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Comparison of ARIMA, ANN and Hybrid ARIMA-ANN Models for Time Series Forecasting

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Abstract: This paper aims to compare between Auto Regressive Integrated Moving Average (ARIMA) model, Artificial Neural Networks (ANN) and hybrid models for time series forecasting. The dataset used on this study is based on the monthly gold prices during Nov-1989 to Dec-2019. This dataset was used to train and test the predictive models. The performances were evaluated based on three metrics Mean Square Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) to determine the more appropriate model and evaluate models' performance. The most important finding was that applying hybrid models can improve the forecasting accuracy over the ARIMA and ANN models. This may suggest that neither ARIMA nor ANN model captures all of patterns in the data.

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

1 Introduction

The study of the relationship between past data and future data is known as the field of time-series analysis. Forecasting time series technique predicts the future events through a set of past observations recorded on time order [1]. This technique is used through many areas of study: econometrics, weather, statistics, earthquake, signal processing, astronomy, etc. Due to many different fields in which getting an accurate forecasting is an important piece, time series data forecasting has been a hot topic of interest both in academia from its origins and in the industry. Several techniques of forecasting have been used to address this problem and forecast the future behavior of a particular series of values. These techniques can be classified into three groups. The first one is linear models assuming the relationship between future data and past data is linear. The second one is nonlinear models assuming a nonlinear relationship between past data and future data. Finally, the hybrid models that combine those two models. Hybrid models decompose the given time-series data into linear and nonlinear parts which are then modelled by linear and nonlinear models, respectively [2]. The common characteristic of all these techniques is they assume an expression of the future values of a time-series as a combination of its historical values. In other words, they use historical values to forecast future values.

ARIMA models have been the utmost prevalent statistical prediction tools. This model gives good prediction for future events, but they are unfortunately, not so accurate for many ones [3]. This is because the predictions converge to the mean of the series after three or four forecast values. The parameters of ARIMA models are usually estimated by the model of maximum likelihood or least squares estimation models. One of the problems of forecasting lies in the use of appropriate models to fit the time series. Most real time-series data are known to either be non-linear or non-stationary, which presents forecasting problems while using the traditional statistical techniques like regression analysis, exponential smoothing, and ARIMA models. The results of forecasting using these models are not easy to use for forecasting when the time series data are nonlinear or nonstationary. Therefore, it was necessary to explore other more appropriate models to produce more accurate forecasts when the data are nonlinear or non-stationary [4].

The researcher found other models that can be applied to such cases and may overcome the problems of nonlinearity. These models include Neural Networks (ANN) models. ANN has been used in prediction in many fields and especially in the field of economics. The use of ANN in time series forecasting increased because of their capability to form a complex

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nonlinear system based on sample data. However, ANN might be ineffective and inefficient for forecasting simple time series, as compared to linear models [5].

Recent studies have suggested using hybrid models as an alternative for linear and nonlinear forecasting technique to deal with linearity and nonlinearity problems. In this paper, the monthly gold price time series data predictions are obtained using individual ARIMA, ANN models, hybrid ARIMA-ANN models of additive, Khashei-Bijari, and multiplicative.

The rest of the paper is structured as follows. The dataset and the predictive methods used in this study are briefly described in Section 2 and Section 3, respectively. Section 4 presents the model evaluation. The model proposed and other models applied to the monthly gold price data are demonstrated in Section 5. Furthermore, the most important finding from the application of hybrid models employed is detailed in Section 6. The paper ends with the conclusion in Section 7.

2 Dataset

The dataset used in this study is based on monthly gold prices obtained from the index Mundi website ¹ from 11-1989 to 12-2019. There are totally 362 observations. The first 325 observations are used as train series. The last 37 observations are testing series. Table 1 represents some descriptive statistics of the training series of a monthly gold price.

2.1 Descriptive Statistics for the Monthly Gold Price

Table 1 shows 325 observations with a mean training set of 673.95. The median value of the monthly gold price is 393.06 with the maximum and minimum numbers of 1772.14 and 256.08 per month respectively while the standard deviation of time series was found to be 451.01.

Table 1: Descriptive Statistics for Training Series.

Statistics	Observations	Min	Median	Mean	Max	Standard deviation
Value	325	256.08	393.06	673.95	1772.14	451.01

Table 2 represents some descriptive statistics of the testing series of a monthly gold price 37 observations. The mean of the test series is 1302.4, the median of 1283.04 while the maximum and minimum of the gold prices are 1510.58 and 1157.36 per month respectively with a standard deviation of 90.93.

Table 2: Descriptive Statistics for Test Series.

Statistics	Observations	Min	Median	Mean	Max	Standard deviation
Value	37	1157.36	1283.04	1302.40	1510.58	90.93

2.2 Data Plot

Figure 1 shows the price of gold from 11-1989 to 12-2019. It is used to evaluate patterns, knowledge of the general trend, and data behavior over time. The positive trend of data is clear.

3 Predictive Methods

This section presents the predictive methods used in this study.

¹ <https://www.indexmundi.com>

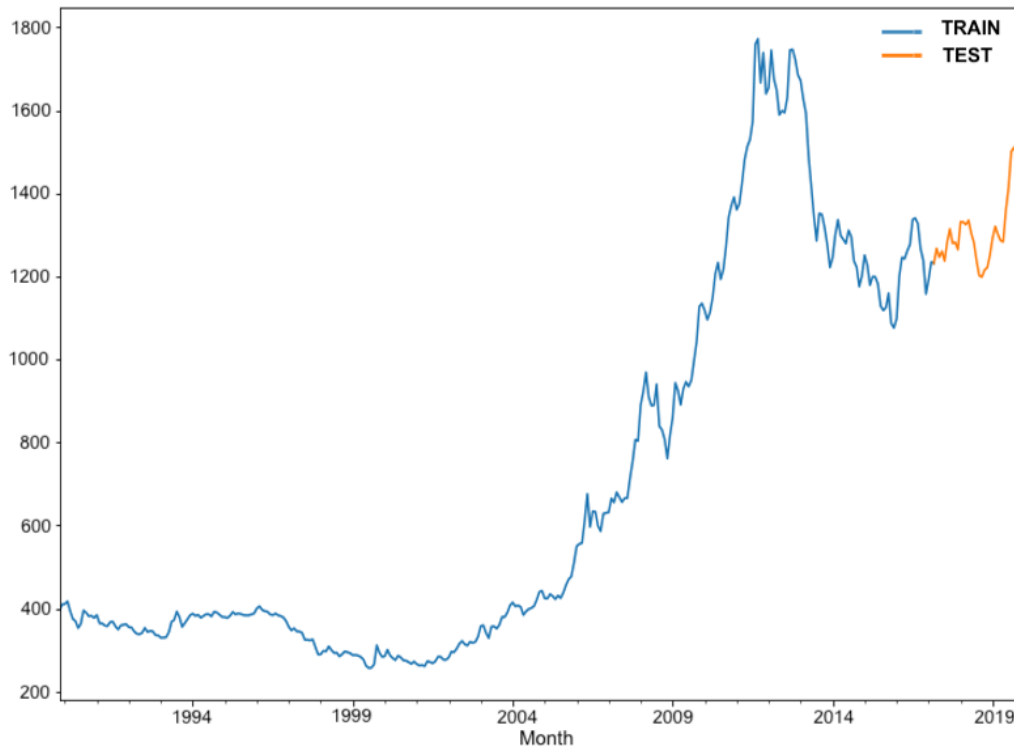


Fig. 1: Time Series Plot of the Monthly Gold Price.

3.1 ARIMA

ARIMA model was mainly popularized by Box and Jenkins (1970) and is considered an all- purpose univariate model for forecasting time series. It models the serial dependence in a time series, where the Autoregressive-terms model the interdependency in dependent variable while the moving average-terms describe dependency of the dependent variable on previous error- terms. It is mainly applied to the stationary data series where the mean, variance, and the autocorrelation function are constant progressively. [3] asserted that the model however is applicable to non-stationarity data series especially after the data series are made stationary by transformations like differencing and logging techniques. ARIMA model is represented by an Autoregressive (AR) component, difference, and Moving Average (MA) part represented by p , d , and q , respectively. Historical data is decomposed an AR process which maintains of past occurrences, an Integrated (I) process that stationarizes data to reduce complexities associated with forecast and a MA process of forecast-errors. The p in the AR components represents linear relationship that dependent variables have with their own lags. An ARMA model is resulted from the combination the AR(p) and MA(q) components /models expressed as:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \tag{1}$$

Where ε_t is white noise $\sim WN(0, \sigma^2)$, $\{\phi = 1, \dots, p\}$ and $\{\theta = 1, \dots, q\}$ are the coefficients of AR(p) and MA(q) components, respectively.

3.2 Artificial Neural Networks (ANN)

ANN is a nonlinear technique for forecasting time series data. ANN has 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 ANN is a general, flexible, nonlinear tool adept of approximating any kind of arbitrary function [5]. The ANN architecture includes of neurons, like the brain’s architecture. Figure 2 shows an example, for ANN with three layers, called as input (feedback layer node), hidden layer node and output layer node.

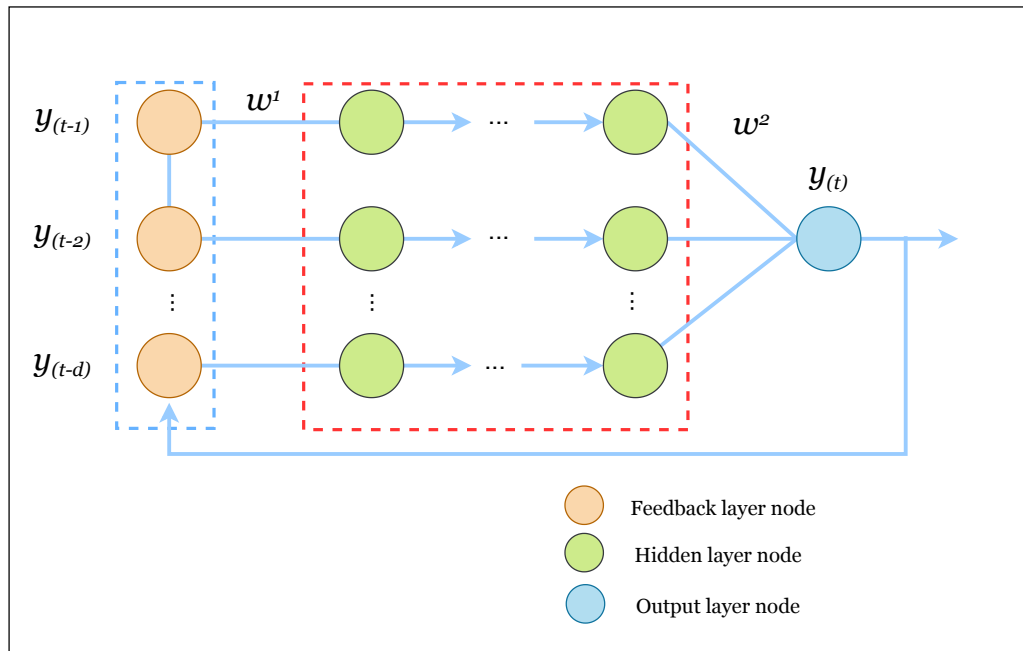


Fig. 2: Artificial Neural Networks (ANN) architecture.

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. DNN network makes the future forecasting of the data by using that data previous values. DNN network structure can be written as:

$$y_t = f(y_{t-1}, y_{t-2}, y_{t-3}, \dots, y_{t-d}) + \varepsilon_t \quad (2)$$

Where y_t is the original series, ε_t is the error term, $f(\cdot)$ is a nonlinear function, and $y_{t-1}, y_{t-2}, y_{t-3}, \dots, y_{t-d}$ are the feedback lags.

3.3 Hybrid Models

Time series data can contain nonlinear and linear component. So, hybrid methods using both nonlinear and linear models are better and more accurate than individual models for forecasting time series data [6]. Various hybrid methods which exist in the literature include the following approach: Given a time series data, ARIMA model is directly modeled on the data. The residuals obtained from ARIMA model is considered as a nonlinear component, and this nonlinear data is modeled using ANN in different methods. Some such hybrid models considered in this paper are those of Additive, Khashei-Bijari, and multiplicative hybrid methods which are shown below.

3.3.1 Additive Hybrid Model

Zhang [7] proposed the additive hybrid model, which assumes the time-series y_t summing the linear and nonlinear components as:

$$y_t = L_t + N_t \quad (3)$$

ARIMA is used in this model to fit the linear part L_t of y_t , and predictions \hat{L}_t are obtained as:

$$\hat{L}_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} + \dots + \theta_q e_{t-q} \quad (4)$$

The linear forecasts from ARIMA model are subtracted from the original series y_t as indicated in Equation (5). Zhang [7] emphasized on this difference series or residuals series to be comprising of nonlinear variations since ARIMA model only accurately fits linear variations.

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

The residual series N_t is fitted and predicted using ANN while the predictions \hat{N}_t are obtained using in Equation (6).

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

Where \hat{N}_t is the forecasted nonlinear error-series, f is a nonlinear function of preceding residuals, while v_t is the component white-noise in the ANN modeling.

The final Additive hybrid model predictions 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).

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

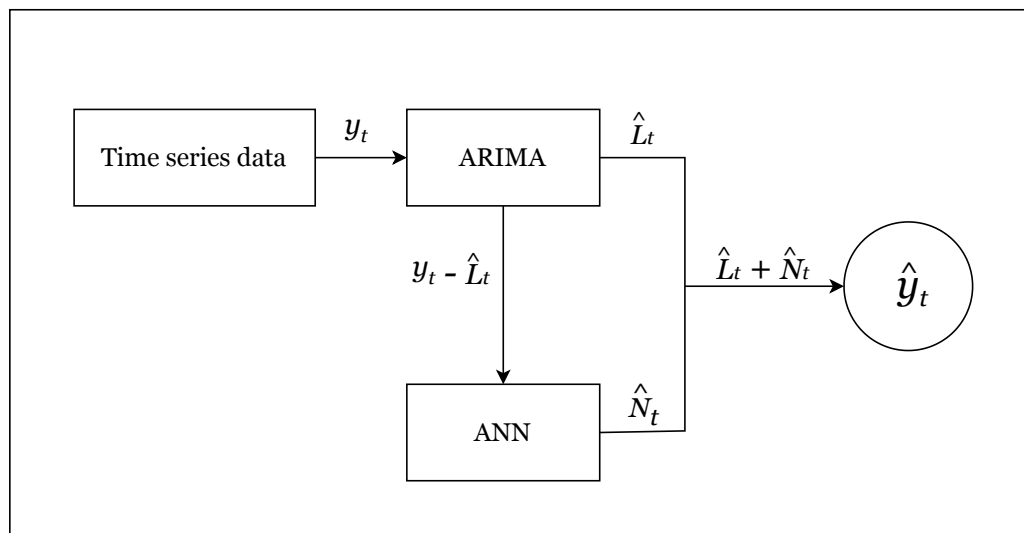


Fig. 3: Additive Hybrid Model.

3.3.2 Khashei and Bijari Hybrid Model

Khashei and Bijari [8] proposed a hybrid prediction model for time series, which assumes that the time series y_t is a sum of linear and nonlinear parts, given in Equation (8):

$$y_t = f(L_t + N_t) \tag{8}$$

This model relates to the Additive model that assumes the composition of linear and nonlinear components in any time-series data. The linear components are modelled by using ARIMA while the residuals assumed to contain nonlinear component cannot be modelled by a linearity approach. In the next stage in which linear forecast and the computed nonlinear residuals are combined, this model is differentiated from the Additive model. This model claims an additive relationship between linear and nonlinear parts. The relation might be underestimated and degrade the performance [9]. Valid nonlinear patterns in the residuals of ARIMA model may further not be guaranteed and therefore assumptions under this approach lowers the performances in another situation [10]. The above reasons permit consideration of linear and nonlinear components as functional time-series shown in the Equation (9):

$$\hat{y}_t = f(\hat{L}_t + \hat{N}_t) \tag{9}$$

Where \hat{L}_t is the linear component which is modelled by ARIMA, \hat{N}_t is the nonlinear one modelled by ANN. In modelling nonlinear component, multi-layer component is used by introducing past original values, present forecast of linear component, and past error data with residuals as inputs to ANN shown in the Figure 4 which simply summarizes the Khashei-Bijari's model. ANN does not only get residuals as input but also takes past linear forecasts and actual values. Therefore, it can undermine the strict assumption that is additive association between linear and nonlinear components. The performed experiments support this approach at outperforms the forecasting accuracy of Additive model in a number of applications.

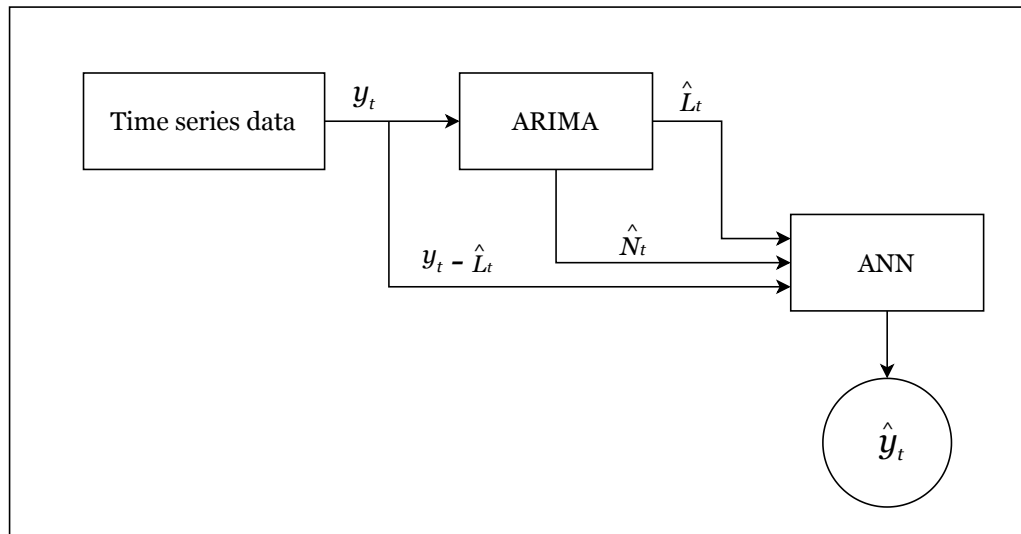


Fig. 4: Khashei and Bijari's Hybrid Model.

Khashei-Bijari's hybrid approach is applied in various applications in literature such as machine industry for prediction of production values [11], inspection facilities for predicting the number of goods subject to inspection [12], finance for predicting carbon price [13].

3.3.3 Multiplicative Hybrid ARIMA-ANN Model

Wang et, al. [14] introduced a multiplicative hybrid-model for predicting time-series data that was contrasted with additive hybrid models. This model assumes that a given time series is the product of a linear and a nonlinear part as shown in Equation (10) not like the additive nature assumed by Zhang [7] in Equation (3). L_t and N_t are the linear and nonlinear parts of Equation (10):

$$y_t = L_t N_t \quad (10)$$

The time series y_t in Equation (10) is modeled using ARIMA additively as in Equation (4). The quotient of y_t by the forecasts \hat{L}_t results to the nonlinear component given by Equation (11).

$$N_t = \frac{y_t}{\hat{L}_t} \quad (11)$$

The nonlinear component N_t is modeled and forecasted using ANN and the final model forecasts obtained using the product of the nonlinear forecasts \hat{N}_t in Equation (5) and linear forecasts \hat{L}_t as illustrated in Equation (12):

$$\hat{y}_t = \hat{L}_t \hat{N}_t \quad (12)$$

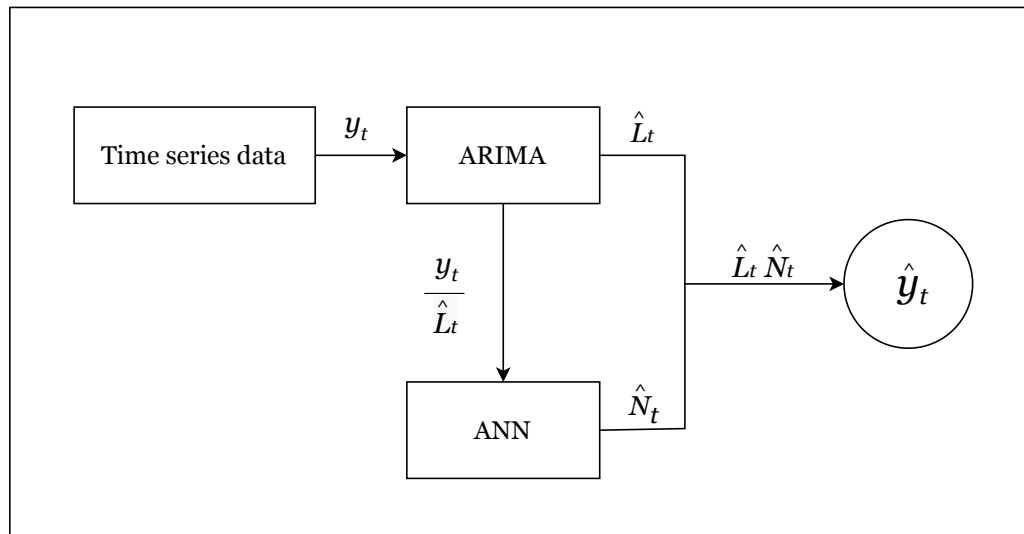


Fig. 5: Multiplicative Hybrid Model.

4 Model Evaluation

It is important to find the best prediction model that produces the most accurate results in the evaluation process. The error metrics define “error” e_t as the difference between actual observed value y_t and its prediction \hat{y}_t at time t . This difference refers to the unpredictable part of the corresponding observation. The well-known error metrics are described below in the literature [15].

Mean Square Error (MSE) is defined by:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \tag{13}$$

MSE measures the average squared prediction error. Because the error metric squares the errors, the knowledge of the direction of the overall error is lost. Because of the same reason, MSE emphasizes the large errors, so that it penalizes extreme prediction errors unlike previous error metrics. MSE is not independent of scale, it is even very sensitive to small scale differences.

Mean Absolute Error (MAE) determined as:

$$MAE = \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{n} \tag{14}$$

MAE measures the amount of overall error of the prediction. Therefore, the smaller the MAE results means that the higher the model success.

Mean Absolute Percentage Error (MAPE) can be defined as:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i} \times 100, \quad y_i \neq 0 \tag{15}$$

MAPE measures the percentage of average absolute difference between predicted values and observed ones. Thus, it is a scale-free error metric like MSE. Since it takes the absolute value into account, it does not give information about the direction of the prediction error. Like MAE, MAPE value should be as small as possible for a good prediction performance.

5 The Monthly Gold Price Model Application

The section demonstrates the model proposed in this section with other models applied to the monthly gold price data.

5.1 ARIMA Model

The “auto.arima” function in *Python 3.7* has aided the development and identification of the best ARIMA model. The function goes through all the possible models for the time series and chooses the model which minimizes the BIC and AIC. The BIC and AIC values for a model is calculated using the following Equations [16].

$$BIC = 1n(n)m - 21n(\hat{L}) \quad (16)$$

$$AIC = 2m - 21n(\hat{L}), \quad (17)$$

The best model that has smaller AIC and BIC because of the number of parameters is the smallest. Different models associated with accuracy criteria are listed in the following Table.

Table 3: The Values of (AIC, BIC) for Different ARIMA Models.

Model	AIC	BIC
ARIMA (0, 1, 0)	3153.97	3161.47
ARIMA (1, 1, 0)	3145.82	3157.17
ARIMA (0, 1, 1)	3144.90	3156.24
ARIMA (1, 1, 1)	3145.55	3160.67
ARIMA (0, 1, 2)	3146.49	3161.62
ARIMA (1, 1, 2)	3146.13	3165.03

Table 3 shows that the appropriate model for the monthly gold prices is ARIMA (0,1,1), represented as in Equation (18):

$$\Delta y_t = 2.6017 + \varepsilon_t - 0.1923\varepsilon_{t-1} \quad (18)$$

After choosing the best ARIMA model, the “predict” built in function in *Python* is used to forecast the monthly gold prices.

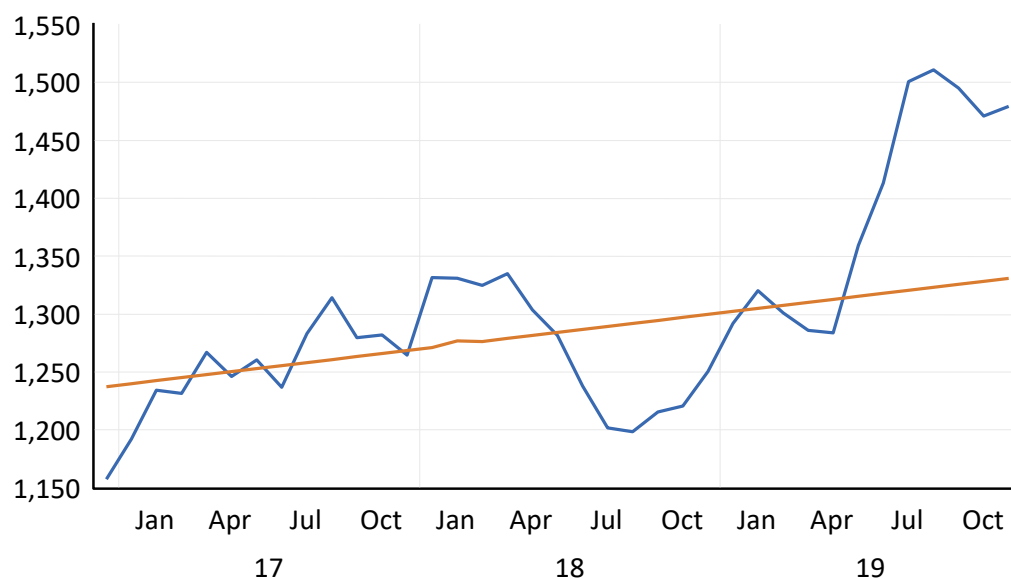


Fig. 6: Actual and Forecast Results by ARIMA Model.

Forecasting:

Since ARIMA (0, 1, 1) is fitted to monthly gold price, so we can use Equation (18) directly to predict monthly gold price for the testing data. Figure 6 shows the comparison of actual with forecast values.

Based on the results in Figure 6, the ARIMA model shows unsatisfactory forecasting performance with the actual data. However, ARIMA model provided a linear forecasting from testing set. The results showed that ARIMA model was not perform correctly in forecasting monthly gold price data.

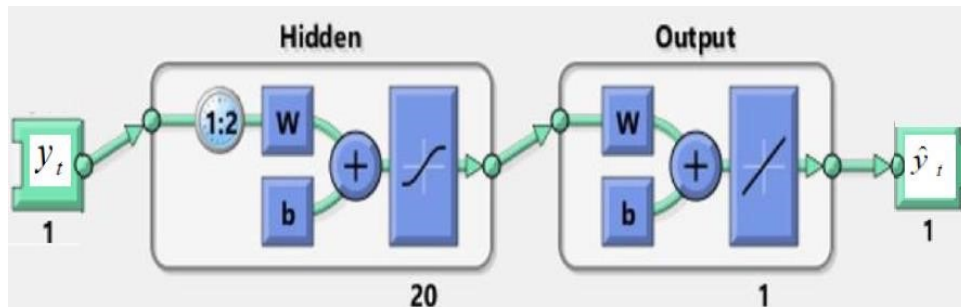


Fig. 7: The ANN Architecture.

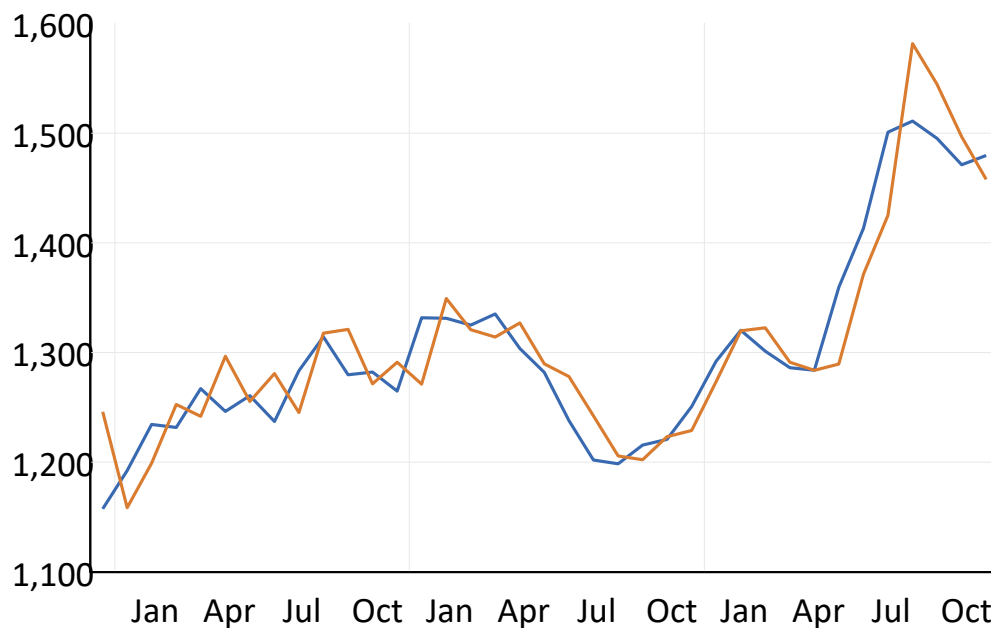


Fig. 8: Actual and Forecast Results by ANN.

5.2 The Artificial Neural Networks (ANN)

ANN was used to forecast the monthly gold prices data. Input variable includes historical monthly gold prices. This variable is fed as a data series to the ANN. 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 ANN for the monthly gold prices consists of three layers, an input layer is represented in the values of monthly gold prices, a hidden layer is composed of 20 processing element, and finally the output layer is the current index values, so the model is ANN(1:20:1). Figure 7 displays the NAR network architecture for the monthly gold price.

Figure 7 shows that, the lags number is 2, and the hidden layers number is 20. This network is chosen by trying different numbers and comparing their performances. For this model, the best fitted model is (1:20:1). Figure 8 shows the comparison of actual with forecast.

5.3 Additive Hybrid Model

After determining an appropriate ARIMA model, ANN was trained by the residuals from the fitted ARIMA model, the ANN applied consists of inputs E , a hidden, and the output layer \hat{y}_t . The model excludes the monthly gold price from ANN since it is already included in the consideration of linearity part. Non-linearity in ANN model is applied to model nonlinear residual components of ARIMA model and network for this model is indicated in Figure 9.

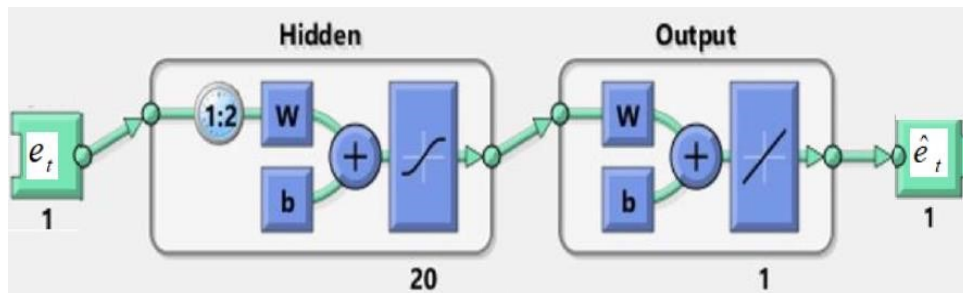


Fig. 9: The ANN Architecture for Additive Hybrid model.

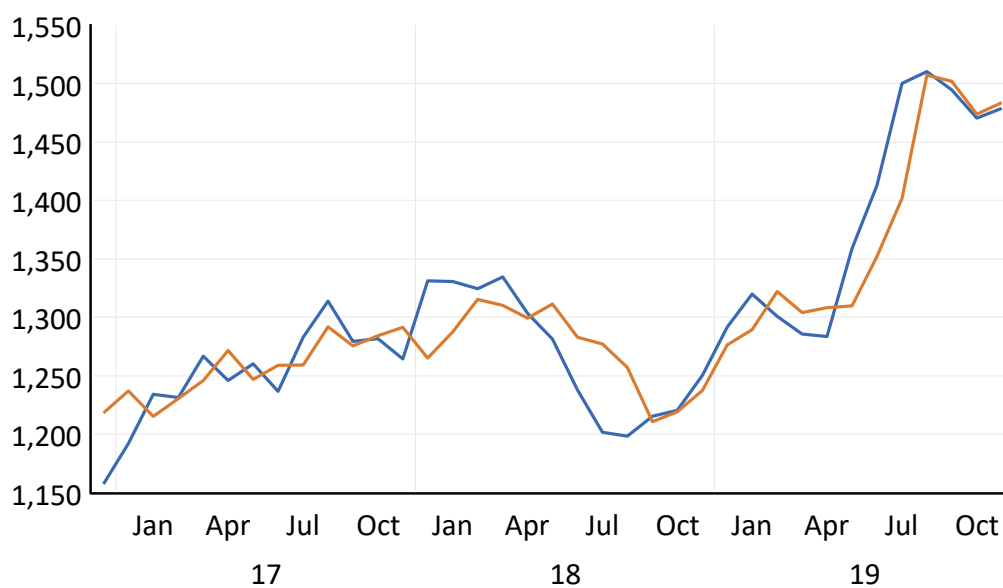


Fig. 10: Actual and Forecast Results by Additive Hybrid Model.

The network has used 20 hidden layers obtained from trials and performance comparison of different numerical. For this model the best fitted model is ARIMA-ANN (0,1,1)(1:20:1). Figure 10 shows how the actual and forecasted values of monthly gold prices fair for test dataset.

5.4 Khashei and Bijari’s Model

Variations in the additive-hybrid and Khashei-Bijari’s hybrid-models are the inclusion of exogenous variable. ARIMA and ANN are individually applied as a forecasting model in additive hybrid-model while the past observed data $y_{t-1}, y_{t-2}, \dots, y_{t-n}$ determines the forecasted results of ARIMA for data \hat{L}_t , while the residuals $e_{t-1}, e_{t-2}, \dots, e_{t-n}$ are fed to ANN.

In this model, ANN was trained by the past observed data to indicate the forecasted result of ARIMA and its residuals and its network presented in Figure 11.

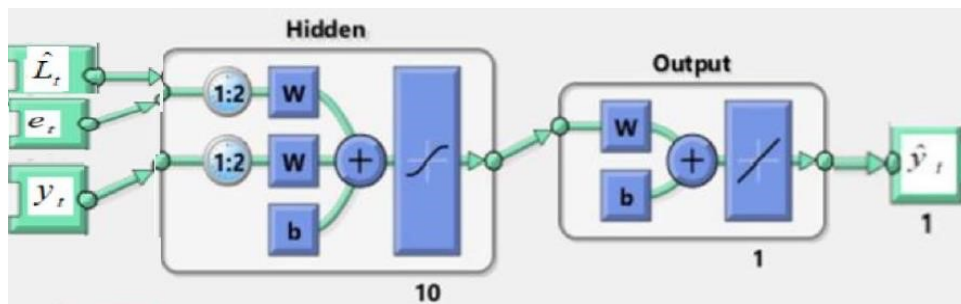


Fig. 11: The ANN Architecture for Khashei and Bijari’s Model.

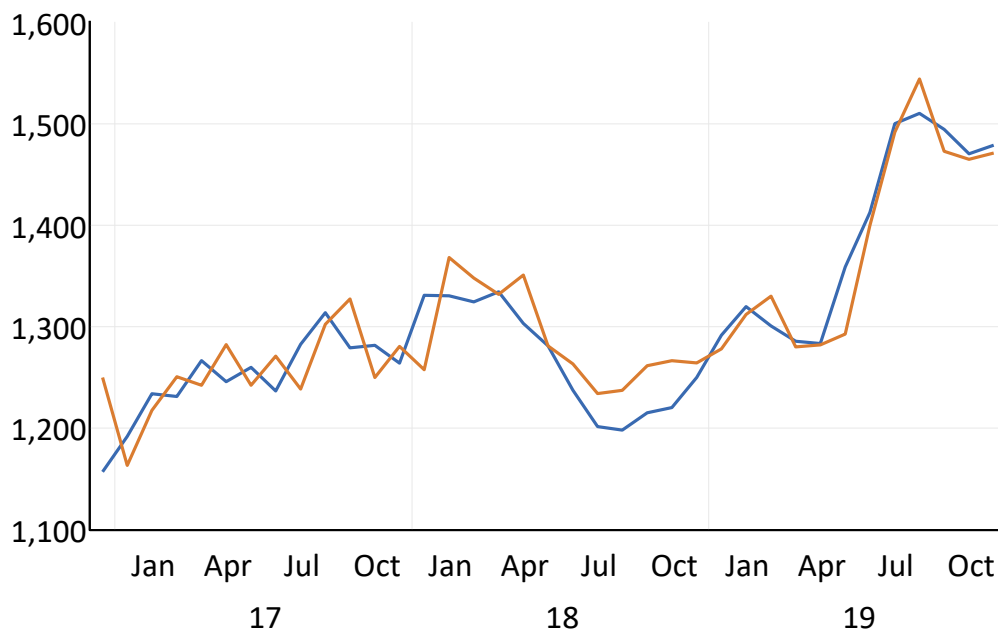


Fig. 12: Actual and Forecast Results by Khashei-Bijari’s Model.

The number of delays in this network is 2 with 10 hidden-layers. The values are reached at from different trials and comparisons of their performances. For this model the best fitted model is ARIMA-ANN (0,1,1)(3:10:1).

Figure 12 depicts the comparison from the actual and forecasted values of monthly gold price dataset. ARIMA-ANN (0,1,1)(3,10,1) model obtained very close predicted values to the actual value with the latter behaving in a similar pattern with the actual data.

5.5 Multiplicative Model

In this model, a given time series data is the product of a linear and a non-linear time series unlike the additive nature assumed by Zhang's model and the Khashei-Bijari's hybrid models. After determining an appropriate ARIMA model, an ANN was trained by the residuals from the fitted ARIMA model while the inputs, a hidden, and output layers included in ANN. The monthly gold price model is excluded in the neural network in this model since it is already considered in the linearity component. ANN is applied in the nonlinearity component that models the residuals of ARIMA model and the network displayed in Figure 13.

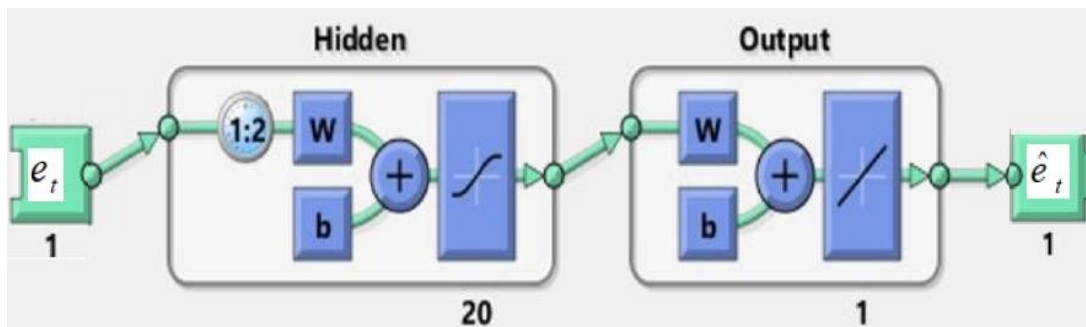


Fig. 13: The ANN Architecture for Multiplicative Model.

The number of delays in this network is 2 with 20 hidden all determined through trials of various numbers while comparing their performances. For this model the best fitted model is ARIMA-ANN (0,1,1)(1:20:1). The actual and forecasted values of monthly gold prices are compared in Figure 14.

6 Results and Discussions

Table 4 presents results of the prediction performance obtained through ARIMA, ANN, and the hybrid models in terms of MSE, MAE, and MAPE. The models are ordered by their performance on the dataset. From Table 4, it can be clearly seen that hybrid models have achieved lower errors than other models. This may suggest that neither ARIMA nor ANN model captures all of patterns in the data.

Table 4: Performance Comparison for the Monthly Gold Price Data.

Model	MSE	MAE	MAPE
Khashei and Bijari's	1192.30	27.73	2.17
Additive	1280.30	27.02	2.09
Multiplicative	1366.10	29.30	2.24
ANN	1800.00	31.12	2.39
ARIMA	5703.41	55.22	4.10

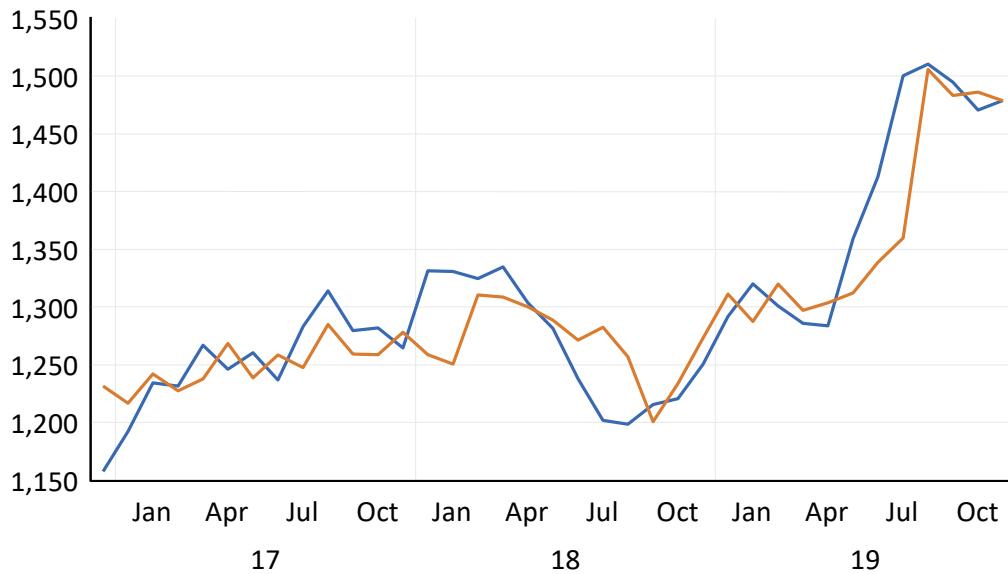


Fig. 14: Actual and Forecast Results by Multiplicative Model.

7 Conclusion

Having an improved time-series forecast is very important but several focuses on the developed forecasting models are on these improvements especially on prediction accuracies that aid forecasts. Hybrid models have currently become a popular forecasting technique combining single models to one or different model types normally applied to linear and nonlinear forecasting models. The hybrid models usually offer better prediction results on average compared to single forecasting models although single models are accurate during some prediction periods. Greater potentials are mainly realized when single and hybrid models are combined to improve the forecasting accuracies. This study aimed to compare between ARIMA, ANN and hybrid models for time series forecasting. The most important finding was from the application of hybrid models that improved the forecasting accuracy over individual models. This further indicated ARIMA and ANN model failures to capture all of patterns in the data. For example, in terms of MSE, the additive hybrid ARIMA-ANN model has lower MSE than ARIMA model and that means the additive model has a better performance than ARIMA in the forecasting accuracy. Another example, in terms of MAE, the Khashei-Bijari hybrid ARIMA-ANN model can give more accurate forecasting than ANN since ANN has higher MAE. As future work, we will further investigate other hybrid models and employing machine learning algorithms in order to increase forecasting accuracy.

Conflict of Interest

The authors declare that there is no conflict regarding the publication of this paper.

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