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Cat Swarm Optimization Algorithm Tuned Multilayer Perceptron for Stock Price Prediction

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Due to the nonlinear and dynamic nature of stock data, prediction is one of the most challenging tasks in the financial market. Nowadays, soft and bio-inspired computing algorithms are used to forecast the stock price. This article assesses the efficiency of the hybrid stock prediction model using the multilayer perceptron (MLP) and cat swarm optimization (CSO) algorithm. The CSO algorithm is a bio-inspired algorithm inspired by the behavior traits of cats. CSO is employed to find the appropriate value of MLP parameters. Technical indicators calculated from historical data are used as input variables for the proposed model. The model's performance is validated using historical data not used for training. The model's prediction efficiency is evaluated in terms of MSE, MAPE, RMSE and MAE. The model's results are compared with other models optimized by various bio-inspired algorithms presented in the literature to prove its efficiency. The empirical findings confirm that the proposed CSO-MLP prediction model provides the best performance compared to other models taken for analysis.

Keywords: bio-inspired algorithm, particle swarm optimization, cat swarm optimization, MAE, MAPE, multilayer perceptron and stock prediction.

1. Introduction

An accurate prediction of the stock market price is a very tough task due to the dynamic, noisy, complex and nonlinear nature of stock data. In addition to this, stock prices are affected by many factors such as a firm's policies, political events, economic conditions, investor expectations and commodity price indices. Therefore, stock market data are characterized by discontinuities and nonlinearities and forecasting stock price is difficult [1]. Over the past years, many researchers attempted to develop a model for stock market prediction. Stock market prediction methods reported in the literature can be categorized into statistical and soft computing methods. Statistical or linear methods are based on past data and are easy to implement. However, statistical methods fail to capture the nonregularity underlying the stock data and thus provided poor performance. Examples of the statistical methods are ARIMA, ARCH and GARCH [2, 3].

To prevent the limitations of conventional models, computational intelligence (CI) techniques such as soft computing methods have been suggested to predict the stock price [4, 5]. Several soft computing techniques, including artificial neural network (ANN), support vector machine (SVM) and adaptive neuro-fuzzy interference system (ANFIS), are popular methods for predicting stock market price. Among many soft computing techniques, ANN is one of the strongest soft computing techniques, which can efficiently find the nonlinear relationship between input and output present in the stock data. Moreover, ANN can approximate any complex and nonlinear function with high accuracy. ANN models such as multilayer perceptron (MLP), radial basis function neural network (RBFNN), probabilistic neural network (PNN), functional link artificial neural network (FLANN), wavelet neural network (WNN) and recurrent neural network (RNN) are popular and commonly used for stock prediction [6, 7].

Most of the ANN-based forecasting models suffer from slow convergence and long training or learning time. Therefore, new algorithms that reduce such limitations are necessary to make accurate predictions. Recently, many bio-inspired algorithms such as a genetic algorithm (GA) [3], differential evolution (DE) [8], modified cuckoo search (MCS) [9], artificial bee colony (ABC) [10], particle swarm optimization (PSO) [11], bacterial foraging optimization (BFO) [12] and biogeography-based optimization (BBO) [24] have been successfully applied to optimize the parameters of ANN.

This paper presents a hybrid model using MLP and CSO for stock price prediction. CSO algorithm is a metaheuristic algorithm used to find the optimal value for weights and bias of MLP. The prediction efficiency of the proposed model was evaluated and its superior performance compared to the other models was demonstrated.

The layout of the paper is as follows. Section 2 provides a brief review of related work in this field. Section 3 describes how CSO-MLP is applied for stock market prediction. Section 4 presents the selected stocks and technical indicators used. Section 5 deals with the experimental results and compares them with a benchmark model and other existing models. Section 6 highlights the findings and provides suggestions for future work, and it is followed by relevant references used in this study.

2. Related works

Over the past two decades, many researchers and specialists have developed models for forecasting stock prices. Table 1 presents a summary of recent stock market prediction methods reported in the current literature. Majhi *et al.* [13] proposed a model for forecasting stock market data. The proposed model is based on RBFNN and a nondominated sorting multi-objective genetic algorithm (NSGA – II). Ten technical indicators, namely exponential moving average (EMA) (EMA10), EMA20, EMA30, accumulation distribution oscillator (ADO), stochastic (STOC), relative strength index (RSI) 19, RSI 14, price rate of change (PROC), closing price acceleration (CPACC) and high price acceleration (HPACC) were computed from past data and used as inputs to the prediction model. The efficacy of the proposed model was measured by using mean absolute percentage error (MAPE), directional accuracy (DA), Thelis' U and average relative variance (ARV) techniques. Minakhi *et al.* [8] forecasted the currency exchange rate by employing ARMA and DE algorithms. DE was used as an optimizer to minimize the mean square error (MSE). The proposed model was compared with PSO-ARMA, CSO-ARMA, BFO-ARMA and forward-backward least mean square (FBLMS)-ARMA to show the prediction ability. Experimental findings demonstrated that satisfactory results could be achieved when combining a bio-inspired algorithm with ANN to predict the financial market.

Table 1. A summary of recent studies.

Authors	Method	Technical indicators	Quality measures
Hung [11]	PSO-adaptive Fuzzy-GARCH	Closing price	MAFE, MPFE
Majhi *et al.* [13]	GA-RBF	EMA10, EMA20, EMA30, ADO, STOC, RSI 19, RSI 14, PROC, CPACC, HPACC	MAPE, DA, Thelis' U, ARV
Minakhi *et al.* [8]	CSO-ARMA	Exchange rate	MAPE, RMSE, MMSE, time
Mustaffa *et al.* [10]	IABC-LSSVM	Closing price, percentage change in closing price, standard deviation	RMSPE, MAPE
Hegazy *et al.* [9]	PSO-LSSVM	RSI, MFI, MACD, EMA, PMO, STOC	RMSE
Prema *et al.* [16]	GA-MLP	Opening price, closing price, lowest price, highest price, volume	NMSE
Rout *et al.* [14]	PSO-RCEFLANN	MA5, BIAS5, SD	RMSE, MAPE, time
Zhang *et al.* [15]	PSO-Elman	Opening price	MSE, MAPE
Garakani [17]	PSO-MLP	Wavelet features	MSE

In 2015, Hegazy *et al.* [9] focused on building a forecasting model employing LS-SVM. Subsequently, an attempt was made to evaluate the prediction ability of LS-SVM with five bio-inspired algorithms, which are flower pollination algorithm (FPA), bat algorithm (BA), MCS, ABC and PSO. Among many technical indicators available, the proposed model used RSI, money flow index (MFI), moving average convergence/divergence (MACD), EMA, price momentum oscillator (PMO) and stochastic oscillator. The authors concluded that the forecasting model developed by combining ANN with a bio-inspired algorithm could enhance the stock prediction ability. Another interesting architecture was introduced by Mustafa *et al.* [10] for forecasting gasoline prices. Hyperparameters of LS-SVM were optimized by an improved ABC algorithm. Performance was measured in terms of MAPE and root mean square percentage error (RMSPE). GARCH is a statistical model used to estimate volatility in financial markets. Hung [11] used adaptive fuzzy-GARCH to forecast the volatility of financial markets. In this approach, parameters of the fuzzy membership function were optimized by the PSO algorithm. The proposed model was tested in Taiwan, Germany and Japan to show the prediction efficiency.

FLANN is a kind of ANN with a single layer hidden layer. Rout *et al.* [14] developed a prediction model using a recurrent computationally efficient functional link artificial neural network (RCEFLANN). Weights of RCEFLANN termed by three bio-inspired algorithms, namely PSO, HMRPSO and DE, were compared. The model's prediction efficiency was also analyzed by using various basis functions, including Chebyshev, Legendre, trigonometric, tangent hyperbolic and Laguerre. An effort toward developing short-term forecasting model for the opening price was made by Zhang *et al.* [15] using the Elman network and PSO. The Elman network is a type of RNN that has strong computing power. The bio-inspired algorithm PSO was adopted to optimize the threshold and weights of the Elman neural network. Results showed that PSO-Elman has the potential to predict the opening price with high prediction accuracy.

Prema *et al.* [16] designed a Neuro-genetic-based stock market prediction model. In this system, opening price, closing price, low price, high price and volume were used as inputs to the MLP. The proposed system was trained with three different training algorithms, namely GDA, GDX and RP, to find an appropriate training algorithm. After selecting the training algorithm, the weight and bias of MLP were optimized by GA to improve the prediction accuracy. Results revealed that accuracy improvement could be obtained with bio-inspired algorithms. Recently, Garakani [17] has designed a forecasting model utilizing MLP by optimizing the frog leaping algorithm (FLA). The most important feature vectors were derived by using the wavelet transform and applied as inputs to the MLP. The proposed model was tested on Tehran stock exchange data. GA, PSO, ICA and FLA were used for this purpose. Karazmodeh *et al.* [18] presented an improved PSO-SVM-based forecasting model for the efficient prediction of stock data. Some technical indicators such as momentum, Williams %R, ROC, disparity (D5), D10, stochastic %K and price volume trend (PVT) were extracted from the historical stock data. Results indicated that IPSO-SVM outperforms the PSO-SVM method.

3. Research methodology

The main focus of this investigation is to develop an efficient forecasting model to enhance the accuracy of closing price prediction of stock data. The forecasting model is designed with MLP and CSO algorithms. CSO is used to determine the appropriate value for parameters of MLP. A multilayer perceptron is a feed-forward, supervised learning network. It consists of an input layer, a hidden layer and an output layer. In this study, MLP is designed with nine input neurons representing nine features, one hidden layer with 20 hidden neurons and one output neuron. The number of neurons in MLP is expressed as:

$$\text{Number of neurons} = (N_i, N_j, N_k),$$

where N_i – number of input neurons, $i = 9$, N_j – number of hidden neurons, $j = 20$ and N_k – number of output neurons, $k = 1$.

Figure 1 depicts the architecture of MLP. Each neuron in the input layer is linked to each neuron in the hidden layer via connection strength (weight), followed by the output layer [19]. Each neuron in the hidden layer sums up the input vectors multiplied by the connection strength (weight) using Eq. (1):

$$H_i = g(h_i) = g\left(\sum_{i=1}^{N} x_i w_i + b\right), \tag{1}$$

where H_i – output of the i-th hidden neuron, $g(.)$ – activation function, $\mathbf{x}$ – input vector, w – weight, and b – bias. The output of the MLP can be defined as:

$$Y_k = g\left(\sum_{j=1}^{N} w_j\left(g(h_i)\right)\right) = g\left[\sum_{j=1}^{N} w_j\left(g\left(\sum_{i=1}^{N} x_i w_i + b\right)\right)\right], \tag{2}$$

where w_i – weight between input and hidden layer and w_j – weight between hidden and output layer. Ayodele *et al.* [20] suggested that the sigmoidal activation function is better suited for stock prediction than other activation functions such as binary function, exponential function and step function. In this study, the tan sigmoidal activation function is used in the hidden layer and the purelin function used in the output layer:

$$g(x) = \frac{1}{1 + e^{-\beta x}}. \tag{3}$$

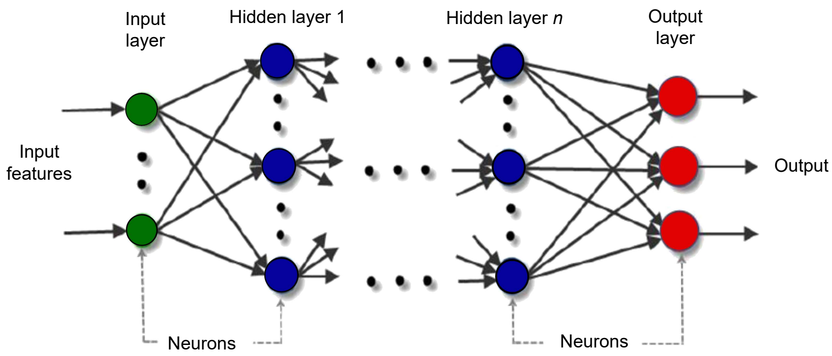

Fig. 1. The general architecture of MLP.

The design procedure of MLP includes finding the number of hidden layers, number of neurons in each hidden layer, weights and biases. These parameters are usually determined by the trial and error method, which results in increased computational cost. To deal with this issue, the proposed model used the CSO algorithm.

3.1. Cat swarm optimization algorithm

CSO is a swarm intelligence (SI)-based metaheuristic algorithm founded by Chu and Tsai [21]. It is inspired by the behavior of cats. CSO mainly depends on the behavioral traits of cats. Based on the behavioral characteristics, CSO is divided into two major modes: seeking mode and tracing mode. Seeking mode is based on the behavior of cats during resting and observing the environment [21] and this mode corresponds to the global search. The tracing mode imitates the characteristics of cats when running after a food source (target) and it corresponds to the local search. A combination of seeking and tracing mode allows the CSO to perform better than other bio-inspired algorithms. Pradhan and Panda [22] showed that the CSO performs better than other population-based optimization algorithms such as GA and PSO in terms of convergence speed and MSE, but it requires higher computation time. In CSO, every cat has position and velocity for each dimension and a fitness value that delineates the accommodation of the cat to the fitness function.

3.1.1. Seeking mode. Seeking mode models the behavioral characteristics during the resting time but being alert, and observing environment for its next move. Seeking mode incorporates four parameters, namely seeking memory pool (SMP), seeking range of the selected dimension (SRD), counts of dimension to change (CDC) and self-position consideration (SPC). The major steps involved in seeking mode are as follows:

1) Generate T copies of j-th cat.
2) Update the position of each copied cat as a plus or minus SRD fraction of the current position and replace the old values.
3) Evaluate the fitness value of all copied and updated cats.
4) Calculate the probability of each cat by using Eq. (4) and select the best one.

$$\mathrm{Prob}_j = \frac{|FV_j - FV_b|}{FV_{\max} - FV_{\min}}, \quad 0 < i < j. \tag{4}$$

To find an optimal solution to a given complex problem, $FV_b = FV_{\max}$ or $FV_b = FV_{\min}$.
5) Replace the i-th cat with the best cat from the j copied cats.

3.1.2. Tracing mode. Tracing mode is characterized by the rapid chasing of cats while hunting. The major steps of tracing mode are given below:
1) Define the position P of the j-th cat in the D-dimensional space:

$$P_j = (P_{j1}, P_{j2}, P_{j3}, ..., P_{jD}) .$$

2) Define the velocity of the j-th cat:

$$V_j = (V_{j1}, V_{j2}, V_{j3}, ..., V_{jD}) , \quad 1 < j < D.$$

3) The global best position of the cat can be expressed as:

$$Gb_k = (Gb_{k1}, Gb_{k2}, Gb_{k3}, ..., Gb_{kD}) .$$

4) Update the position and velocity by using Eqs. (5) and (6):

$$P_{ji} = P_{ji} + V_{ji}, \tag{5}$$

$$V_{ji} = W \times V_{ji} + c \times r \times (Gb_{ki} - P_{ji}) , \tag{6}$$

where W denotes the inertia weight, C is the acceleration constant and r is the random number [0, 1].

3.2. Design of prediction model using CSO-MLP

This subsection explains the functioning of the proposed stock prediction model. Bio-inspired algorithms have been commonly applied to ANN for tuning the parameters of ANN [3]. Though MLP is a promising tool for stock prediction, selecting suitable values of weights plays a pivotal role in prediction efficiency.

In this study, the CSO algorithm is used to determine the optimal weights and biases of MLP for forecasting the stock market. The framework of the proposed prediction model is depicted in Fig. 2. As mentioned above, the proposed prediction uses the CSO algorithm for tuning the parameters of MLP. CSO is a type of swarm intelligence algorithm which operates in two modes: seeking mode and tracing mode. Table 2 presents the parameters used for the CSO algorithm. The proposed prediction model consists of two stages: the training (optimizing) stage and the testing stage. Nine technical indicators, namely SMA7, MACD, RSI, stochastic %K, stochastic %D, PROC, ADO, Williams %R and momentum, are computed from historical data and employed as inputs to the MLP. During the training phase, in-samples are applied to MLP, and the corresponding outputs are observed from MLP. The error between the predicted and the actual value is calculated. Parameters of MLP are tuned by CSO algorithm based on the predefined fitness function. In this study, the MSE is used to calculate the adequacy of each cat and the fittest cat that returns the minimum MSE is chosen as the optimal solution. After finding optimal weights and bias of MLP, the network is

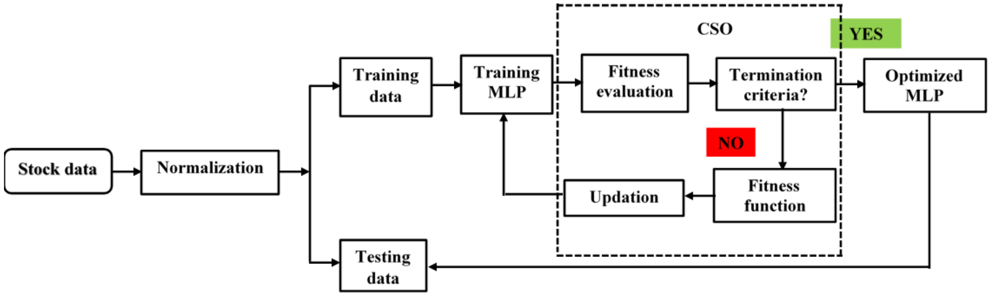

FIG. 2. The framework of the developed stock prediction model.

TABLE 2. Parameters of CSO algorithm used.

Parameters	Value
Population size	50
SMP	5
SRD	0.25
Mixture ratio	0.75
CDC	0.35
C	2.05
W	Linearly decreases between 0.9 and 0.3
Iterations	100
$V_{\max}$	0.9
$V_{\min}$	0.3

saved. At the testing time, the testing sample is used as input to the saved net to predict the closing price of stock data.

4. Data set and experiment

4.1. Dataset used for simulation

The research data used for conducting the simulation were obtained from the publicly available database for the period from May 2016 to September 2018. The total sample consists of 589 trading days. Table 3 lists the selected stocks for implementation.

Table 3. List of stocks used.

Stock name	Stock ID
Goldman Sachs Group Inc.	GS
Oil States International Inc.	OIS
Oracle Corporation	ORCL
Bank of America Corporation	BAC
Morgen Stanley	MS
Citigroup Inc.	C
Schlumberger Limited	SLB
Halliburton Company	HAL
Weatherford International PLC	WFT
Cognizant Technology Solutions Corporation	CTSH

The historical stock data downloaded for the stock indices mentioned in Table 3 consists of the opening price, lowest price, highest price and closing price of stocks traded per day. The whole data set is divided into in-sample and out-sample data. 80% of data was used for training (in-sample), and 20% of data was used for testing purposes.

4.2. Technical indicators

Initially, the data set is normalized into the range of [0, 1]. The scaled value of X' is given in Eq. (7):

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}(h_i - l_i), \tag{7}$$

where X and X' are the actual and normalized values of x, respectively, min is the minimum value of x and max is the maximum value of x. Nine technical indicators are derived from the downloaded historical data and utilized as input feature vectors to the CSO-MLP. The technical indicators and their formula used in this study are summarized in Table 4.

TABLE 4. Selected technical indicators.

Technical indicators	Formula
SMA	$\mathrm{SMA}_t = \frac{1}{t}\sum_{i=1}^{t} C_i$
RSI	$\mathrm{RSI} = 100 - \frac{100}{1 + \frac{\mathrm{EMA}(U,n)}{\mathrm{EMA}(D,N)}}$, $U = C_t - C_{t-1}, \quad D = 0,$ $D = C_{t-1} - C_t, \quad U = 0$
MACD	$\mathrm{MACD} = \mathrm{EMA}(12) - \mathrm{EMA}(26)$ $\mathrm{Signal} = \mathrm{EMA}(\mathrm{MACD}, 9)$ $\mathrm{Histogram} = \mathrm{MACD} - \mathrm{Signal}$
Stochastic %K	$\%\mathrm{K} = 100\frac{C_t - C_l(n)}{C_h(n) - C_L}$
Stochastic %D	$\%\mathrm{D} = \mathrm{EMA}(\%\mathrm{K}, 3)$
ROC	$\left(\frac{\mathrm{Price}(t)}{\mathrm{Price}(t-n)}\right) \times 100$
ADO	$\frac{H_t - C_{t-1}}{H_t - L_t}$
Williams %R	$\left(\frac{H_t - C_t}{H_t - L_t}\right) \times 100$
Momentum	$\mathrm{Price}(t) - \mathrm{Price}(t-n)$

5. Numerical results and discussion

The performance of the proposed stock prediction model is gauged in two cases:

Case 1: Predict the closing price of selected stocks using a hybrid model such as CSO-MLP.

Case 2: Analyze and compare the results obtained employing CSO-MLP, PSO-MLP, BBO-MLP and other existing models in terms of quality measures.

5.1. Performance metrics

There are many statistical parameters available to assess the efficiency of the prediction models. The derived results of the CSO-MLP are evaluated by computing four widely used performance measures, which are mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) [24].

MSE is the mean squared errors between the actual value and predicted values, and can be expressed as:

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}(A_k - P_k)^2\,; \tag{8}$$

MAE is defined as the average absolute error between the actual value and the predicted value. MAE is defined as:

$$\mathrm{MAE} = \frac{1}{N}\sum_{k=1}^{N}|A_k - P_k|\,; \tag{9}$$

MAPE gives the mean absolute percentage error between the actual value and the predicted value, and it is calculated as follows:

$$\mathrm{MAPE} = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{A_k - P_k}{A_k}\right| \times 100; \tag{10}$$

RMSE is defined as the root means squared error between the actual value and the predicted value and can be written as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(|A_k - P_k|)^2}, \tag{11}$$

where A_k – actual value, P_k – predicted value and N – number of samples.

5.2. Efficiency comparison

Out of 589 samples, 471 samples were used to train the model and 118 samples were employed to test the prediction efficiency of the model. Each of the samples consisted of nine technical indicators. Table 5 presents the simulation results of the proposed model. It can be seen that the proposed CSO-MLP model achieved the lowest value for all statistical measures.

Some important observations on the experimental results are given to measure the efficacy of the CSO-MLP-based stock prediction model. Results achieved

Table 5. Efficiency measure.

Stock ID	MSE	MAE	RMSE	MAPE
GS	0.0006	0.019	0.024	2.617
OIS	0.001	0.025	0.033	0.630
ORCL	0.001	0.026	0.036	0.526
BAC	0.0007	0.021	0.027	0.335
MS	0.0006	0.020	0.025	0.530
C	0.0008	0.018	0.028	0.771
SLB	0.0009	0.022	0.030	0.659
HAL	0.001	0.026	0.036	0.402
WFT	0.0009	0.021	0.029	2.143
CTSH	0.0007	0.019	0.026	0.839

from the CSO-MLP model for the test samples for selected stocks are graphically illustrated in Figs. 3a–d.

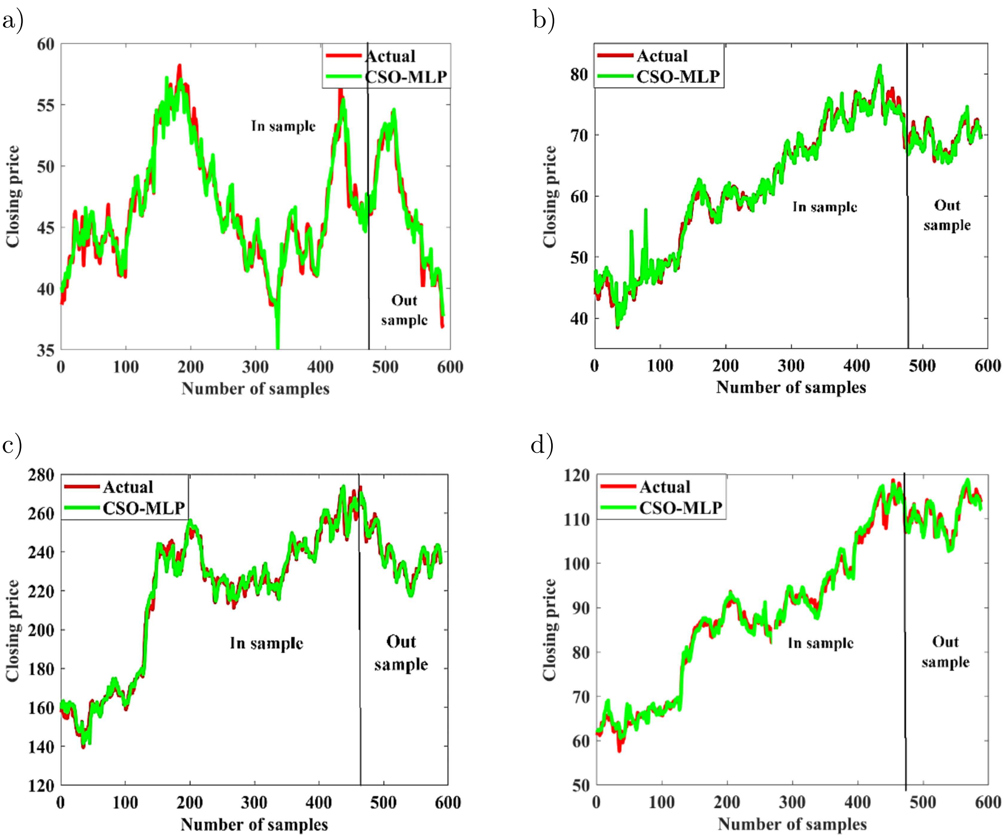

Fig. 3. Sample output of actual and predicted values of a) CTSH, b) C, c) MS, d) HAL.

To prove the efficiency of the proposed model, the performance of the CSO-MLP model is compared with two benchmark models: PSO-MLP, BBO-MLP and other existing models such as GA-RBF [13], GA-LSTM [3], CSO-ARMA [8] DE-FLANN [14] and PSO-ELMAN [15] in terms of statistical measures. Comparison of MSE, MAE, RMSE and MAPE of different prediction models utilizing soft computing and bio-inspired computing algorithms for stock price prediction is presented in Figs. 4–7.

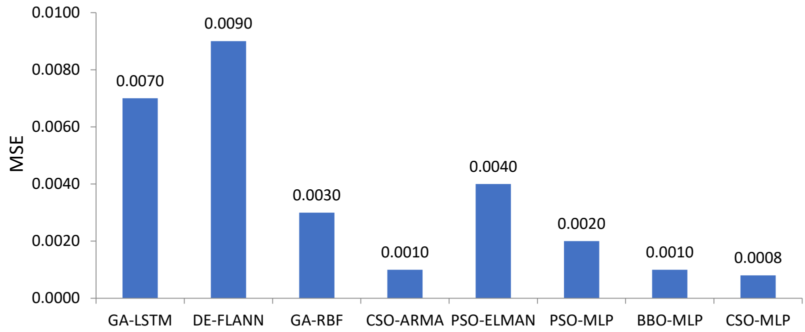

Fig. 4. Comparison of MSE between the proposed model and other models.

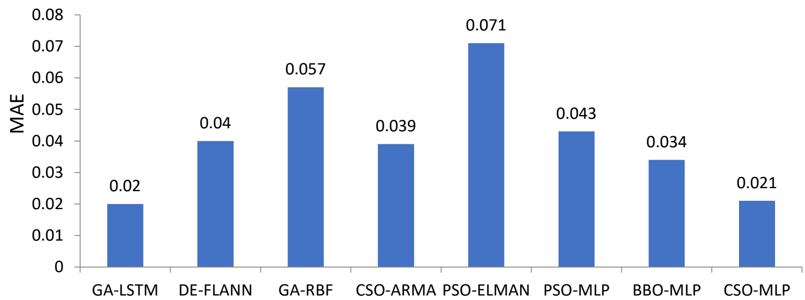

Fig. 5. Comparison of MAE between the proposed model and other models.

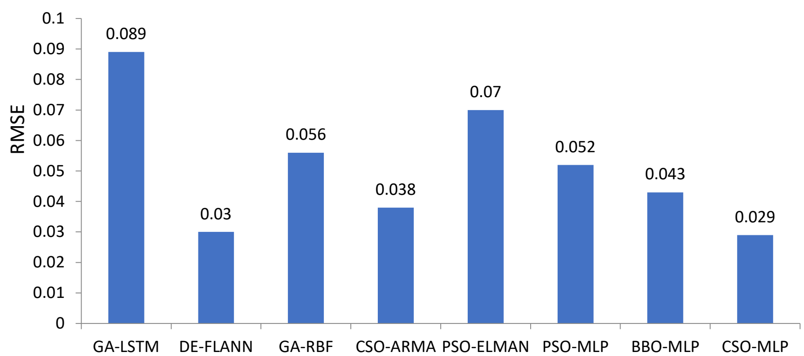

Fig. 6. Comparison of RMSE between the proposed model and other models.

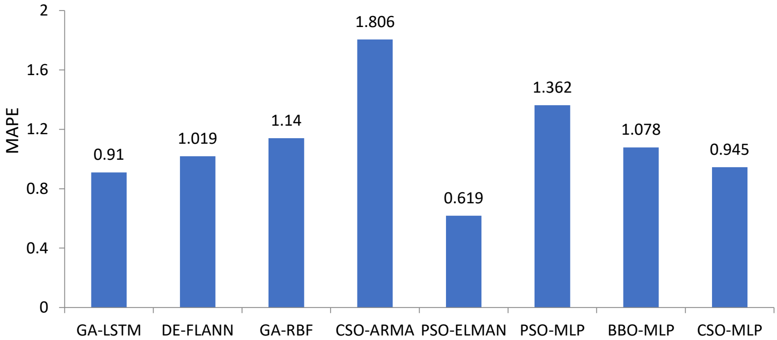

Fig. 7. Comparison of MAPE between the proposed model and other models.

It is observed that the proposed CSO-MLP model's minimum value for MSE, RMSE, MAE and MAPE is 0.0008, 0.029, 0.021 and 0.945, respectively, which is lower than PSO-MLP, BBO-MLP as well as other existing models considered for analysis from the literature. This may be due to the reason that the existing models failed to capture the hidden information existing within the stock data. In addition to this, CSO is a type of the SI algorithm, however the weighting factor of CSO provides better results than other bio-inspired algorithms such as PSO and BBO algorithm [23]. The empirical findings suggested that optimization of parameters of ANN is a very important task to achieve high prediction accuracy.

6. Conclusion

This study has designed an efficient stock market price prediction model using MLP, which is one of the best feed-forward neural networks. We combined MLP and CSO algorithm to find the hidden information of stock and make more accurate predictions. MLP used in this study comprises one input layer with nine neurons, one hidden layer with 20 neurons and an output layer for expressing non-linear patterns of stock price. CSO was adopted to determine the near-optimal value for the weights and bias of MLP. The prediction performance of the proposed hybrid model for ten different stock sectors has been evaluated. Simulation results demonstrated that the proposed hybrid model CSO-MLP showed superior performance compared to bio-inspired computing-based models as well as other models by providing lower MSE, MAE, RMSE and MAPE. Our future research will focus on developing more and more efficient schemes for stock prediction using hybrid bio-inspired computing algorithms.

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