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Prediction of crude oil prices in COVID-19 outbreak using real data
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ARTICLE INFO

Keywords:
Crude oil prices
Fuzzy time series COVID-19
Artificial neural network (ANN)
Support vector machine (SVM)

ABSTRACT

The world has been undergoing a global economic recession for almost two years because of the health crisis stemming from the outbreak and its effects have still continued so far. Especially, COVID-19 reduced consumer spending due to social isolation, lockdown and travel restrictions in 2020. As a result of this, with social and economic life coming to a standstill, oil prices plummeted. With the ongoing uncertainty concerning the COVID-19 pandemic, it has been of great importance for all economic agents to predict crude oil prices. The objective of this paper is to improve a model in order to make more accurate predictions for crude oil price movements. The performance of this model is assessed in terms of some significant criteria comparing our model with its counterparts as well as artificial neural networks (ANNs) and support vector machine (SVM) methods. As for these criteria, root mean square error (RMSE) and mean absolute error (MAE) results show that this model outperforms other models in forecasting crude oil prices. Further, the simulation results for 2021 show that the daily crude oil price forecasts are almost close to the real oil prices. Oil price forecasting has become more and more important for economic agents in COVID-19 period. A consistent model is required to cope with the movements in crude oil prices. A novel method combining fuzzy time series and the greatest integer function is developed. The results show that our model outperforms other counterparts or ANN and SVM methods. We capture non-linearity and volatility in crude oil prices.

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1. Introduction

Known as ‘black gold’, crude oil accounts for a large part of global energy demand throughout the world and so it has been an integral part of the world’s economy. Crude oil has been an indispensable energy source to world economy since many countries, whether developed or under-developed, are heavily dependent on crude oil importing for electricity generation, heating, industrial and agricultural production, transportation etc. [1]. Furthermore, it is inevitably one of the main components of a wide range of daily life products. Taking all these into consideration, in spite of alternative energy sources, crude oil is most likely to remain the primary energy source for the world in the days to come [2]. For energy security, the uninterrupted flow and supply of crude oil at affordable price will be always crucial to all parties, especially to oil importing countries. Crude oil price is a key factor to decisions made by the governments as well [3]. Therefore, the falls and increases in oil prices have important consequences for the global economy, thus leading to economic and social conflicts [4].

No doubt, crude oil prices have many social and economic determinants. Crude oil prices are usually driven by exporting countries’ supply and industrialized countries demand [1,5]. In addition, crude oil prices are remarkably affected by gross domestic product, political events, weather conditions, speculative behaviors by financial investors, stock market, financial uncertainty and trader positions at community markets and economic policy uncertainty [4,6–9]. Crude oil prices are also affected by economic crises and political events. Concerning some significant events affecting the oil prices in the past fifty years, some political turmoil and wars between countries, such as Iran-Iraq War, Gulf War and Iranian Revolution, gave rise to significant increases in oil prices causing huge economic and social consequences for the whole world. On the other hand, with Asian financial crisis of 1997 and global economic crisis of 2008, oil prices witnessed sharp declines [10,11]. Briefly, exogenous political events, which notably take place in the Middle East, and global economic crises are generally held responsible for important fluctuations in crude oil prices [11]. Oil prices are not merely determined by economic variables, but they are also influenced by unexpected events [12]. Generally, oil prices are known to quickly react to these developments.

On the other hand, the path of oil prices is crucial for macroeconomic projections of investors and central banks [13]. The fluctuations in crude oil prices have naturally important effects on a variety of macro-economic indicators such as inflation rate [14], investments and economic growth rate [15], current account deficit, exchange rates [16],...
international trade terms [17] etc. leading to business cycles. Of course, the effect of fluctuations in oil prices varies from country to country. It is generally determined by the extent to what an economy depends on oil importing or exporting to sustain its economic activities.

We have witnessed a health crisis resulting from the COVID-19 outbreak since the first months of 2020. This outbreak was firstly started in December 2019 in China and caused the global economy to shrink. Output losses have been huge for the countries [18]. In particular, consumer spending across the globe dramatically fell due to the lockdown, self-isolation and travel ban [12]. Shortly, the outbreak has severely affected financial markets, commodity markets, stock markets, service sector, real markets etc. with the increasing number of confirmed cases [19–23]. Akbulan [24] points that the most destructive economic effects of this outbreak have been on production, supply chains, unemployment, export and import. For this reason, economic activities almost came to a standstill. There is no doubt that one of the serious effects of the outbreak has been on crude oil prices because of low aggregate demand and the severe collapse in the global economy [25]. With the price war between Russia and Saudi Arabia, crude oil prices saw the sharpest drop by nearly 25% [26]. Furthermore, during this period, the underlying cause of oil price volatility is stated to be mainly connected with the negative oil price news as well [27]. Nonetheless, there has been also an opposing view showing that the negative effects of COVID-19 on crude oil prices are lower and indirect in comparison with the effect of financial volatility and uncertainties about political economy on oil prices. It has been showed that the COVID-19 cases and deaths influence oil price volatility ranging from 8% to 22% on a daily basis. According to hourly data-set used in this study, even if the effect of the COVID–19 outbreak on oil price volatility is evident, the potential effect is up to 22% [28].

Undoubtedly, there have been some uncertainties about how long this epidemic will last. Given that, in addition to the COVID-19 outbreak, there are many variables mentioned above that affect crude oil prices, it has become a complicated task to predict crude oil prices. Since the volatility of crude oil price affects market expectations, industrial sectors [3], investor decisions on risk management and portfolio selection etc. [29], developing a model that accurately predicts crude oil prices has become very important in order to eliminate these uncertainties.

In the literature, the models created to predict crude oil prices generally fall into two categories. One of them refers to traditional approaches such as the autoregressive moving average (ARMA), generalized autoregressive conditional heteroskedasticity (GARCH), random walk (RW), error correction models (ECM) etc. The second one is based on artificial intelligence (AI) models such as artificial neural networks (ANNs) and support vector machine (SVM). Moshiri and Foroutan set up a nonlinear and flexible ANN model forecasting oil futures prices from 1983 to 2003, comparing it with ARMA and GARCH models. In this paper, it is stated that producing the same results is possible by using some nonlinear time series models such as Threshold AR, Exponential AR or Generalized AR as the ANN [30]. A hybrid grey wave forecasting model based on the Heterogeneous Market Hypothesis is proposed by Chen et al. [31] to deal with the irregular periodical fluctuation and the daily random price movements using grey wave forecasting method and RW or ARMA model, respectively. A novel different hybrid model using support vector machine, particle swarm optimization, and Markov-switching generalized autoregressive conditional heteroskedasticity outperforms other models [32]. In comparison with traditional model, artificial intelligence (AI) models are empirically superior in forecasting crude oil prices. For example, according to the empirical results, the performance of a new method for crude oil price forecasting based on support vector machine (SVM) for time series is better than those of ARIMA and BPNN [33]. However, instead of using these models single, hybrid models are recommended to be used [32,34] due to different problems such as loss of time, slow convergence, local minima etc. [9].

The main contribution of our paper to the literature is to propose a novel model to make the closest predictions to daily crude oil prices. It is known that the estimation for crude oil price is known to be a demanding job because of its non-linearity and chaotic behavior [9]. For this reason, using only historical crude oil prices, we aim to actually capture this non-linear behavior in spite of a wide variety of factors affecting crude oil prices. Our model consists of two phases; the first phase includes conventional fuzzy time series steps and the second phase includes how the greatest integer function is used for daily price prediction (see Fig. 1). Besides, this model provides a novel insight into forecasting crude oil prices more effectively, even if a short-term data set is trained. This approach provides more different perspective than that of other classical models which generally train a longer term data-set. Another advantage of our model is that it includes long-term and daily crude oil price forecasts, the empirical results of which are really attractive.

To this end, first of all, the daily crude oil prices (from 02/01/2020 to 31/12/2020) are trained following the steps in the phase 1 (see Fig. 1). Training these data, a long-term crude oil price prediction is made based on data in the phase 1 of our model. Then, to make prediction on daily crude oil prices, these data are used in the phase 2 of the proposed model. The other part of this paper is as follows: Section 2 presents the literature review on some effects of epidemic on economy and oil price volatility. Section 2 explains where the used data is...
drawn, from the evaluation criteria and the compared methods. Then, we summarize the underpinning concepts of fuzzy time series as well as on fuzzy logic and fuzzy time series in Section 3. Section 4 introduces our model. In Section 5, the performance of the proposed model is evaluated. The final section reveals the conclusion of our paper.

2. Data and evaluation

We get a daily data on one year of the crude oil price trend starting from 2nd January 2020 to 31st December 2020. This data is obtained from the Yahoo Finance website Data [35] and includes the different price indicators such as open, high, low and closing prices and volume. In this study, the daily closing price is used. The time interval of our data is from 08:00 am to 17:00 pm. Our all data has 499 observations which are composed of the training and forecasting data-set (see Fig. 2). By the way, the historically lowest value is omitted (on April 20th 2020, oil prices nearly dropped minus $36 for the first time in history).

To evaluate the performance of our model, we use the different standards such as root mean square error (RMSE) and mean absolute error (MAE). These standards are shown as follows:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (\text{actual}(t) - \text{forecast}(t))^2}
\]

(1)

and

\[
MAE = \frac{1}{n} \sum_{t=1}^{n} |\text{actual}(t) - \text{forecast}(t)|.
\]

(2)

In order to be compared with our model, two different fuzzy time series models are selected. One of them is fuzzy time-series based on fibonacci sequence for stock price forecasting [36]. Another one whose prediction values are close to actual ISE (Istanbul Stock Exchange) values has recently been proposed based on golden ratio number [37]. Furthermore, the well known ANN and SVM methods are added for comparison.

3. Fundamentals of fuzzy time series

In this section, the well known concepts of our model and studies are summarized in the literature (see details [38–40]).

Fuzzy logic, which provides basis for our model, was introduced in 1965 by Zadeh [41]. Firstly, fuzzy time series model was proposed by Song and Chissom in Song and Chissom [40] and Song and Chissom [39]. Fuzzy time series have been widely used in a wide range of areas such as stock price [42,43] and exchange rate prediction [44], weather forecasting [45], data mining [46] and enrollments [47] etc. Then, this model is improved by Chen [38]. There are different techniques and approaches to improve the fuzzy time series method [48–50]. A method on high-order fuzzy time series for forecasting the enrollments of the University of Alabama is found by Chen [51]. Now, let us give some basic concepts about fuzzy time series.

Let \( U \) be the universe of discourse. A fuzzy sets \( L_k \), which is a partition of \( U \), can be expressed as follows:

**Definition 1.** For \( f_{L_i}(u_k) \in [0, 1] \) and \( 1 \leq i \leq n \),

\[
L_i = f_{L_i}(u_1)/u_1 + f_{L_i}(u_2)/u_2 + \ldots + f_{L_i}(u_n)/u_n
\]

(3)

where \( f_{L_i}(u_k) \) is the degree of membership of the element \( u_k \) in the fuzzy set \( L_i \).

In fuzzy time series, the fuzzy logical relationships are established using the fuzzified observations \( L_k \).

**Definition 2.** If the crude oil price values in the days \( t \) and \( t+1 \) are \( L_i \) and \( L_j \) respectively, then FLR (fuzzy logic relationship) is showed by \( L_i \to L_j \).

According to **Definition 2**, for example, suppose that \( L_i \to L_1, L_1 \to L_2, L_i \to L_3, \ldots, L_n \to L_m \) for \( i \in \{1, 2, \ldots, n\} \). These FLR can be classified as \( L_i \to L_1, L_2, \ldots, L_m \). On the other hand, the FLR weight of its order of occurrence is found by **Definition 3**:

**Definition 3.** For the FLR, \( W_{L_i \to L_j} \) is named as the assigned weight and it can be defined as follows

\[
W_{L_i \to L_j} = \sum_{k=0}^{n} k
\]

(4)

where occurrence frequency and the order of \( L_i \to L_j \) are \((L_i \to L_j) \) and \( k \), respectively.

In order to find a fluctuation-weighted matrix, the sum of the weight of each FLR should be found. This matrix is called \( W_n(t) \).

**Definition 4.** \( W_n(t) \) is defined as the standardized weight matrix as follows:

\[
W_n(t) = [W_1', W_2', \ldots, W_i'] = \left[ \frac{W_1}{\sum_{k=1}^{n} W_k}, \frac{W_2}{\sum_{k=1}^{n} W_k}, \ldots, \frac{W_i}{\sum_{k=1}^{n} W_k} \right].
\]

(5)

In this way, for the linguistic value \( L_i \), **Definition 5** shows the spread center of the observations, \( v_i \):

**Definition 5.** \( v_i \), which is the spread center of the observations, is defined for each \( L_i \) value as follows

\[
v_i = \frac{\sum_{k=1}^{n} u_k x_k}{\sum_{k=1}^{n} u_k}
\]

(6)

where \( u_k \) is the membership function of linguistic value \( L_i; x_k \) is the observation value.

The linguistic spread center matrix \( L_0(t) \) consisting of these spreading centers of linguistic values is generated in this way. That is,
as a specific example, the spread center of $L_{fl}(t)$ can be obtained in this way:

$$L_{fl}(t) = [v_1, v_2, \ldots, v_n]$$  \hspace{1cm} (7)

where $v_i$ is spread center of $L_i$ for $i = 1, 2, \ldots, n$. By multiplying the linguistic spread center matrix $L_{fl}(t)$ and the standardized weight matrix $W_{fl}(t)$ in Definition 4, the forecasting data is found as stated below.

$$\text{Forecasting Data} = L_{fl}(t) \times W_{fl}(t).$$  \hspace{1cm} (8)

4. Proposed model

In this section, our model is introduced by combining the greatest integer function. With the help of the definitions in the previous section, all steps are explained based on sample crude oil prices. First of all, the universe of discourses of the all data-set is determined. Secondly, linguistic values are derived from the universe of discourse. In this step, using the values at the previous steps, the initial forecasting data is found where $D_{min}$ is 6.40 ($\$/per barrel). After that, the created subranges corresponding to this set are shown as follows. We split $U$ into nine linguistic intervals. Similarly, according to these linguistic intervals, the length of this interval can be seen six unit as in Table 1:

4.1. Step 1: to define the universe of discourse and intervals

In this step, $U = [D_{min} - D_1, D_{max} + D_2]$, the universe of discourses, is determined for observations where $D_1$ and $D_2$ are positive integers. In the light of one year of data-set, $U = [10,64]$ is found where $D_{min}$ is 10.01 ($\$/per barrel). After that, the created subranges corresponding to this set are shown as follows. We split $U$ into nine linguistic intervals. Similarly, according to these linguistic intervals, the length of this interval can be seen six unit as in Table 1.

4.2. Step 2: to establish linguistic values

In this step, for the universe of discourse $U$, the fuzzy sets, $L_1, L_2, \ldots, L_9$ are described for each observation with the help of Definition 1. For the crude oil price data from 02/01/2020 to 31/12/2020, the nine linguistic values are found:

$L_1 = \langle\text{very low price}\rangle, L_2 = \langle\text{low price}\rangle, L_3 = \langle\text{little low}\rangle, L_4 = \langle\text{normal price}\rangle, L_5 = \langle\text{slightly higher than normal price}\rangle, L_6 = \langle\text{higher than normal price}\rangle, L_7 = \langle\text{high price}\rangle, L_8 = \langle\text{very high price}\rangle$ and $L_9 = \langle\text{pretty high price}\rangle$.

4.3. Step 3: to create FLRs

Here, for each linguistic values, we create FLRs. From now on, we shall explain another steps using sample data-set. After finding nine linguistic values in the previous step, we show the linguistic values corresponding to these values in Table 2. The FLR table for this sample data-set is created using Definition 2 (see Table 3).

4.4. Step 4: to build a fluctuation-type matrix

We produce a fluctuation-type matrix for training the fuzzy relations in these FLRs. In order to get this matrix, the FLR weight is computed by its order of occurrence using Definition 3. For the crude oil price data for one year period, the fluctuation-type matrix containing the FLRs values in Table 4 is produced.

4.5. Step 5: to sum up weight for each FLR

Now, the fluctuation weight assignment corresponding to each FLR group is performed by summing up each row. By Definitions 3 and 4, the fluctuation-weighted matrix of all FLR is obtained as in Table 4.

4.6. Step 6: to determine the standardized weights

The standardized weights for each $L_k$, $k = 1, 2, \ldots, 9$ are found using Definition 4. For example, the standardized weight matrix for $L_1$, with the help of Table 4, is constituted as follows:

$$W_1, W_2, \ldots, W_9 = [2/14,9/14,3/14,0,0,0,0,0].$$  \hspace{1cm} (9)

4.7. Step 7: to find the spread center of the linguistic values

With the help of Definition 5, the spread center of the linguistic value is found. For example, since we have six observations named as $L_4$ (see Table 2), the spread center of $L_4$ is found as 32.40. In doing so, the linguistic spread-center matrix for all $L_k$, $k = 1, 2, \ldots, 9$ is found.

4.8. Step 8: defuzzify

In this step, using the values at the previous steps, the initial forecasts are generated. This stage is referred to as ‘defuzzification’. These forecasts are obtained using Eq. (8) (see Table 5).

| Table 1 | A fragmentation of discourse. |
| --- | --- |
| **Partition intervals** | **Ranges** |
| $U_1$ | $[10,16]$ |
| $U_2$ | $[16,22]$ |
| $U_3$ | $[22,28]$ |
| $U_4$ | $[28,34]$ |
| $U_5$ | $[34,40]$ |
| $U_6$ | $[40,46]$ |
| $U_7$ | $[46,52]$ |
| $U_8$ | $[52,58]$ |
| $U_9$ | $[58,64]$ |

| Table 2 | Assignment of linguistic values for each crude oil price. |
| --- | --- |
| **Time** | **Crude oil price ($)** | **Linguistic values** |
| $t = 13.05.2020$ | 27.56 | $L_4$ |
| $t = 14.05.2020$ | 29.43 | $L_4$ |
| $t = 17.05.2020$ | 31.82 | $L_4$ |
| $t = 18.05.2020$ | 32.5 | $L_4$ |
| $t = 19.05.2020$ | 33.49 | $L_4$ |
| $t = 20.05.2020$ | 33.92 | $L_4$ |
| $t = 21.05.2020$ | 33.25 | $L_4$ |
| $t = 25.05.2020$ | 34.35 | $L_5$ |

| Table 3 | The FLR. |
| --- | --- |
| ... | ... |
| $L_1 \rightarrow L_4, L_4 \rightarrow L_4, L_4 \rightarrow L_4$ | $L_4 \rightarrow L_4, L_4 \rightarrow L_4, L_4 \rightarrow L_4$ |
| $L_4 \rightarrow L_5...$ |  |
prediction data by applying all steps as seen in Table 5. After this data, the value of \( \tau \) is found, daily crude oil prices are obtained as stated below:

\[
\text{Golden Forecast}(t) = P(t_{\text{last}}) + \tau \times (\text{Forecast}(t) - P(t_{\text{last}} - 1)) - \tau(\text{Forecast}(t-1) - P(t_{\text{last}} - 2))
\]

where \( \tau = \pm \frac{1}{\phi^2} \approx \pm 0.61803 \).

However, these long-term data are obtained with the help of Eq. (10). With these long-term forecasting values, we predict the daily crude oil prices using the greatest integer function given in the following definition. The part described so far constitutes the first phase of the model (see Fig. 1). In other phase, it is aimed that the not-optimized long-term forecast data approximates the real daily crude oil prices.

**Definition 6.** \( f: \mathbb{R} \rightarrow \mathbb{R}, f(x) = [x] \) is defined as the real valued function: If \( x \) is an integer, then the value of \( f(x) \) will be \( x \) itself. If \( x \) is a non-integer, then the value of \( f(x) \) will be the integer just before \( x \).

 According to Eq. (10) described above, we can create a long-term prediction data by applying all steps as seen in Table 5. After this data is found, daily crude oil prices are obtained as stated below:

| Dates     | Crude oil price ($) | \( f \) (Golden Forecast (t)) | Long-term forecasting | Daily forecasting value | Fibonacci model | Not optimized values |
|-----------|---------------------|-------------------------------|-----------------------|------------------------|-----------------|---------------------|
| 04-01-2021 | 47.62               | 47.24                         | 47.62                 | 47.62                  |                 |                     |
| 05-01-2021 | 49.93               | 47.24                         | 47.62                 | 47.62                  |                 |                     |
| 06-01-2021 | 50.63               | 47.85                         | 49.85                 | 49.85                  | 49.93           |                     |
| 07-01-2021 | 50.83               | 47.81                         | 49.81                 | 50.81                  | 50.63           |                     |
| 08-01-2021 | 52.24               | 47.69                         | 50.69                 | 50.69                  | 50.83           |                     |
| 11-01-2021 | 52.25               | 47.29                         | 51.29                 | 52.29                  | 52.24           |                     |
| 12-01-2021 | 53.21               | 48.25                         | 51.25                 | 51.25                  | 52.25           |                     |
| 13-01-2021 | 52.91               | 48.81                         | 52.74                 | 53.81                  | 53.21           |                     |
| 14-01-2021 | 53.57               | 48.15                         | 51.37                 | 53.15                  | 52.91           |                     |
| 15-01-2021 | 52.36               | 47.74                         | 52.74                 | 52.74                  | 53.57           |                     |
| 18-01-2021 | 52.98               | 47.37                         | 51.37                 | 52.37                  | 52.36           |                     |
| 19-01-2021 | 53.24               | 46.82                         | 52.82                 | 52.82                  | 52.98           |                     |
| 20-01-2021 | 53.13               | 46.65                         | 52.65                 | 52.65                  | 53.24           |                     |
| 21-01-2021 | 52.27               | 46.29                         | 52.29                 | 51.29                  | 53.13           |                     |

**5. Empirical results**

In this section, detailed experiment results are presented using different evaluation standards. The purpose of the first part is to visually simulate the proposed model’s ability to predict real crude oil prices. In addition to the long-term forecast data for 2021, this simulation also includes the daily crude oil price forecast data obtained from the second phase of the model. Besides, the monthly crude oil prices are shown in the period from January 2021 to December 2021, giving a total of 250 observations. In another part of this section, we compare our method with ANN and SVM methods as well as with some fuzzy time methods in terms of RMSE and MAE.

### 5.1. Overview of crude oil prices forecasting

Fig. 3 represents the daily crude oil price movements from 04/01/2021 to 31/12/2021. When Fig. 3 is examined, on January 4, 2021, the barrel price of crude oil saw $47.62 dollars, which is the minimum value of the year (see 35). The general upward trend in crude oil prices continues until the middle of 2021. At the beginning of January, the crude oil price decreased, and then again continued to increase until October 25, 2021 ($84.65/barrel). Then, these increasing and decreasing trends continued until the end of 2021. Fig. 3 shows that the yellow line shows the method's values obtained by using the greatest integer
function, while the blue line shows the actual crude oil prices. Likewise, the orange and green lines refer to the fibonacci and golden ratio method’s results [36], respectively. The purple line shows not-optimized values. Moreover, during testing period, the actual prices of crude oil and our models’ observations are examined. Comparing their maximum and minimum values with our models’ results, we get the values closer to actual prices. Rather, the maximum and minimum values of the proposed model are $84.23 and $47.24 respectively. The maximum and minimum values of actual crude oil prices are also $84.65 and $47.62 respectively. Interestingly, the days when the maximum and minimum values of our model occur coincide with the days when the maximum and minimum values of actual prices occur in 2021. Also, as can be seen from this fig, the not-optimized data with sharp increases and decreases become smoother with this greatest integer function. Furthermore, the forecasting values of the proposed method are very close to the actual crude oil prices. Also, Fig. 3 implies that our method performs better compared to the fibonacci and golden ratio model.

In order to better demonstrate the effectiveness of our model, the monthly comparison with real crude oil prices from January to December in 2021 is presented in Fig. 4. Each chart consists of an average of 20 observations per month. It can be clearly seen from this fig. that our model is already superior in forecasting the up and down movements in crude oil prices, and even in some periods it is exactly the same.

5.2. Comparison of predictions with ANN and SVM

As far as it is known from the literature, ANN and SVM methods, which are used single for crude oil price forecasting, are very popular due to their high accuracy. For this reason, in this subsection, these models are discussed in order to evaluate the performance of our model according to evaluation criteria such as RMSE (Eq. (1)) and MAE (Eq. (2)). Let us focus on the general definitions of the methods before giving the numerical results.

5.2.1. Support vector machine (SVM)

Support vector machine (SVM), developed by Vladimir Vapnik, is used for nonlinear classification or regression problems. In this method, since the distance between multiple planes is solved by optimizing, the number of operations decreases and thus the performance of the method increases. The theoretical details about this method and the use of this method in crude oil pricing studies are included in the study [33].

5.2.2. Artificial neural network (ANN)

It is well known that artificial neural networks (ANN) with learning ability are systems in which each neural network is linked to each other by weight and bias values. It is aimed to minimize the error by continuously updating these values during the training. In addition, ANNs are preferred more than traditional models in crude oil price prediction due to their flexible and non-parametric feature [30]. Additionally, ANN methods can be used to predict some financial problems during financial crisis [52] and stock exchange index [53]. There are two different types of approaches as sensors, single-layer perceptron and multi-layer in ANN models. In this study, single-layer ANN is used because more successful results are obtained than those of multi-layer ANN.

After introducing the models to be compared, we examine all numeric details of the forecasting. In order to find how the forecasts differ among all models, the values of the all months of 2021 are computed for each model. To show this, RMSE and MAE results of all methods are listed in Table 7. It can be drawn from Table 7 that the results obtained using the greatest integer function give the best accuracy in terms of RMSE and MAE. With this analysis, we conclude that our model is the best model compared to ANN and SVM methods as well as some fuzzy time series in terms of statistical standard.

6. Conclusion

 Humanity has been suffering from a deadly virus known as COVID-19 since the beginning of 2020. This virus has continued to spread around the world. This pandemic has had the huge social and economic impacts on all walks of life. Above all, policymakers have had difficulty in making decisions over economy since there have still been uncertainties about how long this outbreak will last. No doubt, one of the economic effects of this outbreak has been on crude oil prices due to economic downturn. From the first four months of year of 2020, crude oil prices suddenly started to fall. Later, oil prices have started to gradually increase since May 2020. Nevertheless, in case of new epidemic waves in the days to come, new fluctuations in oil prices may be expected. So, the forecasting of these fluctuations has become more important for many economic actors such as oil exporting and importing countries, investors and speculators etc.

In this paper, a model for the future behavior of crude oil prices is constructed. Using only the daily crude oil prices data in 2020 when is one of the most volatile periods for these prices, we have obtained a model that can predict these fluctuations and volatility. The difference of our model from other models is that it uses both the data of the previous year and the actual oil price the day before, which enables us to yield more accurate forecasts. In particular, the inclusion of the prices of the previous day into our model makes it possible for us to obtain closer results to actual values on a daily basis.

Fuzzy time series form the core of our two-phase model. In the second phase, we merge the forecasts from this series and the actual crude oil prices from the previous day with the greatest integer function (Fig. 1). Surprisingly, we capture the chaotic and non-linearity behavior of the daily crude oil prices for 2021 thanks to our model (Fig. 4). With this function, it can be seen from the simulation results how the data is optimized (Fig. 3). On the other hand, since ANN and SVM are known to produce better results than traditional methods in crude oil price prediction, we prefer these models to numerically compare them with our model. In terms of both RMSE value and MAE value, the proposed model gives better results among other models. Since our model outperforms its counterparts, notably ANN and SVM, according to the all empirical analysis, it can be said that our study is successful.

In conclusion, crude oil still accounts for most of the globally produced energy and global dependence on oil is likely to continue in the days to come despite the availability of other energy sources. Oil price shocks can be quickly transferred into the macro-economy by different channels and then be passed on to consumers. Or rather, a set of macroeconomic indicators, such as growth rate, employment, inflation rate and exchange rate, and investment decisions are undoubtedly quite sensitive to oil price shocks which are likely to occur. Given globally
drastic increase in energy prices in recent times, the energy studies are likely to be critical for economic and policy. Of course, economic policies of the countries will have to respond to oil price shocks as soon as possible. That is the reason why oil prices should constantly be monitored by many economic agents. Therefore, the models that enable us to make accurate predictions for crude oil prices will always remain to be useful even after the epidemic is over. Considering all of these, our model will be undoubtedly beneficial for a wide range of economic agents from oil exporting and importing countries, households, investors, industrial production, traders in spot and futures markets to policymakers and central banks across the globe because complex features of crude oil prices affect their economic behaviors. In our opinion, the ability to stabilize some of the key macro and micro variables mentioned below should be accompanied by a model that captures the nonlinear properties of oil prices well because these variables tend to react to oil price shocks.

### Table 7
The comparison of the RMSE and MAE values of all models.

| Models                  | Time period     | RMSE  | MAE   |
|-------------------------|-----------------|-------|-------|
| Fibonacci model         | 02/01/2020–31/12/2021 | 2.4600 | 1.3239 |
| Golden ratio model      | 02/01/2020–31/12/2021 | 19.7216 | 18.3263 |
| Not-optimized values    | 02/01/2020–31/12/2021 | 2.0019  | 1.2629 |
| Proposed model          | 02/01/2020–31/12/2021 | 0.6018  | 0.5295 |
| SVM                     | 02/01/2020–31/12/2021 | 17.6535 | 15.4211 |
| ANN                     | 02/01/2020–31/12/2021 | 17.6542 | 15.4046 |

Fig. 4. A detailed view of forecasting results and actual crude oil prices in 2021.
At macro economic level, since fluctuations in crude oil prices are the most important determinant of inflation rates, this model enables the central banks to capture nonlinear features of oil prices when setting targeted inflation rate with higher accuracy. Given that oil price fluctuations lead to international income transfer, it can also enable economies with the high dependency on oil exports or imports to predict their possible gains and losses well. A consistent global economic growth forecasting is clear to require an accurate forecasting of the oil price trend as well. Similarly, at micro economic level, regarding commodity and future markets, this model could guide pricing decisions made by financial investors. Further, increased volatility in oil price causes firms to delay investments. Accurate estimation of oil prices may thus reduce uncertainty for investors in real markets. Using different data-sets, our model can also be applied to forecasting other financial and economic indicators in future. All of these reveal the most important contributions of the proposed model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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