A green energy research: forecasting of wind power for a cleaner environment using robust hybrid metaheuristic model

Alper Kerem1 · Ali Saygin2 · Rasoul Rahmani3

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Abstract
Wind is a stochastic and intermittent renewable energy source. Due to its nature, it is extremely hard to forecast wind power. Accurate wind power forecasting can be encouraging and motivating for investors to shed light on future uncertainties caused by global warming. Thus, CO2 and other greenhouse gases (GHG) 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, wind power forecasting studies with high accuracy have been carried out despite the height differences between the sensors. That is, for WMS-1 and WMS-2, it has succeeded the wind power forecasting at 61 m and 60.3 m using temperature (3 m), humidity (3 m) and pressure (3.5 m) data. The performance results were presented in tables and graphs.

Keywords
Green energy · Wind power forecasting · Sustainability · Renewable energy · Hybrid metaheuristic model · Artificial neural network (ANN) · Particle swarm optimization (PSO) · Radial movement optimization (RMO)

Nomenclature

| Symbol | Description |
|--------|-------------|
| ρ_a | Air density (1.225 kg/m³) |
| A_T | Wing sweeping area (m²) |
| V_r | Wind speed (m/s) |
| T | Temperature (°C) |
| Z | Height (m) |
| E_k | Kinetic energy (Nm) |
| P_T | Wind power (W) |
| c_p | Center point (RMO) |
| R_best | Best radial (RMO) |
| G_best | Best global (RMO) |
| A_i | Actual value (error criteria) |
| F_i | Predicted value (error criteria) |
| N | Number of observations (error criteria) |
| MAXI | Maximum pixel value of the picture (error criteria) |
| ACO | Ant colony optimization |
| ANFIS | Adaptive neuro-fuzzy inference systems |
| ANNs | Artificial neural networks |
| BP | Back propagation |
| CSA | Cluster selection algorithm |
| DWT | Discrete wavelet transform |
| ELM | Extreme learning machine |
| EMD | Empirical mode decomposition |
| EPSO | Evolutionary particle swarm optimization |
| FA | Fuzzy artmap |

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1 Department of Electrical Electronics Engineering, Engineering and Architecture Faculty, Kahramanmaras Sütçü Imam University, K.Maraş, Turkey
2 Department of Electrical Electronics Engineering, Faculty of Technology, Gazi University, Ankara, Turkey
3 Faculty of Science, Eng. and Technology, Swinburne University of Technology, Melbourne, Australia

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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 Eq. (1) (Patel 1942; Golding 1955):

\[ P_T = \frac{1}{2} \rho_a A_T V_r^3 \]  

(1)

where, air density \( \rho_a \) (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 Eq. (2) if the temperature \( T \) and height \( Z \) of the zone are known:

\[ \rho_a = \frac{(353.049 / T) e^{(-0.034Z / T)}}{ } \]  

(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 Eq. (3) (Ragheb and Ragheb 2011; Gourieres 1982):

\[ P_T = \frac{1}{2} \rho_a A_T V_r^3 C_p(W) \]  

(3)

Figure 1 shows energy flows of wind turbine (Rahmani et al. 2010).

Energy of the air passing through the wings can be defined as follows (Eq. (4)) (Çetin 2006):

\[ E_k = E_{kin} - E_{kOut} \]  

(4)

Kinetic energy \((E_k)\) of the wind in motion is calculated in Eq. (5), and wind power \((P_T)\) is shown in Eq. (6):

\[ E_k = \frac{1}{2} \rho_a A_T (V_r^2 - V_{r1}^2) \]  

(5)

\[ P_T = E_k / t = \frac{1}{2} \rho_a A_T (V_r^2 - V_{r1}^2) \]  

(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 mean absolute percent error (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 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 was 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 multilayer ANNs was 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. (2011a, b) 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 was 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

![Fig. 1 Kinetic energy flow of wind around a wind turbine (Rahmani et al. 2010)](image1)

![Fig. 2 Locations of WMS-1 and WMS-2](image2)
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 is, Gaussian kernel, Laplacian kernel, cauchy in distance kernel, R (distance) kernel and thin-plate spline kernel (Tps). The SVM prediction model is 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 1 min. 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

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

| WMSs       | Input variables | Output variable |
|------------|-----------------|-----------------|
|            | Temperature     | Humidity        | Pressure        | Wind power   |
| **WMS-1: Burdur** | 4 m           | 4 m            | 3.5 m         | 61 m         |
| UTM E 263.254 – N 4.173.479 1313-m altitude |                |                |              |              |
| WMS-2: Osmaniye | 4 m           | 4 m            | 3.5 m         | 60.3 m       |
| UTM E 285.866 – N 4.122.267 1028-m altitude |                |                |              |              |

Fig. 3 Installation works of WMS-1 and sensors
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 h
and 84 h. They observed that the direct prediction model had
better prediction performance than the hybrid prediction
model. Catalao et al. (2011a, b) developed a new hybrid mod-
el 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 of
5.99%. Sharifian et al. (2018) designed a new hybrid predic-
tion 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, respec-
tively. To compare the effectiveness of ANNs+(PSO-RMO)
approach, the other hybrids such as ANNs+ACO, ANNs+GA,
ANNs+PSO, ANNs+RMO were designed. Fifty runs were used
to evaluate the performance of all developed hybrid
metaheuristic models.

The main contributions of this study are as follows:

1. Accurate wind power forecasting can be encourag-
ing and motivating for investors to shed light on
future uncertainties caused by global warming. Thus, CO2 and other greenhouse gases (GHG) will

| Parameters | WMS-1 | | | | | | WMS-2 | | | | | |
|------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Wind speed (m/s) | Average 4.592 | Median 4.435 | Std dev. 0.991 | Mod 5.165 | Maximum 8.977 | Minimum 2.432 | Skewness 0.939 | Kurtosis 2.604 | Variance 0.981 | Sample item 4464 |
| Wind aspect (°) | 161.689 | 156.717 | 56.931 | 149.179 | 282.038 | 41.013 | 0.092 | -0.729 | 3241.174 | 4464 |
| Temp. (°C) | 23.101 | 23.356 | 2.356 | 21.087 | 28.409 | 17.217 | -0.259 | -0.436 | 5.551 | 4464 |
| Humidity (%) | 46.638 | 47.642 | 13.329 | 61.67 | 76.673 | 26.791 | 0.292 | -1.089 | 177.654 | 4464 |
| Pressure (mbar) | 865.763 | 866.348 | 2.354 | 867.423 | 870.448 | 861.358 | -0.136 | -0.64 | 5.544 | 4464 |
| Wind speed (m/s) | 3.193 | 2.781 | 1.403 | 4.429 | 7.239 | 0.556 | 1.136 | 0.568 | 1.968 | 4319 |
| Wind aspect (°) | 164.019 | 160.697 | 47.309 | 131.637 | 316.6 | 79.458 | 0.145 | -0.741 | 2238.172 | 4319 |
| Temp. (K) | 2837.722 | 2831.93 | 24.339 | 2829.647 | 2896.92 | 2801.254 | 0.805 | -0.265 | 592.375 | 4319 |
| Humidity (%) | 65.631 | 65.299 | 15.413 | 92.284 | 93.378 | 37.891 | 0.169 | -1.186 | 237.563 | 4319 |
| Pressure (mbar) | 900.241 | 900.801 | 4.003 | 900.552 | 906.0 | 887.388 | -1.288 | 1.678 | 16.022 | 4319 |

Fig. 4 Updating the cp by the up vector (Rahmani and Yusof 2014)
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, rapidity 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 61 m and 60.3 m were performed using temperature (3 m), humidity (3 m) and pressure (3.5 m) 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.

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![Flowchart of the ANN optimization procedure](image1)

**Fig. 5** Flowchart of the ANN optimization procedure

![Pseudo-code of the ANNs+(PSO+RMO) approach](image2)

**Fig. 6** The pseudo-code of the ANNs+(PSO+RMO) approach
Data processing in terrain

The WMS were placed at two separate locations. The WMS-1 was situated at UTM E 263.254 and N 4.173.479 coordinates with an altitude of 1313 m and a 63-m total height in Burdur. The WMS-2 was situated at E 285.866 - N 4.122.267 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. Locations of WMS-1 and WMS-2 are given in Fig. 2.

Technical data for WMS-1 and WMS-2 are given in Table 1. Installation works of WMS-1 and sensors are given in Fig. 3. Statistical values of WMS-1 data (August) and WMS-2 data (October) are given in Table 2.

Powerful hybrid metaheuristic approach

The hybrid approach is composed of two distinct metaheuristic algorithms of PSO and RMO given in the next subsections.

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**Fig. 7** The data set is split into three parts (70% training, 15% validation, 15% testing)

**Fig. 8** Controlling the number of generations and forwarding the algorithm to RMO or PSO
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 and 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 nonlinear 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 and 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 \( V_g \) 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 \( R_{\text{best}} \). The locations of the \( G_{\text{best}} \) and \( R_{\text{best}} \) particles are used to update a new best \( c_p \) position using the \( up \) vector, provided in Eqs. (7) and (8) (Rahmani and Yusof 2014; Mahrami et al. 2016; Seyedmahmoudian et al. 2016):

\[
c_{p_{k+1}} = c_{p_k} + up\tag{7}
\]

\[
u_p = C_1 (G_{\text{best}} - c_{p_k}) + C_2 (R_{\text{best}} - c_{p_k})\tag{8}
\]

The scattering of particles begins again from the updated \( c_p \) after the \( c_p \) is updated. The update of the \( c_p \) by the \( up \) 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 intended to optimize the nonlinear and linear components and, also, randomly occurring wide fluctuations in the data sets.

| Table 3 | Error criteria (Varanasi and Tripathi 2016; Sivakumar 2017; Guo et al. 2011; Kirbas 2018; Zhao et al. 2016) |
|------------------|---------------------------------------------------------------------|
| Peak signal-to-noise ratio (PSNR) | \( PSNR = 10\log_{10}\left(\frac{\text{MAX}}{\text{MSE}}\right) = 20\log_{10}\left(\frac{\text{MAX}}{\text{MSE}}\right) \) |
| 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) | \( MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{A_i - F_i}{A_i} \right| \times 100 \) |
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 $G_{best}$ vector (Rahmani and 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 and Eberhart 1995; Eberhart and Kennedy 1995; Kennedy and 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 and Saygin 2019; Kerem et al. 2019; Kerem 2021).

The first stage in the method is to initialize 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.

| WMS-1: August record frequency: 24-h record time: 15 days | ANNs+PSO | ANNs+ACO | ANNs+RMO | ANNs+GA | ANNs+(PSO+RMO) |
|----------------------------------------------------------|----------|----------|----------|---------|----------------|
| $R$                                                      | 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-h record time: 15 days | ANNs+PSO | ANNs+ACO | ANNs+RMO | ANNs+GA | ANNs+(PSO+RMO) |
|-----------------------------------------------------------|----------|----------|----------|---------|----------------|
| $R$                                                       | 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         |

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

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

| WMS-1: August record freq: 24-h record time: 15 days | ANNs+PSO | ANNs+ACO | ANNs+RMO | ANNs+GA | ANNs+(PSO+RMO) |
|-----------------------------------------------------|----------|----------|----------|---------|----------------|
| 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-h record time: 15 days | ANNs+PSO | ANNs+ACO | ANNs+RMO | ANNs+GA | ANNs+(PSO+RMO) |
|------------------------------------------------------|----------|----------|----------|---------|----------------|
| 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         |
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 Figs. 7. Controlling the number of generations and forwarding the algorithm RMO or PSO is given in Fig. 8.

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 were 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 (3 m), humidity (3 m) and pressure (3.5 m) were used to perform wind power forecasting experiments at 61 m and 60.3 m, respectively. The blog diagram of the model is given in Fig. 9.

Error criteria including PSNR, MSE, RMSE, MAPE are 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.

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

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

According to Table 5, WMS-1 (August) average MAPE (50 runs) 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 (50 runs) 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 is seen that the ANNs+(PSO+RMO) approach is the most efficient model of all the optimization algorithms.

The test error average MAPE values (50 runs) are shown in Fig. 10. 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.

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 11 illustrates actual and estimated wind power curves for WMS-1 for the ANNs+(PSO+RMO) approach.

According to Fig. 11, actual and estimated plots are so close; thus, error values obtained for RMSE, NRMSE, PSNR, MSE, MAPE and $R$ are 2.091, 0.1673, 41.72, 4.732, 2.068 and 0.9993 respectively. Changing of fitness value of ANNs+(PSO+RMO) approach for WMS-1 is given in Fig. 12.

Figure 13 shows actual and estimated curves of wind power forecasting using ANNs+(PSO+RMO) approach for WMS-2. It belongs to the 24-h frequency and the 15-day time record, October.
According to Fig. 13, actual and estimated curves are almost overlapping; thus, error values obtained for 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. 14.

**Conclusion**

Fossil-fueled power plants emit CO$_2$ and other GHG 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.

In future works, machine learning techniques and other metaheuristic models might be tried to reduce errors in wind power forecasting studies.

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**Author contribution**

AK: idea, data gathering, writing—original draft preparation, methodology, software. AS: investigation, draft reviewing, editing, supervision. RR: methodology, software, draft reviewing, editing. All the authors read and approved the final manuscript.

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Not applicable.

**Declarations**

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Not applicable.

**Competing interests**

The authors declare no competing interests.

**References**

Azimi R, Ghofrani M, Ghayekhloo M (2016) A hybrid wind power forecasting model based on data mining and wavelets analysis. Energy Convers Manag 127:208–225

Catalao JPS, Pousinho HMI, Mendes VMF (2011a) Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal. IEEE Trans Sustain Energy 2(1):50–59

Catalao JPS, Pousinho HMI, VMF M (2011b) Hybrid intelligent approach for short-term wind power forecasting in Portugal. The Institution of Engineering and Technology Renewable Power Generation 5(3):251–257
