Gold price prediction using the Box-Jenkins methodology

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ABSTRACT

Information on the speculation and trading of gold abounds. Investors are attracted to moving their funds to gold as guaranteed storage of wealth, while traders capitalize on the dynamism of the market to build capital. The ups and downs in the price of gold and other precious metals can be predicted with proven mathematical and artificial intelligent algorithms. This study used machine learning algorithm in the price prediction of gold over a ten-year period. Autoregressive Integrated Moving Average (ARIMA) model was used in the experiment, while Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) evaluation metrics were used in the evaluation of the performance of the various ARIMA models. The results obtained in the study proved that ARIMA could achieve high prediction performance over the entire period of prediction. The best prediction outcome of 98.23% was obtained during the 52-week period.

Keywords: *gold, prediction, machine learning, ARIMA, artificial intelligence.*

INTRODUCTION

Gold was first introduced as a medium of exchange in 643 BC. The Roman Emperor Augustus became the first ruler to place the price of this precious metal at 45 coins to the British pound. The value of this precious metal has continually been on the rise over a long period, ascending to the value of 1823USD for an ounce August 2011 (Amadeo, 2019). Accumulation and possession of this precious metal have been a tradition of the general public over the years, both as a means of storing wealth and a way of displaying affluence. Traders have also been capitalizing on the value of the metal to make trades, transacting with it as a medium of exchange. Before the adoption of fiat currency, the gold standard was universally accepted and implemented in most countries of the world. The Gold Standard is a money related framework, where a nation's cash has a worth which is equated to the quantity of gold that the nation has in stock. The British government stopped the use of this standard in 1931, the U.S. followed in 1933, and other countries followed suit. Presently, the standard has been replaced in most countries of the world by fiat money, which is money backed by government order as a means of exchange in the country (Lioudis, 2019).

There seems to exist a direct correlation between the price of gold and the US$. Over the long term, the moment the US dollar starts to decline, the cost of gold is observed to be rising. In some shorter intervals, this is not always the case as the relationship can be tenuous at best.

The U.S. dollar's relation to gold prices can be linked to the Bretton Woods System, which was dissolved in 1971. It is essential to remember that gold and money are dynamic and have more than a straightforward input (Mitchell, 2014). Investing in just any investment vehicle might appear to be quite straightforward. This is, however, very far from the expectation of an investor to be successful. It is on record that most retail investors who are not venture experts lose cash each year. In as much as they can be a variety of reasons for this trend, it can be easily observed that most of this category of investors do not make out enough time to research, neither do they have a research team to help in such analysis (Parker, 2020).

The way a market is organized, operated and regulated has a significant impact on the stability of trading instruments and operations as well as the level of confidence investors will have in staking their fund in anticipation for profit maximization. The market is, however, not static but balances itself in tune with the reflection of the economic wellbeing of the country, the financial system and the level of liquidity of the stocks. In a competitive market, the price of any commodity or instrument is a function of demand and supply. It is a stable compromise between the wishes of several people called agents. The dynamic evolution of a price, as a stock exchange curve represents it, shows phenomena which are explicable only by incorporating the formation of such a balance (Remita & Eisele, 2006). As investment advisers and portfolio managers continue to flood investors with overloaded stock information, the task of making effective and efficient investment decisions becomes more challenging because he has to collect, filter, evaluate the available data, and come up with a right decision relevant to the time (Gamil et al., 2007). This, therefore, calls for more far-reaching strategies and efficient decisions considering both environmental and economic factors in addition to utilizing proven fundamental and technical analysis tools. His psychology and trading strategies come into play here as he tries to outperform the market and maximize returns on his investment.

Efficient Market Hypothesis (EMH) is the proposition that the quoted price of a stock of any company at any given time, must have considered all information about the value of the company at such particular time. This implies that there is hardly a way an investor can earn excess profits using this information (Fama, 1970). EMH suggests that profiting from predicting price movements is very difficult and almost unlikely as the main engine behind price changes is the arrival of new information. Malkiel (2003) opined that the intellectual dominance of the EMH revolution has more been challenged by economists who stress both psychological and behavioural elements of stock-price speculation along with econometricians who argue that stock returns are, to a considerable extent, predictable. In the survey, the researcher came to the conclusion that stock markets are efficient and as a result, less predictable. Various researchers have utilized the ARIMA prediction technique using multiple stock market data, both local and foreign. They have concluded that different models fit different stock data depending on the relationship that exists in the stock exchanges and economy of the countries under study. Azzutti (2016) conducted a comparative analysis in predicting gold prices using various methods of prediction and concluded that ARIMA model is capable of outperforming the random walk at every horizon and on average the ARIMA model is seen providing the best forecasts in terms of the lowest root mean squared error over the 36-month forecasting horizons. Most markets however, behave in a normally distributed pattern where in the long run, produces less noise and more predictability ratios. Hybrid prediction methods that combine both statistical and machine learning techniques will probably prove to be more efficient and effective for stock prediction (Isah et al., 2019).

In a similar study using ARIMA, Ali et al. (2016) surveyed the forecasting of the daily price movement of gold using the dataset of USD per ounce from Jan 02, 2014, to Jul 03, 2015. The research found ARIMA (1,1,0) and (0,1,1) to be close to each other in the prediction using MAE and MAPE are evaluation criteria. Using a non-linear approach, Ayodele et al. (2013) explored the prediction of stock prices by combining the variables of technical and fundamental analysis. In this research, the authors emphasized that Artificial Neural Networks (ANN) is one of the prominent data mining techniques that is presently being used in stock prediction due to its learning ability and its inherent capacity to detect relationships among diverse set of variables. ANN also allows for in-depth analysis of a large dataset, especially those that tend to fluctuate within a short period.

Abidin and Jaffar (2014) explored the use of Geometric Brownian Motion (GBM) to forecast two-week investment closing prices. The experiment shows that the use of one-week historical price data is sufficient to predict share prices using GBM. The researchers used MAPE to prove the accuracy of their work with a MAPE level of <10%. Using the same GBM, Adeosun et al. (2015) conducted an analysis of the behaviour of stock prices of few stocks listed in the Nigeria Stock Exchange. The researchers used GBM with volatility and drift for the forecast and found from this simulation and the results that the proposed model is more efficient for the prediction of stock prices than the simple GBM. The research, however, proposed the lognormal distribution model and suggested that accuracy of results can be improved if the drift and the volatility are structured as stochastic functions of time rather than the use of constants as parameters. Also, Reddy and Clinton, in a similar study, used GBM on price data over the period covering between 1st January 2013 and 31st December 2014. The findings from this research was able to prove that in all the time frames considered in the work, the chances of predicted prices simulated using GBM trending as actual prices were a little higher than 50%. This low level of accuracy can be attributed to the limited set of data used in the experiment. The result of the research was validated using the correlation coefficient and MAPE techniques.

METHOD

The aim of this study is to implement the Autoregressive Integrated Moving Average machine learning algorithm on the prediction of the prices of gold over a given period. This is to assist investors and speculators in the decision-making process of when to buy or sell their asset while making profits. The up-and-down movement of the price of gold and other precious metals has made it difficult for speculators to rely on information from journals solely, internet and investment advisers as the volume of data coming from these sources become very voluminous to digest and make a meaningful decision. At present, some informed investors make use of a combination of technical analysis, fundamental analysis and market sentiments to predict price directions. While these analytical tools still leave the choice of positions to take in the hands of investors, it might not be too easy for such investors to see the trends and waves of market dynamics.

In this study, monthly price movements of gold are used to implement the ARIMA model, while the machine learning algorithms are implemented using the R programming language. Predicted values and errors are calculated and plotted for comparative analysis while MAE and MAPE were adopted and used as error metrics.

Checking for Data Stationarity

Time series data is said to be stationary, when the mean and variance of the data are constant over a given time interval. Since stock data is a time-series data, it becomes imperative that the data must be made stationary before prediction. Data differencing is the commonly used technique of transforming such time series data into a stationary one whenever the need arises. Differencing a non-stationary data is an essential step at the data preparation stage using the ARIMA model. This is partly since summary statistics, including mean and variance, do change over time, and this, therefore, provides a drift in the model, making it inappropriate. There are processes and checks to ensure that the dataset used in both the training and forecast stages is neither overfitted nor non-stationary. These steps include:

i. The dataset is checked for stationary using the R function adf.test(). This function performs the Augmented Dickey-Fuller test. An ADF t-statistic test: small p-values suggest the data is stationary and does not need to be differenced. Otherwise, the data will be differenced. Since our data is non-stationary, we apply to difference, and the data became stationary in order of 1. In our experiment, therefore, the value of d for an acceptable model should be a 1.

   Using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, accepting the null hypothesis implies that the data series is stationary, and high p-values is an indication that the series is not stationary and a differencing is required.

   In this experiment, ADF t-statistics test is adopted.
   ADF Test
   Data: Close.data1
   Dickey-Fuller = -1.6698, Lag = 7, p-value = 0.717
   Alternative hypothesis: stationary

The test conducted above shows that the dataset of XUAUSD is not stationary. This, therefore, calls for checking for significant lags to extract acceptable values of p,d,q.

ii. The data is checked for significant lags using ACF and PACF graphs, and at the same time, differencing the dataset. These graphs are drawn with the following R commands: “xauusd %>% diff() %>% ggtsdisplay(main="")”

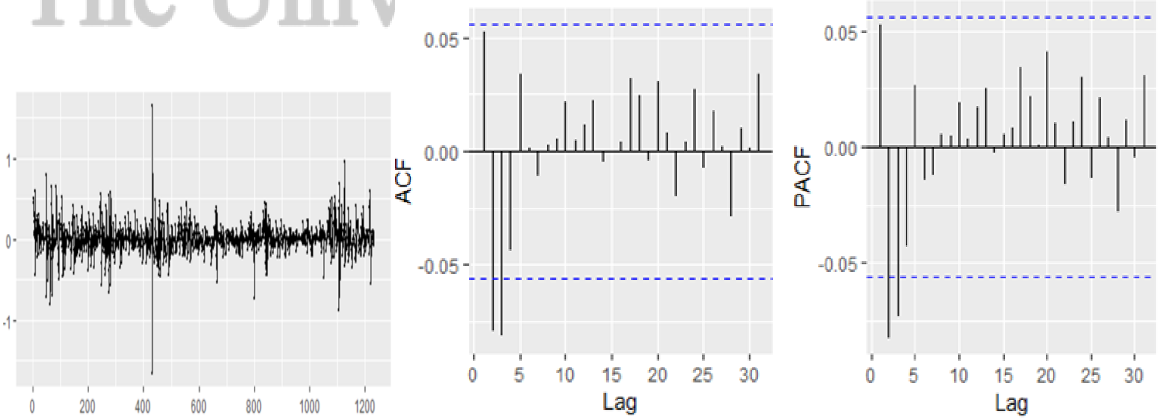

Figure 1. Difference, ACF and PACF for XAUUSD

In most cases, autoregressive processes are identified by possessing highly declining ACF and spikes in the first one or more lags of the PACF. The number of spikes identified indicates the order of the autoregression.

Identification of Autoregressive (AR) model using PACF

To identify the (AR) model, the PACF is expected to extend beyond the order of the model. This implies that in theory, the partial autocorrelations are equal to 0 beyond that point. The number of non-zero partial autocorrelations therefore gives the order of the AR model.

identification of Moving Average (MA) model using ACF

Identifying the MA model is almost the opposite of the AR Model. Here, the theoretical PACF does not shut off but instead tapers toward 0 in some manner. ACF pattern is used in the identification of the MA model. The ACF will have non-zero autocorrelations only at lags involved in the model.

Having established the possible positive values to be used for ARIMA(p,d,q), we proceed to fit the model by calling the R function fit().

Performance Criteria

The prediction performance is evaluated using various error valuation techniques. These include Mean Square Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Equation 1

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|P_t - Z_t|$$

Equation 2

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}|\frac{(P_t - Z_t)}{Z_t}| * 100$$

Equation 3

Data Specification, Collection, Pre-Processing

The primary source of data in this experiment is obtained from the investing.com website where daily, weekly, and monthly price movements of gold and other commodities including stocks are made available to the general public for analysis and guide to investment. Other inputs which may have positive effects on the price of gold, including inflation, interest rates and gross domestic product can as well be in other experiments.

Experimentation

This research focuses on the performance analysis of ARIMA modeling algorithm using the R development platform. Data that was used in the experiment is the weekly time-series data of XAU/USD between 01/01/2009 and 01/06/2018 obtained from investing.com website. Since ARIMA performs its prediction based on a single input variable, there is no need for the inclusion of other input parameters (High, Low, Close, Inflation, GDP, Interest Rate).

Form of ARIMA(p,d,q)

Autoregressive of order *p* model commonly referred to as AR(p) is a discrete-time linear equation with the noise mathematically represented in the form $X_t = \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p}$. Here, p is the order, $\alpha_1 \ldots \alpha_p$ are the parameters or coefficients (real numbers), ε_t is an error term which is usually a white noise. Where p = 1 then AR(1) becomes $_t = \alpha X_{t-1}+\varepsilon_t$ with Abs(α) < 1 and $Var(X_t) = \frac{\alpha^2}{1-\alpha^2}$, it is a wide sense stationary process.

Since AR is a time series model, when we introduce the time lag operator (L) the AR becomes $Lx_t = x_{t-1}$, for all t Є Z (set of real numbers). Since the time lag operator is a linear operator, the powers, positive or negative, can be denoted as:

$$L^{k.} L^k x_t = x_{t-k}, \text{ for all } t \in Z$$

with this lag operation, the AR model becomes:

$$X_t = \alpha X_{t-1}+\varepsilon_t$$
$$X_t - \alpha X_{t-1} = \varepsilon_t$$

Therefore, for $k = 1, p$ we have equation 1 as:

$$\left(1 - \sum_{k=1}^{p} \alpha_k L^k\right) X_t = \varepsilon_t$$

Equation 4

The MA(q) model in ARIMA which is a representative of the moving average with orders (p,q) is a formula for X_t in terms of the noise of the form

$$X_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots .. + \beta_q \varepsilon_{t-q}$$ *Equation 5*

The MA(q) equation (2) becomes

$$X_t = \left(1 + \sum_{k=1}^{q} \beta_k L^k\right) \varepsilon_t$$

Equation 6

Combining equations 1 and 2 for ARMA, we have

$$\left(1 - \sum_{k=1}^{p} \alpha_k L^k\right) X_t = \left(1 + \sum_{k=1}^{q} \beta_k L^k\right) \varepsilon_t$$

Equation 7

or explicitly,

$$X_t = \alpha_1 X_{t-1}+.....+\alpha_p X_{t-p}+\varepsilon_t + \beta_1+\varepsilon_{t-1}+.....+\beta_p+\varepsilon_{t-p}$$

Equation 8

Considering that in ARIMA, the 'I' denotes integration. This implies that it is always imperative to ensure that the data is stationary. This is achieved by integration.

Differencing the operator X, represented as ΔX_t, is defined as:

$$\Delta X_t = X_t - X_{t-1} \, (1 - L) X_t$$

Equation 9

The next difference operator, Δ^2, can also be defined as:

$$\Delta^2 X_t = (1 - L)^2 X_t$$

Equation 10

Introducing the lag(L) in equations 1 and 3 and combining equations 1 and 2 for ARIMA, we have

$$\left(1 - \sum_{k=1}^{p} \alpha_k L^k\right)(1 - L)^2 X_t = \left(1 + \sum_{k=1}^{q} \beta_k L^k\right) \varepsilon_t$$

Equation 11

Equation 11 represents the general form of ARIMA(p,d,q) model which is a discrete-time linear equation

ARIMA Order

This is generally represented as ARIMA(p,d,q), where:

P = order of the autoregressive part
d = degree of first differencing involved
q = order of the moving average part

In this order, if d=0, then the model tends to ARMA which is the linear stationary model. The auto.arima( ) function in R will do it automatically. The model ARIMA(p,d,q) in R programming language comes with various packages that can be used to perform multiple checks on the data before a forecast can adequately be made. Various combinations of p,d,q were tested, and their respective error values were computed in other to determine the best model in each case..

RESULTS AND DISCUSSION

In data analysis, it is often observed that several models can fit a particular set of data. Selecting a particular model over several possible models becomes imperative. Akaike Information Criterium (AIC) is one of the popular methods for model comparison (Merisaari et al., 2018). It is a technique based on in-sample fit to estimate the likelihood of a model to predict/estimate the future values of a series. This method can be used to select between the additive and multiplicative Holt-Winters models. Bayesian information criterion (BIC) is yet another criteria for model selection that measures the relationship between model fit and the complexity of the model. The lower AIC or BIC value, the better the fit. In this research, the AIC selection criterion was adapted for all the models considered in every time interval.

Table 1. 52 Weeks comparison of ARIMA Models and their errors

	52 weeks	
Model	**AIC**	**BIC**
1,1,1	477.05	482.85
2,1,0	478.28	484.08
2,1,1	480.28	488

	52 weeks	
Model	**AIC**	**BIC**
2,1,2	479.78	489.44
2,1,3	478.36	489.95
1,1,0	476.53	480.4

From Table 1, it is evident that ARIMA(1,1,0) with the AIC of 476.53 is the model with the lowest AIC and is therefore used in the experiment.

Table 2: ARIMA(1,1,0) Actual Vs Predicted Values

Week	Close	Predicted	%Error
1	853.45	852.6	0.1
2	843.35	853.42	1.1935
3	899.4	842.51	6.3248
4	927.75	904.03	2.5562
5	911.55	930.09	2.0344
6	942.1	910.21	3.3849
7	993.3	944.63	4.9002
8	945.15	997.53	5.5424
9	937.35	941.17	0.4074
10	928.2	936.71	0.9163

Week	Close	Predicted	%Error
11	952.85	927.44	2.6664
12	923.05	954.89	3.4492
13	893.9	920.59	2.9853
14	881.65	891.49	1.1161
15	868.9	880.64	1.3508
16	913.1	867.85	4.9561
17	887.3	916.75	3.3196
18	917.05	885.17	3.4767
19	931.7	919.51	1.3084
20	957.35	932.91	2.5527

Table 2 is an abridged version of the full table of 52 weeks. On this table, it can be established that the maximum error on this sample is about 6% while recording a minimum of 0.04%. This shows the high level of precision in the use of the ARIMA(1,1,0) model in the prediction of 52-week prices.

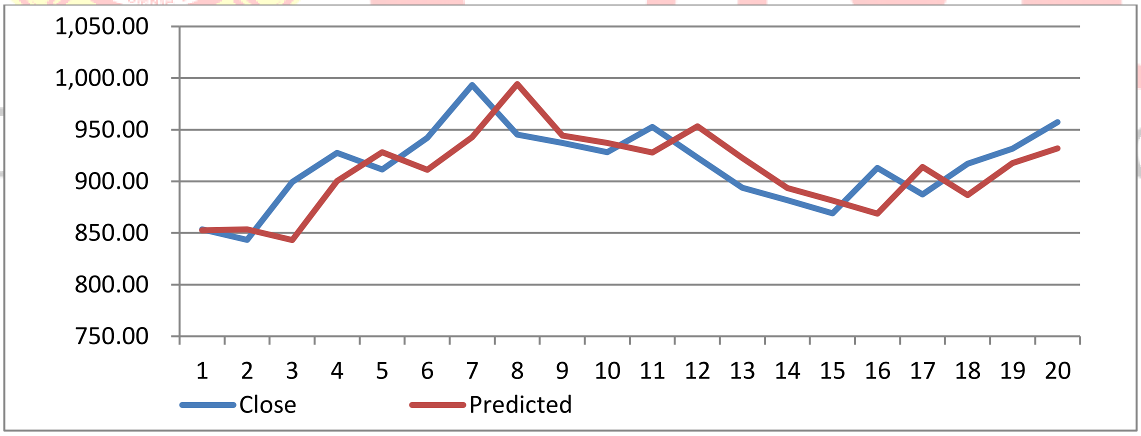

Figure 1. 52-week prediction using the ARIMA(1,1,0) model

Table 3. Error measures for 52-week prediction

RMSE	MAE	MAPE	MASE
24.63006	19.08716	1.95652	0.95802

The error measure shown in Table 3 recorded a MAPE accuracy level of 98.05%.

Table 4. 104-weeks prediction comparison of ARIMA Models and their errors

	104 weeks				104 weeks	
Model	**AIC**	**BIC**		**Model**	**AIC**	**BIC**
1,1,1	959.13	967.03		2,1,2	963.24	976.42
2,1,0	959.97	967.88		2,1,3	963.88	979.69
2,1,1	961.95	972.49		1,1,0	959.08	964.35

From Table 4, it is evident that ARIMA(1,1,0) with the AIC of 959.08 is the preferred model and is there used in the experiment.

Table 5. ARIMA(1,1,0) Actual Vs Predicted Values

Week	Close	Predicted	% Error		Week	Close	Predicted	% Error
1	853.45	852.6	0.1		11	952.85	928.03	2.6044
2	843.35	853.45	1.1974		12	923.05	953.3	3.2768
3	899.4	843.17	6.2523		13	893.9	922.51	3.2006
4	927.75	900.42	2.9463		14	881.65	893.37	1.3296
5	911.55	928.26	1.8335		15	868.9	881.43	1.4418
6	942.1	911.26	3.2739		.	.	.	.
7	993.3	942.65	5.0988		.	.	.	.
8	945.15	994.23	5.1926		103	1,384.75	1,375.22	0.6884
9	937.35	944.28	0.7391		104	1,421.45	1,384.92	2.57
10	928.2	937.21	0.9706					

Table 5 is an abridged version of the full table of 104 weeks.

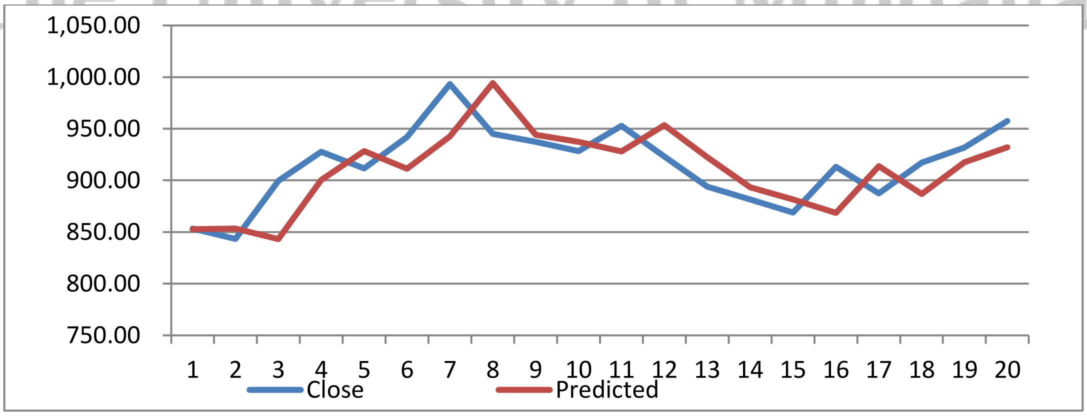

Figure 2. 104-weeks prediction using the ARIMA(1,1,0) model

The Table 6 shows the various error computations for the selected ARIMA model for the 104-weeks prediction.

Table 6. Error Measures for 104-weeks

RMSE	**MAE**	**MAPE**	**MASE**
24.84590	20.23878	1.84868	0.99079

Table 7. 208 Weeks comparison of ARIMA Models and their errors

	208-weeks			208-weeks	
Model	**AIC**	**BIC**	**Model**	**AIC**	**BIC**
1,1,1	2049.68	2059.68	2,1,2	2045.1	2061.76
2,1,0	2048.99	2058.99	2,1,3	2053.53	2072.52
2,1,1	2049.96	2063.29	1,1,0	2048.93	2055.6

From Table 7, it is evident that ARIMA(2,1,2) with the AIC of 2045.10 is the preferred model and is there used in the experiment.

Table 8. ARIMA(2,1,2) Actual Vs Predicted Values

Week	Close	Predicted	% Error	Week	Close	Predicted	% Error
1	853.45	852.6	0.1	11	952.85	936.86	1.6778
2	843.35	853.1	1.1564	12	923.05	957.03	3.6816
3	899.4	844.51	6.1027	13	893.9	911.5	1.969
4	927.75	904.21	2.5369	14	881.65	889.78	0.9223
5	911.55	928.58	1.8677	15	868.9	891.54	2.6051
6	942.1	907.36	3.6877	16	913.1	869.4	4.7854
7	993.3	945.8	4.7819	.	.	.	.
8	945.15	999.71	5.7723	.	.	.	.
9	937.35	937.69	0.0364	206	1,695.47	1,699.64	0.2461
10	928.2	930.99	0.3011	207	1,656.99	1,694.34	2.2543

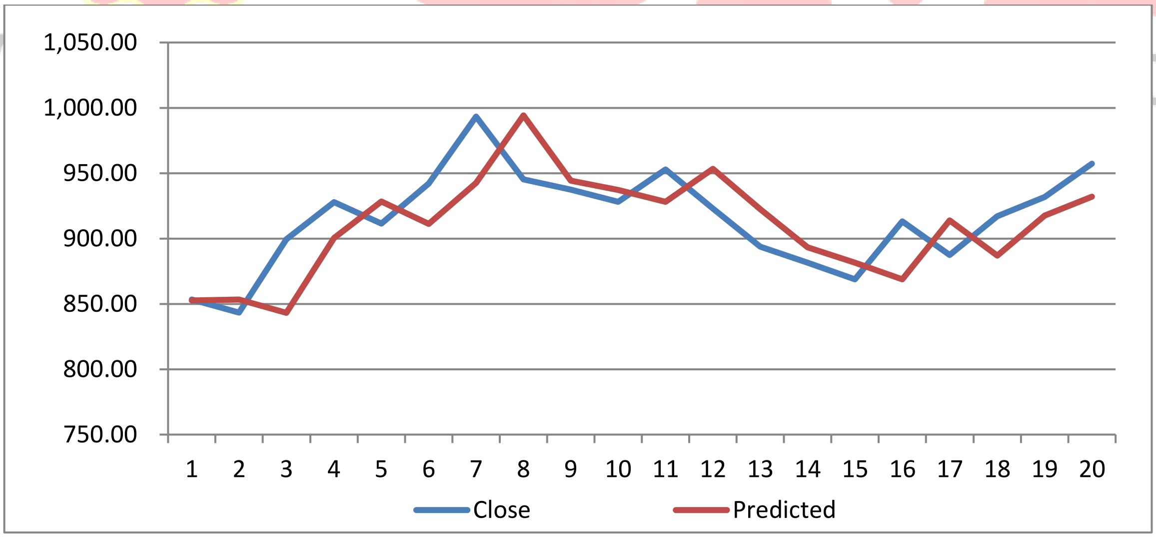

Figure 3. 208-Weeks Prediction using the ARIMA(2,1,2) model

Table 9. Error Computation for ARIMA(2,1,2) Model Error Measures

RMSE	MAE	MAPE	MASE
32.59461	25.08125	1.836789	0.9775577

The Table 9 shows the various error computations for the selected ARIMA model for the 208-weeks prediction.

Table 10. 416 Weeks comparison of ARIMA Models and their errors

	416 weeks	
MODEL	**AIC**	**BIC**
1,1,1	4041.82	4053.91
2,1,0	4041.81	4053.9
2,1,1	4042.46	4058.57

	416 weeks	
MODEL	**AIC**	**BIC**
2,1,2	4038.68	4058.82
2,1,3	4041.83	4066
1,1,0	4039.83	4047.89

Table 11. 416-week actual vs predicted values

Week	Close	Predicted	% Error
1	853.45	852.6	0.1
2	843.35	853.34	1.1849
3	899.4	843.68	6.1953
4	927.75	901.63	2.815
5	911.55	925.69	1.551
6	942.1	908.16	3.603
7	993.3	945.74	4.788
8	945.15	996.24	5.4058
9	937.35	938.59	0.1322
10	928.2	936.19	0.861

Week	Close	Predicted	% Error
11	952.85	934.4	1.9358
12	923.05	954.81	3.4405
13	893.9	915.57	2.4239
14	881.65	892.33	1.2114
15	868.9	889.23	2.3396
.	.	.	.
.	.	.	.
414	1,157.87	1,173.13	1.3183
415	1,134.09	1,159.81	2.2679
416	1,133.49	1,137.63	0.3655

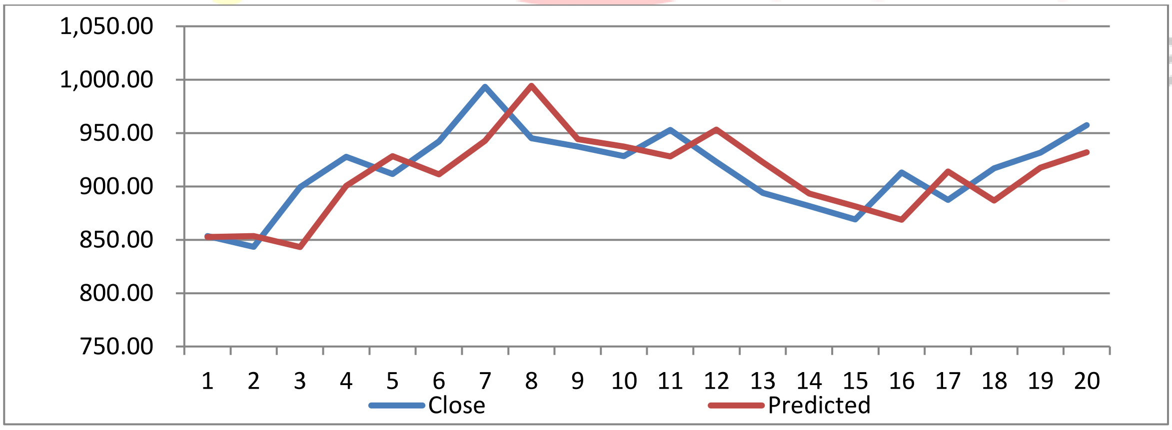

Figure 4. 416-week prediction using the ARIMA(1,1,0) model

The Table 12 shows the various error computations for the selected ARIMA model for the 416-weeks prediction.

Table 12. Error Measures for 416 Weeks

RMSE	**MAE**	**MAPE**	**MASE**
30.98015	23.45768	1.77788	0.99354

From the experiments carried out on the price prediction of gold using ARIMA, it is shown that all the various optimized models performed very well on the periods with minimal error rates. The results from the experiment conducted justifies that this prediction method can be efficiently used to forecast the price of gold, ignoring the negligible error, which the investor can incorporate while placing orders with brokers. The results also show that this method can be used to maximize profits if implemented in an efficient manner using proper ARIMA model.

The Table 13 shows the tabulation of the various error computations for the optimal models used in the prediction of the individual periods.

Table 13. Error Comparison for All Periods

Period	**RMSE**	**MAE**	**MAPE**	**MASE**
52-Weeks	24.63006	19.08716	1.95652	0.95802
104-Weeks	24.84590	20.23878	1.84868	0.99079
208-Weeks	32.59461	25.08125	1.83679	0.97756
416-Weeks	30.98015	23.45768	1.77788	0.99354

The experiment achieved the best result using the MAPE metric during the 416 weeks, recording about 98.23% accuracy, while the accuracy of 98.04% during the 52-week period.

CONCLUSION

The outcome of the research shows that the Autoregressive Integrated Moving Average (ARIMA) prediction method can be used generally for the prediction of the price of gold. This is evident from the results obtained from the 416-week data used in conducting the research. Despite the fact that this data was classified into 52 weeks, 104 weeks, 208 weeks and 416 weeks, all the predictions follow a high percent accuracy. However, it is the opinion of the researchers that higher prediction accuracies may be obtained if other factors affecting the price of gold (GDP, inflation, interest rate, among others) are taken into consideration. This is, however, the limitation of the ARIMA model, which makes use of only a single entity. Other machine learning algorithms like the Artificial Neural Networks (ANN) can equally be explored to examine the effect of these other parameters in the prediction of the price of gold.

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