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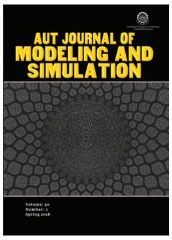

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Forecasting Gold Price Changes: Application of an Equipped Artificial Neural Network

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ABSTRACT: The forecast of fluctuations of prices is the major concern in financial markets. Thus, developing an accurate and robust forecasting decision model is critical for investors. As gold has shown a special capability to smooth inflation fluctuations, governors use gold as a price controlling lever. Thus, more information about future gold price trends will help make the firm decisions. This paper attempts to propose an intelligent model founded by artificial neural networks (ANNs) to project future prices of gold. The proposed intelligent network is equipped with a meta-heuristic algorithm called BAT algorithm to make ANN capable of following fluctuations. The designed model is compared to that of a published scientific paper and other competitive models such as Autoregressive Integrated Moving Average (ARIMA), ANN, Adaptive Neuro-Fuzzy Inference System (ANFIS), Multilayer Perceptron (MLP) Neural Network, Radial Basis Function (RBF) Neural Network and Generalized Regression Neural Networks (GRNN). In order to evaluate model performance, Root Mean Squared Error (RMSE) was employed as an error index. Results show that the proposed BAT-Neural Network (BNN) outperforms both conventional and modern forecasting models.

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1- Introduction

The major concerns in financial markets are fluctuations and price prediction. Similar to other industries, decision makers in mining industries accept or reject the proposed projects based on mineral price prediction [1]. The modern quantitative finance uses mathematical modeling to recognize the hidden patterns of financial asset prices as fundamental information in case of risk management and investment planning [2]. Gold has been traded actively on the international market for long in history [3]. Studies showed gold has a special capability to smooth inflation fluctuations, hence governments use gold as a price controlling and monetary policy lever [3]. Therefore, forecasting gold price has become very important. Gold treats differently from other minerals exclusively in terms of price movement and production [1]. In the 2008 financial crisis, many equities dropped by about 40% and also many key mineral product prices fell while gold price rose by, around, 6%. Previous studies have claimed that gold production is strongly affected by changes in its price [1] and all these instances (the worth of gold demand, the effect of gold price on other economic activities) recall the importance of gold price prediction.

In this research, a prediction model based on artificial intelligence capabilities in pattern recognition has been developed and trained based on existing historical data to predict future prices. A review of the financial literature identified a vast variety of the proposed models aimed at recognizing price trends to cope with the prediction problem [1]. Time series prediction models are widely utilized to help investors make a decision on buying or selling based on the estimation of upcoming prices. There are three different classes of time series prediction in the literature [4],

(1) objective forecast which is based on mathematical calculations and also is called quantitative prediction method,

(2) subjective forecast which relies on expert opinions and is called qualitative prediction methods, and,

(3) finally, prophecy method which is according to educated guessing.

This is aimed at developing an objective forecasting method. As mentioned above, objective forecasting approaches use mathematical and statistical methods to deal with the prediction problem in a quantitative way such as Moving Average (MA), Box-Jenkins methodology, Fuzzy Logic, Genetic Algorithm (GA) and ANNs. Artificial Intelligence (AI) based techniques have been widely used in gold price forecasting problems by which very promising results have been obtained. [5].

This research attempts to develop an intelligence model based on ANNs. The ANNs are known as a comprehensive approximation model and, in recent years, they have been used to forecast many nonlinear trends and time series events [6]. The main idea of neural network methodology is inspired based on a biological nervous system which consists of structured calculating nodes/elements operating in parallel [4]. These elements are connected to each other to carry out a predefined function. Training ability of ANN lets the network adjust the weights between computational nodes, known as weights. In comparison with statistical methods, ANNs define less limitation and few pre-set assumptions on the existing distributions among dataset which allows nonparametric functional forms and provide a much better robustness degree. In addition, an adjusted ANN outperforms the typical regression analysis when ambiguity is seen in independent

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variables [7]. The ability to cope with highly nonlinear problems with unknown functional correlations made ANN a frequently-used technique in financial prediction attempts [8].

The rest of this paper is organized as follows. Section 2 reviews the literature to draw a vision about the trends of previous studies. Section 3 focuses on the purposed model and describes each element of the proposed hybrid method. A case study is conducted in Section 4 and the results will be examined with other benchmark models. The results will also be analyzed at this stage. Finally, Section 5 presents a short summary and conclusions.

2- Literature Review

There are a number of various price modeling approaches that have been investigated in the financial literature. Some are classified under classic approaches such as geometric Brownian motion9-11]], mean reversion [12, 13] and stochastic price forecasting models [14, 15]. These models focus on historical price fluctuations and estimate further prices based on a random term. The main disadvantage of these classic models is that they do not consider price jumps and drips [16]. Lee et al. evaluated temporal properties of some non-renewable natural resource prices series [17]. They found that "the natural resource prices are stationary around deterministic trends with structural breaks in the intercepts and trend slopes" [1, 17, 18]. Moreover, to investigate jump and drip signals, some studies noted the microeconomic theory which claims that in the long-run, the price of a commodity should tie to its marginal production cost [19, 20] that means that the commodity price may present random fluctuations in a short-term period, but they tend to revert to a long-term trend.

Today, enormous efforts have been put in AI models to forecast problems when using AI models or an integration of several models have become a usual practice to increase the forecasting accuracy [21]. Aydinalp-Koksal and Ugursal investigated the use of conditional demand analysis (CDA) to model residential end-use energy consumption at the national level [22]. The prediction performance of CDA model was compared with the earlier NN and an engineering based model, and the results revealed that CDA overcame the other compared models. Shimoda et al. developed a model to simulate nationwide energy consumption of the residential sector while considering the diversity of households and building types [23]. Roger published a research to address the problem of the predicting of demand for the natural gas [24]. In an uncertain environment, there are notable methods that attempt to deal with the inherent instability of the research area [25] in order to guarantee a sustainable decision process [26, 27]. For instance, Alipour et al. proposed a novel fuzzy cognitive map-based scenario planning approach to project various oil production pathways [28]. Hafezi et al. presented a scenario development model to design the future of Iranian oil and natural gas industries [27]. These forecasting methods are appropriate for the situation in which the decision makers are seeking for a long-run insight into future possible trends.

Baumeister and Kilian published a research paper to analyze how policy-relevant forecast scenarios can be constructed from vector autoregression (VAR) models of the global oil market and how changes in probability weights attached to the scenarios affect real-time oil price forecasting [29]. In addition, Dilaver et al. investigated natural gas consumption in Europe to support long-term investments and contracts [30]. They estimated an OECD-Europe natural gas demand function with annual data over the period from 1978 to 2011 by applying structural time series model (STSM). Finally, three scenario streams were developed based on low, reference and high case scenarios.

The prediction of gold price is an important process since it is classified under complex problems category because the investors have to make decision under an uncertain environment due to the fluctuations of gold price and its connections to other economic factors such as oil price [1, 31]. Authors need to use an effective adaptive forecasting model to present meaningful results. Reliable and precise forecasting of future gold prices equip decision makers to perceive fluctuations and patterns behind the historical trend and foreseen behaviors in the next time steps.

ANN and ANFIS (Adaptive Neuro-Fuzzy Inference System) were used by Yazdani-Chamzini et al. who aimed at modeling the gold price historical time series and predicting the trends. The obtained results were compared with those of the well-known statistical model of ARIMA (Auto-Regressive Integrated Moving-Average). The results showed that the ANFIS model outperforms other models [31]. An Enhanced Empirical Mode Decomposition (EMD) meta-learning rate-based model proposed by Zhou et al. to forecast gold price has a good forecasting ability [3]. Genetic algorithm (GA) is combined with a back-propagation neural network by Mirmirani and Li to forecast gold price movements. In this study, they applied neuro-genetic optimizer software to a NYMEX database of daily gold cash price [7]. Liu proposed GA-BP forecasting model composed of a GA to optimize linking weights of the back-propagation (BP) NN and obtained properly acceptable results [32]. Hadavandi et al. suggested a Particle Swarm Optimization (PSO)-based pattern recognition model to forecast gold price and used PSO algorithm to estimate parameters [5]. Hussein et al. developed a system based on existing gold historical data as an input for an ANN algorithm to aid the investor with deciding the best time for selling or buying [4].

A dynamic NN model is suggested by Ghiassi et al. to forecast time series datasets using an novel architecture different from the traditional models [6]. Zhou and Lai suggested an online learning system based on enhanced EMD algorithm in the case of gold market forecasting problem. At the first stage, authors adopted the EMD algorithm to separate historical data into the subsets and, secondly, the prediction phase was investigated using a BP-NN model [33]. Dai et al. proposed a hybrid forecasting model which used wavelet frame to decompose time series of gold price into sub-series with different scales. Then, a support vector regression (SVR) technique was exploited to build a forecasting model using the generated sub-series [34].

A hybrid fuzzy clustering algorithm and RBF-NN were combined with a research carried out by Zhang and Liao to model gold price and forecast future prices. They implemented Principal Component Analysis (PCA) method to integrate parameters dependent to sub-variables of each technical indicator, then results acted as the input data [35]. Kunar et al. mentioned that some fundamental factors such as foreign exchange rates, inflation indexes or interest rates and some behavioral factors, e.g. customer sentiments and global economic stability, play an important role in driving gold price. In addition, they implemented expert model mining system (EMMS) and binary SVM (Support Vector Machine) classifier techniques to demonstrate forecasting performance using difficult features [36].

Pierdzioch et al. forecasted the gold price fluctuations with applying a boosting approach. To evaluate the performance of the developed model, a loss function was implemented based on R^2 statistic [37]. Gangopadhyay et al. developed a model to explain and forecast gold price in India using a vector error correction model. They also presented out-of-sample forecasts of the proposed model [38]. Xian et al. proposed a novel hybrid model which combined Ensemble Empirical Mode Decomposition (EEMD) and Independent Component Analysis (ICA). The proposed model was conducted to analyze gold price trends [39]. To forecast the gold price volatility, an ANN-GARCH model was presented by Kristjanpoller and Minutolo. ANN-GARCH is composed of an ANN model integrated into a GARCH method [40].

Baur et al. proposed a dynamic model averaging, which allows over-time variation of both coefficients and forecasting model [41]. Authors investigated a large series of existing gold price determinants and reported the results. Some recent attempts made in the case of metal price forecasting are summarized as follows:

- Dehghani et al. employed the binomial tree to forecast copper price fluctuations [42, 43].
- Kriechbaumer et al. proposed a wavelet-ARIMA to forecast the monthly prices of copper, zinc, aluminum, and lead [44].
- Chen et al. used gray wave forecasting method to study changes in various metal prices [45, 46].
- Liu and Li presented a random forest-based model to forecast gold price and analyze relevant influence factors [47].
- Decision tree learning method was used by Liu et al. to predict metal price using price volatility of several materials [48].
- Sivalingam et al. implemented extreme learning machine to predict future prices of gold [49].
- ARIMA time series method was used to forecast gold prices [50].
- Sharma proposed a gold forecasting model based on Box Jenkings ARIMA method [51].

To analyze the theoretical gap, Table 1 classifies various forecasting models and reviews their main properties (pros and cons).

In this paper, we propose an ANN algorithm which is optimized via bat algorithm. Bat algorithm proposed by Yang in 2010 [52] is based on the echolocation activity of bats. The bat algorithm has the advantage of combining a population-based algorithm with the local search. This algorithm involves a sequence of iterations, where a collection of solutions changes through random modification of the signal bandwidth which increases using harmonics [53]. Recently some studies have attempted to use the advantages of bat algorithm in order to optimize a basic learning algorithm such as ANNs. Hafezi et al. developed an agent-based model which aimed at predicting stock prices at financial crisis period, which was equipped with a bat-NN model as the forecasting agent [54]. The proposed model overcame comparison models such as a genetic-NN.

Dehghani and Bogdanovic proposed a bat algorithm-based model to predict the copper price volatility [55]. Finally, authors showed that the bat algorithm can overcome classical estimation methods. Jaddi et al. proposed a modified bat algorithm which presents a new solution to optimize both the weights and structure of ANNs [53].Svecko and Kusic applied a combined approach by using a feed-forward neural network (FNN) jointed with a bat search algorithm in order to improve the positional control of an X-PEA mechanism model by also taking into account the hysteresis behavior. The proposed positional controller was successfully implemented, and it was capable of significantly improving the overall control response result of an X-PEA mechanism [56]. Using bat algorithm to optimize neural networks is still novel and a few types of research studies investigated this hybrid model as a forecasting method. This paper aims

Table 1. The main pros and cons of the major forecasting models

Type of Models	Pros & Cons
Classic price modeling/ forecasting	Focus on historical data. Do not consider jumps and drips of the prices. Generally, these models were introduced for stock markets. Do not use unit root test for time series and econometric methods to estimate their parameters.
Time series models	Focus on historical data. Do not cope with extreme jumps and drips. Do not use feedback loops to dynamically upgrade model adjustment features.
Learning forecasting models	Focus on historical data. Generally are able to learn fluctuations and related formerly signals. Use feedback loops to upgrade model adjustment features dynamically.
Qualitative based forecasting models	Rarely depend on quantitative forecasting methods. Donate insights into long-run behaviors of a complex system. Mostly depend on experts' evaluations, instead of historical time series. Are able to dynamically modify input features.

to apply bat-NN to solve well-known gold price forecasting problem and compare outcomes with the other used methods.

3- Materials and Methods

3- 1- A Brief Review of Conceptual Architecture of the Model

The proposed model discussed in this section aims to improve the gold price prediction accuracy. The relevant conceptual model is shown in Fig. 1:

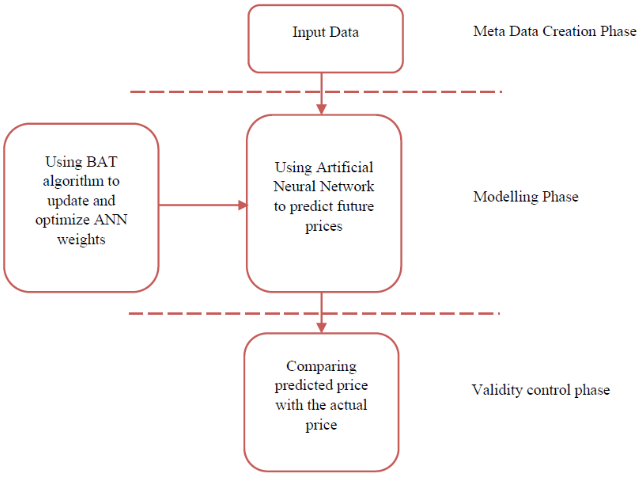

Figure 1. Conceptual model for the prediction process

As Fig. 1 shows, the proposed model consists of three different phases. The first phase, which is named metadata creation phase, attempts to provide the data which contain useful features to help the forecasting model. Features of this kind of data will be discussed in Section 4.1. The second phase focuses on producing an adaptive robust forecasting model based on an ANN. The accuracy of the designed ANN model strongly depends on the method of weight generation [54]. Thus, bat algorithm has been used to help the forecasting process choose the best weights and therefore produce the best outputs. Finally, the predicted prices are compared with an actual price based on RMSE statistic which is a well-known index to show the quality of the model in comparison with other benchmark models.

The rest of this section is organized to illustrate the proposed and competitive models in detail.

3- 2- Artificial Neural Network

These days' intelligence-based models have been commonly used in the studies, some of which had been mentioned in the literature review section. Some of well-known Artificial intelligence (AI) techniques are Fuzzy Logic, GA, ANNs, etc. AI has been applied to many forecasting problems, including financial time series extrapolation [5]. As an AI method, ANN has been used as a framework to structure forecasting model. Many studies showed that ANNs have the ability to classify and recognize the hidden patterns [57]. ANN models are originally developed based on the biological neural system. Simply an ANN uses a part of the data to train and calculate optimum parameters, then a test phase is applied using the rest of the data, and it is clear that a good model must provide an accurate prediction.

In detail, an ANN can be viewed as a combination of interconnected simple processing elements known as neurons which get inputs and calculate outputs using transfer function (the output of a neuron can be the input to other neurons). The first layer which delivers raw data is named input layer and the last layer which produces the final output(s) is called output layer. All layers between these two main layers are known as hidden layers. An ANN may have zero, one, two or more hidden layers. An architecture of an NN is shown in Fig. 2.

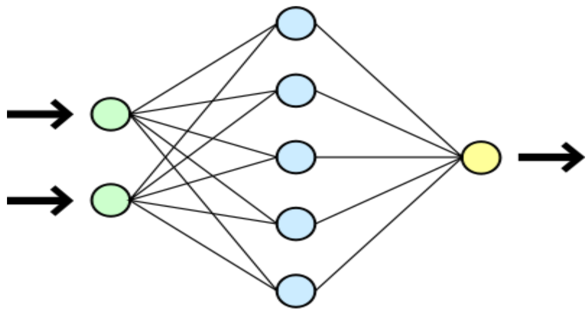

Figure 2: Conceptual architecture of an ANN

There are several reasons to prove that ANN models are well-suited for time series data which contain uncertainty and have complicated and also nonlinear behavior and patterns that cannot easily be recognized:

First, contrary to classical methods, ANNs are data-driven self-adaptive methods [57]. As described before, ANN models use historical data to train and obtain relationship among input features to recognize underlying patterns even when the relationship is unknown or hard to be described. ANNs have a learning ability which is a key factor especially when the goal is to follow and forecast the market price fluctuations.

Second, ANN can be generalized based on the sample data presented to them. Zhang stated, "ANNs can often correctly infer the unseen part of a population even if the sample data contain noise information" [57]. Finally, ANNs are nonlinear universal function approximations. The traditional time series forecasting methods such as Box-Jenkins or ARIMA deal with the problem under a linear assumption process while the real world behaves in a nonlinear way.

In addition, an ANN can be equipped with learning capability that makes the network able to learn from its mistakes and adjust its input weights. Here an ANN has been equipped with a powerful meta-heuristic algorithm known as BAT which is proposed by Yang [52]. This paper proposed a hybrid intelligent model which has the advantage of simulating nonlinear nature of input data when the existing knowledge about the problem structure is insufficient. Fig. 3 shows the flowchart of ANN equipped with BAT algorithm (called BNN).

3- 3- BAT Algorithm

Yang proposed BAT as a meta-heuristic algorithm based on the ecological behavior of bats in nature. Yang noted that "bats are fascinating animals which use a type of sonar, called echolocation, to detect prey, avoid obstacles and locate their roosting crevices in the dark. These bats emit a very loud sound pulse and listen for the echo that bounces back from the surrounding objects [52]. Yang showed that BAT algorithm (BA) performs more accurate than such well-known methods such as PSO, GA and harmony search [52]. BA attempts to eliminate the flaws in the last proposed methods while saving the their advantages. Fig. 4 shows that how the BA works:

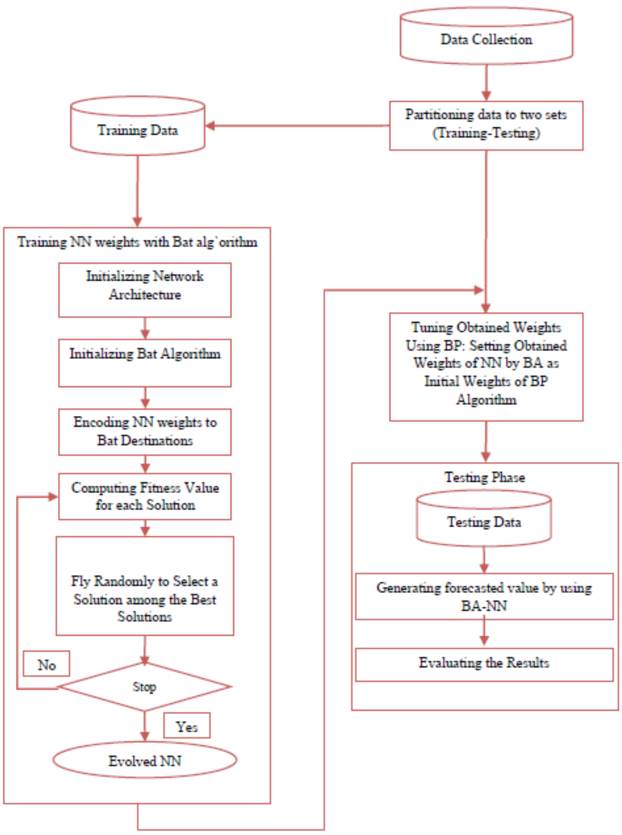

Figure 3: Architecture of an ANN equipped with BAT algorithm

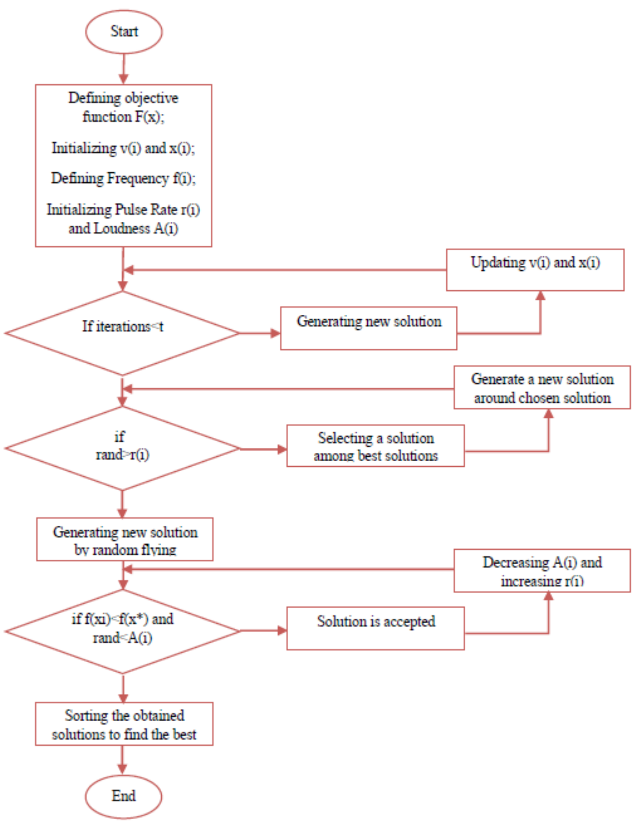

Figure 4: The general procedure of BAT algorithm

As illustrated in Fig. 7, three parameters must be defined, namely, s_i which is representative of position/solution, v_i that refers to velocity and dimension of searching space.
In the next stage, initial frequency has to be determined by the following equation

$$f = f_{min} + \left(f_{max} - f_{min} \right) \beta, \tag{1}$$

where β is a random vector derived from Uniform distribution and f_{min} and f_{max} are predefined parameters that vary with problems.
Then s_i and v_i must be updated using the following equations:

$$v_i^t = v_i^{t-1} + \left(x_i^t - s_* \right) f_i \tag{2}$$

$$s_i^t = s_i^{t-1} + v_i^t \tag{3}$$

Here s_* is the best global solution at the current state/iteration.
Random walk procedure is used to generate a new solution:

$$s_{new} = s_{old} + \varepsilon A^t, \tag{4}$$

where A is a randomly generated value in the range of [-1, 1] and At specifies the mean loudness value at the current iteration. A_i and r_i stand for loudness and pulse rate, respectively. These parameters are updated at each stage using the following equation:

$$A_i^{t+1} = \propto A_i \tag{5}$$

$$r_i^{t+1} = r_i^0 \left[1 - \exp\left(-\gamma t \right) \right]. \tag{6}$$

According to bats' behavior in the nature, loudness, A_i, usually decreases and pulse rate, r_i, usually increases when bat reaches its target, thus they are constant predefined values. Also when:

$$A_i^t \to 0 \quad \text{And} \quad r_i^t \to r_i^0. \tag{7}$$

The next section shows that the ANN equipped with bat algorithm potentially outperforms all the other benchmark models.

4- Study and Results

4- 1- Data

To validate and show the strength of the proposed model, we used the dataset that was employed in an article published on December 2012 by Yazdani-Chamzini et al. (Authors had access to the data) [31]. The authors described data set as follows: "Dataset includes 220 monthly observations of gold price per ounce against its effective parameters from 1990-04 to 2008-07". To evaluate the performance of different methods, the first 200 observations have been used as a training set and consequently the last 20 observations were used as validation or test set. Fig. 5 shows the whole observations in a timeline graph.
To develop an accurate and robust model, it is vital to select relevant and optimized input dataset. Input variables will define the architecture of the forecasting model. Based on 'hunches of experts', seven input variables have been detected as the most relevant features in order to predict future gold prices [31]. Table 2 presents input parameters in detail.

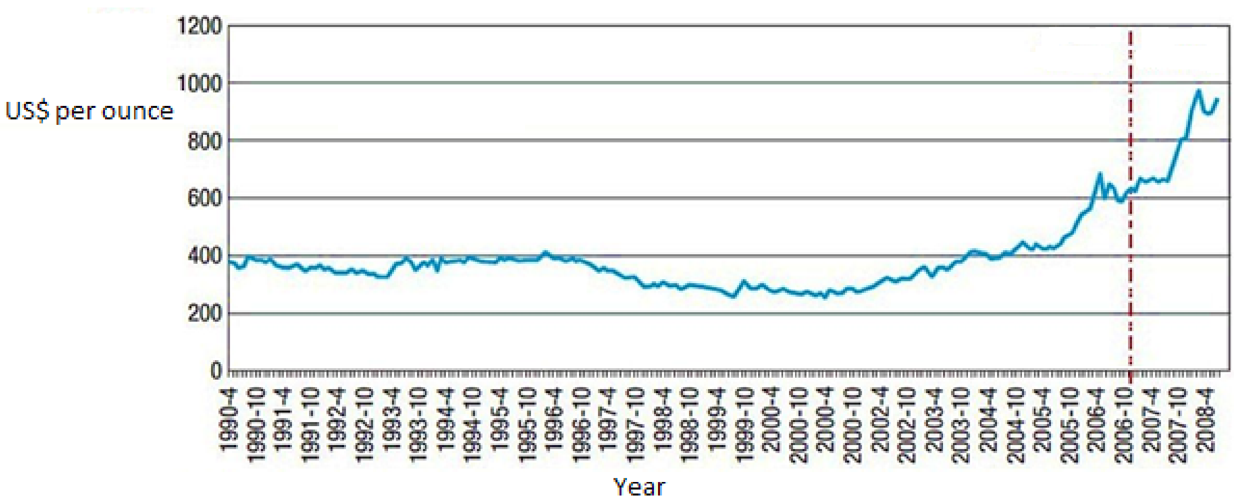

Figure 5: Gold price movements (data resource: www.kitco.com)

Table 2: Investigated parameters and corresponding resources

Variable	Type of data	Symbol	Unit	Max	Min	Resource
Gold price	Monthly	G	\$/ounce	1134.72	256.675	www.kitco.com
Silver Price	Monthly	S	\$/ounce	18.765	3.64	www.kitco.com
US\$ index	Monthly	C	-	1.599	0.967	research.stlouisfed.org
Oil price	Monthly	O	\$/barrel	133.93	11.28	www.economagic.com
Inflation rate	Monthly	Inf	-	0.0628	-0.0209	www.infliationdata.com www.rateinflation.com
Interest rate	Monthly	Int	-	8.89	2.42	www.econstat.com
Stock market index	Monthly	DJ	\$	13930	2442.33	finance.yahoo.com www.google.com
World gold production	Annually	Pg	Ton	216.95	178.195	minerals.usgs.gov

Except for the world gold production, other parameters are presented monthly. To obtain a heterogeneous data set, it is necessary to interpolate the monthly values of the world gold production. Cubic Spline interpolation method has been employed, which is a useful technique to interpolate between the known data points due to its stable and smooth characteristics, in order to convert annual data into monthly data [58].

4- 2- An Introduction to Comparative Models

As this research aims to compare the proposed BNN model with the models proposed or used as benchmarks by Yazdani-Chamzini et al., we have to briefly describe benchmark models that contain ARIMA, (naïve) ANN and ANFIS.

4- 2- 1- ARIMA Model

In the 1970s, Box and Jenkins promoted a forecasting model called ARMA (autoregressive Moving-Average) [59]. The ARMA model developed into an enhanced statistical model, called ARIMA, to obtain more accurate and reliable solutions. ARIMA stands for Auto-Regressive Integrated Moving-Average which assumes that a linear function of previous observations and randomly distributed errors can reflect the future values. Repeated integrating of ARMA process is used to produce ARIMA model. ARIMA (p, q, d) is used to define ARIMA's structure where *p* defines the autoregressive parameters, *q* stands for the number of moving-average parameters and finally, *d* is the number of different passes.

Yazdani-Chamzini et al. used Eviews package software to obtain best-fitted model based on the optimum solution for the parameters and the residuals (white noises). The best-fitted model is ARIMA (1,1,0) as follows [31]:

$$\hat{y} = -1.873 + 1.008 y_{t-1} \quad (8)$$

4- 2- 2- Benchmark ANN Model

Based on the concept of the ANN, this phase determines the optimized architecture of the model. Yazdani-Chamzini et al. showed that the best-fitted model has 7-24-1 where 7 stands for the number of features in the input; 24 shows the number of hidden layers and since the model needs to predict a single value of the gold price, the output layer contains one neuron [31].

4- 2- 3- Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

ANFIS (Adaptive Neural-Fuzzy Inference System) was initially introduced by Jang [31]. ANFIS is the surprised learning network with a multilayer feedforward structure which models the provided training data set using Takagi-Sugeno system. ANFIS contains five layers: (1) Fuzzification,

(2) Inference (3) Normalization (4) Consequent and (5) Output.
ANFIS applies two different phases. The first phase is called backward pass aimed at optimizing premise parameters of fuzzy membership function (MFs) used as an input in layers one to three. The second one is forward pass which tries to optimize the consequent parameter in levels four and five [60].

4- 2- 4- Radial Basis Network (RBF)

Radial Basis Function (RBF)-NN are neural networks based on localized basis functions and iterative function approximation. In terms of structure, an RBF-NN is composed of three layers, namely, an input layer, an output layer, and a hidden layer [61]. These types of networks are of the fixed architecture with a single hidden layer; this is while MLP-NNs may contains more than one hidden layer. Indeed, an RBF-NN represents a special case of an MLP-NN [62]. Owing to their simple design, extremely strong tolerance to input noises, and fast yet pervasive training capabilities, these networks have attracted a great deal of attention [61].

4- 2- 5- Generalized Regression Neural Network (GRNN)

Generalized regression NN (GRNN) was first introduced by Specht [63]. GRNN has several advantages as a meta-modeling algorithm. Based on non-parametric regression, GRNN is established on the basis of sampled data, that executes the Parzen non-parametric estimation, and the network output is calculated based on the maximum probability principle. Therefore, it has a high ability of nonlinear approximation. Compared with the radial basis function neural network, GRNN training is more convenient, and its advantage includes the approximation ability and high learning speed [64].
The only parameter of the model, namely, the smoothing factor, is not highly sensitive to its setting [65]. Due to the low sensitivity of the smoothing factor, the optimal selection of this parameter is not difficult [66]. GRNN considers each training data as a cluster. Once GRNN adopts a new input data for the prediction of the output value, it calculates the Euclidean distance between the input and each training data.

4- 2- 6- Multi-Layer Perceptron Network (MLP)

Multi-layer perceptron (MLP) network is one of the most common and practical architectures of ANN [67]. In MLP, each neuron is connected to several neighbors by varying weights representing the relative influence of the different neuron inputs to the other neurons. The weighted summation of the inputs is transmitted to the hidden neurons, where it is transformed using an activation function. In turn, the outputs of the hidden neurons serve as inputs to the output neuron where they undergo another transformation [68]. MLP has some notable advantages, including the capability to learn nonlinear models, real-time learning capability. MLP models are sensitive to feature scaling.

4- 3- Implementing the Proposed Model

In this research, an NN network is proposed that is equipped with BAT algorithm (BNN). The proposed hybrid model characteristics are shown, below (these parameters are obtained via a try and error process):

Table 3: Parameters of BNN

Parameter	ANN Architecture	Number of Population	Number of Generations	Lambda	Alpha	f_{min}	f_{max}
Value	7-4-1	15	5	1.5	0.5	0	1

Before running the proposed model, data normalization step is investigated to prevent the effects of parameters range on the results and adjust values measured on different financial indexes with various domains and scales. Data normalization

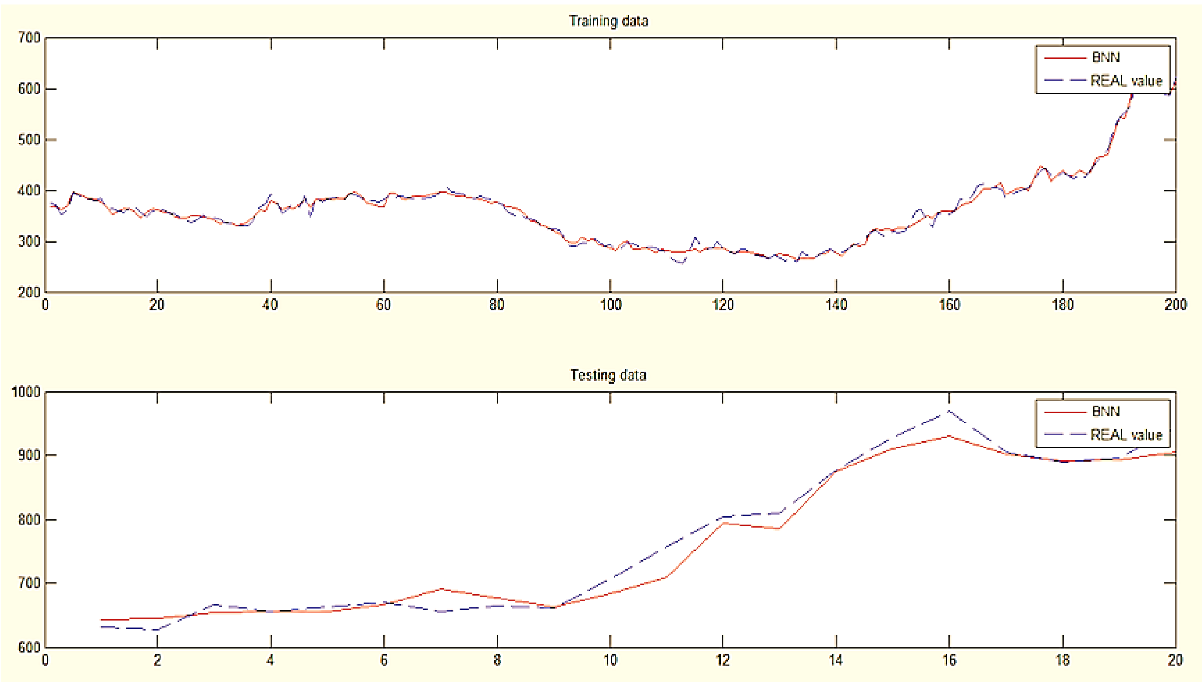

Figure 6: Output of Implementing BNN

Table 4: Forecasting performance for investigated models (based on the RMSE)

Models	ARIMA	ANN	ANFIS	RBF	MLP	GRNN	BNN
RMSE	166.87	118.04	29.48	124.36	74.19	118.96	21.26

Table 5: Results of paired t test carried out between BNN and the compared model

Model	Base Model	*t* test	p-value	Conclusion
ANFIS	BNN	2.5732	3×10^{-2}	$\mu_{ANFIS} > \mu_{BNN}$
ANN	BNN	5.0141	4×10^{-4}	$\mu_{ANN} > \mu_{BNN}$
GRNN	BNN	6.2174	4.4×10^{-4}	$\mu_{GRNN} > \mu_{BNN}$
MLP	BNN	5.5436	2.7×10^{-4}	$\mu_{MLP} > \mu_{BNN}$
ARIMA	BNN	24.1418	8×10^{-6}	$\mu_{ARIMA} > \mu_{BNN}$
RBF	BNN	29.1298	4×10^{-6}	$\mu_{RBF} > \mu_{BNN}$

is simply defined as adjusting values measured on different scales to a notionally common scale. The input dataset consists of different indexes with different domains and scales and data normalization helps access a dataset which contains homogenous data. The "min-max" normalization method is used to reform dataset using the following equation:

Normalized Data= (y(i)- Min{y})/(Max{y}-Min{y}) (9)

Where y(i) is the i^{th} element in the column and Min{x} is the minimum and Max{x} is the maximum of the associated column elements.

As shown in Fig. 6, the proposed and structured BNN model is able to cope with gold price fluctuations and reflects an acceptable prediction accuracy. The proposed BNN model is coded and run using MATLAB software. Stop criteria were set as follows:

- if a maximum number of epochs (iterations) are met (=3000) or,
- achieving the training goal parameter (mean squared error=1e-7)

As shown, Fig. 6 is divided into two sub-plots. The upper subplot indicates training set and BNN performance (red line). However, the lower subplot shows forecasting performance for the proposed BNN model (red line) versus real values. The graph represents a notable forecasting performance which was able to cope with gold price trends and fluctuations.

4- 4- Performance Analysis

To analyze the performance of investigated models (models presented by Yazdani-Chamzini et al. and the proposed BNN model), it was decided to calculate the represented forecasting error for each model. The error is defined as the difference between the actual values and prediction ones. The model with the least error ratio obtains the greatest degree of accuracy. In this paper, Root Mean Square Error (RMSE) statistic is used to compute performance index. RMSE is calculated using the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(A_i - p_i\right)^2}{N}} \quad (10)$$

where A_i represents actual values and p_i stands for the predicted values of gold price while the total number of observations is shown by N. Table 4 shows the forecasting performance RMSE of models for the gold price:

The results of all cases show the proposed BNN model outperforms all cases: ARIMA (166.87 > 21.2693), ANN (118.04>21.2693), ANFIS (29.48>21.2693), RBF (124.36>21.2693), MLP (74.19>21.2693) and GRNN (118.96>21.2693).

To evaluate the prediction accuracy a paired *t* test is carried out between the models mentioned in Table 4. The following hypotheses are proposed.

H0: No meaningful difference exists between BNN and the compared model

H1: There exists a meaningful difference among BNN and the compared model

Results of paired *t* test are shown in Table 5.

As data used for the prediction in all models were the same and according to Table 5 which includes paired *t* test on RMSE statistic as a representative for prediction accuracy, *H1* is proved and we can, therefore, deduce that the proposed BNN model outperformed benchmark prediction models.

5- Conclusion

Nowadays, classical estimation methods are unable to accurately forecast commodity price volatility due to their frequent variations in the last decade. Forecasting process can be explained as uncovering and projecting future trends based on existing historical data. Referring to the reviewed literature, the contribution of the proposed model is to cope with jumps and drips using a learning procedure. Moreover, the model outperformed all well-known benchmark models.

This paper proposed a new forecasting model (BNN) and applied gold price prediction problem. Reviewing the literature reveals that forecasting methods are categorized into three major approaches: (1) classical mathematical models, (2) AI-based models and (3) hybrid models. The hybrid model used in this study aimed at integrating a based model with model(s) to eliminate disadvantages of the based model while keeping the advantages. Successful forecasting procedure empowers investors to make decisions and plan for the future in order to enhance favorable scenarios.
The new proposed model is built upon ANN which based on the previous studies is effective in modeling the time series forecasters especially when dataset trends are nonlinear and under uncertainty. The ANN is equipped with BAT algorithm to reinforce training phase of ANN.
The new BNN model implemented on the dataset of gold prices, and the results showed that the BNN model outperforms other benchmark models such as ARIMA, ANN, and ANFIS. The investigated ANFIS model has been modified and optimized recently by Yazdani-Chamzini et al. Thus, it can be claimed that BNN model is an accurate model that can be used for gold price forecasting and also other financial markets.

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