An Investigation on the Soft Computing Method Performance of the Optimizing Energy Consumption Cost

Mohammed S. M. Nemer[1*], Aqeel Hussain[2], Ali Ihsan Alanssari[3], Suhair Hussein Talib[4], Kadhim Abbas Jabbar[5], Siham Jasim Abdullah[6]

1- Department of Computer Engineering, Bahçeşehir University, Istanbul, Turkey.
Email: mohammed-nemer@hotmail.com (Corresponding author)
2- Medical Technical College, Al-Farahidi University, Baghdad, Iraq.
Email: aq.hussain@gmail.com
3- Al-Nisour University College, Iraq.
Email: aliihsanalanssari@gmail.com
4- Medical Instrumentation Techniques Engineering Department, Al-Mustaqbal University College, Babylon, Iraq.
Email: suhair.hussein1970@yahoo.com
5- National University of Science and Technology, Dhi Qar, Iraq.
Email: kadhim.abbas1jabbar@yahoo.com
6- Department of Dental Industry Techniques, Al-Noor University College, Nineveh, Iraq.
Email: siham.abdullah@gmail.com

Received: 13 October 2022 Revised: 6 November 2022 Accepted: 27 December 2022

ABSTRACT:
During peak demand hours, hydroelectric energy is one of the most significant sources of energy. Power sector restructuring has increased competition among the country's electricity providers. Estimating the future price of energy is critical for producers in order to enhance investment profit and make better use of resources. One of the most significant technologies of artificial intelligence, Artificial Neural Networks (ANN), has various applications in estimating and forecasting phenomena. Combining artificial intelligence models with optimization models (e.g. Artificial Bee Colonoy [ABC]) has recently become quite popular for improving the performance of artificial intelligence models. The goal of this study is to look at the effectiveness of ANN and ABC-ANN models in forecasting the dispersed and sinusoidal data of Angola's daily peak power price. The findings reveal that in this case study, the employment of the ABC-ANN model is not superior to the ANN model and has not resulted in enhanced performance and forecasting of power market data. As a result, the R^2 of the ANN and ABC-ANN models is 0.88 and 0.85, respectively.

KEYWORDS: Artificial Neural Network, Artificial Bee Colony, Energy Cost, Optimization.

1. INTRODUCTION

In recent years, the structure of the electricity industry has changed. when the electricity market was launched, its exclusive structure has turned into a competitive structure [1]. In this market, traders present offers to buy and sell electricity to the market one or more days in advance, and according to these offers, electricity market transactions take place [2]. In these conditions, electricity price forecasting is not only essential in pricing, but also plays an essential role in finding the optimal operation strategy by power plant operators [3].

The results of the research conducted using the available data of the Angolan electricity market regarding the analysis of the pricing pattern of production units and its effect on the market price, show that most of the production units use only one or two power blocks for pricing in the market and about 15% of them, in a smart move, have dedicated a part of their power blocks to identifying the market [4]. Also, the comparison of the distribution of the total power blocks based on the price in different hours shows that the pricing behavior of about one third of the production units in the base load is uneconomical or too cautious [5].

The results of the research conducted in accordance with the methodology of time series analysis with a focus on Artificial Bee Colony (ABC) models regarding

Paper type: Research paper
DOI: 10.30486/mjee.2023.1978858.1061
How to cite this paper: M. S. M. Nemer, A. Hussain, A. Ihsan Alanssari, S. Hussein Talib, K. Abbas Jabbar and S. Jasim Abdullah, **"An Investigation on the Soft Computing Method Performance of the Optimizing Energy Consumption Cost"**, *Majlesi Journal of Electrical Engineering*, Vol. 17, No. 1, pp. 109-115, 2023.

electricity market prices show that these models have a good efficiency in risk management in this field [6]. The statistical characteristics and their capability in evaluating and estimating the prices of the electricity market show that with the current conditions of the electricity market, information asymmetry plays a lesser role and standard GARCH models provide the best simulation [7].

The use of wavelet transform and a combination of neural network (ANN) and fuzzy logic, the use of wavelet transform and a combination of fuzzy neural network in order to provide a short-term prediction model of electricity price in a competitive market have been used by Singh et al [8]. The use of the Bayesian deep learning in the field of forecasting the electricity markets, shows that the predictive method is one of the most suitable price forecasting techniques [9]. Daily price of electricity with improved neural network based on wavelet transform and chaotic gravitational search method shows the high ability of this algorithm in better prediction compared to existing methods [10]. Also, the obtained results show that the electoral algorithm is very successful in sorting the divided data from the wavelet transform.

The results of the research conducted through neural network models and the combination of neural network and optimization algorithm for simulating precipitation and river runoff show the superiority of ABC-ANN algorithm over ANN algorithm [11].

The purpose of this study is to examine the methods that have been recently presented in order to improve the performance of the ANN model and their application in predicting the daily peak price of electricity, in such a way that the parameters of the ANN are once using the optimization model (ABC) and once again with the use of the particle swarm genetic algorithm, model is estimated and finally the performance of two ANN and ABC-ANN models has been compared.

2. METHOD

In this study, in order to predict the daily peak price of electricity, the ANN model was used, and in order to improve the performance of the ANN model and estimate its parameters, ABC optimization models were used.

2.1. Artificial Neural Network

ANN consists of artificial neurons. A neuron or a node is the smallest unit of information processing that forms the basis of the functioning of neural networks [12]. Each of the neurons receives the inputs and produces an output signal after processing them. Fig. 1 shows the structure of a single input neuron, where the numbers p and a are the input and output of the neuron, respectively [13].

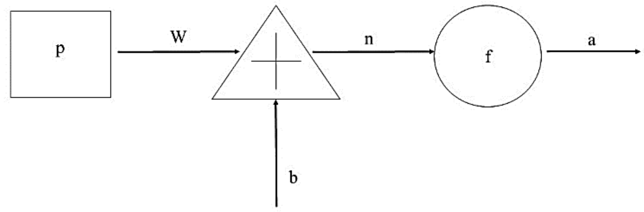


Fig. 1. Single input neuron model.

The effect of p on a is determined by the value of w. The other input is a constant value of one, which is multiplied by b and then added to wp. The resulting n is also a transformation function. In this way, the output of the neuron is the net sum of the input and f can be defined as Equation 1.

$$a = f(wp + b) \quad (1)$$

Parameters w and b are adjustable and the driving function f is also selected by the designer and new learning algorithm, parameters w and b. They are adjusted based on the choice of f [14]. To create a suitable and efficient network, paying attention to the training parameters of the network such as determining the input and output variables, choosing the appropriate size for the training, and testing data, initializing the weights of the network, paying attention to the practical parameters such as the accuracy of the network and, paying attention to the design neural network are essential such as determining the input and output neurons to be used, the number of hidden layers to be used and the number of neurons to be used in each hidden layer [15].

2.2. Artificial Bee Colony Algorithm

The ABC optimization method was introduced by researchers inspired by particle swarm optimization method [16]. In this study, the ABC algorithm has been considered in solving the optimization problem, i.e. finding the location and the amount of electricity prices. The reason for using this algorithm is that the number of control parameters is less than other algorithms such as genetic algorithm [17]. In addition to the general parameters of the population size and the limitation of the maximum number of calculations, there are three other control parameters, namely the marriage rate, the mutation rate, and the generation gap. In the particle accumulation method, the control parameters of cognitive factor, cumulative factor and inertia weight are more than two general parameters that must be determined before implementing the program [18]. This weakness is more or less visible in other algorithms. In the ABC algorithm there is only one other control parameter. This parameter, which determines the limit to the completion of the algorithm, is the number of attempts without improvement in the answers and the search is stopped after the specified number of repetitions. Therefore, compared to other met exploration algorithms, the honey bee algorithm is simple and flexible [19].

The ABC algorithm was first proposed by the researchers in 2005 to solve the optimization problem, and further modifications were made on it [20]. In this method, which is based on the intelligent collective behavior of bees to find the nectar of flowers, bees are divided into three groups: workers, spectators and scouts. Every bee that goes in search of food is considered a worker [21].

The onlookers in the hive wait to receive the information that the worker bee has brought to the hive about the food to use in the next search. The scout bee is one of the hands that randomly explores the space around the hive to find nectar.

Each food source is considered as a solution to solve the optimization problem. The quality of this answer is evaluated based on the amount of nectar in the food source. In the bee optimization method, half of the bees are assumed to be workers and go looking for food [22]. It is also assumed that the number of food sources is the same as the number of worker bees. If the quality of the food source is not recognized after several attempts, that source will be removed in the next search and the worker bee will become a scout and will search for a new random space ABC.

Like other optimization methods, the method is based on iteration. According to the bee algorithm, the three required parameters are:

a) The number of initial population is twice the number of food sources

b) Search limiting parameter if the quality of the answer does not improve.

c) Limiting the maximum number of calculations.

If we assume that it is the number of sources, the same number should be considered for worker bees or scout food NF, which is also half of the hive population. In the problem of this research, which is the detection of structural failure, the goal is to reach the correct value of the length vector of the solution (the number of members of the structure), while D is the number of the population that searches the response space for the optimal solution every time. The iterative process of the bee algorithm until reaching the optimal solution can be explained as following [23].

1-The initial population ($X_1,X_2,...,X_{NF}$) is formed for the initial and random search, so that each of its components is the possible vector of the answer to the problem, that is, $X = (X_{11},X_{12},..., X_{iD})$ whose components are determined from the Equation 2.

$$X_{ij} = X_{\min j} + \text{rand}\,[0 \quad 1]\left(X_{maxj} - X_{\min j}\right) \quad j = 1.2.\ldots.Di = 1.2.\ldots.N' \tag{2}$$

Rand [0 1] is a random number with uniform distribution in the range of zero to one, $X_{\min j}$ and $X_{maxj}$are the upper and lower limits of the answers to the problem, in the present problem, the value zero means the member without failure and the value one means complete failure. In order to prevent the solution from diverging due to the instability of the structure, the upper limit value is always smaller than one goal. After the initial population is produced, the quality of each food source is calculated

2-Each worker bee searches the neighborhood of the found food source to find a new food source using the Equation 3.

$$X_{ij}^{new} = X_{ij} + \varphi_{ij}\left(X_{ij} - X_{kj}\right) \quad j = 1.2.\ldots.Dk = 1.2.\ldots.NFj \neq k \tag{3}$$

φ_{ij} is a random function in the interval between -1 and 1 and with a uniform distribution.

3- After moving to a new food source that is located in the neighborhood of the old source, if the quality is equal or better than the previous source, the new source will replace the old source.

4- After completing the search, the probability of each answer is calculated using the Equation 4.

$$\mathrm{P}_i = \mathrm{Fit}_i / \textstyle\sum_{N=1}^{NF} \mathrm{Fit} \tag{4}$$

In this regard, the quality of the food source, Fit_i, is defined by the Equation 5.

$$\mathrm{Fit} = \begin{cases} \frac{1}{1+f_i} & \mathrm{f}_i \geq 0 \\ 1 + |\mathrm{f}_i| & \mathrm{f}_i < 0 \end{cases} \tag{5}$$

f_i Is the objective function value for food source i.

5- At this stage, the new population of worker bees leaves the hive based on the relationship (7) and based on the quality of the food source obtained in the previous stage, and based on the criteria presented in the third stage, a decision is made regarding choosing a new source or continuing to work with the same old sources.

6- As the quality of the food source did not improve after several specific repetitions, this source will be removed as a valuable source and a new source will be replaced based on the relationship (6) and the scout bees will start looking for another point.

9- If the search process has reached its end based on the specified limit, the best answer will be reported, otherwise the algorithm will reach the second stage. A relationship to determine the limiting parameter has been proposed by researchers and colleagues, which is the product of the number of sources (MCN = NF × D). During the response vector, the damage indices ABC of the members are expected to be determined in such a way as to minimize the vector to F (β). In other words, the vector ($\beta^T = \beta_1, \beta_2 ... \beta_{me}$) is such that F ($\beta$) should be the minimum.

In this section, the effectiveness and accuracy of the bee algorithm to solve the optimization problem of are examined. The computer code in MATLAB is expanded based on the bee algorithm. Usually, the minimum colony population is twice the parameters of each problem.

The maximum number of attempts of the worker bees that do not lead to a better result is introduced as the limitation of the algorithm. According to the analysis, it is clear that the limit of 100 numerical repetitions is appropriate and in any of the executions, the program will not be stopped based on the limit number. The considered limitation in cases where the dimensions of the structure are large can reduce the ineffective repetitions, which results in faster reaching the final answer.

The suggestion given for the numerical number of repetitions in the bee algorithm was large for this example, so according to the convergence of the answers, this number was reduced to 200 after several analyzes.

According to the ABC algorithm, the calculation of the objective function in each analysis step is equal to the number of bee colonies or twice the number of food sources.

2.3. ANN Training using ABC Optimization Algorithms

Optimization variables in training a network are weights and biases related to the network. In this article, the optimal value of the variables is obtained by the ABC algorithm. The work process is as follows: first, the optimization algorithm considers random values for the vector coefficients of the weights and biases of each neuron. The neural network is executed for parameters equal to the variables of these vectors and the error obtained from each execution is considered as the fitness of the vector of the variables of that network. In the next step, the variables are updated based on the Equations 8 and 9 of the optimizer algorithm [24].

$$\text{Min } \sum_{i=1}^{n} (y_{i.act} - y_{i.est})^2 \tag{8}$$

$$y_{i.\,\text{est}} = f(ABC - ANN \text{ OR } ABC), \tag{9}$$

where $y_{i.act}$ is observational data and $y_{i.est}$ is estimated data by the optimization algorithm. This training process continues until the termination condition is satisfied. When the training process is finished, the weights are used to calculate the error for the training patterns. Then a set of weights is used to test the network using test patterns [25].

Numerical optimization techniques can be used to solve problems with the inverse analysis approach, such as the problem of structural damage detection. In recent years, natural science researchers have found out that their collective behavior has been a smart and cheap solution; providing them with a fee to find the way or food. Based on this, the researchers of engineering and mathematics sciences, inspired by this collective behavior, have developed numerical optimization methods that can be used in solving complex and expensive optimization problems. Fig. 3 shows the convergence of the results using ABC method after about 200 repetitions.

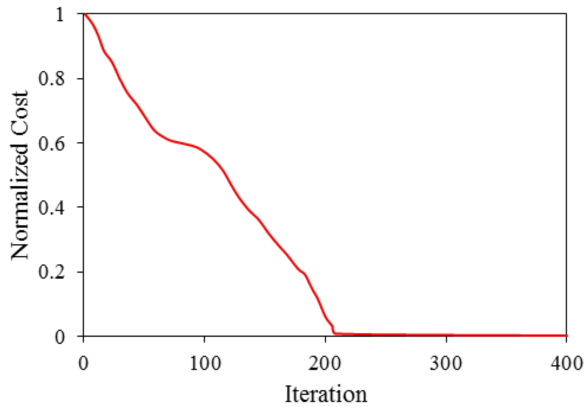


Fig. 2. The convergence of the ABC method for the normalized cost function.

3. RESULT AND DISCUSION

In this research, a two-brain perceptron network with one hidden layer with 15 neurons and one output layer with one neuron has been used once with Multi Layers Perceptron (MLP) training algorithm and once with ABC algorithm.

The sigmoid tangent function for the hidden layer and the linear function for the output layer are considered as the transformation function. The input data has been divided into two parts, 80% of which are used for training, and 20% of which are used for testing.

It is worth mentioning that the input data to these algorithms is the price of electricity in the past periods of time, in other words, these algorithms will predict the price of electricity in the future by using the price of electricity in the past periods of time.

The simulation results of ANN simulation for the whole data are shown in Fig. 3. In this figure, the value of the regression coefficient and the mean square error have been calculated, which shows the efficiency of the model in predicting the cost of energy. Considering that the simulation result is usually based on the test data, as can be seen in Fig. 3-b, this model has correlation coefficient (R), Mean Squared Error (MSE), and coefficient of determination (R^2) of 0.98, 0.0014, and 0.88 respectively. Therefore, it can been seen that the ANN model has a suitable ability to predict future when information is available.

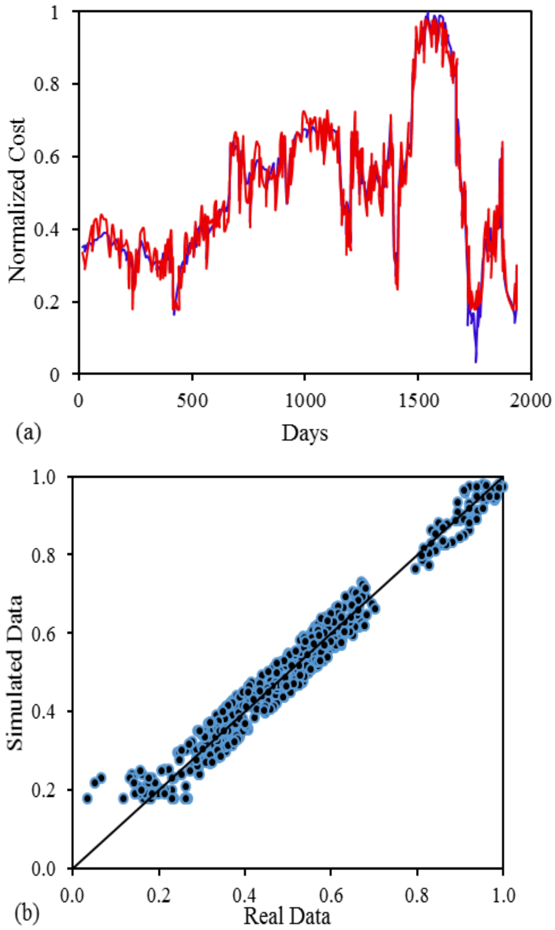
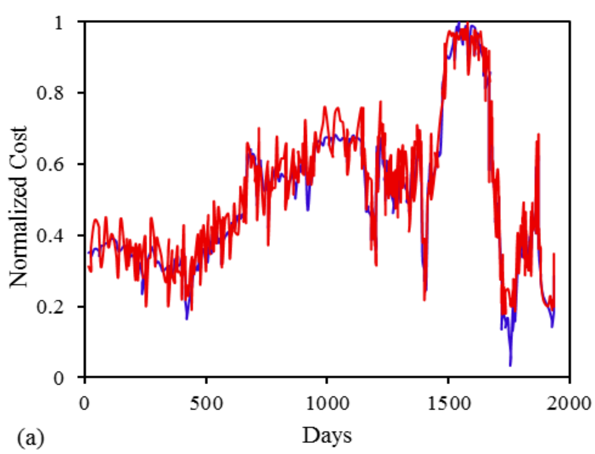


Fig 3. a) The comparison of the time series of the read data and ANN forecasted **b)** The scatter plot of the real data and ANN forecasted.

The simulation results for the whole data of ABC-ANN model are shown in Fig. 4. The statistical results of model for R, MSE, and R^2 are 0.90, 0.0019, and 0.85, respectively.



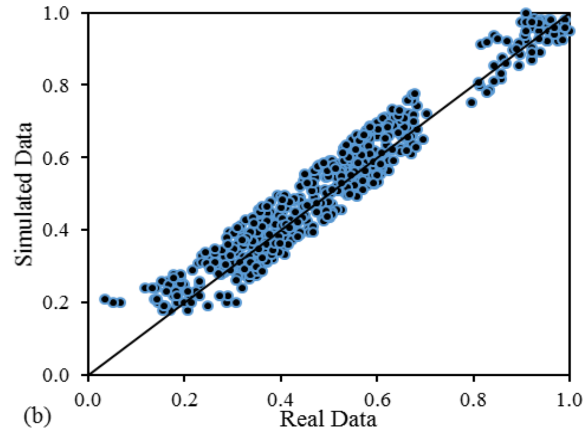


Fig 4. a) The comparison of the time series of the read data and ABC-ANN forecasted **b)** The scatter plot of the real data and ABC-ANN forecasted.

Table 1 summarizes the results of the two mentioned methods, as it can be seen the ANN method has relatively better results than the ABC-ANN method. The unit of MSE in Table 1 is Thousand dollars per megawatt hour.

Table 1. Comparison of ANN and ABC -ANN methods

	ANN			ABC-ANN		
	R	MSE	R^2	R	MSE	R^2
Total	0.95	0.0014	0.88	0.90	0.0019	0.85
Training	0.98	0.0006	0.91	0.93	0.0011	0.87
Test	0.89	0.0023	0.84	0.88	0.0029	0.81

The reason for the superiority of ANN method over other methods can be attributed to the complete and correct training of ANN. As explained in the materials and methods section, the success of the ANN method depends on the correct and complete training, and this is done by choosing the right number of layers, the right number of nodes in the layer, choosing the right transfer function and also the right ratio of the number of training data, testing and the validation is in such a way that the network does not suffer from the problem of over-education even though it is fully trained.

4. CONCLUSION

Recently, many studies have been conducted on improving the performance of ANN models using optimization models, and in most of the studies, the superiority of combined optimization and ANN models has been reported. Considering the importance of electricity price forecasting in the planning of hydroelectric power plants, in this article price forecasting using two methods of neural networks, the combination of ABC-ANN has been discussed. The results show that the neural network method has better accuracy than other methods. The reason for this issue can be attributed to the complete and correct training of the ANN model in a way that it has been more successful than other models even in predicting sinusoidal data such as the daily peak electricity price. In other words, this research shows that it is not possible to conclude the weakness of the ANN model based on only superficial training for ANN and its comparison with hybrid models. Perhaps, if the ANN model is trained with the number of nodes, the number of neurons, the training method and appropriate functions, it will be so accurate that there is no need to use optimization models to improve its performance.

REFERENCES

[1] L. Pietrosemoli and C. Rodríguez-Monroy, "**The Venezuelan energy crisis: Renewable energies in the transition towards sustainability,"** *Renewable and Sustainable Energy Reviews*, vol. 105, pp. 415–426, May 2019, doi: 10.1016/j.rser.2019.02.014.

[2] D. Shah and S. Chatterjee, **"A comprehensive review on day-ahead electricity market and important features of world's major electric power exchanges,"** *International Transactions on Electrical Energy Systems*, vol. 30, no. 7, Jul. 2020, doi: 10.1002/2050-7038.12360.

[3] Z. Yi, Y. Xu, J. Zhou, W. Wu, and H. Sun, **"Bi-Level Programming for Optimal Operation of an Active Distribution Network With Multiple Virtual Power Plants,"** *IEEE Transactions on Sustainable Energy*, vol. 11, no. 4, pp. 2855–2869, Oct. 2020, doi: 10.1109/TSTE.2020.2980317.

[4] E. D. G. Constantino, S. F. C. F. Teixeira, J. C. F. Teixeira, and F. V. Barbosa, "Innovative Solar Concentration Systems and Its Potential Application in Angola," *Energies*, vol. 15, no. 19, p. 7124, Sep. 2022, doi: 10.3390/en15197124.

[5] E. Guelpa and V. Verda, **"Demand response and other demand side management techniques for district heating: A review,"** *Energy*, vol. 219, p. 119440, Mar. 2021, doi: 10.1016/j.energy.2020.119440.

[6] G. Zhou, H. Moayedi, M. Bahiraei, and Z. Lyu, **"Employing artificial bee colony and particle swarm techniques for optimizing a neural network in prediction of heating and cooling loads of residential buildings,"** *Journal of Cleaner Production*, vol. 254, p. 120082, May 2020, doi: 10.1016/j.jclepro.2020.120082.

[7] S. Westgaard, S.-E. Fleten, A. Negash, A. Botterud, K. Bogaard, and T. H. Verling, **"Performing price scenario analysis and stress testing using quantile regression: A case study of the Californian electricity market,"** *Energy*, vol. 214, p. 118796, Jan. 2021, doi: 10.1016/j.energy.2020.118796.

[8] N. Singh, S. R. Mohanty, and R. Dev Shukla, **"Short term electricity price forecast based on environmentally adapted generalized neuron,"** *Energy*, vol. 125, pp. 127–139, Apr. 2017, doi: 10.1016/j.energy.2017.02.094.

[9] A. Brusaferri, M. Matteucci, P. Portolani, and A. Vitali, **"Bayesian deep learning based method for probabilistic forecast of day-ahead electricity prices,"** *Applied Energy*, vol. 250, pp. 1158–1175, Sep. 2019, doi: 10.1016/j.apenergy.2019.05.068.

[10] A. Heydari, M. Majidi Nezhad, E. Pirshayan, D. Astiaso Garcia, F. Keynia, and L. De Santoli, "**Short-term electricity price and load forecasting in isolated power grids based on composite neural network and gravitational search optimization algorithm,"** *Applied Energy*, vol. 277, p. 115503, Nov. 2020, doi: 10.1016/j.apenergy.2020.115503.

[11] J. F. Farfán and L. Cea, **"Coupling artificial neural networks with the artificial bee colony algorithm for global calibration of hydrological models,"** *Neural Computing and Applications*, vol. 33, no. 14, pp. 8479–8494, Jul. 2021, doi: 10.1007/s00521-020-05601-3.

[12] V. Nourani, A. Molajou, S. Uzelaltinbulat, and F. Sadikoglu, **"Emotional artificial neural networks (EANNs) for multi-step ahead prediction of monthly precipitation; case study: northern Cyprus,"** *Theoretical and Applied Climatology*, vol. 138, no. 3–4, pp. 1419–1434, 2019, doi: 10.1007/s00704-019-02904-x.

[13] T. Minemoto, T. Isokawa, H. Nishimura, and N. Matsui, "**Feed forward neural network with random quaternionic neurons,"** *Signal Processing*, vol. 136, pp. 59–68, Jul. 2017, doi: 10.1016/j.sigpro.2016.11.008.

[14] D. Lee, S. Derrible, and F. C. Pereira, **"Comparison of Four Types of Artificial Neural Network and a Multinomial Logit Model for Travel Mode Choice Modeling,"** *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2672, no. 49, pp. 101–112, Dec. 2018, doi: 10.1177/0361198118796971.

[15] O. I. Abiodun, A. Jantan, A. E. Omolara, K. V. Dada, N. A. Mohamed, and H. Arshad, **"State-of-the-art in artificial neural network applications: A survey,"** *Heliyon*, vol. 4, no. 11, p. e00938, Nov. 2018, doi: 10.1016/j.heliyon.2018.e00938.

[16] O. Ertenlice and C. B. Kalayci, **"A survey of swarm intelligence for portfolio optimization: Algorithms and applications,"** *Swarm and Evolutionary Computation*, vol. 39, pp. 36–52, Apr. 2018, doi: 10.1016/j.swevo.2018.01.009.

[17] S. Balochian and H. Baloochian, **"Social mimic optimization algorithm and engineering applications,"** *Expert Systems with Applications*, vol. 134, pp. 178–191, Nov. 2019, doi: 10.1016/j.eswa.2019.05.035.

[18] A. Nabaei *et al.*, **"Topologies and performance of intelligent algorithms: a comprehensive review,"** *Artificial Intelligence Review*, vol. 49, no. 1, pp. 79–103, Jan. 2018, doi: 10.1007/s10462-016-9517-3.

[19] J. C. Bansal, A. Gopal, and A. K. Nagar, **"Stability analysis of Artificial Bee Colony optimization algorithm,"** *Swarm and Evolutionary Computation*, vol. 41, pp. 9–19, Aug. 2018, doi: 10.1016/j.swevo.2018.01.003.

[20] J. Tang, G. Liu, and Q. Pan, "**A Review on Representative Swarm Intelligence Algorithms for Solving Optimization Problems: Applications and Trends,"** *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 10, pp. 1627–1643, Oct. 2021, doi: 10.1109/JAS.2021.1004129.

[21] A. Madureira, B. Cunha, and I. Pereira, **"Cooperation Mechanism for Distributed resource scheduling through artificial bee colony based self-organized scheduling system,"** in *2014 IEEE Congress on Evolutionary Computation (CEC)*, Jul. 2014, pp. 565–572. doi: 10.1109/CEC.2014.6900574.

[22] S. Fernando and N. Kumarasinghe, **"Modeling honeybee communication using network of spiking neural networks to simulate nectar reporting behavior,"** *Artificial Life and Robotics*, vol. 23, no. 2, pp. 241–248, Jun. 2018, doi: 10.1007/s10015-017-0418-6.

[23] T. Davidović, D. Ramljak, M. Šelmić, and D. Teodorović, **"Bee colony optimization for the p-center problem,"** *Computers & Operations Research*, vol. 38, no. 10, pp. 1367–1376, Oct. 2011, doi: 10.1016/j.cor.2010.12.002.

[24] S. M. Awan, M. Aslam, Z. A. Khan, and H. Saeed, **"An efficient model based on artificial bee colony optimization algorithm with Neural Networks for electric load forecasting,"** *Neural Computing and Applications*, vol. 25, no. 7–8, pp. 1967–1978, Dec. 2014, doi: 10.1007/s00521-014-1685-y.

[25] M. Yaghini, M. M. Khoshraftar, and M. Fallahi, **"A hybrid algorithm for artificial neural network training,"** *Engineering Applications of Artificial Intelligence*, vol. 26, no. 1, pp. 293–301, Jan. 2013, doi: 10.1016/j.engappai.2012.01.023.