Financial prediction using back propagation neural networks with opposition based learning

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Abstract. Stock price prediction has recently brought together significant attention among the researchers. In the past decades, the stock price prediction has contributed a primary role in the stock market. The shareholder and investigators should give concentration a reliable method to predict stock price/index. An accurate prediction is an important to enlarge an effective market trading strategies. A back propagation neural network is widely used well known multi-layer supervised feed forward neural network algorithm since its simplicity and high problem-solving ability. In the traditional back propagation neural network, weight updating done by gradient decent based learning algorithm which is falling into local minima and learning rate is slow. Hence, keep away from above mentioned drawbacks; the opposition based learning (OBL) algorithm is used for weight adjustment in a back propagation neural network. The empirical result shows that the proposed prediction model demonstrates a superior performance in financial time series forecasting. For evaluating the performance of the proposed model, the empirical research is applied to well known stock market data sets such as S & P BSE Sensex and Nifty 50.

Keywords: Financial Prediction, Back Propagation Neural Networks, Opposition Based Learning,

1. Introduction

The stock market is a most famous and important issues to growth or decide the status of the country economy. As well, an extremely challenging task to prediction of stock market due to the complex system, unstable and nonlinear of the stock market data. It is affected by many natural events including economic policy of the country, government announcements, political situation and investor psychology [1]. The stock market prediction has contributed a primary responsibility of the shareholder and the investigator that pay more concentration to a reliable technique to predict stock market price. A perfect prediction is an important to develop a successful market trading strategy [2]. In the earlier period, the prediction of stock market is carried out with the help of the statistical learning techniques including moving average (MA), auto regressive integrated moving average (ARIMA), exponential smoothing moving average (EMA) [3] and etc.

However, the conventional statistical techniques are very complicated to manage the stock market data since the non-stationary scenery of the stock market data. To solve above addressing shortcomings,
the artificial neural networks (ANNs) model has been extensively used in the time series forecasting [4] and the ANNs models are proficient to approximate different nonlinearities in the data. The most significant advantages of ANNs are the capability of their flexible nonlinear model [5].

In ANNs, A back propagation neural network is extensively used well famous supervised feed forward neural network algorithm due to its simplicity and high problem-solving capability [3]. In the conventional back propagation neural network, the weight updating process has done by gradient descent algorithm. However, it has some disadvantages such as learning rate is poor, problem in local optima, over fitting / under fitting and low prediction accuracy. Therefore, the present study uses the opposition based learning (OBL) algorithm [6] for fine-tune the weights of a back propagation neural network to obtain better generalization performance and overwrite the insufficiency of the conventional back propagation neural network.

The main objectives of the paper are
- To improve the generalization performance of BPNN
- To enhancing the prediction accuracy
- To reduce computation cost

2. Motivation the research works
The stock market prediction is most important to the customer for trading the share on the right to obtain more profit or avoid the loss the money. Hence, the accurate prediction model is an essential to support the sell or buy the product at the right time by the customer. The motivation of this work is to improve the trading efficiency and accurate prediction with the help of the neural network predictor.

3. Methods
The stock market prediction is an important area of forecasting, in which the past history of data to be used for predicting the future performance. The conventional statistical methods appear to be unsuccessful to imprison the discontinuities, the nonlinearities and the high complication of datasets in the time series analysis. The ANNs offers enough learning ability and capture the complex nonlinear representation than the elementary statistical prediction techniques.

3.1. Autoregressive Integrated Moving Average (ARIMA)
One of the most important and generally used statistical predictions methods is autoregressive integrated moving average (ARIMA) prediction model. The attractiveness of the ARIMA method is due to its statistical parameter [7]. The future price of a variable is thought to be a linear function of moderately a few past observations and random errors. The original process produce the prediction is as follows,

\[ y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} \]
\[ + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \ldots - \theta_q \epsilon_{t-q} \]  

(1)

Where \( y_t \) and \( \epsilon_t \) are the actual value and random error at ‘t’ time period respectively.
\( \phi_i \) (i = 1, 2, ..., p) and \( \theta_j \) (j = 0, 1, 2, ..., q) are parameter and \( p, q \) are integer and often referred to as orders of the models. Additionally, the ARIMA models can execute a variety of exponential smoothing models [3] and quite supple in that they can signify numerous different types of stock market data. The ARIMA model guesses that the future values of a stock market data have a linear relationship with past and present price as well as white noise therefore an approximation by ARIMA models may not be sufficient for difficult nonlinear stock market prediction [8].

3.2. Back Propagation Neural Networks
Please The Back Propagation Neural Network [9] (BPNN) is a well known multi-layer feed forward training model that has been proposed by Rumelhart and McClelland [10]. In BPNN, three layer
networks are mostly used including input layer, hidden layer, the output layer. Each one of the 
abovementioned layers has quantity of processing units and each unit is completely interconnected 
with adjustable weights. The BPNN has a superior generalization ability to work out the many 
applications with extremely nonlinear solutions. It has a well-known powerful tool in problem solving 
for a wide area of stock price predictions [3].

In the literature, many learning methods have used to improve the performance of the BPNN namely 
Levenberg-Marquardt Algorithm [11], Quickprop [12], Deterministic Weight Modification [13], 
opposition based learning algorithm [14]. Hence, this research works proposed Opposition Based 
Learning algorithms to overwrite the shortcoming of the conventional Back Propagation Neural 
Networks. An objective of proposed Opposition Based Learning algorithm is to minimize the error of 
the networks and finds the optimal network weights.

3.3. Opposition based learning
Opposition-based learning (OBL) was established by Tizhoosh in 2005 which is a machine 
intelligence algorithm, it is reflected on present estimate and its opposite assess at the same time to 
accomplish an improved approximation for a present candidate solution. Opposition-based Learning 
(OBL) is a newest idea in computational intelligence, and has been used for numerous optimization 
algorithms to improve the results of the solution. In the conventional neural network methods, the 
weight and other parameter values has been initialized randomly. The random weight is trying to 
achieve the global optimum or toward closer to the optimal weight to get the optimal solution with low 
errors. The random initialization of the weight has taken more computation time to reach optimal 
solutions. Consequently, if the random initialization is too near to the optimum weight, then it has 
potentially accelerated the convergence. To accelerate the convergence rate of the neural network 
algorithm, we used opposite weight values to reach the global optimum weight values [6].

An opposition based weight can be defined as follows, 

Let \( w \in [a, b] \) be a real number. The opposition number \( \hat{w} \) is defined by

\[
\hat{w} = a + b - w
\]

Similarly, the opposite weight in the \( N \) dimensional space, it can define as follows,

Let, \( W = (w_1, w_2, ..., w_N) \)

Where \( w_1, w_2, ..., w_N \in \mathbb{R} \) and \( w_i \in [a, b] \forall i \{1, 2, ..., N\} \)

The opposite points

\[
\hat{W} = (\hat{w}_1, \hat{w}_2, ..., \hat{w}_N)
\]

The above equation (3) is defined with the help of its coordinates as follows,

\[
\hat{w} = a_i + b_i - w_i
\]

Meanwhile, the opposition based learning algorithm can define by employing the definition of 
opposite values and the according to the definition of the opposite weight, the values of 
\( \hat{W} = (\hat{w}_1, \hat{w}_2, ..., \hat{w}_N) \) is the opposite function of the \( W = (w_1, w_2, ..., w_N) \). Hence, compare with both 
two values, \( f(W) \geq f(\hat{W}) \). That is, \( \hat{W} \) has a better fitness than \( W \).

3.4. Proposed BPNN with OBL
Evolutionary algorithms (EAs) are famous optimization come close to deal with nonlinear and 
complex problems. There are many optimization algorithms used to update weight of the BPNN but it 
may suffer from long computational period because of their evolutionary personality. This 
fundamental weakness sometimes limits their application to offline problems with slight or no real-
time constraints. In this proposed method, we incorporate the opposition based learning with BPNN 
to fine-tune the weights. A proposed method is used to current weight into a new optimal weight that 
is transforming the new weight from the present weight as an opposite manner. It can offer more 
possibilities for finding the weights closer to the optimum weight values [15].
The opposition based learning algorithm has been applied to many algorithms to boost up their abilities. Namely shuffled differential evolution algorithm[16], Constrained differential evolution [17], Artificial Bee Colony [18], Global harmony search [19], Firefly Algorithm [20]. In this manner, we used OBL algorithm to improve the performance of the BPNN to fine-tune the weight. The following section discusses about the generalized opposition based learning algorithms.

3.5. Updating the weight using OBL

In the conventional BPNN, the gradient decent learning algorithm is used to weight updating. But, it has many remarkable drawbacks. Hence, the opposition based learning algorithm is used to adjust the weight associated with the error function as opposite manner. In this proposed method, rewriting the weight and bias updating as per proposed oppositions based learning as follows,

\[ W_{jk}(t) = \Delta W_{jk} + W_{jk}(t-1) - \Delta W_{jk} \]  \hspace{1cm} (6)

\[ \Delta W_{jk}(t) = \Delta W_{jk} + W_{jk}(t-1) - \Delta W_{jk} \]  \hspace{1cm} (7)

Figure 1: Overview diagram of the proposed model
Therefore,

\[ V_{ij}(t) = \Delta V_{ij} + V_{ij}(t-1) - \Delta V_{ij} \] (8)

\[ \Delta V_{ij}(t) = \Delta V_{ij} + V_{ij}(t-1) - \Delta V_{ij} \] (9)

Hence, overview of the proposed model has shown as graphical representation in Figure 1.

4. Experimental Results and Discussions

4.1. Stock Market Predictions

The stock price prediction is one of the major issues and extremely crucial in the stock market. Many researchers have been determined in finding the efficient stock market forecasting method. The prediction of time series analysis is a fundamental problem and not an easy task to the investigator in order to improve the level of superior accuracy. The usual statistical methods appear to be ineffective to capture the discontinuities [10], the nonlinearity, and the difficulty of data set in time series analysis.

Based on many parameters, since the learning method may be comprehensible to any level of accuracy, the learning process in the neural network paradigm yields an alternate solution to capture the nonlinearity among data in a better way than the fundamental statistical prediction methods. This research works talk about the daily closing index price of the well known dataset such as S & P BSE Sensex and Nifty 50 Index, which are used for both training and testing related to their historical datasets obtained from the finance section of yahoo.

| Parameters                          | Values  |
|------------------------------------|---------|
| Inputs Neuron                      | 4       |
| Hidden Neurons (2n^a+1)            | 9       |
| Output Neurons                     | 1       |
| Bias value (Both Hidden, Output unit) | 1       |
| Weight values between connections  | Random values |
| Learning Rate                      | 0.6     |
| Maximum Iteration                  | 1000    |

\( a \) is the number of input neurons in BPNN

4.2. Data Collections

The robustness of the proposed model are evaluated using two well known stock indices such as Nifty 50 and S&P BSE Sensex that datasets cover the periods from January 3, 2005 to June 30, 2018. In this research works, connection weights are initiated random values the range between [-1.0, 1.0], its error termination environment is set 0.0005. The original datasets are normalized into the range [-1.0, 1.0] as follows.

\[ X'_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} (X_{\max} - X_{\min}) + X_{\min} \] (10)

Where, \( X_{\max}, X_{\min} \) is the minimum and maximum target value, \( X_i \) are the present actual input data, \( X'_{\max}, X'_{\min} \) maximum and minimum values of scaling factors such as 0, 1 respectively. The sigmoid
activation function is applied to both input and output layer as an activation function and it is defined as follows,

\[ g(x) = \frac{1 - \exp(-x)}{1 + \exp(-x)} \]  

(11)

4.3. Performance Evaluations

In order to evaluate the performance of the proposed Opposition Based Learning-Back Propagation Neural Network model is contrasted with conventional Back Propagation Neural Network and ARIMA. The proposed model is applied to predict the future closing stock index of the stock index. The performance of the proposed model is assessed based on various statistical parameters. The following performance measures are used to work out the prediction accuracy of the prediction algorithms include the Mean Square Error, Root Mean Square Error (RMSE)

\[ MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \]  

(12)

\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \]  

(13)

Where ‘N’ is the number of data samples, ‘y_i’ is the actual price of the stock closing index price, and ‘y_i’ is the predicted value which is obtained from the neural network predictor.

4.4. Performance Comparisons

For the stock closing index predictions, we employ two kinds of stock market datasets such as Nifty 50 and S &P BSE Sensex that are used in this research for investigating the performance of the proposed model.

| Table 2. Performance of proposed methods for Nifty 50 Index dataset. |
|------------------|---|---|
| Methods           | MSE  | RMSE |
| ARIMA             | 0.00638 | 0.0798 |
| BPNN              | 0.00591 | 0.0768 |
| OBL-BPNN          | **0.00512** | **0.0715** |

The performance comparison of the proposed model is against BPNN and ARIMA method. When applying the Nifty 50 index, the proposed model produces 7.9 % improved results compared with BPNN, 12.6 % improved results are showing in Table 2 and its graphical representation of the performance comparison is shown in Figure 2. The performance results of the benchmark algorithms are shown Table 3 for S & P BSE Sensex. Its graphical representation is shown in Figure 3.

| Table 3. Performance of proposed methods for S & P BSE Sensex 50 Index dataset |
|------------------|---|---|
| Methods           | MSE  | RMSE |
| ARIMA             | 0.00614 | 0.0783 |
| BPNN              | 0.00563 | 0.0750 |
| OBL-BPNN          | **0.00497** | **0.0704** |
From the Table 3, the proposed method produces 6.6% enhance results compared with BPNN and 11.7 enhanced results compared with ARIMA model. The performance of the proposed method is constructed with a better global convergence rate, and provides higher prediction accuracy than other algorithms. The experimental results are implemented using MATLAB 2015.

5. Conclusions
In this study, we empirically investigated that proposed method is applied to the stock closing indices prediction and comparison made against on ARIMA and BPNN, which have a low convergence rate in the both methods. The proposed model is an improvement on the convergence rate, least error and higher prediction accuracy than the ARIMA and BPNN. The performance of the training and testing is analyzed by statistical measures such as MSE and RMSE. The proposed model has formed
considerable improvement in achieving the stock market forecasting and it shows excellent prediction performance in all datasets which is better than ARIMA and standard BPNN.

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