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Forecasting gold price fluctuations using improved multilayer perceptron neural network and whale optimization algorithm

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ABSTRACT

Developing an accurate forecasting model for long-term gold price fluctuations plays a vital role in future investments and decisions for mining projects and related companies. Viewed from this perspective, this paper proposes a novel model for accurately forecasting long-term monthly gold price fluctuations. This model uses a recent meta-heuristic method called whale optimization algorithm (WOA) as a trainer to learn the multilayer perceptron neural network (NN). The results of the proposed model are compared to other models, including the classic NN, particle swarm optimization for NN (PSO–NN), genetic algorithm for NN (GA–NN), and grey wolf optimization for NN (GWO–NN). Additionally, we employ ARIMA models as the benchmark for assessing the capacity of the proposed model. Empirical results indicate the superiority of the hybrid WOA–NN model over other models. Moreover, the proposed WOA–NN model demonstrates an improvement in the forecasting accuracy obtained from the classic NN, PSO–NN, GA–NN, GWO–NN, and ARIMA models by 41.25%, 24.19%, 25.40%, 25.40%, and 85.84% decrease in mean square error, respectively.

1. Introduction

Volatility modeling and forecasting is a significant issue in risk management, asset allocation, commodity pricing, and policy-making. Moreover, volatility forecasting is an essential task in economic markets, which has gained the interest of academics and practitioners for many years (Fang et al., 2017). Gold is a major commodity that is used for financial purposes; it is part of the international reserves in most national banks, indicating its fundamental role in the global economy (Wen et al., 2017). Among all the precious metals, gold is the most common choice for investment (Gangopadhyay et al., 2016). The capacity to forecast gold price fluctuations with high accuracy is significant for both commodity markets and the global economy (Kristjanpoller and Minutolo, 2015). Furthermore, forecasting gold price fluctuations is a crucial concern in the financial industry. Notably, small improvements in predictive accuracy can generate huge profits (Liu and Li, 2017). Gold and crude oil are strategic resources that are extensively used in different national economic activities and in social security. Predicting the future fluctuations of these resources plays a key role in minimizing the issues confronting market participants such as producers, consumers, and investors (Bouri et al., 2017). Thus, researchers face the challenge of improving the accuracy of forecasting models for gold, silver, and copper price fluctuations, as these improvements are fundamental for related companies and stakeholders (Kristjanpoller and Hernández, 2017).

In the new global economy, forecasting gold price fluctuations has become a central issue for government agents in countries where their economies depend on gold, as well as for investors who make investment decisions in the commodity market. In addition, forecasting future gold prices has become a critical concern for mining projects and related companies. Hence, developing an accurate model is essential for making the right decisions in advance, such that the option to accept or reject the project at the outset is available. Furthermore, during the mine life, it helps to choose more options such as the delay and abandon option, the temporary closure option, and the accelerate/decelerate option and the expansion option for mine operations (Abdel Sabour and Poulin, 2006; Aminrostamkolaee et al., 2017).

Selecting the input variables to develop an accurate forecasting model is one of the major challenges. Ten input variables are used in the current study as predictors for future gold price fluctuations, namely

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three exchange rates (South African rand (ZAR), Indian rupee INR, and Chinese yuan (RMB)); two inflation rates (inflation rates of US and China); oil prices (West Texas intermediate crude oil prices); and copper, silver, iron, and past gold prices.

The significance of using foreign exchange rates in the commodity price forecasting process is highlighted in the literature. For instance, (Chen et al., 2010) reported that exchange rates have a strong power for forecasting commodity prices in both training and validation periods. They also proved that the exchange rates of commodity-exporting nations could forecast the commodity prices. Meanwhile, (Sari et al., 2010) established a significant relationship between the spot precious metal markets and both the other metal prices and the exchange rates. Furthermore, (Bodart et al., 2015) provided experimental evidence of the relationship between exchange rates and commodity prices for developing nations that depend on the exports of their main products. (Ciner, 2017) confirmed that the exchange rate of ZAR has a significant predictive power to forecast palladium and platinum prices, and to a lesser degree silver price. They also established a positive and statistically significant relationship between the South African currency and white metals, which confirms the assumption that the prices of white metal are the determinant for the volatility of the South African currency. (Reboredo, 2013) studied the possibility of using gold as a safe-haven asset against the U.S. dollar (USD) depreciation. The empirical results revealed a positive and significant relationship between gold and USD depreciation against various currencies.

Crude oil likewise plays an essential role in several production processes throughout the world (Zhao et al., 2018). Extensive studies have confirmed that oil prices are the leading cause of commodity price fluctuations. Crude oil price is used as a predictor for commodity price changes because oil remains one of the most commonly used sources of energy (He et al., 2010; Lardic and Mignon, 2008). (Behmiri and Manera, 2015) examined the influence of oil price shocks on the price fluctuations of metals such as aluminum, copper, lead, nickel, tin, zinc, gold, silver, palladium, and platinum. They suggested that oil price shocks individually and unequally influence the price fluctuations of these metals. (Mo et al., 2018) also explored the dynamic linkages between the USD and the gold and crude oil markets and reported that the dynamic relationship between gold and oil is constantly positive. Moreover, (Teetranont et al., 2018) used the interval data in COMEX and NYMEX trading to investigate the relationship between gold and crude oil prices and established a positive relationship between gold and crude oil prices.

Copper is included as a predictor variable for gold because copper has become an alternative to precious metals such as gold and silver in investment portfolios that are diversified over equities (Buncic and Moretto, 2015). (Liu et al. (2017) used crude oil, natural gas, gold, silver, lean hogs and coffee, Dow Jones index, and past copper prices as predictor variables for copper prices. They observed a strong correlation between copper prices and each of the prices of oil, gold, and silver.

The findings from the current study are expected to contribute to the literature in several aspects:

(i) The conventional training algorithms of artificial neural networks have been proved to have poor forecasting accuracy. Thus, the new training algorithm based on the proposed whale optimization algorithm (WOA) is expected to demonstrate high performance.
(ii) To the best of our knowledge, this research represents the first attempt to use a WOA–NN model for forecasting gold price fluctuations.
(iii) This study confirms the following predictor variables' power to forecast gold price fluctuations: crude oil, iron, silver, and copper prices; ZAR, INR, and RMB exchange rates; and inflation rates of US and China.
(iv) This study also contributes a method for forecasting long-term commodity price fluctuations.

The rest of the paper is organized into several sections. The related works for time series forecasting models are presented in Section 2. The basic concepts of multilayer perceptron (MLP) neural network and WOA are discussed in Section 3. The proposed model based on a novel meta-heuristic algorithm WOA to train the MLP neural network for forecasting gold price fluctuations is described in Section 4. The data set used in this study and the results obtained are discussed in Section 5. Finally, the main conclusions of this study are summarized in Section 6.

2. Related works

Data from several studies suggested that the methods used in the forecasting process can be applicable to an extensive variety of commodities. Several types of models have been adopted to forecast the volatility of commodity prices. Therefore, this section offers a brief review of the applications of various forecasting models, including traditional mathematical models, artificial neural networks (ANNs), and hybrid models.

2.1. Forecasting commodity prices using traditional mathematical models

Autoregressive integrated moving average (ARIMA) is one of the most frequently used traditional mathematical models for time series forecasting over the past decades; its applications include forecasting social, economic, engineering, energy, foreign exchange, and stock problems (Dooley and Lenihan, 2005; Ediger and Akar, 2007; Kriechbaumer et al., 2014; Parisi et al., 2008). Jump and dip diffusion is similarly one of the conventional methods of forecasting time series data, and it is employed for forecasting gold prices (Shafiee and Topal, 2010). In addition, some researchers such as (Angus et al., 2012) used linear regression models in the forecasting process. (Wang et al., 2017) developed a cradle-to-cradle model of predicting and quantifying the Chinese steel flow from 2012 to 2100. Wang et al. (2014) used a scenario analysis method of quantifying the future steel flow from 2013 to 2050. Moreover, Wang et al. (2018) proposed a system dynamic model for forecasting the change in China's coal production capacity. Gangopadhyay et al. (2016) developed a model for forecasting gold prices in India using a vector error-correction model. Chatterjee et al. (2016) utilized sequential Gaussian simulation algorithm to generate the iron price simulations based on the historical data for iron ore prices from 1982 to 2011.

2.2. Forecasting commodity prices using artificial neural networks

Artificial neural networks are one of the most important types of machine learning models, which have been introduced and examined for forecasting commodity prices (Khashei and Bijari, 2010; Lineesh et al., 2010; Parisi et al., 2008). Hamid and Iqbal (2004) compared volatility forecasts from NNs with implied volatility from S&P 500 Index futures options. They indicated that NNs provided better volatility forecasts than implied volatility forecasts on S&P 500 future stock indices, and they suggested that the results of NNs are very close to the reality. Meanwhile, Ramyar and Kianfar (2017) developed an MLP neural network model to forecast crude oil prices and compared its results with vector autoregressive model. Their empirical results demonstrated the superiority of the MLP neural network compared to the VAR model.

Additionally, Kim and Ahn (2012) optimized multiple architectural factors and feature transformations of ANN using a genetic algorithm to overcome the limitations of the traditional back-propagation algorithm. Experiments revealed that the proposed model outperformed the conventional approaches in predicting the stock price index. Ignácio et al. (2017) built an MLP neural network with the aid of the Levenberg–Marquardt training algorithm to forecast oil prices. The results demonstrated the accuracy of ANNs in the one-step-ahead forecasting of oil prices. Meanwhile, Fischer and Krauss (2018) applied long short-

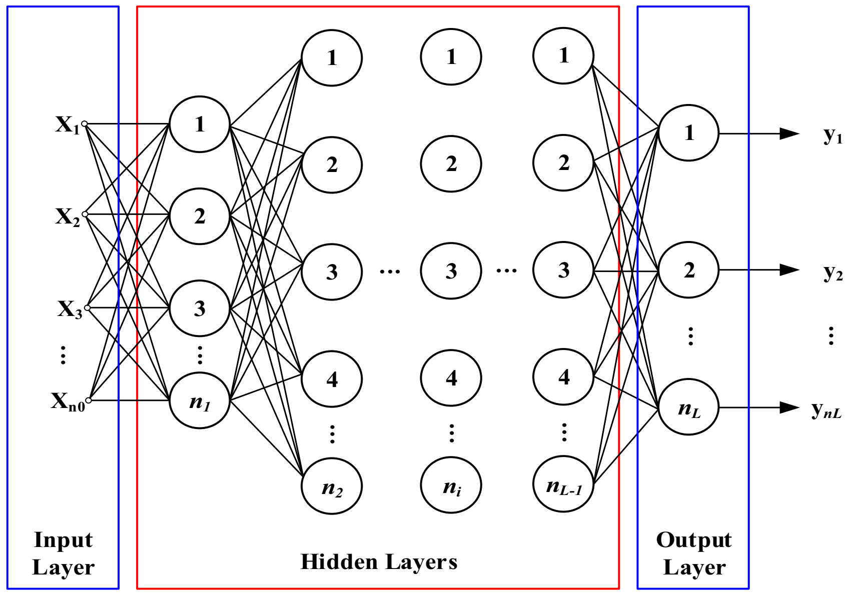

Fig. 1. Basic architecture of an MLP neural network.

term memory networks for predicting the out-of-sample directional movements for the constituent stocks of the S&P 500 from 1992 to 2015. Fan et al. (2016) also proposed an MLP network model to forecast the volatility of chaotic coal prices. Geng et al. (2015) employed data mining techniques to develop models for forecasting the financial distress of Chinese-listed companies based on 31 financial indicators.

2.3. Forecasting commodity prices using hybrid models

Interest in using hybrid models to overcome the limitations of individual models and increase forecasting accuracy has grown. Moreover, simply knowing the features of data in real-life problems is difficult; hence, a hybrid approach that has modeling capabilities for both linear and nonlinear can be a central strategy for solving such problems (Khashei and Bijari, 2011). Artificial NNs have been combined with several models to forecast the fluctuations of commodity prices. Kristjanpoller and Minutolo (2016) proposed a hybrid model for forecasting oil price volatility by combining an ANN with generalized autoregressive conditional heteroskedasticity (GARCH). They concluded that the proposed model increased the volatility forecasting accuracy by 30% over earlier models. Meanwhile, Bento et al. (2018) presented a novel hybrid method for the one-day-ahead forecasting of electricity price; their proposed method was used alongside the bat and scaled conjugate gradient algorithms to improve the traditional NN learning capability. Nguyen-ky et al. (2017) similarly proposed a hybrid ANN–Bayesian model to increase the accuracy of forecasting seasonal water allocation prices. They demonstrated the superiority of the proposed model over the conventional ANN. Meanwhile, El Aziz et al. (2017) proposed an intelligent learning technique called adaptive neuro-fuzzy inference system–particle swarm optimization (ANFIS–PSO) to forecast biochar. Ewees et al. (2017) improved ANFIS using social-spider optimization algorithm to forecast biochar yield.

Kristjanpoller and Minutolo (2018) suggested a hybrid ANN–GARCH model with preprocessing to predict the price volatility of bitcoin. Sánchez Lasheras et al. (2015) examined the predicting performance of ARIMA and two ANN models (MLP and Elman) using the data of copper spot prices. The numerical results indicated the superiority of both NN models over the ARIMA model. Ahmed et al. (2016) proposed a hybrid krill–ANFIS model to forecast wind speed. Meanwhile, Kristjanpoller and Hernández (2017) implemented a hybrid NN model and GARCH model to predict the volatility of the spot prices of gold, silver, and copper. The results implied that using the hybrid NN model increased the forecasting accuracy of the out-of-sample volatility for the three metals. Nazemi et al. (2018) employed support vector techniques, linear regression, and regression tree to predict the recovery rates of defaulted corporate bonds using different explanatory variables.

3. Methods

This section briefly reviews the computational intelligence methods used in this study, namely MLP and WOA.

3.1. MLP neural network

Artificial NNs are intelligent and nonparametric mathematical models inspired by the biological nervous system. The increasingly rapid developments in applying ANNs in the field of classification, pattern recognition, regression, and forecasting problems have occurred in the past 30 years (Chatterjee et al., 2017; Rezaeianzadeh et al., 2014). The learning process for ANNs has a substantial effect on their efficiency. Feedforward neural networks (FFNNs) are a specific form of supervised NNs. They comprise a set of processing elements called “neurons.” These neurons are distributed on numerous stacked layers where every layer is completely connected with the next one. The MLP architecture can be described as follows: the first layer that feeds the network with the input variables is denoted as the input layer, the final layer is termed the output layer, and all the layers between the input and output layers are referred to as hidden layers (Basheer and Hajmeer, 2000). Multilayer perceptron neural network is one of the most commonly applied FFNNs. The neurons in MLP are interconnected in a one-way and one-directional fashion. Connections between neurons are represented by weights that are the actual numbers located in the interval [−1. 11]. Fig. 1 illustrates the basic architecture of an MLP neural network. Each layer in an MLP can be described mathematically, as depicted in Eq. (1).

$$O_i^{(\ell)} = \varphi(u_i^{(\ell)}) = \varphi\left(\sum_{j=1}^{n_\ell} O_j^{(\ell-1)} w_{j,\ i}^{(\ell)} + w_{0,\ i}^{(\ell)}\right), \quad 1\le\ell\le L, \tag{1}$$

where $\varphi(.)$ is the activation function of the layer. It is usually configured as a nonlinear tangent hyperbolic function for the intermediate layers, which are also recognized as hidden layers, and a linear function to generate the results of the output layer. Index ℓ identifies the real layer in a network of L non-input layers, n_ℓ denotes the number of neurons of layer ℓ O_i^ℓ representing the output of neuron i in the real layer ℓ, $w_{j,i}^{(\ell)}$,$1 \le \ell \le n_{\ell-1}$ are the weights related to the connections of neuron i of layer ℓ with the neurons of the earlier layer $\ell-1$, and $w_{0,i}^{(\ell)}$ is the bias of neuron i of the real layer. The output vector of layer $\ell = 0$ of length n_0 coincides with the input characteristics vector, that is, $O^{(0)} = x$. Furthermore, the output vector of the final layer $\ell = L$ of length n_L, which is the output layer of the network, coincides with the network result, that is, $O^{(L)} = y$.

3.2. Whale optimization algorithm

Whale optimization algorithm is a recent extension to meta-heuristic algorithms, which was proposed by Mirjalili and Lewis (2016). It is inspired by the hunting behavior of humpback whales, which is termed bubble-net hunting strategy. These whales use two mechanisms for searching the location of prey and subsequently attacking it. They initially encircle the prey and eventually create bubble nets. In view of an optimization point, the exploration of search space is achieved when the whales look for prey, and exploitation occurs during the attack behavior.

The major difference between WOA and other algorithms lies in the rules that improve the candidate solutions in every step of optimization. In WOA, the bubble nets are simulated using a spiral movement. This procedure mimics the helix-shaped movement from actual humpback whales. The bubble-net feeding behavior of the humpback whale model is illustrated in Fig. 2. In other words, whale $x(t)$ has a position that can be updated by moving it in a spiral around the prey x_{best}. This procedure is described mathematically as follows:

$$x(t+1) = D.\ e^{bl}.\ \cos(2l) + x_{best}(t), \tag{2}$$

where $D = |x(t) - x_{best}(t)|$ is the distance between $x(t)$ and $x_{best}(t)$ at iteration t, $l \in [-1,1]$ is a random number, and b is a constant variable used to define the logarithmic spiral shape.

The whales can update their positions using an encircling behavior (Mirjalili and Lewis, 2016) based on $x_{best}(t)$ as follows:

$$D = |C.\ x_{best}(t) - x(t)| \tag{3}$$

$$x(t+1) = x_{best}(t) - A.\ D \tag{4}$$

C and A are coefficient vectors and defined as follows:

$$C = 2rA = 2a.\ r - a, \tag{5}$$

where r is a random vector and a is linearly decreased from 2 to 0 along iterations (t); the value of a is then computed in Eq. (6):

$$a = a - t\frac{a}{t_{max}}. \tag{6}$$

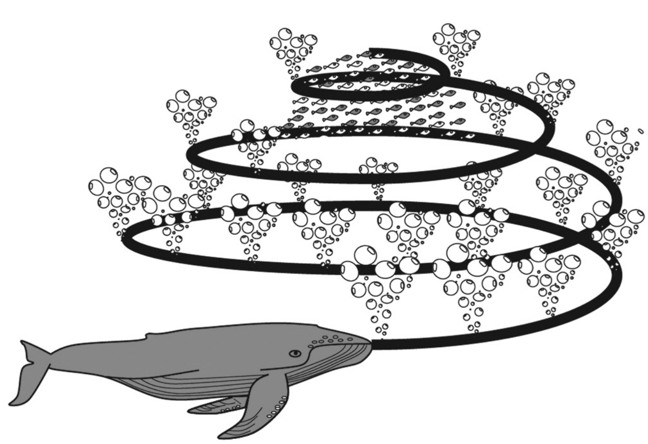

Fig. 2. Bubble-net feeding behavior of humpback whales (Mirjalili and Lewis, 2016).

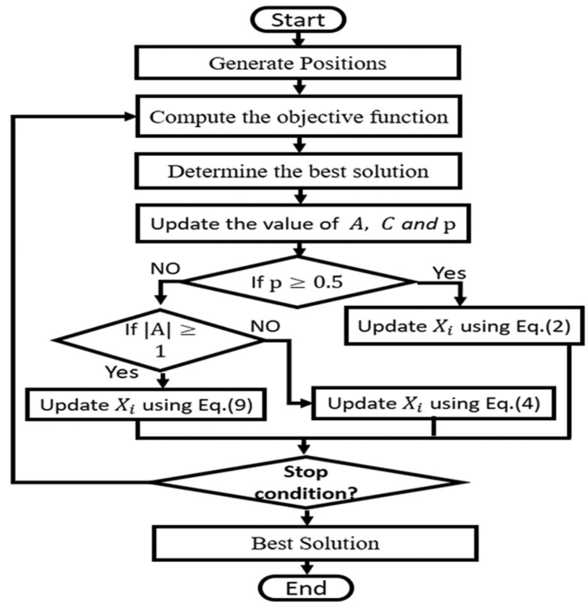

Fig. 3. Flowchart of the proposed WOA–NN method.

According to the standard WOA (Mirjalili and Lewis, 2016), the whales can simultaneously swim around their prey along a spiral-shaped path and through a shrinking circle. This behavior is defined in Eq. (7):

$$x(t+1) = \begin{cases} x_{best}(t) - A.\ D \ if \ r_1 < 0.5 \\ D.\ e^{bl}.\ \cos(2\pi l) + x_{best}(t) \ if \ r_1 > 0.5 \end{cases} \tag{7}$$

where $r_1 \in [0,1]$ is the probability of selecting the method of swimming around the prey (spiral model or shrinking encircling mechanism). However, humpback whales may be searching for prey in an indiscriminate manner, and their position is updated based on a randomly selected whale $x_{rand}(t)$ as follows:

$$D = |C.\ x_{rand}(t) - x(t)| \tag{8}$$

$$x(t+1) = x_{rand}(t) - A.\ D \tag{9}$$

3.3. Performance measures

This investigation verifies the effectiveness and accuracy of the proposed model for forecasting gold price fluctuations and compares the results of the proposed model to other forecasting models. Several performance measures are employed for forecast models; however, mean square error (MSE) and root mean square error (RMSE) are extensively used (Atsalakis, 2016). These measures are defined as follows:

$$Mean\ Square\ Error\ (MSE) = \frac{1}{N}\sum_{t=1}^{N} e_t^2 \tag{10}$$

$$Root\ Mean\ Square\ Error\ (RMSE) = \sqrt{\frac{\sum_{t=1}^{N} e_t^2}{N}} \tag{11}$$

Furthermore, these measures are comprehensively used for assessing the differences between forecasts provided by prediction models and actual values. Additionally, standard deviation STD are calculated to assess the spread of data from the mean for all forecasting models employed in this study.

4. Formulation of the proposed model

This section describes the proposed model based on a novel meta-heuristic algorithm WOA to train the MLP neural network; the model is

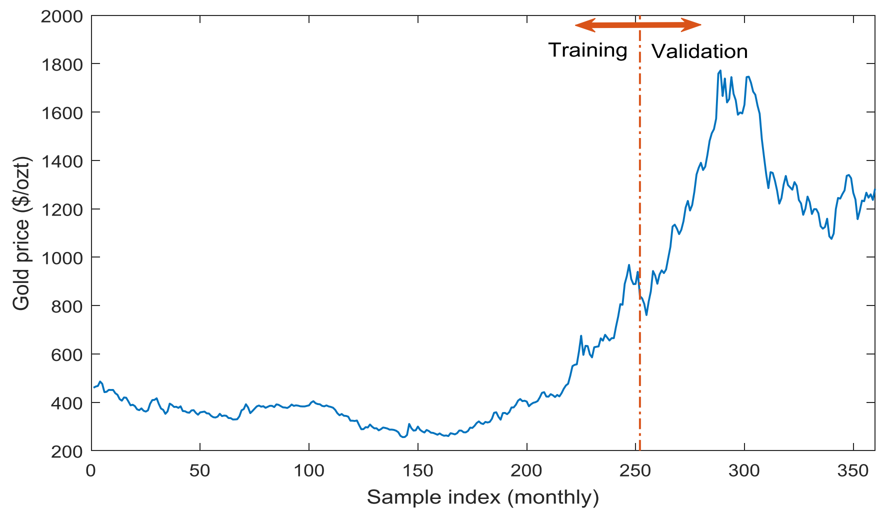

Fig. 4. Historical gold prices from September 1987 to August 2017.

identified as WOA–NN. Whale optimization algorithm is applied for training an MLP network to solve a nonlinear regression (forecasting gold price fluctuations). The major difficulty in developing an accurate NN model lies in training a neural network to obtain the best set of main weights and biases. The key disadvantages of traditional training algorithms include local optima stagnation and slow convergence speed, thus motivating the researchers to search a reliable alternative for addressing these drawbacks. Viewed from this perspective, MLP optimizes using WOA to set the weights and biases of NN. The proposed model uses NN as an object function of WOA to evaluate its solutions in the training phase. This evaluation uses the current solution as weight and bias vectors and passes it to NN; MSFE performance measure is subsequently calculated according to the prediction of NN. This scenario is repeated until the max iteration is reached. The best solution is eventually passed to the NN as a vector of weights and biases for usage in the testing phase. Fig. 3 illustrates the overall WOA–NN model.

5. Experimental data

This section comprises four main subsections. The first subsection describes the data used in this study and their collection sources. The second subsection investigates the correlation between gold prices and predictor variables. The third subsection evaluates the accuracy of the proposed WOA–NN for forecasting the fluctuations of gold prices and compares the predictive capacity of the proposed model to the classic NN and other meta-heuristic trainers such as PSO–NN, GA–NN, GWO–NN and ARMIA using the same data sets. Finally, the fourth subsection investigates the statistical analysis.

5.1. Data description

The data analyzed in this research included 360 monthly observations of the gold prices ($/ozt) from September 1987 to August 2017. These prices were divided into training and test sets, as depicted in Fig. 4. Zou et al. (2007) mentioned that although there is no consensus on how splitting the data series for the applications of neural networks, A search of the literature revealed that a considerable amount of literature allocated more data for training and building the model. More specifically, these studies have been split the data series for in- and out-of-sample such as 70:30%, 80:20%, or 90:10%.

In this work, the data for training and test were split into a ratio of 70:30, respectively; the first 252 observations (from September 1987 to August 2008) were used for training the model, whereas the final 108 observations (from September 2008 to August 2017) were employed to validate the performance and accuracy of the proposed model. In addition, to increase the accuracy of the proposed model, a group of predictor variables with a significant correlation with gold prices was added to the forecasting model. Notably, our predictor variables consist of multiple financial indexes with various scales and domains, therefore, data normalization assistances us to access a homogeneous dataset. In this study, we normalized the original data series of all variables X_i to $X_{i(norm)}$ using the following Eq.

$$X_{i(norm)} = \frac{X_i - X_{min}}{X_{max} - X_{min}}, \text{i} = 1, 2, 3, \ldots\ldots, 360 \tag{12}$$

where X_{min} and X_{max} are the minimum and maximum value of the original series, respectively. The description of the predictor variables will be introduced in the following paragraph.

A significant step in developing an accurate forecasting model is the selection of input variables. Hence, this study identified nine predictor variables to improve the performance of forecasting models: three exchange rates (measures the performance of USD against ZAR, INR, and RMB). Following the well-known results of (Chen et al., 2010) that exchange rates can forecast commodity prices.

The other variable that influences gold prices is inflation rate because it is one of the major macroeconomic variables affecting the commodity market. However, the existing literature on metal price forecasting lacks clarity regarding the examination of the relationship between inflation and commodity prices (Batten et al., 2014; Shafiee and Topal, 2010; Yazdani-Chamzini et al., 2012). The current study selected the inflation rates of US and China as predictor variables for the forecasting model because these countries are the largest and second largest economies in the world, respectively, and their inflation rates are assumed as a proxy for world inflation.

Data from several studies suggested that gold prices may correlate with energy sources such as crude oil (Gil-Alana et al., 2017; Jain and Biswal, 2016; Kristjanpoller and Minutolo, 2015; Raza et al., 2018; Reboredo and Ugolini, 2016; Sephton and Mann, 2018; Shafiee and Topal, 2010). Some studies also reported the relationship between the prices of gold and other metals (Bhatia et al., 2018; Eryigit, 2017; Klein, 2017; Liu et al., 2017; Mei-Se et al., 2018; Schweikert, 2018).

Based on the aforementioned rationale and according to data availability, the monthly observation data of ZAR, INR, and RMB exchange rates, inflation rates of US and China, and oil, copper, silver, and iron prices were collected from September 1987 to September 2017. The data used in this study were downloaded from several sources, as presented in Table 1.

Table 1
Input data sets considered in this study.

Variables	Period	Unit	Data source	Data availability
Gold price	Monthly	$/ozt	World Bank http://www.indexmundi.com/commodities/	Freely available
Silver price	Monthly	$/ozt	Thomson Reuters Datastream; World Bank http://www.indexmundi.com/commodities/	Freely available
Copper and Iron	Monthly	$/ton	Thomson Reuters Datastream; World Bank http://www.indexmundi.com/commodities/	Freely available
Oil price	Monthly	$/barrel	U.S. Energy Information Administration https://www.eia.gov/dnav/pet/pet_pri_spt_s1_m.htm	Freely available
Exchange rates	Monthly	–	Central banks http://fxtop.com/	Freely available
China Inflation rate	Monthly	–	National Bureau of Statistics of China https://ieconomics.com/china-inflation-rate	Freely available
US Inflation Rate	Monthly	–	The U.S. Bureau of Labor Statistics https://inflationdata.com/Inflation/Inflation_Rate/Monthly_Inflation.aspx	Freely available

Table 2
Correlation matrix between the variables.

		Gold price	Copper price	Iron ore price	Silver price	Oil price	China exchange rate	India exchange rate	South Africa exchange rate	China inflation rate	U.S inflation rate
Gold price	Pearson Correlation	1									
	Sig. (2-tailed)										
	N	360									
Copper price	Pearson Correlation	0.872**	1								
	Sig. (2-tailed)	0.000									
	N	360	360								
Iron ore price	Pearson Correlation	0.788**	0.909**	1							
	Sig. (2-tailed)	0.000	0.000								
	N	360	360	360							
Silver price	Pearson Correlation	0.956**	0.893**	0.847**	1						
	Sig. (2-tailed)	0.000	0.000	0.000							
	N	360	360	360	360						
Oil price	Pearson Correlation	0.810**	0.918**	0.926**	0.840**	1					
	Sig. (2-tailed)	0.000	0.000	0.000	0.000						
	N	360	360	360	360	360					
China exchange rate	Pearson Correlation	-0.230**	-0.158**	-0.083	-0.169**	-0.047	1				
	Sig. (2-tailed)	0.000	0.003	0.115	0.001	0.379					
	N	360	360	360	360	360	360				
India exchange rate	Pearson Correlation	0.619**	0.473**	0.408**	0.536**	0.539**	0.410**	1			
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000				
	N	360	360	360	360	360	360	360			
South Africa exchange rate	Pearson Correlation	0.605**	0.439**	0.365**	0.493**	0.477**	0.236**	0.935**	1		
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000			
	N	360	360	360	360	360	360	360	360		
China inflation rate	Pearson Correlation	-0.202**	-0.146**	-0.181**	-0.190**	-0.279**	-0.299**	-0.567**	-0.536**	1	
	Sig. (2-tailed)	0.000	0.006	0.001	0.000	0.000	0.000	0.000	0.000		
	N	360	360	360	360	360	360	360	360	360	
U.S inflation rate	Pearson Correlation	-0.380**	-0.190**	-0.121*	-0.284**	-0.169**	-0.328**	-0.690**	-0.626**	0.365**	1
	Sig. (2-tailed)	0.000	0.000	0.022	0.000	0.001	0.000	0.000	0.000	0.000	
	N	360	360	360	360	360	360	360	360	360	360

** .Correlation is significant at the 0.01 level (2-tailed).
* .Correlation is significant at the 0.05 level (2-tailed).

5.2. Correlation analysis

The purpose of this investigation is to explore the relationship between gold prices and predictor variables. Several studies such as the work of Haque et al. (2015) have confirmed that correlation analysis is a powerful tool for determining the strength of this relationship. To describe this relationship clearly, the current study attempts to establish a correlation that is essentially concerned with determining the relationship between two logically linked variables and ascertaining its direction and strength. Such correlation signifies that either a positive or a negative change in one variable affects the other (Ho, 2006; Molugaram and Rao, 2017).

The present study used the Pearson's correlation coefficient to determine the relationship between copper prices and predictor variables. Pearson's correlation coefficient measures the degree of linear correlation between two variables, providing a value of between $+1$ and -1; $+1$ denotes a completely positive correlation, 0 a lack of correlation, and -1 a completely negative correlation.

Table 2 presents the pairwise correlation coefficients between the variables under study. The correlation analysis was performed using SPSS software (version 21).

Notably, all the correlations between gold prices and predictor variables are statistically significant with p-value < 0.01.

5.3. Results and discussion

The findings confirm the high capacity of predictor variables (crude oil, iron, silver, and copper prices; ZAR, INR, and RMB exchange rates; and inflation rates of US and China) to forecast gold price fluctuations. Such high capacity results in the significant correlation between gold prices and all the predictor variables. A validation procedure was implemented in this work to evaluate the performance of the proposed model, in which the final 108 observations (30%) were employed as validation data.

This section presents a comparison of the predictive capacity of the proposed model to the classic NN and other meta-heuristic trainers such as PSO–NN, GA–NN, GWO–NN and ARMIA using the same data sets. Notably, several researchers proved the high level of accuracy of these algorithms, and they used these algorithms for improving many problems. Moreover, these algorithms are highly popular and strong techniques for forecasting commodity prices (Chen, 2014; Fan et al., 2016; Zou et al., 2007). We used RMSE and MSE to measure and evaluate the performance and accuracy of the proposed model against the other forecasting models. As depicted in Table 3 the proposed model provides the highest out of sample R^2 value coupled with the lowest mean squared error and root mean squared error among all the models used in this study, indicating that data variability is well captured in the fitted model. In addition, the fitted model is generalized and is likely to perform equally well with other additional evaluation periods.

Table 3
Out-of-sample performance comparison of the models.

Models	RMSE	MSE	STD	R^2
NN	0.02793	0.00080	0.00419	0.9965
WAO-NN	**0.02131**	**0.00047**	**0.00340**	**0.9989**
GA-NN	0.02473	0.00063	0.00444	0.9966
PSO-NN	0.02418	0.00062	0.00565	0.9980
GWO-NN	0.02308	0.00063	0.00963	0.9977
ARIMA	0.05751	0.00332	0.01671	0.96981

Table 4 summarizes the improvement percentage of the WAO–NN model in comparison to the other five models. The proposed model evidently presented several noteworthy contributions to improve the accuracy of the forecasting process.

Table 4
Percentage improvement of the proposed model in comparison to other models.

Models	RMSE	MSE	STD
NN	23.70%	41.25%	18.85%
GA-NN	13.83%	25.40%	23.42%
PSO-NN	11.87%	24.19%	39.82%
GWO-NN	7.67%	25.40%	64.69%
ARIMA	62.95%	85.84%	79.65%

The performances of WOA–NN, GA–NN, PSO–NN, GWO–NN, classic NN, and ARMIA models during the training process are illustrated in Fig. 5. The figure indicates that the gold price forecasted using WAO–NN is extremely close to reality.

Additionally, the predicted values of each model (WOA–NN, PSO–NN, GA–NN, GWO–NN, classic NN and ARMIA) for the test data are plotted in Fig. 6.

Moreover, to assess the predictive performance of the WOA-NN as forecasting model relative to the ARIMA model that considered as benchmark, the cumulative sum of the differences of the squared forecast errors (CSD) is used. The CSD is defined as (Buncic and Moretto, 2015; Welch and Goyal, 2008):

$$CSD_t^{ARIMA,WOA-NN} = \sum_{k=1}^{K} (e_{t+1|t}^{2(ARIMA)} - e_{t+1|t}^{2(WOA-NN)}) \tag{13}$$

where $e_{t+1|t}^{2(ARIMA)}$ and $e_{t+1|t}^{2(WOA-NN)}$ represent the squared error of the ARIMA model and WOA-NN, respectively. When $CSD_t^{ARIMA,WOA-NN}>0$, this indicate the WOA-NN model gives better forecasts.

Fig. 7 depicts the evolution of the WOA-NN and classical NN, relative to the results of ARIMA benchmark. It can be observed from this figure that both models provide good results since CSD for WOA-NN and classical NN is 52.53, and 48.19, respectively.

5.4. Statistical analysis

To further add analysis to the comparison between the proposed model and others, the Wilcoxon rank sum test is used. The Wilcoxon rank sum test and also named Mann–Whitney U test is a nonparametric test (Larson and Farber, 2010) this test aims to determine if there exist a significant difference between the models or not based on the significant level (in this study, 0.05). Table 5 shows the results of Wilcoxon rank sum test in which the control group is the proposed method. From this Table it can be noticed that there is a significant difference between the proposed WOA-NN and the PSO-NN and ARMIA models, while, no significant difference with other models.

In view of all these points, we argue that the proposed model can be successfully applied for forecasting gold price fluctuations. Also, we can confirm that it can be used for future predictions, not only for gold prices, but also for all metals, ores, and commodities.

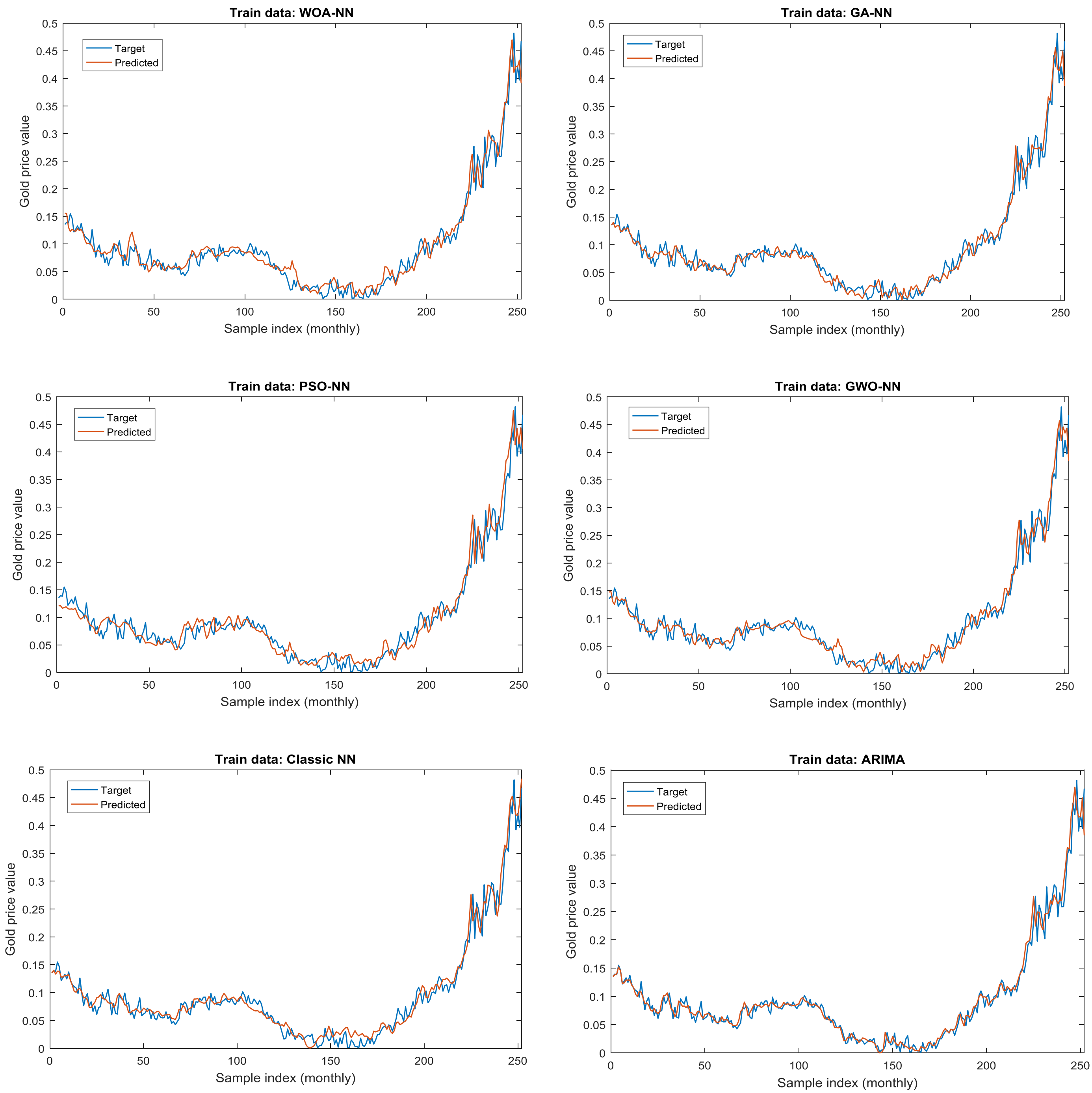

Fig. 5. Performances of WOA–NN, GA–NN, PSO–NN, GWO–NN, classic NN, and ARIMA over the training set.

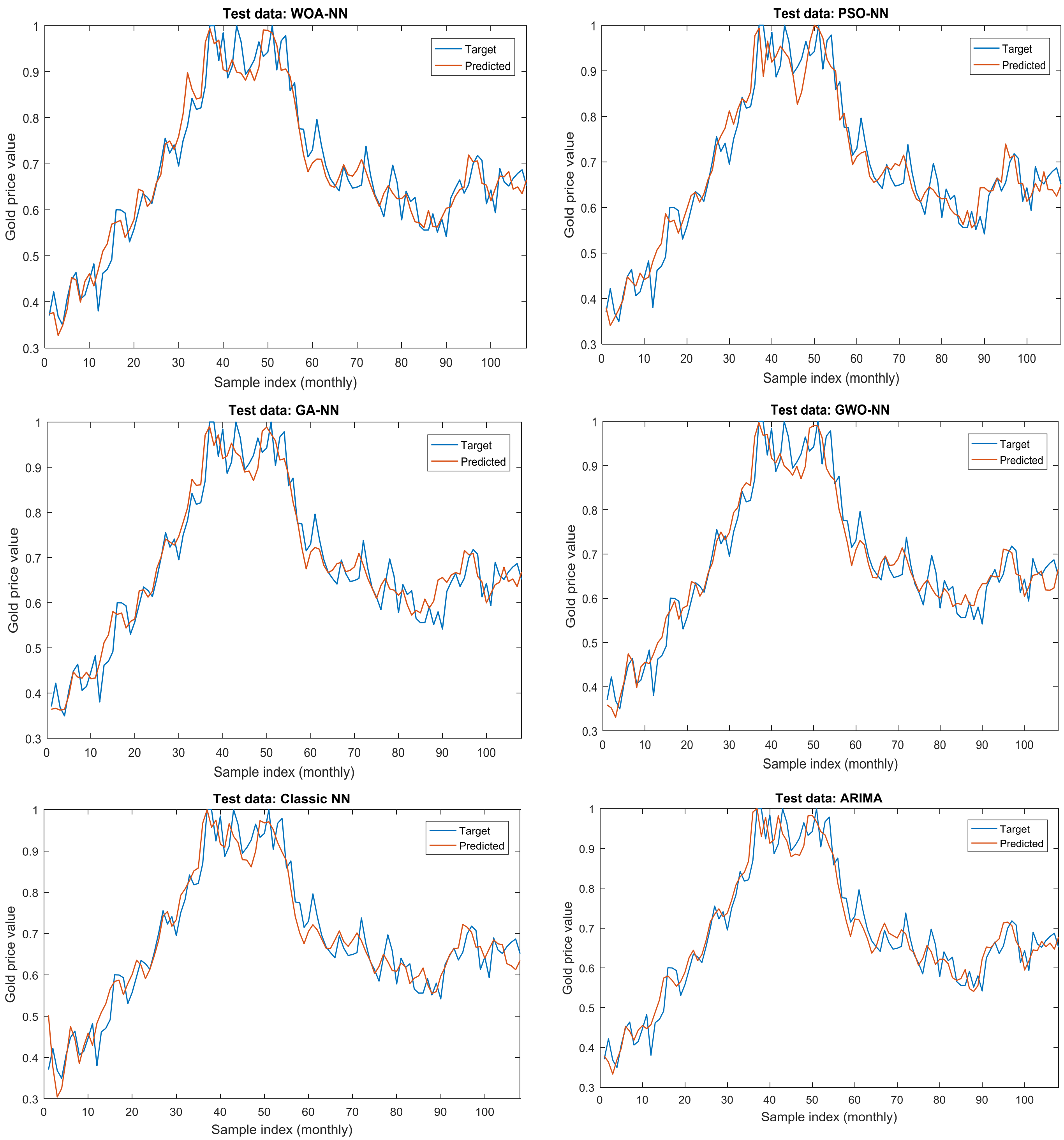

Fig. 6. Performances of WOA–NN, PSO–NN, GA–NN, GWO–NN, classic NN, and ARIMA over the test set.

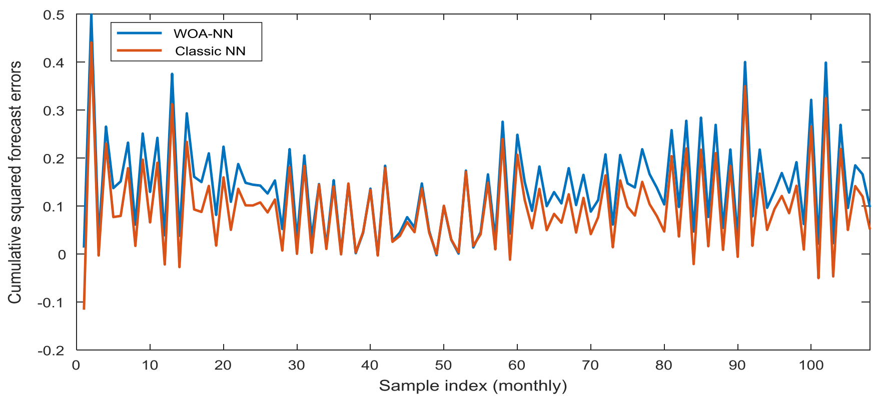

Fig. 7. The results of Cumulative difference between the squared forecast errors of the ARIMA model and WOA-NN model.

Table 5
the statistical results using Wilcoxon rank sum test.

	GA-NN	GWO-NN	PSO-NN	NN	ARMIA
P-value	0.0211	0.0312	0.1041	0.0140	0.080

6. Conclusions

Developing an accurate forecasting model for gold price fluctuations helps to foresee the market trends in the future, which provides stakeholders with valuable information for making the right decisions to prevent or mitigate risks. Notwithstanding the availability of numerous forecasting models, research on the process of improving the performance of these models continues. In this work, we proposed a new model for forecasting gold price fluctuations using a novel meta-heuristic algorithm WOA for training MLP neural network and compared the results of this model to the classic NN and other meta-heuristic trainers such as PSO–NN, GA–NN, and GWO–NN. Moreover, ARIMA models were employed as the benchmark for assessing the effectiveness of the proposed model. The results suggested the superiority of the WOA–NN model over the other models.

Furthermore, the numerical results indicated that the WOA–NN model provided the highest out of sample R^2 0.9989 coupled with the lowest MSE, RMSE, and STD of 0.00047, 0.02131, and 0.00340, respectively. In addition, the numerical results implied that the WOA–NN model improved the forecasting accuracy compared to the classic NN, PSO–NN, GA–NN, GWO–NN, and ARIMA models by a 23.70%, 11.87%, 13.83%, 7.67%, and 62.95% decrease in RMSE, respectively. Moreover, the superior performance of the proposed model was further confirmed by the Wilcoxon rank sum test, wherein, the results of Wilcoxon rank sum test demonstrated that WOA–NN performed a significant difference compared to PSO-NN and ARMIA; on the contrary, small changes emerged with other models. To the best of our knowledge, this work is the first attempt at using the WOA–NN model to forecast gold price fluctuations. Thus far, the WOA–NN model is assumed to be a promising technique for forecasting commodity prices with high accuracy.

This study also examined the forecasting power of predictor variables (crude oil, iron, silver, and copper prices; ZAR, INR, and RMB exchange rates; and inflation rates of US and China) to predict future gold prices. The results indicated the predictor variables' high capacity to forecast future gold price volatility. Furthermore, this study investigated the correlation between gold prices and predictor variables using a long-term data set (from September 1987 to August 2017). The results provided significant correlations among gold prices and all the predictor variables.

Finally, one direction for future research is the application of the proposed model in estimating the future mining, milling, refining, and fixed costs of mining projects.

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