A Green Energy Research: Forecasting of Wind Power For A Cleaner Environment Using Robust Hybrid Metaheuristic Model

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Abstract

Wind is a stochastic and intermittent renewable energy source. Due to it's nature, it is extremely hard to forecasting of wind power. Accurate wind power forecasting can be encouraging and motivating for investors to shed light on future uncertainties caused by global warming. Thus, CO_2 and other greenhouse gases which are harmful to the environment will not be released into the atmosphere, while generating electrical energy. This paper presents a novel precise, fast and powerful hybrid metaheuristic wind power forecasting approach based on statistical and mathematical data from real weather stations. The model was developed as a hybrid metaheuristic algorithm based on Artificial Neural Networks (ANNs), Particle Swarm Optimization (PSO) and Radial Movement Optimization (RMO). Real-time wind data was gathered from Wind Measuring Stations (WMS) at two separate places in Burdur and Osmaniye cities, Turkey. The key contribution of this new model is the ability to perform wind power forecasting studies, without needing wind speed data, with high accuracy and rapid solutions. Also, it has been carried out wind power forecasting studies with high accuracy despite the height differences between the sensors. That is, for WMS-1 and WMS-2, it has succeeded the wind power forecasting at 61m and 60.3m using temperature (3m), humidity (3m), and pressure (3.5m) data. The performance results were presented in tables and graphs.

Introduction

Because of the world's increased population and developing industries, the demand for electrical energy is increasing. It is known that the fossil-based sources will be consumed in the future, therefore, sustainable and renewable types of energy resource such as wind energy has become very popular in the past decade. Wind energy has a wide range of applications that are rapidly expanding, unlimited, environmentally friendly, and cost-effective. It has a bright feature, however, due to its stochastic and intermittent nature, it is hard to predict accurately (Xiaochen et al., 2011; Yang et al., 2013; Yang & Shaoshuai, 2016).

Wind power forecasting is highly dependent on the wind speed forecasting process. The wind power forecast is essential and significant for determining the locations of wind plants to be built in (Varanasi & Tripathi, 2016), power system quality, grid reliability, energy planning (Rahmani et al, 2013; Lund, 2005; Debbağ & Yilmaz, 2015), energy transformation efficiency and interconnected network operations (Riahy & Abedi, 2008).

The wind parameters such as wind speed, wind direction, temperature, humidity, and pressure must be measured and recorded for at least 12 months to determine the power of the wind power plant to be constructed. This period may be extended due to climate changes caused by global warming (Kerem et al, 2014). The most accurate wind power forecasting studies depending on the collected data might be encouraging and motivating for investors by providing light on future concerns. Thus, the significance of accurate wind power forecasting studies is once again highlighted.

The wind is a flow of air in motion and there is the kinetic energy of an object in motion. Thus, the theoretical power obtained from the wind can be calculated with (1) (Patel, 1942; Golding, 1955);

$P_r = ½ \rho_a A_T V_r^3$ (W) (1)

where, air density *(ρ_a: 1.225 kg/m^3*), wing sweeping area *(A_T, m^2*) and wind speed *(V_r, m/s).* Temperature, atmospheric pressure, slope and air components are effective in air density. Thus, the air density can be calculated with (2) if the temperature *(T)* and height *(Z)* of the zone are known;

$\rho_a = (353.049 / T). e^{(-0.034^Z/T)}$ (2)

The above equations explain the theoretical wind power. In fact, according to Betz Law, the power value to be taken from the unit wind is 59% of the wind power it carries *(C_p=0.59).* The max power to be taken from the wind turbine is calculated in (3) (Ragheb & Ragheb, 2011; Gourieres, 1982);

$P_r = ½ \rho_a A_T Vr^3 C_p$ (W) (3)

Figure 1 Kinetic energy flow of wind around a wind turbine (Rahmani et al., 2010)

Energy of the air passing through the wings can be defined as follows (4) (Çetin, 2006);

$E_k = E_{kIn} - E_{kOut}$ (Nm) (4)

Kinetic energy *(E_k)* of the wind in motion is calculated in (5) and wind power *(P_T)* is shown in (6);

$E_k = ½ \rho_a A_T V_{r1} (V_r^2 - V_{r2}^2)$ (Nm) (5)

$P_T = E_k/t = ½ \rho_a A_T V_{r1} (V_r^2 - V_{r2}^2)$ (W) (6)

In literature, Rahmani et al., (2013) developed a hybrid model of Ant Colony Optimization (ACO) and PSO for short term wind energy estimation. To observe the performance of the hybrid model they used 364 days data from Binaloud wind farm. The proposed model predicted wind power as 3.513% using MAPE. Pousinho et al., (2010) developed a hybrid model of Particle Swarm Optimization (PSO) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) models for short-term wind power estimation. They analyzed the performance of the model and found the Mean Absolute Percent Error (MAPE) as 5.41%. Liang et al., (2015) designed a hybrid model of Hilbert Hur Huang Transform (HHT) and Hurst Analysis (HA) for wind power estimation. Using the Empirical Mode Decomposition (EMD) + Least Square Support Vector Machine (LSSVM) + Extreme Learning Machine (ELM) hybrid models they decreased to error values from 49.45% and 44.30% to 37.96 and 27.12%, respectively. Zhang et al., (2015) designed a hybrid estimation model of EMD + Support Vector Machine (SVM) for wind power estimation. They used the EMD to convert the wind energy sequence into a variety of internal functions, and the SVM used to optimize the optimal parameters and each component of the kernel function. According to analysis results, it is observed that the developed EMD + SVM hybrid model has significantly increased the wind power estimation accuracy. Kassa et al., (2016) designed a hybrid estimation model that includes ANN based Genetic Algorithm (GA) + Back Propagation (BP) models for wind power prediction. GA -optimized and BP - trained algorithm of multi-layer ANNs were used in this model. In order to test the performance of the model, they used the data of 2.5 MW wind turbine in Beijing. Catalao et al., (2011) developed a triple hybrid prediction model of Wavelet + PSO + ANFIS models for short term wind power estimation. In order to test the performance of the proposed model, they used data from the National Electricity Network (REN) in Portugal. They were compared to the success of the new model with other models such as Persistence, NRM, ARIMA, Neural Networks (NN), NNWT, NF and Wavelet + Neuro + Fuzzy (WNF). It was observed that the new hybrid model had better MAPE and NMAE error values. Osório et al., (2015) developed a hybrid estimation model of Wavelet Transform (WT), ANFIS, Evolutionary Particle Swarm Optimization (EPSO) and Mutual Information (MI) algorithms for short term wind power estimation. They observed the performance of the WT + ANFIS + EPSO + MI hybrid model were more successful than previous prediction algorithms. Azimi et al., (2016) designed a hybrid model based on time series that includes Time-Series Based K-Means Clustering Method (TSBK) and Cluster Selection Algorithm (CSA) for wind power estimation. In this model TSBK, Discrete Wavelet Transform (DWT) and Harmonic Analysis Time Series (HANTS) and Multilayer Perceptron Neural Network (MLPNN) algorithms were used to increase the accuracy of wind energy estimation. The task of TSBK is to separate the data into separate groups, identifying abnormal and irregular patterns and providing more appropriate learning for neural networks. That improves the accuracy of the estimated results. They applied the CSA to identify the best-trained cluster for MLPNN. The data were separated by Daubechies D4 wavelet transform and filtered by HANTS. They tested the performance of the developed model on the data obtained from different wind farms in the USA. The new hybrid model showed superior success according to the results of the analysis. Liu et al., (2015) developed a hybrid Relevance Vector Machine (RVM) model for wind power estimation. There are five Kernel Functions in this model that Gaussian Kernel, Laplacian Kernel, Cauchy in Distance Kernel, R (distance) Kernel and Thin-plate spline Kernel (Tps). The SVM prediction model used one by one with each Kernel. According to the analysis they observed that the proposed hybrid RVM model was more compatible with the Kernel parameters and obtained more accurate results than the other individual kernel models. Haque et al., (2014) designed the WT + FA + FF + SVM hybrid model for wind power estimation consisting of WT, Fuzzy Artmap (FA), Firefly (FF) and SVM. They have combined WT and FA algorithms for wind power estimation and optimized with FF. They used SVM to minimize wind power estimation errors obtained from WT + FA + FF. They tested the success of the hybrid model by using the wind power data from the Cedar Creek wind farm in Colorado. Chitsaz et al., (2015) used the Wavelet Neural Network (WNN) model trained with the Enhanced Clone Selection Algorithm (CSA) for wind power estimation. They used the Maximum Correntropy Criterion (MCC) instead of MSE in the estimation process. They used real-time hourly data of the wind turbine in Alberta, Canada in order to test the performance of the model. They compared the success of the model with other techniques and observed that this new model obtained more successful results. Osório et al., (2012) developed a hybrid prediction model of the WT, EPSO and ANFIS models for short-term wind power estimation. They found that the proposed model had MAPE of 4.28% and calculation time of less than 1min. Thus, they have obtained much more accurate estimation and short computation time than the other techniques in the literature. Kusiak et al., (2009) designed the MLP + kNN hybrid model for wind power estimation. And, they presented two basic estimation studies. The first one is the direct prediction model where the power estimate is derived directly from

the weather forecast data. The other one is an integrated forecasting model which is produced by the estimated air data of the wind speed and then generated by the estimated wind speed and power. They examined the performance of the model for different time periods of 12 hours and 84 hours. They observed that the direct prediction model had better prediction performance than the hybrid prediction model. Catalao et al., (2011) developed a new hybrid model based on the WT model and a hybrid of NNs + Fuzzy Logic (FL) model for short term wind power estimation in Portugal. The proposed WNF hybrid model obtained MAPE value as 5.99%. Sharifian et al., (2018) designed a new hybrid prediction model called T2FNN + PSO to develop Type-2 Fuzzy Neural Network (T2FNN). This new model combines both the expert knowledge of the fuzzy system and the ability of the NNs to learn for accurate estimation of wind power.

In this study, to make a highly accurate wind power prediction, a newer and powerful hybrid metaheuristic approach called ANNs+(PSO-RMO) was used. Data was gathered from Wind Measuring Stations (WMS) located at various locations in the Burdur and Osmaniye cities for WMS-1 and WMS-2, respectively. To compare the effectiveness of ANNs+(PSO-RMO) approach, the other hybrids such as ANNs + ACO, ANNs + GA, ANNs + PSO, ANNs + RMO were designed. 50run was used to evaluate the performance of all developed hybrid metaheuristic models.

The main contributions of this study are;

1. Accurate wind power forecasting can be encouraging and motivating for investors to shed light on future uncertainties caused by global warming. Thus, CO_2 and other greenhouse gases will not be released into the atmosphere as a consequence of focusing energy generation to clean, ecologically friendly, and renewable energy rather than fossil-fueled power plants.

2. The ANNs+(PSO-RMO) model is able to perform wind power forecasting studies with high accuracy, rapid and reliability without needing wind speed data, which is a vital parameter.

3. Wind power forecasting studies could be performed despite the height differences between the sensors. That is, wind power forecasting studies at 61m and 60.3m were performed using temperature (3m), humidity (3m) and pressure (3.5m) data for WMS-1 and WMS-2, respectively.

4. The effectiveness of the designed hybrid metaheuristic approach has been tested on real-time data taken from two distinct coordinates and the model success has been confirmed even at abrupt fluctuations.

5. This proposed model is proved to be more effective than the GA, ACO, PSO, and RMO models commonly used in the literature.
6. With this study, the wind power forecasting studies have been applied to ANNs+(PSO-RMO) model for the first time in the literature.

Data Processing In Terrain

The WMS were placed at two separate locations. The WMS-1 was situated at UTM E263.254 and N4.173.479 coordinates with an altitude of 1313 m and a 63 m total height in Burdur. The WMS-2 was situated at E285.866 - N4.122.267 coordinates, 1028 m altitude and 60.3 m total height in Osmaniye. WMS-1 and WMS-2 data were gathered in 2014 (August) and 2009 (October), respectively.

Technical data for WMS-1 and WMS-2 are given in Table I. Installation works of WMS-1 and sensors are given in Fig. 3.

Table 1
Technical data for WMS-1 and WMS-2

WMSs	input variables			output variable
	temperature	humidity	pressure	wind power
WMS-1: Burdur UTM E263.254 - N4.173.479 1313m altitude	4m	4m	3.5m	61m
WMS-2: Osmaniye UTM E285.866 - N4.122.267 1028m altitude	4m	4m	3.5m	60.3m

Table 2
Statistical values of WMS-1 data (august) and WMS-2 data (october)

Parametreler	WMS-1					WMS-2				
	Wind speed (m/s)	Wind aspect (º)	Temp. (ºC)	Humidity (%)	Pressure (mbar)	Wind speed (m/s)	Wind aspect (º)	Temp. (K)	Humidity (%)	Pressure (mbar)
Average	4.592	161.689	23.101	46.638	865.763	3.193	164.019	2837.722	65.631	900.241
Median	4.435	156.717	23.396	47.642	866.348	2.781	160.697	2831.93	65.299	900.801
Std dev.	0.991	56.931	2.356	13.329	2.354	1.403	47.309	24.339	15.413	4.003
Mod	5.165	149.179	21.087	61.67	867.423	4.429	131.637	2829.647	92.284	900.552
Maximum	8.797	282.038	28.409	76.673	870.448	7.239	316.6	2896.92	93.378	906
Minumum	2.432	41.013	17.217	26.791	861.358	0.556	79.458	2801.254	37.891	887.388
Skewness	0.939	0.092	-0.259	0.292	-0.136	1.136	0.145	0.805	0.169	-1.288
Kurtosis	2.604	-0.729	-0.436	-1.089	-0.64	0.568	-0.741	-0.265	-1.186	1.678
Variance	0.981	3241.174	5.551	177.654	5.544	1.968	2238.172	592.375	237.563	16.022
Sample item	4464	4464	4464	4464	4464	4319	4319	4319	4319	4319

Powerful Hybrid Metaheuristic Approach

The hybrid approach composed of two distinct metaheuristic algorithms of PSO and RMO given in Sect. 3.1 and 3.2.

Particle Swarm Optimization (PSO)

PSO is a two-dimensional model of the combined behavior of bird and fish swarms in food-search scenarios. It is a metaheuristic algorithm which, in terms of computation, is quick and effective, and simple in terms of understanding and implementation (Kennedy & Eberhart,1995).

Radial Movement Optimization (RMO)

RMO is a metaheuristic optimization algorithm that fastly works, swarm-based, simple and effective. It was structured to optimize complex and non-linear issues spherically, using a vector's spherical limits in the quest space to find the optimum solution. The algorithm is initialized by launching the particles in the search space that demonstrates the solutions to the problem (Rahmani & Yusof, 2014; Mahrami et al., 2016; Seyedmahmoudian et al., 2016).

Once the center point *(c_p)* has been achieved the next step is to scatter the particles from the c_p. The particles are moved through the V_{ij} vector based c_p through the radius in straight lines. The next step is to evaluate the appropriateness of all particles after scattering. The particle containing the best fit value is taken as the best radial *(Rbest).* The locations of the *Gbest* and *Rbest* particles are used to update a new best c_p position using the *up* vector, provided in (7) and (8) (Rahmani & Yusof, 2014; Mahrami et al., 2016; Seyedmahmoudian et al., 2016);

$c_p^{k+1} = c_p^k + up$ (7)

$u_p = C_1 (G_{best} - c_p^k) + C_2 (R_{best} - c_p^k)$ (8)

The scattering of particles begins again from the updated c_p after the c_p is updated. The update of the c_p by *up* vector is seen in Fig. 4.

The ANNs+(PSO-RMO) Approach

The main strategy here is to ensure reliable and efficient operations with highly accurate rates for wind power forecasting studies. Thus, ANNs are used for the forecasting process and the PSO-RMO model is then used to train ANNs, in this approach. In this training procedure, it was intented to optimise the nonlinear and linear components, and also, randomly occurring wide fluctuations in the data sets.

The RMO in the model has been used to construct the hybrid model thanks to its ability to focus strongly around the target point and ability to search around the target point, its low memory requirement, its rapid operation, and its ability to continue the search without missing in the local maximum with its *Gbest* vector (Rahmani & Yusof, 2014; Mahrami et al., 2016; Seyedmahmoudian et al., 2016; Rahmani et al, 2015). Also, the PSO, which is also included in the model, is able to memorize the coordinates of the particles, their velocities, the best suitability amounts it has achieved so far and the coordinates it has obtained, and to take into account its own best past coordinates and the experiences of its most successful neighbor while determining its next movements (Kennedy & Eberhart,1995; Eberhart & Kennedy, 1995; Kennedy & Eberhart, 1997; Kennedy et al., 2001) features were used.

The ANNs+(PSO-RMO) approach was designed to be able to obtain these two unique features from a single algorithm by taking advantage of the distinguishing singular characteristics of PSO and RMO, increasing system stability, more reliability and rapid forecasting studies (Kerem & Saygin, 2019; Kerem et al., 2019; Kerem, 2021).

The first stage in the method is to initialization the weight parameters of the ANNs. Second, it continues with the application of problem restrictions and bounds, as well as the preservation of the best values by assessing all particle positions. After controlling the generation number, if it is even, RMO runs, otherwise, PSO runs, and the particles are scattered. After this process, the ANNs' location matrix-weight parameters are updated, and the stopping criteria are re-evaluated. If the criteria are not sufficient, the process returns to the "Evaluate all particles locations and store best values" section, and if sufficient, the process ends with bringing the best values. The model's flowchart is shown in Fig. 5.

The pseudo-code for the ANNs+(PSO-RMO) approach is shown in Fig. 6.

In the model, the data set was separated into 70 % for training process, 15 % for validation process and 15 % for testing process using MATLAB R2017b, as shown in Fig. 7.

Performance Evaluation

The effectiveness of the novel hybrid metaheuristic approach for wind power forecasting studies is examined in this section. With the exception of wind speed data, all wind power forecasting performances carried out using temperature, humidity, and pressure data. Indeed, it is a major obstacle to prevent the success rate, and it was deliberately created. The other obstacle is the height difference between the sensors. It means the WMS-1 and the WMS-2 data for temperature (3m), humidity (3m), and pressure (3.5m) were used to perform wind power forecasting experiments at 61m and 60.3m, respectively. The blog diagram of the model is given in Fig. 9.

The performance results were recorded for ANNs+(PSO-RMO) approach and the other four hybrid metaheuristics. The performance of these hybrid models has been seriously affected by making wind power predictions with no wind speed data. That is, all hybrid

models performed wind power predictions using temperature, humidity and pressure data. Figure 10 illustrates actual and estimated wind power curves for WMS-1 for the ANNs+(PSO-RMO) approach.

According to Fig. 10 actual and estimated plots are so close, thus, error values are RMSE, NRMSE, PSNR, MSE, MAPE and R obtained 2.091, 0.1673, 41.72, 4.732, 2.068, 0.9993 respectively. Changing of fitness value of ANNs+(PSO-RMO) approach for WMS-1 is given in Fig. 11.

Figure 12 shows actual and estimated curves of wind power forecasting using ANNs+(PSO-RMO) approach for WMS-2. It belongs to the 24-hour frequency and the 15-day time record, October.

According to Fig. 12, actual and estimated curves are almost overlapping, thus, error values are RMSE, NRMSE, PSNR, MSE, MAPE and R are 0.5857, 0.03425, 52.78, 0.343, 1.379 and 0.9995 respectively. Changing of fitness value of ANNs+(PSO-RMO) approach for WMS-2 is given in Fig. 13.

Error criteria includes PSNR, MSE, RMSE, MAPE is given in Table 3. Here, A_i represents the actual value, F_i is the predicted value, N is the number of observations and $MAXI$ represents the maximum pixel value of the picture.

Table 3 Error criteria (Varanasi & Tripathi, 2016; Sivakumar, 2017; Guo et al., 2011; Kirbas, 2018; Zhao, 2016)

Peak Signal to Noise Ratio (PSNR)	$PSNR = 10\,log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20\,log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$
Mean Squared Error (MSE)	$MSE = \frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)^2$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - F_i)^2}$
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{A_i - F_i}{A_i}\right\rvert * 100$

The test errors for WMS-1 and WMS-2 (50run) and the comparative results of MAPE of test error (50run) are given in Table 4 and Table 5, respectively. According to Table 4, the ANNs+(PSO-RMO) approach is the most effective with the lowest errors in all performances.

Table 4
Test errors for WMS-1 and WMS-2 (50run)

		ANNs + PSO	ANNs + ACO	ANNs + RMO	ANNs + GA	ANNs+(PSO-RMO)
WMS-1: August record frequency: 24-hour record time: 15-day	R	0.999	0.999	0.996	0.999	0.999
	MAPE	2.108	2.165	4.807	2.100	2.068
	PSNR	41.990	42.797	34.670	43.031	41.720
	MSE	4.109	3.414	22.210	3.235	4.372
	RMSE	2.027	1.847	4.712	1.798	2.091
	NRMSE	0.162	1.231	0.377	1.199	0.167
WMS-2: October record frequency: 24-hour record time: 15-day	R	0.999	0.994	0.992	0.983	0.999
	MAPE	1.428	6.796	6.102	12.391	1.379
	PSNR	52.62	40.507	40.950	35.764	52.780
	MSE	0.355	5.784	5.227	17.245	0.343
	RMSE	0.596	2.405	2.286	4.152	0.585
	NRMSE	0.034	0.320	0.133	0.553	0.034
	Abbreviation- ACO: Ant Colony Optimization, GA: Genetic Algorithm, PSO: Particle Swarm Optimization, RMO: Radial Movement Optimization					

Table 5 provides comparative MAPE results for test errors, including the best, average, worst and standard deviation values.

Table 5
Comparative results of MAPE of test error (50run)

		ANNs + PSO	ANNs + ACO	ANNs + RMO	ANNs + GA	ANNs+(PSO-RMO)
WMS-1: August record freq: 24-hour record time: 15-day	best	2.108	2.165	4.807	2.100	2.068
	average	2.861	3.552	14.488	3.055	2.118
	worst	7.450	6.602	23.440	5.911	2.871
	standard deviation	0.977	1.154	5.670	0.946	0.161
WMS-2: October record freq: 24-hour record time: 15-days	best	1.428	6.796	6.102	12.391	1.379
	average	5.481	17.592	23.885	17.587	3.078
	worst	11.150	31.622	33.990	29.030	3.113
	standard deviation	2.584	5.831	9.051	3.618	0.245

According to Table 5, WMS-1(august) average MAPE (50run) values are 2.861, 3.552, 14.488, 3.055 and 2.118 for ANNs + PSO, ANNs + ACO, ANNs + RMO, ANNs + GA and ANNs+(PSO-RMO), respectively. For WMS-2 (October) average MAPE (50run) values are 5.481, 17.592, 23.885, 17.587 and 3.078 for ANNs + PSO, ANNs + ACO, ANNs + RMO, ANNs + GA and ANNs+(PSO-RMO), respectively. Thus, when Table 5 is analyzed, it has seen that the ANNs+(PSO-RMO) approach is the most efficient model of all the optimization algorithms.

The test error average MAPE values (50run) are shown in Fig. 14. Average test error values are 2.118 and 3.078 for WMS-1: August and WMS-2: October, respectively. Thus, the ANNs+(PSO-RMO) model achieved the most impressive results among the other hybrid metaheuristic models.

Conclusion

Fossil-fueled power plants emit CO_2 and other greenhouse gases into the atmosphere while generating electricity energy. These gases are harmful to the environment and ecosystem, and also threaten all living organisms. However, wind power plants, on the other hand, do not affect the environment while generating electricity; they are an environmentally friendly and clean energy source. One of the biggest obstacles for these power plants can be the difficulty of accurate wind power forecasting due to the intermittent and stochastic structure of the wind.

Wind power forecasting studies were performed in this research study using ANNs+(PSO-RMO) approach, a stronger and more powerful hybrid metaheuristic model. The model's performance was evaluated using real-time data gathered from two separate locations (WMS-1 and WMS-2). All of the performances were carefully plotted and recorded. The efficiency of the hybrid metaheuristic approach was compared to other hybrids such as ANNs + PSO, ANNs + ACO, ANNs + RMO, and ANNs + GA.

According to the error values, the newer hybrid metaheuristic approach has the smallest test errors among the existing hybrid models (see Table 4). Also, it was found that the ANNs+(PSO-RMO) approach provided a strongly accurate and consistent performance for wind power forecasting studies, even at abrupt fluctuations. Thus, with the smallest error rate, system reliability, and compact structure, a novel hybrid metaheuristic approach for wind power forecasting studies has contributed to the literature.

Declarations

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Figures

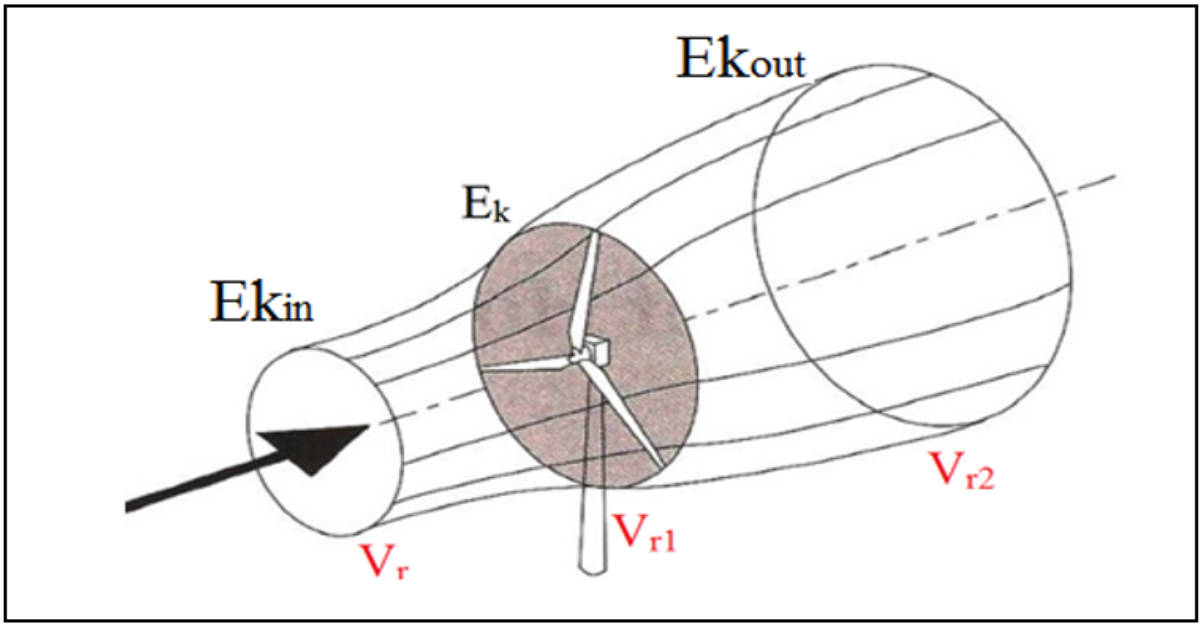

Figure 1

Kinetic energy flow of wind around a wind turbine (Rahmani et al., 2010)

Figure 2

Locations of WMS-1 and WMS-2

Figure 3

Installation works of WMS-1 and sensors

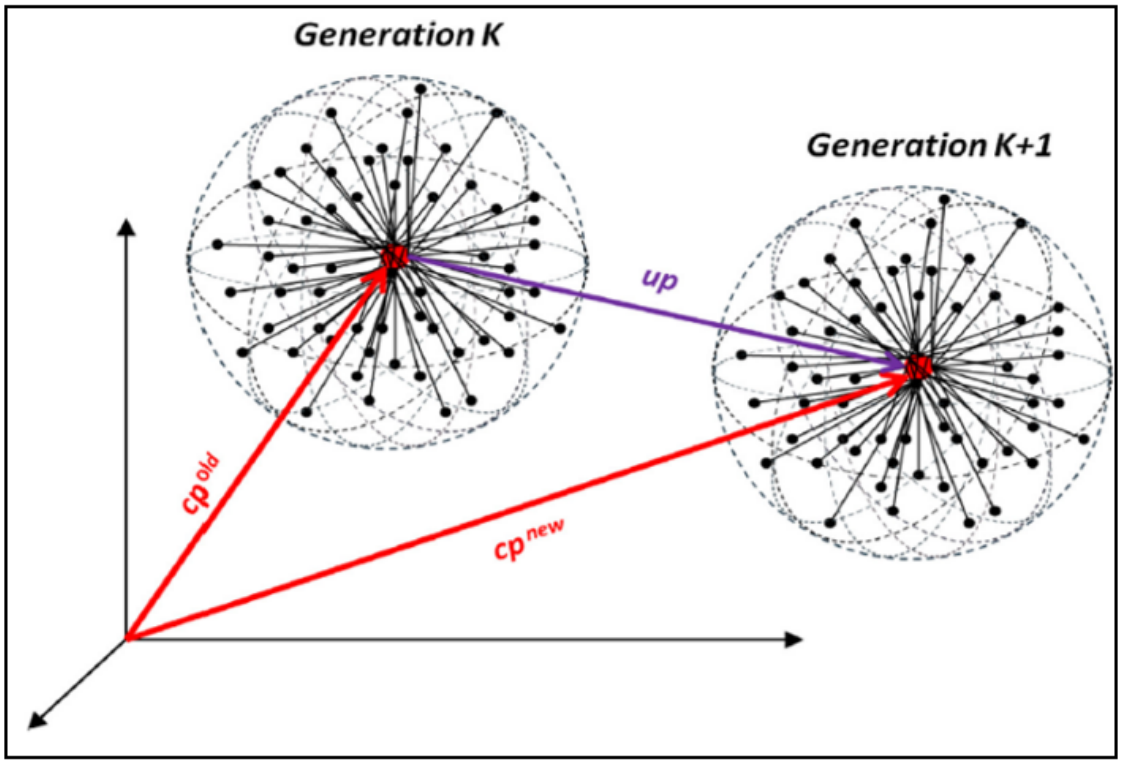

Figure 4

Updating the cp by up vector (Rahmani & Yusof, 2014).

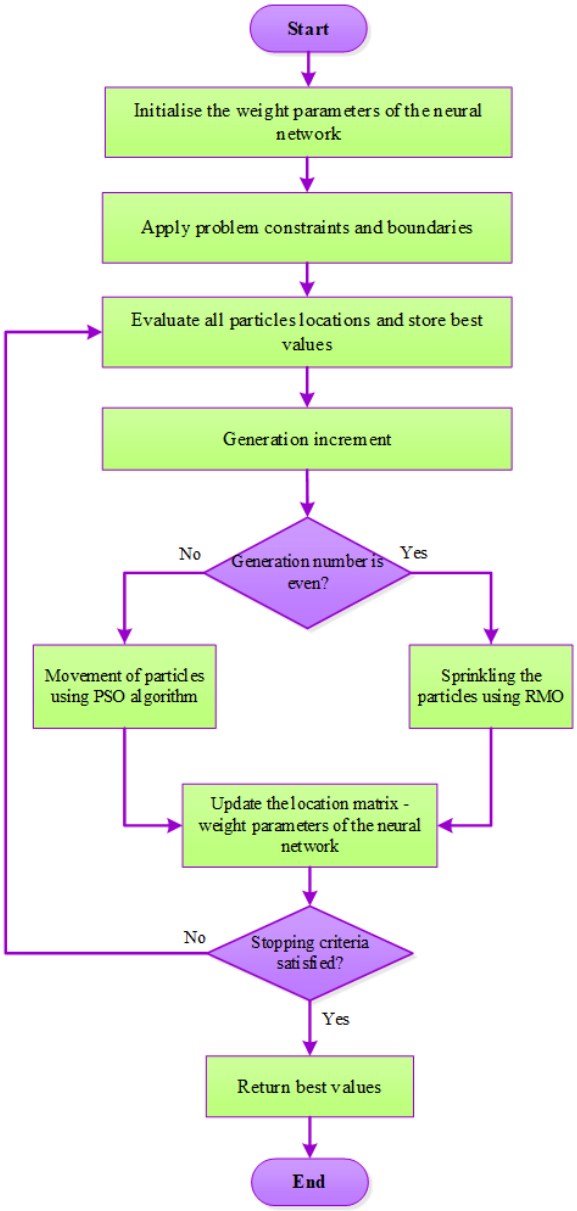

Figure 5

Flowchart of the ANNs optimization procedure

```
Develop solution space by setting parameter space used in the algorithms
Set parameters of RMO W,C1,C2,C3
FOR every sample in population
        FOR every dimension in a sample
                X0 <- Initialize corresponding sample dimension as the
                difference of  upper boundary and lower boundary
                multiplied with a random number in space 0 and 1
        END FOR
END FOR
Set initial population as X0
Set velocity vector as 0.7 times X0

FOR every sample in population
        F0 <- Evaluate initialized samples
END FOR
Store minimum value and index of Initialized samples F0
Set PBEST as X0 and GBEST as the minimum valued sample of X0 obtained
from F0 in the previous step
Initialize RMO with parameters and store Xi and CENTRE values
FOR every sample in population
        F1 <- Evaluate samples obtained as Xi
END FOR
Store minimum value and index of evaluated samples F1
Set best index as RBESTLOC of minimum value and best sample as RBEST
obtained from the minimum value of F1 through Xi
Set GBESTLOC as RBESTLOC and GBEST as RBEST
Set Iteration count and tolerance to 1
WHILE Iteration count and tolerance criterias are not met
        IF Iteration count is even
                Run RMO algortithm with calculated parameters
                FOR every sample in population
                        Evaluate sample and store in fitness matrix
                        Find the best sample through this matrix and
                        update GBEST iteration vector and
                        GBESTLOC vector
                END FOR
        ELSE iteration count is odd
                Repeat same procedure for PSO algorithm in the above
IF-END IF code clock
        END IF
Show best generation of the iteration
Update iteration count by adding one
END WHILE
```

Figure 6

The pseudo-code of the ANNs+(PSO-RMO) approach

```
x = inputs';
t = target';

trainFcn = 'trainlm';  % Levenberg-Marquardt

% Create a Fitting Network
hiddenLayerSize = 5;
net = fitnet(hiddenLayerSize,trainFcn);

% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

app.DurumLabel.Text="training the network.";
% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y);
genFunction(net,'neuralNetwork','MatrixOnly','yes')
system('DosyaHazirla')
app.DurumLabel.Text="Ağ eğitimi bitti, lütfen metod seçiniz.";
%HyRP_main();
```

Figure 7

The data set is split into three parts (70 % training, 15 % validation, 15 % testing)

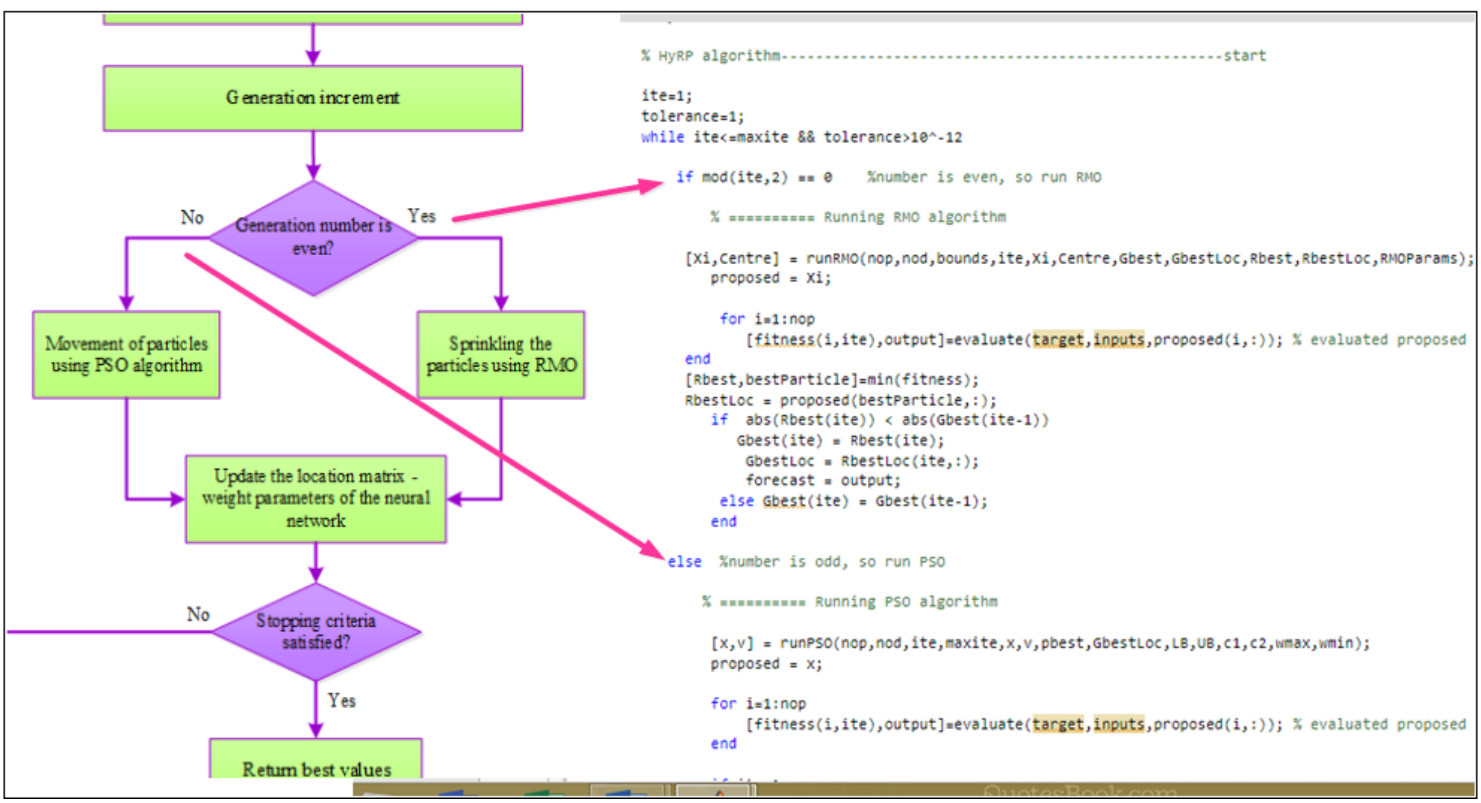

Figure 8

Controlling the number of generations and forwarding the algorithm to RMO or PSO

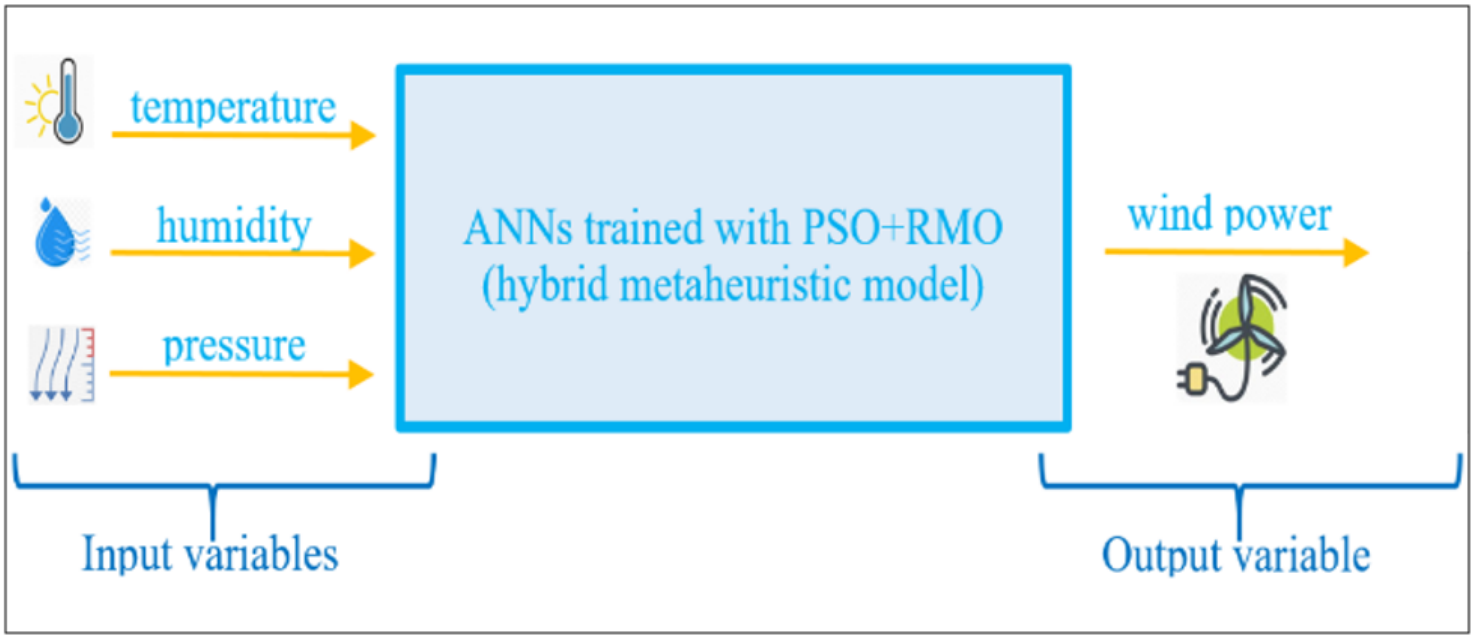

Figure 9

The blog diagram of the model

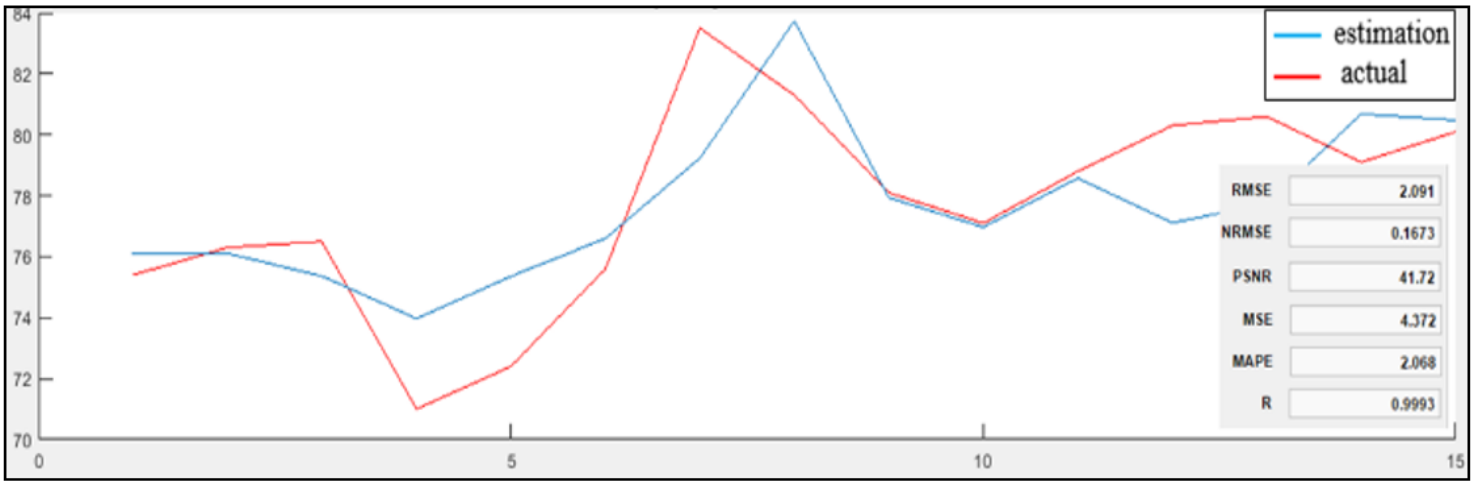

Figure 10

Wind power forecasting curves, both actual and estimated using ANNs+(PSO-RMO) approach (WMS-1: record frequency: 24-hour, record time: 15-day, August)

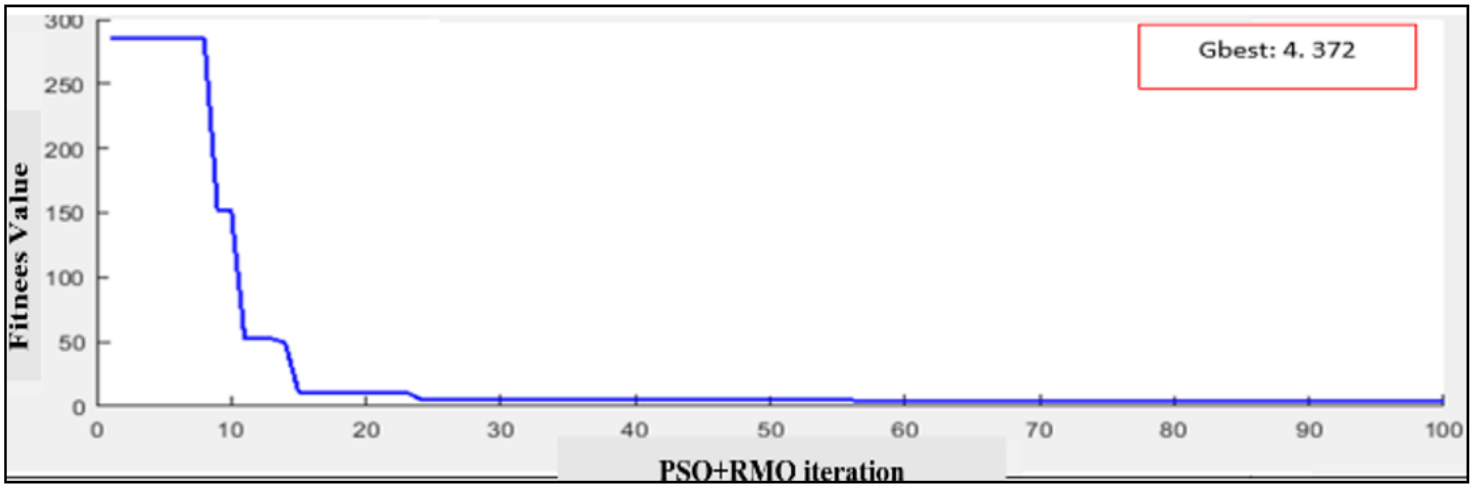

Figure 11

Changing of fitness value of ANNs+(PSO-RMO) approach (WMS-1: record frequency: 24-hour, record time: 15-day, August)

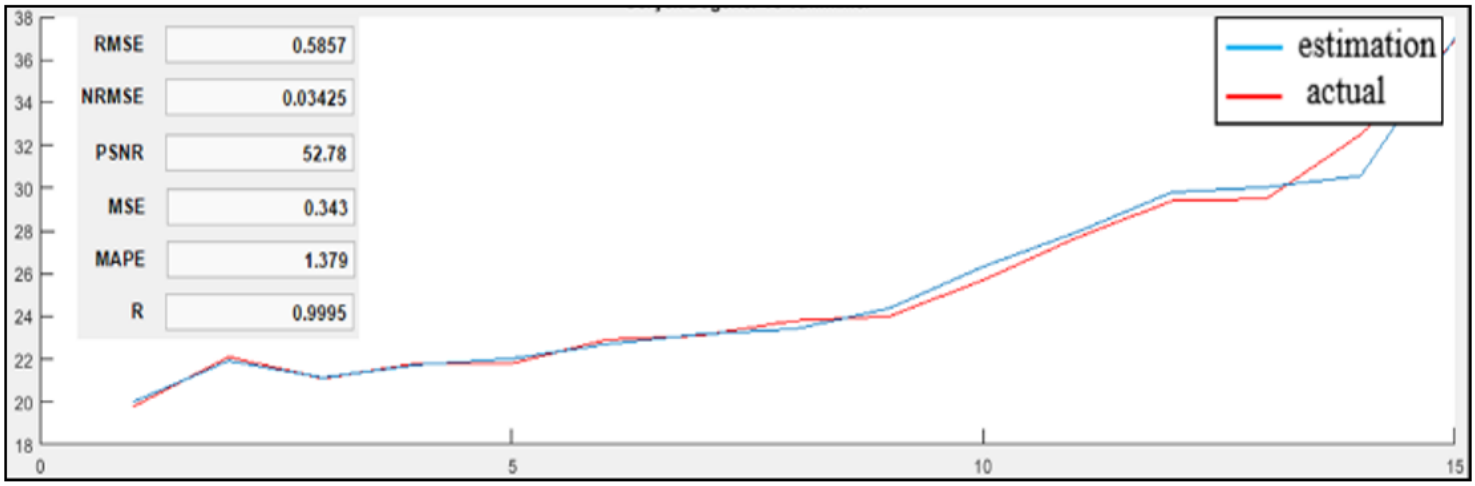

Figure 12

Wind power forecasting curves, both actual and estimated using ANNs+(PSO-RMO) approach (WMS-2: record frequency: 24-hour, record time: 15-day, October)

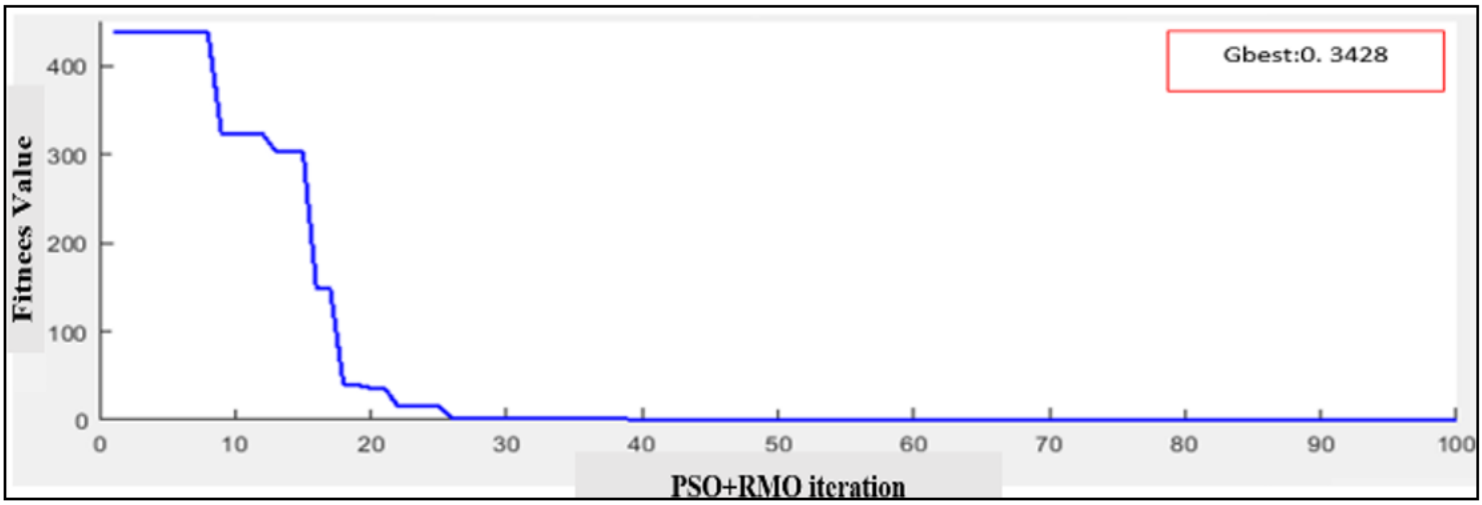

Figure 13

Changing of fitness value of ANNs+(PSO-RMO) approach (WMS-2, record frequency: 24-hour, record time: 15-day, October)

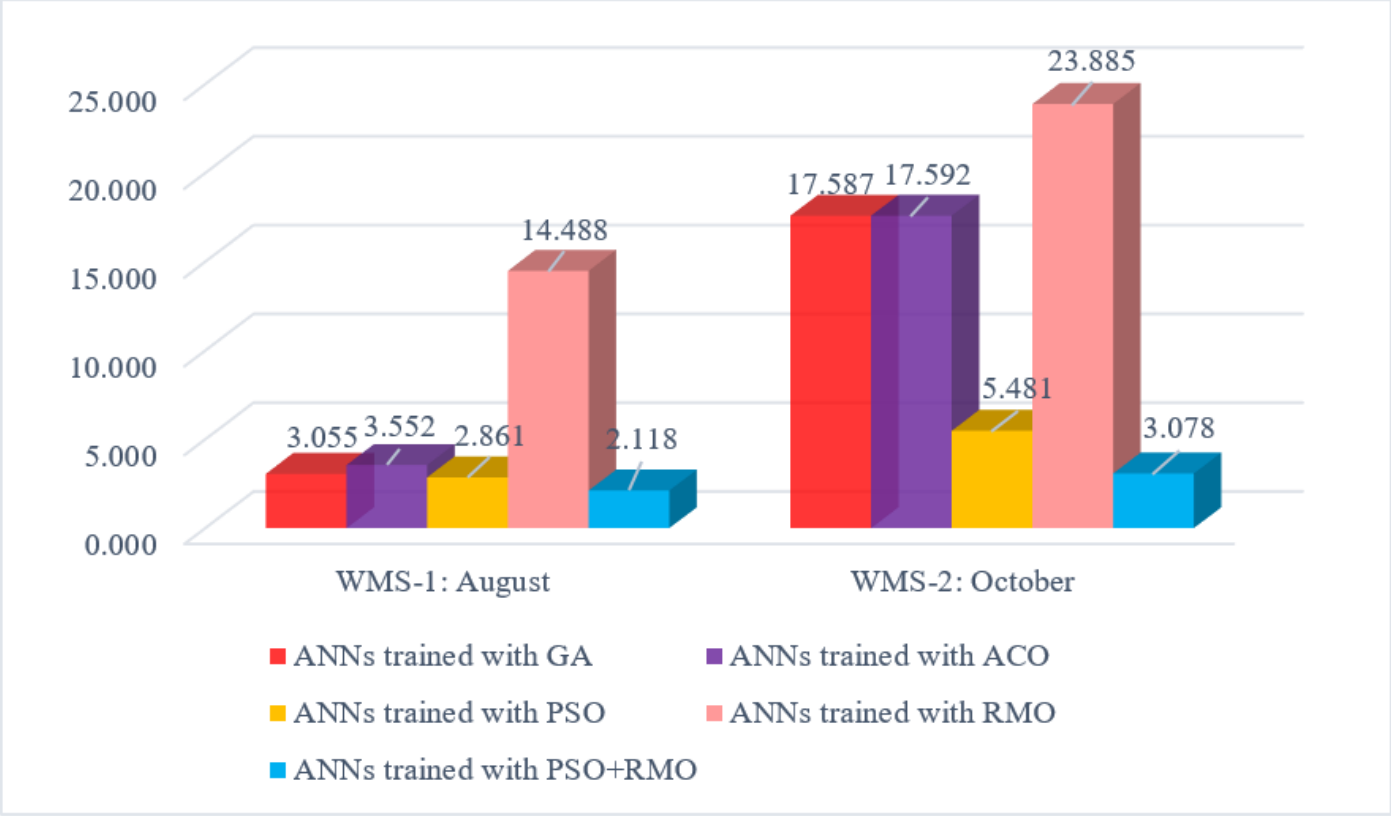

Figure 14

Average MAPE values of test error for wind power forecasting (50run)