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Designing a model for financial forecasting using the integration of neural networks with the Box-Jenkins and Holt-Winters methodologies

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Abstract

The present study designs a model for financial forecasting by integrating neural networks. This retrospective comparative study uses the average price data of OPEC oil from 2003 to 2022 to forecast the period from June 2022 to May 2024. To this end, two time-series models (Box-Jenkins and Holt-Winters) were examined, which in the second stage were incorporated into a hybrid model based on artificial neural networks. The neural network model was developed using Matlab, and the Box-Jenkins time-series model was constructed using SPSS and Eviews software. Based on the results of the error analysis of the Box-Jenkins methodology, among the time series processes ARIMA(5,1,5), ARIMA(4,1,5), ARIMA(3,1,5), and ARIMA(5,1,3), the models demonstrated the best accuracy with MSE values of 61.86, 63.21, 63.29, and 63.62, respectively. The accuracy of the Holt-Winters method was not suitable for time-series forecasting due to the nature of the data. Therefore, the best artificial neural network was designed for combining forecasting methods. This neural network included an input layer with 5 neurons, a hidden layer with 5 neurons, and a single-neuron output layer. The network was trained using the Levenberg-Marquardt algorithm and employed a linear sigmoid activation function. The results indicated that the designed hybrid neural network significantly improved the accuracy of the forecasting methods and enhanced the MSE, MAPE, AIC, and BIC indices.

Keywords: forecasting, neural network integration, time-series models, Box-Jenkins methodology, Holt-Winters
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1 Introduction

Forecasting is a science because the researcher must act systematically at all stages, from understanding the problem and analyzing data to research methodology and critical reasoning. On the other hand, future studies are considered a type of science because the findings of futurists can be transformed into various forms of social and economic values [6]. Forecasting methods have always been an important tool in the hands of futurists [5]. Researchers have published complex forecasting techniques related to various fields of mathematics, statistics, and artificial intelligence. Since World War II, scientists, sociologists, operational research professionals, and many other academics who consider themselves futurists have established and expanded quantitative and qualitative methods to

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make rational future predictions [19]. Quantitative forecasting methods can be divided into two main categories: those based on mathematical knowledge and those based on intelligent systems. Each category has its own advantages and disadvantages. Forecasting plays a crucial role in management and future studies, serving as a tool for projecting the necessary parameters and variables within a system boundary. The forecasting process provides the information needed for decision-making and scenario planning. It is considered an essential tool for strategic decision-making among managers and decision-makers [2].

Forecasting methods are utilized in various economic and social fields, with significant applications in analyzing and forecasting energy systems. Energy is considered one of the main pillars of development and progress for human societies, which is why it holds strategic importance in international relations [10]. In this context, energy has become a prerequisite for achieving development programs in different countries. It is a fundamental component of any industrial society; without sufficient, efficient, and accessible energy, industrial development is inconceivable [9]. Currently, energy, particularly oil, serves as a foundation of global power and wealth, playing a crucial role in determining countries' positions in the hierarchy of global power and wealth [23]. Oil is a substance that underpins most economic and industrial activities due to its significant role. Consequently, the demand for oil and its fluctuations (increase or decrease) in international markets can lead to changes in the prices and demand for other goods and services. Therefore, examining the trends in oil demand changes among OPEC member countries, identifying the factors influencing their crude oil demand, and making efforts to predict it are of particular importance. Since 1970, when energy drew the attention of policymakers due to the first oil crisis, the study and research on energy demand have significantly increased to overcome the limited knowledge regarding the nature of energy demand and its response to external shocks. Since then, the dynamic and active discussion among engineers and economists in the energy field has led to significant developments in methods to enrich the energy decision-making process as a whole. A wide range of models has been developed for analyzing and forecasting energy demand, which has become available to researchers [3]. Forecasting energy demand is essential for energy planning, strategy formulation, and defining and recommending energy policies. This is not only necessary for developing countries, which face challenges related to data availability, institutional capacity, and appropriate models, but it also constitutes a fundamental component for developed countries, where these limitations are less pronounced [17]. Therefore, in recent years, numerous studies have been conducted in the field of energy price forecasting using modern computational techniques to overcome issues related to the nonlinear and volatile nature of energy demand and its explanatory variables [14].

Thus, studying and developing forecasting methods for OPEC oil prices is of great importance. In this research, we aim to present a model to improve the accuracy of global OPEC oil price predictions using artificial neural networks combined with advanced statistical methods. Accuracy and enhanced performance of forecasting methods have always been a concern for experts and managers in the forecasting field. Forecasting results can serve as a basis for decision-making if they demonstrate adequate accuracy and correctly identify the underlying data structure. The more accurate the forecast-based planning, the more likely an organization will succeed and achieve its objectives. Conversely, inaccurate forecasting can lead an organization away from its goals [16]. To this end, experts have published complex forecasting techniques. Today, phased and combined approaches are considered the latest strategies for forecasting variables. Experts believe that a more accurate model can better simulate complex market conditions. However, advanced forecasting techniques are only useful when applied within the decision-making and planning processes of organizations. Improving the accuracy of many oil price forecasting models requires identifying all trends, variables, and strategies impacting international oil markets. As we know, the oil pricing system is highly complex and opaque, so providing a model that enhances forecasting accuracy in this area is of great importance. This research holds significance and necessity from several dimensions, as it is, for the first time, using a multivariate neural network as a tool to enhance accuracy. In previous studies, the multivariate neural network was used only as a forecasting method, where independent variables were regressed on the dependent variable. However, in this study, the artificial neural network is used as an accuracy-enhancing tool, with its inputs being forecasted values generated by time series methods, univariate artificial neural networks, and the Holt-Winters method. Additionally, the primary predictive models in this research include four models based on the Box-Jenkins methodology with appropriate accuracy and the Holt-Winters model. For the first time in a study, '56 models' are assessed for accuracy simultaneously. No prior research has been analyzed with such a variety and number of methods. One of the key criteria determining the accuracy of a forecasting method is the nature of the data. In this study, the methods and models are not tested on a single data series; instead, data from products with varying data characteristics are utilized, and the results from each are evaluated. Previous studies often limited their scope to forecasting and presenting predicted values. However, this study, by staging and combining methods, not only achieves high-accuracy forecasts but also introduces an approach for enhancing accuracy. A critical factor influencing the accuracy of artificial neural network-based methods is the training applied to the neural network. This research also assesses the impact of training on neural network accuracy. In time series forecasting using ARIMA, researchers typically select the best forecasting equation by examining correlation and partial correlation structures. However, in this study, for the first time, four-time series models are identified by comparing the errors of each forecast. No accuracy improvement method has been used previously to enhance OPEC crude oil price forecasts, and this study introduces an accuracy-improving model in this context. Based on the discussion of forecasting methods, the main research question is to what extent an artificial neural network, when combined with the OPEC crude oil price forecasting process, can improve the accuracy of forecasts generated by the Box-Jenkins methodology and Holt-Winters method.

2 Research background

2.1 The concept of forecasting

Each quantitative or qualitative forecasting technique has its drawbacks, and foresight seeks to align forecasting results more closely with reality by applying the influence of qualitative forecasting techniques on the outcomes of quantitative methods. Foresight can be applied in all fields where forecasting the future of complex variables, such as price, supply, and demand, is important. Energy-related data, due to its volume, is well-suited to numerical methods such as time series and trend lines. However, due to the particular significance of the subject, numerous experts engage in qualitative speculations and forecasts in the realm of energy foresight [6]. Rationality and scientific rigour have guided forecasting in two distinct directions. The first approach involves utilizing past and present knowledge, identifying patterns, processes, algorithms, and frameworks of change, and then predicting the future. This approach, relying on historical data, primarily seeks to find patterns in data flows with accurate changes and subsequently forecasts the future with high precision. Techniques associated with this approach include all econometric techniques, trend lines, and time series methods. All these forecasting methods fall under non-surprise methods, meaning they never expect events to occur that haven't happened in the past, and they always predict the future based on past patterns [12]. The second approach takes a qualitative stance on forecasting. This approach posits that in many scientific fields, the forecasted parameter depends on a large number of factors, making it impractical to identify all of them, and these factors don't follow a comprehensive, precise pattern. The objective of future studies is to bridge these approaches. In the first phase, quantitative techniques are relied upon as much as possible, and then the obtained outputs are analyzed with the insights and intuition of field experts, thus addressing the inaccuracy of purely qualitative methods. This also increases the adaptability of quantitative techniques to unprecedented events, moving away from a non-surprise state. One of the fundamental goals in estimating a regression model is to be able to predict changes in the endogenous variable using a certain amount of the exogenous variable. Prediction is a process that estimates a variable for the past or future using an objective or subjective model. To predict a variable, it is necessary first to forecast it within the sample and select the best method. Then, based on the best model, the variable is predicted for the future. Prediction is generally divided into two categories: in-sample prediction and out-of-sample prediction. In in-sample prediction, the variable of interest can be estimated based on a mathematical or qualitative model and then compared with the actual variable. This assesses the predictive power of the models; however, out-of-sample prediction estimates the variable of interest for future or past periods (outside the sample). Prediction of a variable can be done in two ways: prediction using objective models such as mathematical, statistical, and econometric models; and prediction using subjective models such as Delphi methods, expert opinions, and the use of experiences and knowledge from experts. In the subjective method, there is no need to present a mathematical model, and the variable of interest is estimated qualitatively; however, for predicting economic variables, that is, to approximately estimate an economic variable in the future, mathematical and statistical models are typically used. In other words, presenting a model is essential in the objective method [5].

2.2 Neural network prediction methods

For more than twenty years, artificial neural networks (ANN) have been recognized as a general numerical tool with various applications. McCulloch and Pitts introduced the fundamentals of the ANN model in [8] to solve a numerical problem in a way similar to how the human brain solves it. Their paper showed remarkable results, indicating that with a suitable combination of simple processing units, the ANN model is capable of computing any computable function [15]. Following this claim, methods using neural networks began and progressed.

To understand how ANN is recognized, we first provide an introduction to the human brain. The biological brain is a powerful processor capable of performing physical tasks like pattern recognition in a very short time. Studies in neuroscience regarding the human brain indicate that this powerful function begins with a series of basic components called neurons, each of which is connected to other neurons through complex relationships [13]. ANN can intelligently discover the relationships between independent variables in training data during the training process. The ANN model is also capable of influencing other observable characteristics of the model, such as error tolerance and the time taken to obtain the input-output relationship [11]. The successful application of ANN has been frequently observed in various cases. Most applications of ANN are related to prediction and function estimation. Short-term price forecasting is an example of this application, where a nonlinear function is estimated. Artificial neural networks are particularly used in pattern recognition. Extensive research has been conducted on defining handwriting for individuals who are deaf and mute. Other areas of application for ANN include robotics, speech recognition, signal processing, optimization, and control systems.

2.3 Time series forecasting based on the Box-Jenkins methodology

The objective of time series analysis is to describe, explain, and forecast the future values of a process. Describing the process includes plotting data, detecting its stationarity or non-stationarity, and examining the autocorrelation of the series. Forecasting involves estimating future values of the series based on observed data. Time series can be divided into two types: stationary and non-stationary series. A series is considered stationary when there are no regular changes in its mean and variance, and any seasonal variations have been eliminated. Non-stationary series can be transformed into stationary series by differencing or stabilizing their variance. The changes observed in time series can result from natural factors or other influences, and therefore, it's essential to identify and measure the underlying components. A time series model typically consists of a random process that includes N observations, which represent an infinite population of random occurrences. The primary goal of time series analysis is to find a model for these variations and predict future values. The purpose of forecasting in time series is to estimate values from a dataset that are unknown at the time of analysis. One of the forecasting techniques for time series behaviour is the Box-Jenkins method. The foundation of the Box-Jenkins approach to time series forecasting is based on a wide range of predictive models for a time series. The general group of models in the Box-Jenkins methodology consists of integrated autoregressive and moving average models, known in statistics as ARIMA models. The time series model is expressed in the form ARIMA(p, d, q), where p determines the autoregressive order (AR), indicating the dependence of a current element on previous effective values. In this model, the regression of each element is determined based on its previous values. The autoregressive process is useful for expressing states in which the current value of the time series depends on its previous values plus a random coefficient. The q parameter also determines the order of the moving average, which defines the dependency of the series on current and past random elements. The combined autoregressive model with a moving average of order (p, d, q) is represented as follows. The construction and forecasting of time series models involve four stages: pattern identification, parameter estimation, model validation, and forecasting.

2.4 The Holt-Winters exponential smoothing methods

In this research, the Holt-Winters exponential smoothing method has been used, which differs from the simple or double exponential smoothing methods in that the simple or double method has a single constant parameter in the equation, whereas the Holt method employs two parameters, α and β. This method is used for time series with a linear trend and non-seasonal series. The general form of the Holt-Winters model is represented in Equation (2.1).

$$\hat{Y}_{t+k} = a + bk \tag{2.1}$$

where a and b are components of the permanent factors. These two coefficients are defined by Equations (2.2) and (2.3).

$$A(t) = \alpha yt + (1-\alpha)(\alpha(t-1) + b(t-1)) \tag{2.2}$$

$$B(t) = \beta(a(t)–a(t-1)) + 1–\beta b(t-1) \tag{2.3}$$

where $0 < \alpha, \beta, \gamma < 1$ are the adjusting factors. The forecasts are calculated using equation (2.4).

$$Y_{t+k} = a(t) + b(t)k \tag{2.4}$$

These forecasts are used in a linear trend with an intercept $a(T)$ and a slope $b(T)$.

2.5 Experimental backgrounds

Tan et al. [15] developed a hybrid method utilizing three individual methods—wavelet transformation, ARIMA, and GARCH—for forecasting electricity prices, which improved the accuracy of the predicted values. Similarly, Li et al. [7] employed three different methods, including artificial neural networks with backpropagation algorithms, growth-based models, and logistic models, to study gasoline demand. These models were evaluated based on goodness of fit and forecasting accuracy. Subsequently, the combination of these methods was assessed, and the results showed improvements in measurement indices of accuracy.

Chen and Guo [1] utilized a combination of gray models and Markov chains to enhance the forecasting of financial crises. Their research findings indicated that the integration of these two methods could improve the prediction of financial crises. Xue et al. [20], considering the complexity and nonlinear characteristics of the Chinese energy consumption system, proposed a combined model using neural networks, gray forecasting, and time series based on historical data on Chinese energy consumption. By applying the standard deviation method, they assigned appropriate weights to each method. The results showed that this combination could better forecast energy consumption in China over the next six years. Hezhabr Kiani et al. [4] utilized a two-stage method in their article to estimate taxes from gasoline. Initially, they estimated the tax base using gasoline demand functions and then applied the relevant tax rate to this estimated base to derive the desired value-added tax. For estimating and forecasting the trend of gasoline consumption in the country, they employed a combined ARIMA and neural network approach. Wang and Meng [18] highlighted the advantages and disadvantages of both linear and nonlinear time series methods in their article, where they predicted energy consumption in China for the upcoming period using artificial neural networks, as well as a combination of these two models. The evaluation of the performance of these models indicated that the combined model had a greater impact on improving the results of energy consumption forecasting during the study period. Zhao et al. [22] focused on combining electricity consumption forecasting with variable weights updated by a high-order Markov chain model. They evaluated the effectiveness of their approach by comparing it with several existing models. The results indicated that the combined method demonstrated greater accuracy compared to SARIMA, LSSVR, ARIMA, and BPN methods.

2.6 Research questions

1. What is the accuracy of forecasting methods based on the Box-Jenkins methodology for predicting OPEC crude oil prices?
2. Among the models based on the Box-Jenkins methodology, which model has higher accuracy?
3. What is the accuracy of the Holt-Winters forecasting method for predicting OPEC crude oil prices?
4. Among the Box-Jenkins forecasting methods, which one has higher accuracy in predicting OPEC crude oil prices: Box-Jenkins or Holt-Winters?
5. What is the appropriate design for neural networks to achieve high accuracy in forecasting?
6. To what extent does creating a second stage of forecasting and combining forecasting methods improve the accuracy of forecasting methods?

3 Research methodology

The present research is descriptive and analytical of a comparative type, focusing on predicting the future using historical data. The method of data collection for this study is field-based, utilizing global statistics on OPEC crude oil prices. The data obtained from crude oil prices will serve as a basis for future predictions. The tool for data collection is a checklist of monthly time series prices of OPEC crude oil, which will be obtained from the OPEC website. The geographical scope of the research pertains to the economies of certain countries and utilizes statistical data on OPEC oil prices reported by the OPEC organization. The information used in this study includes 250 monthly data points of OPEC oil prices up to the year 2021. It is worth noting that the monthly data reflects the average prices for each month. The required statistical data has been collected through library methods. To process the information, software such as Eviews, Matlab, and Games has been utilized. This research has been conducted in two stages, as illustrated in Figure 1. In the first stage, the monthly time series data of OPEC crude oil prices has been obtained. The obtained data was then used for forecasting. In this stage, if there were any missing data points, the nearest neighbour method was utilized. Forecasting in this stage was performed both in-sample and out-of-sample. The methods employed in this section of the research included time series based on the Box-Jenkins methodology, Holt-Winters, and univariate ANN (Artificial Neural Network). After forecasting and assessing the accuracy of each forecasting method and the predicted values for both in-sample and out-of-sample, the second stage was conducted to combine the forecasting methods. In this stage, the predicted values were entered as independent variables into the multivariate ANN and regressed against the actual values.

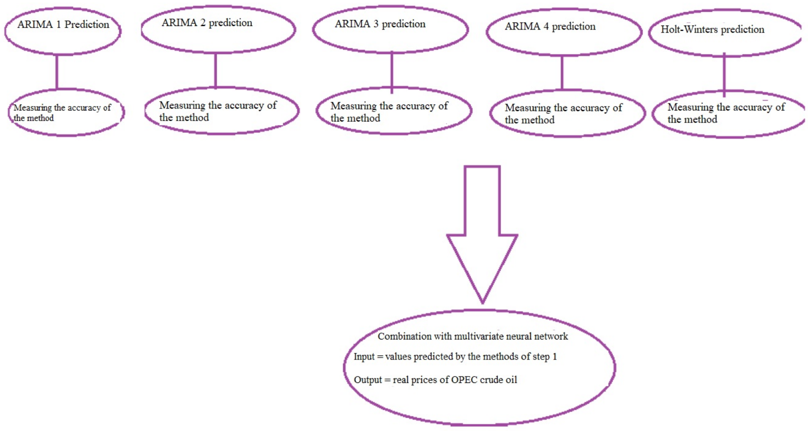

Figure 1: Steps of conducting research

4 Research findings

4.1 Forecasting or time series based on the Box-Jenkins methodology

4.1.1 Data stationary test

The main point in time series models is that if the series used in the model are non-stationary or exhibit a trend, the results obtained from the model will not be valid. Therefore, before estimating the proposed models, it is essential to first test the variables for stationarity and then select the appropriate form of the variables in the model based on the results obtained. The Dickey-Fuller test is utilized to determine the stationarity of the variables. The results of this test are presented in Table 1.

Table 1: Dickey-Fuller test for the data used in the research

Data	T statistic before differentiation	Dickey-Fuller test statistic before differentiation (critical value at the 5% level)	Differentiation order	t statistic after differentiation	Dickey-Fuller test statistic after differentiation (critical value at 5%)
Oil price	1.021	1.5146	1	5.1678	3.5107

In this test, if the absolute value of the T-statistic is greater than the critical values, the hypothesis of the time series being stationary is confirmed. As seen in Table 1, the time series data for oil prices becomes stationary after first differencing.

4.2 Diagnosis based on the Box-Jenkins methodology

After stabilizing the data, the appropriate model for the data is identified using the shapes of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). The ACF and PACF of oil prices are shown in Figure 2.

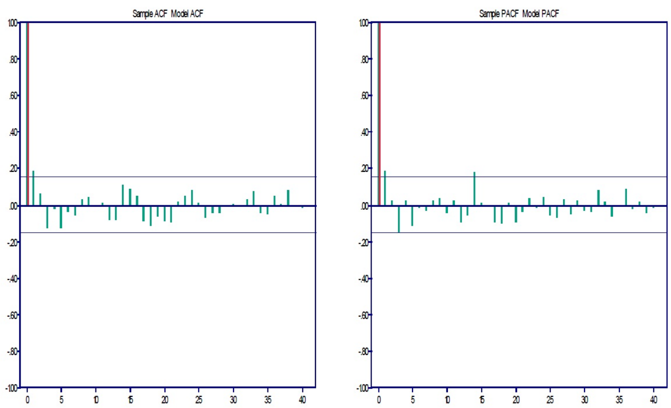

Figure 2: ACF and PACF functions of oil prices

In the ARIMA method, or the Box-Jenkins model, a model is developed for the time series that considers the behaviour of a variable, or a set of variables, based on their past behaviour. These models are fundamentally based on a relatively small number of variables and do not prioritize theoretical assumptions as a prerequisite. To use the Box-Jenkins model to forecast oil prices for upcoming months, a suitable model for each series should be chosen based on the lowest MSE and the significance of the model. According to the previously performed augmented Dickey-Fuller stationary test, the oil price time series stabilized at level and intercept after a single differencing. Therefore, ARIMA is used for forecasting the series with the Box-Jenkins method.

Table 2: ARIMA(p, d, q) models for oil prices

Model type	**AR process rating**	**MA process rating**	**Order of difference**	**MSE index**
ARIMA (1.1.1)	1	1	1	69.7565
ARIMA (1.1.2)	1	2	1	67.6026
ARIMA (1.1.3)	1	3	1	68.1315
ARIMA (1.1.4)	1	4	1	66.9464
ARIMA (1.1.5)	1	5	1	66.4456
ARIMA (2.1.1)	2	1	1	68.3238
ARIMA (2.1.2)	2	2	1	66.4269
ARIMA (2.1.3)*	2	3	1	65.9390
ARIMA (2.1.4)	2	4	1	65.9677
ARIMA (2.1.5)	2	5	1	65.9891
ARIMA (3.1.1)	3	1	1	68.1033
ARIMA (3.1.2)	3	1	2	67.1036
ARIMA (3.1.3)	3	3	1	65.8350
ARIMA (3.1.4)	3	4	1	68.0145
ARIMA (3.1.5)*	3	5	1	63.2919
ARIMA (4.1.1)	4	1	1	68.0992
ARIMA (4.1.2)	4	2	1	65.9736
ARIMA (4.1.3)	4	3	1	66.0377
ARIMA (4.1.4)	4	4	1	63.5430
ARIMA (4.1.5)	4	5	1	63.2150
ARIMA (5.1.1)	5	1	1	66.8641
ARIMA (5.1.2)	5	2	1	66.8177
ARIMA (5.1.3)	5	3	1	63.6299
ARIMA (5.1.4)	5	4	1	63.7311
ARIMA (5.1.1)*	5	5	1	61.8630

Based on the results obtained and the comparison of the mean squared error (MSE), the ARIMA (5,1,5) model had the lowest mean squared error value (61.8630) among the various ARIMA models tested. Subsequently, the ARIMA (4,1,5), ARIMA (3,1,5), and ARIMA (5,1,3) models also showed low error values.

4.3 Forecasting using the Holt-Winters method

In Table 3, the data and smoothing parameters on which the Holt-Winters forecast is based are shown.

Table 3: Input data for the Holt-Winters model

Data name	**Series**
Number of samples	167
Number of predictions	24
Type of fluctuation (Seasonality)	Monthly
Smoothing parameters	
alpha	0.96
Beta	0.34
gamma	1

The forecast results using the Holt-Winters method showed that the alpha parameter is 0.96, and the beta parameter is 0.34, with a monthly fluctuation pattern. Figure 3 illustrates the residuals from the forecast using the Holt-Winters method.

Sample Mean = 67.7784

Sample Variance = 0.718376E+03

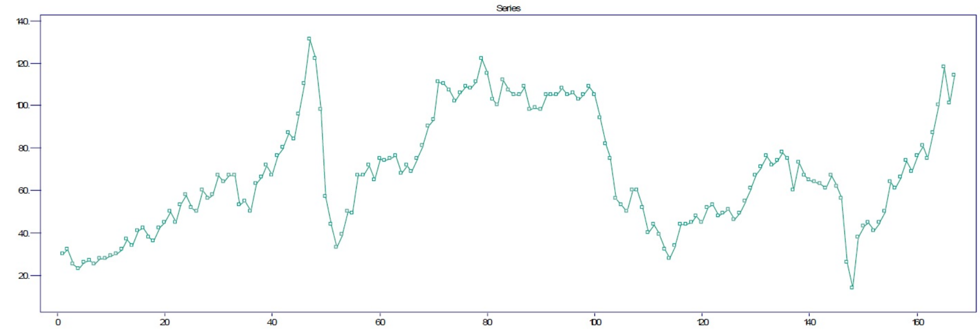

Figure 3: The residuals of the Holt-Winters forecast

The forecasted values based on the Holt-Winters forecasting method are shown in Table 4.

Table 4: The Holt-Winters forecast values

Forecasting step	**Forecast month**	**Forecasted price**
1	2022.06	113.34
2	2022.07	115.55
3	2022.08	117.42
4	2022.09	114.83
5	2022.10	113.70
6	2022.11	115.12
7	2022.12	115.70
8	2023.01	116.59
9	2023.02	117.77
10	2023.03	117.70
11	2023.04	121.00
12	2023.05	120.34
13	2023.06	122.55
14	2023.07	124.43
15	2023.08	121.83
16	2023.09	118.49
17	2023.10	120.70
18	2023.11	122.12
19	2023.12	122.70
20	2024.01	123.59
21	2024.02	124.77
22	2024.03	124.07
23	2024.04	128.00
24	2024.05	129.12

4.4 Forecasting based on a combined neural network

The initial method for training the network was based on the Levenberg-Marquardt algorithm, which is a standard approach for finding the minimum of a multivariable nonlinear function, especially in least squares problems. The Levenberg-Marquardt algorithm interpolates between the Gauss-Newton method and gradient descent. It is more robust than Gauss-Newton, meaning that it can find a solution even when starting far from the final minimum. However, for well-behaved functions and reasonable initial parameters, Levenberg-Marquardt may be slightly slower than Gauss-Newton. Despite this, it remains the most popular curve-fitting algorithm, and users may find fewer needs for other fitting methods.

Then, a combined prediction was made using the designed neural network. Out of 168 data points, 128 were selected as training data and 40 as test data. Table 5 shows the breakdown of training and test data.

Table 5: Data separation, training and testing

Training data	128
Testing data	40
Stop condition	Repetition of 25,000 acceptable errors

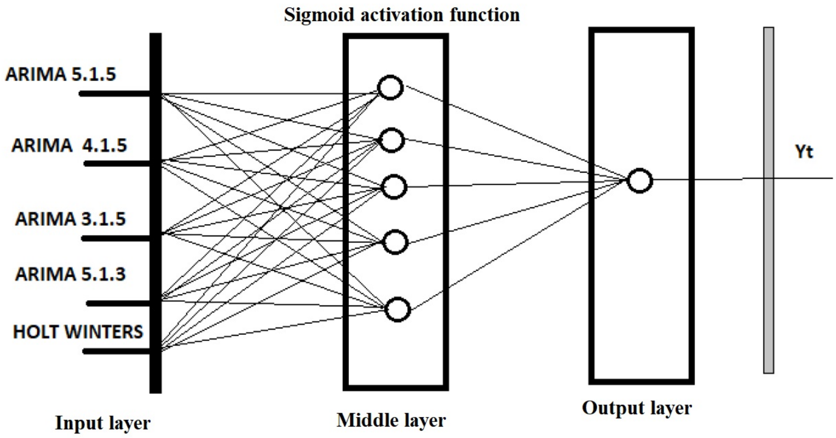

Figure 4: The best-designed network for predicting oil prices

Based on the results in Table 5, the stopping criterion was set at 25,000 iterations, which is considered an acceptable error.

Table 6: The accuracy of the combined neural network in predicting prices

	Testing data	**Training data**
Number of data	40	128
MSE mean	46.57	46.21
Number of correct (good) predictions	88%	81%
Number of incorrect (bad) predictions	12%	19%
MAPE		

The MSE index indicated that the best-designed network for forecasting includes 5 input neurons, 1 output neuron, and 5 hidden neurons. The best activation function is the linear sigmoid function, and the optimal number of layers consists of 1 output layer, 1 hidden layer, and 1 output layer.

The predictions made based on the designed combined network are shown in Table 7.

Table 7: Prediction using the combined method

Forecasting step	**Forecast month**	**Forecasted price**
1	2022.06	117.37
2	2022.07	120.10
3	2022.08	106.98
4	2022.09	113.94
5	2022.10	111.39
6	2022.11	117.16
7	2022.12	122.26
8	2023.01	119.85
9	2023.02	119.90
10	2023.03	117.25
11	2023.04	112.96
12	2023.05	117.50
13	2023.06	119.24
14	2023.07	121.94
15	2023.08	126.59
16	2023.09	122.58
17	2023.10	121.11
18	2023.11	120.58
19	2023.12	117.65
20	2024.01	122.87
21	2024.02	125.88
22	2024.03	126.24
23	2024.04	129.43
24	2024.05	125.32

Comparison of the accuracy of prediction methods shown in Table 8 indicates that, based on the obtained results, the combined approach has played a significant role in improving the accuracy of the prediction methods, markedly enhancing MSE, MAPE, AIC, and BIC indicators.

Table 8: Prediction accuracy of methods

	MSE	MAPE	AIC	BIC
ARIMA 5.1.5	61.8630	10.1%	1184	1175
ARIMA 4.1.5	63.2150	11.7%	1194	1184
ARIMA 3.1.5	63.2919	12.02%	1202	1196
ARIMA 5.1.3	63.6299	12.46%	1214	1198
HOLT	69.2561	17.25%	1424	1412
ANN+ARIMA+HOLT	46.6987	6.41%	1014	1012

The results in Table 8 indicate that the MSE value for ARIMA(5,1,5) is the highest, equaling 61.8630.

5 Conclusion

This section addresses the research questions, starting with the first question: What is the accuracy of forecasting methods based on the Box-Jenkins methodology in predicting OPEC crude oil prices?

According to the research results, among the ARIMA models tested, four models—ARIMA (5,1,5), ARIMA (4,1,5), ARIMA (3,1,5), and ARIMA (5,1,3)—showed better accuracy compared to other methods. The error analysis revealed that the MSE for the ARIMA (5,1,5) model was 61.86, with an AIC of 1184 and a BIC of 1175. For the ARIMA (4,1,5) model, the MSE was 63.215, with an AIC of 1194 and a BIC of 1184. The accuracy for ARIMA (3,1,5) yielded an MSE of 63.2919, with AIC and BIC values of 1202 and 1196, respectively. Additionally, the MSE for ARIMA (5,1,3) was 63.6299, with AIC and BIC values of 1214 and 1198. After various ARIMA processes, these four models proceeded to the combination phase.

The second research question investigates: which of the Box-Jenkins methodology-based models has the highest accuracy? To measure the accuracy of the prediction processes under the Box-Jenkins methodology, four indicators were used: Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Among the 25 models studied in this research, the ARIMA (5,1,5) model demonstrated superior accuracy compared to other models, as it had lower values for MSE, MAPE, AIC, and BIC.

The third research question assesses the accuracy of the Holt-Winters forecasting method for predicting OPEC crude oil prices. For this prediction, the Holt-Winters method in this study used an alpha coefficient of 0.96, beta of 0.34, and gamma of 1. The accuracy analysis indicated that the prediction error for the Holt-Winters method, based on the MAPE (Mean Absolute Percentage Error) metric, was 17.25%, which is relatively high.

The fourth research question examines which forecasting method—Box-Jenkins or Holt-Winters—has higher accuracy for predicting OPEC crude oil prices. A comparison of the accuracy between the Holt-Winters method and the Box-Jenkins methodology indicated that the Holt-Winters method had a higher error rate than the Box-Jenkins approach. This finding aligns with previous research by Yousefi et al. [21], and Omidi et al. [9], where time series methods were reported to have greater accuracy than Holt-Winters, supporting the results of this study.

The fifth question of the research: What is the appropriate design of a neural network for combination to achieve high accuracy?

The error-index MSE indicated that the best-designed network for forecasting includes 5 input neurons, 1 output neuron, and 5 hidden neurons. The optimal activation function is the linear sigmoid function, with 1 outer layer, 1 hidden layer, and 1 output layer. In the study by Omidi et al. [9], the most suitable designed network for combined forecasting also had 1 input layer, 1 middle layer, and 1 output layer, aligning with the current research.

Question six: To what extent does the creation of a second forecasting stage and the combination of forecasting methods improve the accuracy of forecasting methods? The use of the combined ANN-ARIMA-Holt method demonstrated greater accuracy compared to using individual forecasting methods. Specifically, the Mean Squared Error (MSE) improved from 61.86 to 46.69 compared to the best forecasting process, ARIMA 5.1.5. Additionally, the Akaike Information Criterion (AIC) decreased from 1184 to 1014, and the Bayesian Information Criterion (BIC) also dropped from 1175 to 1012. Moreover, the average Mean Absolute Percentage Error (MAPE) reached 6.41%, indicating that the predicted values using the combined method accounted for 93.59%, demonstrating the high accuracy of this proposed method. Using a combined algorithm results in higher accuracy than using methods individually. Also, the accuracy of combined methods is higher than that of single methods. Omidi et al. [9] indicated that the accuracy of combined artificial neural network forecasting methods is greater than that of Box-Jenkins-based time series methods.

In light of the research findings, several recommendations have been made. The high and suitable accuracy of the forecasting methods indicates that these methods can effectively estimate trends in economic variables, including oil prices. Given that forecasting provides managers with a glimpse into the future for tactical and strategic decision-making, it is recommended that experts utilize the methods proposed in this study for forecasting and decision-making. The results of the research specified the priority of using forecasting methods for accidents; therefore, it is suggested that, due to the higher accuracy of ARIMA compared to other methods, this method should be prioritized for forecasting oil prices. To enhance accuracy through a combined approach, it is recommended to apply this method not only for analyzing future trends in oil prices but also for other financial and economic issues. Providing forecasting software based on the methodology presented in this study can increase the speed of delivering predicted values, facilitating their incorporation into forecasting.

References

[1] L.-H. Chen and T.-Y. Guo, *Forecasting financial crises for an enterprise by using the Grey Markov forecasting model*, Qual. Quant. **45** (2011), no. 4, 911–922.

[2] C.-W.J. Chiu, H. Mumtaz and G. Pinter, *Forecasting with VAR models: Fat tails and stochastic volatility*, Int. J. Forecast. **33** (2017), no. 4, 1124–1143.

[3] H.B. Ghassan and H.R. AlHajhoj, *Long run dynamic volatilities between OPEC and non-OPEC crude oil prices*, Appl. Energy **169** (2016), 384–394.

[4] K. Hezhabr Kiani, E. Gholami, and J. Nobakht, *Estimation of the optimal rate of value added tax using the Diamond model*, Quart. J. Econ. Res. **32** (2012), no. 2, 11–22.

[5] R.J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and practice*, Monash University, Australia, 2019.

[6] W. Kristjanpoller and M.C. Minutolo, *Forecasting volatility of oil price using an artificial neural network-GARCH model*, Expert Syst. Appl. **65** (2016), 233–241.

[7] Z. Li, J.M. Rose and D.A. Hensher, *Forecasting automobile petrol demand in Australia: An evaluation of empirical models*, Transport. Res. Part A: Policy Practice **44** (2010), no. 1, 16–38.

[8] W.S. McCulloch and W. Pitts, *A logical calculus of the ideas immanent in nervous activity*, Bull. Math. Biophys. **5** (1943), 115–133.

[9] M.R. Omidi, N. Omidi, H.A. Asgari and H. Meftahi, *Mathematical analysis of traffic accidents using gray and rotational models*, Traffic Manag. Stud. **42** (2021), no. 11, 97–112.

[10] H. Poursalimi and R. Shirzadi, *Developments in the relations between Iran and Saudi Arabia and its impact on the oil market*, J. Explor. Prod. Oil Gas **2015** (2015), no. 141, 40–44. [In Persian]

[11] R. Prasad, R.C. Deo, Y. Li, and T. Maraseni, *Input selection and performance optimization of ANN-based streamflow forecasts in the drought-prone Murray Darling Basin region using IIS and MODWT algorithm*, Atmosph. Res. 197 (2017), 42–63.

[12] K. Shahbazi and S. Salimian, *Oil price forecasting using meta-analysis method*, Energy Econ. Quart. **2014** (2014), no. 29, 67–93.

[13] B. Sivaneasan, C.Y. Yu and K.P. Goh, *Solar forecasting using ANN with fuzzy logic pre-processing*, Energy Procedia **143** (2017), 727–732.

[14] H. Sohrabi Vafa, F. Nouri and M. Ebadi, *Energy demand prediction by using neural network based on patricle swarm optimization*, Iran. Energy J. **16** (2019), no. 3, 6.

[15] Q.-F. Tan, X.-H. Lei, X. Wang, H. Wang, X. Wen, Y. Ji, and A.-Q. Kang, *An adaptive middle and long-term runoff forecast model using EEMD-ANN hybrid approach*, J. Hydrol. **567** (2018), 767–780.

[16] C. Troise, D.Matricano, E. Candelo, and M. Sorrentino, *Entrepreneurship and fintech development: comparing*

reward and equity crowdfunding, Meas. Bus. Excell. **26** (2021), no. 1, 52–63.

[17] M.H. Vatter, *OPEC's Risk premia and volatility in oil prices*, Int. Adv. Econ. Res. **25** (2019), no. 2, 165–175.

[18] X. Wang and M. Meng, *A hybrid neural network and ARIMA model for energy consumption forcasting*, J. Comput. **7** (2012), no. 5, 1184–1190.

[19] R. Wongsathan and S. Chankham, *Improvement on PM-10 forecast by using hybrid ARIMAX and neural networks model for the summer season in Chiang Mai*, Proc. Comput. Sci. **86** (2016), 277–280.

[20] Y. Xue, T. Teng, F. Dang, Z. Ma, S. Wang, and H. Xue, *Productivity analysis of fractured wells in reservoir of hydrogen and carbon based on dual-porosity medium model*, Int. J. Hydrog. Energy **45** (2020), no. 39, 20240–20249.

[21] M.G. Yousefi, T. Mohammadi, and N. Maarrefzadeh, *Forecasting the amount of crude oil demand in Iran using artificial neural networks (ANN) and ARMAX model*, Iran. Energy Econ. Quart. **2** (2012), no. 7, 147–170.

[22] W. Zhao, J. Wang, and H. Lu, *Combining forecasts of electricity consumption in China with time-varying weights updated by a high-order Markov chain model*, Omega **45** (2014), 80–91.

[23] S.H. Zolnoor and S. Mateen, *Optimizing Iran's oil production path: A dynamic planning optimal control model*, Plan. Budget. Quart. **20** (2014), no. 4.