A Metaheuristic Evolutionary Algorithm for Accurate Global Gold Rate Prediction with ANFIS- Particle Swarm Optimization Model

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Abstract. The global market value of gold price decides the economic and the monetary systems of a country. In the volatile gold market, a forecasting prediction model is needed to lower the risk of financial deprivation in the event of a sudden market crisis. The proposed work is to build prediction models for monitoring the daily gold price variations using the machine learning algorithm based models. Adaptive NeuroFuzzy Inference System (ANFIS)-Particle Swarm Optimization (PSO) and the Neural Network (NN) algorithms. ANFIS-PSO and Neural Network (NN) based machine learning models have an outsized number of features and the parameters like Root Mean Square Error (RMSE) and accuracy are utilized in estimating the market value of gold rate. The performance analysis is executed with the ANFIS-PSO model in the monitoring of gold rates, by comparing it with the NN model. The results suggest that ANFIS-PSO model incorporating both neural network and fuzzy logic with the PSO technique is a powerful machine learning tool in forecasting the gold rates.

Keywords: Neural Network, Particle Swarm Optimization, ANFIS, Root Mean Square

1 Introduction

Gold and other assets' prices are frequently correlated to each other in deciding the economic system of a country. The gold rate in the commodity market is less volatile than other valuable commodities because the supply chain of gold is built up for a long period of time [1]. Investors have recently placed gold at the top of their commodity priority list for short-term and long-term investments. The perspective of gold as a buffer against other investments in the unexpected events that might cause market volatility [2]. The current gold market price is heavily influenced by the unexpected market crisis. Due to the fluctuation in the gold market, the customers during boom invest money in gold and during times of market crisis transfer to some other equity [3]. The forecasting model designed to know the gold price is to provide knowledge to the stakeholders to mitigate risks that could happen resulting in financial losses [4].The forecasting model poses a significant impact in order to predict the future gold rates [5], [6]. For the forecast of the gold price the three approaches are classified as classical mathematical models, artificial intelligence (AI), and hybrid models [7]. The conventional approach for predicting gold rates include Multi-linear regression, GARCH models and Autoregressive Integrated Moving Average (ARIMA) [8]. The models using the multiple

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regressions approach have the accuracy rate of 96.22% in the analysis and Radial Basis Function neural (RBF) networks were also used [9]. The soft computing algorithms using artificial intelligence have been explored to predict the gold price [10]. Artificial Neural Networks (ANN) and other soft computing approaches such as Genetic Programming Algorithm (GP) and the support vector (SVM) machine have been widely used in the prediction [11]. For the goal of making predictions, the author [12] looked into the elements that influence gold's price and fed that information into a neural network.

The evolutionary algorithms were used to improve the performance of the back propagation algorithm for neural networks [13]. With this hybrid strategy, higher convergence is achieved with a simpler structure for neural network design. In the evaluation during the training and validation phases, the output results show that ANFIS, GP, and SVM have the best performance [14]. In recent years, the PSO method has been improved by a number of academics, and some of these studies have been successful. Prediction results suggest that the revised PSO-BP approach described in this research may effectively increase the accuracy of grain yield predictions. Prospective mining enterprises and their associated businesses depend on reliable long-term gold price forecasting models for their investments and choices [15]. Gold price changes may be successfully predicted using a unique model proposed in this research work. ANFISPSO is one of the models used to compare the suggested model to other models, such as the standard neural network, the evolutionary algorithm, and gray wolf optimization for neural networks. The existing current research has the lack of accuracy and precision in gold rate forecasting. The advantages of Neuro-fuzzy systems include faster convergence, higher prediction accuracy, and the elimination of any assumptions about the statistical properties of data, defining their structures is not an easy task. The performance of ANFIS - PSO for the proposed work is compared with neural network (NN) to demonstrate its accuracy and precision.

2 Materials and Methods

The dataset preparation and training dataset for ANFIS-PSO model and Neural Network model were estimated and evaluated.

$$RMSE = 1N\sum i = 1N(yi - y\hat{}i)2 \quad (1)$$

$$Accuracy = (1 - \sum i = 1N \mid yi - y\hat{}i \mid \sum i = 1Nyi) \times 100 \quad (2)$$

$$f(x) = \sum j = 1Mwj \cdot fj(x) \quad (3)$$

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (pbest_i - x_i^t) + c_2 \cdot r_2 \cdot (gbest - x_i^t) \quad (4)$$

2.1 ANFIS-PSO Model

Adaptive Neuro-fuzzy inference (ANFIS) system is a hybrid approach for the detection and control of complicated non-linear systems that employs fuzzy-inference systems integrated with the adaptive neural network framework. Even while artificial neural networks (ANN) are often regarded as a potential tool for simulating a broad range of real-world issues, they are not without their drawbacks. Problems with input data that are either unclear or prone to significant uncertainty are better handled by ANFIS. There are further drawbacks to fuzzy inference systems, such as the need for a subject matter expert to generate fuzzy rules and the design of non-adaptive fuzzy sets are addressed by ANFIS. ANFIS deployed with Particle Swarm Optimization (PSO) was all employed to train the dataset and evaluate the models. The proposed model constructs a fuzzy inference system provided with the input datasets and outputs of a dataset as represented in the Fig.1. The parameter values of the membership functions are adjusted using a back propagation algorithm or a least-squares algorithm. ANN and fuzzy logic are combined in ANFIS to create the model. There are five layers in the traditional ANFIS model.

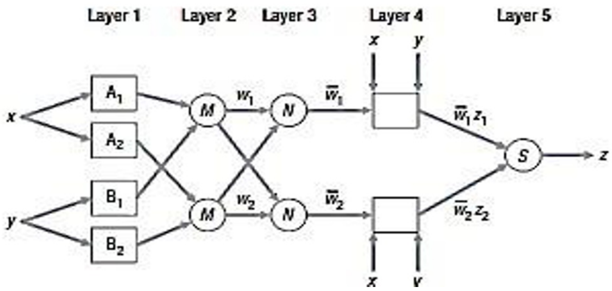

Fig. 1. ANFIS architecture

Two separate sets of datasets containing data points were used in this research work. The first step involved is the preparation of datasets for both the models. The closing values of gold price on a daily basis are employed to forecast the next day's closing price. Two different datasets are created using the historical closing prices of the ANN. The first dataset is made up of the last five days' daily closing market rates. The second data set is made up of closing prices of t- 5 (last week, same day), t- 10, t- 15, t- 20, and t- 25. The proposed model are not influenced by outside economic factors. The historical records of closing prices are involved in the proposed model, which is established on historical prices with their overtime changes in values. The training dataset and test datasets are generated by splitting the total data into two parts without reorganizing, because the dataset contains time-series data. The training set of ANFISPSO gold prediction model is portrayed in Fig.2.The data has not been shuffled and no sampling methods are used. The training set consists of 1000 data points, while the test dataset point is the next day's closing price. To generate outputs, the dataset is looped in the same way for the next 42 days and the predictions were built on the closing prices of the SNP500 index.

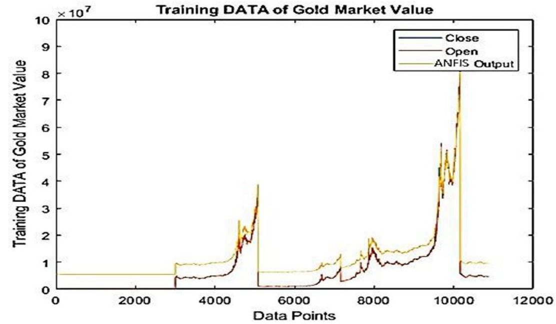

Fig. 2. Training dataset for ANFIS-PSO based gold prediction model

2.2 NN Model

The NN model used the same training dataset, testing dataset, the normalization approach and the kernel function as in ANFIS-PSO model. Its behavior is determined by the way its components are linked and the weights of those connections. To ensure that the artificial neural network (ANN) accomplishes the required objective, these weights are automatically updated based on a predetermined learning algorithm. A neural network mimics the structure of a biological nervous system by combining numerous levels of processing with basic pieces that act in parallel. An input NN layer, an output NN layer with one or more hidden layers make up the architecture of NN and is presented in Fig.3.

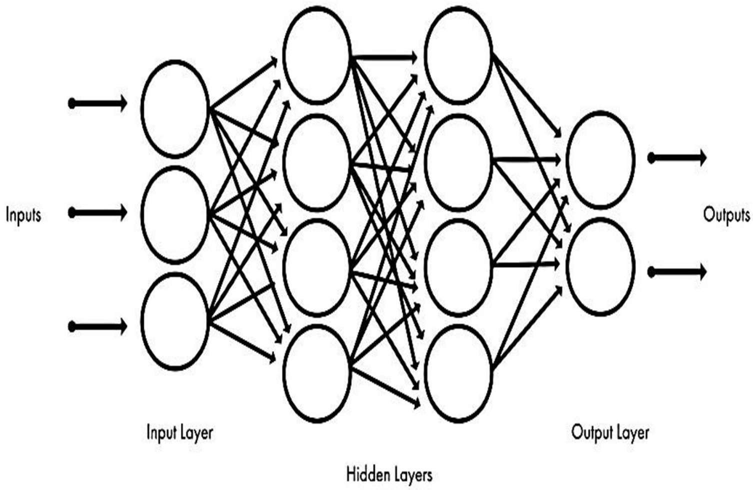

Fig.3. Neural Network Architecture

The neurons in each layer use the outputs of all the nodes in the preceding layer as inputs, resulting in a network of neurons connecting with all of the nodes in the system. The intensity of a neuron's signal can be changed by reducing or increasing its weight, which is normally allocated to each neuron throughout the learning process. NNs are formed on biological neural networks, with neurons serving as the fundamental building blocks. A synthetic NN neuron is a replica of a biological human neuron. An artificial synthetic neuron receives signals from other nearby neurons, collects them, and when it fires, sends a signal to all connected neurons. Adaptive systems that learn by employing linked neurons or nodes, in a layered structure resembling a human brain are referred to as neural networks (NN). A NN is trained to recognize patterns categorize data, and anticipate future occurrences based on the data it has to access. The input is broken down into levels of abstraction by a neural network. Just like the human brain, it can be trained to identify patterns in speech or pictures by providing it with a large number of examples. Its behaviour is determined by the way its components are linked and the weights of those connections. Fig.4. represents the training dataset for the NN model in forecasting the market value of the gold price. The opening value and the closing value are recorded.

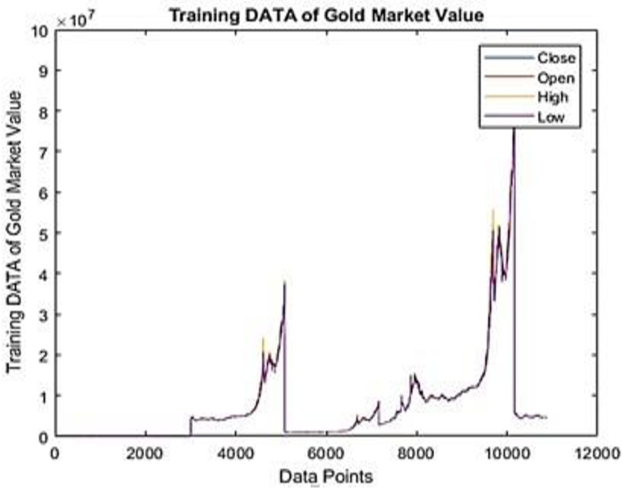

Fig. 4. Training dataset for NN based gold prediction model

3 Results and Discussions

For the purposes of this research work, dataset from Perth Mint, Australia's official source of gold bullion was applied. The simulation of the models is based on 2206 data samples spanning from May 4, 2009, and July 7, 2020. Root mean square error (RMSE) was utilized as statistical assessment criteria for the models' efficiency and prediction errors. The root means the square error is a metric for gauging the degree of discordance between the actual and expected values of something

3.1 Parameter Estimation of NN model

The RMSE was used to create and compare these models. Fig 5 portrays the gold rate open price and close price of the NN gold rate prediction model. The gold market open and close value is estimated using the training data points and is able to provide high RMSE values. Fig. 5 displays the actual and predicted value of gold rate prediction for closing market value using the NN model. From Fig 5, it is observed that the actual closing value is 0.4 x 10^7 but the predicted value is 4.8 x 10^7 indicating that this model is not accurate in gold market value calculation. Fig. 6 shows the root mean square error of the NN prediction model. RMSE at different epoch data points were noted and the mean RMSE value is 15222.93.

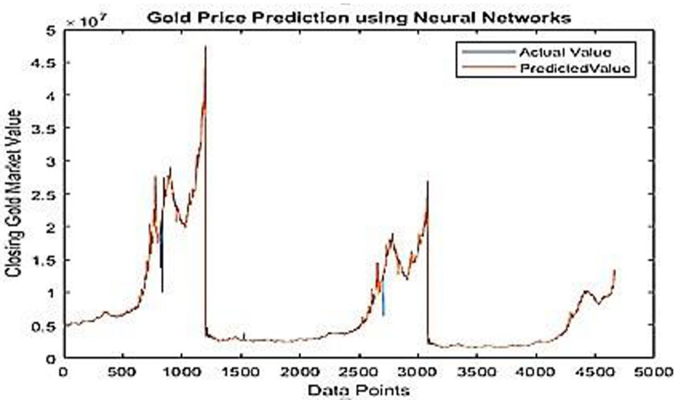

Fig. 5. Gold price prediction using Neural Network

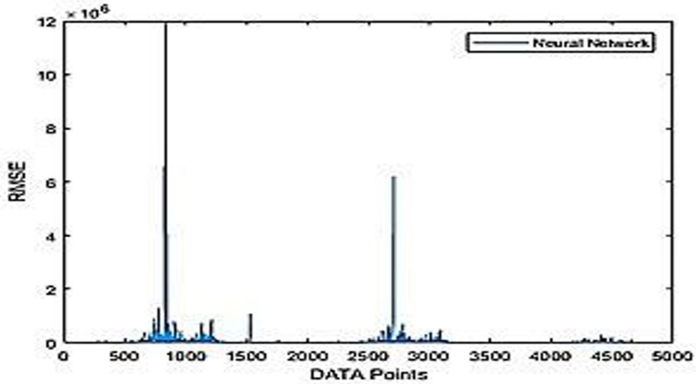

Fig. 6. RMSE value for NN model

3.2 Parameter Estimation of ANFIS-PSO

The gold rate open price and close price by the ANFIS-PSO model was portrayed in Fig. 7. At different epochs, the closing and opening market values are closer to the ANFIS-PSO outputs. Fig. 8 displays the actual and predicted value of gold rate prediction using ANFIS. It infers that at the different data points the actual and predicted value is exactly matching each other. At epoch no 6, the actual is 2.8 x 10^7 and the predicted value is 2.6 x 10^7. Fig. 9 shows the Root mean square error of the proposed prediction for the gold price and the mean RMSE value recorded is 4976.26.

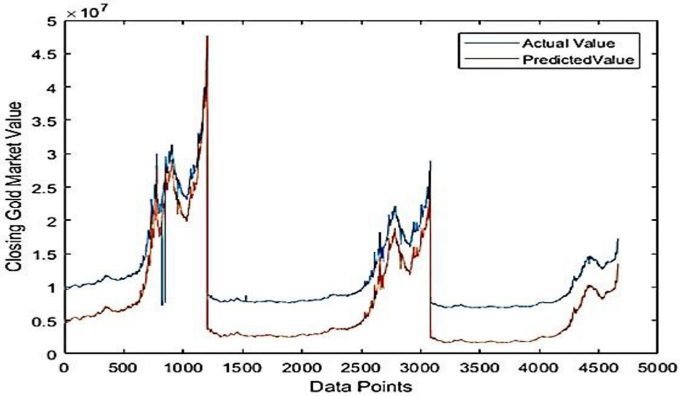

Fig. 7. Gold rate prediction using the ANFIS-PSO model

3.3 Comparative Evaluation of Gold Rate Prediction Models

Further evidence that ANFIS was more accurate in forecasting gold provided by the root mean squared error lower in the case of neural network model. Table 1 shows the RMSE values for various data points and the observed RMSE value is higher when using the NN method. The gold rate prediction model was compared for its performance to best suit for the research work. ANFIS, a neural network, was all employed to train and evaluate the models. The outcomes of building the ANFIS, and Neural Network models. The ANFIS-PSO model was found to be the closest to 1, signifying a greater level of efficiency. Mean square value and MAPE values were also estimated and tabulated. The comparative values show that ANFIS-PSO models provide better significant values.

Table 1. Performance Analysis of ANFIS-PSO and NN model

Data Points	**Forecasting**					
	RMSE		**MAE**		**MAPE**	
	ANFIS-PSO	NN	ANFIS-PSO	NN	ANFIS-PSO	NN
300	5.941	6.567	0.012	0.03	0.72	1.23
600	5.123	5.894	0.013	0.04	0.63	2.28
1000	5.824	6.874	0.015	0.04	0.56	2.56

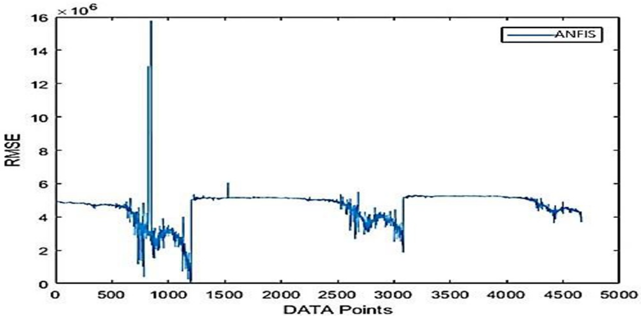

Fig. 8. Root mean square error (RMSE) for gold price

Fig.9. displays the output bar graph for RMSE analysis of both the models. The root means the squared error was lower in the case of the ANFIS prediction model, providing additional evidence that ANFIS were more accurate in forecasting gold. The graph shows that ANFIS-PSO has a low RMSE value when compared to NN in the gold rate prediction Fig 10. There is a significant difference in gold rate prediction of the two algorithms with the significant value of ANFIS-PSO being closer to the accuracy rate.

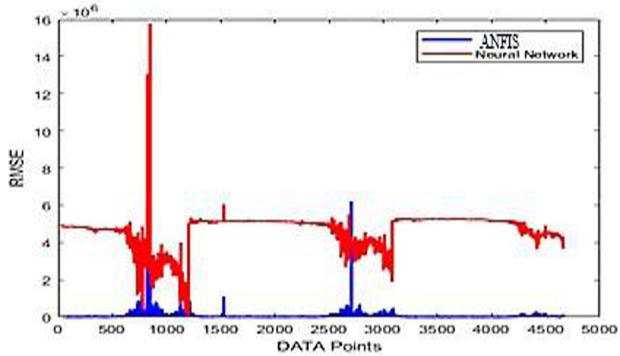

Fig. 9. RMSE Comparison

ANFIS algorithm gives the best result without performing parameter tuning when compared with other different prediction models. It outperforms the ensemble models as well as all NN models. The overall R squared and mean squared error values are much higher than the final training setup with 85 % of the dataset and then predicting the remaining 15 % of the values. The use of parameter tuning significantly improves prediction accuracy.

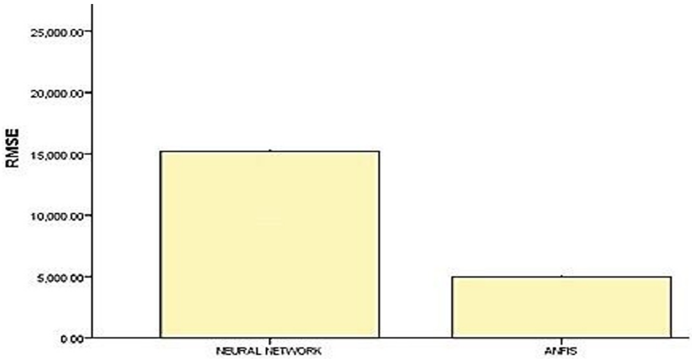

Fig. 10. Graphical Comparison of mean RMSE of ANFIS-PSO and NN models

4 Conclusion

The research work forecast the gold market value using the existing knowledge-based and gold rate prediction models to make them more accurate enough to be used in reallifetime scenarios. In this research, two distinct models for predicting the gold rate in the world gold market have been created. Training and validation findings show that ANFIS PSO is capable of delivering the best outcomes under various assessment criteria and during validation ANFIS-PSO forecasts outperformed NN significantly better in accurate prediction.

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