Forecasting Monthly Prices of Gold Using Artificial Neural Network

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Abstract

This study successfully fitted an artificial neural network to a series on gold prices. The data used was monthly gold prices in US dollars and cents per troy ounce from October 2004 to February 2020. Of the 17 suggested Artificial Neural Network structures, the one with 2, 6 and 1 neurons in the input, hidden and output layers (ANN (2-6-1)) was adjudged the best because it had the least error, Mean Square Error (MSE) and Mean Absolute Error (MAE). The adequacy of the selected model was further confirmed by graphical examination of the actual values of gold prices and the ones predicted by the model as well as graphical residual analysis. Consequently, forecasts were made using the chosen network. The forecasts suggest a decline in gold prices in the coming months.

Keywords: Gold, Forecasting, ANN.

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1 Introduction

Gold is a precious metal which has always been considered valueable to man from time immemorial. In order to underscore the importance of crude oil, it is called the liquid black gold in some quarters. Gold has shown a remarkable ability to retain its value even during periods of economic, financial and political crises. Central banks across the globe maintain gold reserves to guarantee the money of depositors, foreign-debt creditors and currency holders. Central banks also use gold reserves to control inflation which is a situation where money loses value because too much money is chasing too few commodities as well as strenghten their country's financial standing, [1]. It was reported that gold maintained a fair price during the five known pandemics within the period of 1957 to 2009, [1,2]. Given the popularity and consequent relevance of gold in the world, forecasting of its price has become an increasingly explored area. This study contributes towards this area by using a non-linear model to forecast future prices of gold. It is the hope of the authors that this will guide interested individuals in investment decisions especially at a time that the novel coronavirus pandemic dupped COVID-19 is ravaging the world with multisectorial implications including a possible worldwide recession.

[1] presented a review of literature concerned with a variety of methods that had been previously applied in time series forecasting in the field of economics and finance. It is their submission that with the fast growing of recorded data, traditional statistical analyses methods need to combine with computational skills to boost their performance in statistical analysis. They also opined that data mining techniques that could complement the traditional statistical analysis should be considered in time series analysis and forecasting in future. [3] fitted an autoregressive integrated moving average model to the figures of gold prices from July 2013 to June 2018. In effect, the authors modelled daily prices of gold during that period. Autocorrelation, Partial Autocorrelation, Akaike Information Criterion and Bayesian Information Criterion were used to estimate the accuracy of the model. ARIMA(3,1,2) was seen as the finest model to predict the gold price. [4] concluded that ARIMA (1,1,1) was the best fit for the prices of gold series. The authors themselves confirm that the linear nature of the ARIMA model is a constraint and suggested implementing nonlinear forecasting techniques using soft computing techniques. [5] used ARIMA (0,1,1) to predict gold proces using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) as error indicators. [6] applied Box-Jenkins ARIMA model of order (1,0,1) to model and forecast incidence of neonatal mortality in Abia State of Nigeria.

[7] proposed a model; A neural network equipped with BAT algorithm (BNN) which is to cope with jumps and drips using a learning procedure and results from the study showed the model outperformed all well-known benchmark models considered in the study. [8] used machine learning approach to predict the future gold rates. Artificial Neural Network (ANN) and Linear regression are the two approaches considered. Even though the performance of the Linear Regression was lower than that of the ANN, the difference was not statistically significant. Linear regression had a faster learning rate. Their study took into consideration various economic indicators of various companies and countries. According to them, it is the first time that stock value of major gold trading/producing companies and Russia's interest rates have been successfully used as an indicator for forecasting gold rates. They also found that the stock value of a major company has more influence on gold rates than the US economy.

[9] compared the performance of ANN and ARIMA in modelling prices of gold. The performance indicators they used were coefficient of determination, RMSE and MAE. Results from the study showed that the ANN outperformed the ARIMA. A similar study was conducted by [10] using Stock Prices as the variable to be predicted. Results from the study also show that the ANN outperformed the ARIMA using Mean Square Error (MSE) as an indicator of performance.

[11] found that an ARIMA-ANN hybrid model outperformed the individual ARIMA and ANN models when predicting stock market returns using MSE as a means of comparison. It is also lucid from the study that ANN outperformed the linear ARIMA model.

2 Methodology

The data used for this study was monthly prices of gold in US dollars and cents per troy ounce from October 2004 to February 2020. The data was obtained from the Index Mundi website [12] which claims its source is the World Bank. Zaitun Time Series version 0.2.1 was used for the analysis. According to [13], most economic and financial time series exhibit nonliearity and nonstationarity and as such, modelling and forecasting such with linear models such as the Autoregressive Integrated Moving Average (ARIMA) Models leaves the nonlinear behaviour uncaptured. Gold price series is an economic series and as such, our fitting of Artificial Neural Network (ANN) which is non-linear is justified.

The Artificial Neural Network (ANN) are a class of flexible computing framework which operate by mimicking the intelligent working paradigm of the human brain for solving a broad range of nonlinear and complex problems, [14]. They are data-driven, self-adaptive methods with fewer prior assumptions, [15]. Amongst the advantages of Artificial Neural Networks is that they are universal approximators and no prior knowledge of the model form is required. Since they are data-driven, the attributes of the data determines the network model, [11]. An Artificial Neural Network typically consists of an input layer, hidden layer(s) and output layer. The number of neurons in the input layer stands for the independent or input variable(s) and the number of neurons in the output layer stand for dependent variable(s). The number of neurons in the hidden layer(s) is usually determined by experimentation.

The relationship between the inputs $(G_{t-1}, G_{t-2}, ..., G_{t-p})$ and output G_t is given mathematically as:

$$G_t = \alpha_0 + \sum_{j=1}^q \alpha_j f\left(\beta_{0j} + \sum_{i=1}^p \beta_{ij} G_{t-i}\right) + \varepsilon_t \tag{1}$$

where $G_{t-i}(i = 1, 2, ..., p)$ are the *p* inputs and G_t is output. *p* and *q* stands for number of input and hidden neurons respectively. $\beta_{ij} = (i = 0, 1, ..., p; j = 0, 1, ..., q)$ are connection weights while ε stands for random shock. Finally, α_0 and β_{0j} are bias terms which are usually 1.

A single hidden layer Feed Forward Neural Network (FFNN) was used in this study. The Feed Forward Neural Network essentially performed a nonlinear functional mapping of past observations of prices of gold to the future value. That is, $G_t = f(G_{t-1}, G_{t-2}, ...,$

 $G_{t-p}, \mathbf{w}) + \varepsilon_t$ where \mathbf{w} is a vector of all parameters and f is a function determined by the network structure and connection weights, [16, 17]. The data was scaled such that the highest value was 1 and the lowest was 0 using the Min-Max Normalization approach (See Eq. 2). The scaling helps the network to converge faster and model better, [18]. During the training of the model, the number neurons in the input and hidden layers were varied by method of trial and error until the network structure with least Error, Mean Square Error (MSE) and Mean Absolute Error (MAE) was obtained as there is no systematic method of choosing them. Learning rate was 0.01 while momentum was 0.9 and this was constant all through the experimentation.

$$Z_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{2}$$

where Z_i is the scaled variable value, X_i is the original variable value, X_{min} is the minimum value in the series and X_{max} is the maximum value in the series.

3 Main Results

Seventeen networks were suggested and fitted to the data set. However, the authors discovered that error was most minimized when the number hidden neurons was 6. Therefore, we then kept the number of hidden neurons fixed at 6 and varied number of input neurons until least error was observed which was when input layer had two nodes. All the tentative models with their error indicators are as shown in table 1 below with the one with least error indicators in bold for ease of identification.

Error	MSE	MAE
2.76564	0.00988	0.08287
1.55402	0.00536	0.05915
3.98598	0.01460	0.10439
3.45535	0.01255	0.09294
3.13194	0.01131	0.08920
2.64645	0.00951	0.07716
3.74842	0.01346	0.09265
3.47470	0.01247	0.09535
3.33804	0.01192	0.08876
2.15322	0.00743	0.07057
2.29018	0.00794	0.06851
2.02693	0.00710	0.07660
1.46300	0.00501	0.05678
0.70710	0.00241	0.03887
0.68626	0.00232	0.03829
0.65110	0.00219	0.03750
1.42441	0.00475	0.05710
	2.76564 1.55402 3.98598 3.45535 3.13194 2.64645 3.74842 3.47470 3.33804 2.15322 2.29018 2.02693 1.46300 0.70710 0.68626 0.65110	2.765640.009881.554020.005363.985980.014603.455350.012553.131940.011312.646450.009513.748420.013463.474700.012473.338040.011922.153220.007432.290180.007942.026930.007101.463000.005010.707100.002410.686260.002320.651100.00219

 Table 1: Tentative Networks and associated error indicators.

The neural network with least error was ANN(2-6-1) (See Table 1) and thus forecasts made using the said network are deemed to be the best amongst the competing networks. Furthermore, from figure 1, it can be easily seen that the selected network reasonably modelled the series adequately. This is further buttressed by figure 2 which is a plot of the actual values against those predicted by the model. There appears to be a strong positive correlation between both sets of values and this is desirable. Figure 3 is a graph of the residuals. It is clear that the residuals snap around zero which shows that they are random shock.

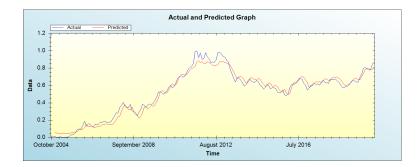


Figure 1: Graph of Actual Prices of gold and the prices predicted by ANN(2-6-1)

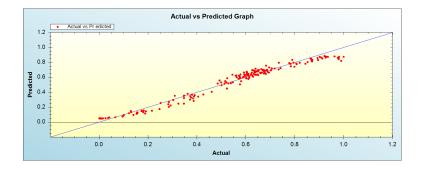


Figure 2: Graph of actual values of gold plotted against predicted values of ANN(2-6-1)

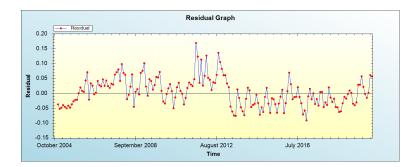


Figure 3: Graph of the Residuals

Lastly, we present forecasted prices of gold in US dollars and cents per troy ounce from March 2020 to December 2021.

Month/Year	Forecasted Price
Mar-20	1543.44
Apr-20	1523.16
May-20	1508.29
Jun-20	1498.70
Jul-20	1492.07
Aug-20	1487.61
$\operatorname{Sep-20}$	1484.50
Oct-20	1482.20
Nov-20	1480.72
Dec-20	1479.50
Jan-21	1478.69
Feb-21	1478.15
Mar-21	1477.74
Apr-21	1477.47
May-21	1477.34
Jun-21	1477.20
Jul-21	1477.06
Aug-21	1476.93
Sep-21	1476.93
Oct-21	1476.93
Nov-21	1476.79
Dec-21	1476.79

Table 2: Forecasted Monthly Prices of Gold in USD per troy ounce.

4 Conclusion

An Artificial Neural Network has been successfully fitted to the data series and the network to a reasonable extent modelled the series adequately. Forecasts has been provided upto December 2021. It is the hope of the authors that the results of this study will guide individuals and even central banks in investing in gold. Furthermore, further studies should consider hybrid models especially linear-nonlinear hybrid models which can combine the strengths of these type of models to improve forecasts.

References

- Yong W. and Sufahani S. (2018). Research review on time series forecasting of gold price movement. International Journal of Multidisciplinary Research and Development, vol. 5, issue 5, pp. 44-49.
- [2] Patton M. (2020). How Stocks Reacted During Past Flu Pandemics And Steps You Can Take To Minimize Losses. Forbes, https://https://www.forbes.com/sites/mikepatton/2020/02/28/howstocks-reacted-during-past-flu-pandemics-and-steps-you-can-take-tominimize-losses/30a88cba448d, date accessed: 19/04/2020, 12:55pm.
- [3] Yang W. (2018). The Prediction of Gold Price Using ARIMA Model. Advances in Social Science, Education and Humanities Research, vol. 196, pp. 273-276.
- [4] Guha B. and Bandyopadhyay G. (2016). Gold Price Forecasting Using ARIMA Model. Journal of Advanced Management Science, vol. 4, no. 2, pp. 117-121.
- [5] Khan, M. M. A. (2013). Forecasting of Gold Prices (Box Jenkins Approach). International Journal of Emerging Technology and Advanced Engineering, vol. 3, issue 3, pp. 662-670.
- [6] Nwokike, C. C., Offorha, B. C., Obubu Maxwell, Uche-Ikonne, O. O. and Onwuegbulam, C. C. (2020). ARIMA Modelling of Neonatal Mortality in Abia State of Nigeria. Asian Journal of Probability and Statistics, Volume 6, Issue 2, pp: 54-62.
- [7] Hafezi R. and Akhavan, A. N. (2018). Forecasting Gold Price Changes: Application of an Equipped Artificial Neural Network. AUT Journal of Modeling and Simulation, vol. 50, no. 1, pp. 71-82.
- [8] ul Sami I. and Junejo, K. N. (2017). Predicting Future Gold Rates using Machine Learning Approach. International Journal of Advanced Computer Science and Applications, vol. 8, no. 12, pp. 92-99.
- [9] Mombeini H. and Yazdani-Chamzini A. (2015). Modeling Gold Price via Artificial Neural Network. Journal of Economics, Business and Management, vol. 3, no. 7, July 2015, pp. 699-703.

- [10] Adebiyi, A. A., Adewumi, A. O. and Ayo, C. K. (2014). Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction. Journal of Applied Mathematics, Volume 2014, 7 pages.
- [11] Musa Y. and Joshua S. (2020). Analysis of ARIMA-Artificial Neural Network Hybrid Model in Forecasting of Stock Market Returns. Asian Journal of Probability and Statistics, vol. 6, no. 2, pp. 42-53.
- [12] https://www.indexmundi.com/commodities/?commodity=gold&months=60
- [13] Maravall A. (1983). An application of nonlinear time series forecasting. Journal of Business and Economic Statistics, vol. 1, pp. 6674.
- [14] Adhikari R. and R. K. Agrawal, R. K. (2012). Forecasting strong seasonal time series with artificial neural networks. Journal of Scientific and Industrial research, vol. 71, pp. 657-666.
- [15] Khashei M. and Bijari M. (2010). An artificial neural network (p, d, q) model for time series forecasting. Expert Systems with Applications, vol. 37, no. 1, pp. 479489.
- [16] Zhang G., Patuwo, B. E. and Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting, vol. 14, pp. 35-62.
- [17] Zhang G. (2003). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, vol. 50, pp. 159-175.
- [18] C. P. Obite, N. P. Olewuezi, G. U. Ugwuanyim, and D. C. Bartholomew, "Multicollinearity Effect in Regression Analysis: A Feed Forward Artificial Neural Network Approach," Asian Journal of Probability and Statistics, vol. 6, no. 1, 2020, pp. 22–33.