,4950,5050)
[3150,3250]	(3050,3150,3250,3350)	[4950,5050]	(4850,4950,5050,5150)
[3250,3350]	(3150,3250,3350,3450)	[5050,5050]	(4950,5050,5150,5250)
[3350,3450]	(3250,3350,3450,3550)	[5150,5250]	(5050,5150,5250,5350)
[3450,3550]	(3350,3450,3550,3650)	[5250,5350]	(5150,5250,5350,5450)

Step 3: The historical data were fuzzified using the defined trapezoidal fuzzy numbers. Hence, 36 fuzzy sets were obtained:

$$\gamma_1 = 1/1794.5 + 1/1830.5 + 0.71/1789 + 0.465/1903.5 + 0.035/1946.5$$
$$\gamma_2 = 0.445/1794.5 + 0.805/1830.5 + 1/1879 + 1/1903.5 + 1/1946.5 + 0.82/1968 + 0.315/2018.5 + 0.13/2037$$
$$\gamma_3 = 0.29/1879 + 0.535/1903.5 + 0.965/1946.5 + 1/1968 + 1/2018.5 + 1/2037 + 0.835/2066.5 + 0.76/2074 + 0.68/2082 + 0.53/2097 + 0.495/2100.5 + 0.46/2104$$
$$\vdots$$
$$\gamma_{36} = 0.91/5341$$

Step 4: Using Atanassov's conversion method, the fuzzy sets were converted into IFS. Hence, the following IFS were obtained:

$$I_1 = \{(1794.5, 0.965, 0), (1830.5, 0.965, 0), (1879, 0.685, 0.280), (1903.5, 0.449, 0.516), (1946.5, 0.034, 0.931)\}$$

$$I_2 = \{(1794.5, 0.387, 0.483), (1830.5, 0.700, 0.170), (1879, 0.87, 0), (1903.5, 0.87, 0), (1946.5, 0.87, 0), (1968, 0.713, 0.157), (2018.5, 0.274, 0.596), (2037, 0.113, 0.757)\}$$

$$I_3 = \{(1879, 0.206, 0.504), (1903.5, 0.380, 0.330), (1946.5, 0.685, 0.025), (1968, 0.71, 0) (2018.5, 0.71, 0), (2037, 0.71, 0), (2066.5, 0.593, 0.117), (2074, 0.540, 0.170), (2082, 0.483, 0.227), (2097, 0.376, 0.334), (2100.5, 0.351, 0.359), (2104, 0.327, 0.383)\}$$

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$\vdots$

$$I_{36} = \{(5341, 0.156, 0.015)\}$$

Step 5: The score function for each IFS was calculated and the score value was obtained by subtracting the non-membership value from the membership value according to Definition 4. Hence, the element and its score were paired and gathered in score sets as follows:

$$S_1 = \{(1794.5, 0.965), (1830.5, 0.965), (1879, 0.405), (1903.5, -0.068), (1946.5, -0.897)\}$$
$$S_2 = \{(1794.5, -0.965), (1830.5, 0.531), (1879, 0.87), (1903.5, 0.87), (1946.5, 0.87), (1968, 0.557), (2018.5, -0.322), (2037, -0.644)\}$$
$$S_3 = \{(1879, -0.298), (1903.5, 0.050), (1946.5, 0.660), (1968, 0.71), (2018.5, 0.71), (2037, 0.71), (2066.5, 0.476), (2074, 0.369), (2082, 0.256), (2097, 0.043), (2100.5, -0.007), (2104, -0.057)\}$$
$\vdots$
$$S_{36} = \{(5341, 0.141)\}$$

Step 6: Based on the score function values, the IFS for historical data was defined. For instance, element 1830.5 is present in both IFS I_1 and I_2. However, its score functions are 0.965 and 0.531 for I_1 and I_2, respectively. Hence, 1830.5 was assigned with I_1 since it has a higher score than I_2. Next, the intuitionistic fuzzy logical relationships (IFLR) can be constructed as shown in Table 2.

Table 2: Intuitionistic Fuzzy Logical Relationships (IFLR)

Group	IFLR	Group	IFLR	Group	IFLR
1	$I_1 \to I_1, I_3$	10	$I_{10} \to I_7, I_9, I_{10}$	19	$I_{23} \to I_{25}$
2	$I_2 \to I_3, I_4$	11	$I_{11} \to I_{10}, I_{11}, I_{12}, I_{14}$	20	$I_{24} \to I_{29}$
3	$I_3 \to I_2, I_4$	12	$I_{12} \to I_{11}, I_{12}, I_{17}$	21	$I_{25} \to I_{29}$
4	$I_4 \to I_1, I_2, I_4, I_7, I_8$	13	$I_{14} \to I_{10}$	22	$I_{29} \to I_{22}, I_{29}, I_{34}$
5	$I_5 \to I_5$	14	$I_{16} \to I_{12}, I_{16}$	23	$I_{34} \to I_{36}$
6	$I_6 \to I_4, I_5$	15	$I_{17} \to I_{19}$	24	$I_{36} \to I_{34}$
7	$I_7 \to I_6, I_7, I_8$	16	$I_{19} \to I_{20}$	25	$I_{34} \to \phi$
8	$I_8 \to I_7, I_8, I_{11}$	17	$I_{20} \to I_{22}$		
9	$I_9 \to I_9, I_{11}$	18	$I_{22} \to I_{23}, I_{24}$		

Step 7: Each IFS was defuzzified using equation (6). Hence, $\kappa_1 = 1858.97$, $\kappa_2 = 1929.94$, $\kappa_3 = 2007.17$, ..., $\kappa_{36} = 5341$.

Step 8: Finally, the forecasted prices were calculated using the rules proposed in the previous section. For example, the IFLR for July 2018 is $I_5 \to I_5$ and it has only one IFLR, based on Table 2. Hence, the forecasted price for August 2018 is κ_5, which is RM2,166.38. Another example includes the IFLR for December 2017, which is $I_7 \to I_6, I_7, I_8$. The forecasted price for January 2018 is the average of κ_6, κ_7, and κ_8 which is obtained as RM2,410.92. As for

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December 2021, the IFLR is $I_{34} \to \phi$. Thus, the forecasted price for January 2022 is κ_{34}, which is RM5,060.50. The rest of the forecasted results are presented in the next section.

6. RESULTS AND DISCUSSION

Table 3 presents the actual and forecasted prices of Malaysian CPO from January 2017 until January 2022.

Table 3: Actual and Forecasted Malaysian CPO Prices

Month	Actual Price (RM)	Forecasted Price (RM)	Month	Actual Price (RM)	Forecasted Price (RM)
Jan-17	3,268.00	-	Aug-19	2066.50	2045.638
Feb-17	3,233.00	3083.073	Sep-19	2097.00	2157.335
Mar-17	2,955.50	3083.073	Oct-19	2104.00	2157.335
Apr-17	2,752.50	3008.006	Nov-19	2493.50	2157.335
May-17	2,803.50	2855.984	Dec-19	2813.00	2566.301
Jun-17	2686.00	2855.984	Jan-20	3013.50	2855.984
Jul-17	2629.50	2585.487	Feb-20	2714.50	2712.753
Aug-17	2633.00	2707.534	Mar-20	2382.00	2585.487
Sep-17	2780.50	2707.534	Apr-20	2299.00	2410.921
Oct-17	2736.00	2855.984	May-20	2074.00	2125.246
Nov-17	2689.00	2585.487	Jun-20	2411.50	2157.335
Dec-17	2407.00	2585.487	Jul-20	2519.00	2410.921
Jan-18	2486.50	2410.921	Aug-20	2815.00	2566.301
Feb-18	2488.00	2566.301	Sep-20	2924.00	2855.984
Mar-18	2426.50	2566.301	Oct-20	2979.50	3008.006
Apr-18	2418.00	2410.921	Nov-20	3422.00	3008.006
May-18	2396.00	2410.921	Dec-20	3620.50	3683.525
Jun-18	2324.00	2410.921	Jan-21	3748.50	3747.282
Jul-18	2215.00	2125.246	Feb-21	3895.50	3928.914
Aug-18	2183.50	2166.385	Mar-21	4041.50	4087.995
Sep-18	2177.50	2166.385	Apr-21	4220.00	4186.78
Oct-18	2082.00	2166.385	May-21	4572.00	4561
Nov-18	1830.50	2157.335	Jun-21	3830.50	4516.805
Dec-18	1794.50	1933.068	Jul-21	4128.50	4087.995
Jan-19	2037.00	1933.068	Aug-21	4555.00	4561
Feb-19	2100.50	2007.022	Sep-21	4556.00	4516.805
Mar-19	1903.50	2157.335	Oct-21	5051.00	4516.805
Apr-19	2018.50	2045.638	Nov-21	5341.00	5341
May-19	1946.50	2007.022	Dec-21	5070.00	5060.5
Jun-19	1968.00	2045.638	Jan-22	-	5060.5
Jul-19	1879.00	2007.022			

The performance of the proposed model was evaluated based on the difference between the actual and forecasted prices, which is measured using mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE), as shown in Table 4.

Table 4: Actual and Forecasted Malaysian CPO Prices

Model	MSE	RMSE	MAE
[17]	31725.08	178.1154	120.8164
[22]	39011.32	197.5128	131.5872
Proposed	31226.64	176.7106	119.1992

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In reference to Table 4, the proposed model exhibits the smallest error values among all models in predicting the Malaysian CPO prices. Even though the three models are based on intuitionistic fuzzy sets, different defuzzification methods were used.

The defuzzification process in [22] only considers the IFLR and the midpoint of each interval. Since the main properties of IFS, which are the membership and non-membership functions were not considered, its role in handling the uncertainty was not highlighted. Meanwhile, the model in [17] used induced fuzzy sets for the defuzzification process. The hesitation index was added to the major degree between the membership and non-membership functions. This process might cause a loss of information since the IFS was not preserved in its initial form.

The proposed model considers both membership and non-membership functions in calculating the defuzzified output. Since the main properties of IFS were fully utilized, the model managed to handle uncertainty in the fluctuating data and reduce the error values of the forecasted data.

7. CONCLUSION

A new procedure of forecasting time series data based on the IFS has been proposed in this paper. The model was implemented in the Malaysian CPO prices data from January 2017 until December 2021. A forecasted price was obtained for January 2022 using the proposed model and the proposed model was further compared with two other intuitionistic FTS forecasting models. The proposed model also uses a defuzzification formula that fully utilizes the main properties of IFS, which entail the membership and non-membership functions. The defuzzification process in this paper has also played a major role in reducing the forecasting error. Despite the volatility of CPO prices, this model has managed to yield forecasting results with significant performance. The proposed model also resulted in smaller error values, which indicates that the forecasted prices are not extensively different from the actual prices. Hence, it is recommended that the decision-makers from respective parties make the right decision based on the forecasted prices to maintain Malaysia as one of the largest CPO producers.

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