A Hybrid Model of Artificial Neural Network and Genetic Algorithm in Forecasting Gold Price

Azme Khamis and Phang Hou Yee

Abstract—The goal of this study is to compare the forecasting performance of classical artificial neural network and the hybrid model of artificial neural network and genetic algorithm. The time series data used is the monthly gold price per troy ounce in USD from year 1987 to 2016. A conventional artificial neural network trained by back propagation algorithm and the hybrid forecasting model of artificial neural network and genetic algorithms are proposed. Genetic algorithm is used to optimize the of artificial neural network neurons. Three forecasting accuracy measures which are mean absolute error, root mean squared error and mean absolute percentage error are used to compare the accuracy of artificial neural network forecasting and hybrid of artificial neural network and genetic algorithm forecasting model. Fitness of the model is compared by using coefficient of determination. The hybrid model of artificial neural network is suggested to be used as it is outperformed the classical artificial neural network in the sense of forecasting accuracy because its coefficient of determination is higher than conventional artificial neural network by 1.14%. The hybrid model of artificial neural network and genetic algorithms has better forecasting accuracy as the mean absolute error, root mean squared error and mean absolute percentage error is lower than the artificial neural network forecasting model.

Index Terms—Artificial Neural Network; Forecasting; Genetic Algorithm; Gold Price; Machine Learning.

I. INTRODUCTION

Gold is one of the most precious elements on earth. After that, activity of gold price trading is become more common and hence gold price fluctuates. Gold price per troy ounce shows the steady upward trend since the early of 2008 because demand increases as in [1]. According to [2], the gold price plays an important role in economic. Most of the commodities are correlated with gold price. Many researchers claim that gold price is an important indicator because gold is one of the most popular financial instruments. For instance, [3] devotes forecasting of gold price is an essential issue because gold price serves as the expectation of investors and the reflection of the trend of the world's economic. Moreover, [4] claims that forecasting gold price is beneficial to the investors and companies. With data-decision making, uncertainty can be decreased. Therefore, forecasting the future price of gold by using suitable models is essential.

There are a lot of gold price forecasting model proposed by the researchers. As an example, [5] discussed on forecasting monthly gold price by using linear regression model. In addition, [6] proposed Box-Jenkins model to forecast gold price. In the research, ARIMA (0,1,1) is the optimal forecasting model for gold price. Box-Jenkins model is supported by [7].

In addition, machine learning techniques such as artificial neural network (ANN) [8] can be used to forecast gold price. In [8], USD index, silver price, interest rate, oil price and stock market index are used as the predictor variables of the ANN model to predict gold price.

ANN is effective in forecasting. In previous studies, ANN is applied in different field. In [9], the result shows ANN has ability to handle complex model, it can predict electricity price effectively despite of the volatility of the data. Moreover, ANN can be used in modelling. A study [10], ANN is used to model palm oil yield and the result is compared with multiple linear regression model (MLR). The result shows ANN has outperformed MLR in predicting palm oil yield. However, [11] claims that ANN may lead to local minima and should be overcome. GAs can be used to overcome the local minima issue in ANN [12]. In [13], and [14], GAs was used to improve the learning algorithm of ANN and result shows GAs improved ANN model. Hence, by combining these two techniques can be useful in solving the real-world problem especially in forecasting field.

The activity-based costing and assign quantities of indirect cost behave non-linear pattern. Though the hybrid model uses fewer cost drivers than traditional ANN, it has outperformed the traditional model [14]. The hybrid model is better because it will not be interrupted by the variations in the number hidden nodes. As a result, it can yield better performance in allocating the indirect cost. The weakness of this research is that the data used is simulated data. The model may perform well for the studies but it may not be applicable in the actual problem in life as the real-life problem may be affected by other external factors.

In addition, the hybrid model of ANN and GAs can be employed to forecast gold future price. For instance, [12] suggested by equipping GAs with ANN as it can be useful to cope the problem of the scarce prior knowledge about the structure of problem domain. The hybrid model can solve the problem by simulating the non-linear models. Improvement of the hybrid model compare to the traditional ANN model is shown in the result of the hybrid model yielded forecast with lower error [12].

The hybridization model of ANN and GAs can perform effectively in the environmental field as well. A study conducted by [15] optimize the feedforward network in ANN coupling the GAs and back propagation learning to forecast rainfall. GAs determines the suitable input for the forecasting rainfall network structure. By integrating GAs with ANN, the forecast performance is more reliable than

the ordinary ANN model as there was improvement for the error.

Gold price is hard to be predicted as there are many contributing factors affecting gold price. Furthermore, gold is one of the most important financial instruments. By having an accurate gold forecasting model, Malaysia government and investors can make a better decision. Hence, there are tons of forecasting model can be used to forecast gold price. One of the most popular techniques is by using ANN. However, the ANN forecasting model has limitations. As a result, by using monthly gold price per troy ounce from year 1987 to 2016 provided by World Gold Council, this research aims to propose acquire an ANN forecasting model and to acquire the hybrid ANN and GAs forecasting model. Forecasting performance of conventional ANN forecasting model and the ANN and GAs hybrid model will be evaluated by using suitable forecasting accuracy measures. Finally, the best model will be proposed to forecast the monthly gold price per troy ounce.

II. RESEARCH METHODOLOGY

The gold price per troy ounce data in USD starting from January 1987 to December 2016 was obtained from the official website of World Gold Council. The data was separated by using 80-20 proportion. Eighty percent of the data (288 observations) was used for training of the model. Meanwhile, the other twenty percent of the data, which is 72 observations was reserved for testing of the forecasting mode. ANN Forecasting Model: Before constructing the ANN, autocorrelation plot and partial autocorrelation plot were used to determine the significant lag and seasonality of monthly gold price per troy ounce data. Moreover, the gold price per troy ounce is normalized to ensure standardization as (1) [8].

$$normalized\ Y_t = \frac{Y_t - Y_{min}}{Y_{max} - Y_{min}} \qquad (1)$$

where Y is the gold price at t, $Ymax$ is maximum gold price and $Ymin$ is the mean of observation value.

ANN is a computational model that consists of three fundamental layers which are input layer which are input layer, hidden layer and output layer. In feedforward NN, unidirectional transferring of data occurs from the input layer to the hidden layer and eventually reaches the output layer. The architecture of ANN in this research is shown in Fig. 1 [16]. The input node value is duplicated and multiplied by the corresponding weight and its summation is known as activation value. Subsequently, activation function is applied to the activation value to obtain output. The activation used in this research is sigmoid function as (2).

The sigmoid function has range from 0 to 1 and it is effective for the weight updating process in the training algorithms of ANN [16]. The output value is obtained by the summation of the value of hidden node with its corresponding weight. Then the result is compared with the targeted result in order to improve the model. The margin of error of the output is determined before the change in the output weight of the ANN model. The weight of the hidden layer to the output sum is revised by using delta sum to decrease the margin of error. In addition, in back propagation, the weight of input layer to the output layer is revised accordingly to the requirement.

$$\Phi = \frac{1}{1+e^{-\sum_{i=1}^{n}(y_i \cdot w_i)}} \qquad (2)$$

where y_t is the gold price, w_i is the associated weight, Φ is the activation function.
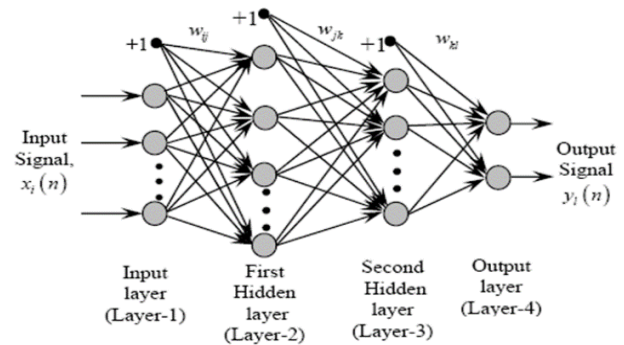

Fig. 1. Feedforward ANN Architecture

The input value for the ANN is the monthly gold price per troy and its significant lag. In this research, the ANN model with two hidden layers has been constructed by using back propagation learning (Fig. 1). Sigmoid function is the activation function used to train and calculate the output. The margin of error of the output is determined in order to revise the weight of neurons. The learning iteration is terminated when the improvement is not significant.

III. HYBRID ANN AND GAS FORECASTING MODEL

For the hybrid model, GAs is used to optimize the error by revising the weight of neurons. First and the foremost, the ANN model is selected based on the lowest root mean squared error (RMSE). Then, weight of the neurons in ANN is trained by using GAs operators including selection, crossover, mutation and evaluation. The weight of the neurons in the best ANN model are encoded as string and it is evaluated based on the fitness function. When it fulfills the termination condition, GAs will stop. Otherwise, it will continue with selection, crossover and mutation. The fitness function is based on RMSE equation (5).

Selection operator in GAs will select the chromosomes from the population chromosomes with higher fitness and pass it to next generation for crossover process. The lower the RMSE, the higher the fitness and it has higher chance to be selected to next generation. There is an additional operation in selection process, which is elitism process. It is used to prevent the best chromosome lost from selection process. After the selection process, GAs continue the crossover and mutation process.

The objective of crossover is to create new individual by combining two individuals based on the probability. Crossover is adapted to converge the solution to certain point. Single-point crossover is used in this research. Two new offspring are formed after the exchange of the string has been performed at a single-point of the two parents'

chromosome. Single point crossover will produce two offspring.

Then, mutation occurs after the crossover process in which it involves flipping of some bits in a chromosome to avoid convergence. The flipping of the chromosomes is to generate a new chromosome. After one iteration, the fitness value will be evaluated and the evolutionary GAs cycle is terminated when the satisfied solution is obtained [17]. In this research, the optimal combination of selection ratio and mutation rate is determined by trial and error.

The model selection is based on the coefficient of determination value equation (3) [8]. After the model was built, R^2 value and RMSE is obtained. R^2 is used to determine the fitness of the forecasting model in this research. When the R^2 value is higher, the more uncertainty is explained by the model. In addition, RMSE is used for model selection. RMSE is the square root of the average squared error.

The lower the error, the higher the accuracy of the forecasting model. Hence, the model with higher coefficient of determination and lower RMSE will be chosen as the forecasting model. After model is selected, normality test is done to ensure the model is suitable to be used to forecast monthly gold price per troy ounce.

$$R^2 = 1 - \frac{\sum(\hat{y}_t - y_t)}{\sum(y_t - \bar{y})} \quad (3)$$

where Y_t is the actual observation value, $\hat{y}_t$ is the forecasted value and $\bar{y}$ is the mean of observation value.

IV. FORECASTING ACCURACY MEASURES

Performance of the forecasting model is assessed by using mean absolute error (MAE), mean absolute percentage error (MAPE) and RMSE. MAE is the average of the absolute error, where the error is the difference between the actual observation value and the corresponding forecast. The higher the MAE and RMSE, the lower the accuracy. The value of MAPE is between 0% to 100%, where the forecast accuracy is high when the MAPE is lower. When the forecasting model has lower MAE, MAPE and RMSE value, the more accurate the model is.

$$MAE = \frac{\sum_{t=1}^{n}|Y_t - F_t|}{n} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - F_t)2}{n}} \quad (5)$$

$$MAPE = \frac{\sum\left|\frac{Y_t - F_t}{Y_t}\right|}{n} \times 100 \quad (6)$$

where Y_t is the actual observation value, F_t is the forecasted value and n is the number of non-missing data points.

Anderson-Darling (AD) test is used to assess the residual of the forecasting model. When the p-value of the residual is larger than 0.05, null hypothesis is not rejected, where the residual follows normal distribution. Normality testing is done to ensure the forecasting model is suitable to be used in the future.

V. RESULTS AND DISCUSSIONS

ANN Model Building: Three ANN models were built by using significant lag of gold price per troy ounce. The ANN 1's inputs are gold price per troy ounce and lag 1. While ANN 2's inputs are gold price per troy ounce and lag 2 and ANN 3 has gold price, lag 1 and lag 2 as input. The epochs taken to build the model 1, 2 and 3 is 805 epochs, 790 epochs and 801 epochs respectively as shown in Table I. This shows ANN 2 is most efficient among the three models. On the other hand, R^2 value indicates ANN 1 has better fitness compare to the other two models. 90.92% of the forecast value is explained by the monthly gold price per troy ounce and lag 1 of gold price.

However, model 2 has R^2 value 74.88%. This means that model 2 does not explain the forecast value as good as model 1. The R^2 value of model 3 falls between model 1 and 2. 88.91% of monthly forecasting gold price explained by the model. The RMSE of ANN 1 is 10.4626 and it is lowest RMSE among the three models. Based on the R^2 and RMSE value, model 1 that contains monthly gold price and lag 1 of gold price per troy ounce can be concluded as the best model among the three possible models because it has highest R^2 value and with lowest RMSE. Then the ANN 1 1 will be used to hybrid with GAs.

TABLE I: COMPARISON OF ANN TRAINING MODEL

Model	Input Variable	Epoch	RMSE	R^2 (%)
ANN 1	Gold price, Lag 1	805	10.4626	90.92
ANN 2	Gold price, Lag 2	790	12.2648	74.88
ANN 3	Gold price, Lag 1, Lag 2	801	11.2824	88.91

GA-NN Model Building: The weights of neurons in ANN 1 is hybridized by using GAs with different crossover probability and mutation probability. The crossover probability that chosen for this research is 0.7 and 0.8. Moreover, 0.01 and 0.02 probability were used for mutation probability. The RMSE for GA-NN 1, GA-NN 2, GA-NN 3 and GA-NN 4 are 12.37, 1016, 12.85 and 11.08 respectively. GA-NN 2 has the best forecasting performance as it has the lowest RMSE. Moreover, as depicted in Table II, R^2 of GA-NN is 92.18% which is the highest among the four hybrid models. This indicates GA-NN 2 has higher fitness compare to the other forecasting model. The crossover rate and mutation rate of GA-NN 2 is 0.7 and 0.02. It is chosen to compare the forecasting accuracy with the classical ANN 1.

TABLE II: COMPARISON OF GA-NN TRAINING MODEL

Model	Crossover Rate	Mutation Rate	RMSE	R^2
GA-NN 1	0.7	0.01	12.37	89.78%
GA-NN 2	0.7	0.02	10.16	92.18%
GA-NN 3	0.8	0.01	12.85	89.14%
GA-NN 4	0.8	0.02	11.08	90.51%

VI. Comparison Of ANN And GA-NN Forecasting Model

After diagnostic checking on the residual of ANN 1 and GA-NN 2, both models were used for model testing. From AD test, both models are suitable to be used as they have normally distributed residuals. Then comparison of forecasting performance between the two models are made based on MAE, RMSE and MAPE. Moreover, R^2 is used to determine the fitness of the forecasting model.

ANN 1 and GA-NN 2 forecasting model's MAE value are 22.1249 and 18.0679 respectively. GA-NN 2's MAE is lower than ANN 1's MAE by 4.057. Furthermore, ANN 1's RMSE is 22.2911. While RMSE of GA-NN 2 is 18.5437 which is lower than ANN's RMSE by 3.7474. In addition, ANN 1 model has the higher MAPE value than GA-NN 2 model on average, ANN 1 model's forecast is off by 7.6316%. On the other hand, MAPE value of GA-NN 2 is 6.3374%. By using R^2 value, GA-NN 2 model has better fitness compare to the ANN 2 model as R^2 of GA-NN 2 is higher than ANN 1 by 1.14%. As a result, GA-NN forecasting model is outperformed ANN model as it has higher forecasting accuracy and better fitness.

The result shows GAs can improve the forecasting performance of ANN model because the forecasting performance of GA-NN is outperformed the traditional ANN forecasting model. GAs is a global searching technique that is commonly used to generate high quality solution. The improvement of the forecasting model is due to the global search ability of GAs in optimizing the weights of the neurons in ANN. GAs prevents ANN falls into local minima.

TABLE III: Forecasting Performance of ANN and GA-NN Model

Model	MAE	RMSE	MAPE	R^2
ANN 1	22.1249	22.2911	7.6316	85.92%
GA-NN 2	18.0679	18.5437	6.3374	87.18%

In short, the gold price per troy ounce has trend from year 1987 to 2016 and it is quite volatile. Yet the gold price per troy ounce can be predicted by using suitable forecasting model. Gold price per troy ounce and lag 1 of gold price per troy ounce were used for classical artificial neural network model and the hybrid of artificial neural network and genetic algorithm model building. As shown in the result, hybrid GA-NN model has better forecasting accuracy compare to classical ANN as hybrid GA-NN 2 model has lower MAE, RMSE and MAPE value. As a result, GA-NN 2 is suggested to be used in forecasting monthly gold price per troy ounce.

VII. Conclusions

In this study, two forecasting models are proposed to forecast the gold price per troy ounce for year 1987 to 2016. The first forecasting model is classical artificial neural network forecasting model with two hidden layers and 5 hidden nodes in each hidden layer trained by back propagation. Then the second forecasting model has the same architecture with the first forecasting model and the model is trained by using genetic algorithms (GAs). GAs is used to optimize the weight of neurons in ANN. ANN 1 was used to hybrid with GAs with different parameter. Four GA-NN models were proposed and GA-NN 2 was chosen as it has best fitness and accuracy performance. The crossover rate and mutation rate used for GA-NN2 were 0.7 and 0.02 respectively. The R^2 value of GA-NN 2 is 92.18 which is highest among the four GA-NN models. In term of forecasting accuracy, GA-NN 2 has the best forecasting performance because it has the lowest RMSE. The RMSE for GANN 2 is 10.16.

GA-NN forecasting model is more accurate compare to ANN model as it has lower MAE, MAPE and RMSE of both model. Moreover, R^2 of GA-NN is higher than ANN model by 1.14%. This shows the GA-NN model has better fitness for monthly gold price compare to ANN model. Hence, the forecasting performance of hybrid model of ANN and GAs is outperformed the conventional ANN forecasting model. This study can conclude that GAs can improve the performance of ANN model because GAs is a global searching technique that is commonly used to generate high quality solution. The results of this research show GA-NN forecasting model is outperformed ANN model with back propagation learning because GA-NN forecasting model can produce the monthly gold price forecast with lower error. The improvement of the forecasting model is due to the global search ability of GAs in optimizing the weights of the neurons in ANN.

References

[1] S. Shafiee and E. Topal, "An Overview of Global Gold Market and Gold Price Forecasting", Resources Policy, 35(3), pp. 178-189, 2010.
[2] H. Mombeini and A. Yazdani-Chamzini. "Modeling Gold Price Via Artificial Neural Network". Journal of Economics, Business and Management, 3(7), pp. 699-703, 2015.
[3] B. Li, "Research on WNN Modeling for Gold Price Forecasting Based on Improved Artificial Bee Colony Algorithm." Computational intelligence and neuroscience, 2014(2), pp. 1-10 2014.
[4] W. Kristjanpoller, and M. C. Minutolo, "Gold Price Volatility: A Forecasting Approach Using the Artificial Neural Network–Garch Model." Expert Systems with Applications, 42(20), pp. 7245-7251, 2015.
[5] Z. Ismail, A. Yahaya, and A. Shabri, "Forecasting Gold Prices Using Multiple Linear Regression Method." American Journal of Applied Sciences, 6(8), pp. 1509-1514, 2009.
[6] M. M. A. Khan, "Forecasting of Gold Prices (Box Jenkins Approach)." International Journal of Emerging Technology and Advanced Engineering, 3(3), pp. 662-670, 2003.
[7] R. Davis, V. K. Dedu and F. Bonye, "Modeling and Forecasting of Gold Prices On Financial Markets." Am. Int. J. Contemp. Res, 4(3), pp. 107-113, 2014.

[8]   H. Mombeini and A. Yazdani-Chamzini, "Modeling Gold Price Via Artificial Neural Network." Journal of Economics, business and Management, 3(7), pp. 699-703, 2015.

[9]   H. Y. Yamin, S. M. Shahidehpour and Z. Li, "Adaptive Short-Term Electricity Price Forecasting Using Artificial Neural Networks in The Restructured Power Markets." International journal of electrical power and energy systems, 26(8), pp. 571-581, 2014.

[10] A. Khamis, Z. Ismail, K. Haron and A. T. Mohammed, "Neural Network Model for Oil Palm Yield Modeling." Journal of Applied Sciences, 6(2), pp. 391-399, 2006.

[11] D. J. Montana and L. Davis, "Training Feedforward Neural Networks Using Genetic Algorithms." In IJCAI 89, pp. 762-767, 1989.

[12] S. Mirmirani, and H. C. Li, "Gold Price, Neural Networks and Genetic Algorithm." Computational Economics, 23(2), pp. 193-200, 2004.

[13] K. J. Kim and I. Han, "Genetic Algorithms Approach to Feature Discretization in Artificial Neural Networks for the Prediction of Stock Price Index." Expert systems with Applications, 19(2), pp. 125-132, 2000.

[14] K. J. Kim and I. Han, "Application of A Hybrid Genetic Algorithm and Neural Network Approach in Activity-Based Costing." Expert Systems with Applications, 24(1), pp. 73-77, 2003.

[15] M. Nasseri, K. Asghari, and M. J. Abedini, "Optimized Scenario For Rainfall Forecasting Using Genetic Algorithm Coupled With Artificial Neural Network". Expert Systems with Applications, 35(3), pp. 1415-1421, 2008.

[16] S. Haykin, and N. Network, "A Comprehensive Foundation." Neural Networks, 2, pp. 41, 2004.

[17] M. Mitchell, "An introduction to genetic algorithms." England: MIT press, 1998.