Wind Power Optimization: A Comparison Of Meta-Heuristic Algorithms

Rashmi.P.Shetty\textsuperscript{a}, A.Sathyabhama\textsuperscript{b}, and Srinivasa.Pai.P\textsuperscript{c}
\textsuperscript{a} PhD Research scholar Department of Mechanical Engineering NITK, Surathkal, India Email: iprashmi@nitte.edu.in
\textsuperscript{b} Assistant Professor Department of Mechanical Engineering NITK, Surathkal, India
\textsuperscript{c} Professor Department of Mechanical engineering NMAMIT, Nitte, India

Abstract. The wind being a most promising renewable energy, has become a strong contender for fossil fuels. Optimizing the blade pitch angle of a wind turbine is important to obtain the maximum power output, as the other variables are considered to be uncontrollable. In this paper an effort has been made to compare performances of three different optimization algorithms namely Particle swarm optimization (PSO), Artificial bee colony (ABC) and cuckoo search (CS) for optimizing the blade pitch angle and hence optimize the power output of a 1.5 MW capacity, pitch regulated, three-bladed horizontal axis wind turbine operating at a large wind farm in central dry zone of Karnataka. The objective function development is done using Artificial Neural Network. The CS algorithm is found to be faster and more efficient as compared to ABC and PSO for the problem under consideration.

Keywords: Particle swarm optimization (PSO), Artificial bee colony (ABC), cuckoo search (CS), Wind power optimization.

1. Introduction

There is a growing interest in recent decade towards renewable energy, as it is a potential source to meet the energy requirements associated with minimal environmental impact. Wind is a clean and sustainable energy which is most economical in comparison to others due to the rapid development of wind turbine technology. Thus wind energy is emerging as a solution to most of the problems posed by the fossil fuels and can meet the power demand of most of the countries including India. India provides great opportunities to investors, being world’s third largest wind power market [1]. Though wind energy is said to be most economical and is fully competitive with conventional power generation, it still suffers from the higher cost of operation and maintenance [2]. The key areas of wind energy in which reduction of cost can be achieved include, site selection, layout design, predictive maintenance etc. [3-6]. On the other hand, maximizing the power output of a wind turbine for a given wind speed between a cut in and cut out wind speeds through effective control strategies can also fetch benefits [7, 8].

Optimization is searching an alternative with a highest achievable performance by maximizing the desired and minimizing the undesired factors, under the given constraints. The main objective of the energy industry is to maximize the power generation at minimum cost. Many of the researchers have focused in this direction. A. Kusiak et al. [9] optimized the power factor as well as the output of a wind turbine by using evolutionary computation approach. M.A. Yurdusev et al. [10] predicted optimum power factor and tip speed ratio of a wind turbine using the artificial neural network (ANN). A. Kusiak et al. [11-14] presented multi-objective optimization models of wind turbine performance for optimizing various objectives such as vibration of the drivetrain, vibration of the tower, generator torque ramp rate and wind power output. A combination of optimization and data-driven models were used to achieve this. Further the authors have proved in [13] that, for maximizing the energy capture of a wind turbine, blade pitch angle is an important variable. Kongnam. C et al. [15] proposed PSO to
determine optimum rotor speed and tip speed ratio of the wind turbine to maximize the energy capture of the wind turbine.

ANN is widely used in a broad spectrum of applications that are data-intensive such as medical, marketing, prediction and forecasting to name a few [16, 17]. Meta heuristic optimization algorithms are useful in solving non-differentiable and nonlinear-objective functions, where the classical optimization techniques fail. A large number of meta-heuristic optimization methods are used in the renewable energy field to solve a wide set of problems [18]. In this paper, ANN is used to capture the wind turbine power generation process for developing the objective function. Three Meta-heuristic optimization algorithms namely ABC, CS and PSO have been used to optimize the controllable parameters to maximize the power output of a horizontal axis wind turbine under the given constraints. The performance of the three optimization algorithms have been compared to identify the best algorithm that results in maximum power output from the wind turbine.

2. Wind power modelling and optimization

Power production in a wind turbine is due to the interaction of the rotor and the wind. The kinetic energy of the moving air gets transformed into mechanical energy with the help of a blade of specific geometric shape.

The equation (1) represents the theoretical power obtained from a wind turbine.

\[ P = \frac{1}{2} \rho \pi R^2 C_p(\lambda, \beta) u^3 \]  

where,

- \( P \) is the power obtained from a wind turbine, kW
- \( \rho \) is the density of air, kg/m³
- \( R \) is the radius of rotor of the wind turbine, m
- \( C_p \) is the power coefficient
- \( \beta \) is the blade pitch angle, degree
- \( \lambda \) is the Tip Speed Ratio (TSR)
- \( u \) is the wind speed, m/s

\( C_p \) the power coefficient is a function of tip speed ratio \( \lambda \) and blade pitch angle \( \beta \). TSR is defined as the ratio of the tangential velocity of wind turbine blade tips and the actual wind speed. \( \lambda \) can be obtained from Equation (2) [19].

\[ \lambda = \frac{R \Omega_r}{V_e} \]  

where, \( R \) is the radius of the rotor in meters, \( \Omega_r \) is the speed of the rotor in radians/second, and \( V_e \) is the effective wind speed that is perpendicular to the plane of the rotor in meter/second.

The wind is assumed to be blowing orthogonally to the turbine rotor, thus is not considered in the power equation, but the wind blows from different directions in practice, and hence direction also has to be considered as one of the variables.

Hence the parameters directly influencing the wind power generation of a wind turbine are wind speed, air density, blade pitch angle, rotor speed and wind direction. Out of these the important controllable parameter is blade pitch angle. Thus these controllable and non-controllable parameters are used in developing the objective function to maximize the power output of a wind turbine.

While designing the optimization problem, if there are any constraints to the problem, it should be considered. The power that a wind turbine can produce has practical and theoretical constraints, which need to be taken into consideration. The maximum power generation of the turbine under consideration is 1600kW. Hence it is the practical constraint of the turbine. According to Betz law, the theoretical maximum power that a turbine can generate cannot exceed 59% of the kinetic energy in the wind [19].

Hence in the wind power equation \( P = \frac{1}{2} \rho \pi R^2 u^3 \). The swept area of the turbine under consideration is 5281 m² the average air density in the area is 1.15 kg/m³. Thus the theoretical power of the turbine should be smaller than 3.036u³. Hence by considering both of these constraints, the
power output of the turbine under consideration should be a minimum of 1600 kW and 3.036u° for a given wind speed.

3. Data description and pre-processing

The data for this study is collected from a supervisory control and data acquisition (SCADA) system of a turbine located in Central dry zone of Karnataka, which is a region having good wind potential and is ideal for harvesting wind energy [21]. The data at 10 min sampling interval, collected over a period of six months during June - December 2013, from a 1.5 MW capacity, pitch regulated, upwind horizontal axis wind turbine has been used. The cut-in, cut-out, and rated wind speed are 4, 20 and 14 m/s respectively. To improve the accuracy of the model, data pre-processing is necessary. The erroneous data may result due to the failure of sensors during measurement and various other subsystems. In this work, all such erroneous and missing data have been removed and then it has been averaged to 1-hour interval. The data has been normalized between 0 and 1 for training of neural network, so that each data provide an equal contribution to ANN prediction.

4. Optimization algorithms

The Meta heuristic optimization algorithms are inspired by natural processes. These methods evolve to reach the global minimum or maximum of the objective function by beginning with an initial set of variables. They are robust to dynamic changes, have broad applicability and are capable of solving the problems with high complexity. These Metaheuristic algorithms work on the concept of patterns. In each of these algorithms say PSO, ABC and CS, the pattern refers to a particle, a nectar source and an artificial nest respectively [22, 23]. These three algorithms have been used in this study. The performances of CS and ABC algorithms are compared with PSO, as it is a widely used optimization algorithm.

4.1. Artificial Bee Colony (ABC) optimization algorithm

This algorithm works based on the nectar searching behavior of bees and is proposed by Karaboga in 2005 [24]. The ABC algorithm targets the location of nectar source having the maximum amount of nectar. The nectar in the source refers to the value of objective function. The algorithm works as follows:

Step 1. Initialize the nectar sources randomly according to equation (3)

\[ X_{ij} = X_{jm} + (X_{jm} - X_{jm}) \cdot \text{rand} \]  \hspace{1cm} (3)

where i=1,2,…SN, j=1,2,…m. SN, m are the number of food sources and optimization parameters respectively and calculate the nectar amount.

Step 2. Searching for the new food source in the neighbour to be used, if it is better than the old one. This search for new food source is defined by (4)

\[ v_{ij} = X_{ij} + (X_{ij} - X_{jk}) \cdot \phi_{ij} \]  \hspace{1cm} (4)

where, \( \phi_{ij} \) is the uniformly distributed random number in the range [-1,1], \( j \) is the random integer in the range [1,m], \( k \in \{1,2,\ldots, SN\} \).

Step 3. Calculating the probability values related to the nectar amount in the source to choose the best food source. The probability values can be obtained using the equation (5)

\[ P_{i} = \frac{\text{Fitness}_i}{\sum_{i=1}^{SN}\text{Fitness}_i} \]  \hspace{1cm} (5)

where, \( \text{Fitness}_i \) is the cost value for the solution \( v_{ij} \).

Step 4. Check for abandonment
If a food source cannot be improved in steps 3 and 4 for a predetermined number of trials (Abandonment Limit) is abandoned in each cycle and is replaced by a new randomly discovered food source.

These steps are repeated until the stopping criteria is reached [24].

In this study, the number of nectar sources is set to 10, and the stopping criteria is set as 100 iterations.

The algorithmic control parameter namely Abandonment Limit Parameter is set 0.6*m*SN based on trial and error method.

4.2. Cuckoo Search (CS) optimization algorithm

This algorithm is inspired by the life of a cuckoo bird and its characteristics in egg laying and breeding and was developed by Yang and Deb in 2009 [25].

The steps involved in CS algorithm are as follows:

Step 1. Initialization

The host nest location is initialized by using equation (6)

\[ \text{nest}_{i,j} = L_{b_{min,j}} + (U_{b_{max,j}} - L_{b_{min,j}}) \times \text{rand}_1 \] (6)

where, \( \text{nest}_{i,j} \) denotes the \( i \)th host nest in the population, \( \text{nest}_{i,j} = \{ \text{nest}_{i,1}, \text{nest}_{i,2}, \ldots \text{nest}_{i,n} \} \) they are m number of randomly generated n-dimensional real valued vectors.

where, \( j = 1, 2, \ldots, n \).

\( L_{b_{min,j}} \) and \( U_{b_{max,j}} \) are the lower and upper boundary values of the dimension \( j \) and \( \text{rand}_1 \) is a random number within the range of (0,1).

Step 2. Evaluate the fitness function to find \( X_{best_i} \) and \( G_{best} \)

Step 3. Generation of new nests by Levy flights based on the previous best nest.

For each of the nest, the new solution can be calculated by using equation (7)

\[ X^{\text{new}}_{i,j} = X_{best_i} + \alpha \times \text{rand}_2 \times \Delta X^{\text{new}}_i \] (7)

where, \( \alpha > 0 \) and \( \text{rand}_2 \) is a random number, \( \Delta X^{\text{new}}_i \) can be calculated using equation (8)

\[ \Delta X^{\text{new}}_i = v \times \frac{\sigma_x(\beta)}{\sigma_y(\beta)} \times (X_{best_i} - G_{best}) v = \left( \frac{\text{rand}_x}{\text{rand}_y} \right)^{\frac{1}{\beta}} \] (8)

where, \( \text{rand}_x \) and \( \text{rand}_y \) are the random numbers with the standard deviation \( \sigma_x(\beta) \) and \( \sigma_y(\beta) \) given by equations (9) and (10) respectively.

\[ \sigma_x(\beta) = \left[ \Gamma(1 + \beta) \times \sin \left( \frac{\pi \beta}{2} \right) \times \beta \times 2^{\frac{\beta-1}{2}} \right]^\frac{1}{\beta} \] (9)

\[ \sigma_y(\beta) = 1 \] (10)

where, \( \Gamma(.) \) denotes the gamma function, \( \beta \) is the distribution factor varying between 0.3 and 1.99.

Step 4. Alien egg discovery and randomization

The new solution is created to the problem based on the discovery action of the alien egg in the nest of a host bird with the probability \( P_a \) by using equation (10).

\[ X^{\text{dis}}_i = X_{best_i} + K \times \Delta X^{\text{dis}}_i \] (10)

where \( K \) is the updated coefficient based on the probability that the host bird discovers in its nest the alien egg. \( K = \begin{cases} 1 & \text{if } \text{rand}_3 < P_a \\ 0 & \text{otherwise} \end{cases} \)

The value \( \Delta X^{\text{dis}}_i \) is calculated using equation (11)

\[ \Delta X^{\text{dis}}_i = \text{rand}_3 \times [\text{rand}p_1(X_{best_i}) - \text{rand}p_2(X_{best_i})] \] (11)

where, \( \text{rand}_3 \) is the random number in the range [0,1], \( \text{rand}p_1(X_{best_i}) \) and \( \text{rand}p_2(X_{best_i}) \) are the random perturbation for positions of nests in \( X_{best_i} \).

Step 5. Compare the fitness value corresponding to old and new nest and keep the nest owning best fitness value. Repeat the procedure till the stopping criteria is reached.

In this study, the stopping criteria is set as 100 iterations. The value of \( n, \beta \) and \( P_a \) is set to be 10, 1.5 and 0.25 respectively.
5. **Objective function development**

In solving an optimization problem, the objective function development plays a major role. An objective function should properly describe the relationship between controllable and uncontrollable input parameters with that of the output mathematically.

In a previous study by the authors, it has been established that the objective function developed using an ANN technique is superior to that based on Response Surface Method (RSM) [20]. Hence the ANN based objective function developed using Radial Basis Function neural network model with centers selected using conditional fuzzy c-means clustering algorithm and extreme learning machine algorithm has been used in this study. The training of the ANN model has been carried out by using 2522 (85%) data instances out of 2966 total data. Each data consists of five input parameter namely wind speed, blade pitch angle, wind direction, density and rotor speed and an output parameter that is the wind power output.

6. **Results and discussion**

To maximize the power output of a wind turbine, the only controllable parameter is blade pitch angle, which is optimized by keeping the non-controllable variables unchanged. The objective function is developed using the RBF neural network model. The 444 test patterns are optimized to get the maximum power output. The range of the blade pitch angle is set as \([-2.616, 19.733]\] based on the analysis of the available data. The common control parameters of the optimization algorithms used in this study namely population size and number of iterations are set to be the same.

Two metrics, Mean PG and Mean Relative PG as given by equation (12) and (13) which indicates how much kW of the power will be gained on an average for every hour due to optimization, have been used to evaluate the performance of the algorithms.

\[
\text{Mean PG} = \frac{1}{N_{\text{Test}}} \sum_{t \in \text{Test}} (P_{\text{optimized}}(t) - P_{\text{actual}}(t))
\]  

\[
\text{Mean relative PG} = \frac{1}{N_{\text{Test}}} \sum_{t \in \text{Test}} \frac{(P_{\text{optimized}}(t) - P_{\text{actual}}(t))}{P_{\text{actual}}(t)}
\]

where,

- \(P_{\text{optimized}}\) = Optimal power in kW
- \(P_{\text{actual}}\) = Actual power in kW
- \(N_{\text{test}}\) = Total number of test patterns
- \(\text{Test}\) = Set containing all test patterns

6.1. **Artificial Bee Colony (ABC)**

The variation of cost value that is power in this study with the iterations for ABC algorithm is shown in Fig 1. It can be seen that ABC reached global maximum at 33rd iteration. Fig 2 and 3 shows the comparison of actual and optimized power and blade pitch angles obtained from ABC algorithm for 50 randomly selected test patterns. It has been observed that the Mean PG and Mean Relative PG obtained from ABC algorithm are 87.013kW and 17.183% respectively.
Fig 1. Variation of fitness value with iterations for ABC

Fig 2. Comparison of optimal power obtained by ABC with actual power
6.2. Cuckoo Search (CS)
The variation of cost value with the iterations for CS algorithm is shown in Fig 4. The CS converges faster because it uses Levy flight search while generating new solution. It can be seen that CS reached global maximum at 26\textsuperscript{th} iteration. Fig 5 and 6 shows the comparison of actual and optimized power and blade pitch angles obtained from CS algorithm for 50 randomly selected test patterns. From Fig 5 it can be observed that, the actual and optimized power values are close at higher power range above 1000kW, but the optimized power values are higher than actual for lower range of power. It was observed that the Mean PG and Mean Relative PG obtained from CS algorithm are 87.668kW and 17.329\% respectively.
The performances of ABC and CS algorithms have been compared with PSO, a most widely used optimization algorithm. The variation of cost value with the iterations for PSO algorithm is shown in Fig 7. It can be seen that PSO reached global maximum at 33rd iteration. The algorithmic control parameters of PSO namely acceleration constants C1 and C2 are set as 2 on trial and error basis.

Comparing Fig 1, 4 and 7 it can be observed that, CS algorithm converges faster than the other two algorithms. The power gain of all the three algorithms have been summarized in Table 1. It can be observed that Mean PG and Mean Relative PG values are higher for CS and lower for ABC algorithm. From Fig 8 and 9 it can be seen that the values of blade pitch angle as well as the optimized power obtained from CS and PSO algorithms are close to each other. But the optimized power values
obtained from ABC are lower at few points as such as 22\textsuperscript{nd} and 45\textsuperscript{th} points out of the 50 randomly selected values plotted.

It can be observed that for the current problem, the performance of CS and PSO algorithms are better than ABC. Since in CS and PSO algorithms, the stochastic behavior capacity in searching the global optimum value is maintained better than ABC. Since CS algorithm uses more efficient method of exploring the search space, namely Levy flight while generating the new solutions, the chances of trapping in local minima are less. The local search is fast in CS due to the generation of new solutions by the Levy flight around the best solution obtained so far [25]. However, the decision mechanism of ABC algorithm that assists in identifying the potential search space requiring a more detailed survey in discovering new nectar source is powerful.

![Graph showing variation of fitness value with iteration for PSO](image)

Fig 7. Variation of fitness value with iteration for PSO

| Optimization algorithm | Mean PG (kW) | Mean Relative PG (%) |
|------------------------|-------------|----------------------|
| ABC                    | 87.013      | 17.183               |
| CS                     | 87.668      | 17.329               |
| PSO                    | 87.637      | 17.316               |

Table 1. Power Gain Summary
Fig 8. Comparison of optimized power obtained by ABC, CS and PSO with Actual

Fig 9. Comparison of optimized Blade Pitch Angle obtained by ABC, CS and PSO with Actual

7. Conclusion
In this paper an attempt has been made to compare the performances of three meta heuristic optimization algorithms namely ABC, CS and PSO, for optimizing the blade pitch angle and hence the power output of a horizontal axis wind turbine. It has been found that CS converged faster to global maxima in less iterations and resulted in higher values of Mean PG and Mean Relative PG thus proved to be superior. It has been observed that mean relative hourly power output of the wind turbine under consideration can increased by 17.329 (%) if the optimized values of the blade pitch angle is set. Which is a significant contribution in making the wind energy more economical.

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