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Original Research Article

Stock Price Forecasting With neural Network Using a New Training Algorithm

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Abstract: Publication of bond and stock through stock market, is a way in order to prepare the capital for investment. According to this fact that stock price is the first and important issue for an investor, evaluating and forecasting of the future price will be propounded. Artificial Neural Network (NN) is a way of stock price forecasting. High efficiency of NNs in forecasting and importance of forecasting in different fields, have caused researchers to search the ways of improving the strategies used for increase of the accuracy of forecasting by neural networks. Accuracy level of a NN greatly depends on its weight and bias values. In a NN, weight and bias values depend on the kind of training algorithm. In this article, the NN using for stock price forecasting is trained by a new metaheuristic training algorithm, named bird mating optimizer (BMO). Effectiveness and efficiency of this algorithmis compared with NN trained by Genetic Algorithm (GA) algorithm based on the average, median and standard deviation of the Mean Square Error (MSE).The experimental results show that the BMO lends itself very well to forecast of stock price.
Keywords: Learning neural network, Bird Mating Optimizer algorithm (BMO), Stock price forecasting.

INTRODUCTION

Stock price forecasting is an important issue in financial markets. This issue has attracted many researchers and experts during last decades. Stock price forecasting in financial markets is an important variable in field of investment decisions, bonds pricing and risk management. Because of this fact that the investors of stock markets are always interested in knowing about next trend of prices, they attempt to reach and employ the ways of stock price forecasting in order to increase the profits of their investment. So, it is essential to identify proper ways and scientific methods of determining of future stock price [1].

The viewpoint of training in order to solve the problem and recognition of complicated patterns are really challenging for researchers. NNs are the simple computational tools for modeling with data structures. NNs employ the training data to learn patterns hidden inside the data and use them to get outputs and different results [2]. Application of NN in economic and econometric, has been started with White's studies in the fields of financial markets and IBM Company since last years of eightieth decade [3].Testing of efficient market hypothesis was the main aim of White. After White, different studies in field of NN were done successfully. Success of NN in area of financial economic catches the attention of experts of macroeconomic and econometric. Using NNs in order to forecast, has been started since 90th decade.

Afolabi and Oludeh [4] forecast by employing the hybrid models which consist of Self Organizing Map (SOM) and Multi-Layer Perceptron (MLP). Results show that the performance of hybrid NN is better than two other models for forecasting of stock price of Lucent Company [5]. Hanafizadeh and Jafari show summary of studies about stock price forecasting with FNN based on specified parameters such as aim of study, NN architecture, training algorithm, activation function, criterion of forecasting accuracy and the number of hidden layers. In all of these studies, just one type of NNs named Feed Forward Neural Network (FNN) is used. Also, they show that forecasting with the hybrid of FNN and SOM has better accuracy than forecasting with FNN [5]. These works use different versions of Back Propagation (BP) to train NN model [4, 2, 5, 1].

Recently, with advances in computer and artificial intelligent, different efforts in field of stock price forecasting were done. Artificial intelligent techniques, such as NNs, GA algorithm and fuzzy logic have successful results in field of solving the complicated problems [2].

High ability of predicting with NN and importance of prediction in all fields and all times, make researchers to search methods of improving the accuracy of predicting with NN.

Accuracy level of a NN greatly depends on its weight and bias values. In a NN, weight and bias values depend on the kind of training algorithm. NN training process is an optimization task with the aim of finding a set of weights to minimize an error measure. Owing to this fact that search space is high dimensional and multimodal which is usually polluted by noises and missing data, the problem of NN training needs powerful optimization techniques. Often, gradient descent algorithms, such as BP, are used for solving the problem [8]. Gradient based algorithms are the most frequent training algorithms with several drawbacks [7]. The gradient-based algorithms are susceptible to be converged at local optima, because they are local search methods that the final result depends strongly on the initial weights. If the initial weights are located near local optima, the algorithm would be stuck at them [8].

To tackle the complexity of NN training problem, metaheuristic optimization algorithms such as genetic algorithm (GA), particle swarm optimization (PSO) and ant colony optimization (ACO) have been highly proposed to search for the optimal weights of the network. In contrast with conventional methods, metaheuristic algorithms do not use any gradient information, and have more chance to avoid local optima by sampling simultaneously multiple regions of search space [8].

Since 2000, a lot of efforts related to NNs training algorithms have been done. Kaviani et al., train NN with PSO algorithm [9]. Ragers uses GA algorithm to calculate the weights of NN [10]. Also bayesian method is used for NN training [11]. Kulluk and Ozbakir present application of Self-adaptive Global Best Harmony Search (SGHS) algorithm for the supervised trainingof feed-forward neural networks (NNs) [12]. Piotrowski *et al.* perform detailed comparison of the performance of nature-inspired optimization methods and Levenberg–Marquardt (LM) algorithm in ANNs training, based on the case study of water temperature forecasting in a natural stream, namely Biala Tarnowska River in southern Poland [13].

Askarzadeh and Rezaadeh [6] present a novel metaheuristic algorithm, named bird mating optimizer (BMO). At first, they use it for modeling of proton exchange membrane fuel cell (PEMFC) system [6]. Then, the proposed algorithm is employed for NN training and compared with other algorithms. The results are as follows:

CNNE > BMOANN > COOP > GANetbest> SVM-best > CCSS = EDTs > OC1-best > MGNN

Also, this algorithm is usedto build an ANN-based model for proton exchange membrane fuel cell (PEMFC) system. Also, this model is trained with PSO and BP algorithms. BMOANN yields better result than the other ANNs [8].

Piotrowski shows a drawback of Differential Evolution algorithms, and clarifies why these methods usually perform poorer than classical Levenberg–Marquardt algorithm [14].

Yaghini et al. [7], propose the algorithm that merges the global ability of metaheuristics and the local greedy gradient based algorithm resulting in a superior hybrid method [7]. Mirjalili et al. [15] propose a hybrid of PSO and Gravitational Search Algorithm (GSA) to resolve slow searching speed in the last iterations [15].

In this article, a Neural Network model of the stock price forecasting is trained by the new metaheuristic training algorithm, named BMO. The rest of the paper is organized as follows: Section 2 presents a brief introduction to the concept of BMO. Section 3 discusses architecture of FNN using in this paper, the method of applying GA and BMO to FNNs as evolutionary training algorithms and parameter values. The experimental results are demonstrated in Section 4. Finally, Section 5 concludes the paper.

THEORY AND DEFINITIONS

Bird mating optimizer algorithm

The novel metaheuristic algorithm(BMO), is used for NN training by Askarzadeh and Rezazadeh [8]. In engineering optimization, decision variables are given values in the search space and a solution vector is made. The population of BMO algorithm is called a society and each individual in the society is called a bird. The society consists of four types of birds: “mg” birds (monogamous), “pg” birds (polygynous), “pa” birds (polyandrous), and“pr” birds(promiscuous), breeding in a d-dimensional search space, to find the optimum solution. Assume that we have a set of birds ina society indicated byλ. The birds of the society are categorized based on their fitness values so that $\lambda=\mu \cup \xi \cup \psi \cup \kappa$, where μ, κ, ψandξrepresent the set of “mg”, “pg”, “pa”,and “pr” birds, respectively. Each bird is shown by a vector$\vec{x}(\lambda)$=(x(λ,1), x(λ,2), ..., x(λ,d)). Any bird is a feasible solution ofthe problem with a fitness function represented by$fit(\vec{x}(\lambda))$.“Mg” and “pg” types have a great portion and “pa” and “pr” types have a low percentage of the society. As the algorithm progresses, the quality of the bird's society improves. Here, it's assumed that only one brood is created when a bird mates with other one(s). The society is then updated with the better birds. Termination criterion of algorithm indicated bygen_{max}. At each generation (iteration), the birds that have best fitness values, are chosen as "pa" birds (females). A predefined percentage of the other solutions (birds) with worst fitness are deleted from the society and replaced by new ones produced by using a chaotic sequence. The new birds are considered as "pr" birds. "Mg" birds are selected from remaining birds that have the best fitness. After choosing the "Mg" birds, the remaining birds are "pg" birds. "Mg" birds, "pg" birds and "pr" birds are the males of the society. "Mg" birds tend to mate with one female. The "mg" bird evaluates the quality of the females. It employs a probabilistic approach and selects one of them as his interesting female, and mates with her. Besides, each gene of the brood may be produced by mutation in the bird gene. The probability of mutation is controlled by a factor named mutation control factor, *mcf*, which varies between 0 and 1. This factor helps the algorithm maintains the diversity and avoids premature convergence. As a result, the resultant brood is produced byEq (1):

For j=1:d
If $r_1 < mcf$
x(brood,j)=x(μ,j)+w*r_2*(x(ef,j)-x(μ,j)) Else 1)
x(brood,j)=x(μ,j)+m_w*($r_3 - r_4$)*(u(j)-l(j))
End
End

where x(brood),x(μ), and x(ef)are, respectively, the produced brood, "mg" bird, and interesting female, d denotes the problem dimension, j is the variable index, w is a time-varying weight to adjust the importance of the female,r_1,r_2 , r_3 and$r_4$are normally distributed random numbers between 0 and 1,$m_w$denotes mutation weight, and u(j) and l(j) are the upper and lower bounds of variable jth, respectively. In order to select the interesting elite, roulette wheel approach is used. In this approach, as the quality of a bird increases, the probability of its selection increases, too. In roulette wheel approach, the selection probability of the bird kth from a group including m birds is defined by the following formula:

$$\mathrm{p_k} = \frac{1/\mathrm{fit}(\vec{x})}{\sum_{i=1}^{m} 1/\mathrm{fit}(\vec{x})} \quad (2)$$

Based on its selection probability, each candidate bird is devoted arrange between 0 and 1. The birds with better qualities have wider range than the others. Then, a random number is uniformly generated between 0 and 1. That range which includes the generated number is specified and the corresponding bird is selected as the interesting bird. Birds with better quality have more chance of being selected. "pg" birds tend to mate with several "pa" birds. By mating a "pg" bird with several females, only one brood is produced which its genes are a combination of the females' genes. After mating a "pg" bird with his interesting females, the produced brood is given as follows:

For j=1:d
If $r_1 < mcf$
x(brood,j)= x(κ,j)+w *$\sum_{i=1}^{n_{fe}} r_i$ * (x(ef_i,j)- x(κ,j))
Else (3)
x(brood,j)=x(κ,j)+m_w*($r_2 - r_3$)*(u(j)-l(j))
End
End

Where x(κ) and x(ef_i)are, respectively, the "pg" bird and ithelite female, n_{fe} denotes the number of elite females, and r_i are normally distributed random numbers between 0 and 1. A "pg" bird combines the information of solutions, selects "pa" bird(s), and produces just a new solution (brood).A "pg" bird selects a female by use of an annealingfunction with the following probability:

$$pr = exp(\frac{-\Delta f}{T}) \quad (4)$$

Where *pr* is the probability of selecting,Δf denotes the absolute differencebetween the objective functions (fitness functions) of the "pg" bird and "pa" one, and T is an adjustable parameter to control the probability. Then a random number between 0 and 1is generated and compared with the calculated probability. If it is less than the calculated probability, that "pa" bird is selected formatting. Otherwise, the selection of that female is failed.

In BMO, each "pa" bird tends to mate with several males which have the best fitness functions. These male birds are the best ones among "mg" birds. The "pa" bird evaluates the quality of the males and select her interesting males by employing a probabilistic approach, then mates with them. Each gene of the produced brood is obtained as follows:

For j=1:d
If $r_1 < mcf$
x(brood,j)= x(ψ,j)+w *$\sum_{i=1}^{n_{em}} r_i$ * (x(em_i,j)- x(ψ,j))
Else (5)
x(brood,j)=x(ψ,j)+m_w*($r_2 - r_3$)*(u(j)-l(j))
End
End

Where x(ψ) is the "pa" bird, x(em_i)is the ith male, andn_{em} denotes the number of interesting males. "Pa" birds use the annealing function to select the ir males, too. However, in order to increase the probability of raising a good brood a predefined percentage of "mg" birds with better qualities participate in this rituals. As previously mentioned, “pr” birds are produced by using a chaotic sequence. With different qualities, they attend during each generation and mate with their interesting females. The behavior of each “pr” bird is the same as that of “mg” bird. As a result, each gene of the resultant brood is given as follows:

For j=1:d
If $r_1 < mcf$
x(brood,j)=x(ξ,j)+w*r_2*(x(ef,j)-x(ξ,j))
Else (6)
x(brood,j)=x(ξ,j)+m_w*($r_3 - r_4$)*(u(j)-l(j))
End
End

Where x(ξ,j)denotes the “pr” bird. Using a chaotic sequence to produce new feasible solutions in the search space increases the capability of the algorithm to discover potential solutions in as yet untested regions of the space. At the initial generation, each “pr” bird is produced using Eq. (7) where z is chaos variable and its initial value is a random number between 0 and1 (not the points of 0.25, 0.50 and 0.75). At the next generation, the parameter z is firstly updated by the well-known Logistic map using Eq. (8) and then, the new “pr” bird is produced.
For j=1:d
x(ξ,j)= l(j) + z^{gen} *u(j)-l(j)) (7)
End

$$z^{gen+1} = 4 * z^{gen} * (1 - z^{gen}) \quad (8)$$

After mating, next step is replacement. In this step, fitness function of bird is compared with its brood. If the brood has better fitness function, it will put in the bird (parent) situation. Otherwise, the brood is abandoned and the bird stays in the society. The pseudo code of BMO algorithm have been represented in Fig. 1[6]:

Initialization:
Determine the society size, percentage of “mg”, “pg”, “pr”, and “pa” birds, maximum number of generations, and the other parameters
Do
Compute objective (fitness) function of the birds
Sort birds based on their objective function
Partition the society into males and females
Specify “mg”, “pg”, and “pa” birds
Remove the worst birds and generate “pr” birds based on the chaotic sequence
Compute objective function of the “pr” birds
For*i*= 1 **to** number of “mg” birds
Select interesting bird
Produce the brood based on Eq. (1)
Next*i*
For *i*= 1 **to** number of “pg” birds
Select interesting elite birds
Produce the brood based on Eq. (3)
Next*i*
For*I* = 1 **to** number of “pa” birds
Select interesting birds
Produce the brood based on Eq. (5)
Next*i*
For*i*= 1 **to** number of “pr” birds
Select interesting bird
Produce the brood based on Eq. (6)
Next*i*
Compute objective function of the broods
Perform replacement step
Update the parameters
Until termination criterion is met

Fig. 1. Pseudocode of BMO algorithm[8]

PROCESSES USED

NN architecture used in this study

First step in Neural Network (NN) training is determination of testing set and training set. Training set is used for training of NN [1].Then, in order to evaluating of NN performance, trained NN is tested by testing set.

Resultant accuracy is greatly related to the size of training set [1]. In this study, the data set is randomly partitioned into two sets: the training set with 70% of data set and the testing set with 30% of data set.

Before using dataset in NN, it should be normalized. Data normalizing means data preprocessing and data post processing. It makes NN have a better performance. Before Neural network training, preprocessing should be done. After training and achieving results, outputs should be altered to primitive status. This stage is called post processing. There are different ways for data normalizing [2].

The architecture of ANN which is used in this article is acquired from Makyan and Mousavi,2012 [1]. It is considered as follows:

Number of nodes in the input layer is 4. These are the Brent oil price, maximum price, minimum price, first (opening) price. Closing price is the output of network. Feed forward Neural Network (FNN) using in this study, has three layers. According to Makyan and Mousavi2012 [1], the number of hidden nodes is fourteen. But, in this paper, the number eleven for hidden layer nodes have shown the better fitness for stock price forecasting by NN. So, the architecture of NN is 4-11-1. Hidden units employ hyperbolict zangent as their activation function, while output units make use of linear function. If we want to use this model for time series prediction, we will have:

$$P_t = f(P_{max,t-1}, P_{min,t-1}, P_{open,t-1}, P_{oil,t-1}) \quad (9)$$

Where, P_t is the closing price at time "t", and it is defined as output of network. $P_{max,t-1}$, $P_{min,t-1}$, $P_{open,t-1}$, denote maximum, minimum and first (opening)stock price of "Oil Industry Investment Company" at time "t-1". $P_{oil,t-1}$, is the Brent oil price at time "t-1".

Fitness function

In this study, the fitness function is calculated as follows[15][18]:

Fig. 2 shows a FNN with three layers, where the number of input nodes is equal to n, the number of hidden nodes is equal to h, and the number of output nodes is m. In each epoch of learning, the output of each hidden node is calculated as follows:

$$f(s_j) = 1 \Big/ \left(1 + exp\left(-\left(\sum_{i=1}^{n} w_{ij} * x_i - \theta_j\right)\right)\right), j = 1,2, \dots, h \quad (10)$$

Where $s_j = \sum_{i=1}^{n} w_{ij} * x_i - \theta_j$, and n is the number of the input nodes. w_{ij}, is the connection weight from the ith node in the input layer to the jth node in the hidden layer, θ_j is the bias (threshold) of the jth hidden node, and x_i is the ith input.

After calculating outputs of the hidden nodes, the final output can be defined as follows:

$$o_k = \sum_{i=1}^{h} w_{kj} * f(s_i) - \theta_k \quad , \ k = 1,,2, \dots, m \quad (11)$$

Where, w_{kj} is the connection weight from the jth hidden node to the kth output node and θ_k is the bias (threshold) of the kth output node.

Finally, the learning error, E (fitness function), is calculated as follows:

$$E_k = \sum_{i=1}^{m} (o_i^k - y_i^k)^2 \ E = \sum_{k=1}^{q} \frac{E_k}{q} \quad (12)$$

Where q is the number of training samples, O_i^k is the desired output of the ith output unit when the kth training sample is used, and y_i^k is the actual output of the ith output unit when the kth training sample is used.

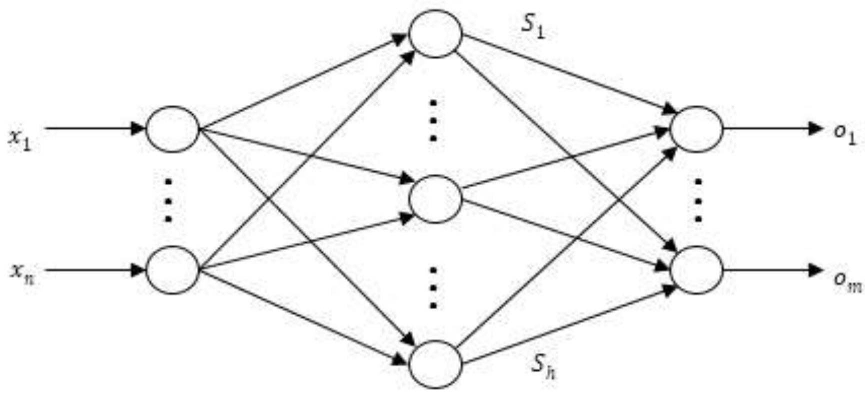

Fig. 2.Architecture of two-layer FNNs[15]

Therefore, the fitness function of the ith training sample can be defined as follow[15]:

$$Fitness(x_i) = E(x_i) \quad (13)$$

Encoding strategy

After defining the fitness function, choosing an encoding strategy is the next stage. It means that weights and biases of the NN would be represented for every agent in FNNGA and FNNBMO. According to [15], there are three methods for encoding that are the vector, matrix, and binary encoding methods.

In vector encoding, every agent is encoded as a vector. To train a FNN, each agent represents all the weights and biases of the FNNs structure. In matrix encoding, every agent is encoded as a matrix. In binary encoding, agents are encoded as strings of binary bits. In the first strategy, the encoding phase is easy, but the decoding process (decoding particles' vectors to a weights and biases matrix) is complicated. This method is often used in the function optimization field. In the second strategy, the decoding stage is easy but the encoding is difficult for neural networks with complex structures. This method is very suitable for the training processes of neural networks because the encoding strategy makes it easy to execute decoding for neural networks. In the third strategy, we need to represent particles' variables in binary form. The length of each particle will increase when the structure becomes more complex. Therefore, the process of decoding and encoding becomes very complicated [15]. An example of this encoding strategy for the FNN of Fig. 3 is provided as follows:

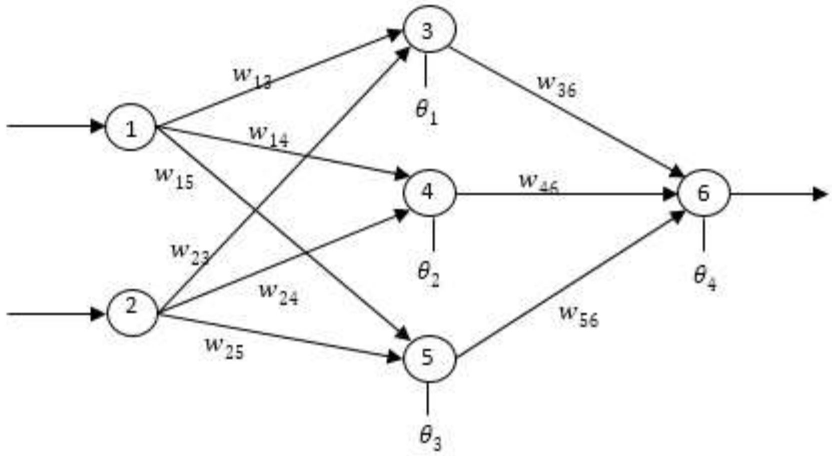

Fig. 3. FNN with a 2-3-1 structure[15]

Bird(:,:,i)=[W_1 , B_1 , W'_2 , B_2]

$$W_1 = \begin{bmatrix} w_{13} & w_{23} \\ w_{14} & w_{24} \\ w_{15} & w_{25} \end{bmatrix}, B_1 = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}, W'_2 = \begin{bmatrix} w_{36} \\ w_{46} \\ w_{56} \end{bmatrix}, B_2 = [\theta_4] \quad (14)$$

Where W_1 is the hidden layer weight matrix, B_1 is the hidden layer bias matrix, W'_2 is the output layer weight matrix, W'_2 is the transpose ofW_2, and$B_2$is the output layer bias matrix. In this article, the matrix encoding strategy has been used because we are dealing with training FNNs. Connection weights are adjusted by our BMO algorithm as represented in Fig.4.

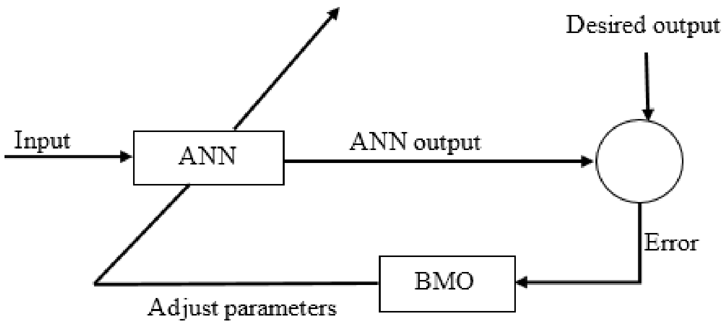

Fig. 4. Schematic diagram of BMO-based ANN[8]

Brent oil price can be acquired from the Eranico Website. Maximum price, minimum price, first (opening) price of "Oil Industry Investment Company" have been extracted from *Tehran* Securities *Exchange* Technology Management Co.. Time period in this study is from seventh September 2013 to third September 2014.Data has been collected and stored in EXCEL environment.

MATLAB environment is implemented to code FNNGA and FNNBMO. Due to the fact that the nature of metaheuristic algorithms is stochastic, the results obtained in one attempt will differ from the results obtained in another attempt. Therefore, the performance analysis must be statistically based.

Assumptions and parameter values

In the experiments, parameter setting of FNNBMO and FNNGA algorithms is as follows:

For FNNGA, percentages of reproduction and crossover are 15% and 50%, respectively. It is assumed that every chromosome is randomly initialized. *Parent selection* strategy using in this algorithm is Imperialist Competitive Algorithm (ICA).

Parameter setting of FNNBMO algorithm is according to the Askarzadeh and Rezazadeh [8]; "Mg", "pg","pa", and "pr" birds make 50%, 40%, 5%, and 5% of the society, respectively; T, w, and$m_w$are defined as decreasing linear functions where T_{max} = 300,T_{min} = 50, w_{max} = 2.5, w_{min} = 0.5, $m_{w,max}$ = 0.01, and $m_{w,min}$ = 0.0001; mcf is selected 0.9.

Minimum and maximum values of variables in each algorithm are set to -1 and 1, respectively. It should be noted that the parameter setting is based on trial and error and no attempt has made to optimize it. For two algorithms, the society size is set to 100 and maximum number of generations (epochs) is set to 50.Results of FNNGA and FNNBMO are compared based on average, median and standard deviation of the Mean Square Error (MSE) for training set and testing set over 35 independent runs. Termination criterion of NN training is maximum epochs.

DATA AND RESULTS

In this section, GA and BMO algorithms are used for training of FNN model of stock price forecasting and abilities of FNNGA and FNNBMO in training FNNs are compared.

The statistical performance of FNNBMO and FNNGA over 35 runs in order to solve the stock price forecasting problem for training set has been summarized in Table1. The results obtained for testing set are shown in Table 2. The best average, median or best values are bolded.

As can be inferred from Table 1, Average and median of MSE for all training set show promising results for FNNBMO.

Table 2 shows that the values of median and average for MSE of testing set for FNNBMO is better than FNNGA.

Table1:Average, median, standard deviation, and best of MSE for all training set over 35 independent runs for FNNGA, FNNBMO in order to modelling of stock price forecasting.

Min	Max	Average MSE	Std dev MSE	Median MSE	Algorithm
0.0208	0.0548	0.0399	0.0088	0.0411	**FNNGA**
0.0093	**0.0488**	**0.0228**	0.0088	**0.0222**	**FNNBMO**

Table 2: Average, median, standard deviation, and best of MSE for all testing set over 35 independent runs for FNNGA, FNNBMO in order to modelling of stock price forecasting.

Min	Max	Average MSE	Std dev MSE	Median MSE	Algorithm
0.0152	**0.0828**	0.0426	**0.0142**	0.0413	FNNGA
0.0072	0.0850	**0.0303**	0.0214	**0.0212**	FNNBMO

CONCLUSIONS

In this paper, impact of two metaheuristic algorithm on stock price forecasting NN model is investigated and FNNBMO shows better results than FNNGA.

Aspreviously mentioned, from 2007 to now, new and different efforts have been done in area of NN training algorithms. Examination of accuracy of these algorithms for forecasting, for example stock price forecasting, or hybrid of these algorithms in order to achieve to a new algorithm which have better convergence speed and can escape from local optimum traps, can be the new and suitable subjects for searching.

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