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Forecasting Gold Prices by Hybrid ANFIS-Based Algorithm

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ABSTRACT

In this article, the high accuracy and effectiveness of forecasting global gold prices are verified using a hybrid machine learning algorithm incorporating an Adaptive Neuro-Fuzzy Inference System (ANFIS) model with Particle Swarm Optimization (PSO) and Gray Wolf Optimizer (GWO). The hybrid approach had successes that enabled it to be a good strategy for practical use. The ARIMA-ANFIS hybrid methodology was used to forecast global gold prices. The ARIMA model is implemented on real data, and then its nonlinear residuals are predicted by ANFIS, ANFIS-PSO, and ANFIS-GWO. The results indicate that hybrid models improve the accuracy of single ARIMA and ANFIS models in forecasting. Finally, a comparison was made between the hybrid forecasting models ARIMA-ANFIS, ARIMA-ANFIS-PSO, and ARIMA-ANFIS-GWO and the results showed the superiority of the ARIMA-ANFIS-PSO model.

1. Introduction

Forecasting gold prices is important because it helps understand market movement and make smart investment decisions. Companies and investors use gold price forecasting as a crucial tool to plan, evaluate, and analyze potential gains and risks, it is essential due to the great importance of this precious metal to international trade and the economy. As a result, using fuzzy neural networks can be a useful approach to increase the accuracy of forecasting changes in the price of gold.

For Forecasting gold prices, we suggest a hybrid model of ARIMA (Auto Regressive Integrated Moving Average) - ANFIS (Adaptive Neuro-Fuzzy Inference System). To effectively train the ANFIS network parameters and raise Forecasting accuracy, the (Particle Swarm Optimization) PSO and (Grey Wolf Optimizer) GWO algorithms were also applied.

Adaptive Neural Fuzzy Inference System (ANFIS) has been widely used in many fields for modeling and forecasting. In the first model, ANFIS combines the benefits of fuzzy inference systems (FISs) and artificial neural networks (ANNs) (Jang, 1993)[6].

It has been used to model nonlinear functions, identify nonlinear components in control systems, and predict chaotic time series (Jang, 1993) [6].

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The usefulness of ANFIS was highlighted by comparing ANFIS and artificial neural network (ANN) models with the traditional ARIMA model for calculating gold prices [14].

Dube (2016) highlighted the application of ANFIS models to forecast gold prices, demonstrating their potential in contrast to traditional techniques such as multilinear regression and ARIMA [2].

ANFIS has been used to estimate the material removal rate and surface roughness of particular materials in electrical discharge machining, demonstrating its application in materials science [7].

ANFIS has proven to be effective in the wire electro-discharge machining (WEDM) arena when compared with artificial neural networks (ANNs) for machining response Forecasting, including material removal rate and surface roughness [9].

An adaptive neuro-fuzzy inference system model combined with a new version of the firefly algorithm called the Firefly Gender Difference Algorithm was used to predict the hourly energy consumption of a college of chemistry building located in Murcia, Spain [5]
.

2. Adaptive neuro-fuzzy inference system

One of the most widely used artificial intelligence models that combines the benefits of fuzzy and neural networks is the ANFIS (Adaptive Neuro Fuzzy Inference System) model.

Jang's work [6] is the first example of using ANFIS for time-series Forecasting.

Fuzzy If-Then rules in ANFIS illustrate the relationships between variables [1].

The neural network's educational algorithms establish the membership component's parameters, while the fuzzy part establishes a link between inputs and outputs [9].

The five-layer network structure of the ANFIS is shown in Fig. 1.

Let us assume that the fuzzy inference system that is being studied has one output, f, and two inputs, x_1 and x_2.

The following are the fuzzy if-then rules for the first-order Takagi-Sugeno model under consideration.

Rule 1: if x_1 is A_1 and x_2 is B_1 then $f_1 = p_1x_1 + q_1x_2 + r_1$

Rule 2: if x_1 is A_2 and x_2 is B_2 then $f_2 = p_2x_1 + q_2x_2 + r_2$

In the premise/if part

acquiring each linguistic label's membership values (fuzzification).

combining the membership values to determine the firing strengths (weights) for each rule.

In the consequent/then part

producing the qualified result based on the firing power.

the qualified consequent's aggregate (defuzzification).

The similar ANFIS architecture shown in Fig. 1 is as follows:

Layer 1 is the fuzzification layer, where each node is an adaptive node with the following node function.

$O1, i = \mu_{Ai}(x_1)$ For i=1,2 (1)

$O1, i = \mu_{Bi-2}(x_2)$ For i=3,4 (2)

where μ_{Ai} and μ_{Bi} represent the degrees of membership of x_1 and x_2 in the A_i and B_i fuzzy sets, respectively, and x_1 and x_2 are the inputs.

Layer 2: The input signals in this layer are multiplied by one another to produce the following outputs:

$O2, i = \varphi_I = \mu_{Ai}(x_1) * \mu_{Bi}(x_2)$ For i=1,2 (3)

Layer 3: This layer computes the ratio of each rule firing strength to the total of all rule firing strengths.

$O3, i = \overline{\varphi}_i = \frac{\varphi_i}{\varphi_1+\varphi_2}$,   For i=1,2 (4)

Normalized firing strengths are the results of this layer.

Layer 4: Every node in this layer is an adaptive node with node functions given by:

$$O4,i \ = \ \overline{\varphi}_1\, fi = \ \overline{\varphi}_1\, (pi\, x_1 \ + \ qi x_2 \ \ + \ ri) \qquad \text{For i=1,2} \qquad (5)$$

where {pi, qi, ri} are the consequent parameters and inputs x1, x2 are once more employed.

Layer 5: The final layer computes the overall output, which is the total of the layer 4 output.

$$O_5 = \sum_i \overline{\varphi}_1 f_i = \frac{\sum_i \varphi_i f_i}{\sum_i \varphi_i} \qquad \text{For i=1,2} \qquad (6)$$

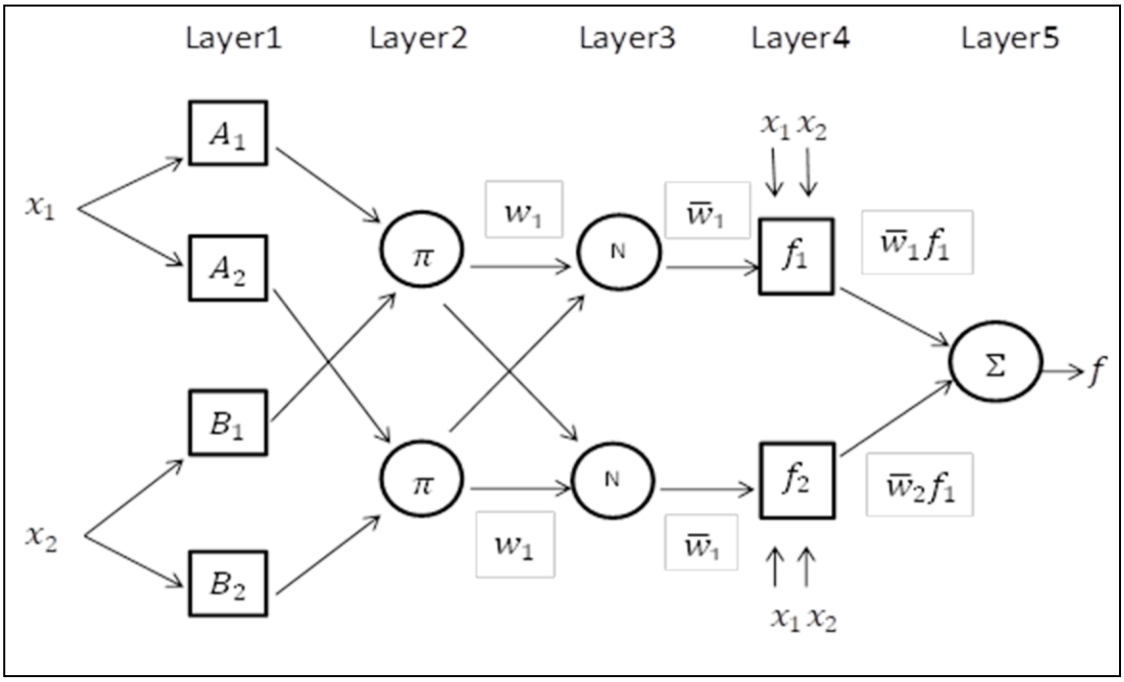

Figure 1 Structure of ANFIS for a model with two inputs.

The membership functions (MFs) parameters and the unknown consequent parameters {pi, qi, ri} in the ANFIS model are among the various unknown premise parameters that the application of met heuristic optimization algorithms must precisely find.

In this article, Particle Swarm Optimization (PSO) and Gray Wolf Optimizer (GWO) algorithms are used to train ANFIS parameters and to increase the quality of prediction accuracy [5].

3. Particle Swarm Optimization

Eberhart and Kennedy first developed and presented particle swarm optimization (PSO) in 1995.

The PSO is a population-based search algorithm that mimics the social interactions between fish, birds, and bees.

The original goal of this algorithm was to visually represent the exquisite and erratic dancing of a bird people.

Every individual in the swarm is represented by a vector in the multidimensional search space.

This vector also has an assigned vector known as the velocity vector, which dictates the particle's subsequent motion.

The PSO algorithm also decides how to update a particle's velocity.

Based on its current velocity, the best place it has previously investigated, and the global best position the swarm has explored, each particle modifies its velocity.

After that, the PSO procedure is repeated a certain number of times or until the target performance index-based minimum error is reached.

It has been demonstrated that this straightforward approach may effectively handle challenging optimization issues.

We shall now provide a brief overview of the PSO algorithm [3].

Assume that the ith particle of the swarm may be represented by a dimensional position vector and our search space is d-dimensional.

$X_i = \left(x_i^1, x_i^2, \dots x_i^d\right)$

The particle's velocity is indicated by:

$V_i = \left(v_i^1, v_i^2, \dots v_i^d\right)$

Take into account that the particle's best-visited position is:

$P_{ibest} = \left(p_i^1, p_i^2, \dots p_i^d\right)$

furthermore, the best position explored so far is:

$P_{gbest} = \left(p_g^1, p_g^2, \dots p_g^d\right)$

The following equations are therefore used to update the particle's position and velocity:

$$v_i(t+1) = wv_i(t) + c_1 r_1\big(p_i(t) - x_i(t)\big) + c_2 r_2\left(p_g(t) - x_i(t)\right) \quad (6)$$

$$x_i\,(t+1) = x_i\,(t) + v_i\,(t+1) \quad (7)$$

where r_1 and r_2 are two uniformly distributed numbers between 0 and 1, and c_1 and c_2 are positive constants.

W: is the inertia weight, illustrating how the prior velocity vector affected the current vector.

During optimization, the value of the inertia weight W, which balances local and global searches, may change.

When a better site for a particle or the entire swarm is found, the P_{ibest} for each particle is updated with each iteration.

Social engagement serves as PSO's primary motivator.

Within the swarm, individuals (particles) exchange knowledge with one another and then move to resemble both their "better" neighbor and their "better" previously attained location [4].

4. Grey Wolf Optimizer (GWO)[8]

It is an optimization algorithm inspired by the way gray wolves hunt. The wolves are divided into three groups during the hunt, and each group has a specific task to optimize effectiveness and reduce effort.

The first of these types is the alpha wolf, or the one in command who makes the choices. Gray wolves have a hierarchy, with the beta being the second-ranking subordinate wolf that helps the alpha with decision-making and other pack responsibilities.

The omega group, at the lowest level, the third, is the group that besieges the prey to keep it from moving until the alpha attacks and hunts.

If a wolf is not an alpha, beta, or omega, they are called subordinate (or delta in other cases).

Although they are subservient to alphas and betas, delta wolves rule the omega. This group includes Scouts, guardians, seniors, hunters, and caretakers.

Scouts are responsible for monitoring the boundaries of the territory and informing the pack of any threats. This behavior inspired the development of this algorithm, which improves our problem-solving abilities. To represent encircling behavior analytically, the following equations are proposed:

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right| \quad (7)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}\vec{D} \quad (8)$$

where $\vec{A}\ and\ \vec{C}$ are coefficient vectors, $\vec{X}_p$ is the prey's position vector, and $\vec{X}$ denotes the position vector of a grey wolf. Additionally, t represents the current iteration.

The following formula is used to determine the vectors $\vec{A}\ and\ \vec{C}$:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \quad (9)$$

$$\vec{C} = 2.\vec{r}_2 \quad (10)$$

where $r1, r2$ are random vectors in [0, 1] and components of $\vec{a}$ are linearly lowered from 2 to 0 during iterations.

Using Eqs. (7) and (8), A grey wolf can change its location at any time within the area surrounding its victim. Grey wolves can find their prey and follow their path around it. The hunt is usually led by the alpha. The beta and delta may occasionally go hunting as well. However, we have no idea where in an abstract search space the optimal (prey) is located.

To mathematically recreate the hunting behavior of grey wolves, we assume that the alpha (best candidate solution), beta, and delta have superior knowledge regarding the potential location of prey.

As a result, we reserve the top three results thus far and require the other search including the omegas-to adjust their places by the top search agents' locations. In this context, the following formulas are suggested.

$$\mathrm{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right| , \mathrm{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right| , \mathrm{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \quad (11)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\mathrm{D}_\alpha) , \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\mathrm{D}_\beta) , \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 .(\mathrm{D}_3) \quad (12)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (13)$$

The prey's position is estimated by alpha, beta, and delta, and other wolves update their positions randomly around the prey.

5. The proposed model structure

The MF parameters and the unknown consequent parameters {pi, qi, ri} in the ANFIS model are among the various unknown premise parameters that must be precisely identified using either metaheuristic optimization methods or the conventional method-based error backpropagation.

Two algorithms (PSO, and GWO) are used to train these parameters to increase the speed of convergence during the training phase. This lowers the possibility of becoming stuck in local optimization and increases the prediction accuracy of the conventional ANFIS technique.

6. The hybrid methodology

While both the ANFIS and ARIMA models perform well in both linear and nonlinear structures, none of them is comprehensive enough to anticipate different types of time series structures.

A competent hybrid model consisting of two phases was proposed by Zhang: The linear model is applied in step 1, and the nonlinear model is applied in step 2 utilizing the residuals of the linear model.

Lastly, the forecasted outcomes for both models are summed.

$$\mathrm{yt} = \mathrm{l_t} + \mathrm{n_t} \quad (14)$$

$$e_t = \mathrm{yt} - \mathrm{l_t} \quad (15)$$

The data structure (yt) is assumed to consist of two components, a linear part (l_t) and a nonlinear part (n_t), According to (14).

Initially, a linear model is used to forecast the data, and the residuals (e_t) are examined for nonlinear patterns. The ARIMA model forecasts the data in the first place, followed by the ANFIS model for its residuals, and finally, the combination of the ANFIS and ARIMA models yields forecasting [14].

7. Application and results

The global gold price series used for the period from 11/12/2017 to 21/12/2023 was obtained from the Nasdaq website.

There are 1575 observations in the sequence above. Two groups have been created using the data. 80% of the data are in the training group and the remaining 20% are in the test group.

Using the Eviews program, the ARIMA model was determined to forecast gold prices.

The ARIMA (2,1,3) model was chosen because it is the best model according to the (AIC, and BIC) comparison criteria.

After finding the residual of the ARIMA model, which has a nonlinear pattern as shown in Figure 2.

A combination of the ARIMA model and the appropriate nonlinear ANFIS model is implemented. The residuals are used as inputs to the ANFIS network according to the hybridization method mentioned in the previous paragraph. In this study, the Gaussian membership function MF was used.

The ANFIS network is trained using the PSO and GWO algorithms and a comparison is made between the models: ARIMA-ANFIS, ARIMA-ANFIS-PSO, and ARIMA-ANFIS-GWO.

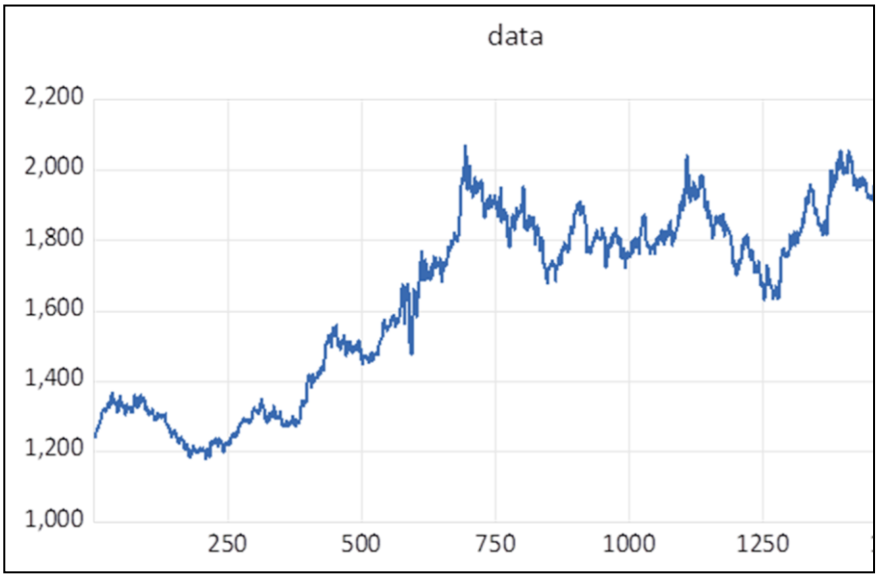

Figure 2 International gold price time series

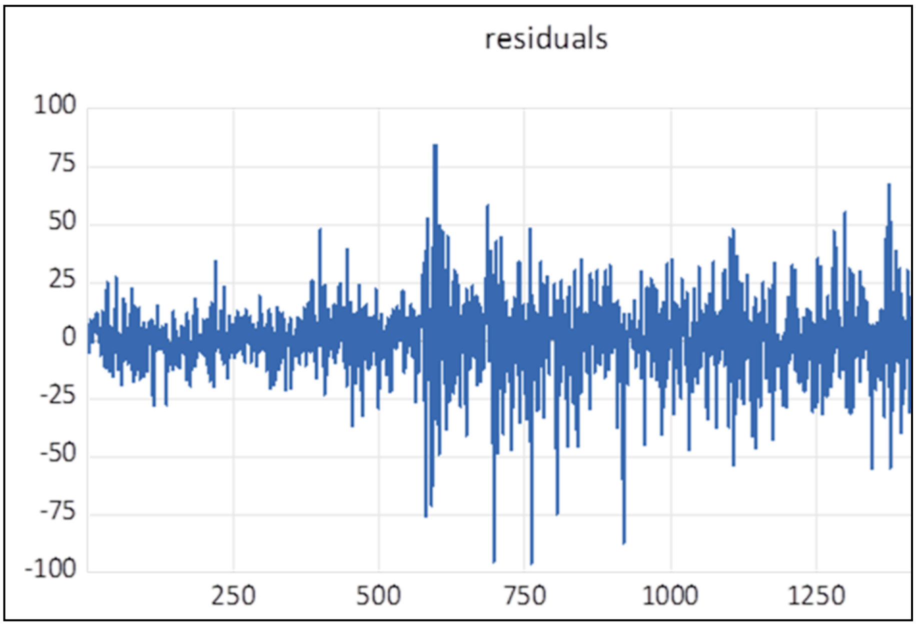

Figure 3 Residuals of the time series

The MSE values for the different ARIMA-ANFIS hybrid models throughout the testing period are shown in Table 1

Table (1)
MSE criterion results of test data (ARIMA-ANFIS-test)

Model	MSE
mse_test_ANFIS	0.0110284
mse_test_ANFIS_PSO	0.0000820
mse_test_ANFIS_GWO	0.0000856

8. Conclusion

This paper proposes a new improved adaptive neuro-fuzzy inference system enhanced with PSO and GWO algorithms for forecasting global gold price time series. The time series was modeled by the Box-Jenkins method and the ARIMA (2,1,3) model was chosen. The residuals of this model were used as inputs to the ANFIS neural network to formulate the hybrid model. It is clear from Table (1) that the hybrid model (ANFIS- PSO) has the least test error. According to the results, the ARIMA-ANFIS- PSO hybrid model has better results and the MSE decreases. Therefore, this model can be successfully used to predict gold prices.

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