Ç.Ü. Sosyal Bilimler Enstitüsü Dergisi, Cilt 24, Sayı 1, 2018, Sayfa 63-78

ASSESSMENT OF HYBRID ARTIFICIAL NEURAL NETWORKS AND METAHEURISTICS FOR STOCK MARKET FORECASTING

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ABSTRACT

Even though a number of stock market forecasting studies are done related with hybrid Artificial Neural Network (ANN) models, no standard procedures are available in the literature for each stock. This causes a growing interest in using metaheuristic for the designing of appropriate ANN architecture. Therefore, this study used ten different metaheuristics including Ant Lion Optimization (ALO), Bird Swarm Optimization (BSA), Differential Evolution (DE), Grey Wolf Optimization (GWO), Moth-Flame Optimization (MFO), Multi-verse Optimizer (MVO), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Weighted Superposition Attraction (WSA), and Firefly Algorithm (FFLY) to improve the performance of the ANN models. Proposed hybrid ANN models lead to significant opportunities to forecast stock market more effectively. Based upon results of performance measures, we also expect hybrid ANN models provide a remarkable solution for other forecasting problems.
Keywords: Stock Market Forecasting, Metaheuristics, Artificial Neural Network

MELEZ YAPAY SİNİR AĞLARI VE METASEZGİSELLERİN BORSA TAHMİNİNDE DEĞERLENDİRİLMESİ

ÖZ
Melez Yapay Sinir Ağı (ANN) modelleri kullanılarak birçok borsa tahmini çalışması yapılmış olmasına rağmen, literatürde her hisse senedi için standart bir prosedür bulunmamaktadır. Bu durum uygun ANN yapısını oluşturmak için metasezgisel kullanılması konusuna olan ilginin artmasına neden olmaktadır. Bu nedenle, ANN modellerinin performansını iyileştirmek için bu çalışmada Karınca Aslanı Optimizasyonu (ALO), Kuş Sürüsü Optimizasyonu (BSA), Diferansiyel Gelişim (DE), Gri Kurt Optimizasyonu (GWO), Güve Optimizasyonu (MFO), Çoklu Evren Optimizasyonu (MVO), Parçacık Sürüsü Optimizasyonu (PSO), Tavlama Benzetimi

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Araştırma, Gönderim Tarihi: 24.02.2018 Kabul Tarihi:30.03.2018

(SA), Ağırlıklı Süperpozisyon Çekimi (WSA) ve Ateş Böceği Algoritması (FFLY)'nı içeren on farklı metasezgisel kullanılmıştır. Tasarlanan melez ANN modeli borsayı daha etkili bir şekilde tahmin etmek için önemli fırsatlar sunmaktadır. Ayrıca, performans ölçütlerinin sonuçları dikkate alındığında, melez ANN modelinin diğer tahminleme problemlerinde de kayda değer sonuçlar vereceği beklenmektedir.
Anahtar Sözcükler: Borsa Tahmini, Metasezgiseller, Yapay Sinir Ağı

Introduction

Finding exact solutions is intractable for many problems encountered in the stock market. Therefore, researchers and individual investors are generally satisfied with solutions that are obtained by metaheuristics. Unlike exact solution methods, metaheuristics do not guarantee the global optimal solutions or even bounded solutions. However, metaheuristics can provide acceptable solutions in a reasonable time for solving large and complex problems (Talbi, 2009). Therefore, metaheuristic methods have received more and more popularity during the past two decades. Although each metaheuristic method has a different architecture, almost all metaheuristics have some common characteristics. Firstly, they are inspired by nature. They use stochastic components and have some parameters that require to be fitted to the specific problem at hand. Finally, they do not use the Hessian or gradient matrix of the objective function (Boussaïd et al., 2013).

In this study, metaheuristics including ALO, BSA, DE, GWO, MFO, MVO, PSO, SA, WSA, and FFLY are used to improve the performance of the ANN. Thus, this study draws attention to the integration of ANN model with metaheuristics in stock market forecasting. Well-created ANN models can provide an attractive alternative method for stock market forecasting. Especially, several distinguishing properties of ANN models make them attractive and valuable for a forecasting task. Firstly, they are data-driven self-adaptive methods. Second, ANN models can generalize. Third, they are universal functional approximators. Lastly, ANN models are nonlinear (Zhang et al., 1998). On the other hand, the architecture of ANN embodies much uncertainty. No exact values are still available for parameters of ANN and it is not obvious to determine optimal values of parameters for each specific problem. Hence, parameters tuning have a great effect on the efficiency and effectiveness of the ANN models. Appropriate parameter combination can allow a larger robustness and flexibility for problem-solving.

The remainder of this paper is created as follows. Section 2 summarizes the studies related to stock market forecasting. The main structure of the hybrid ANN models is described in Section 3. In Section 4, a detailed analysis of proposed models is given. Section 5 is devoted to conclusions.

Literature Summary

The stock market handles various tasks. It provides the investors' protection and transactions' transparency. Furthermore, stock market ensures the optimal frame for the market transactions and the division and the cover of the risk, among others. The prices are harmonized for the entire economy and the correct price is generated (Rusu and Rusu, 2003). For these reasons, the stock market can be considered as primary indicators of a country's economic strength and development. Furthermore, business investment and company profitability can be increased by controlling the behavior of the stock markets (Preethi and Santhi, 2012). Therefore, companies use various types of forecasting methods to evaluate possible outcomes for the stock market (Hadavandi et al., 2010). In general, complexity, assumptions, and requirements change according to these forecasting methods. In this case, the determination of parameter values is of extreme importance. Each method gives satisfying results under well-created circumstances (Rusu and Rusu, 2003).

There have been a number of studies in the ANN literature which demonstrate that ANN is one of the most efficient methods for stock market forecasting. However, ANN should be improved to promote forecasting performance in the stock market. In literature, researchers use various methods to improve the ANN structure. Briza and Naval (2011) described the multi-objective optimization problem and the PSO algorithm to use in the development of the stock trading system. Also, nondominated sorting genetic algorithm is utilized to optimize the weights of the indicators and compared with the results of the proposed system. Nhu et al. (2013) used the FFLY to train the parameters of ANFIS. The proposed method includes three parts that are pre-processing, processing and post-processing. In the first part, the training, validation and testing data are determined; the operating parameters are defined; the encoding strategy is determined. In the second part, the population of fireflies is initialized and the solution of each firefly is evaluated. The final part includes result and visualization. To predict stock market price, Kazem et al. (2013) proposed a chaotic FFLY to optimize the support vector regression hyperparameters. In the study, the reconstructed phase space matrix is also fed into the ANN and ANFIS models to compare the results with the proposed model. Xiong et al. (2014) focus on extending the multi-output support vector regression (MSVR) whose generalization ability depends on adequately setting parameters such as the penalty coefficient and kernel parameters. The FFLY-based approach is proposed to appropriately determine the parameters of MSVR for interval-valued stock price index forecasting. Detailed analysis of various optimization methods on stock market forecasting can be found in Das et al. (2017).

Rather et al. (2017) observed that the field of hybrid forecasting has received lots of attention from researchers so as to form a robust model. At this point, ANN proves successful results in stock market forecasting for different stocks. Atsalakis and Valavanis (2009) presented the applications of intelligent methods to forecast stock market indexes and stock prices. Neural and neuro-fuzzy methods are classified considering input data, forecasting methodology, performance evaluation and performance measures. Guresen et al. (2011) compared the ANN models to among themselves. In the study, the performance of multi-layer perceptron, dynamic artificial neural network, and the hybrid ANN that uses generalized autoregressive conditional heteroscedasticity are compared in forecasting time series used in market values.

Chen et al. (2013) integrated traditional design of experiment and back propagation neural network to improve the performance of stock price forecasting. Design of experiment provides a systematic research method for parameter design optimization. Qiu et al. (2016) implemented the fuzzy surfaces in the selection of optimal input variables. In the study, the optimal set of initial weights and biases is determined by means of GA or SA to increase the accuracy of an ANN. Hassanin et al. (2016) used the GWO to provide good initial solutions to the ANN. The results showed that GWO based ANN outperforms both GA based ANN and PSO based ANN. Faris et al. (2016) presented that MVO shows very competitive optimization results of the set of weights and biases for multi-layer perceptron networks. In addition, GA, PSO, DE, FFLY and Cuckoo Search are used to compare the performance of the proposed method.

Obviously, forecasting is an important task in stock market. However, it is a general accepted wisdom that any single forecasting method is available for stock market forecasting. Also, making a decision can be a more difficult than producing forecasting results. Therefore, this paper seeks to further our understanding of stock market and provide a comprehensive review of the available literature. In addition, the main aims of this study are summarized as follows:

● Using different hybrid ANN models in stock market forecasting. To the best of our knowledge, no systematic papers are devoted to a study of ALO-ANN, BSA-ANN, GWO-ANN, MFO-ANN, MVO-ANN, and WSA-ANN for optimizing the parameters of ANN in stock market forecasting.

● Selecting the relevant input variables for ANN models using ALO, BSA, DE, GWO, MFO, MVO, PSO, SA, WSA, and FFLY,

● Determining the proper number of hidden neurons for ANN models using ALO, BSA, DE, GWO, MFO, MVO, PSO, SA, WSA, and FFLY,

● Determining the appropriate activation function type for ten different hybrid ANN models,

● Comparing the forecasting performance of the models, different performance measures namely mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), mean absolute relative error (MARE), mean squared relative error (MSRE), root mean squared relative error (RMSRE), mean absolute percent error (MAPE), mean squared percentage error (MSPE), and root mean squared percentage error (RMSPE), and return from investment (Return), are considered.

Proposed Methods

Metaheuristics Optimization

In this study, following metaheuristics are used to systematically assign the optimal setting of parameters in ANN models.

Weighted Superposition Attraction

WSA is a new swarm based optimization algorithm in which superposition and attracted movement of agents are used as two basic mechanisms. At initialization phase, pre-defined numbers of feasible solutions are generated in WSA. In addition, some parameter values are set during its search. Then, the discovery of WSA is started on the solution space by means of its special search mechanism. Details about the WSA can be found in Baykasoğlu and Akpinar (2015).

Ant Lion Optimizer

Mirjalili (2015) presented the ALO that mimics the hunting mechanism of antlions in nature. In ALO, the first population of ants and antlions is randomly initialized. ALO is based on the interaction between ants and antlions. The fitness values of ants and antlions are calculated. The best antlions are determined. Until termination creation is satisfied, an antlion is selected using roulette wheel. Then, a random walk is created. The position of ant is updated. The performance of best antlion obtained in each iteration is compared with elite antlion. After that, elite is updated if an antlion becomes fitter than the elite. Details about the ALO can be found in Mirjalili (2015).

Bird swarm algorithm

Meng et al. (2016) proposed the BSA which is based on the swarm intelligence extracted from the social interactions and social behaviours in bird swarms. BSA mimics the birds' foraging behaviour, vigilance behavior, and flight behaviour. In BSA, related parameters such as the maximum number of iteration and the frequency of birds' flight behaviours are first defined and the population is initialized. The fitness value of individuals is evaluated and the best solution is found. Finally, the individual with the best objective function value in the population is determined. Details about the BSA can be found in Meng et al. (2016).

Grey Wolf Optimizer

Mirjalili et al. (2014) presented the GWO inspired by grey wolves. It mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. To simulate the leadership hierarchy, four types of grey wolves such as alpha, beta, delta, and omega are used. Furthermore, the three main steps of hunting, searching for prey, encircling prey, and attacking prey, are applied. In GWO algorithm, a random population of grey wolves is created in the search process. The probable position of the prey is estimated by alpha, beta, and delta wolves over the course of iterations. Each candidate solution updates its distance from the prey. The parameters are defined to emphasize exploration and exploitation. Finally, the GWO algorithm is terminated by the satisfaction of an end criterion.

Moth-flame optimization algorithm

Mirjalili (2015) presented the MFO algorithm. The main inspiration of this optimizer is the navigation method of moths in nature called transverse orientation. In fact, the spiral convergence toward artificial lights was the main inspiration of the MFO algorithm. The algorithm was equipped with several operators to explore and exploit the search spaces. In MFO algorithm, the population of moths is implemented to perform optimization. Moth positions are updated according to the flame. These serve as guidance for the moths. Details can be found in Mei et al. (2017).

Multi-Verse Optimizer

Mirjalili et al. (2016) proposed the MVO that is inspired by the theory of multi-verse in physics. The main inspirations of MVO are based on three concepts of the multiverse theory: white hole, black hole, and wormhole. To perform exploration, exploitation, and local search, these three concepts are developed. In the optimization process, a set of random universes is created. In each iteration, objects in the universes with high inflation rates tend to move to the universes with low inflation rates via black/white holes. At the same time, every single universe faces random teleportations in its objects through wormholes towards the best universe. Finally, the MVO algorithm is terminated by the satisfaction of an end criterion.

Firefly algorithm

Yang (2010) presented the FFLY that includes two important issues: the variation of light intensity and formulation of the attractiveness. In the study, some of the flashing characteristics of fireflies are idealized to develop firefly-inspired algorithms. They used following rules: (1) all fireflies are unisex, (2) attractiveness is proportional to their brightness, (3) the brightness of a firefly is influenced or defined by the landscape of the objective function. Details can be found in Yang (2010).

Differential Evolution

DE algorithm resembles the structure of GA. They use similar operators which are crossover, mutation, and selection. To construct better solutions, GA relies on crossover while DE relies on mutation operation. Details can be found in Abdul-Kader and Salam (2012).

Particle Swarm Optimization

PSO is derived from the behavior of social groups like bird flocks or fish swarms. In PSO, position, velocity, personal best position, and neighborhood best position are used to characterize each individual that is also called particle. Fitness values are used to evaluate individuals. Then, velocities and positions are updated. These steps are repeated until satisfactory solution has been found. Details can be found in Abdul-Kader and Salam (2012).

Simulated Annealing

The main inspiration of this optimizer is the ‘‘annealing” process used in the metallurgical industry. The optimization procedure of SA searches for a (near) global minimum mimicking the slow cooling procedure in the physical annealing process. Random initial solution is used to start the process of SA. In each iteration, a new solution is taken from the predefined neighborhood of the current solution. The value of objective function is compared to improve the solution. If the objective function value of the new solution is better, the new solution becomes the current solution. Details can be found in Yu et al. (2010).

Hybrid ANN models

In order to improve the forecasting accuracy of stock market, it is necessary to closely determine the characteristics of ANN models. In this study, three elements that comprise the ANN’s architecture are taken into account by propose. These elements:

- The input variables
- The number of neurons in hidden layers
- The type of the activation function

The determination of parameter values is basically problem-dependent for these elements. Thus, it is not possible to theoretically determine exact value of parameters for each problem. The improper parameters values in ANN’s architecture exhibit poor generalization and may be insufficient to examine the solution. Therefore, the objective is to find the relevant input variables (technical indicators), the number of neurons in hidden layers, and the type of the activation function by means of ten different metaheuristics including ALO, BSA, DE, GWO, MFO, MVO, PSO, SA, WSA and FFLY. The block diagram of proposed hybrid models is given in Figure 1.

Testing of the models is made with Ford Motor Company that is selected among the S&P 500 companies. Detailed information about the dataset is given in Table 1. To ensure comparability between different metaheuristics, an initial population is created, and all of the metaheuristics are started optimization with this initial population. Also, random number stream is returned to its original state before running any model.

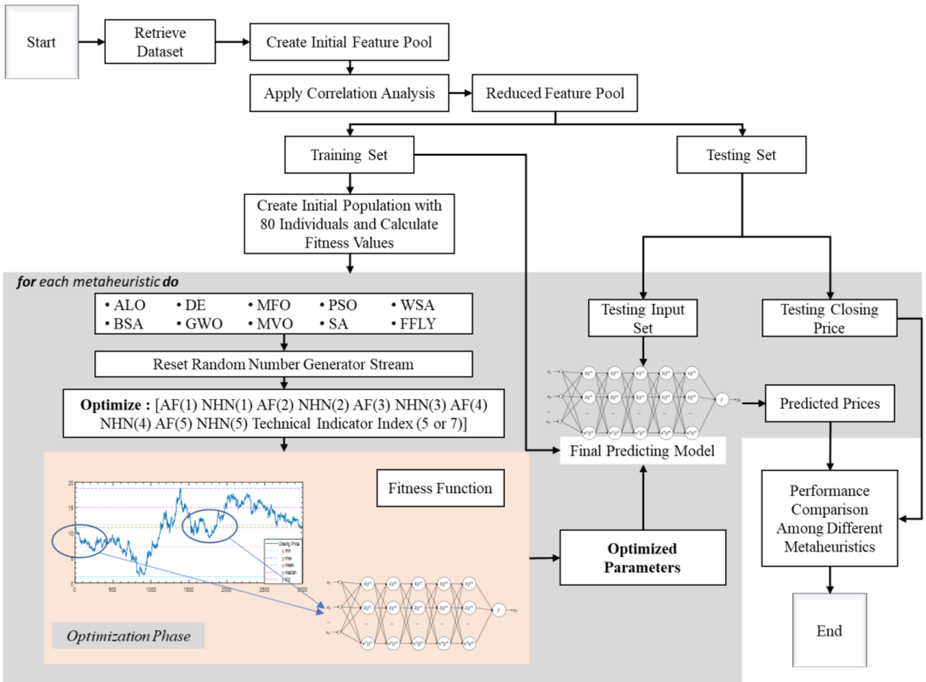

Figure 1: The proposed hybrid models

Population size is fixed at 80 and number of iteration is fixed at 100 for each forecasting model. All metaheuristics tried to minimize the same fitness function. The training set is divided into 10 equal sub-parts with 300 trading days in each. The first 240 observations are used for training the model, and the last 60 observations are used for out-of-sampling performance measurement (80% training and 20% testing).

Table 1: Descriptive statistics of the dataset

	Training Set	**Testing Set**
Minimum ($)	1.26	10.56
Maximum ($)	18.79	11.83
Mean ($)	11.0993	11.1445
Median ($)	11.5050	11.15
Standard Deviation	3.8914	0.3196
Skewness	-0.3169	0.2049
Kurtosis	2.3813	2.2809
Number of Price Increase (trading day)	1529	36
Number of Price Decrease (trading day)	1471	24
Starting Date	18 July 2005	16 June 2017
Ending Date	15 June 2017	11 September 2017
Number of Observations	3000 trading days	60 trading days

Training model is created with first sub-part. The trained model is tested with following 4 sub-parts. Another training model is created with fifth sub-part. The model is tested with following 4 sub-parts. Finally, mean MAPE is calculated with overall eight sub-parts.

Table 2: Initial feature pool

Index	Feature Name
1	Accumulation / Distribution Oscillator
2	Chaikin Oscillator
3	Moving Average Convergence/Divergence (MACD)
4	9-Day Moving Average of (MACD)
5	Acceleration – Opening Price
6	Acceleration – High Price
7	Acceleration – Low Price
8	Acceleration – Close Price
9	Momentum – Opening Price
10	Momentum – High Price
11	Momentum – Low Price
12	Momentum – Close Price
13	Chaikin Volatility
14	Fast Stochastic %K
15	Fast Stochastic %D
16	Slow Stochastic %K
17	Slow Stochastic %D
18	William's %R
19	Negative Volume Index
20	Positive Volume Index
21	Relative Strength Index
22	Accumulation / Distribution Line
23	Bollinger – Middle Band
24	Bollinger – Upper Band
25	Bollinger – Lower Band
26	Highest High
27	Lowest Low
28	Median Price
29	On Balance Volume
30	Price Rate of Change
31	Price and Volume Trend
32	Typical Price
33	Volume Rate of Change
34	Weighted Close
35	William Accumulation / Distribution
36-55	From Close Price (t-1) to Close Price (t-20), respectively
56-75	From Adjusted Close Price (t-1) to Adjusted Close Price (t-20), respectively
76-95	From Highest Price (t-1) to Highest Price (t-20), respectively
96-115	From Lowest Price (t-1) to Lowest Price (t-20), respectively
116-135	From Opening Price (t-1) to Opening Price (t-20), respectively
136-155	From Volume (t-1) to Volume (t-20), respectively
156-175	Simple Moving Average of Closing Price with Degree (1) to (20), respectively
176-195	Exponential Moving Average of Closing Price with Degree (1) to (20), respectively
196-215	Triangular Moving Average of Closing Price with Degree (1) to (20), respectively

There are 215 variables in initial feature pool (Table 2). Initial feature pool is analyzed considering the correlation analysis that is applied to see the degree of relation between features. Correlation heat map is also used to understand the relationship between technical indicators. At this point, heat map helps to explore and interpret the results effectively Perez-Llamas and Lopez-Bigas (2011).

Table 3: Reduced feature pool

Index	Indicator Name
1	Accumulation / Distribution Oscillator
2	Chaikin Oscillator
3	Moving Average Convergance/Divergance
4	Acceleration – Opening Price
5	Momentum – Opening Price
6	Chaikin Volatility
7	Fast Stochastic %K
8	Negative Volume Index
9	Positive Volume Index
10	Relative Strength Index
11	Accumulation / Distribution Line
12	Bollinger – Middle Band
13	On Balance Volume
14	Price Rate of Change
15	Volume rate of change
16	William Accumulation / Distribution
17-36	From Volume t – 1 to Volume t – 20

Sixteen technical indicators and twenty historical volume data are determined from initial feature pool. Thus, reduced feature pool is created as seen in Table 3. To create hybrid ANN models, five inputs or seven inputs are then selected separately from reduced feature pool.

Table 4: The activation function types of ANN

Index	Activation Functions
1	Tangent Sigmoid Activation Function
2	Elliot Sigmoid Activation Function
3	Hard Limit Activation Function
4	Log Sigmoid Activation Function
5	Radial Basis Activation Function
6	Pure Linear Activation Function
7	Normalized Radial Basis Activation Function
8	Soft Max Activation Function
9	Triangular Basis Activation Function
10	Net Inverse Activation Function

The activation function type of ANN models is selected from ten different activation function types that are seen in Table 4. The Levenberg–Marquardt (LM) algorithm has been used to train the ANN with optimum network parameters. The details about the LM algorithm can be found in Göçken et al. (2016). In this study, five hidden layers are used to create ANN models.

Results and Discussion

Many studies showed that non-linearity exists in the stock markets and that ANN can be effectively used to solve this problem. However, ANN model is characterized by its selected parameters such as the input variables, the number of neurons in hidden layers, and the type of the activation function. The analysis of literature related with ANN and stock market forecasting showed that the selection of input variable(s) is one of the most important problems. Especially, the determination of the most relevant technical indicator(s) is the critical one. In addition, we determined that the effect of the activation function is generally not taken into account. Sigmoid and linear activation functions are often used but the performance of the other activation function is generally not evaluated for forecasting problem. However, in addition to optimization of the input variables and the number of neurons, the optimization of the type of the activation function is also considered. Selected relevant technical indicators, activation function type and the number of hidden neurons are given in Table 5. Each model has a different configuration of ANN. To compare the forecasting performance of proposed ANN models, MAE, MSE, RMSE, MARE, MSRE, RMSRE, MAPE, MSPE, and RMSPE are considered. The formulation of these performance measures can be found in Göçken et al. (2016). One of the most commonly used performance measure is MSE. In addition, MAE, MAPE, and RMSE are widely used to evaluate the stock market forecasting. Performance measures are significantly important to evaluate the forecasting model. Therefore, different measures are considered to increase the understandability of the forecasting capability of metaheuristics based ANN models.

According to the values of MAE and RMSE for five variables, the best hybrid ANN model is FFLY-ANN while the worst model is ALO-ANN. For seven variables, the best model is PSO-ANN while DE-ANN is the worst one according to the values of MAE and RMSE. Note that the smaller difference between RMSE and MAE means the smaller variance in the individual errors of the sample Göçken et al. (2017). In this study, the difference between RMSE and MAE is quite small.

DE-ANN, MFO-ANN, MVO-ANN, PSO-ANN, and FFLY-ANN give the best values of MSE while ALO-ANN gives the worst MSE values for five variables. BSA-ANN, MFO-ANN, PSO-ANN, and SA-ANN give the best values of MSE while DE-ANN gives the worst MSE values for seven variables.

According to the values of MSRE for five variables, the best hybrid ANN model is DE-ANN, PSO-ANN, and FFLY-ANN while the worst model is ALO-ANN. For seven variables, the best models are MFO-ANN, PSO-ANN, and SA-ANN while DE-ANN model is the worst one according to the MSRE values. FFLY-ANN model gives the best values of MARE, RMSRE, MAPE, MSPE, and RMSPE while ALO-ANN gives the worst values of MARE, RMSRE, MAPE, MSPE, and RMSPE for five variables. PSO-ANN gives the best values of MARE, RMSRE, MAPE, MSPE, and RMSPE while DE-ANN gives the worst values MARE, RMSRE, MAPE, MSPE, and RMSPE for seven variables.

Table 5: Optimized parameter values for proposed hybrid ANN models

NIV*	TM*	Optimized parameters																
		1. layer		2. layer		3. layer		4. layer		5. layer		Selected technical indicators						
		AF*	NHN*	AF	NHN	AF	NHN	AF	NHN	AF	NHN							
5 variables	ALO-ANN	4	2	6	6	1	1	5	1	8	8	2	5	8	9	23	-	-
	BSA-ANN	4	9	8	20	2	13	6	15	5	11	2	5	12	19	35	-	-
	DE-ANN	6	5	5	1	8	4	7	17	6	14	12	14	25	26	36	-	-
	GWO-ANN	8	11	4	8	6	10	1	14	2	13	5	7	8	9	12	-	-
	MFO-ANN	1	1	8	19	8	20	7	13	1	17	1	10	12	15	35	-	-
	MVO-ANN	8	18	5	18	4	19	8	17	6	6	1	12	19	20	34	-	-
	PSO-ANN	1	1	8	16	6	15	4	18	1	19	1	3	12	14	32	-	-
	SA-ANN	3	6	2	5	9	1	9	1	1	5	12	17	23	26	30	-	-
	WSA-ANN	4	9	8	20	2	13	6	15	5	11	2	5	12	19	35	-	-
	FFLY-ANN	4	10	4	11	4	10	5	10	4	12	12	14	18	22	28	-	-
7 variables	ALO-ANN	4	9	6	8	2	15	8	3	2	7	8	9	12	14	20	28	30
	BSA-ANN	8	9	8	18	8	19	8	7	10	18	3	5	12	15	21	26	36
	DE-ANN	7	2	8	20	5	11	5	20	1	14	1	2	12	26	28	32	36
	GWO-ANN	1	1	4	1	8	11	8	7	1	10	3	5	12	15	19	26	31
	MFO-ANN	8	6	8	7	8	20	2	20	1	20	1	4	7	12	14	20	33
	MVO-ANN	1	1	6	2	7	2	5	18	6	5	4	5	9	10	12	18	32
	PSO-ANN	6	8	2	1	1	4	4	13	6	13	7	12	14	17	18	21	28
	SA-ANN	7	6	6	10	8	8	5	6	7	16	2	6	11	12	15	18	25
	WSA-ANN	5	1	1	7	8	14	5	15	4	17	7	8	13	15	18	25	34
	FFLY-ANN	3	8	5	11	5	11	6	10	7	13	7	9	12	18	22	25	29

*NIV is the number of input variables. TM denoted the types of metaheuristics based ANN. AF represents the selected activation function type. NHN denotes the determined number of hidden neurons.

Table 6: The values of performance measures for proposed hybrid ANN models

NIV*	TM*	MAE	MSE	RMSE	MARE	MSRE	RMSRE	MAPE	MSPE	RMSPE	Return	Time
5 variables	**ALO-ANN**	0,146	0,021	0,146	0,436	0,192	0,438	43,587	1920,810	43,827	0,049	4363
	BSA-ANN	0,089	0,008	0,090	0,267	0,072	0,269	26,665	721,698	26,864	0,092	1
	DE-ANN	0,006	0,000	0,008	0,018	0,000	0,022	1,835	4,911	2,216	-0,017	5558
	GWO-ANN	0,037	0,002	0,039	0,110	0,014	0,116	10,969	135,531	11,642	0,055	4731
	MFO-ANN	0,009	0,000	0,011	0,027	0,001	0,033	2,750	10,916	3,304	0,029	15843
	MVO-ANN	0,010	0,000	0,012	0,031	0,001	0,038	3,080	14,107	3,756	-0,030	21852
	PSO-ANN	0,006	0,000	0,007	0,017	0,000	0,022	1,743	4,769	2,184	-0,044	20269
	SA-ANN	0,055	0,003	0,056	0,164	0,028	0,168	16,399	282,728	16,815	0,034	42
	WSA-ANN	0,089	0,008	0,090	0,267	0,072	0,269	26,665	721,698	26,864	0,092	6279
	FFLY-ANN	0,004	0,000	0,005	0,012	0,000	0,016	1,203	2,442	1,563	-0,035	7055
7 variables	**ALO-ANN**	0,030	0,001	0,030	0,089	0,008	0,090	8,883	81,416	9,023	-0,028	5023
	BSA-ANN	0,016	0,000	0,017	0,046	0,003	0,052	4,619	26,874	5,184	0,072	1
	DE-ANN	0,162	0,026	0,163	0,485	0,237	0,487	48,467	2373,044	48,714	0,088	4767
	GWO-ANN	0,024	0,001	0,026	0,070	0,006	0,076	7,040	58,350	7,639	0,009	4367
	MFO-ANN	0,009	0,000	0,011	0,026	0,001	0,031	2,587	9,795	3,130	0,118	9160
	MVO-ANN	0,028	0,001	0,030	0,083	0,008	0,088	8,285	77,211	8,787	0,051	2475
	PSO-ANN	0,008	0,000	0,009	0,023	0,001	0,028	2,328	7,904	2,811	0,010	2303
	SA-ANN	0,011	0,000	0,012	0,032	0,001	0,036	3,198	12,720	3,567	0,026	108
	WSA-ANN	0,047	0,002	0,049	0,140	0,021	0,144	14,025	206,388	14,366	0,044	7636
	FFLY-ANN	0,088	0,011	0,106	0,266	0,102	0,320	26,582	1024,504	32,008	0,029	4881

Return from investment is also used to evaluate the financial performance of forecasting models. For five input variables, BSA-ANN model and WSA- ANN model yield maximum return of 9.2% profit while PSO based ANN model yields a loss of 4.4%. For seven input variables, MFO-ANN model yields maximum return of 11.8% profit while ALO-ANN model yields a loss of 2.8%.

The computation time of each model (unit is seconds) is also given in Table 6. When computation time is taken into account, BSA-ANN is the best model and MVO-ANN is the worst one for five variables. For seven variables, BSA-ANN model is the best one while MFO-ANN is the worst model.

To this end, our findings suggest that stock market forecasting will remain one of the most difficult forecasting problems because stock markets are affected by various factors such as political events. It is also determined that the best ANN model depends on the selected performance measures, the selected input variables, and the number of input variables. At this point, different performance measures can be used to provide the wide range of evaluation for each hybrid model.

Conclusions

To earn more and more money, the businesses, brokers, speculators, and investors get anxious about stock market's future. Therefore, forecasting has been a major challenge for them. At this point, ANN models are viable candidates for stock market forecasting. They can capture nonlinear relationships in the stock market. However, the selection of appropriate parameters for ANN models is critical for stock market forecasting because improper parameters can lead to lower accuracy. Therefore, we use different ANN models to improve the accuracy of the stock market forecasts by combining metaheuristics and ANN model together. The results of this study showed that integrating metaheuristics and ANN has valuable merits. Firstly, well-created ANN models can provide a real-time stock market forecasting result. Furthermore, improved ANN models can give a remarkable result even if the stock market data are noisy. Proposed methods can encourage further development of the hybrid ANN models. In future work, ANN parameters can be determined to improve the accuracy of the model by combining other metaheuristics.

Teşekkür

Bu çalışma Adana Bilim ve Teknoloji Üniversitesi Bilimsel Araştırma Projeleri Komisyonu tarafından desteklenmiştir. Proje Numarası: 17103015.

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