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Black gold falls, black plague arise - An Opec crude oil price forecast using a gray prediction model

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1. Introduction

Different Crude oil prices are among the most important key variables that have a significant impact on the performance strategy of international financial markets [1]. Therefore, forecasting oil prices not only plays an effective role in government policy and programs but also greatly affects the optimization of long-term production. The Effect of oil price fluctuations on the economic structure of OPEC members has progressed to the point that researchers call it black gold or black plague.

Energy, especially oil, is the driving force of any economic and most productive activities, so it has a special place in economic growth and development ([31]; 26). Oil shocks caused by changes in oil prices can have different effects on the economies of OPEC member countries. They can be due to differences in the infrastructure of the economic, political, and social sectors of each society or the dependence of its budget on foreign exchange earnings from oil sales or in the system of the tax authorities of those countries [2]. Therefore, a correct estimate of the price of the crude oil portfolio of OPEC member countries can play a significant role in securing the economy of these countries against the effects of these fluctuations. The trend of changes in oil prices can change the production advantages in domestic and international markets, as well as change the volume of exports and imports due to changing competitive advantages. Now, given the above, the importance of predicting and being aware of the future of oil price changes is no longer hidden from anyone. Therefore, the use of quantitative methods to predict financial markets to improve the decisions of politicians, economic researchers, and industry owners has become an undeniable necessity in today’s world (Atiq et al., 2020).

Increasing the accuracy of many oil price forecasting models requires identifying all the trends and variables and strategies affecting the international oil financial markets, and as we know, the structure of the oil pricing system is very complex and opaque. Therefore, the researchers of the present study, using the theory of gray systems, consider the gray prediction model as a suitable model for improving the predictive performance of crude oil prices, and the present study is an attempt to explain the performance of this model [3]. What distinguishes this research from other research is the use of fewer time data in a short period because the use of large amounts of data can lead to incorrect behavior patterns or, in other words, can lead to incorrect background information [4]. Ultimately, this can reduce the reliability of these prediction results. Lack of need for complex and difficult calculations and specialized programming are the most important advantages of using the gray model, while this simplicity does not reduce the accuracy of the model. The present study is an attempt to predict and compare the accuracy of OPEC crude oil price forecast in two time periods, one of the is short-term two and three consecutive working weeks and the other is a long-term for 2000–2020, and to evaluate and compare the results of the other machine learning or econometric models with the improved gray model [5]. In the following section, experimental studies conducted by other researchers will be reviewed, and then the methodology section will introduce the model and how to collect data and analyze it during the process. Model estimation, model analysis, and ultimately the conclusions and suggestions of researchers are the last section of the article to be mentioned before the references [6].

The main aim of this paper is to find a model to provide clear projections for the future of oil prices and the oil industry. Also, current oil price shocks emphasized more researches on the machine learning and
economic models for the future of the oil and gas industry to help the investors and shareholders of the energy industry in a time of similar crisis, which may constantly occur in the coming years and lead us to a fall of the oil age [26].

2. Oil prices projection methods

Research on the literature in the subject of forecasting in financial systems as well as numerous studies conducted in various markets, especially financial markets such as foreign exchange markets, stock market, coin and gold market, precious metals market, and the oil market, which is the most important economic market [7].

In recent years, optimizing structural models has provided an important framework for studying the dynamics of inflation, monetary policy rules, and stabilization policies ([1]: 3). It’s not an easy task and needs much mathematical and theoretical modeling and calculation. The introduction of the Box-Jenkins models was a turning point in the economic models which have been used to predict several social, economic, engineering, and financial issues and have yielded useful and effective results. Predicting prices plays an important role in optimizing the future production and strategy of financial markets, and this importance is multiplied in the case of strategic goods such as oil. For this reason, the oil field has long been of interest to many researchers and has been the subject of much research in various fields. This section summarizes the common methods for predicting oil prices (18); Donghui et al., 2020).

The first group of researches focuses on the mechanisms of supply and demand for the product to predict oil prices. They have predicted oil prices by using behavioral functions and variables of economic activity, such as dynamic imbalance adjustment (DDAM). The second group of researchers believe that to check the price of oil, it is necessary to focus on the quantities of supply and demand of oil in the oil markets [9].

The Third group is ARCH models family; such models are mostly used to estimate and measure uncertainties in oil prices. The most prominent of these models are DeVolvis (1994), Zotiil, Duffy Wegri, and Nelson (1996). The Fourth group of Researchers has provided models for simulating and predicting oil prices. Such as simulation methods provided by Kim Woolgani (1992), Absfeld and Rogoff (1995), and others. The results of all the research have led to the fact that the most influential effects on oil prices are monetary and sometimes international financial variables.

The Fifth group is the multimodal method developed by Mark Hooker (1997). Benjamin Hunt and his assistants have worked with Douglas Langston (2001) and others. It has been proven that there is a two-way relationship between monetary parameters - monetary policy and global oil prices. The sixth group is the Authoritarian reversal methods, in these models, the two-way effect of OPEC oil production quotas, oil profit gap, and the role of government spending in the developed countries on oil prices have also been used [10].

The seventh group is value methods, in the articles reviewed in these methods, respectively, to examine the combination of Monte Carlo simulation estimates and historical trends using instrumental variables, exchange rate, inflation, oil supply, OECD demand of virtual variables, exchange rates of the dollar-euro-yen and its impact on the Nymex market on crude oil futures prices and commodity demand, the type of trade, the share to which GDP depends on crude oil, and technical advances in the oil industry (Hsu, 2007; [12]). Thus, what is more, tangible in these articles is to identify the economic and political factors that affect the risk and uncertainty of oil prices.

The eighth group is the demonstration smoothing method, researchers in this group have introduced and influenced the effectiveness of some parameters such as strong market demand, unfavorable weather conditions, political conditions, low reserves, etc., they cite these factors as the main causes of disruption in the price of oil and gas (Hsu et al., 2011).

The Ninth group is the researchers who use time-series predictive methods to predict oil prices. A time series is a collection of data that has been sampled and collected over time. The main hypothesis of such models is the use of past values of time series to determine the functional relationship between past data and current data series and, consequently, to project the future values of time series. In general, time series prediction methods can be divided into three categories: linear methods, non-linear methods, and hybrid methods [13,14].

The first category: ARMA family models are the most widely used linear forecasting methods. Today’s model of global financial markets is often non-linear patterns and models, and economists use these methods dramatically (20); 106).

The second category: methods based on artificial intelligence. Neural networks can be considered as the most widely used and valid methods of this group. The main advantage of neural networks is their non-linear modeling capability and flexibility (Jinyu et al., 2020). Despite all the benefits of using neural networks, these types of models also have disadvantages. One of the most important disadvantages is the need for a lot of data to get accurate results. It should be noted that collecting the data needed to build a neural network is very costly, and it takes a long time to provide a sufficient amount of data (Khashieh, 2010: 47).

The third category includes hybrid methods, and the materials mentioned above have led to more use of the third category methods. In this regard, Shembara and Rossiter (2005) used artificial neural networks and intermediate moving averages to predict crude oil prices in futures markets, and Wang et al. [34] modeled crude oil prices based on a hybrid of the linear and non-linear model which is called the TEI model. The results predicted using the hybrid models were superior to predictions with a stand-alone neural network.

Bow et al. (2007) examined the price of oil based on the hybrid model (LSSVM-DWS). Yu et al. (2007) used an EMD-based multidimensional neural network. Alexander and Levannis (2008) predicted the price of crude oil using the Mojak neural network (Behrad Mehr, 2002: 87). However, many studies have been conducted in the field of oil price forecasting. But these models have many advantages and disadvantages. OPEC member countries are often among the developing countries (Jianliang et al., 2020). The economic characteristics used in forecasting models in these countries, even in the long term, are highly volatile due to the unstable economic structure of these countries, and this economic instability causes a reduction in the confidence and the accuracy of the Oil price projections by these models, which in the long term will lead to instability in the economic policies of these countries [15]. Therefore, predicting oil prices in the short term, if it is through a correct method, can reduce the adverse effects of political and economic events at the international level. To use the mentioned models and to correctly predict oil prices, it is necessary to know the structure of the oil pricing system at the international level (khashei et al., 2012). However, is the structure of the pricing system internationally well-known and transparent? Do researchers use all the influential factors in their forecasting models? Is the information used by these researchers quite clear and sufficient? These are the questions that reduce the degree of trust in the accuracy and precision of these predictive models. Undoubtedly, identifying and applying all the parameters affecting global markets leads to the greater complexity of the proposed models and, in some cases, leads to the ineffectiveness of these models. It should be noted that despite the numerous forecasting methods, accurate forecasting in the financial markets is still not an easy task. Besides all of these concerns, the oil price projections in the short-term periods is an important task which can be useful for policy-makers, traders, investors, industry holders, etc. especially in the time of trend shifts or unstable economic status [26,37].

3. Methodology

3.1. Experimental studies

The analysis of the relationship between changes in oil prices and the economy is a bit complicated. According to economic theories, changes
in crude oil prices affect the economy through two channels of supply and demand. Extensive studies have been conducted to identify the factors and the impact of oil price changes on economic markets. This section summarizes some of the available articles. In 2013, Shabazi et al. published an article entitled “The effect of oil price shocks on stock returns on the Tehran Stock Exchange: SVAR approach.” The purpose of this paper was to investigate the effect of oil price shocks on the supply and demand of crude oil on stock returns on the Tehran Stock Exchange. In their paper, they used the SVAR structural self-regression model (Akdogan, 2020). In 2011, Salmani et al. published an article entitled “The Role of Institutional Quality concerning the Real Exchange Rate with Oil Prices 1995–2006”. Faridzad and his colleague also published an article entitled “Investigating the Price Relations of Crude Oil in Spot and Futures Markets based on Risk and crude Oil Storage Using the GARCH Model in 2011”. The main purpose of this study was to investigate the relationship between crude oil prices in the spatial and futures markets and the impact of reserve inventory and risk based on adjusted interest rates of financial markets on changes in these prices.

3.2. Theory of the gray systems

In 1982, Deng from the department of Science and Technology at Hamzong University in China published his first research paper on the concepts of gray theory in the International Journal of Gray Systems Control [8,16]. Deng has done extensive research on the prediction and control of economic and fuzzy systems and has faced high uncertainty of the systems. The characteristics of these systems were difficult to describe with fuzzy mathematics or statistics and probabilities. Fuzzy mathematics generally deals with issues that uncertainty can be expressed by experts through discrete/continuous membership functions. Statistics and probabilities also require high distribution and sampling functions to achieve the required validity (Liusif, 2006). Both of these methods require a large amount of data. The main advantage of gray systems theory is the low volume of data required. The theory of gray systems has been proposed as a very effective way to solve problems with discrete data and incomplete information ([34]: 616, [33]: 367).

The theory of gray systems consists of five main parts, which are: gray prediction, gray relation, gray decision, gray planning, gray control. The gray prediction model can be considered as the core of the gray theory (see Fig. 1). The main application of gray theory is in conditions of uncertainty with low data and insufficient information [8,17,18]. The advantage of gray theory over the fuzzy theory is that gray theory includes fuzzy conditions and advantages. In other words, gray theory can be accurate in fuzzy conditions [8]. The use of fuzzy theory requires the recognition of the relevant membership function based on the experience of experts. But gray theory works well without considering the function of membership and the range of information available (Lucifeng, 2006; Lin et al., 2009; [19]). Finally, the main advantages and disadvantages of the gray model prediction method are described in Table 1 below.

3.3. Model development

3.3.1. Standard gray model

In gray prediction models, future values are predicted for a series of time measured in the same time frame. The prediction of these models is based on the latest data set, and all the data used for prediction have positive values, and this sequence of data is constant [16]. The main task of gray systems theory is to derive the relations governing the system, using the sequence of available data. This process is known as the production of the gray sequences (Lin and Liu 1998; Kaikan, 2010). In gray systems theory, the GM (n, m) model is defined as the gray prediction model in which n represents the degree of the differential equation used in the model and m represents the number of variables in the model. The GM model (1,1) is the basis of the classical gray prediction model (Line, 2009). The classic (1,1) GM model is essentially a display model (Shang, 2012). One of the most important reasons for using the GM model (1,1) to predict oil prices can be considered in the simplicity of modeling, model implementation, and also in the use of quantitative time data. As can be seen, a time series has been used to develop the model (1,1) GM, so the variable m, which represents the number of variables in the model, is considered equal to 1. Gray prediction researchers are more likely to use a first-order differential equation to model because they introduce the GM model (1,1) as the main prediction model in gray theory [17,18]. The model linear differential equation is defined as Eq. (1) (Chen, 2010; [20]).

\[
\frac{dx^{(1)}}{dt} + a_1 x^{(1)} = 0
\]

Now, if \( m = 1 \) and \( n = 1 \), the differential equation in Eq. (2) is obtained.

\[
\frac{dx^{(1)}}{dt} + a_1 x^{(1)} = b
\]

These data are subjected to the AGO (Accumulating Generation Operation) of the collector operator to permanently randomize the initial trajectory of the model data for use in the GM model (1,1) ([8,16,21]; Motunrayo et al., 2020). The most important and general procedure in the production process of the gray sequence can be considered as an AGO operator [19]. In other words, the operator displays the pattern of the internal order of the data or the data series process (Van et al., 2009; [22]). \( x^{(0)} \) is considered as the main sequence of data. \( x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \) and after the operation of the AGO operator, the sequence \( x^{(1)} \) is obtained.

\[
x^{(0)}(k) \in \left\{ \sum_{k=1}^{n} x^{(0)}(k), \sum_{k=1}^{2} x^{(0)}(k), \ldots, \sum_{k=1}^{n} x^{(0)}(k) \right\}
\]

The differential equation used in the gray model is different from other differential equations. Other differential equations are used for continuous and differential concepts. But if the gray system can use the discrete data sequence is to build the model. In the sense that concepts
are neither differentiated nor continuous, normal differential equations are used in infinite information environments, whereas gray data sequences belong to finite information space (Van Hyo, 2012). The GM model (1,1) in the gray theory is defined as follows (Van et al., 2009; 23)).

\[
\frac{d x_1^{(0)}}{dt} + a_1 x_1^{(0)} = b_1
\]

(4)

And if \( h = 1 \) and \( N = 2 \),

\[
\frac{d x_1^{(0)}}{dt} + a_1 x_1^{(0)} = b_2 \rightarrow \frac{d x_1^{(0)}}{dt} + a_1 x_1^{(1)} = b
\]

(5)

As a result, the gray differential equation of model GM(1,1) is obtained.

\[
x^{(0)}(k) + a z^{(1)}(k) = b_1 \rightarrow x^{(0)}(k) + a z^{(1)}(k) = b
\]

(6)

The \( a \) is called the development coefficient, and \( b \) is called the gray input factor or the gray control parameter ((36); Imran (24)). The bleached gray differential equation can be generated by these two values.

\[
\frac{d x_1^{(0)}}{dt} + a_1 x_1^{(1)} = b
\]

(7)

The relationship between the gray differential equation and its bleached equation is described in Eq. (8) (19; Nunes (25)).

\[
x^{(0)}(k) = x^{(1)}(k) - x^{(1)}(k-1) \approx \frac{d x^{(1)}(k)}{dt}
\]

(8)

In order to solve and obtain the values \( a \) and \( b \), the sequence of the principal data and the value must be placed in the gray differential equation, thus obtaining the n-1 linear equation ((19); Kirici (27)).

\[
x^{(0)}(2) + a z^{(1)}(2) = b
\]

\[
x^{(0)}(3) + a z^{(1)}(3) = b
\]

\[
\vdots
\]

\[
x^{(0)}(n) + a z^{(1)}(n) = b
\]

The production of the sequel is as follows.

\[
Z^{(1)} = (z^{(1)}(2), \ldots, z^{(1)}(n))
\]

(9)

\[
Z^{(1)}(k) = a x^{(1)}(k) + (1 - a) x^{(1)}(k - 1)
\]

k = 2, ..., n \ a ∈ (0, 1)

Chen usually considers the value to be 0.5 so that the sequence can be considered the sequence of the mean series. Of course, determining and applying different values has been the subject of research for many researchers, and also determining the model for the sequel has led to the presentation of improved gray models which Chen and Chang (2008) stated in their paper that,

\[
\frac{d x_1^{(1)}}{dt} = \lim_{\Delta t \to 0} \frac{x_1^{(1)}(t + \Delta t) - x_1^{(1)}(t)}{\Delta t}
\]

(10)

Linear equations can be converted to the following matrix form [28].

\[
Y = \begin{bmatrix}
\dot{x}^{(0)}(2) \\
\vdots \\
\dot{x}^{(0)}(n)
\end{bmatrix}, \quad B = \begin{bmatrix}
a \\
\vdots \\
a
\end{bmatrix}, \quad \dot{x}_1^{(1)}(t) = \begin{bmatrix}
a \\
\dot{b}
\end{bmatrix}
\]

(11)

The following equation is stated using the least-squares method,

\[
\dot{\theta} = \begin{bmatrix}
a \\
\dot{b}
\end{bmatrix} = (B^T B)^{-1} B^T Y
\]

(12)

The second solution to calculate the values \( a \) and \( b \) is to use multi-sentence equations.

\[
a = \frac{D_{(a-1)F-C}}{n^{-1} F-C} ; \quad b = \frac{DF-C}{n^{-1} F-C}
\]

(13)

Now, by determining the values \( a \), \( b \) of the following bleached equation can be solved.

\[
\frac{d x_1^{(1)}(t)}{dt} + a x_1^{(1)}(t) = b
\]

(14)

And from solving it, the following results are obtained.

\[
\frac{d x_1^{(1)}(t)}{dt} = -a \left( x_1^{(1)}(t) - \frac{b}{a} \right)
\]

(15)

Now, if \( x_1^{(1)}(t) = \frac{b}{a} = a, x_1^{(1)}(t) = x_1^{(1)}(t) = 1 \), the model’s formula is calculated as follows [19,29].

\[
\hat{x}_1^{(1)}(n+1) = \left( \hat{x}_1^{(1)}(1) - \frac{b}{a} \right) e^{-\frac{b}{a}} + \frac{b}{a}
\]

(16)

As can be seen in the above process for model formulation, in this process, instead of using the main data sequence, the sequence generated by the AGO operator is used (Safang et al., 2020). Therefore, it is necessary to introduce a new operator. The reverse operator of IAGO, this operator is equal to,

\[
x_1^{(0)}(t) = \hat{x}_1^{(1)}(t) - \hat{x}_1^{(1)}(t-1) \quad, \quad x_1^{(0)}(1) = x_1^{(1)}(1)
\]

(17)

Now the prediction model of the model using the inverse operator is equal to,

\[
\hat{x}_1^{(0)}(k+1) = \left( \hat{x}_1^{(0)}(1) - \frac{b}{a} \right) e^{-ak} (1-e^a); k = 1, 2, \ldots
\]

(18)

The following formula can be used to predict the “p” step using the initial data sequence.

\[
\hat{x}_1^{(0)}(k+p) = \left( \hat{x}_1^{(0)}(1) - \frac{b}{a} \right) e^{-ap} (1-e^a) e^{-ap(k-1)}
\]

(19)

3.3.2. Improved gray model

After the introduction of the gray prediction model, many researchers have sought to improve these models. Each researcher presented a variety of methods based on the information load in their area of expertise (Saud, 2020). It should be noted that the methods presented by them had better results in increasing the accuracy of predictions. Some researchers have combined gray models with conventional predictive models, such as combining gray models with neural network models or combining these models with genetic algorithms. Some other researchers (Hes et al. and Wong, 2007; Shang-[30]) estimated the model parameters using the business method. Another group focused on the rest of the series. They believed that the efficiency of the GM model

| Advantages | Disadvantages |
|------------|--------------|
| Short term effectiveness | Long term ineffectiveness |
| Lesser statistical calculations | Complex analytic calculations |
| Smaller historical data set size is needed | Inaccurate during the unstable periods |
| Lesser statistical error in the short term | Larger calculation-based errors |
| Simple conceptual model | Inaccurate in the trend change situations |
residual series (1,1) depended on the similarity of the model residual sign, while we know that this event happens very rarely in general ([13,14]; Sifeng and Lin, 2006). Much research has been done to increase the efficiency of the rest of the GM model residuals. Some studies estimate the remnants of the model. In 2003, for example, an article entitled "Improved Gray Prediction Model" was published (Hesso and Chen, 2003; Shaista et al., 2020). In this paper, neural networks were used to estimate the remnants of the model and to predict the energy demand; they used a combination of the residuals and estimated the remnants of the model. In the same year, another article (Hesso 2003) used the Markov chain to estimate the residual mark. An article was published in Taiwan in 2011 (or Shine Lee, 2011). The researchers used a genetic algorithm to estimate the residual sign of the GM model (1,1). They believed that using this method over other methods would increase the accuracy of the predictions. In this paper, a simple linear regression model is used to estimate the residual sign to maintain the simplicity and reduce the calculation cost and the increasing accuracy of the model for short-term predictions. First, a prediction based on the (1,1) GM model is made, and the following model is obtained [32].

\[ r_{GM}^{(0)}(k) = \left( r(0) - \frac{b}{a} \right) (1 - e^{rk(2-k)}) , \quad k = 1, 2, \ldots \]  

(21)

As mentioned, in this model, we use linear regression to estimate the residual signal sign if we consider \( r \) as the error resulting from the processing of the linear regression model and define it as follows (or Shine Lee, 2011; [33,34]).

\[ r_k = X_{data} - X_{estimated,k} \]  

(22)

And based on that,

\[ c(k) = \begin{cases} 1 & \text{if } r_k > 0 \\ 0 & \text{if } r_k \leq 0 \end{cases} \]  

(23)

We come to another function such as Eq. (24),

\[ i(k) = \begin{cases} 1 & \text{if } c(k) = 1 \\ -1 & \text{if } c(k) = 0 \end{cases} , \quad k = 1, 2, \ldots \]  

(24)

Now, based on the application of the models presented in the articles (or Shine Lee, 2011, [13]), we get the following model.

\[ \hat{x}(0)(k) = x_{GM}^{(0)} + i(k) r_{GM}^{(0)}(k) \]  

\[ = \left( \hat{x}(0)(1) - \frac{b}{a} \right) (1 - e^{rk(2-k)}) + i(0)(r(0) - \frac{b}{a}) (1 - e^{rk(2-k)}) \]  

(25)

3.3.3. Model evaluation criteria

In 1989, Martin and Watt noted that in order to compare predictive models, not only must the techniques used in the model be compared with each other, but this comparison also must be made across the predicted data (Hesso, 2001; [35]). According to the mentioned standards, We use three factors, MSE, MAE, and MAPE, to compare the accuracy of the models presented.

\[ MAE = \frac{1}{n} \sum_{k=1}^{n} |\hat{x}(0)(k) - \hat{x}(0)(k)| \]  

\[ MSE = \frac{1}{n} \sum_{k=1}^{n} (\hat{x}(0)(k) - \hat{x}(0)(k))^2 \]  

\[ MAPE = \frac{1}{n} \sum_{k=1}^{n} \left| \frac{\hat{x}(0)(k) - \hat{x}(0)(k)}{\hat{x}(0)(k)} \right| \times 100\% \]  

(26)

Levi’s in 1982 and Delivering’s in 1998 determined four factors to compare the predictive strength of the models with the MAPE and RMSE tools. If these values are less than 10%, the predictive power of the model can be considered as excellent prediction accuracy, and if it is between 10% and 20%, it is a right prediction, and if it is in the range of 20% to 50%, the predictive power is acceptable ([36]; Xiang et al., 2020). And if it is more than 50%, the prediction is inaccurate [35].

### 4. Results and discussion

#### 4.1. Static data analysis

Because it is not efficient to use the usual unit root test in seasonal, monthly, and daily data, such as Dickie Fuller, etc., single root tests such as the HEGY test should be more suitable options and will be used in this paper. The HEGY test is a test for the root of units in any part of the body without preserving that the roots of the unit are present in other non-uniforms. This test is useful for identifying and analyzing possible problems that may arise for statistical inferences [28]. In this test, a single root with zero frequency, a single root with a frequency of 2, and two roots with a frequency of 1 are examined. Table 2 shows the output results of the STATA software.

At this stage, the optimal price of oil is determined. For this purpose, two criteria of business acoustic quartz are used, which confirm the results of an optimal interval. The Heilberg statistical test with zero frequency is 4.35, and the critical value is 3.71, so there is no single root with zero frequency. Also, the statistic with two times frequency is equal to 3.74, and the critical value in the level of 5% is 3.08, so there is no single root with a frequency of 2. Also, the unit root with all effects is equal to 6.82, and the critical value at the level of 5% is equivalent to 6.53, so there is no single root.

According to the Heilberg test, the statistic factor with zero frequency is estimated at 4.31, and the critical value is 5.65, so there is no single root with zero frequency. Also, the statistic with a frequency of 2 is equal to 3.70, and the value of the critical at the level of 5% is 3.04. So there is no single root with a frequency of 2. Also, the statistical value with a frequency of 1 is equal to 4.75, and the critical value at the level of 5% is equivalent to 3.62. Therefore, there is no single root with a frequency of 1. Also, the statistic of a unit root with all the effects is equal to 6.76, and the critical value at the level of 5% is equivalent to 6.46, so there is no single root.

#### 4.2. Implementation of the model

The data used in this study is the daily price data of OPEC’s crude oil portfolio, which is extracted from the official OPEC website (www.opec.org). The implementation of the model is also done using Excel software. In order to implement the model, first, the data related to three consecutive working weeks are used. The first data series used from April/01/2020 to April/21/2020 (three consecutive working weeks) and the second data series from Jan/25/2020 to Feb/07/2020 to evaluate the performance of the model and forecast the short-time oil prices. The data used in the time series of the model process is presented in Figs. 2 and 3. The main advantage of the gray model is its capability to project significantly accurate in short term investigations using the small data sets. In this study, for a one-week projection, a one-week historical data set is used. For example, in a two weeks time period, we have one-week historical data for model development and one-week data to test the projection results.

| Stat | level 5% | level 10% |
|------|----------|----------|
| T(91) | −4.3134 | −3.6729 | −3.3363 |
| T(91) | −3.7055 | −3.0492 | −2.7027 |
| T(91) | −4.7529 | −3.6234 | −3.2472 |
| T(91) | −2.2284 | −1.9404 | −1.4652 |
| F(3–4) | 6.57063 | 6.4845 | 5.3163 |
| F(2–4) | 6.94089 | 6.0291 | 5.0787 |
| F(1–4) | 6.76071 | 6.4647 | 5.6529 |
The estimated parameters of the model with 14-time series data are as follows,
\[a = 0.003530842327, \quad b = 57.2768538, \quad x_{k+1}^{(0)} = 57.69168.e^{-ak}\]

According to the structure of the prediction series model and the residual series starts from the second set of data. Therefore, the prediction series and the residual series are calculated and presented in Figs. 4 and 5, and Table 3.

As mentioned earlier, three standard and efficient criteria are used to measure the accuracy of the model. In this study, in order to evaluate the performance of the model, the process series and model testing are evaluated separately. The values of these three criteria for the model are presented in Table 3.

![Fig. 2. first data series from April/01/2020 to April/21/2020 (three consecutive working weeks).](image)

![Fig. 3. second data series from Jan/25/2020 to Feb/07/2020 (source: by the author(s)).](image)

| Corresponding date | k | Projected | Error |
|--------------------|----|-----------|-------|
| 25-Jan              | 1  | 61.81669927| 0.008303593|
| 26-Jan              | 2  | 63.02376233| -0.013546674|
| 27-Jan              | 3  | 61.39062772| 0.009600362|
| 28-Jan              | 4  | 60.04591535| 0.010393457|
| 29-Jan              | 5  | 61.13575935| -0.001566339|
| 30-Jan              | 6  | 59.83626131| -0.017318283|
| 31-Jan              | 7  | 59.23093825| -0.00491193|
trend and test series are:

\[
\begin{align*}
MSE &= 0.0971, \quad 0.0995 \\
MAE &= 0.2431, \quad 0.2563 \\
MAPE &= 0.0021\%, \quad 0.0025\%
\end{align*}
\]

At this stage, in order to implement the model, we use data related to two consecutive working weeks (second data set), and finally, we compare the results of the implementation of the model using three consecutive working weeks (first data set). The model parameters of the estimations for the first data set is measured for the first data set and are as follows:

\[
a = 0.003530842327, \quad b = 19.336, \quad x_k^{(0)} = 19.78124e^{-ak}
\]

Oil price and model residuals are calculated and presented in Figs. 6 and 7 and Table 4 using the estimated model parameters.
The calculated amounts for the first data set (source: by the author(s)).

The estimated amounts for the model development set of first time series test (source: by the author).

| Corresponding date | k  | Projected | Error       |
|--------------------|----|-----------|-------------|
| 25-Jan             | 1  | 16.90954672 | -0.00353393 |
| 26-Jan             | 2  | 18.70022918  | 0.01109316  |
| 27-Jan             | 3  | 22.22143856  | -0.00918898  |
| 28-Jan             | 4  | 23.52779564  | -0.01121228  |
| 29-Jan             | 5  | 23.52779564  | -0.000804608 |
| 30-Jan             | 6  | 23.52779564  | 0.01363957  |
| 31-Jan             | 7  | 22.92418237  | -0.001131065 |

Table 4

Also, the estimation for an extended period in 2000–2020 using the gray prediction method is done, and the results of the model are presented in Figs. 8 and 9.

The evaluation criteria of the model process and the test are equal to,

\[
\begin{align*}
MSE &= 0.4967, \quad 0.4478 \\
MAE &= 0.5234, \quad 0.4876 \\
MAPE &= 0.05922\%, \quad 0.05112\%
\end{align*}
\]

As can be seen, in order to predict the price of OPEC crude oil basket, it is better to use data related to three consecutive weeks of work, because the criteria for evaluating the performance of the model for three consecutive working weeks (first data set) have lower values and the trends are more similar in their behavior, which makes forecasting more accurate. In the real world, a series of data closer to the time of prediction provides more and better information for the prediction model. Therefore, it is suggested that to use the gray forecast model in the short term, to predict the price of OPEC crude oil portfolio, the time efficiency of two-three weeks should be used instead of the long-term

The evaluation criteria of the model process and the test are equal to,

\[
\begin{align*}
MSE &= 0.0865, \quad 0.0837 \\
MAE &= 0.2134, \quad 0.2086 \\
MAPE &= 0.0017\%, \quad 0.0016\%
\end{align*}
\]
periods. This fact can be seen clearly in the results of the gray method for the long term in Fig. 8, in which the residual of the process is estimated at more than 120% for 2020 and also the evaluation criteria is evaluated (>0.5) that means the estimation is not accurate.

4.3. comparison with the other methods

To compare the performance of the main techniques of prediction with the gray prediction method, an article entitled “Combination of neural network models and fuzzy regression to predict time series” has been used (Khastieh, 2008). The author of the article uses six models to predict the time series, as described in Table 5.

The gray prediction model can be considered as the core of the gray theory. The main application of gray theory is in conditions of uncertainty with low data and insufficient information [8]. The advantage of gray theory over the fuzzy theory is that gray theory includes fuzzy con-

Table 5
Accuracy evaluation criteria comparing the gray model with the other prediction models (source: by the author(s)).

| Model                                           | MSE  | MAE  |
|------------------------------------------------|------|------|
| ARIMA                                          | 0.1225 | 0.2310 |
| Chen’s fuzzy time-series (first-orderer)        | 0.8362 | 0.6534 |
| Chen’s fuzzy time-series (second-orderer)       | 0.7929 | 0.6424 |
| Yu's fuzzy time-series                          | 0.8362 | 0.6534 |
| ANNS                                           | 0.0865 | 0.3740 |
| Gray method (results of the first short-term data set) | 0.0865 | 0.2134 |
ditions and advantages. In other words, gray theory can be accurate in fuzzy conditions [8]. The use of fuzzy theory requires the recognition of the relevant membership function based on the experience of experts. But gray theory works well without considering the function of membership and the range of information available (Lucifeng, 2006). Also, the gray theory is more accurate in the short-term analysis of the markets. Especially in the oil market, accurate short-term predictions are required since the oil is effective in every aspect of the economy. To get a better overview of the accuracy of the different methods, they must be investigated in the term of length of their investigation period. Fig. 10 shows the results of projection (calculated for 2018-2019) for 14 to 364 days long periods, and the MAE factor is calculated for different methods. This figure clearly illustrates the capability of the Gray model in the short-term predictions.

Fig. 10 shows that the gray model is significantly accurate comparing to other traditional projection methods in the short-term projection periods. The gray method is the most accurate projection model in 14-64 days of investigation periods. ARIMA is the second most accurate method in the short term investigation, is the most accurate method for the 64-114 days investigation period. And for the 114-364 days period, ANN is the most accurate projection method. Results state that the fuzzy method is not suitable for the short term projections, and it can be used for more than 364 days of investigation periods. Figs. 11(a)–(j) illustrate the implementation of different projection methods in the first two weeks of 2010–2019 for a better comparing between ARIMA, fuzzy, ANN, and gray methods. Results show that the gray model was the most accurate method in all of the projections done in Figs. 11(a)–(j).

4.4. Discussion

The main goals of this paper were to introduce a novel prediction method suitable for short-term oil price predictions, which are defined and presented in the methodology and previous three sub-sections of the results and discussion section. In this section, the main goal is to answer the following questions:

• Why short-term oil price predictions?
• What is happening to the oil market?

• What are the applications of these short-term predictions?

To answer the mentioned questions, first, we have to discuss the oil price economic impacts.

4.4.1. Oil price impacts on the gross domestic product

Coronavirus spread, and the tensions in the middle east significantly changed the petroleum market in late 2019–2020. Most of the prior general economic equilibrium models and scenarios planned are based on the increase in oil prices due to the growing population and industrial demands. Timilsina [11] studied the impacts of 25%, 50%, and 100% increase (comparing to 2010) in the global oil price by 2020. The results show that the leading oil producers would enjoy a 0.7 to 1.0% increase in their real GDP, but the economies of the oil costumers would be damaged from 0.2% in Russia to 3.1% in India. The 100% increase in the oil price would decrease by 1.86% of the global GDP by 2020, and if the rise in the oil price had continued to grow, the GDP of the world would be gravely damaged by 2030 [11].

While the Gross domestic product of the world (size of the economy) is expected to be dropped by the rise of the oil price, but all of the regions and the countries will not face a similar and uniform trend. For a 50% increase in the oil price compared to the reference year 2010, Timilsina [11] states that the GDP reduction would be smaller than 1% in most of the developed countries. However, this GDP loss would be higher and more harmful to the economies of developing countries like China and India. This more significant damages would be caused because of the oil intensive production and manufacturing industries that hold a more significant share from the overall size of the economy [26,37]. Although a vast majority of the countries would be damaged by the oil price increase, it would be entirely different for the Middle East and the North Africa (MENA) countries, since most of them are net oil exporters and they would be enjoyed by a 0.7–1.0% increase in their GDP (Xu et al., 2020).

In other to discuss the impacts of the oil price on the economy, some parameters must be taken into account, and these parameters are varied from country to country, and it is the reason why the oil price changes affect countries differently. The most critical factors are the oil intensity of the economy (total oil consumption per capita of GDP) and the
import dependency (an energy security factor which is determined by the energy portfolio of each country). The economic indicators illustrate that the oil intensity is the most crucial factor in the term of the oil price impacts on the economy. For example, the oil price impact on France, Spain, Germany, and Italy despite their complete dependency on the oil import is relatively low compared to China and India which have their oil sources and this fact notes the greater importance of the oil intensity on the economic status of each country in the term of the oil price change (Xiang et al., 2020; [38]).

The oil price drop is not a global issue, but it can be fruitful for most of the countries throughout the world. However, its impacts on the oil producers and exporters can be severe and significantly affect their economies if the share of oil export is significant in the overall GDP of those countries. As a case, the impacts of the early 2020 oil drop will be studied and discussed for the USA in this section.

The oil industry in America had a total of 1.5 million jobs in 2019, but more than 945,000 of those jobs are in the downstream, and services related to the energy and oil price changes will not increase the risk of losing their jobs. Oil and gas extraction, exploration, and pipelines are accounted for 471,000 jobs, while refineries are accounted for 69,000 of those jobs. The first sign of the oil price drop in the USA will be in the Wallstreet as oil stocks will be plunged along with the oil price, and this may decrease the mean stocks index. The severe oil price drops intensify because no major oil producer would reduce its production to save its market share, and this will cause more price to drop (Xu et al., 2020). There is a significantly important fact in the USA economy which is the

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**Fig. 11.** implementing Gray, ANN, ARIMA, Chen fuzzy methods for two weeks investigation period (1-Jan to 14-Jan) (a) for 2019 – (b) for 2018 – (c) for 2017 – (d) for 2016 – (e) for 2015 – (f) for 2014 – (g) for 2013 – (h) for 2012 – (i) for 2011 – (j) for 2010.
little share of the oil and gas industry from the US economy (1.7% in 2019 and this means that the oil industry is not that important for much of the investors and stockholders comparing to 80 s or 90 s in which ExxonMobil was the most valuable company in the world not Amazon or Apple in 2020. An in-depth structural analysis is needed, but in the more oil-dependent economies such as MENA countries, the oil price drop can be crushing, which states the need for economic reforms in those regions to analyze the oil drop impact on the economies [32].

4.4.2. Reasons for oil price changes

There are three reasons that oil price changes:

1. Decrease in Demand
2. Increase In Supply
3. Power struggles

In the oil price drop of early 2020, the COVID-19 and power struggles played the critical roles of sth that is mentioned to be the fall of the oil age. The slow down of the world economy due to the COVID-19 and the people’s responses to the pandemic situation sounded the first bell and started what would be known as the most significant oil drop in the history of the oil market. The economic slowdown causes a decrease in the demand for oil [26]. This decrease starts the oil price reduction, and in the time of the oil price reduction, unlike other ideal free markets oil market cannot respond quickly and decrease the amount of oil production since there are technical limitations in the oil market. Different characteristics of the crude oils around the world make it hard to be replaceable with another type of oil since the refineries can work with a particular type of crude oil resource unless a significant investment cost is made to switch the facilities to another crude oil type [23]. This fact caused that the oil-exporting countries continue to produce to keep their share of the market even at the very low prices, which have been detected for the first time in the 21st century in April 2020 for West Texas oil and Brent oil prices. The oil price drop intensifies the struggles between the oil-producing countries, and this struggle makes the situation worse than before (Ruso-Arabian Price War 2020), which led OPEC oil price to below the 20$/bbl in April 2020 (lowest since 2000–2001). Considering the mentioned facts about all of the oil price changes, the black plague and black gold trends of oil, which show oil price drop and oil price increase respectively, are shown as follows [26].

Figs. 12 and 13 show that the relationship between the oil producers is the most effective factor in the oil price change, which controls the other two factors.

4.4.3. future of the oil industry

Norouzi et al. [26] examine the future of the world’s oil industry by 2040 in three scenarios, in which we analyze two (best and worst cases) in this paper. The future of the oil industry will be discussed in the term of three main factors of the oil supply, oil intensity, and the future economic status of the industry. The economic situation is one of the essential factors of these scenarios and is an uncertain part of the oil industry’s foresight planning. Best case scenario “The true me” assumed firm cooperation between the leading oil producer, which, according to Fig. 13, leads to the blooming of the oil industry [26]. The worst-case or “the death of unity” scenario assumes tensions and conflicts between leading oil producers, especially in the MENA region. This conflict between China and Russia supported Iran, and US-supported Arabian countries will cause a 2–3% decrease in the real GDP growth of the region and about a 1% decrease in the global economic growth rate. The GDP growth is profoundly affected by different aspects of the conflict or cooperation situations (as it was mentioned in Figs. 12 and 13). “True me” assumes an increase in the share of the non-governmental economy in the oil industry of the net exporters, and this event causes less political market in the oil industry, which can significantly help to active cooperation [22]. This event stabilizes a moderate increase
Fig. 12. the schematics of the drop in the oil price (source: by the author).

Fig. 13. the schematics of the controlling and possible increase of the oil prices (source: by the author).
in economic status and good growth in the oil market and reasonable prices (expected to be around 40$/bbl). “Death of unity” scenario assumes conflict between net oil exporter countries, and this lack of efficient cooperations will drop the oil price and makes a significant share of the oil extraction industry infeasible to be produced. This infeasible part cannot sustain for a long time in a falling price situation, and soon a share of oil supply will be cut off. The oil price will be unstabilized and lack of sustainable oil supply forces central oil-importing countries move toward the more secure alternatives such as renewables, nuclear, solar fuel, etc. this event is called “fall of the oil age” and will permanently decrease the oil demand and the oil prices fall and stabilized in the dirt-cheap prices (estimated 4–10$/bbl). The low level of the oil price in the long-term makes a more significant share of the oil industry infeasible (US shale oil is feasible in the prices more than 22.1$/bbl), and this will significantly decrease the oil supply steadily [3].

4.4.4. destination of the current situation

Current oil events in the oil industry show that “death of unity” scenario is played by the key role players in the oil industry. This scenario leads to an imminent fall of the oil industry in the mid of the 2020s [26]. Also, the oil industry will be unstable during this period, and conventional oil price forecast and projection methods cannot provide accurate results for the strategists and policy-makers in this industry. Therefore, the short-term gray system prediction analysis is suggested for the short-term studies and projections of the oil industry to help the shareholders and policy-makers to plan for the short-period aims of the market [2]. Although the long-term analysis is not recommended for the current trend of the oil market, the accuracy of the oil projection can be increased using some innovative mathematical performances developed for the gray prediction method (DGPM). In this method, the long-term prediction is estimated using the constant short-term forecasts. This method is more accurate than the single-phase
long-term forecasting, and also the step-wise short time predictions are far easier to be controlled. Also, in each step, it is possible to enter the significant events that occurred or predicted in a term of disruption to the differential equation, which significantly increases the accuracy of the model. Fig. 14 presents the flowchart of the DGPM.

The algorithm mentioned in Fig. 14 is used to project the oil price for 52 weeks from 18 April 2020, to 18 April 2021. The results presented in Fig. 15, show that the oil price will be unstable in the following weeks remaining to the USA presidential elections, and after the elections, if the current trends continue, the oil prices will fall regularly and stabilized around the 6–10 $/bbl.

5. Conclusion

The rapid growth of technology and the globalization of financial markets and the strategic importance of commodities such as oil have multiplied the need for accurate and efficient forecasting of oil prices. Due to the rapid changes in the economic, political and social environments in oil-producing and consuming countries, it has made it difficult for forecasters to obtain the necessary data in order to obtain effective research results, and because of the social, economic and political conditions today, the time series has become very difficult to predict prices in financial markets, so researchers are looking for models to predict with lesser need for data and higher accuracy. One of these models, which is more widely used in interdisciplinary scientific environments today, is the gray model. This group of predictive models does not require complex and difficult mathematical calculations or complex computer programming compared to other conventional predictive models but provides acceptable results. This advantage of gray models has led to the application of these models. From the results of the present study, we can point to the compatibility and consistency of the results of this study with the usual studies and methods of predicting oil prices, such as regression and neural networks. One of the most important features of gray models is forecasting in environments with uncertainty conditions and lack of sufficient information about how the forecasted system works and running the model with a limited number of data. Given these conditions, oil markets are among the most prominent financial markets that can be classified as gray systems.

The results of this study indicate that to predict oil prices in the short term has better results than the long-term predictions. This confirms the claim of gray prediction researchers that it is better to use gray prediction models that require fewer data in order to predict oil prices. Because of a smaller number of data series, which is closer to the prediction time of the model, can contain more useful and practical information for modeling. Based on the results of the model evaluation criteria, it can be claimed that, as the gray prediction researchers suggested, the results of the present study showed that the use of the developed gray prediction model (DGPM) leads to more accurate results in the long-term predictions. As mentioned, we use MSE and MAE criteria to compare and evaluate gray models and the other models provided by the literature of this field. From the results, it can be seen that the accuracy and efficiency of the gray models can be better in some systems at the same level. However, it should be noted that this conclusion can only be expressed about the gray systems (i.e., oil, gold, and stocks market), and for a more comprehensive conclusion, it is necessary to examine other different systems in the future studies.

Declaration of Competing Interest

None.

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