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An artificial neural network optimized by grey wolf optimizer for prediction of hourly wind speed in Tamil Nadu, India

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ABSTRACT

The growing population has tremendously increased the daily energy demand all around the world. India is the second-most crowded nation in the world with approximately 1.4 billion people. New and renewable energy is on the agenda of India and in 2021 India possesses the fourth-largest installed capacity of wind power. Accurate prediction of wind speed is vital in wind farm design and operation. In this work, an hourly wind speed prediction with an artificial neural network optimized by a metaheuristics approach is conducted. A feed-forward (FF) multi-layer perceptron (MLP) artificial neural network (ANN) is used for the prediction of the hourly wind speed. In this study, 38 years of hourly wind data belonging to 5 cities (Ambur, Hosur, Kumbakonam, Nagapattinam, and Pudukottai) were used. These cities have different specific properties such as latitude, longitude, and altitude. The FF MLP ANN is optimized by 9 state-of-art metaheuristic algorithms. In this work, Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Biogeography Based Optimization (BBO), Evolutionary Strategy (ES), Genetic Algorithm (GA), Grey-Wolf-Optimizer (GWO), Population-Based Incremental Learning (PBIL), Particle Swarm Optimization (PSO), Tree-Seed Algorithm (TSA) have been used to optimize the weights of the ANN. GWO outperforms other metaheuristic algorithms in the prediction of wind speed with a FF MLP ANN model, with a success percentage rate of approximately 3% to 10,000%.

1. Introduction

India is witnessing several encounters in fulfilling the ever-rising energy demands from different sections of society. Population explosion, environmental pollution, socio-economic crises, rapid industrialization, and urbanization are some of the causes of the surge in energy demand. Exhaustion of the non-renewable energy sources and the need for environmental sustainability has urged scientists and researchers to explore novel non-conventional energy sources such as wind, solar, tidal, geothermal, biogas, biofuels, etc. Renewable energy has shown tremendous development worldwide with substantial progress in wind and solar photovoltaic in the last decade (IEA, 2012). The total power generated by non-conventional energy has attained 2351 Gigawatts (GW) globally in 2018. Among the various renewable energy sources, wind energy seems to be a favorable resource due to its abundance, environment-friendliness, ease of harvestability, and affordability (Rehman, 2004, 2020). India possesses the fourth highest mounted capacity of wind power after China, the USA, and Germany, with 37.7 GW as of December 2020.[1] India has planned to attain 60 GW of power from wind by the year 2022.[2] To efficiently use this wind energy, it is mandatory to assess the locations with high prospective for wind energy and predict the wind speed (WS) characteristics in such regions. Moreover, precise estimation of WS is vital in the wind farm design and operation (Liu et al., 2018).

Metaheuristic algorithms are widely used in many areas of the research field. Genetic Algorithm (GA), Population-Based Incremental Learning (PBIL), and Evolutionary Strategy (ES) have mimicked the evolutionary operators such as crossover and mutation. Grey-Wolf-Optimizer (GWO), Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO), Biogeography Based Optimization (BBO), and Ant Colony Optimization (ACO) are inspired by animal behaviors such as hunting, feeding, and exploring the new areas. The Tree-Seed Algorithm

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[1] https://mnre.gov.in/wind/current-status/ (Accessed on 9th March 2021)

[2] https://indien.um.dk/en/innovation/sector-updates/renewable-energy/wind-energy-in-india/#:~:text=India%20has%20the%204th%20largest,m%20hub%2Dheight%20in%20India. (Accessed on 9th March 2021)

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Table 1
The geographical information of the selected sites.

S. No.	Location	Latitude (0 N)	Longitude (^{0}E)	Altitude (m)
1	Ambur	12.78	78.71	324
2	Hosur	12.74	77.82	872
3	Kumbakonam	10.96	79.38	32
4	Nagapattinam	10.76	79.84	9
5	Pudukottai	10.38	78.80	101

(TSA) (Gharehchopogh, 2022) is a newly developed metaheuristic that mimics the relationship between trees and their seeds. All these algorithms start with a random population and use various techniques and local search mechanisms (Koçer & Uymaz, 2021) to find the optimum values of the given optimization problem.

In this work, ABC, ACO, BBO, ES, GA, GWO, PSO, PBIL, and TSA have been used to optimize the weights of the ANN. Nine hybrid algorithms, namely, ANN-ABC, ANN-ACO, ANN-BBO, ANN-ES, ANN-GA, ANN-GWO, ANN-PBIL, ANN-PSO, and ANN-TSA have been adopted in forecasting the wind speed at five stations located in the state of Tamil Nadu, India. The main aim of this work is to present the comparison of the feed-forward multi-layer perceptron artificial neural network models which are optimized by 9 state-of-the-art metaheuristic algorithms.

The organization of the paper is as follows: The related works, study area and data description are given in Sections 2 and 3, respectively. The proposed artificial neural network optimized by metaheuristics and the experimental setup are presented in Sections 4 and 5, respectively. The results and discussion are given in Section 6. The paper is concluded with Section 7.

2. Related works

Wind speed prediction (WSP) is carried out using statistical, artificial intelligence, and hybrid models. Statistical methods are generally adopted for short-term WSP, and historical data is employed for the determination of the WS. Statistical methods can be both linear as well as non-linear. Commonly used statistical methods for WSP include auto-regressive (AR) (Poggi et al., 2003), linear regression (Kani et al., 2008), moving average (MA) (Riahy & Abedi, 2008), Kalman filter (Shamshad et al., 2005; Erdem & Shi, 2011), Auto-Regressive Moving Average (ARMA) (Cassola & Burlando, 2012), Markov Chain (Kavasseri & Seetharaman, 2009), Auto-Regressive Integrated Moving Average (ARIMA) (Zuluaga et al., 2015), Seasonal ARIMA (Al Dhaheri et al., 2017). If the non-linearity is prominent in the collected data, the prediction results by the above-mentioned methods will not be satisfactory (Zhang et al., 2016). In such cases, non-linear models like nonlinear autoregressive

Table 2
Statistical analysis of the data.

S. No	Location	Mean WS (m/s)	Maximum WS (m/s)	Standard deviation (m/s)
1	Ambur	5.41	9.36	1.24
2	Hosur	5.47	9.74	1.36
3	Kumbakonam	5.75	8.72	1.08
4	Nagapattinam	6.26	8.96	1.14
5	Pudukottai	5.30	8.48	1.02

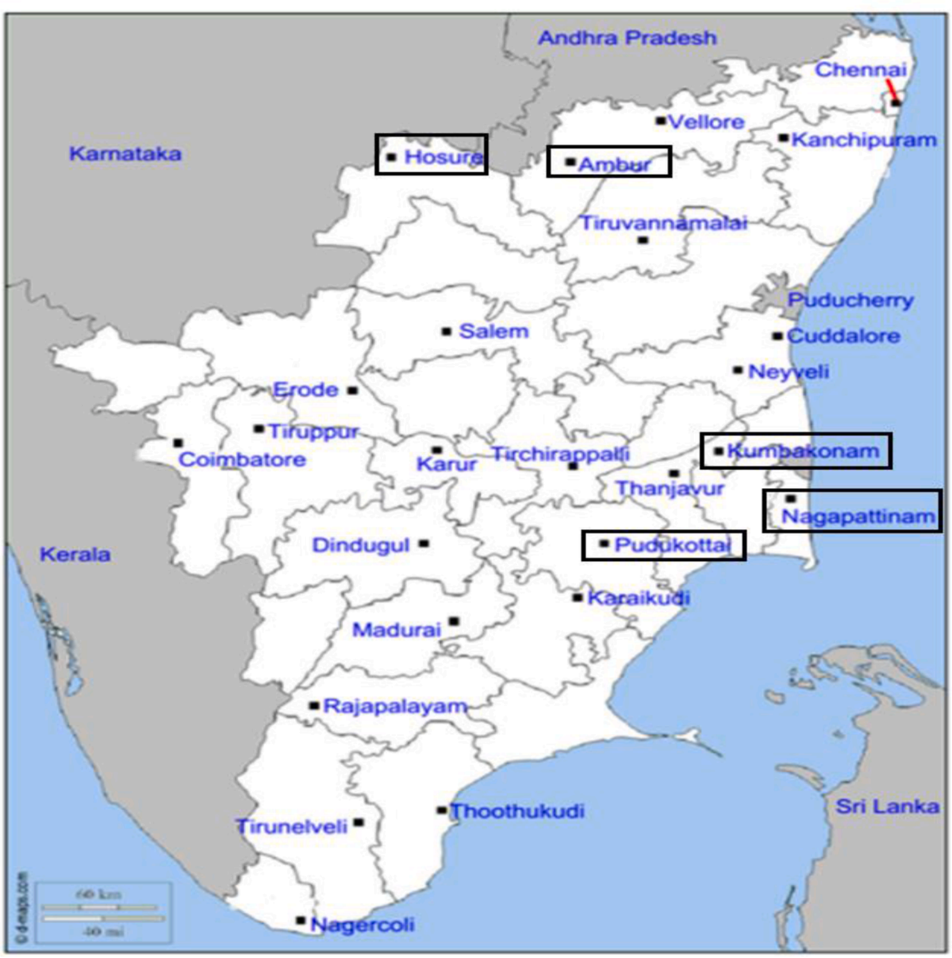


Fig. 1. Location of the selected sites in Tamil Nadu.

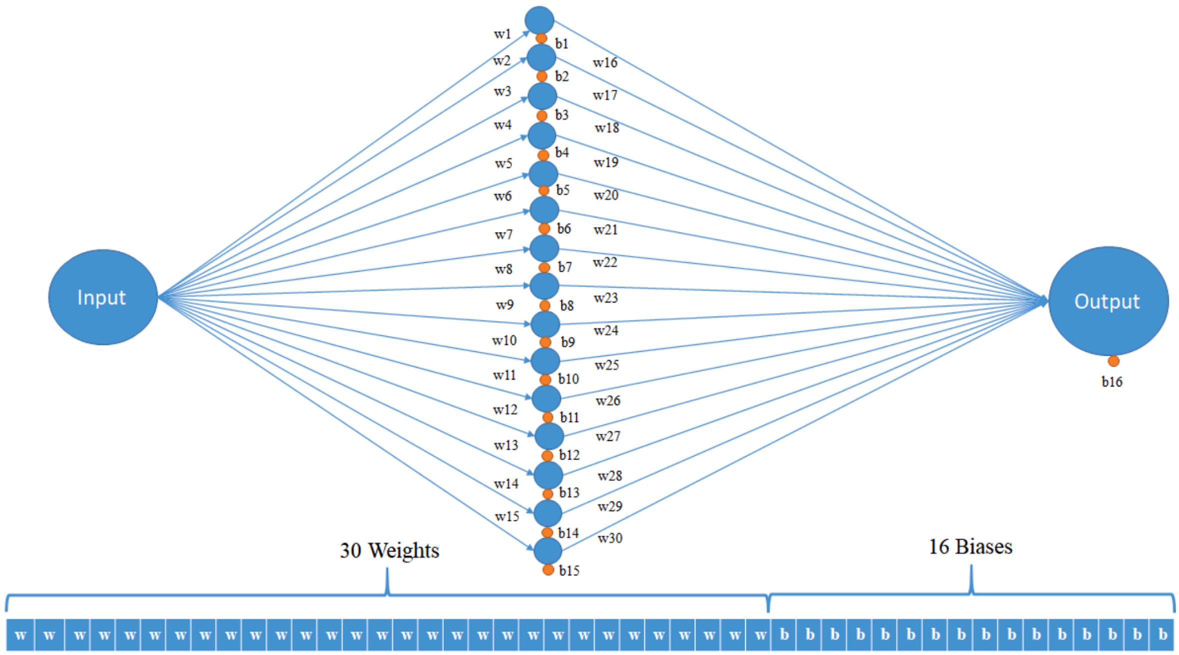


Fig. 2. Design of FF MLP ANN.

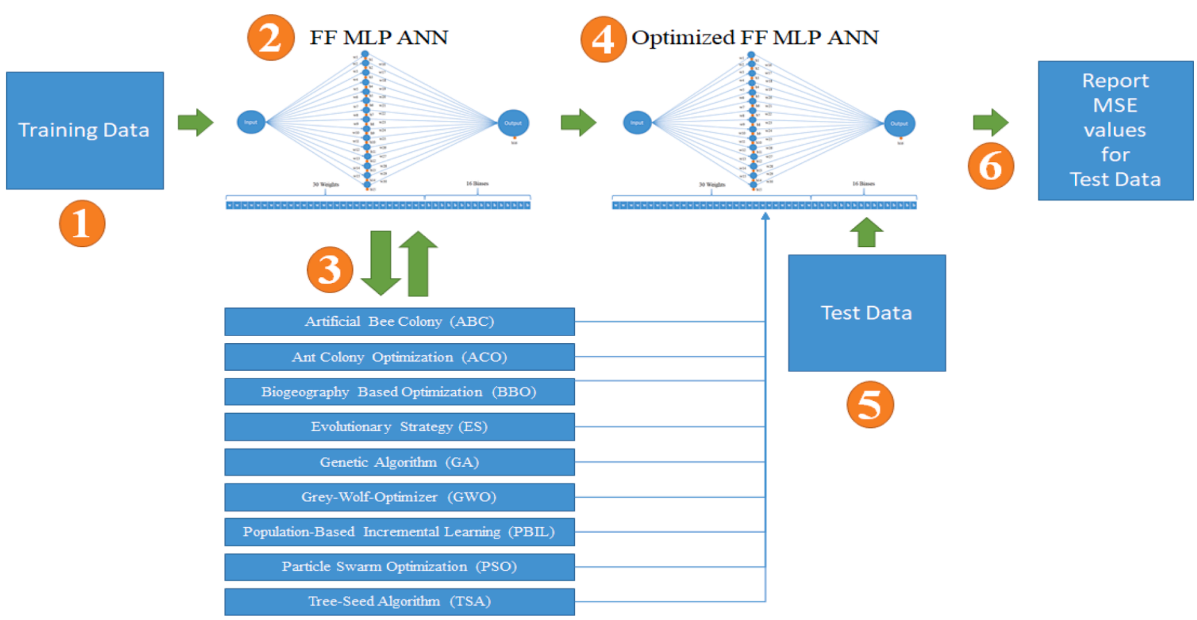


Fig. 3. The proposed artificial neural network optimized by the metaheuristics approach.

Table 3
The experimental results of Ambur.

Ambur	ANN-ABC	ANN-ACO	ANN-BBO	ANN-ES	ANN-GA	ANN-GWO	ANN-PBIL	ANN-PSO	ANN-TSA
Mean	2.01E-02	6.60E+00	8.48E-03	1.18E+01	3.96E-02	5.68E-03	5.84E+00	4.84E+00	4.09E+00
Best	4.51E-03	3.47E-01	8.48E-03	4.16E-01	4.62E-03	4.51E-03	2.30E-01	1.57E-02	2.17E-02
Worst	1.16E-01	2.04E+01	8.48E-03	5.77E+01	3.48E-01	1.09E-02	2.70E+01	3.42E+01	1.77E+01
SD	2.56E-02	6.01E+00	1.76E-18	1.24E+01	7.18E-02	1.42E-03	7.23E+00	6.62E+00	3.96E+00
Median	1.13E-02	4.65E+00	8.48E-03	9.21E+00	9.56E-03	5.08E-03	4.00E+00	2.22E+00	2.34E+00
Mean Time	700.89	579.19	587.28	721.36	578.16	580.00	592.85	579.10	738.48
Friedman Rank	2.83	7.27	2.67	7.83	3.10	1.43	6.67	6.60	6.60
MSE test	0.0038	0.2773	0.0086	0.47	0.0039	0.0038	0.2673	0.0162	0.0238

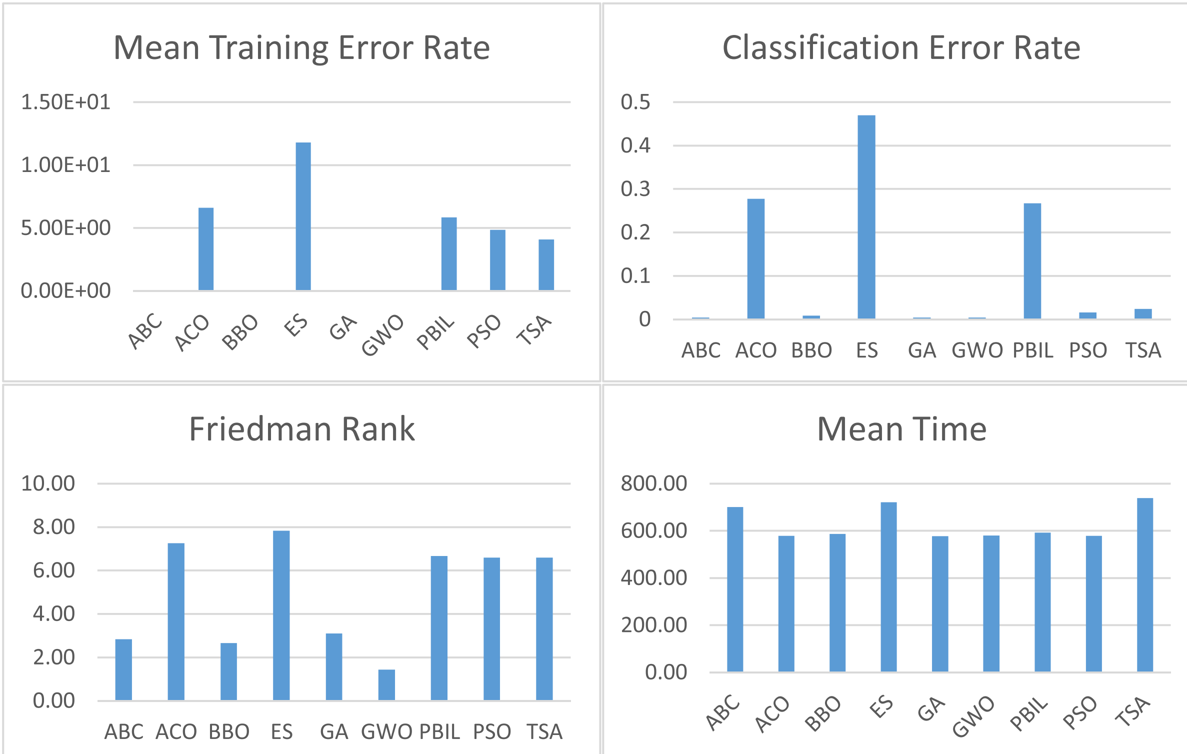


Fig. 4. Visualization of the experimental results of Ambur.

Table 4
The experimental results of Hosur.

Hosur	ANN-ABC	ANN-ACO	ANN-BBO	ANN-ES	ANN-GA	ANN-GWO	ANN-PBIL	ANN-PSO	ANN-TSA
Mean	1.82E-02	7.60E+00	7.08E-03	1.81E+01	2.44E-02	6.26E-03	6.80E+00	5.12E+00	3.10E+00
Best	4.26E-03	2.28E-01	7.08E-03	2.03E-01	4.49E-03	4.28E-03	2.19E-01	1.55E-01	2.03E-01
Worst	8.22E-02	3.34E+01	7.08E-03	5.65E+01	1.16E-01	1.46E-02	2.90E+01	1.84E+01	6.83E+00
SD	2.13E-02	7.88E+00	4.41E-18	1.35E+01	2.95E-02	2.37E-03	6.85E+00	4.30E+00	2.18E+00
Median	9.63E-03	4.82E+00	7.08E-03	1.59E+01	8.55E-03	5.35E-03	3.67E+00	3.93E+00	2.65E+00
Mean Time	702.16	575.13	591.64	732.43	577.52	573.36	584.08	577.10	752.52
Friedman Rank	2.77	7.00	2.47	8.23	3.00	1.77	6.73	6.70	6.33
MSE test	0.0046	0.221	0.0078	0.1964	0.0049	0.0046	0.2116	0.1548	0.1968

(NAR) and nonlinear autoregressive exogenous (NARX) models tend to perform better (Cadenas et al., 2016; Karasu et al., 2017a, b).

Soft computing methods have been used in the recent past due to their self-learning abilities and hence can approximate the non-linear functions (Catalão et al., 2009; Chang et al., 2017). The most widely used methods to predict the WS include different types of Artificial Neural Network (ANN) like Multi-Layer Perceptron (MLP) (Ak et al., 2018), Back Propagation Neural Network (BPNN) (Wang et al., 2016), Long Short Term Memory (LSTM) (Hu & Chen, 2018; Liu et al., 2018), Radial Basis Function (RBF) (Zhang et al., 2016), Recurrent Neural Network (RNN) (Qian-Li et al., 2008), Elman Neural Network (ENN) (Liu et al., 2015), Convolution Neural Network (CNN) (Mehrkanoon, 2019), Wavelet Neural Network (Xiao et al., 2017). Apart from ANN, there are other techniques like Support Vector Machine (SVM) (Mohandes et al., 2004; Liu et al., 2014; Gani et al., 2016), fuzzy logic (FL) (Damousis et al., 2004), Bayesian maximum entropy approach (Baydaroğlu & Koçak, 2019) and extreme learning machine (Peng et al., 2017; Hu & Chen, 2018; Liu et al., 2018). Even though the soft computing models have the capability to acquire knowledge from the historical data, identify the patterns to describe the relationship prevalent in the past data, and provide imminent predictions, they possess some drawbacks. These models may easily fail due to local optimum or over-fitting, thus exhibiting a low rate of convergence and difficulty in determination of some of the critical parameters (Bashir & El-Hawary, 2009; Yu et al., 2017; Wang et al., 2018, 2019).

To combat these shortcomings, optimization algorithms were introduced. These algorithms provide a potential role in enhancing the performance of the ANN models. These are generally denoted as hybrid or combined models. Especially, ANN models have been improved using various optimization algorithms in the past. It is evident from the literature (Cinar, 2020; Turkoglu & Kaya, 2020) that the performance of ANN has improved considerably with the help of optimization algorithms.

Gao and Billinton (2009) proposed a model to simulate hourly WS using an ARMA model, in which the optimum random number of seeds was selected by GA. Li et al. (2009) coupled BPNN with GA to optimize the structure, bias, and weights of the neural network. Welch et al. (2009) proposed Recurrent Neural Networks (RNN) trained with PSO for short-term WSP. Alanis et al. (2012) developed a model using Extended Kalman Filter (EKF) and Particle Swarm Optimization (PSO) for the training process of Recurrent MLP for wind prediction. Islam et al. (2017) proposed two ANN hybrid systems using GA and PSO, namely GA-ANN and PSO-ANN for vertical extrapolation of WS. Khosravi et al. (2018) adopted three models to predict the WS, namely, multilayer feed-forward neural network (MLFFNN), Support Vector Regression (SVR) with Radial Basis Function (RBF), and adaptive neuro-fuzzy

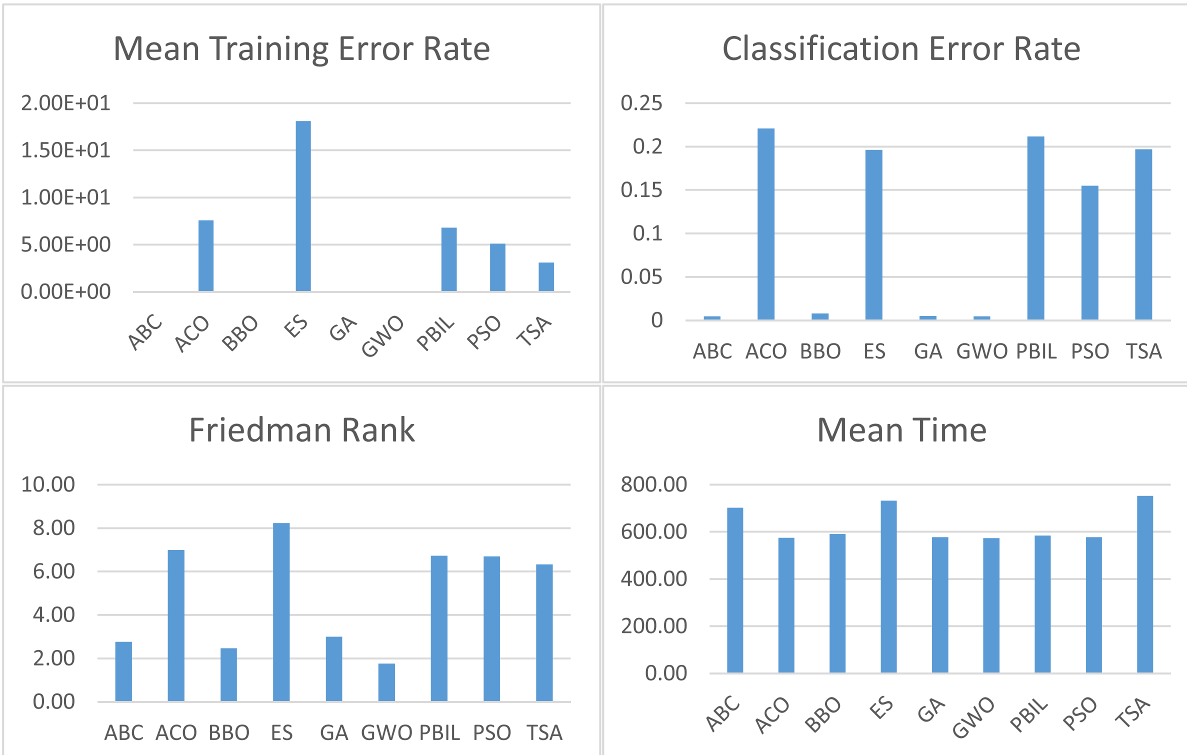


Fig. 5. Visualization of the experimental results of Hosur.

Table 5
The experimental results of Kumbakonam.

Kumbakonam	ANN-ABC	ANN-ACO	ANN-BBO	ANN-ES	ANN-GA	ANN-GWO	ANN-PBIL	ANN-PSO	ANN-TSA
Mean	1.10E-02	5.51E+00	2.68E-02	1.37E+01	1.18E-02	7.27E-03	5.76E+00	3.74E+00	3.36E+00
Best	3.52E-03	6.09E-01	2.68E-02	4.89E-01	3.49E-03	3.53E-03	1.53E-01	4.63E-02	2.28E-01
Worst	4.71E-02	1.60E+01	2.68E-02	6.09E+01	7.50E-02	3.72E-02	1.87E+01	1.41E+01	1.39E+01
SD	9.58E-03	4.02E+00	5.76E-18	1.49E+01	1.43E-02	7.71E-03	4.94E+00	3.69E+00	3.02E+00
Median	7.65E-03	4.58E+00	2.68E-02	8.52E+00	7.34E-03	4.50E-03	4.29E+00	2.55E+00	2.42E+00
Mean Time	691.77	569.58	586.12	724.05	568.99	571.84	578.20	566.72	743.17
Friedman Rank	2.30	7.17	3.80	8.10	2.27	1.63	7.10	6.40	6.23
MSE test	0.1336	0.1336	0.1336	0.5441	0.0043	0.0044	0.1336	0.1336	0.1336

inference system (ANFIS) coupled with PSO to predict the WS and direction in Bushehr, Iran. Jawad et al. (2018) developed a hybrid model by combining GA-based non-linear AR with exogenous inputs for neural network short term and medium term WSP.

Gani et al. (2016) adopted a new hybrid approach by integrating of SVM and firefly algorithm (FFA) for WSP on a daily and monthly basis. The approach was found to perform accurately for monthly scales since a lot of fluctuations were observed on the daily basis. Deo et al. (2018) adopted a novel approach to construct an MLP hybrid model integrated with FFA trained with a limited set of historical data for a set of stations located nearby to predict the WS at target sites of north-west Iran.

Du et al. (2017) used a multi-objective ant lion optimization algorithm to optimize the initial weights between layers and thresholds of the ENN for refining the accuracy of WSP. Wang et al. (2017) used the Multi-Objective Whale Optimization Algorithm (MOWOA) to optimize the weights and thresholds of the ENN so as to accurately predict the WS. They compared the obtained results with Multi-Objective Ant Lion Optimizer and Multi-Objective Drangonfly Algorithm (MODA) and concluded that the MOWOA optimized ENN outperforms other models. Samadianfard et al. (2020) utilized the combination of MLP with Whale optimization algorithm (WOA) for forecasting the WS at specific stations in the north of Iran with a limited dataset. They compared the results of MLP-WOA with MLP-GA and standalone MLP, and found that MLP-WOA outperformed the other models. Sağ and Abdullah Jalil Jalil (2021) use a vortex search algorithm for optimizing the ANN. Turkoglu and Kaya (2020) used an artificial algae algorithm for optimizing the ANN.

3. Study area and data description

Tamil Nadu is a state situated in the southernmost part of India. Five cities selected for this study include Ambur, Hosur, Kumbakonam, Nagapattinam, and Pudukottai. The geographical information of the selected sites is provided in Table 1 and the location of these is illustrated in Fig. 1.

It can be observed from Table 1 that the cities chosen for this study are located at different altitudes ranging from 9 m to 872 m.

WS speed data from 1980 to 2018 was collected for this study from the MERRA-2 reanalysis database (NASA). The statistical analysis of the WS data from these sites is provided in Table 2 below.

The mean WS ranges from 5.41 m/s to 6.26 m/s. A maximum WS of 9.74 m/s is observed at Hosur. The standard deviation is the least at Pudukkotai and the largest at Hosur.

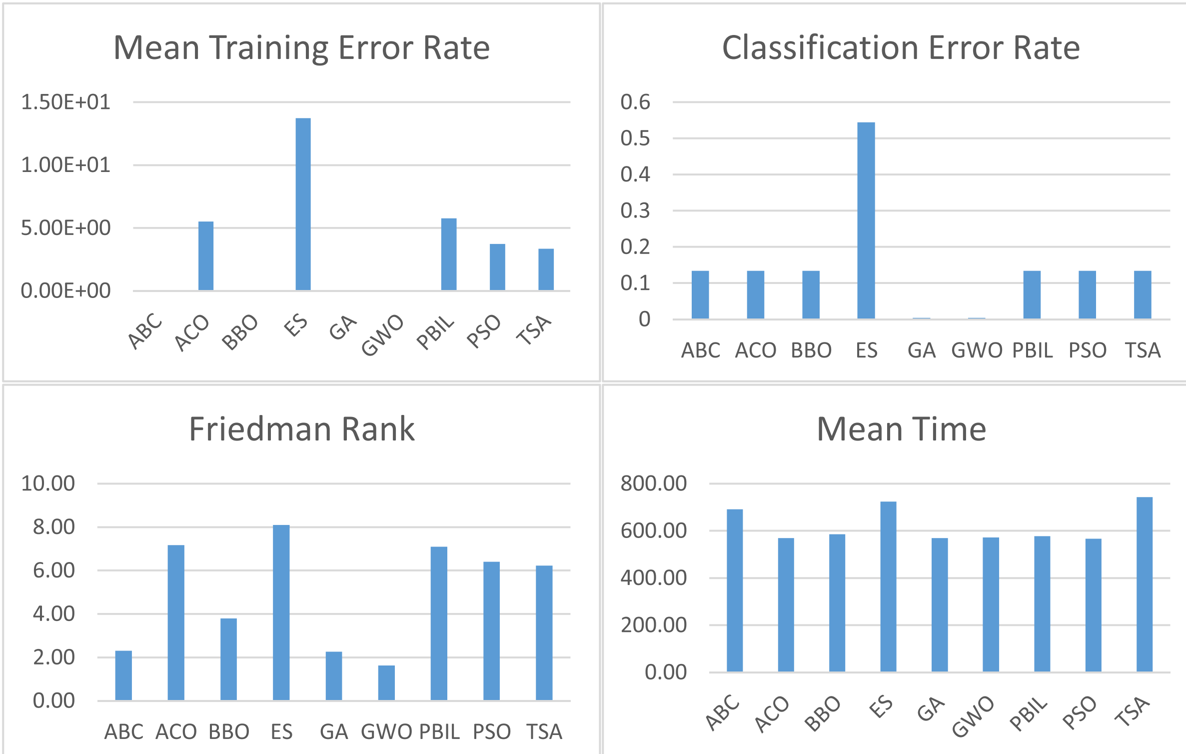


Fig. 6. Visualization of the experimental results of Kumbakonam.

Table 6
The experimental results of Nagapattinam.

Nagapattinam	ANN-ABC	ANN-ACO	ANN-BBO	ANN-ES	ANN-GA	ANN-GWO	ANN-PBIL	ANN-PSO	ANN-TSA
Mean	1.95E-02	6.12E+00	1.85E-01	1.31E+01	3.18E-02	3.36E-03	8.18E+00	3.92E+00	4.02E+00
Best	2.09E-03	1.60E-01	1.85E-01	5.64E-01	2.10E-03	2.07E-03	2.08E-03	2.27E-01	1.68E-01
Worst	1.48E-01	1.45E+01	1.85E-01	4.43E+01	2.73E-01	7.49E-03	3.27E+01	1.42E+01	1.37E+01
SD	3.24E-02	4.43E+00	0.00E+00	1.02E+01	5.35E-02	1.36E-03	7.70E+00	3.63E+00	3.53E+00
Median	8.83E-03	6.10E+00	1.85E-01	1.25E+01	1.10E-02	3.07E-03	6.09E+00	2.61E+00	3.30E+00
Mean Time	698.31	571.75	586.40	714.56	572.50	574.62	583.61	574.12	735.36
Friedman Rank	2.27	7.20	4.10	8.03	2.63	1.27	6.97	6.37	6.17
MSE test	0.0019	0.1911	0.2204	0.652	0.0019	0.0019	0.0019	0.2199	0.1957

4. Proposed artificial neural network optimized by metaheuristics

In this work, 9 metaheuristic algorithms are used for optimizing the weights and biases of a feed-forward (FF) multi-layer perceptron (MLP) artificial neural network (ANN). The detailed architecture of the FF MLP ANN is given in Fig. 2.

The input is the current hour WS, and the output is the next hour WS. In Cinar (2020), Cinar suggested that time series prediction with ANN with 15 hidden nodes produced eligible solutions. The same FF MLP ANN structure is used for the time series prediction in this study. 46 decision variables in the search range [−10, +10] are optimized by 9 metaheuristic algorithms. The detailed scheme of the suggested artificial neural network optimized by the metaheuristics approach is given in Fig. 3.

In Fig. 3, in the first phase, the training data is loaded. In the second phase, the FF MLP ANN is constructed. In the third phase, the FF MLP ANN parameters are optimized by 9 metaheuristic algorithms. In the fourth and fifth phases, the optimized FF MLP ANN is constructed, and test data is introduced. Finally, in the sixth phase, the mean square error (MSE) value for test data is reported.

5. Experimental setup

The WS (m/s) data at 50 m height observed in Indian cities (Ambur, Hosur, Kumbakonam, Nagapattinam, and Pudukkotai) between 01/01/1980 and 31/08/2018 were used in the experiments. The dataset was split into training and test. The values between 01/01/1980 and 31/12/2009 were used as a training dataset. The values between 01/01/2010 and 31/08/2018 were used as a testing dataset. The total dataset sample size is 338,952 for each city, out of which 262,991 values were used in training and 75,961 values were used in testing. Approximately 78% of data was used as a training dataset and 22% of data were used as a testing dataset. MSE is used as a statistical parameter to assess the performance metric. The formula of MSE is given in Eq. (1).

$$\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2 \tag{1}$$

Where n is the sample size, O_i is the observed value, P_i is the predicted value. The parameters of the 9 metaheuristic algorithms are the same as that of Cinar (2020). To avoid repetition, the readers are requested to refer to the same. 30 different runs were conducted on a PC with Intel(R) Core(TM) i5-9400F CPU @ 2.90 GHz and 8 GB of RAM. All experimental processes were performed using the MATLAB program. The population

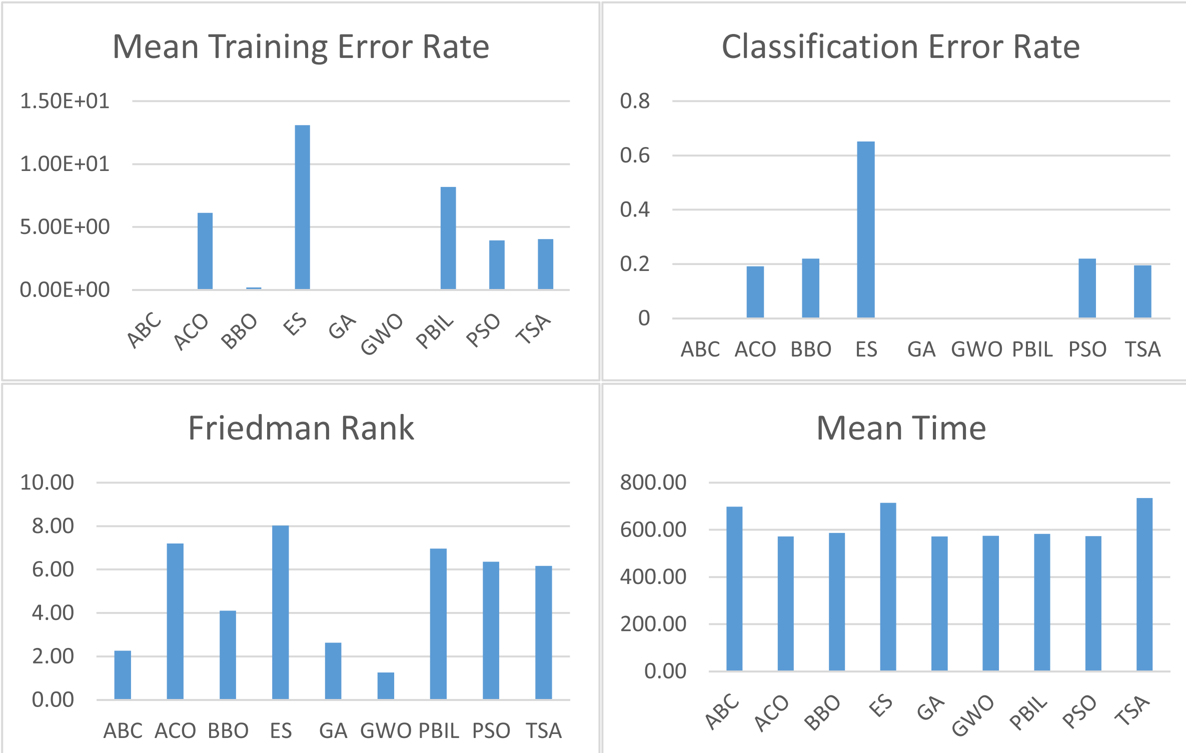


Fig. 7. Visualization of the experimental results of Nagapattinam.

Table 7
The experimental results of Pudukkotai.

Pudukkotai	ANN-ABC	ANN-ACO	ANN-BBO	ANN-ES	ANN-GA	ANN-GWO	ANN-PBIL	ANN-PSO	ANN-TSA
Mean	2.09E-02	7.33E+00	1.09E-01	1.75E+01	2.68E-02	6.09E-03	7.37E+00	4.23E+00	4.22E+00
Best	4.37E-03	4.74E-01	1.09E-01	1.50E-01	4.55E-03	4.37E-03	2.08E-01	6.84E-02	1.21E-01
Worst	9.77E-02	3.59E+01	1.09E-01	8.52E+01	1.15E-01	1.56E-02	2.67E+01	2.91E+01	1.31E+01
SD	2.14E-02	8.62E+00	0.00E+00	1.68E+01	2.85E-02	2.34E-03	6.79E+00	5.62E+00	3.52E+00
Median	1.47E-02	5.22E+00	1.09E-01	1.43E+01	1.47E-02	5.12E-03	5.16E+00	2.20E+00	3.42E+00
Mean Time	676.62	554.65	578.92	691.94	554.25	554.50	566.57	554.72	715.20
Friedman Rank	2.20	7.10	4.00	7.77	2.50	1.33	7.20	6.40	6.50
MSE test	0.0055	0.5902	0.1642	0.1374	0.0057	0.0055	0.1795	0.0870	0.1496

size (N) is considered as 40. The maximum iteration number is considered as 50. The maximum function evaluation number is fixed as 2000. The dimension (D) is considered as 46.

6. Results and discussions

In Tables 3-7, training MSE values are reported as Mean, Best, Worst, Standard Deviation (SD), and Median along the rows. The Mean Time refers to the mean runtime consumed for each method. The Friedman Rank indicates the Friedman's test value. The MSE test refers to the MSE values of the testing results of the method.

The experimental results of Ambur are given in Table 3 and the visualization of the experimental results of Ambur is shown in Fig. 4. ANN-ACO, ANN-ES, and ANN-PBIL produced higher MSE values for test data. The best method is ANN-ABC, and the second-best is ANN-GWO. ANN-BBO is trapped in the same local optima in all runs, and ANN-ABC is observed to be slower than ANN-GWO.

The experimental results of Hosur are given in Table 4 and the visualization of the experimental results of Hosur is shown in Fig. 5. ANN-ACO, ANN-ES, ANN-PBIL, ANN-PSO, and ANN-TSA produced higher MSE values for the test data. The best methods are ANN-ABC and ANN-GWO in terms of the MSE test. ANN-BBO is trapped in the same local optima in all runs, and ANN-ABC is observed to be slower than ANN-GWO.

The experimental results of Kumbakonam are given in Table 5 and the visualization of the experimental results of Kumbakonam is shown in Fig. 6. ANN-ABC, ANN-ACO, ANN-BBO, ANN-ES, ANN-PBIL, ANN-PSO, and ANN-TSA produced higher MSE values for test data. The best method is ANN-GA and the second method is ANN-GWO in terms of MSE test. ANN-BBO is trapped in the same local optima in all runs, and ANN-GA is observed to be faster compared to ANN-GWO.

The experimental results of Nagapattinam are given in Table 6 and the visualization of the experimental results of Nagapattinam is shown in Fig. 7. ANN-ACO, ANN-BBO, ANN-ES, ANN-PSO, and ANN-TSA produced higher MSE values for test data. The best methods are ANN-ABC, ANN-GA, ANN-GWO, and ANN-PBIL in terms of MSE test. ANN-BBO is trapped in the same local optima in all runs. ANN-GA is faster than ANN-ABC, ANN-GWO, and ANN-PBIL.

The experimental results of Pudukkotai are given in Table 7 and the visualization of the experimental results of Pudukkotai is shown in Fig. 8. ANN-ACO, ANN-BBO, ANN-ES, ANN-PBIL, ANN-PSO, and ANN-TSA produced higher MSE values for test data. The best methods are ANN-ABC and ANN-GWO in terms of MSE test. ANN-BBO is trapped in the same local optima in all runs, and ANN-GWO is observed to be faster than ANN-ABC. The Friedman's test values are provided in Table 8 and the comparison of the same has been illustrated in Fig. 9.

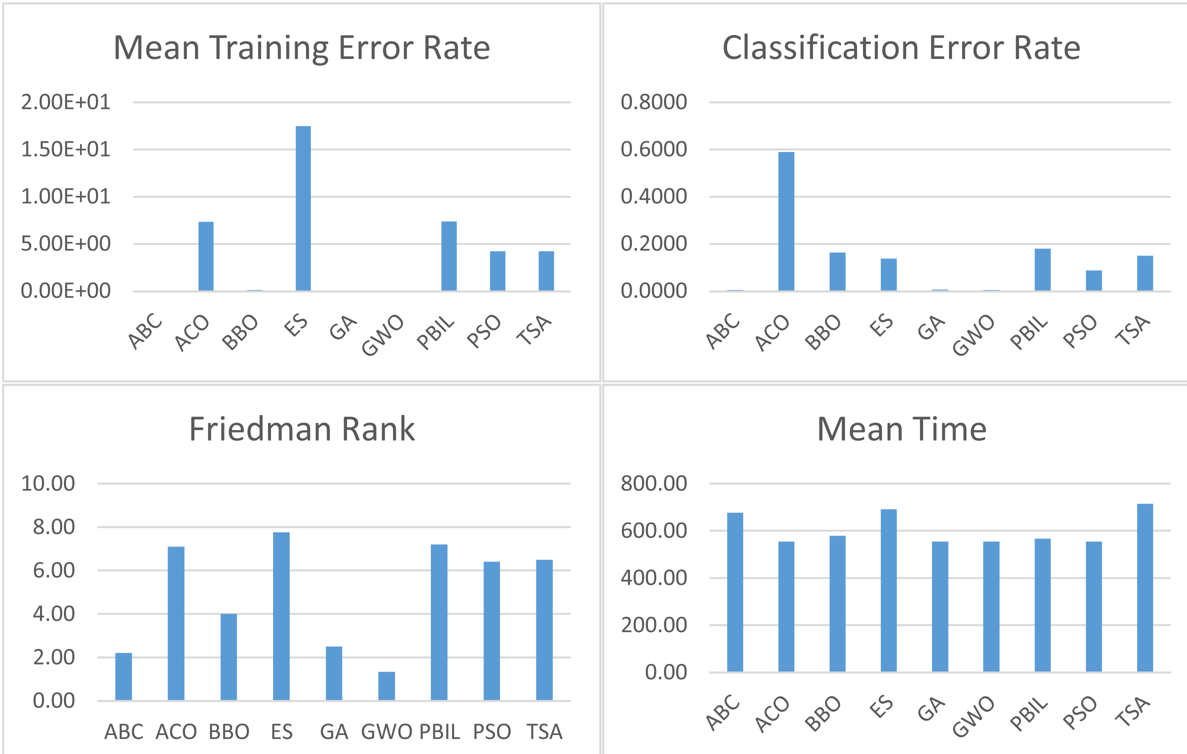


Fig. 8. Visualization of the experimental results of Pudukkotai.

Table 8
The Friedman's test values.

Friedman Rank	ANN-ABC	ANN-ACO	ANN-BBO	ANN-ES	ANN-GA	ANN-GWO	ANN-PBIL	ANN-PSO	ANN-TSA
Ambur	2.83	7.27	2.67	7.83	3.10	1.43	6.67	6.60	6.60
Hosur	2.77	7.00	2.47	8.23	3.00	1.77	6.73	6.70	6.33
Kumbakonam	2.30	7.17	3.80	8.10	2.27	1.63	7.10	6.40	6.23
Nagapattinam	2.27	7.20	4.10	8.03	2.63	1.27	6.97	6.37	6.17
Pudukkotai	2.20	7.10	4.00	7.77	2.50	1.33	7.20	6.40	6.50
Mean	2.47	7.15	3.41	7.99	2.70	1.49	6.93	6.49	6.37

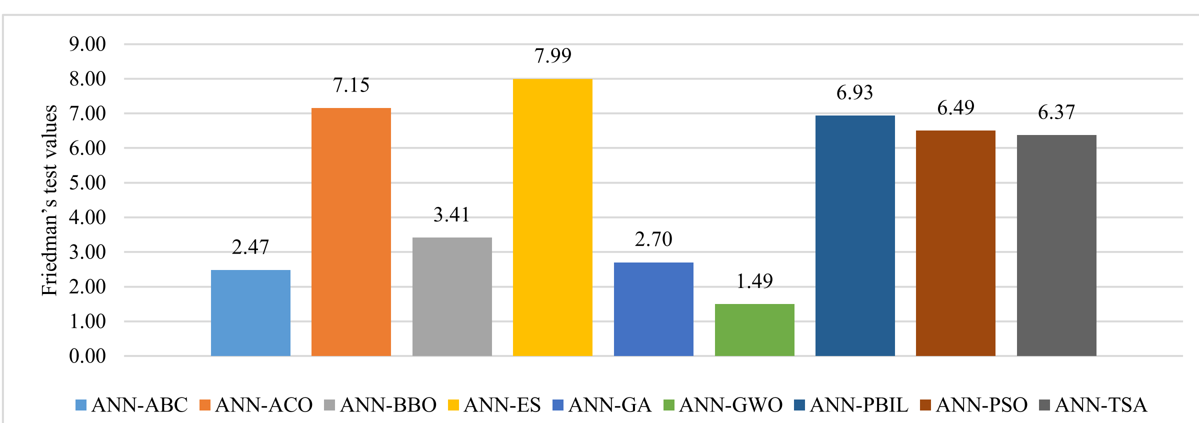
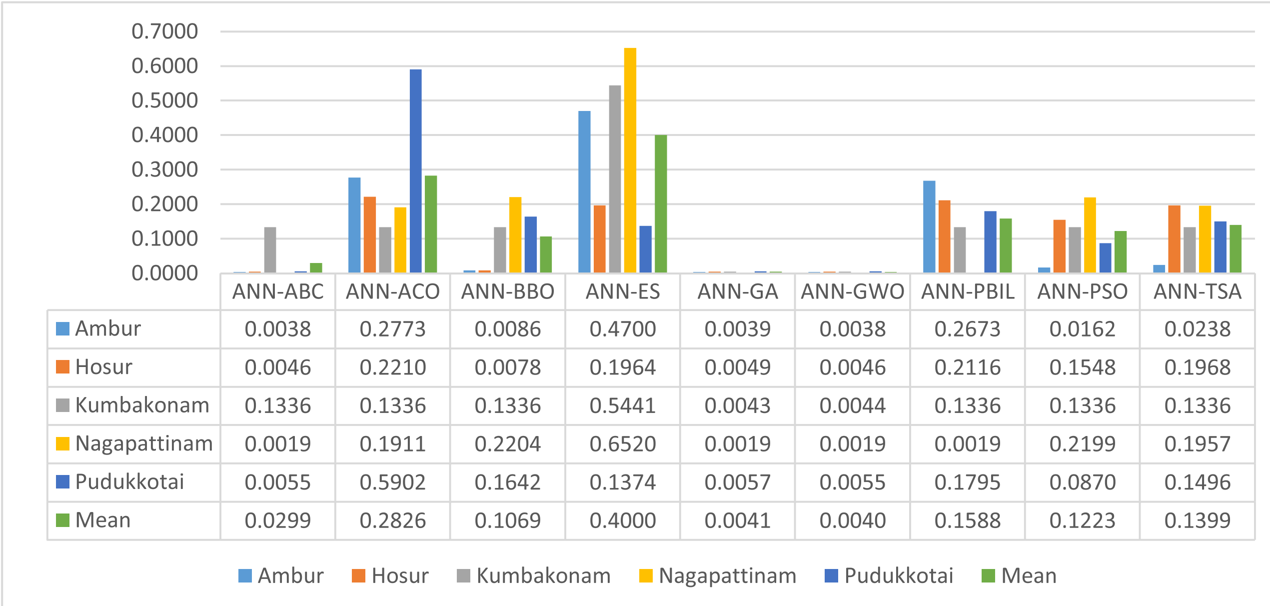


Fig. 9. Comparison of Friedman's test values for the proposed hybrid models.

According to Tables 3-8 and Fig. 9, the best approach is ANN-GWO. The second one is ANN-ABC and the third one is ANN-GA. ANN-GWO has high exploration and exploitation capability due to its individual organization.

The comparison of classification error rate values for all the models is shown in Fig. 10. The best approach is ANN-GWO. The second one is ANN-GA and the third one is ANN-ABC.

The success percentage of ANN-GWO vs. other models in terms of classification error rate is shown in Fig. 11. GWO outperforms the other metaheuristic algorithms in the prediction of wind speed with a FF MLP



	ANN-ABC	ANN-ACO	ANN-BBO	ANN-ES	ANN-GA	ANN-GWO	ANN-PBIL	ANN-PSO	ANN-TSA
Ambur	0.0038	0.2773	0.0086	0.4700	0.0039	0.0038	0.2673	0.0162	0.0238
Hosur	0.0046	0.2210	0.0078	0.1964	0.0049	0.0046	0.2116	0.1548	0.1968
Kumbakonam	0.1336	0.1336	0.1336	0.5441	0.0043	0.0044	0.1336	0.1336	0.1336
Nagapattinam	0.0019	0.1911	0.2204	0.6520	0.0019	0.0019	0.0019	0.2199	0.1957
Pudukkotai	0.0055	0.5902	0.1642	0.1374	0.0057	0.0055	0.1795	0.0870	0.1496
Mean	0.0299	0.2826	0.1069	0.4000	0.0041	0.0040	0.1588	0.1223	0.1399

Fig. 10. Comparison of classification error rate values for all models.

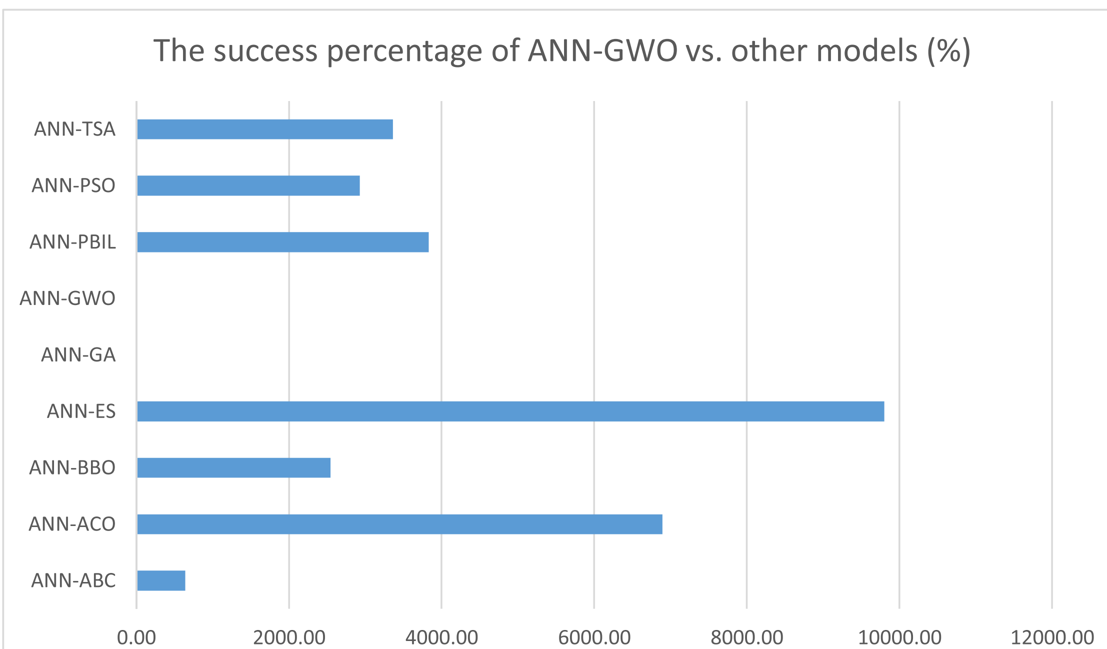


Fig. 11. The success percentage of ANN-GWO vs. other models.

ANN, with a success percentage rate of approximately 3% to 10,000%.

7. Conclusion

In this study, a feed-forward (FF) multi-layer perceptron (MLP) artificial neural network (ANN) is used for the prediction of the hourly WS. For conducting the numerical experiments, 38 years of hourly wind speed data belonging to 5 cities (Ambur, Hosur, Kumbakonam, Nagapattinam, and Pudukottai) were used. These cities have different specific properties such as latitude, longitude, and altitude. The FF MLP ANN is optimized by 9 state-of-art metaheuristic algorithms. In this work, Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Biogeography Based Optimization (BBO), Evolutionary Strategy (ES), Genetic Algorithm (GA), Grey-Wolf-Optimizer (GWO), Population-Based Incremental Learning (PBIL), Particle Swarm Optimization (PSO), Tree-Seed Algorithm (TSA) have been used to optimize the weights of the ANN. The main aim of this work is to present the comparison of the feed-forward multi-layer perceptron artificial neural network models which are optimized by 9 state-of-the-art metaheuristic algorithms. All these algorithms start with a random population and use various techniques and mechanisms to find the optimum values of the given optimization problem. The obtained experimental results show that GWO provided the most accurate output in terms of mean square error (MSE), Friedman's test value, mean training error rate, and execution time. GWO has five steps of the hunting mechanism of the grey wolf which are its social hierarchy, prey encircling, chasing, prey attacking, and prey searching.

These phases produce more accurate solutions, balance exploration and exploitation in the optimization process.

Statements and Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

All data generated or analysed during this study are included in this published article.

Competing interests

The authors declare that they have no competing interests.

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CRediT authorship contribution statement

Ahmet Cevahir Cinar: Software, Validation, Visualization, Supervision, Writing – original draft, Writing – review & editing. **Narayanan Natarajan:** Investigation, Conceptualization, Methodology, Data curation, Writing – original draft, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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