Efficient Prediction of Stock Price Using Artificial Neural Network Optimized Using Biogeography-Based Optimization Algorithm

Hitesh Punjabi, Somaiya Institute of Technology, India*
Kumar Chandar S., CHRIST University (Deemed), India

ABSTRACT

Stock market price prediction has always drawn attention from researchers and analysts. Prediction of the stock price is an extremely tough task due to the nature of stock data. Therefore, it is needed to develop an efficient model for predicting stock price. This paper explored the use of feed forward neural network (FFNN) and bio-inspired algorithms to develop two efficient models for prediction. The proposed model is based on the 10 indicators derived from historical data. Particle swarm optimization (PSO) algorithm inspired from the behavior of bird flocking and biogeography-based optimization (BBO) algorithm driven by the geographical distribution of biological organisms are adopted to optimize the parameters of FFNN. Prediction ability of the proposed models is evaluated by using statistical measures. The experimental results demonstrate that the proposed BBO-FFNN is superior to PSO-FFNN and existing methods taken for comparison in terms of prediction accuracy. It is proved that the proposed BBO-FFNN can effectively enhance stock prediction and reduce the prediction error.

KEYWORDS

Bio-Inspired Algorithms, Biogeography-Based Optimization, Feed Forward Neural Network, Hit Rate, Particle Swarm Optimization and Prediction Accuracy

1. INTRODUCTION

Stock price prediction is one of the interesting fields of research in financial world. Since, the stock data are nonlinear, noisy, complicated, dynamic and non-parametric in nature (YakupKara et al., 2011). The ultimate goal of stock market price prediction is to develop a powerful model or system for predicting the stock value to gain high profits. Over the past decades, lots of research works have been devoted to the development and enhancement of stock market price prediction models. One of the most popular and widely used models is the ANN model. ANN is a powerful tool for stock market prediction due to its capability of mapping non-linear input-output data (Awad et al., 2009; Handa et al., 2015; Sharma et al., 2015).

Although soft computing models (ANN) can be a promising statistical tool for stock market prediction, several research studies showed that neural networks had some drawbacks in training the input data due to non-stationary characteristics of stock data (Hiransha et al., 2018; Khare et al., 2017; Mohapatra et al., 2012). To address this issue, many researchers and analysists have attempted to

DOI: 10.4018/IJWLTT.303112 *Corresponding Author

develop more and more efficient models by combining ANN with bioinspired computing algorithms. Some studies proved that the integrated model, ANN with bio inspired algorithms outperform over traditional models such as RBF-GA (Sheta & DeJong, 2001), ANN-FSA (Shen et al., 2011), SVM-PSO (Mohammed et al., 2018; AlaaF et al., 2015), ANN-BFO and ANN-ABFO (Essam, 2016), ANN-PSOCoM (Majhi et al., 2009) and MLP-BBO (Hesam & Mahsa, 2018).

The core objective of this study is to predict the stock price employing ANN and bio inspired computing algorithms and to evaluate them with some statistical metrics. Instead of finding the optimal weights of FFNN by trial and error method, PSO and BBO algorithm is proposed for the FFNN. Ten technical indicators obtained from the historical data are utilized as the inputs for the proposed prediction model. The main focus of this study is also to show and prove the predictability of stock price using soft computing and bio inspired computing algorithms and to compare the efficiency of these models. In addition to this, proposed prediction model is compared with some other existing models to demonstrate its efficiency.

The remainder of the paper is structured as follows: Section 2 provides a brief review of related work in stock market predictions. Section 3 explains the functioning of FFNN followed by the details of PSO and BBO algorithms. Section 4 describes the detailed steps of proposed prediction model. Section 5 reports the empirical findings obtained from the comparative analysis. Finally, Section 6 concludes the contribution of this study followed by relevant references.

2. REVIEW OF RELATED WORKS

Stock market prediction methods can be classified into fundamental analysis and technical analysis (Sureskumar & Elango, 2012). Fundamental analysis involves financial status like interest rate, supplies, debts, divided yields and lagged returns etc. and macroeconomic data of the company. Technical analysis is based on the past historical data. Technical indicators calculated from the historical price and then used to predict the future value of stock (Oriani et al., 2016). Stock market prediction using ANN has been a very active area of research in financial word since 1980s (White, 1988). Numerous works found in the literature uses ANN and technical indicators to predict the future value of stock. Most of researchers are tried to enhance the prediction accuracy. (Yakupkara et al., 2011) presented two models based on ANN and SVM for predicting future price of stock. SMA10, weighted MA10, Momentum, Stochastic %K, Stochastic %D, RSI, MACD, Williams %R, ADO and CCI are computed from the historical price and used as inputs of the proposed models. They tested these models on Istanbul stock data and found that ANN model performs well than SVM model. A stock market prediction method using DE based FLANN to predict the Indian Stock Market Indices proposed (Mohapatra et al., 2012). Weights of FLANN are optimized by using DE and BP algorithm. Results proved that DE outperformed the BP algorithm. (Khare et al., 2017) had a main objective to build ANN model for stock market prediction. They authors used MATLAB to test the ANN with EMA, MACD, RSI, SMA and closing price as input to the proposed ANN model. Prediction model is developed using ANN and SVM. Results demonstrated that acceptable results can be achieved when using ANN for stock market prediction. (Essam, 2016) introduced a new PSOCoM algorithm to train the MLP weights and adopted this model in the predicting of NASDAQ100, DJIA and S&P 500 stock prices. Seven indicators namely EMA10, EMA20, EMA30, SMA10, RSI9, RSI14 and ROC27 are utilized as inputs. They reported that the proposed MLP beat the other MLP based models in terms of accuracy. (Hesam & Mahsa, 2018) forecasted the crude oil based on the combination of BMMR process and BBO optimization algorithm. (Pushpanjali & Soumya, 2013) presented a survey on applications of bio inspired computing for stock market prediction. They suggested that SMP using traditional approaches was proven to be difficult task, but the integration of ANN with bio inspired computing algorithms may be a good candidate for this task. Forecasting stock price data has proposed using technical indicators by (Yauheniya et al., 2014). The prediction model is constructed using some technical indicators like SMA, EMA, MACD, ADI, ATR, OBV, oscillator, CC1, momentum, ROC, RSI, stochastic %K, stochastic % D, William's %R along with the opening, closing, low and high values. The highest prediction accuracy is obtained by SVM model is 85%. (Victor et al., 2013) used ANN tool for predicting stock price. Results proved that the ANN offers the potential to predict the stock price with higher prediction accuracy. (Kumar, 2018) reviewed the recent articles for the stock market prediction in the field of soft computing and bio inspired computing algorithms. These articles are segmented into the field of input valuables, prediction models utilized, technical indicators and performance measures used. Finally, ANN with bio inspired computing algorithms recognized as efficient technique in stock market prediction. (Sedighi et al., 2019) combined SVM and metaheuristic algorithm for forecasting stock market price. The authors used ABC algorithm for optimizing technical indicators and SVM for predicting stock price. The results showed that their hybrid model supported to stock price prediction. (Das et al., 2019) investigated the feature optimization capacity of metaheuristic algorithms. Technical indicators are computed from historical data. To reduce the dimension of features, both statistical methods such as PCA and FA and metaheuristic algorithms, GA and FA are used. ELM and recurrent BPNN are performed the prediction task. Results proved that FA with machine learning model outperformed the other models. (Nayak & Misra, 2018) developed condensed polynomial neural network for forecasting stock prices. Parameters of the developed network are optimized by using GA. Results showed outstanding performance.

ANNs have been popular and commonly used in financial world for predicting stock market data. Based on the surveyed articles, FFNN is chosen as main soft computing model in this study and parameters of FFNN is tuned by using PSO and BBO algorithm separately.

3. PRELIMINARIES

Though ANNs have been proven itself to be very powerful tool for stock price prediction, creating an optimum structure is a complex task. Efficiency of the ANN is heavily relying on the number of hidden layers, number of neurons per hidden layer, number of input neurons, input data, activation function and learning algorithm.

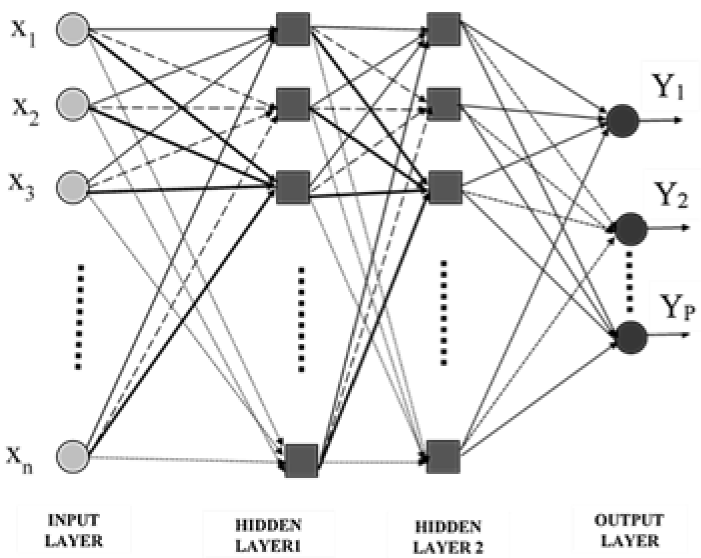
3.1 Feed Forward Neural Network

ANNs are soft computing models which perform in a similar manner to that of biological neural systems such as human brain. ANN has many processing elements, named as neurons. Each neuron is linked to other neurons through a weight. ANN has become an important tool for stock price prediction due to their ability to deal with dynamic and uncertainty data. Among various ANNs, feed forward neural network is the popular and commonly used. FFNN has three layers: an input layer, hidden layer and an output layer. Figure 1 shows the architecture of FFNN with two hidden layers. Input neuron receives the inputs and multiplied with the associated weights. The resultant value is added with bias. By applying activation function, output of neuron would be computed. The output of neuron K is defined as follows:

$$I_K = \sum_{i=1}^{n} X_i W_i \tag{1}$$

$$Y_K = \varnothing\left(I_K + B_K\right) \tag{2}$$

Figure 1. Architecture of FFNN with two hidden layers



Where, X_i is the input, W_i is the weights, I is the input adder, B represents the bias Y is the output and $\varnothing$ denotes the activation function. In this study, FFNN was trained by the LM algorithm. LM algorithm is one of the most popular algorithms used for training the neural networks. It estimates the error of the network with a second order expression which is in contrast to the gradient descent algorithm which follows a first order expression. It outperforms simple gradient descent and other conjugate gradient methods in a wide variety of problems. In addition to this, PSO and BBO have been used for tuning the weights of FFNN.

3.2 Particle Swarm Optimization

PSO is a kind of meta-heuristic optimization algorithms which is motivated by bird flocking and fish schooling. PSO was introduced by (Kennedy & Eberhart, 1995). It can be used for nonlinear function optimization. Each member in PSO is called as particle flies through multi-dimensional search space with a velocity and adjusts its position in every phase till it reaches the optimum solution. The position of a particle is influenced by the best position visited by its own experience and the position of the best particle in its neighborhood. Velocity and position of the particle is updated by using Equation (3) and Equation (4) respectively.

$$V^i\left(t+1\right) = V^i\left(t\right) + c_1 * r_1 * \left[p^i_{best} - p^i\left(t\right)\right] + c_2 * r_2 * \left[g_{best} - p^i\left(t\right)\right] \tag{3}$$

$$p^i\left(t+1\right) = p^i\left(t\right) + V^i\left(t\right) \tag{4}$$

In this study, PSO is employed for finding optimal weights of FFNN.PSO prevents the trapping in a local minimum since it is not based gradient information.

3.3 Biogeography-based Optimization

BBO is one of the stochastic optimization algorithms, introduced by (Simon, 2008) for solving multidimensional optimization problems. BBO algorithm was inspired by the biogeography. Biogeography is the study of geological distribution of biological organisms in nature over space and time. i.e immigration and emigration of species between habitats. BBO algorithm described in (Hesham & Mahsa, 2018; Seyedali et al., 2014) adopted for tuning the parameters of FFNN.

Different habitats are examined to discover the relationships between different habitants in terms of immigration, emigration, and mutation. BBO uses a number of search agents called habitats. The BBO algorithm assigns each habitat a vector of habitants which represents the variables of problems. In addition, a Habitat Suitability Index (HSI) defines the overall fitness of a habitat. The higher the HSI, the more fit the habitat (Hesham & Mahsa, 2018; Seyedali et al., 2014).

The BBO optimization algorithm starts with a random set of agents (habitats). Each habitat has m different habitants that correspond to the number of variables of a particular problem. In addition, each habitat has its own immigration, emigration, and mutation rates. This mimic the characteristic of various geographically separated locations in nature.

According to (Seyedali et al., 2014), immigration (δ_p) and emigration (μ_p) are formulated as:

$$\mu_p = \frac{e \times m}{M} \tag{5}$$

$$\delta_p = I \times \frac{1 - m}{M} \tag{6}$$

Where, m is the current number of habitants, M is the maximum number of habitants, e is the maximum emigration rate, and I indicate the maximum immigration rate. Mutation enhances the exploration of BBO and keeps habitats as diverse as possible. Mutation is defined as follows:

$$n_m = N \times \left(1 - \frac{P_m}{P_{max}}\right) \tag{7}$$

The aim of training is to find the optimal parameters of ANN to achieve the minimum error for testing sample. However, error of ANNs stays constant for some period during learning process which results in local minima problem. To prevent this, BBO is used in this study. Compared with PSO, BBO has one additional operator called mutation operator which improves the exploitation capability. This allows BBO to outperform PSO and other algorithms in training ANN.

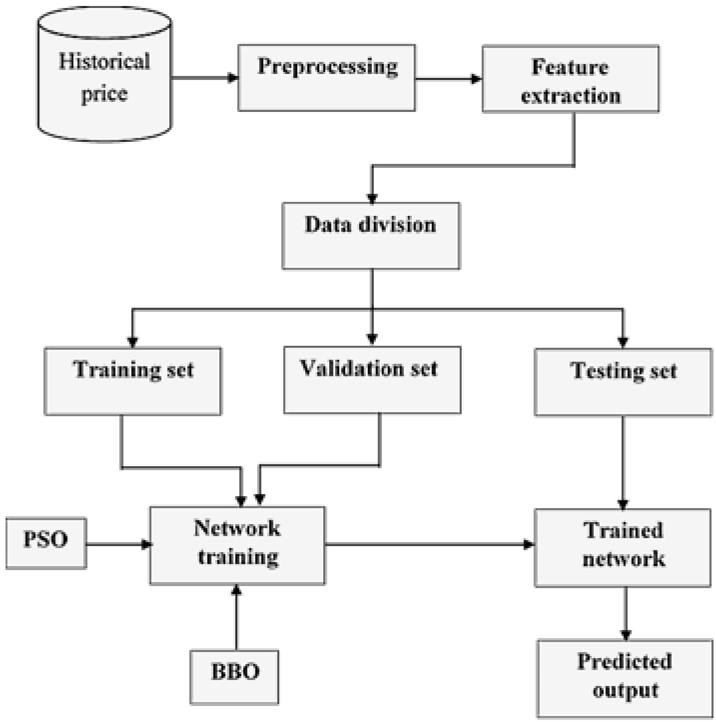
4. PROPOSED METHOD

Many techniques like regression, statistical, fundamental and technical analysis used for stock market prediction. However, no one technique provides consistent result. To improve the prediction accuracy, this study presents bio inspired computing algorithms based FFNN for predicting stock price. Figure 2 demonstrate the framework of proposed prediction model. The following steps are involved in the proposed model:

- Data normalization

- Feature extraction
- Prediction model creation and training using BIC.

Figure 2. Proposed prediction model



4.1 Data Normalization

The collected data was normalized into the range [0, 1] using Equation (8), since ANNs are known to be sensitive to unnormalized data. Normalization is used to bring all the samples into a common range (Nayak et al., 2014).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \left(h_i - l_i\right) \tag{8}$$

Where, X_{norm} -Normalized value of X

X -Real or original value
X_{min} _ Minimum value
X_{max} -Maximum value
h_i- Upper bound of the normalizing interval (in this case 1) and
l_i -Lower bound of the normalizing interval (in this case 0)

4.2 Feature Extraction

Technical indicators are extracted from the normalized data. Subsequently, extracted features are given as the input to the proposed model to predict the closing price. Finally, the output from the model was subjected to De-normalization to obtain predicted values. In literature, researchers have used many indicators to predict the future price of stock. In this study, 10 popular technical indicators which are SMA, EMA, RSI, MACD, stochastic %K, stochastic %D ROC, CCI, ADO and %William's R are selected as input to the developed model. The technical indicators are calculated from past historical data. The selected technical indicators and their descriptions are given in Table 1.

4.3 Prediction Model Creation and Training Using BIC

FFNN is a multilayer and supervised network. In this study, we have used a network with 10 input neurons representing the normalized 10 indicators, one hidden layer with 15 neurons and one output neuron for producing the closing value. Hidden neurons are fixed by trial and error method. Tangent sigmoidal and linear activation used at the hidden and output layer respectively. FFNN is trained with LM algorithm. Two bio inspired algorithms, PSO and BBO are employed to obtain optimal weight.

Table 1. Technical indicators

Technical indicators	Formula
SMA	$\mathrm{SMA}_t = \frac{1}{t}\sum_{i=1}^{t} C_i$
EMA	$\mathrm{K}\left(C_t - EMA\left(t-1\right)\right) + EMA\left(t-1\right)$ $K = \frac{2}{1+n}$
RSI	$\mathrm{RSI} = 100 - \frac{100}{1+RS}$ $RS = \frac{EMA\left(U,n\right)}{EMA\left(D,N\right)}$ $U = C_t - C_{t-1} \qquad D = 0$ $D = C_{t-1} - C_t \qquad U = 0$
MACD	$MACD = EMA\left(12\right) - EMA\left(26\right)$ $Signal = EMA\left(MACD, 9\right)$ $Histogram = MACD - Signal$
Stochastic %K	$\%K = 100\frac{C_t - C_l\left(n\right)}{C_h\left(n\right) - C_L}$

Table 1 continued on next page

Table 1 continued

Technical indicators	Formula
Stochastic %D	$\%D = EMA\left(\%K, 3\right)$
ROC	$\left(\frac{Price\left(t\right)}{Price\left(t-n\right)}\right)*100$
ADO	$\frac{H_t - C_{t-1}}{H_t - L_t}$
William's R %	$\left(\frac{H_t - C_t}{H_t - L_t}\right)*100$
CCI	$\frac{S_t - SS_t}{0.015K_t}$ $S_t = \frac{H_t + L_t + C_t}{3}$ $SS_t = \sum_{i=1}^{n} \frac{S_{t-i+1}}{n}$ $K_t = \sum_{i=1}^{n} \frac{S_{t-i+1} - SS_i}{n}$

5. EMPIRICAL STUDY

In this section, simulation results of the proposed model are presented and analyzed. The results have been obtained from the testing sample, which is 15% of complete data set considered. To prevent over fitting problem, proposed model had a validation data set during training process. First, this study analyzes the individual performance of PSO-FFNN and BBO-FFNN and then compares their efficiency. Further to this, performance of the proposed model is also compared with the other existing prediction models including ANN (Khare et al. 2017; YakupKara et al., 2011), DE-ANN (Mohapatra et al., 2012), ANN-PSOCom (Essam, 2016) and SVM (Yauheniya et al., 2014) in terms of prediction accuracy.

5.1 Research Data Set

The data sets used in this study are the highly traded stock of different sectors which are Information Technology (IT), Banking and automobile sectors. The corresponding stock prices from the above-mentioned sectors are Oil States International, Inc. (OIS), Oracle Corporation (ORCL), Bank of America Corporation (BAC), Morgan Stanley (MS), Citigroup Inc. (C), Schlumberger Limited (SLB), Halliburton Company (HAL) and Weatherford International plc (WFT). Each sample contains information like opening, low, high and closing price of stocks traded per day. The data sample of each stock covers the period from May 2016 to April 2018. The complete data is divided into three sets: First 70% of data are chosen as training data, 15% of data are used for validation and the last 15% of data are utilized for testing the prediction ability of the proposed model.

5.2 Performance Evaluation

Performance of the proposed model is measured using seven statistical metrics. Statistical measures used in this study is presented in Table 2.HR is high indicates that the predicted value is close to actual value. If MSE, MAPE, RMSE and MAE are small, predicted value is identical to the original value.

Table 2. Evaluation metrics

Metrics	Formula
MSE	$MSE = \frac{1}{N}\sum_{k=1}^{N}\left(A_k - P_k\right)^2$
MAE	$MAE = \frac{1}{N}\sum_{k=1}^{N}\left\|A_k - P_k\right\|$
RMSE	$MAE = \frac{1}{N}\sum_{k=1}^{N}\left\|A_k - P_k\right\|$
MAPE	$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left\|\frac{A_k - P_k}{A_k}\right\| X100$
HR	$Hitrate = \frac{1}{N}\sum_{k=1}^{N} A_k = P_k$
ER	$MAE = \frac{1}{N}\sum_{k=1}^{N}\left\|A_k - P_k\right\|$

Table 3 shows the efficiency of proposed prediction models. From the Table 3, it is observed that the proposed BBO-FFNN provide better performance compared to PSO-FFNN in terms of all evaluation parameters in almost all the stocks. For example, in case of predicting price of ORCL, MSE obtained by BBO-FFNN is very low and is almost half of that obtained by PSO-FFNN. For BAC stock, the developed PSO-FFNN has value for MSE, MAE, RMSE, MAPE, HR, ER and accuracy to be 0.011, 0.083, 0.107, 0.278, 0.955, 0.044 and 91.66% respectively. BBO-FFNN possess value for MSE, MAE, RMSE, MAPE, HR, ER and accuracy to be 0.006, 0.060, 0.082, 0.203, 0.966, 0.033 and 93.90%. With respect to HR and Accuracy, BBO-FFNN has higher value than PSO-FFNN. It shows the superiority of BBO algorithm.

The comparative graph presenting the output predicted by the proposed two models and actual value for selected eight companies are depicted in Figure 3 (a)-(h). The comparison plot revealed that the prediction by BBO-FFNN model more closely follows the actual value in almost all the companies when compared with PSO-FFNN model.

Table 3. Performance of the proposed model

Stock name	Predictive models	Evaluation metrics						
		MSE	MAE	RMSE	MAPE	HR	ER	Prediction accuracy (%)
Oil States International, Inc. (OIS)	**PSO-FFNN**	0.064	0.187	0.253	0.556	0.820	0.179	81.21
	BBO-FFNN	0.061	0.151	0.247	0.449	0.847	0.157	84.83
Oracle Corporation (ORCL)	**PSO-FFNN**	**0.017**	0.097	0.132	0.209	0.876	0.123	90.22
	BBO-FFNN	**0.008**	0.068	0.091	0.145	0.943	0.056	93.19
Bank of America Corporation (BAC)	**PSO-FFNN**	0.011	0.083	0.107	0.278	0.955	0.044	91.66
	BBO-FFNN	0.006	0.060	0.082	0.203	0.966	0.033	93.90
Morgan Stanley (MS)	**PSO-FFNN**	0.045	0.156	0.212	0.311	0.887	0.112	84.39
	BBO-FFNN	0.028	0.131	0.170	0.262	0.898	0.101	86.83
Citigroup Inc. (C)	**PSO-FFNN**	0.038	0.160	0.194	0.231	0.876	0.123	83.96
	BBO-FFNN	0.036	0.149	0.191	0.216	0.820	0.179	85.02
Schlumberger Limited (SLB)	**PSO-FFNN**	0.052	0.179	0.228	0.266	0.764	0.198	82.09
	BBO-FFNN	0.050	0.169	0.224	0.252	0.848	0.159	83.09
Halliburton Company (HAL)	**PSO-FFNN**	0.062	0.175	0.249	0.389	0.865	0.134	82.46
	BBO-FFNN	0.037	0.147	0.193	0.326	0.875	0.123	85.26
Weatherford International plc (WFT)	**PSO-FFNN**	0.002	0.043	0.052	1.362	0.910	0.089	95.63
	BBO-FFNN	0.001	0.034	0.043	1.078	0.943	0.056	96.59

5.3 Comparison with the State-of-art Techniques

Several stock market prediction techniques are reported and compared in (Kumar, 2018; Pushpanjali & Soumya, 2013). Prediction accuracy obtained by ANN model (YakupKara et al., 2011) is lower than other methods. DE-ANN (Handa et al., 2015) based model can predict the stock value with high accuracy. ANN with seven technical indicators model (Khare et al., 2017) provides better performance. Stock prediction using SVM model (Sedighi et al., 2019) outperforms PSOCoM and DE-ANN but need a greater number of technical indicators which result in increased computational complexity. Hence, there is a need for developing an efficient model for stock market prediction. Table 4 compares the proposed model with the existing methods in terms of prediction accuracy to demonstrate the efficiency of the prediction model. From the Table 4, it is observed that the performance of proposed scheme is superior to other methods considered for comparison from the literature.

Table 4. Efficiency comparison

Authors	Number of technical indicators used	Model	Prediction accuracy (%)
Yakupkara et al. (2011)	10	ANN	75.74
Mohapatra et al. (2012)	2	DE-ANN	85.89
Khare et al. (2017)	7	ANN	86.89
EssamEl.Seidy (2016)	7	PSOCoM-ANN	83.5
Yauheniya et al. (2014)	20	SVM	85
Sedighi et al. (2019)	-	ABC-SVM	84
Das et al. (2019)	-	FA-OSELM	83.2
Nayak and Misra (2018)	-	GA-PNN	81.9
Proposed	**10**	**PSO-FFNN**	**86.2**
	10	**BBO-FFNN**	**88.58**

Figure 3. Actual and predicted values of different companies by the proposed models

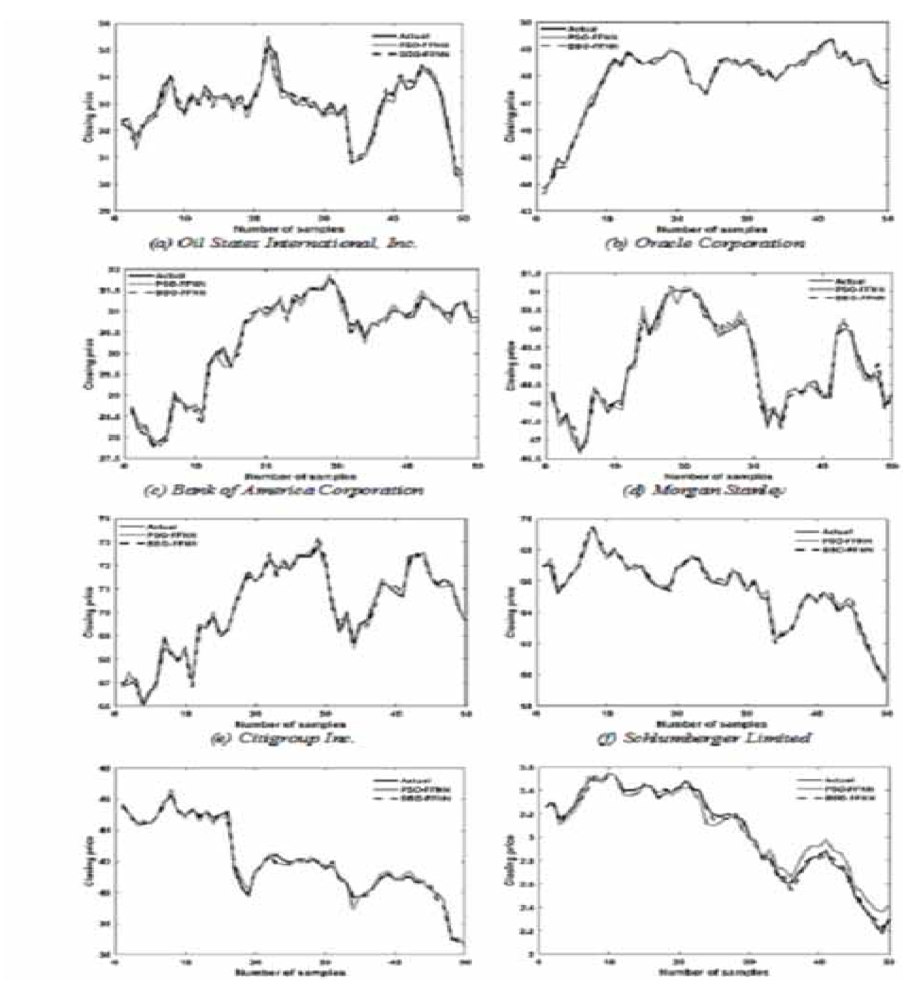


Figure 4. Performance comparison

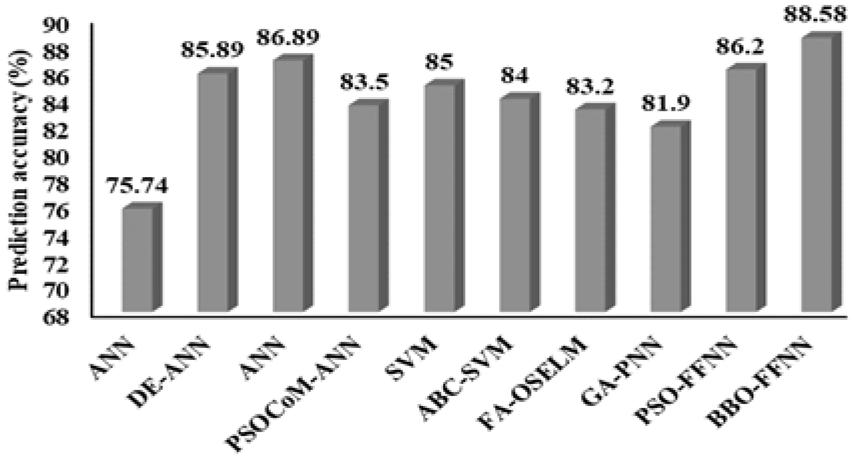


Figure 4 graphically compares the prediction accuracy of the proposed models with the other models. From the Figure 4, it is obvious that the predicted curve is closer to actual curve in almost all the stock which prove the strength of proposed BBO-FFNN model.

6. CONCLUSION AND ENHANCEMENT

This study explored the use of FFNN and two different Bio Inspired computing algorithms, PSO and BBO to build the systems, PSO-FFNN and BBO-FFNN for predicting stock market price. FFNN is designed with an input layer, a hidden layer and an output layer. PSO and BBO used separately for optimizing the FFNN parameters. Ten technical indicators which influence the stock price were computed from historical data and taken as feature vectors. The obtained feature vectors are divided into two parts: training and testing part. Training samples are used for developing the models and testing samples are used for validating the performance of the models. The research data were sampled on daily bases. The simulation results are measured using some evaluation parameters. From the empirical results, it can be clearly seen that the developed FFNN with BBO optimization technique, topology of 10-15-1 provided better results with respect to PSO-FFNN and other models taken for analysis. PSO algorithm solutions do not change directly. It is rather their velocities change and this indirectly changes the solution. In BBO algorithm, solutions are changed directly via migration from other solutions. This makes the BBO algorithm to be better than PSO algorithm. BBO-FFNN provided better result than PSO algorithm. However, it needs more time for computation. Future research work will focus on using other bio inspired computing algorithms and deep learning models to address the stock market problems.

FUNDING AGENCY

The publisher has waived the Open Access Processing fee for this article.

REFERENCES

Alaa, F., Sara, S., Elsir, M. A., & Hossam, F. (2015). A comparison between regression, artificial neural networks and support vector machines for predicting stock market index. *International Journal of Advanced Research in Artificial Intelligence*, *4*(7), 55–63.

Awad, M., Pomares, H., Rojas, I., Salameh, O., & Hamdon, M. (2009). Prediction of time series using RBF neural networks: A new approach of clustering. *The International Arab Journal of Information Technology*, *6*(2), 138–143.

Das, S. R., Mishra, D., & Rout, M. (2019). Stock market prediction using firefly algorithm with evolutionary framework optimized feature reduction for OSELM method. *Expert Systems with Applications*, *X*, 4.

Essam, E. S. (2016). A new particle swarm optimization based stock market prediction technique. *International Journal of Advanced Computer Science and Applications*, *7*(4), 322–326.

Handa, R., Hota, H. S., & Tandan, S. R. (2015). Stock Market Prediction with various technical indicators using Neural Network techniques. *International Journal for Research in Applied Science and Engineering Technology*, *3*(4), 604–608.

Hesam, D., & Mahsa, Z. (2018). Crude oil price forecasting: A biogeography-based optimization approach. *Energy Sources. Part B, Economics, Planning, and Policy*, *2018*(7), 328–339. Advance online publication. doi:10.1080/15567249.2018.1501121

Hiransha, M., Gopalakrishnan, E. A., Vijaykrishan, M., & Soman, K. P. (2018). NSE stock market prediction using deep learning models. *Procedia Computer Science*, *132*, 1351–1362. doi:10.1016/j.procs.2018.05.050

Kara, Y., Acar Boyacioglu, M., & Baykan, Ö. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. *Expert Systems with Applications*, *38*(5), 5311–5319. doi:10.1016/j.eswa.2010.10.027

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. *Proceedings of the IEEE International Conference on Neural Networks*, 4, 1942–1948. doi:10.1109/ICNN.1995.488968

Khare, K., Darekar, O., Gupta, P., & Attar, V. Z. (2017). Short term stock price prediction using deep learning. *Proceedings of the 2nd IEEE International Conference on Recent Trends in Electronics Information and Communication Technology*, 482-486. doi:10.1109/RTEICT.2017.8256643

Kumar, C. S. (2018). Soft computing and bio inspired computing techniques for stock market prediction: A comprehensive survey. *IACSIT International Journal of Engineering and Technology*, *7*(3), 1836–1845. doi:10.14419/ijet.v7i3.14716

Majhi, R., Panda, G., Mahji, B., & Sahoo, G. (2009). Efficient prediction of stock market indices using adaptive bacterial foraging optimization (ABFO) and BFO based techniques. *Expert Systems with Applications*, *36*(6), 10097–10104. doi:10.1016/j.eswa.2009.01.012

Mohammed, S., Debdulal, P., Sumanjit, D., & Sudhir, K. M. (2018). Hybrid forecasting model for prediction of stock value of tata steel using support vector regression and particle swarm optimization. *International Journal of Pure and Applied Mathematics*, *119*(14), 1719–1727.

Mohapatra, P., & Alok, R. (2012). Indian stock market prediction using differential evolutionary neural network model. *International Journal of Electronics Communication and Computer Technology*, *2*(4), 159–165.

Nayak, S. C., & Misra, B. B. (2018). Estimating stock closing indices using a GA-weighted condensed polynomial neural network. *Financial Innovation*, *4*(21).

Nayak, S. C., Misra, B. B., & Behera, H. S. (2014). Impact of Data Normalization on Stock Index Forecasting. *International Journal of Computer Information Systems and Industrial Management Applications*, *6*, 257–269.

Oriani, F. B., & Guilherme, P. C. (2016). Evaluating the impace of technical indicators on stock forecasting. *Proceedings of the IEEE Symposium Series on Computational Intelligence*.

Pushpanjali, M., & Soumya, D. (2013). Stock market prediction using bio inspired computing: A survey. *International Journal of Engineering Science and Technology*, *5*(4), 739–745.

Sedighi, M., Jahangirnia, H., Gharakhani, M., & Fard, S. (2019). A novel hybrid model for stock price forecasting based on metaheuristics and support vector machine. *Data*, *4*(75), 75. doi:10.3390/data4020075

Seyedali, M., Seyed, M. M., & Andrew, L. (2014). Let a biogeography-based optimizer train your Multi-Layer Perceptron. *Information Sciences*, *269*, 188–209. doi:10.1016/j.ins.2014.01.038

Sharma, D. K., Sharma, H. P., & Hota, H. S. (2015). Future Value Prediction of US Stock Market Using ARIMA and RBFN. *International Research Journal of Finance and Economics*, *134*, 136–145.

Shen, W., Guo, X., Wu, C., & Wu, D. (2011). Forecasting stock indices using radial basis function neural network optimized by artificial fish swarm algorithm. *Knowledge-Based Systems*, *24*(3), 378–385. doi:10.1016/j.knosys.2010.11.001

Sheta, A., & De Jong, K. (2001). Time-series Forecasting using GA-tuned radial basis functions. *Information Sciences*, *133*(3), 221–228. doi:10.1016/S0020-0255(01)00086-X

Simon, D. (2008). Biogeography-based optimization. *IEEE Transactions on Evolutionary Computation*, *12*(6), 702–713. doi:10.1109/TEVC.2008.919004

Sureshkumar, K. K., & Elango, N. M. (2012). Performance analysis of stock price prediction using artificial neural network. *Global Journal Computer Science and Technology*, *12*(1).

Victor, D. A., & Antony, A. L. T. (2013). Stock prediction using artificial neural networks. *International Journal of Data Mining Techniques and Applications*, *2*, 283–291.

White, H. (1988). Economic predictions using neural networks. In *Proceedings of the IEEE International Conference on Neural Networks* (vol. 2, pp.451-458). doi:10.1109/ICNN.1988.23959

Yauheniya, S., McGinnity, T. M., Sonya, C., & Yuhua, L. (2014). Forecasting stock price directional movements using technical indicators: investing window size effects on one-step-ahead forecasting. In *Proceedings of the IEEE Conference on Computational Intelligence for Financial Engineering and Economics* (pp.341-347). IEEE.

Hitesh Punjabi is a Professor, Department of Finance, K J Somaiya Institute of Management Studies and Research, Mumbai. He is MBA (Finance), B.E. (Chemical) and Pursuing PhD and Alumina of IIM Indore. He has more than 15+ years of experience in industry & education. He was with Corporate industries like Anand Rathi Securities, Religare Securities, HSBC Invest Direct Securities, East India Securities, ARJ Securities in the field of Equity Research and Chetana's Institute of Management & Research. He has conducted FDPs/ MDPs on various topics for several organizations. He has chaired many research conferences/workshops/seminars. He has published research papers in national and international publications. Presently, he is on the reviewer for one of the journal. He is active Member of Indian Pharmaceutical Association. He is Mentor for Atal Incubation Centre supported by NITI-AAYOG. He has been a Visiting Faculty for Finance at various institutes of Management since 2003. His areas of expertise are of Security Analysis & Portfolio Management, Equity Research- Fundamental Analysis, Technical Analysis, Mutual Funds, Behavioral Finance, Fixed Income Securities and Algorithm Trading.

S. Kumar Chandar is working as an Associate Professor in School of Business and Management – CHRIST (Deemed to be University), Bangalore, having 21 years in wide variety of technical, managerial and teaching roles. He has published and presented over 50 research papers in international and national journals in the area of computer science and management. He is an AIMA certified Accredited Management Teacher in the Area of Information Technology and SMFI certified Strategic Management Teacher. His Areas of Interest includes Business Intelligence, Knowledge Management, Strategic Management, Social Networking Analysis, Nature inspired algorithms and Artificial Neural Networks.