# "ANALYSIS OF GOLD PRICEUSING ARTIFICIAL NEURAL NETWORK"

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*Abstract*-- **The purpose of this research is modelling and data analysis for gold price behaviour. To design the functional relationship between the gold price and influencing parameter crude oil price using artificial neural network modelling technique. To analyze the price behaviour of gold. The traditional Back-propagation Neural Network (BPNN) Algorithm is used. In this research, taking the output of the neural network, it has been implemented using R software.**

**Keywords: ANN (Artificial Neural Network), Back Propagation Neural Network(BPNN), Gold Price, Crude oil price.**

## 1 Introduction

In the globalised era, financial markets had undergone continuous and significant changes. These changes have affected growing and grown economies, especially in termsof eliminating restrictions with regard to capital movements. Further, due to technological advances, individual and institutional investors are allowed to trade in worldwide financial and commodity markets on a twenty-four hours basis. The liberalised and technically advanced markets have become more integrated over time and it is particularly true in the case of financial markets. In many developing countries like India, there has been marked change in the principles of the government towards integration of Indian economy with the world economy. When the markets experience an increase in their level of integration, shocks and events that happen in one market immediately affects the other interlinked financial markets and it has an impact upon the benefits that investors obtain from diversifying their portfolios internationally. If this is the case, and the markets are highly integrated, these benefits will get eradicated in the long-term and investors with long horizons may not benefit from their portfolios [1]. There will be a direct effect on the stability of the financial market since the negative and positive effects will spread among the co-integrated capital markets.

On the other hand, there is a common belief that the prices of commodities tend tomove in unison since they are influenced by common macroeconomic factors like interestrate, exchange rate and inflation rate [2].Forecasting the price of gold and its changes as an economic event has long been within the interest area of investors and financial analysts. This study aims to make gold -price forecast modelling using Multilayer Perception neural network (MLP), as well as determination of top model using performance evaluation criteria.

The present study is based on analysis of secondary data collected from Reserve Bank of India's data warehouse (database on Indian economy) RBI publishes the database on Indian Economy[19] and indexmundi.com[20]. The study has made use of 25 years of monthly data of gold price, dollar price from the year Mar 1992 to July 2016, consisting of 293 observations. We have used Indian rupee/US dollar exchange rate for our study keeping in view the fact that US is the major trading partner of India. And of course, the US dollar is regarded as the best hedging currency in the world. The data are collected from Reserve bank of India database. Price of gold in US dollar is taken as base price and the price of gold is converted into Rupees, import duties added to the converted value. The crude oil price is in US dollar per barrel. And inflation rate is in percentage. The study period has been chosen purely on the basis of availability of data, and keeping in mind that neural network estimation requires a long time user.

## 2. Research Methodology

Artificial neural network (ANN), a computing system containing many simple nonlinear computing units as neurons interconnected by links, is a well-tested method for financial analysis. Neural networks have been shown to be able to decode nonlinear financial time series data.

### 2.1 Artificial neural networks modelling

The artificial neural network is useful computational way for predicting and modelling abstruse relationships among parameters, especially when there is no explicit relation among parameters [4]. The structure of artificial neural network basically including three layers, the input layer that all the data are imported to the network and calculation the weight of each input variables are done, the hidden layer or layers, that data are computed, and the output layer, that the artificial neural network results are obtained. Every single layer includes one or more fundamental section(s) called a node or a neuron [6]. The problem is the key factor can determined the number of neurons in the layers. The small number of hidden neurons is a limiting factor to learn the process carefully even though too high number can be very time consuming and the network may over fit the data [7] . In this study, three-layer neural networks were constructed for computation of the gold price parameters. In our research, we used R software to develop our model. The **neuralnet** package of the R software is specifically used for implementation..

In order to generalize the model to unknown outputs, its performance must be tested by comparing outputs estimated by the each model with real outputs. The performance of the each model is evaluated by three performance measures: Coefficient of determination ($R^2$ ) and Root Mean Square Error (RMSE).

### 2.2 ANN Description

The network includes an input layer, hidden layers and an output layer. The inputs for the network include US Dollar price(DP),Crude oil price(COP), and Inflation rate (IR). The scaled values have been passed into the input layer and after that propagated from the input layer to the next layer which is called hidden layer, before reaching the output layer of the network[8]. Each node in the both hidden and output layer in the first place will act as a summing junction with the use of the following equation inputs combine and modify from the previous layer [13].

$$Y_i = \sum_{j=1}^{i} X_i W_{ij} + b_j$$

Where $Y_i$ is the net input to node j in hidden or output layer, the weight related to neuron i and neuron j are indicated as $W_{ij}$ , $X_i$ is the input of neuron j, $b_j$ is the bias connected to node j [9]. Sigmoid transfer function usually use for nonlinear relationship [14],[10]. The general form of this function is showed below [13]:

$$Z_i = \frac{1}{1+e^{-\ Yy}}$$

Where $Z_i$ is the output of node i, is also an element of the inputs to the nodes in the next layer. The sigmoid function is bounded between 0 and 1, so the input and output data should be normalized to the range between 0 and 1 [10]. During the initial training of the neural network, weights are randomly chosen. Hence, normalization of values within a uniform range is vital to prevent data with larger magnitude from overriding the smaller ones. In the present work, scaling of the data to the range of 0–1 was carried out as follows[11] :

$$\mathrm{Xn} = \frac{\mathrm{X} - \mathrm{Xmin}}{\mathrm{Xmax} - \mathrm{Xmin}}$$

Where X is the original value. Xmin and Xmax are the minimum and maximum values in the series respectively. Xn is the normalized data.
The data of the interconnection weights are determined by the training or learning process using a set of data. The purpose is to find the weight value that minimizes the error[13]. Performance of the developed network was tested by the mean squared error (MSE) and the coefficient of correlation ($R^2$) as follows [12]:

$$\mathrm{R}^2 = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{Ai} - \mathrm{Pi})^2}{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{Ai} - \overline{\overline{\mathrm{Ai}}})^2}$$

$$\mathrm{MSE} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{Ai} - \mathrm{Pi})^2}{\mathrm{N}}$$

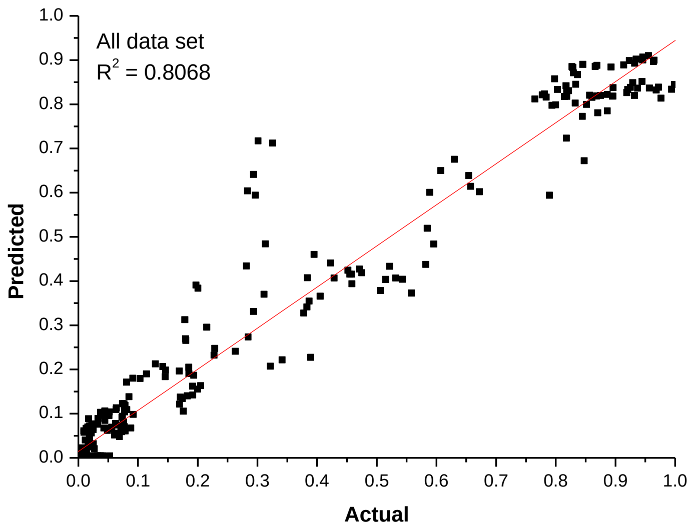
Where Pi is predicted values, Ai is observed values, $\overline{\overline{\mathrm{A}}}$i is average of observed set and N is number of datasets.

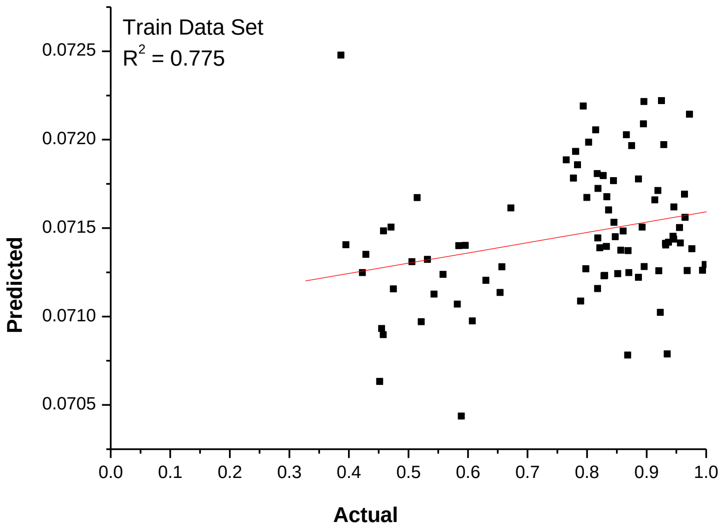
## 3. Results and Discussion

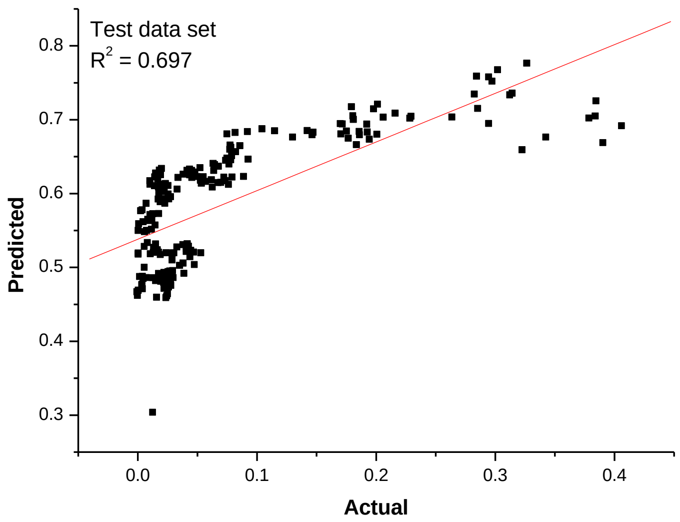
To enable modeling of nonlinear and complicated functions feed-forward neural network has been used with one or more hidden layers[13]. Even though, it is very hard to choose the number of hidden layers [14]. Most of literatures indicate that one hidden layer is good enough to validate the prediction and maybe the best decide for all applied feed-forward network design [21]. Thus, in this paper one hidden layer has been chosen for modeling. It is crucial to highlight that the determination of the number of neurons in hidden layers. Neuron were played an important role that effected on the general characteristics of network and training time [8]. The complexity of relationship among parameters determined the number of neuron in the hidden layer [15]. The optimum number of neurons in a hidden layer was found by trial and error.

There are many types of learning algorithms in the literature which can be used for the training of a network. However, it is difficult to know which learning algorithm is more efficient for a given problem. The algorithm used to train ANN in this study was Levenberg–Marquardt back propagation (LM). The LM is an approximation to the Newton's method]16]. This is very well suited to the training of the neural network [17]. The algorithm uses the second-order derivatives of the mean squared error between the desired output and the actual output so that better convergence behaviour can be obtained[18].

The results of this study showed the network consisted of three layers: input, hidden and output with 5 nodes in hidden layer has produced the best performances. The mean squared error (MSE) and coefficient of correlation (R) between the actual and predicted values were determined as 0.720 and 0.775 for training set and 0.696 and 0.697 for testing set. The MSE and R for all data sets were also calculated as 0.074 and 0.806, respectively. These results show that the predictive accuracy of the model is high.




Train Data Set
R2 = 0.775
0.0725
0.0720
0.0715
0.0710
0.0705
Predicted
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Actual


Test data set
R2 = 0.697
0.8
0.7
0.6
0.5
0.4
0.3
Predicted
0.0
0.1
0.2
0.3
0.4
Actual

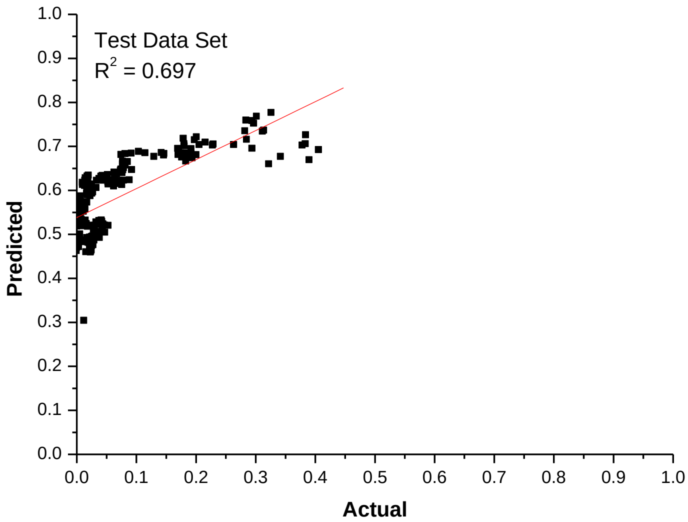

Test Data Set
R2 = 0.697
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Predicted
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Actual

**Figure 1**: The scatter plots of ANN model predicted versus actual values for training; testing and all data sets.

### 3.1 Sensitivity analysis

In this study, a sensitivity analysis was carried out to determine the effectiveness of a variable using the suggested ANN model in this work. In the analysis, performance evaluations of different possible interaction of variables were investigated. Therefore, performances of the three groups (one, two and three) variables were investigated by the optimal ANN model using the LMA with 5 neurons in the hidden layer. The groups of input vectors were defined as follow form: P1, US Dollar Price (DP); P2, Crude Oil Price (COP); P3, Inflation Rate(IR).

The results are summarized in Table 1. The results in Table 1 were showed that P1 (DP) to be the most effective parameter in the group of one variable, due to it has lower MSE (0.178). As shown in Table 1, the minimum value of MSE in the group of two was determined to be 0.177 with interaction of P1 (DP) and P3 (IR). The smaller values of MSE determine when the interaction of P1 + P3 (the best case of group of two variables) was used with P2 (COP). The minimum value of MSE in the group of three variables was 0.074 using the interaction of P1 + P2 + P3; the value of MSE was decreased from 0.177 to 0.074 when P2 (COP) was used in interaction with other variables in the after group of three variables. The experimental data and ANN modeling prediction were juxtaposed in Figure 1. According to Figure 1, excellent agreement between experimental data and ANN results was indicated.

Table 1: Performance evaluation of interactions of input variables for sensitivity analysis (P1, DP; P2, COP; P3, IR)

| No | Combination | MSE |
|---|---|---|
| Group of one variables | | |
| 1 | P1 | 0.178 |
| 2 | P2 | 0.216 |
| 3 | P3 | 0.340 |
| Group of two variables | | |
| 4 | P1+P2 | 0.703 |
| 5 | P1+P3 | 0.177 |
| 6 | P2+P3 | 0.216 |
| Group of three variables | | |
| 7 | P1+P2+P3 | 0.074 |

## Coclusion

In this paper artificial neural network were identified for computation of the gold price and its affecting parameters. The identified model were trained, and tested on datasets collected from secondary data sources. A network architecture consisting of three input neurons, five hidden neurons, and one output neuron was found to be suitable for this study. A good agreement between actual data and the ANN outputs was seen for training and testing data sets. Hence, it can be indicated that the ANN model explained in this study is an applied tool to predict the gold price. The ANN can be seen to be a powerful predictive alternative to traditional modelling techniques.

The proposed models are quite useful in future prediction of the gold prices depending on the influence parameters. In future, one can may increase the input parameters to see whether the accuracy level will be maintained or not. Also, one can perform the sensitivity analysis by taking number of iterations up to their desirable limits.

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