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Forecasting Crude Oil Prices Using an ARIMA-ANN Hybrid Model

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Abstract: This paper aims to use a hybrid ARIMA-ANN model for time series forecasting by combining Auto Regressive Integrated Moving Average (ARIMA) model and the Artificial Neural Networks (ANN). The hybrid ARIMA-ANN model is flexible enough to capture two kinds of time series: the linear model that can only model the linear relationship and nonlinear that can only model the nonlinear relationship. The time series data for the Crude Oil (petroleum) Monthly Price - Saudi Riyal per Barrel was used during the period from Jul-2001 to May-2021, which represents 239 observations. The first 215 observations are used as train series and the last 24 observations are used as testing series. The accuracy measures, Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) for the hybrid combination ARIMA and ANN were compared against ARIMA and ANN methods. The results indicate significant improvement in (MSE, MAPE, and MAE) values for the hybrid ARIMA-ANN method.

Keywords: Time Series, ARIMA, ANN, Hybrid Models, MSE, MAE, MAPE.

1 Introduction

Time series data can define as a set of observations recorded on time order. There is usually a fixed time interval between these observations. (Every minute, hour, day, week, etc.,). With the developing technology, several applications in various areas produce huge amount of time series data [1]. For example, weather conditions such as precipitation, temperature, wind speed in the meteorological domain; stock indexes, currency exchange rates and spreads in economy domain; renewable power production and electricity consumption in energy domain; voltage and sensor data in industry domain; heartrate, pulse, and electrocardiogram signals in biomedical domain; search engine logs and user click in web technologies domain [2-6].

Time series prediction uses methods that predict future values based on historically observed values [7-10]. It is necessary and important to make good prediction models in different domains where the time series is produced. For example, determining the routes of cruise ships requires weather forecasts; deciding whether a coal power station produce electricity considering costs requires the electricity price forecast; determining how much of a good will be produced on a production line requires the forecasts of the consumption of that product; adjusting the capacity of a server for load balancing requires the forecasts of the number of users coming to the website [1]. Moreover, the forecast horizon may vary according to the area where time series is used. For example, it is important to reach forecasts in areas such as telecommunications minutes ago; it is necessary to obtain day-ahead forecasts in electricity trading; it may be enough to have yearly forecasts with large capital. As a result, a good forecasting model in the time series from different areas with different requirements is an effective and efficient way for decision makers.

2 Related Works

In the literature, there are a small number of studies on forecasting time series using hybrid models, from researchers of diversified areas of economic, statistics, engineering, and science [2]. The study introduced meteorological types of heating period and non-heating period were classified using the method of regression tree classification, and meteorological types which are likely to cause severe pollution were identified. The daily mean value prediction model of

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PM2.5 concentration of different meteorological types was established using the combination of ARIMA and SVM, which takes the emission of pollution sources as independent variables. In this study daily mean PM2.5 concentration of 9 environmental monitoring points with continuous data in Shenyang during Jan 2013 to June 2017 was analyzed. The results show that, compared with ordinary machine learning model without weather classification, the prediction of daily mean PM2.5 concentration using ARIMA-SVM combined model based on meteorological classification has a better agreement with actual value, and its ability to identify the peak and valley values is much stronger.

In heating and non-heating period, this combined model has the advantages of lower average error and higher prediction accuracy [3, 11-15]. Applied a hybrid ARIMA-SVM model instead of using single model (ARIMA or SVM) for forecasting a time series data of Natural rubber prices [16-23]. The study results indict that, using hybrid ARIMA–SVM model can give better forecasting accuracy than the single models. For example, based on MSE, the hybrid ARIMA-SVM model improves 6.31% over than ARIMA model. In addition, the hybrid ARIMA-SVM model improves 3.97% over than SVM model in the testing dataset [4], used a combination ARIMA and SVM to predict the COVID-19 trend.

The results show that, using hybrid ARIMA–SVM model can give better forecasting performance than the individual models. For example, based on MSE, the hybrid ARIMA-SVM model improves 98.59% over than ARIMA model. In addition, the hybrid ARIMA-SVM model improves 88.94% over than SVM model in the testing dataset [5] used tree-based methods for time series forecasting and compared the correctness of those methods with the correctness of conventional statistical methods. The results indicated that the random forest method had a better forecast quality (in terms of MSE, MAE and MAPE) than other methods [6] used a combination ARIMA and ANN to predict of the monthly gold price data. The study results indict that, using hybrid ARIMA–ANN model can give better forecasting performance than the individual models. For example, based on MSE, the hybrid ARIMA-ANN model improves 82.93% over than ARIMA model. In addition, the hybrid ARIMA-ANN model improves 6.28% over than ANN model in the testing dataset.

3 Predictive Models

3.1 Autoregressive Integrated Moving Average Model (ARIMA)

ARIMA model forecasts variable based on linear dependency to the past values to it. The models we have discussed in previous sections, are used when the data series is stationary. However, in real life, time series data are mostly non-stationary. To fit stationary models, it is essential to get rid of the variation of non-stationary sources in time series. One solution to this, Box and Jenkins introduced the ARIMA model which can effectively transform the non-stationary data into stationary by introducing a differencing process and overcome the limitation [7].

In ARIMA models, the initial step is to eliminate this non-stationarity using differencing. It is done by subtracting a current observation from at the previous observation. As an example, a first-order differencing can be done by replacing the original value y_t via $y'_t = y_t - y_{t-1}$.

The general form of the ARIMA(p, d, q) model is described as:

$$y'_t = c + \sum_{i=1}^{p} \phi_i y'_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad (1)$$

where y'_t is the differenced new series (after the subtractions). ε_t is white noise $\sim WN(0, \sigma^2)$, and $\{\phi = 1, ..., p\}$, and $\{\theta = 1, ..., q\}$ are respectively the coefficients of the AR(p) and MA(q).

- **Steps for building ARIMA model**

1- Identification:

The primary step in developing ARIMA is to make sure that the series is stationary and using PACF and ACF plots of the data to choose the suitable values of p, d, q of the order of general ARIMA model.

2- *Parameters Estimation*:

After the nomination of one or more appropriate models, we estimate parameters of the model using one of estimation methods.

3- Model Diagnostic:

It is the most important step to modeling ARIMA model in time series. in this step we test whether the residuals and parameters of the ARIMA are significant. Estimated residuals of ARIMA model should be distributed normally if the estimated model is correctly.

4- Forecasting:

The final model is used to generate future predictions and then calculate the prediction errors that occurred. Figure 1 simply summaries Box-Jenkins modeling method.

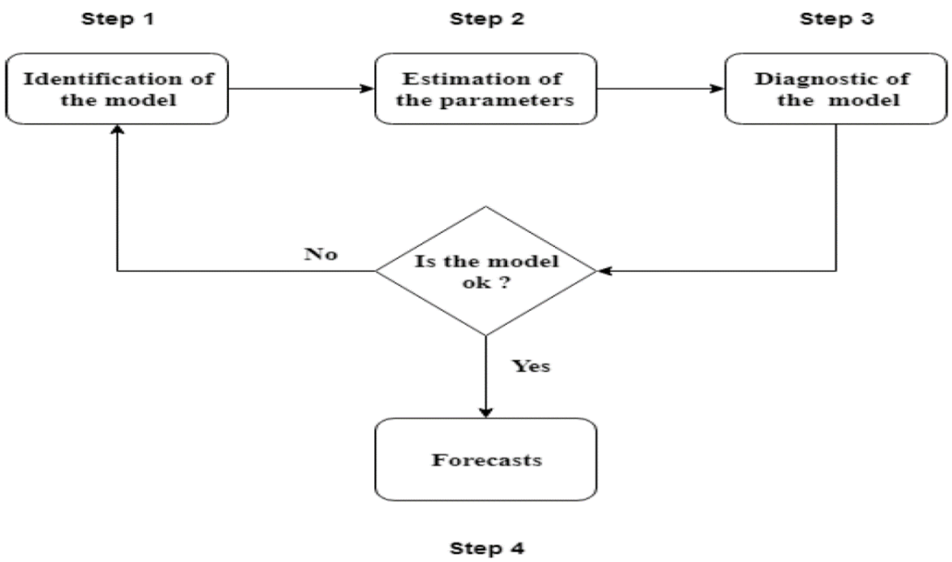

Figure 1. Box-Jenkins Modeling Approach.

3.2 Artificial Neural Networks (ANNs)

ANNs are a part of Artificial Intelligence that have improved the mechanism of human thinking. ANNs can be considered as a computer model or mathematical algorithms based on biological Neural Networks (brain). The idea of ANNs revolves around how to simulate the brain through computers. The main feature of ANN is its capability to learn [8]. ANNs have aroused considerable interest in such diverse fields as medicine, biology, psychology, computer science, mathematics, economics, and statistics. The main reason behind this interest lies in the fact that ANNs are a general, flexible, nonlinear tool adept of approximating any kind of arbitrary function [9]. In this study, we have chosen the nonlinear autoregressive networks (NAR), which used to predict univariate time series data. The chosen network allows us to work with both individual and hybrid methods [13-15].

NAR Network

For the problems of time series forecasting, it is suitable to use the dynamic neural networks (DNN), where the network output depends on the present and previous values. NAR network makes the future forecasting of the data by using that data previous values. NAR network structure can be written as:

$$y_t = f(y_{t-1}, y_{t-2}, y_{t-3}, ..., y_{t-p}) + e_t \, , \quad (2)$$

Where y_t is the original series, e_t is the error term, $f(.)$ is a nonlinear function, and $y_{t-1}, y_{y-2}, y_{t-3}, ..., y_{t-p}$, are the feedback lags.

Figure 2 shows the graphical illustration of the NAR, where y_t is the data that we need to forecast.

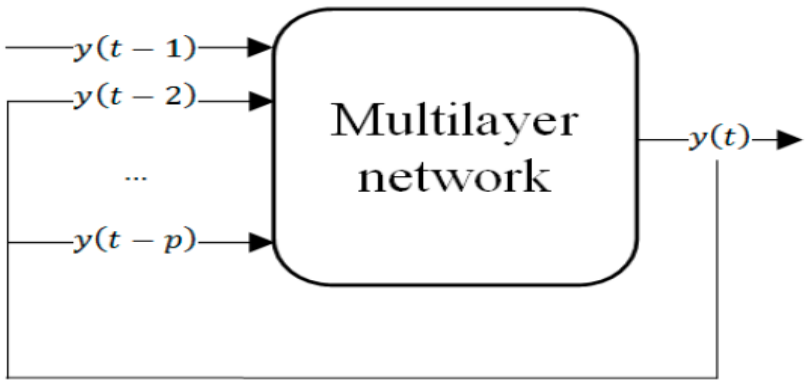

Figure 2. NAR network.

3.3 Hybrid ARIMA-ANN Model

Time series data can contain nonlinear and linear components. So, hybrid methods using linear and nonlinear methods are better and more accurate than single methods for forecasting time series data. Many hybrid methods in literature include the following approach: Given a time series data, ARIMA is applied to fit the data. The residuals obtained from ARIMA is considered as a nonlinear part, and this nonlinear data is modeled by using ANN in various methods.
According to [10], we can consider the time series as the composition of a linear and a nonlinear component as:

$$y_t = L_t + N_t \tag{3}$$

Where L_t is the linear component and N_t is the nonlinear component.
According to this model, ARIMA model is applied to model the linear component L_t of a given series y_t, and predictions are obtained, which are notated as $\hat{L}_t$.

$$\hat{L}_t = c + \sum_{i=1}^{p} \phi_i y'_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{4}$$

After getting the linear predictions from the linear model (ARIMA), the forecasted values are subtracted from the original series y_t, and the difference series is obtained as in Equation 5. According to this model, the residuals series includes of nonlinear part because ARIMA can only fit the linear part accurately.

$$N_t = y_t - \hat{L}_t \tag{5}$$

The residual series N_t, is fitted and forecast using ANN and the forecasts $\hat{N}_t$ are obtained by using Equation 6.

$$\hat{N}_t = f(n_t, n_{t-1}, \ldots, n_{t-n}) + \nu_t \tag{6}$$

In Equation 6, $\hat{N}_t$ is the forecasted of the nonlinear series, and *f* is a nonlinear function of previous residuals values. ν_t is the error term used in the ANN.
The final predictions of the hybrid method are obtained by the sum of the ARIMA forecasts in Equation 4 and the ANN predictions in Equation 6, which is given in Equation 7.

$$\hat{y}_t = \hat{L}_t + \hat{N}_t \tag{7}$$

For modelling nonlinear component, the past error data, is used as input to ANN, as seen in the Figure 3 which simply summaries additive hybrid method.

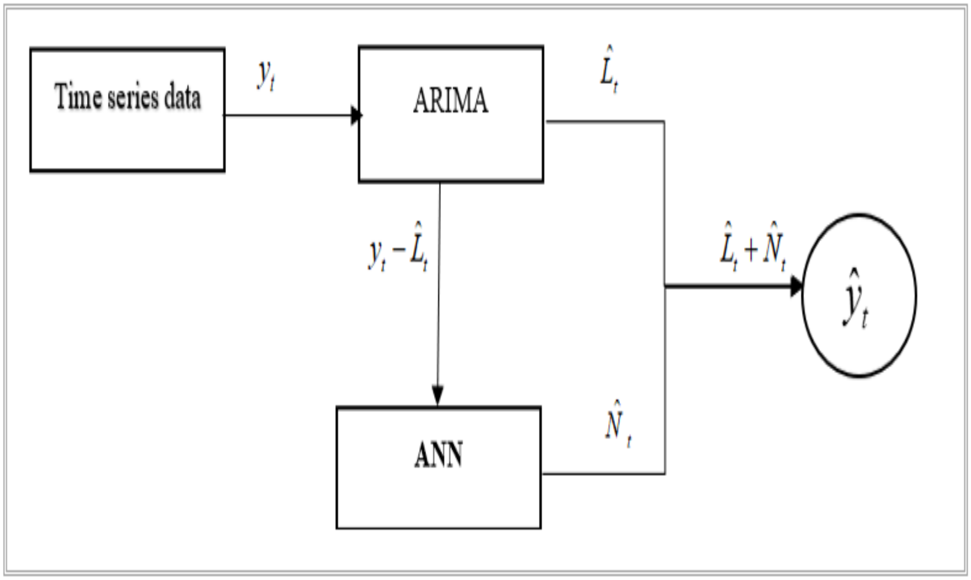

Figure 3. Flowchart of the hybrid ARIMA -ANN model

4 Dataset and Model Evaluation

In this Section, we present the data used in this study. Additionally, we present the model evaluation criteria carried out in this study.

4.1 Dataset

The dataset used in this study is based on Crude Oil (petroleum) Monthly Price - Saudi Riyal per Barrel. It was obtained from the index Mundi website www.indexmundi.com from Jul-2001 to May-2021. There are totally 239 observations. The first 215 observations are used as train series. The last 24 observations are testing series.

Data Plot

Figure 4 shows the price of Crude Oil on the y-axis against the equally spaced time intervals (i.e., months) on the x-axis. It is used to evaluate patterns, knowledge of the general trend, and data behavior over time [11].

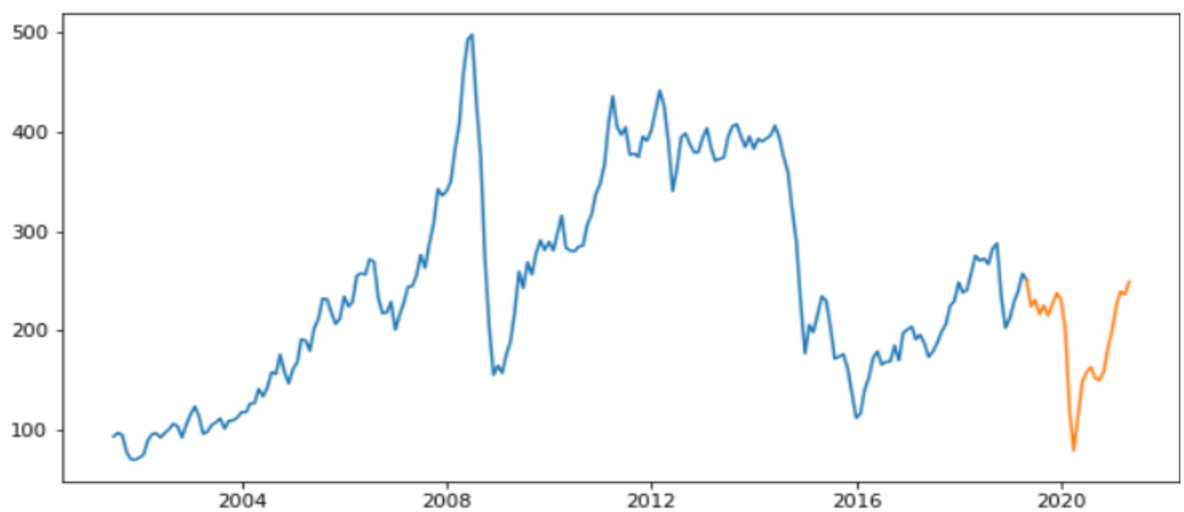

Figure 4. Time Series Plot of the Monthly Crude Oil Price.

4.2 Model Evaluation

Model evaluation process is as important as model development process. According to accuracy performance results, the process of model development including selection of a proper method, hyperparameter optimization, etc. could be reevaluated until obtaining the most appropriate model. In this study we used three well-known error metrics to evaluate models' performances.

- **Mean Squared Error (MSE)** is defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{8}$$

- **Mean Absolute Error (MAE)** is defined as follows:

$$MAE = \sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{n}, \tag{9}$$

- **Mean Absolute Percentage Error (MAPE)** is defined as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \times 100, \qquad y_i \neq 0 \tag{10}$$

Where n is the number of test data; y_t is the actual value and $\hat{y}_t$ is the predicted value.

5 Determination Parameters of Model

5.1 Fitting ARIMA Model

The section aims to use ARIMA model to forecast the price of Crude Oil. The "auto_arima" function in Python helped us to choose the best ARIMA model. The function goes through all the possible models for the time series and chooses the choose the model which minimizes the AIC. The AIC values for a model is calculated using the following Equation:

$$AIC = 2m - 2\ln(\hat{L}), \tag{11}$$

Where $\hat{L}$ denotes the maximum value of the likelihood function for the model and m is the number of parameters estimated by the model. The best model that has smaller AIC because of the number of parameters is the smallest. Different models associated with accuracy criterion are listed in Table 1.

Table 1. The Values of AIC for Different ARIMA Models.

Model	AIC
ARIMA (0, 1, 0)	1905.13
ARIMA (1, 1, 0)	1864.86
ARIMA (0, 1, 1)	1873.65
ARIMA (1, 1, 1)	1866.83
ARIMA (2, 1, 0)	1866.82
ARIMA (2, 1, 1)	1866.13

Based on "auto_arima" function, the appropriate model for the price of Crude Oil is ARIMA (1,1,0). After choosing the best ARIMA model, the "predict" built in function in Python is used to forecast the price of Crude Oil.

Forecasting:
Since ARIMA (1, 1, 0) is fitted to the price of Crude Oil, therefore we can use this model directly to forecast the price of Crude Oil for the testing data. Table 2 indicates forecast and actual values for last 24 observations.

Table 2. Observed and Forecasted Values Using the ARIMA Model.

Month	Actual	Forecast	Month	Actual	Forecast
Jun-19	224.1	248.25	**Jun-20**	147.98	254.67
Jul-19	230.55	247.67	**Jul-20**	157.76	255.39
Aug-19	216.26	247.85	**Aug-20**	162.9	256.11
Sep-19	225.15	248.34	**Sep-20**	152.25	256.83
Oct-19	214.76	248.96	**Oct-20**	149.63	257.55
Nov-19	226.5	249.64	**Nov-20**	158.63	258.28
Dec-19	237.56	250.35	**Dec-20**	182.74	259
Jan-20	231.11	251.06	**Jan-21**	201	259.72
Feb-20	200.06	251.78	**Feb-21**	226.73	260.44
Mar-20	120.75	252.5	**Mar-21**	239.36	261.17
Apr-20	78.9	253.22	**Apr-21**	236.06	261.89
May-20	113.93	253.94	**May-21**	249	262.61

5.2 Fitting the ANN

The nonlinear autoregressive models (NAR) predict future values based only on several past values. The NAR neural network has great fitting ability for a nonlinear time series. NAR network containing three layers (input, hidden, and output layers). NAR network was used to forecast the price of Crude Oil. Input variable includes historical monthly Crude Oil prices. This variable is fed as a data series to the NAR network. NAR network is then initialized by using “ntstool” which is available in MATLAB software. In this study, we divide up the 100% of the target timesteps into 80% for train the network, 10% for model validation and 10% for model testing. The appropriate NAR network for the monthly Crude Oil prices consists of three layers, an input layer is represented in the values of monthly Crude Oil prices, a hidden layer is composed of 10 processing element, and finally the output layer is the current index values, so the model is NAR(1:10:1). Figure 5 display the NAR network architecture for the monthly Crude Oil price.

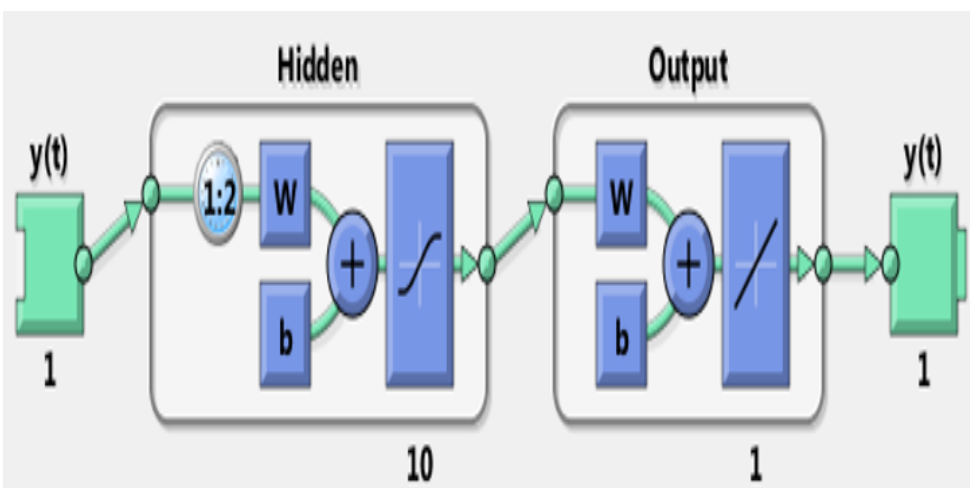

Figure 5. The NAR Network Architecture.

Figure 5 shows that, the lags number is 2, and the hidden layers number is 10. This network is chosen by trying different numbers and comparing their performances. For this model, the best fitted model is (1:10:1). Table 3 indicates forecast and actual values for last 24 observations.

Table 3. Observed and Forecasted Values Using the ANN Model.

Month	Actual	Forecast	Month	Actual	Forecast
Jun-19	224.1	245.855	**Jun-20**	147.98	126.941
Jul-19	230.55	246.45	**Jul-20**	157.76	135.841
Aug-19	216.26	244.595	**Aug-20**	162.9	147.416
Sep-19	225.15	247.21	**Sep-20**	152.25	118.393
Oct-19	214.76	245.132	**Oct-20**	149.63	97.2753
Nov-19	226.5	248.982	**Nov-20**	158.63	129.401
Dec-19	237.56	249.452	**Dec-20**	182.74	221.603
Jan-20	231.11	248.9	**Jan-21**	201	244.808
Feb-20	200.06	235.766	**Feb-21**	226.73	258.853
Mar-20	120.75	18.2379	**Mar-21**	239.36	260.787
Apr-20	78.9	60.8011	**Apr-21**	236.06	259.528
May-20	113.93	168.057	**May-21**	249	262.098

5.3 Fitting the Hybrid ARIMA-ANN

The section focuses on using the hybrid ARIMA-ANN model as described in Section 3 to forecast the monthly Crude Oil price. After determining an appropriate ARIMA model a NAR network was trained by the residuals obtained after fitting with ARIMA Thus, the (NAR) network used consists of three layers. The inputs layer E, a hidden, and finally the output layer $\hat{y}_t$.

In this model, monthly Crude Oil price is not involved in the NAR network because it is included in ARIMA as a linear part. So, NAR Network is used to model the residuals of ARIMA model as a nonlinear part. Figure 6 display the NAR network architecture for the residuals of ARIMA model.

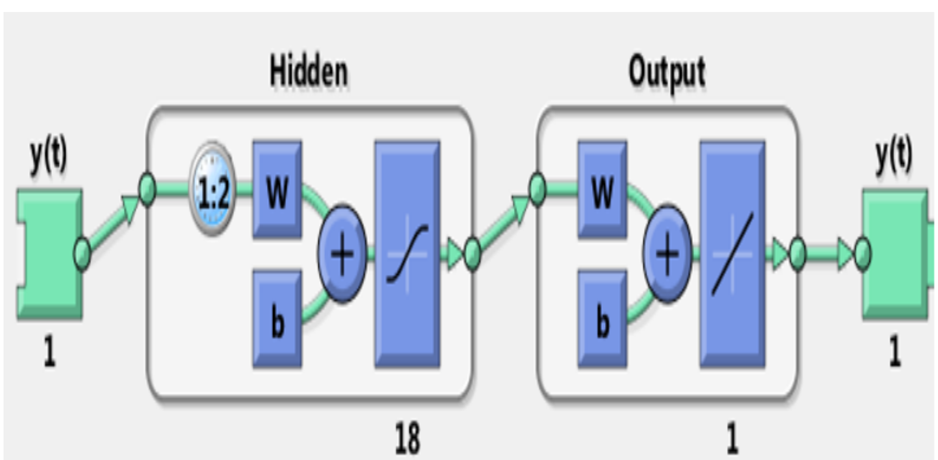

Figure 6. The NAR Network Architecture.

In this model, the number of delays is 2 and the number of hidden layers is 18. This model is determined by trying various numbers and comparing their performances. For this model the best fitted model is ARIMA-ANN (1,1,0)(1:18:1). Table 4 indicates forecast and actual values for last 24 observations.

Table 4. Observed and Forecasted Values Using the Hybrid Model.

Month	Actual	Forecast	Month	Actual	Forecast
Jun-19	224.1	232.967	**Jun-20**	147.98	165.329
Jul-19	230.55	213.665	**Jul-20**	157.76	171.004
Aug-19	216.26	228.77	**Aug-20**	162.9	158.711
Sep-19	225.15	213.651	**Sep-20**	152.25	157.114
Oct-19	214.76	230.687	**Oct-20**	149.63	166.343
Nov-19	226.5	240.495	**Nov-20**	158.63	190.398
Dec-19	237.56	230.063	**Dec-20**	182.74	209.16
Jan-20	231.11	192.301	**Jan-21**	201	233.534
Feb-20	200.06	98.2316	**Feb-21**	226.73	242.5
Mar-20	120.75	79.1655	**Mar-21**	239.36	235.721
Apr-20	78.9	121.678	**Apr-21**	236.06	251.864
May-20	113.93	151.019	**May-21**	249	238.697

6 Results

To evaluate the prediction capability of the predictive models, the predictive models are applied to the monthly Crude Oil price. The prediction performance measures involved in this paper consist of three measures: mean square error (MSE), mean absolute error (MAE) and mean absolute error (MAPE).

Table 5 presents the obtained prediction performance results through ARIMA, ANN, and the hybrid ARIMA-AANN model in terms of MSE, MAP, and MAPE. From Table 5, it can be clearly seen that hybrid model have achieved lower errors than other models. This may suggest that neither ARIMA nor ANN model captures all of patterns in the data. For example, model one, in terms of MAPE, the hybrid ARIMA-ANN model can improve 85.09% over than ARIMA model in the test data. In addition, the hybrid ARIMA-ANN can improve 27.36% over than ANN model in the test data.

Table 5. The obtained prediction performance results.

Model	MSE	MAE	MAPE
ARIMA-ANN	**922.86**	**22.58**	**13.95**
ANN	1270.40	30.32	18.51
ARIMA	6189.43	63.48	44.51

Figure 7 indicates the comparison of predicted values and actual values of the monthly Crude Oil price for test series. The hybrid ARIMA-ANN model was found to forecast closer to the actual value and have a similar pattern with the actual data. Meanwhile, ARIMA and ANN show unsatisfactory forecasting performance with the actual data.

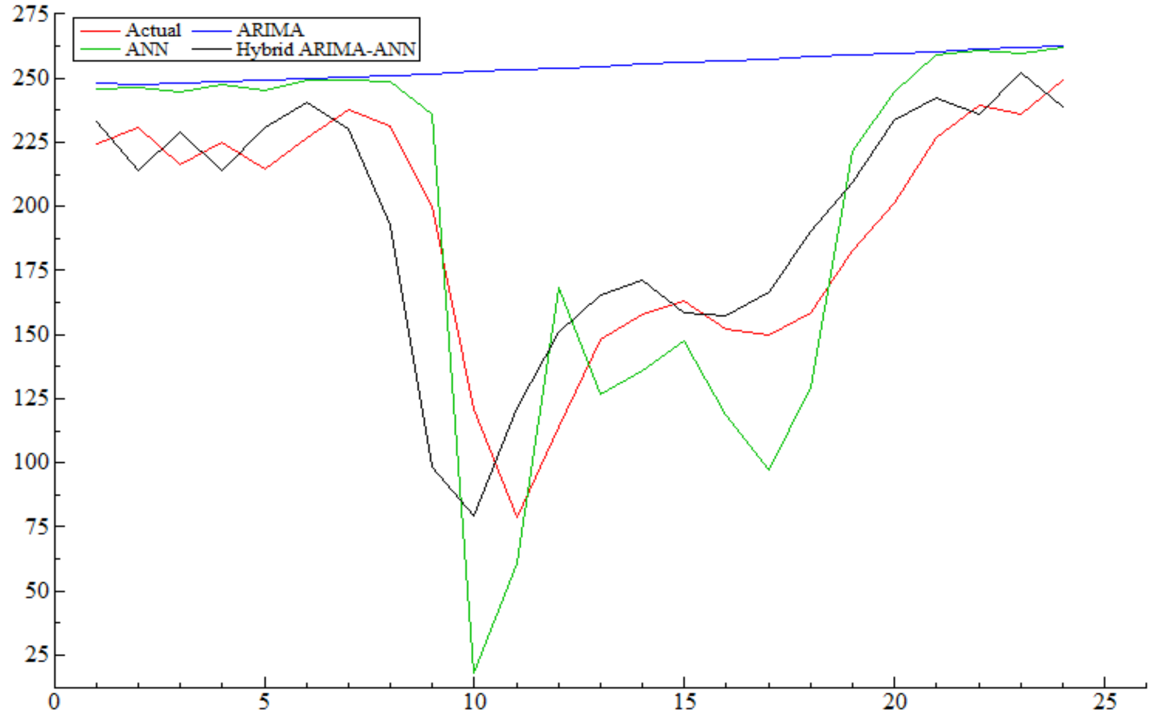

Figure 7. Forecasting of monthly Crude Oil price

7 Conclusion

The paper aimed to compare between ARIMA, ANN, and ARIMA-ANN models for predicting the Crude Oil (petroleum) Monthly Price - Saudi Riyal per Barrel. The results of applying the ARIMA, ANN and hybrid ARIMA-ANN models were compared through the (MSE, MAE, and MAPE) results. From this study, it can be concluded that the results of hybrid model ARIMA-ANN were more accurate (with the lowest error), and the hybrid model is the most efficient forecasting model for monthly Crude Oil (petroleum) price than ARIMA and ANN models. In future, we intend to improve our results by using a hybrid method of ARIMA and Support Vector Regression (SVR) to benefit from qualities of both models.

Conflicts of Interest: The authors declare that there is no conflict of interest regarding the publication of this article.

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