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HYBRID INTELLIGENT OPTIMIZATION METHODS FOR OPTIMAL DESIGN OF HORIZONTAL-AXIS WIND TURBINE BLADES

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ABSTRACT

Designing the optimal shape of MW wind turbine blades is provided in a number of cases through evolutionary algorithms associated with mathematical modeling (Blade Element Momentum Theory). Evolutionary algorithms, among the optimization methods, enjoy many advantages, particularly in stability. However, they usually need a large number of function evaluations. Since there are a large number of local extremes, an optimization method has to find the global extreme accurately. The present paper introduces a new population-based hybrid algorithm called Genetic-Based Bees Algorithm (GBBA). This algorithm is meant to design the optimal shape for larg scale wind turbine blades. The current method employs crossover and neighborhood searching operators taken from the respective Genetic Algorithm (GA) and Bees Algorithm (BA) to provide a method with good performance in accuracy and speed convergence. Different blade designs, 21 to be exact, were considered based on the chord length, twist angle and tip speed ratio using GA results. They were compared with BA and GBBA optimum design results targeting the power coefficient and solidity. The results suggest that the final shape, obtained by the proposed hybrid algorithm, performs better compared to either BA or GA. Furthermore, the accuracy and speed convergence increases when the GBBA is employed.

KEYWORDS: Blade Design; Optimization; Genetic Algorithm (GA); Bees Algorithm (BA); Genetic-Based Bees Algorithm (GBBA); Large Wind Turbine.

INTRODUCTION

There are a lot of environmental concerns related to the use of fossil fuels. These issues have caused the quick development of clean and sustainable sources of energy such as wind power. As a fact, there has been a considerable growth in the market of wind power that stands out between sustainable energy technologies and is even estimated to develop in a more remarkable way. Among all types of wind energy machines, Horizontal Axis Wind Turbines (HAWTs) are proved to be the most efficient tools for exploiting the power of wind .These kinds of wind turbines have a lot of privileges compared to the Vertical Axis Wind Turbines (VAWTs). Some of these advantages include higher energy output, more mechanical resistance, less sensitivity to off-design situations, etc. Therefore, sufficient exploitation of the wind power with less energy loss, acquiring a significant understanding of the energy conversion phenomena and economic evaluation of these machines have attracted the attention of many technology leaders as well as researchers [1]. The present study uses different methods to optimize geometrical characteristics of the wind turbines. A complicated issue that deals with trade-off decisions is the blade design for a horizontal axis wind turbine rotor. The main objective of this study is to specify the optimal performance for a range of determined conditions. The present study investigates the optimization of blades for a horizontal axis wind turbine by using BEM theory in addition to three evolutionary optimization algorithms. Furthermore, the BEM theory has been employed to design the optimal shape of MW wind turbine blades. On the other hand, the evolutionary algorithms are used to choose the decision variables [1].The geometry of the blade consisting of the chord, twist, and airfoil type distributions along the span reacts to the output characteristics of the blade performance. Thus, the optimum wind blade geometry can enhance the whole efficiency of the wind turbine. Among EAs, Genetic Algorithm (GA) is the most popular algorithm which has been extensively used to find optimum parameters in different fields. GA, an iterative optimization method, relies on the principles of natural selection, genetic, and evolution. The main characteristics of this algorithm are thorough exploration in the entire search space and relatively poor efficiency in finding the precise location of optima at the same time [2]. Several attempts have been made with the aim of designing the optimal shape of wind turbine blades of genetic algorithm in optimization problems, for instance [1], [3], [4]. Another population-based algorithm is the Bees Algorithm (BA), which is used to optimize the purposes originally proposed by Pham [5]. The behavior of bees in a hive inspires this algorithm to explore nectar in the surrounding fields. The BA has been applied to a wide range of engineering problems, [6-8]; however, the application of this algorithm for designing the optimal shape of wind turbine blades has not been considered. The primary goal of combining optimization algorithms is to gain an advantage of various methods in one algorithm to achieve better performance. Several attemps have been made to hybridize optimization algorithms, including the combination of gradient-based and evolutionary mathods [9], combined artificial network and evolutionary algorithms [10], Performance of two hybrid variants of GA and PSO have already been studied [2], designed a concurrent-hybrid non-dominated sorting genetic algorithm (hybrid NSGA-II) for wind-turbine blade optimization [11].This study is aimed at presenting a new optimization method called Genetic-Based Bees Algorithm (GBBA) derived from GA and BA operators in the context of designing the optimal shape. Furthermore, the application of GBBA for blade shape optimization has been studied in this paper. Both performances of the algorithm proposed and the original algorithm are examined on the chord and twist distributions as well as the airfoil section of blade. Twenty-one different blade designs are considered through capriciously selecting the chord length and angle using the results of Genetic Algorithm (GA) optimization, being further compared with the results of Bess Algorithm (BA) and GBBA optimum design results targeting the power coefficient and solidity. Finally, the accuracy and speed convergence of three algorithms have been examined. The results achieved prove the superiority of the GBBA compared to other algorithms in accuracy and convergence rate. The main contributions of the present work with respect to previous research work are summarized as follows:

• The present study uses a new method which is obtained by combining Genetic Algorithms and Bees Algorithms called Genetic-Based Bees Algorithm (GBBA).According to the description given in the 6.1.(Idea of hybrid algorithms) of the paper on the advantages of hybrid methods, the authors of the present study succeeded in moderately increasing the accuracy and speed convergence of the results by using the top features of the present methods (GA and BA) and also utilizing these features for the respective issue which led to a new hybrid method. These features have been used for the first time to design wind turbines, regarding the pervious invaluable researches.

• In This study, considering the importance of twist and chord distributions for wind turbine designs, uses 21 models from twist and chord different distributions. Some of these distributions are used for the first time and have never been used in previous studies. Seeking to achieve an optimal choice other than the invaluable previous studies, different distributions for twist and chord have been examined. Finally, according to the results, a useful method designing wind turbine blades has been obtained using a combination of mathematical modeling and useful features of evolutionary algorithms.

• Another important consideration in designing wind turbines blades is the blade sections. In this study, the authors use and combine different airfoil sections (10 sections) and have finally achieved the best combination for the development of large wind turbines. Considering the invaluable previous studies, an investigation and combination of wind turbine blades sections, with such a substantial number of sections, has not been used so far.

The article is presented in 11 Sections. Introduction is described in Section 1. In Section 2 Blade Element Momentum (BEM) Theory under the study is explained. The Wind turbine rotor performance analysis is explained in Section 3. GA, BA and Hybrid Algorithm (GBBA) are described in Sections 4, 5 and 6. Objective function is presented in Section 7. Section 8 contains the Wind PACT 1.5 MW wind turbine for validation. In Section 9 Blade design optimization is explained. Determination of the appropriate weighting factor is presented in Section 10 and section 11 is the conclusion and future work.

BLADE ELEMENT MOMENTUM (BEM) THEORY

The blade element theory is based on the airfoil aerodynamic characteristics, and the momentum theory considers the blade as a number of independent stream tubes and ignores the spanwise flow. Glauert combines these two theories to improve the original BEM theory. [12]. In the BEM theory, the air that flows through the rotor is assumed axisymmetric. Equations (1) and (2) explain the momentum theory for each stream tube according to the conservation of momentum in both rotational and axial directions:

$$dT = \rho V^2 4a(1-a)\pi dr \tag{1}$$

$$dQ = 4a'(1-a)\rho V\pi r^3 \Omega dr \tag{2}$$

Where dT and dQ are the differential thrust force and torque, r is the stream tube radius (or blade element), and U is the wind turbine rotor angular velocity. Equations (3) and (4) explain the aerodynamic normal force and the torque of the blade element, which equal to the thrust force in Equation (1) and the torque in Equation (2), based on the known coefficients of airfoil lift and drag C_l and C_d using assumed induced relative wind velocity U_{rel} to the airfoil:

$$dF_n = B\,\frac{1}{2}\,\rho U_{rel}^2 (C_l \mathrm{Cos}\varphi + C_d \mathrm{Sin}\varphi)cdr \tag{3}$$

$$dQ = B\frac{1}{2}\,\rho U_{rel}^2 (C_l \mathrm{Sin}\varphi + C_d \mathrm{Cos}\varphi)crdr \tag{4}$$

Where B is the number of blade, ρ is the density of air, φ is the relevant wind angle. Combining the momentum theory and blade element theory causes both axial and angular induction parameters a anda', which are then utilized for calculating the induced relative wind velocity U_{rel} to the airfoil. Then, in order to calculate the blade element aerodynamic forces, the induced wind velocity is used again, and the above process is repeated as long as the newly calculated induction parameters a and a′ reach to an acceptable tolerance of the previous ones. In the BEM theory, the essential thing for the blade design, load analysis and power performance prediction of a wind turbine is the accuracy of the airfoil aerodynamic model, i.e. the lift and drag coefficients. Designing the wind turbine blade is enhanced by a well-established airfoil aerodynamic model. However, the BEM theory does not correctly explain the real physics of a wind turbine as it is based on a few assumptions. The air flow through the rotor is axisymmetric is the first and most important assumption that is only an approximation with a finite number of blades, typically 3. The finite number of blades impacts on the efficiency losses concentrated near the blade tip, which is known as the tip losses and can be used with the correction factor of well-accepted tip loss reported by Prandtl [12, 13]:

$$F = \frac{2}{\pi}\cos^{-1}\left(\exp\left(-\left(\frac{B\left(1-\frac{r}{R}\right)}{2\left(\frac{r}{R}\right)\sin\varphi}\right)\right)\right) \tag{5}$$

The correction factor of tip loss is always between 0 and 1 and characterizes the decrease in the forces at a radius r along the blade caused by the tip loss at the blade end. The obtained results from the BEM theory with correction of tip loss are generally in good accordance with field measurements for flows attached on the blades' surface, i.e. under condition of stall free while the blade TSR is maintained at design TSR or higher. This confirms the BEM theory as a standard tool for designing wind turbine blade [13].

WIND TURBINE ROTOR PERFORMANCE ANALYSIS

Every blade section of the three blades affects the power of wind turbine rotor. Therefore, the calculation is based on the analysis of efficiency of each blade section. By using an iterative method, the factor of performance for every blade element is predicted [12, 13], that is briefly described as follows:

(1) Approximate a primary (the first iterative) value for the axial induction and angular induction parameters a and a′:

$$\varphi_{i,1} = \left(\frac{2}{3}\right)\tan^{-1}\left(\frac{1}{\lambda_{r,i}}\right) \tag{6}$$

$$a_{i,1} = 1/[1 + \frac{4\sin^2(\varphi_{i,1})}{\sigma_i' C_{l,design}\cos\varphi_{i,1}}] \tag{7}$$

$$a_{i,1}' = \frac{1 - 3a_{i,1}}{(4a_{i,1} - 1)}$$

Where i represents the ith blade element. σ_i' Indicates the local solidity, defined by:

$$\sigma_i' = \frac{Bc_i}{2\pi r_i} \tag{9}$$

(2) Begin the iterative process for the jth iteration. For the first iteration, follow step 1), j = 1. Compute the relative wind angle and Prandtl tip loss factor:

$$\tan\varphi_{i,j} = \frac{1-a_{i,j}}{(1+a_{i,j}')\lambda_{r,i}} \tag{10}$$

$$F_{i,j} = \left(\frac{2}{\pi}\right)\cos^{-1}[\exp(-(\frac{\left(\frac{B}{2}\right)\left\{1-\left(\frac{r_i}{R}\right)\right]}{\left(\frac{r_i}{R}\right)\sin\varphi_{i,j}}))] \tag{11}$$

(3) Then compute the local angle of attack of the ith blade element:

$$\alpha_{i,j} = \varphi_{i,j} - \theta_{p,i} \tag{12}$$

(4) Then for next iteration, update the axial and angular induction factors a and a′, considering the drag impacts:

$$a_{i,j+1} = \frac{1}{\left[1+\frac{4F_{i,j}\sin^2(\varphi_{i,j})}{\sigma_i'(C_{l,i,j}\cos\varphi_{i,j}+C_{d,i,j}\sin\varphi_{i,j})}\frac{1}{H}\right]} \quad (13)$$

$$a'_{i,j+1} = \frac{1}{\frac{4F_{i,j}\sin\varphi_{i,j}\cos\varphi_{i,j}}{\sigma_i'(C_{l,i,j}\sin\varphi_{i,j}-C_{d,i,j}\cos\varphi_{i,j}}-1} \quad (14)$$

The factor H is presented for the condition when large induction parameters occur. When the axial induction parameter a is greater than 0.5, the expression for thrust coefficient is as follow [12]:

$$C_T = 4a(1-a) \quad (15)$$

must be replaced by the empirical expression:

$$C_T = 0.6 + 0.61a + 0.79a^2 \quad (16)$$

GH-bladed adopted a transition to the empirical model for axial induction factor greater than 0.3539 rather than 0.5 to achieve a smoother transition. The factor H is defined as following:

$$\text{for } a_{i,j+1} \le 0.3539, H = 1.0 \quad (17)$$

$$\text{for } a_{i,j+1} > 0.3539, H = \frac{4a(1-a)}{(0.6+0.61a+0.79a^2)} \quad (18)$$

If the deviance deviation between the j+1th and the jth induction factors parameters is within in an acceptable tolerance range, then confirm the angle of local relative wind angle φ_i, tip loss factor F_i and angle of attack angle α_i , which determines the coefficients of local lift and drag coefficients $C_{l,i}$ and $C_{d,i}$ for the ith blade element; (if not, then go back to step 2).

Having obtained the mentioned performance factors for each blade element, based on Equation 4, the torque produced by the blade element is as same as [12]:

$$dQ_i = F_i B \frac{1}{2}\rho U_{rel,i}^2 (C_{l,i}\sin\varphi_i - C_{d,i}\cos\varphi_i) c_i r_i dr \quad (19)$$

The total rotor torque and power are computed from [12]:

$$Q = \sum_{i=1}^{n} dQ_i \quad (20)$$

$$P = Q\Omega \quad (21)$$

Then, the power coefficient of wind turbine rotor is determined by [13]:

$$C_P = \frac{P}{\frac{1}{2}\rho\pi R^2 V^3} \quad (22)$$

In this study, the topic is approached from a manufacturer perspective and concentrate on the decrease of solidity and the development of output power (power coefficient). Low solidity values are commonly associated with low weight blades and low total cost. Generally, the key purpose of designing and optimizing a blade of wind turbine is to maximize the output power. However, other goals must sometimes be noticed during the optimization procedure. Thrust is a factor that must be minimized to develop high efficiency of wind turbines.

GENETIC ALGORITHM

The formulation of Genetic Algorithm was suggested by Holland a decade after the first evolutionary strategies and evolutionary programming applications [14].GA is an iteration-based method which is related to the concept of natural selection, genetic and evolution in which each candidate solution is encoded in strings called chromosome. Each string, which is called chromosome, is made by chaining a number of sub-strings, and each sub-string represents portrays one of the futures of candidate solutions. Different encoding strategies are applied in this algorithm such as binary, real-valued and complex-valued encoding.In most of the cases, individuals are fully described by single bit-strings, thus leading to the identification of the genotype with one single chromosome. Several other encoding procedures have been examined, which provoked a debate on the most appropriate choice.The choice of the proper encoding method is dependent on the application. For instance, Joodaki et al. [15] have proved than continuous GA supplies better convergence rate in fluid flow shape design problems.The GA operators are the crossover, mutation and selection. Among iterations of the algorithm, population of solutions interacts with each other in order to evolve to a higher overall fitness level using crossover and mutation operators. Individuals are chosen for reproduction with a probability subject to their fitness. Here, GA allocates the mating probability of each individual proportionally to its fitness (proportional selection) and chooses (selects) the parents set through the roulette wheel selection procedure [16]. Fitness ranking and tournament selection are other examples of popular selection schemes. The reader can refer to [17] for a comparison of selection schemes. Crossover is the main search operator in GA, creating offspring by randomly mixing sections of the parental genome. The number of sections exchanged varies widely with the GA implementation. The most common crossover procedures are one-point the crossover, two point crossover, uniform and arithmetic crossover [18].The factor that controls the frequency of the operator is defined as crossover probability. In this paper, crossover probability is set at 0.67 and scattered crossover is used. A small fraction of the offspring is randomly selected to undergo genetic mutation. The mutation operator randomly picks a location from a bit-string and flips its contents in a limited range. The primary objective of mutation is to preserve diversity of the population through iterations. The GA uses generational replacement similar to the other EAs.First; a number of guesses for solutions are made as the initial population. Then the loop of algorithm is started, in which, after the fitness evaluation for all individuals is carried out, some of them are selected for crossover and mutation and the new population is generated via these operators. The loop iterates over a large number of generations until stop criteria is satisfied. The stop criteria used here is to reach a certain number of cost evaluations in the entire algorithm. Figure 1 shows the procedure of GA used here:

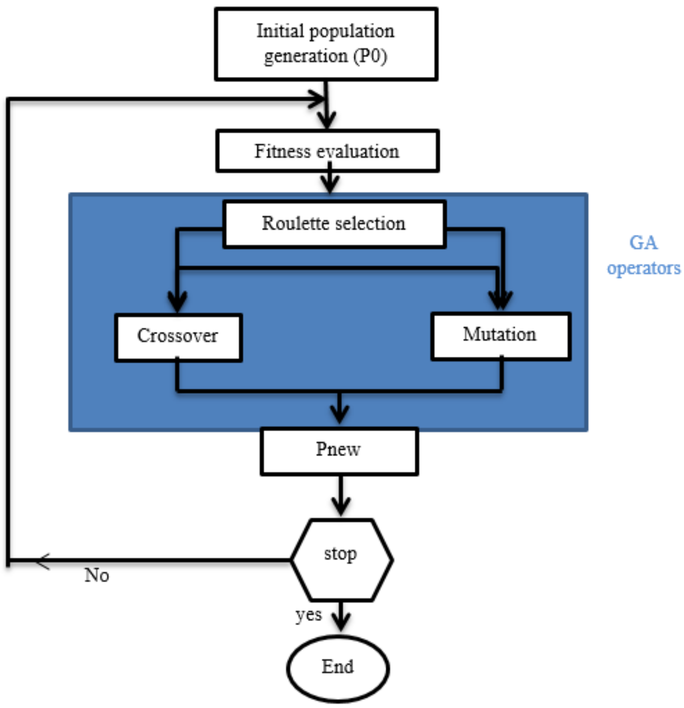

Figure 1. Flowchart of the genetic algorithm used in this study.

BEES ALGORITHM

The Bees Algorithm (BA) is a method which is inspired by bees' plans and actions to discover nectar in the regions around the hive [5]. This method begins with n scout bees randomly scattered in the search space and each single bee considers one site. After testing the compatibility of each site (i.e., the performance of the volunteer solutions), m sites with more fitness are considered as "selected sites" and are appointed for neighborhood search. Between the selected sites, e sites with the highest fitness are considered as 'elite' (top-rated) sites. Afterwards, the algorithm looks for a better solution around the selected sites. This can be achieved by employing more bees for the best e sites than that of the other (m-e) selected sites. After the searching process for every selected site, just one bee with the highest compatibility value is selected to make the next bee population. The rest of bees in the population coming back from 'unselected sites' (sites with lower fitness) are issued randomly around the search area to discover new potential results. At the end of each duplication, the colony has two groups of bee to form its new population: returned from the selected sites, and scout bees established to fulfill random discoveries. These procedures are repeated until a stopping criterion is met. Accordingly, the important parameters of this algorithm are: the number of scout bees (n), number of sites selected for neighborhood search (m), and number of elite sites among m selected (e), number of bees enrolled for the best e sites (nep), number of bees recruited for the other (m-e) selected sites (nsp), and the stopping criterion.

The BA algorithm used in this research is a little different from the one which is explained above. Here, the selected sites chosen and the concept of elite site are appointed in a different behavior: For each site, a probability is described based on its compatibility such that sites with better fitness would have more ability to be assigned as a selected site by a probability function. The utilized function in this research is described according to Equation 23:

$$p_i = \begin{cases} 0.4 & f_i < 0.9 \\ 0.8 & 0.9 < f_i < 0.95 \\ 0.95 & 0.95 < f_i < 1.15 \\ 1 & f_i > 1.15 \end{cases} \tag{23}$$

Where p_i is the probability of site, i is considered as a selected site, and f_i is the fitness of site i. The number of bees enrolled for seeking neighborhood of selected sites corresponds to the fitness of the site by a parameter which is defined as "n Bees" according to Equation 24:

$$nsp_i = n\ Bees \times f_i \tag{24}$$

n Bees is a constant value equal to three, unless it is defined differently. The flowchart of the Bees Algorithm which is applied in this research is demonstrated in Figure 2.

HYBRID ALGORITHM

Idea of hybrid algorithms

The principle of hybrid algorithms and hybridization of intelligent techniques, coming from different computational intelligence areas, has recently become the subject of many research papers because of the growing awareness. The principle of hybrid algorithms and hybridization of intelligence techniques, coming from different computational intelligence areas, has recently become the subject of many research papers due to the growing awareness. These types of combinations often perform better than individual techniques coming from computational intelligence (neurocomputing, fuzzy systems, rough sets, evolutionary algorithms, etc.).Practical experience has proved that hybrid intelligence techniques can be very useful to solve some of the real world's challenging problems. A synergistic combination of multiple techniques, in a hybrid intelligence system, is used to build solutions that can efficiently deal with particular problems.

Hybrid BA and GA Method

As mentioned earlier, GA is capable of searching well in large spaces; however, it suffers from being trapped in the local optima. The performance of BA in finding global optima is precise and faster, whereas its convergence is slow for problems involving big spaces. This paper uses crossover and neighborhood searching operators given from GA and BA respectively to create an algorithm that can be as beneficial as the original algorithms. The number of applied operators in this algorithm in each iteration can be different. Here, diversity is suggested as the criterion to choose the number of GA and BA operators which can be applied. The concept of diversity in evolutionary algorithms varies by application [19].The formula below shows the magnitude of exploring space:

$$d = \frac{\sum_{i=1}^{nPop} |f_i - \bar{f}|}{\bar{f}} \tag{25}$$

Where f is the fitness of the individual i and $\bar{f}$ is the mean fitness of the whole individuals in the population. The portion of population selected for crossover operator (m) is calculated as a function of diversity calculated below:

$$m = \min\{100\%, (d \times A)\} \tag{26}$$

Variable A is a constant which can be varied based on different problems. Here, A is set at 80 unless stated otherwise. The rest portion of the population is selected for neighborhood searching. Diversity is calculated after generation and fitness evaluation of initial population in the proposed hybrid algorithm. Afterwards, the number of m and n individuals from the present population is chosen for crossover and neighborhood searching operators by using roulette selection mechanism. In spite of the individual affected by crossover, neighborhood searching for every individual is permitted to occur. The results of population provided by these operators are combined with old population and then the new population is obtained by sorting and selecting the best individuals. Finally, if the stop criteria for the best individual of the population are not satisfied, the algorithm goes back to fitness evaluator section, otherwise algorithm stops. Figure 3 shows the procedure of proposed hybrid algorithm:

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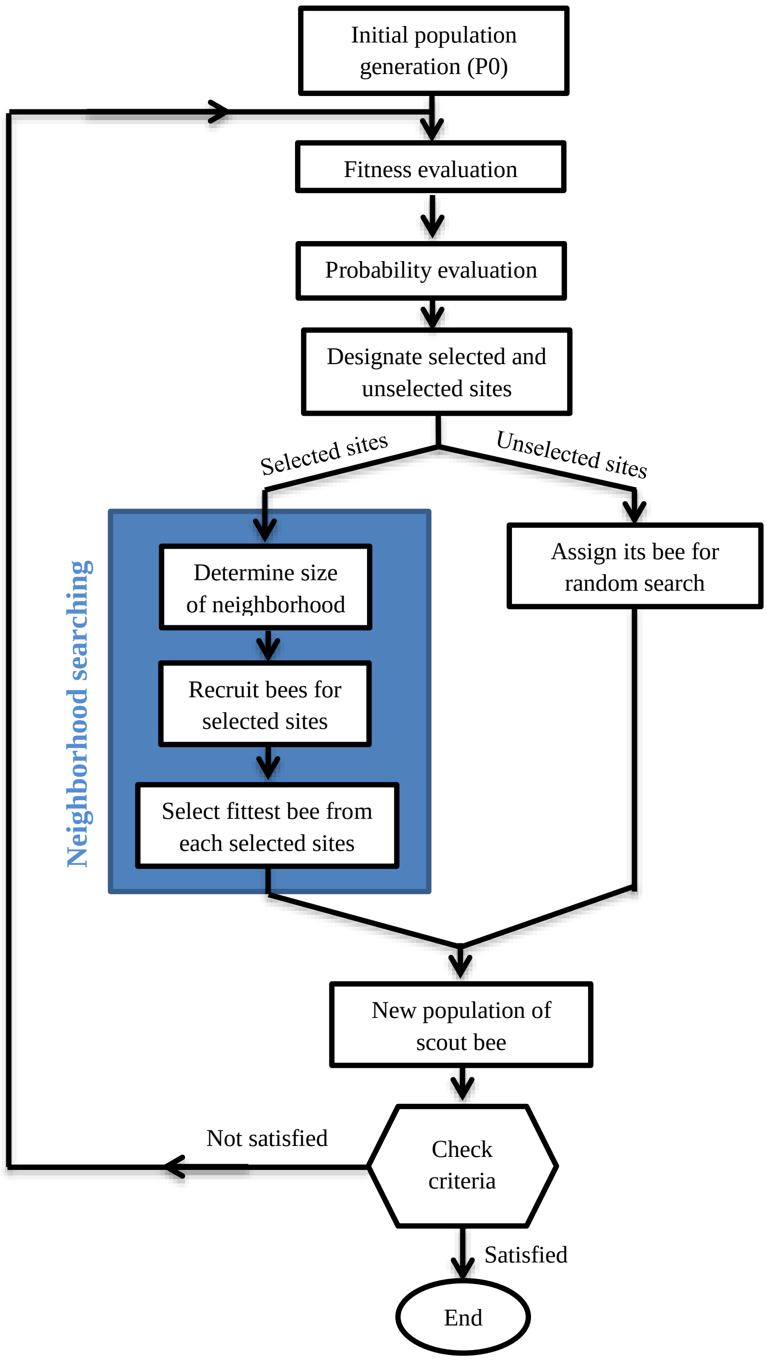

Figure 2. Flowchart of the Bees Algorithm

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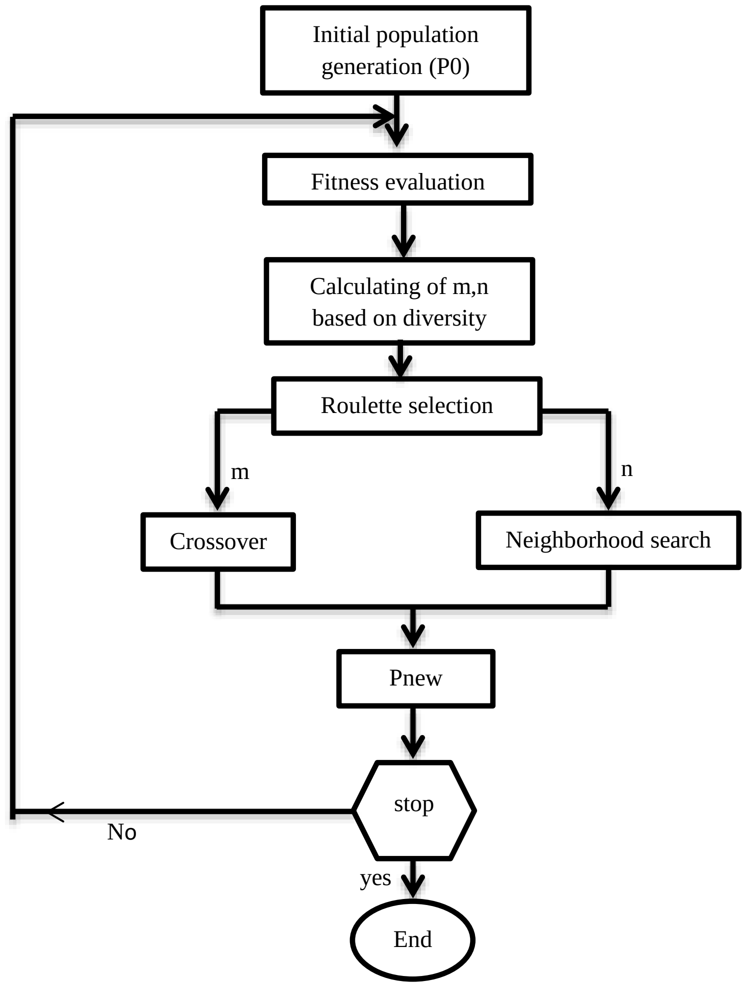

Figure 3. Flowchart of the hybrid algorithm (GBBA) used in this study.

OBJECTIVE FUNCTION

In order to maximize the output power and minimize the solidity, the objective function is defined as:

$$\text{Objective function} = w\left(C_p\right) + (1 - w)\sigma^{-1} \tag{27}$$

Where w, such that $0 < w < 1$, is the weighting coefficient which determines the contribution of each goal in the objective function: the Output power to be maximized and the solidity to be minimized. It is expected that higher values of w will lead to high output Power while lower values result in low solidity. Low solidity values are related, commonly, with low weight blades and low overall cost.

WINDPACT 1.5 MW WIND TURBINE FOR VALIDATION

In this study, the information from WindPACT 1.5 MW wind turbine model with a capacity of 1.5 MW was used to verify the blade shape optimization method. The WindPACT 1.5 MW turbine has been designed for a wind energy project called "Advanced Component Technologies" which was launched by the National Renewable Energy Laboratory (NREL) during two years from 2000 to 2002. The specific information about the parts of each turbine and the design assumptions are demonstrated in the project reports [20-24].

The design of the studied wind turbine is based on a horizontal axis wind turbine (HAWT) with 3 blades. The cross-sections of the blade are made of the NREL S8xx airfoil type. Figure 4 shows the studied part of the blade. The removed component of the blade does not have a considerable effect on the overall aerodynamic efficiency. It is supposed to develop gradually from the cylindrical shape in the hub connecting the cross-section to the root section of the studied component. The twist, chord and airfoil type distributions for the studied component of WindPACT 1.5 MW turbine blade is demonstrated in Table 1.

Table 1. Chord, twist and airfoil distributions along the Original blade.

R,m	Chord,m	Twist,deg	Airfoil
7.875	2.72	0.1	S818
9.625	2.64	0.2	S818
11.375	2.52	0.3	S818
14.875	2.27	0.5	S818
16.625	2.14	0.8	S825
18.375	2.02	1.2	S825
20.125	1.9	1.7	S825
21.875	1.77	2.1	S825
23.625	1.65	2.6	S825
25.375	1.53	3.4	S825
28.875	1.3	6.1	S825
30.625	1.18	7.6	S826
32.375	1.07	9.1	S826
34.125	0.96	10.5	S826

Figure 4. Investigated part of wind turbine blade with introduced definitions

Also, in order to verify the optimum shape design module of the Matlab software (Based Wind turbine rotor performance analysis) developed in this study, the specifications for the reference model D_{rotor} =70 m, λ_0=7 and V_{rated}=10.7 m/s, which corresponds to a blade tip speed of 75 m/s and rated power of 1.5 MW at 20.5 rpm. Considering the operation wind speed from V_{cut-in}=3 m/s to $V_{cut-out}$=25 m/s. chord and twist distribution shown in table 1 were introduced as input parameters for a new 1.5 MW blade design, which were used to compare the distribution of chord lengths and the twist angles with the reference model. The performance analysis results obtained from the Matlab software (Based Wind turbine rotor performance analysis) in this research are λ =6.5 and c_p=0.4577 The obtained value of the aerodynamic efficiency for the initial blade geometry is C_p=0.4519 and $\lambda = 7$ by [21] for Wind PACT 1.5 MW turbine blade. The figure 4 shows that the result from Matlab software (Based Wind turbine rotor performance analysis) agrees with Wind PACT 1.5 MW turbine blades run by [21] the National Renewable Energy Laboratory (NREL) very well.

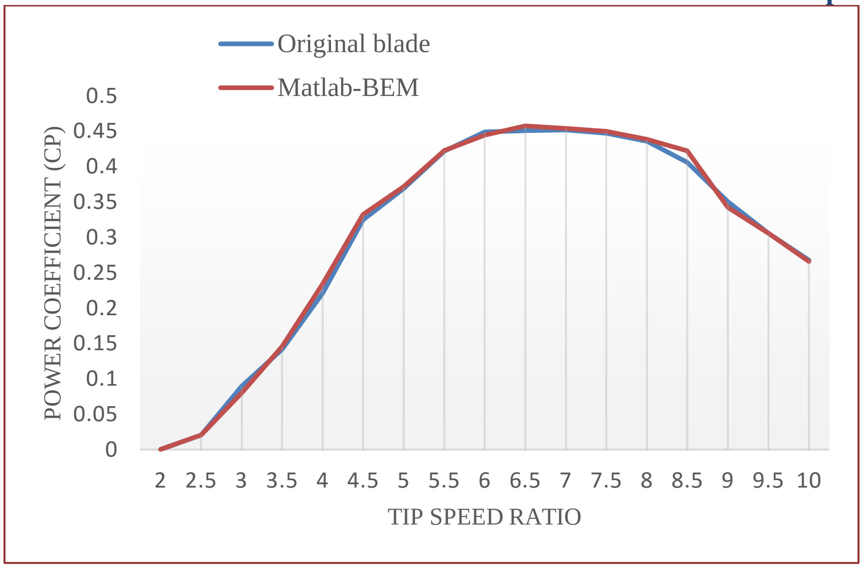

Figure 4. Calculated Power coefficient-Tip speed ratio curve

BLADE DESIGN OPTIMIZATION

Method

In order to reach the maximum power output and minimum solidity, the optimal design of the large wind turbine blades using intelligent optimization techniques, such as Genetic Algorithm, Bees Algorithm and the Proposed Algorithm, is done and the results of this optimization have been compared with the initial wind turbine blade design (Wind PACT 1.5 MW wind turbine) for verification and validation. Therefore, the key parameters, such as chord length, tip speed ratio, airfoil sections, and twist angel in designing the optimal blade of wind turbine for aerodynamic efficiency, have been considered and different cases, which are shown in tables 2, 3, 4, 5 and, 6 have been analyzed.

Airfoils selection

The National Renewable Energy Laboratory (NREL) has constructed many types of airfoils for horizontal axis wind turbines. Each type can be used for a special purpose [25]. In order to fulfill and evaluate the design process of the blade, ten airfoil types were chosen; the blade radius of the studied types was suggested to be 35 meters. Tables 2 and 3 show the details of the selected airfoil types. More experimental information concerning the airfoil types can be found on the official website of NREL and XFoil software. The Reynolds number for the presented simulations is considered to be 10^6. The experimental information concerning the lift and drag factors, as well as the angle of attack is demonstrated in the figure 6 to 8 for Optimum blade model. According to the Fig 6 to 8, it is clear that the lift factors show great compatibility throughout all investigated angles of attack.

Table 2.NREL airfoil families under study.

Airfoil family	Root	Mid-span	Tip
preliminary Blade	S818	S825	S826
Blade model 1	S814	S825	S826
Blade model 2	**S811**	**S809**	**S810**
Blade model 3	S815	S812	S813
Blade model 4	S818	S812	S810
Blade model 5	S811	S825	S813

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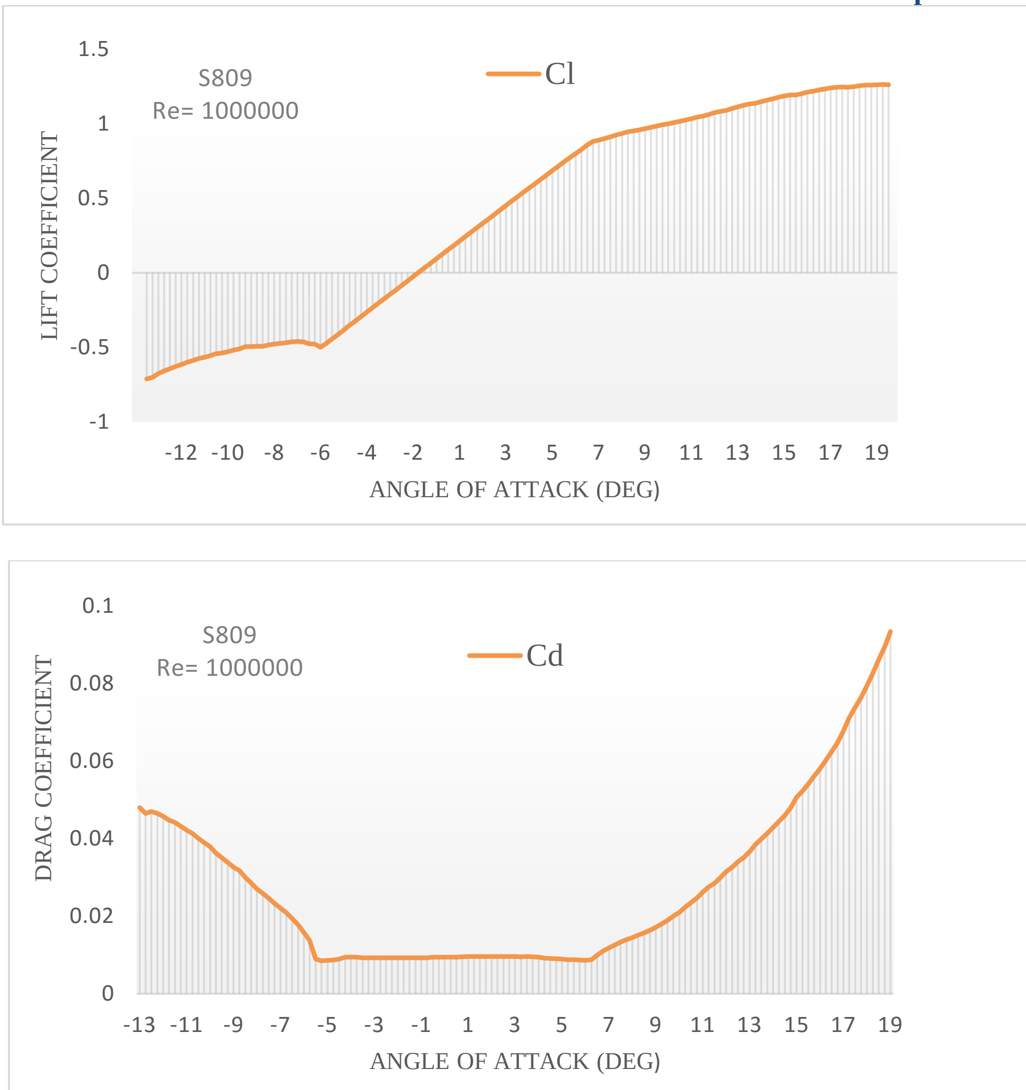

Figure 6. Aerodynamic characteristics of S809 airfoil at Re =1,000,000.

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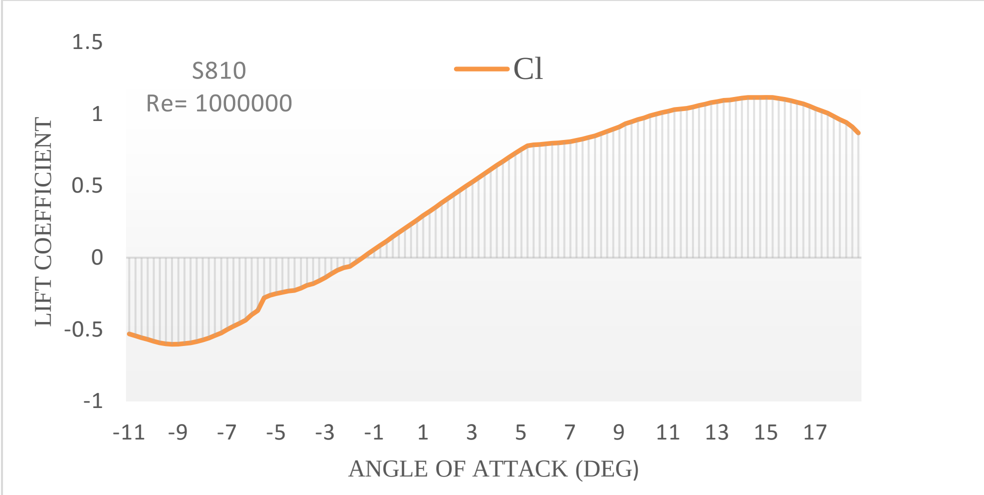

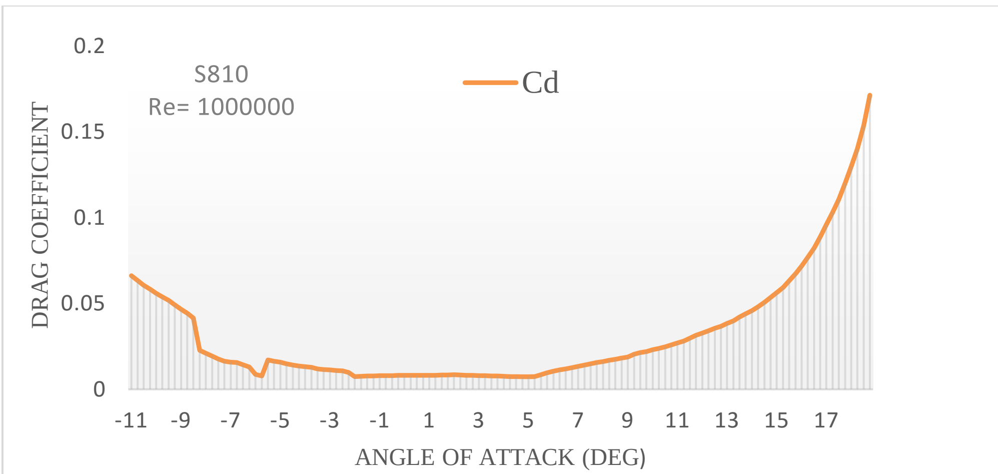

Figure 7. Aerodynamic characteristics of S810 airfoil at Re =1,000,000.

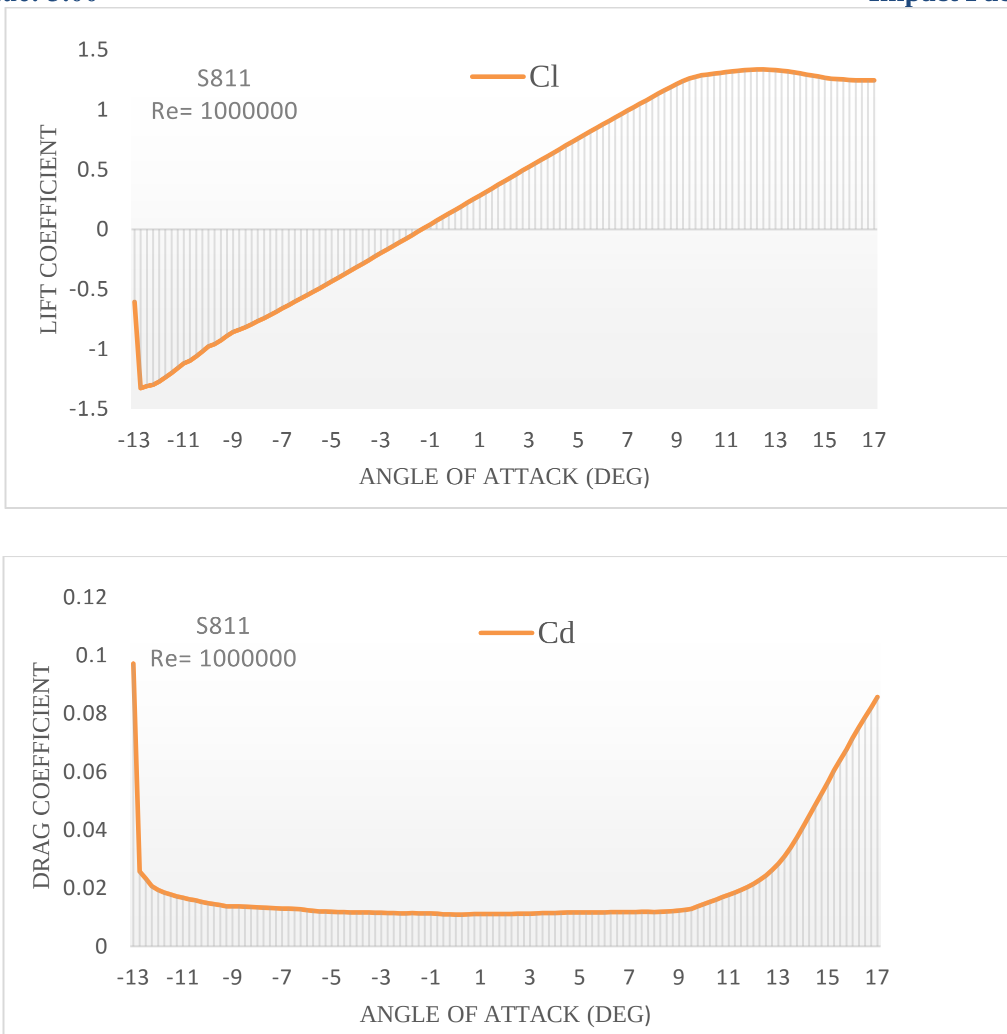

Figure 8. Aerodynamic characteristics of S811 airfoil at Re =1,000,000.

The schematic shapes of the selected airfoil family are presented in table 3.

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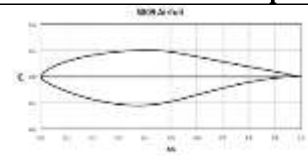
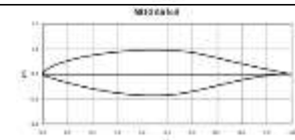
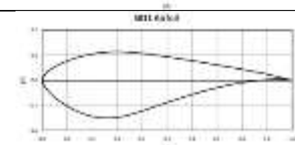
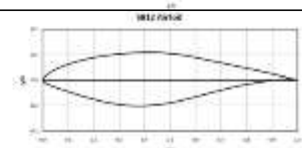
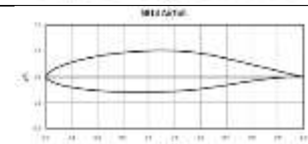
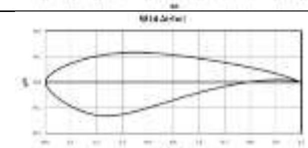
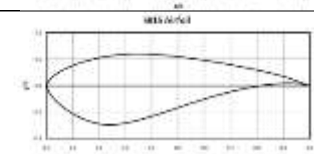
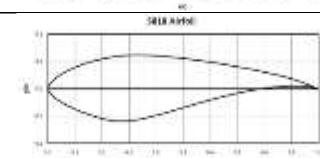
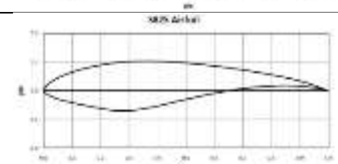
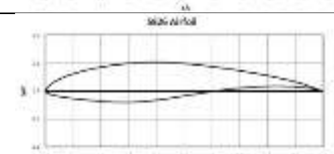
Table3. Geometrical depiction of the selected airfoil family.

Airfoil name	schematic airfoil shape
S809	
S810	
S811	
S812	
S813	
S814	
S815	
S818	
S825	
S826	

Aerodynamic characteristic

The base optimal design is based on a large wind turbine blades such that blade cross-sections are composed of NREL S8xx airfoil family, which are shown as models 1 to 5 (blade 1, blade 2, blade 3, blade 4, and blade 5) in table 2. In order to reach the optimal blades shape, different analyses of twist, chord distribution and optimal tip speed ratio in cases 1 to 21 have been carried out in tables 4, 5 and 6. The results obtained from cases 1 to 21 have been evaluated for cases 1 to 5 (blade models) and the optimal case for blade design is chosen. For cases 1 to 21, tip speed ratio has been optimally calculated.

Table 4. Characteristics for rotor blade configurations under study (for GA optimization method)

Design name	**Chord distribution**	**Twist distribution**
Case 1	linear distribution	linear distribution
Case 2	linear distribution	optimal set by GA
Case 3	Exponential distribution	Exponential distribution
Case 4	Quadratic distribution	Quadratic distribution
Case 5	burton equation	optimal set by GA
Case 6	Betz equation	optimal set by GA
Case 7	optimal set by GA	optimal set by GA

Table 5. Characteristics for rotor blade configurations under study (for BA optimization method)

Design name	**Chord distribution**	**Twist distribution**
Case 8	linear distribution	linear distribution
Case 9	linear distribution	optimal set by BA
Case 10	Exponential distribution	Exponential distribution
Case 11	Quadratic distribution	Quadratic distribution
Case 12	burton equation	optimal set by BA
Case 13	Betz equation	optimal set by BA
Case 14	optimal set by BA	optimal set by BA

Table 6. Characteristics for rotor blade configurations under study (for GBBA optimization method)

Design name	**Chord distribution**	**Twist distribution**
Case 15	linear distribution	linear distribution
Case 16	linear distribution	optimal set by GBBA
Case 17	Exponential distribution	Exponential distribution
Case 18	Quadratic distribution	Quadratic distribution
Case 19	burton equation	optimal set by GBBA
Case 20	Betz equation	optimal set by GBBA
Case 21	optimal set by GBBA	optimal set by GBBA

Additionally after the preliminary optimization, the distributions of twist angles and chord lengths do not represent a continuous orientation. This is mainly due to the fact that different airfoil types (in the present study, blades 1-5 in table 2) are applied to large blades and the optimization of calculation is performed respectively for local elements. To overcome this problem, an alternative for limiting the rate of change for the chord length and the twist angle of the neighboring elements is accessible. In order to make the shape of the blade globally smooth, it is necessary to consider many orders of curve fitting for chord length and twist angle distributions.

RESULTS AND DISCUSSION

21 different blade designs with a capricious selection of chord length and twist angle using Genetic algorithm (GA) optimization results are considered to be compared with Bees algorithm (BA) and proposed method (GBBA) optimum design results targeting the power coefficient**.**

The customary methods utilized for defining the geometrical characteristics of the blades include linear distribution, exponential distribution, quadratic distribution, Betz method**,** burton equation, optimal set by BA, optimal set by GA, optimal set by GBBA for chord length determination and twist angle selection. Tables 4, 5, and 6 tabulate the information about the utilized methods in each design.

The optimal fitness (Pareto) front for the power coefficient and solidity are demonstrated in the Figures 9, 10 and 11.The "fitness front" (Also called "Pareto front") is the subgroup of the blades in a way that at least one part of objective function, power coefficient or inverse of solidity, is larger than every other blade. "W" which is the weighting factor, is ranged from 0 to 1. It determines the contribution of all goals in the objective function. In order to satisfy the defined objective function the out power coefficient and solidity are the maximum and minimum coefficients respectively. Consequently, blade model 2 for case 21 is proposed as the optimal case for blade design. The optimized blade model 2 for case 21 was evaluated at the other cases (Figure 11).

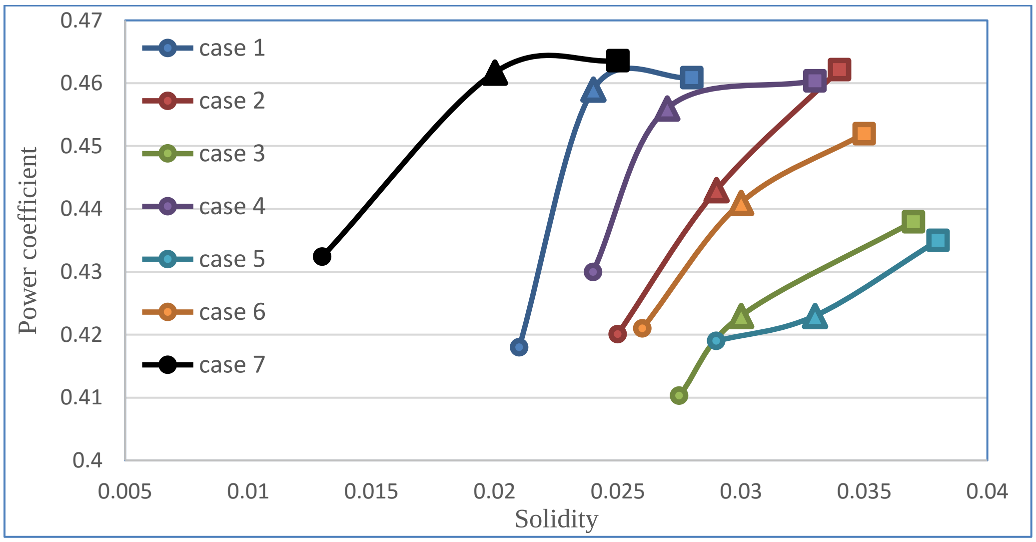


Figure 9. The optimal fitness front for Genetic algorithm optimization method (●w=0.7 ▲ w=0.8 ◆w=0.9)

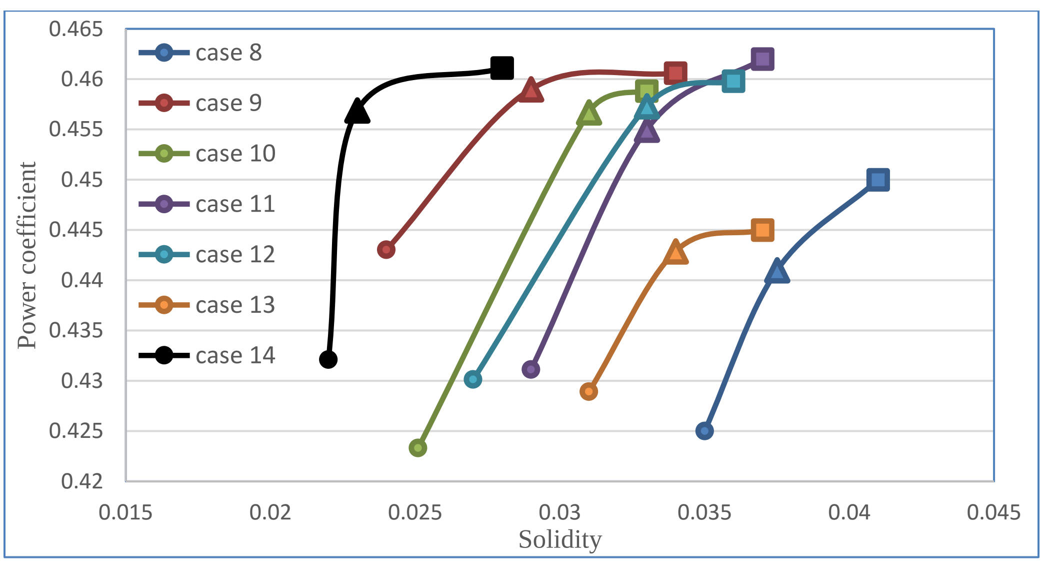


Figure 10. The optimal fitness front for Bees algorithm optimization method (●w=0.7 ▲ w=0.8 ◆w=0.9)

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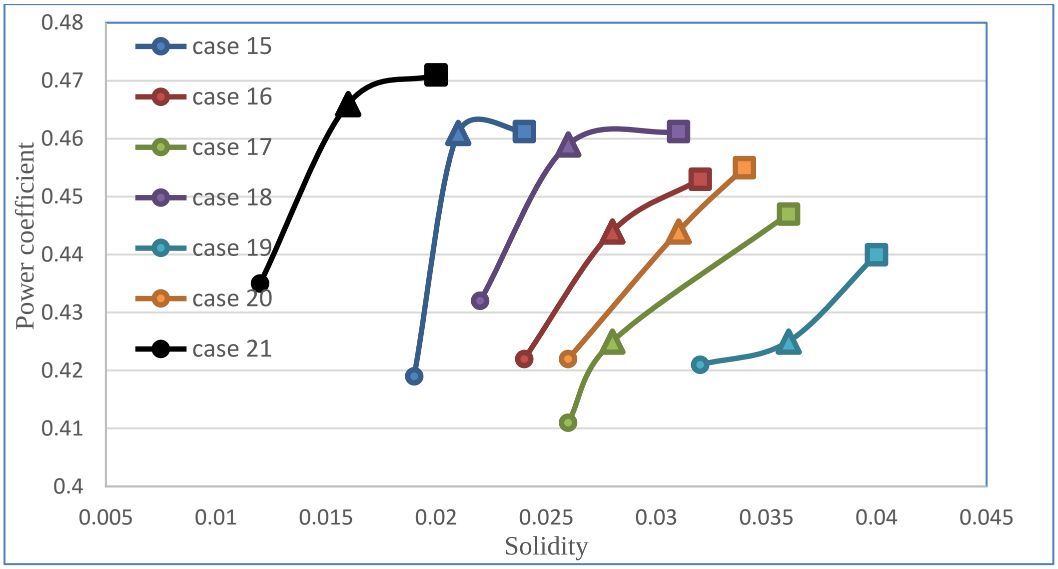

Figure 11. The optimal fitness front for GBBA optimization method (●w=0.7 ▲ w=0.8 ◆w=0.9)

Figures 9, 10 and 11 show the results of optimization using the GA, BA and GBBA methods. The optimum case, which meets the conditions, is case 21 for blade model 2 (S809-S810-S811), noting that this study is seeking the maximum power coefficient and minimum solidity. Considering the importance of the parameters twist, chord, and λ in designing the wind turbines, several designing strategies in tables 2 and 3 have been perceived. Table 6 shows in detail C_P and solidity values for different scenarios of weighing factor. As can be seen, increasing the weighting factor results in increasing the C_P and σ. Figure 11 shows the results obtained by examining the linear distribution of chord and twist considering the optimum λ, for case 15. The results of case 16 shown in Figure 11 are obtained by examining the linear distribution of chord, also for this case the optimum λ and twist is calculated using GBBA optimization method and BEM theory. According to Figure 11 increasing the weighting factor results in increasing the C_P and σ. the exponential distribution of blade design for chord and twist has been considered in case 17. A quadratic distribution to distribute chord and twist has been considered for case 18, Figure 11 shows the results of case 18. The Pareto results of cases 19 and 20 shown in Fig 11 are obtained using the chord equations, which are presented by Burton and Betz, after examining the optimum λ and twist using GBBA optimization method and BEM theory. For case 21, GBBA optimization method has been used to develop the optimum λ, chord and twist using BEM mathematical theory. The results are shown in Figure 11 that all the points, with different weighting factors, obtained for this case have higher C_P factors than other cases. However, solidity values of this case (case 21) are lower than all the weighting factors of other cases. Therefore, case 21 performs better than other cases for designing the wind turbine blades. The results of optimization using GA and BA for cases 1-14 are shown in Figure 9 and 10. Comparing the results of GBBA with GA and BA, it can be found that the GBBA presents better results for this paper. λ has been optimized in all the cases using the proposed method. In this study, number of wind turbine blades is 3 (B=3) and the radius blade is equal to 35 m. Air density has been considered according to the case study and the height above sea level. Under these conditions, the changes of C_P and solidity, cl/cd ratio for the section of blade, wind speed, and tip speed ratio depend greatly on chord and twist. This study seeks to achieve the maximum power output and the minimum solidity by analyzing and using different strategies. Low solidity values are commonly related to low weight blades and low overall cost, which leads to optimum design of the wind turbine blades and high performance of the wind turbine. Furthermore, the performance of the optimal blade is given in Table 6 in more detail.

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Table 6. Values of power coefficient and solidity for Optimal case (case 21) studies for blade model 2.

Case study	**w**	**Solidity**	**Power coefficient**
Case 1	W = 0.7	0.021	0.418
	W = 0.8	0.024	0.459
	W = 0.9	0.028	0.4609
Case 2	W = 0.7	0.025	0.4201
	W = 0.8	0.029	0.443
	W = 0.9	0.034	0.4622
Case 3	W = 0.7	0.0275	0.4103
	W = 0.8	0.03	0.423
	W = 0.9	0.037	0.438
Case 4	W = 0.7	0.024	0.43
	W = 0.8	0.027	0.456
	W = 0.9	0.033	0.4604
Case 5	W = 0.7	0.029	0.419
	W = 0.8	0.033	0.423
	W = 0.9	0.038	0.435
Case 6	W = 0.7	0.026	0.421
	W = 0.8	0.03	0.441
	W = 0.9	0.035	0.452
Case 7	W = 0.7	0.013	0.4324
	W = 0.8	0.02	0.4617
	W = 0.9	0.025	0.4636
Case 8	W = 0.7	0.035	0.425
	W = 0.8	0.0375	0.441
	W = 0.9	0.041	0.45
Case 9	W = 0.7	0.024	0.443
	W = 0.8	0.029	0.459
	W = 0.9	0.034	0.4606
Case 10	W = 0.7	0.0251	0.4233
	W = 0.8	0.031	0.4567
	W = 0.9	0.033	0.4588
Case 11	W = 0.7	0.029	0.4311
	W = 0.8	0.033	0.455
	W = 0.9	0.037	0.462
Case 12	W = 0.7	0.027	0.4301
	W = 0.8	0.033	0.4573
	W = 0.9	0.036	0.4598
Case 13	W = 0.7	0.031	0.4289
	W = 0.8	0.034	0.4429
	W = 0.9	0.037	0.445
Case 14	W = 0.7	0.022	0.4321
	W = 0.8	0.023	0.4569
	W = 0.9	0.028	0.4611
Case 15	W = 0.7	0.019	0.419
	W = 0.8	0.021	0.461
	W = 0.9	0.024	0.4612

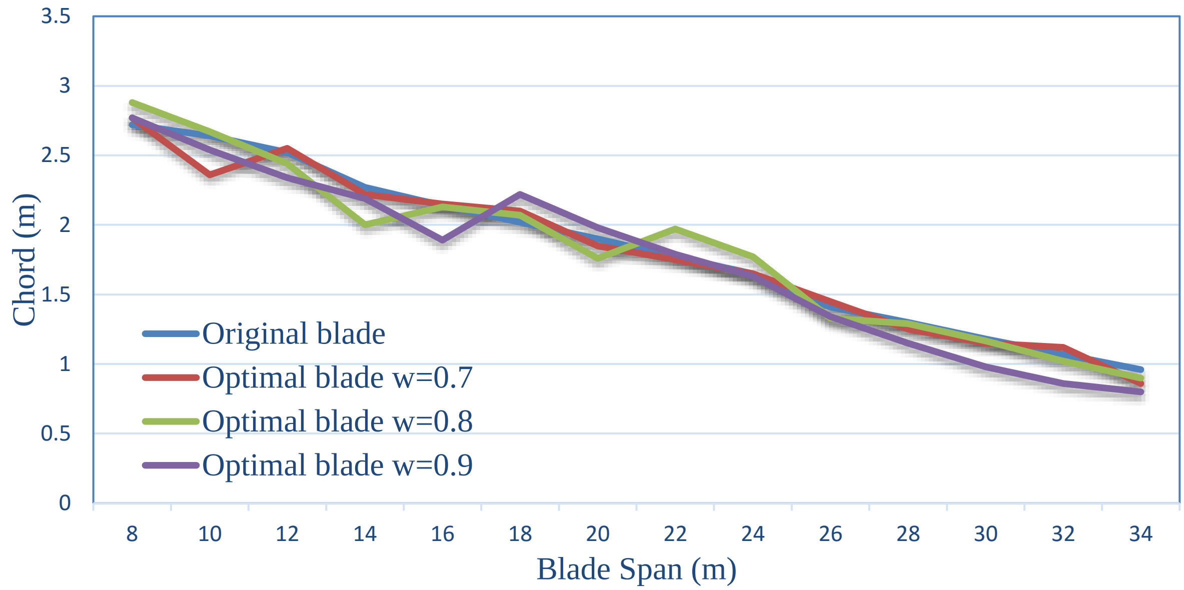
Case 16	W = 0.7	0.024	0.422
	W = 0.8	0.028	0.444
	W = 0.9	0.032	0.453
Case 17	W = 0.7	0.026	0.411
	W = 0.8	0.028	0.425
	W = 0.9	0.036	0.447
Case 18	W = 0.7	0.022	0.432
	W = 0.8	0.026	0.459
	W = 0.9	0.031	0.4612
Case 19	W = 0.7	0.032	0.421
	W = 0.8	0.036	0.425
	W = 0.9	0.04	0.44
Case 20	W = 0.7	0.026	0.422
	W = 0.8	0.031	0.444
	W = 0.9	0.034	0.455
Case 21	**W = 0.7**	**0.012**	**0.435**
	W = 0.8	**0.016**	**0.466**
	W = 0.9	**0.02**	**0.471**

In order to evaluate the accuracy of the optimization procedure, the distributions of the chord and twist have been compared with preliminary blade in the figure 12 for different weighting coefficients (w=0.7, w=0.8,w=0.9) and optimal case 21.

Table 7. Airfoil distribution for original and optimized blades with modified airfoils

Radial distance, m	Type of the blade cross section	
R,m	Original airfoils	Mod. Airfoils
7.875	**S818**	**S809**
9.625	**S818**	**S809**
11.375	**S818**	**S809**
14.875	**S818**	**S809**
16.625	**S825**	**S810**
18.375	**S825**	**S810**
20.125	**S825**	**S810**
21.875	**S825**	**S810**
23.625	**S825**	**S811**
25.375	**S825**	**S811**
28.875	**S825**	**S811**
30.625	**S826**	**S811**
32.375	**S826**	**S811**
34.125	**S826**	**S811**

The table 7 shows airfoil distribution for original and optimized blades with modified airfoils, table 8 shows Aerodynamic properties of the optimal blade and table 9 shows The power coefficient of the case 21 for blade model 2 (optimal blade) has higher value than that of the original blade.



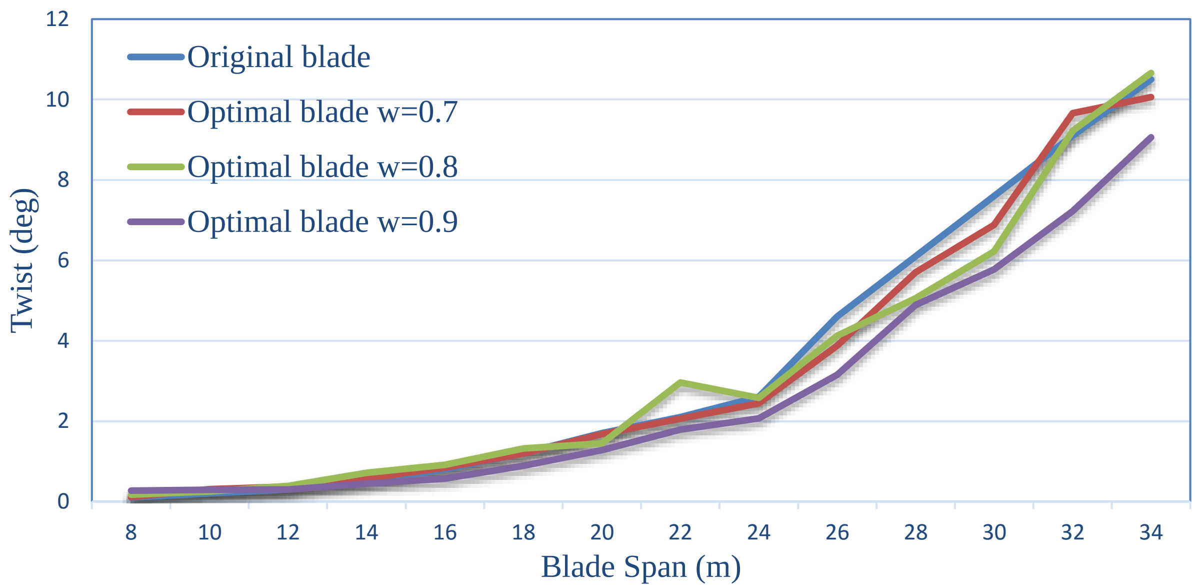


Figure 12.comparison of chord and twist distribution.

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Table8. Aerodynamic properties of verification model.

section	Position(m)	Chord(m) w=0.7	Twist(m) w=0.7	Chord(m) w=0.8	Twist(m) w=0.8	Chord(m) w=0.9	Twist(m) w=0.9
1	8	2.77	0.11	2.88	0.17	2.77	0.27
2	10	2.36	0.31	2.67	0.25	2.54	0.29
3	12	2.55	0.37	2.44	0.39	2.34	0.3
4	14	2.22	0.57	2	0.71	2.19	0.44
5	16	2.15	0.84	2.13	0.91	1.89	0.57
6	18	2.1	1.19	2.07	1.32	2.22	0.89
7	20	1.85	1.68	1.76	1.45	1.98	1.28
8	22	1.75	2.06	1.97	2.96	1.79	1.79
9	24	1.65	2.44	1.77	2.58	1.63	2.07
10	26	1.45	3.88	1.33	4.12	1.34	3.15
11	28	1.25	5.7	1.29	5.06	1.15	4.89
12	30	1.15	6.88	1.167	6.22	0.98	5.77
13	32	1.12	9.66	1.02	9.22	0.86	7.22
14	34	0.86	10.06	0.8989	10.66	0.8	9.06

Table9. Performance analysis results.

Model	C_p	$C_{p,max}$
	$\lambda = 7$	
Original blade	0.4519	0.4525 at $\lambda = 6.9$
Case 20 – blade model 1	0.4522	0.4533 at $\lambda = 7.45$
Case 21 – blade model 2 (optimal case)	0.471	0.475 at $\lambda = 7.3$
Case 17 – blade model 3	0.4602	0.4609 at $\lambda = 7.55$
Case 15 – blade model 4	0.4502	0.4515 at $\lambda = 7.1$
Case 21 – blade model 5	0.4543	0.4554 at $\lambda = 7.25$

Determination of the appropriate weighting factor

In the multi-dimensional optimization method, usually a single optimum design is rarely attained. Additionally as it is clear, the Pareto fronts represent the locus of optimum blades for two- dimensional optimization method. The most important problem is to designate the suitable value of w for the final design; on the other hand, it is important to determine which point along the Pareto front forms the final design which is optimum. Regarding Figure 8, W=0.9 is an appropriate weighting factor and could be selected for final design but a blade with w=0.7 obviously has a better solidity. It is important to consider that for multi-dimensional analysis, we usually choose the "w" values bigger than 0.7. This is due to the fact that for lower values of w, the importance of the output power which is a primary aim for designing the wind turbine blade drops in the objective function. Thus BEM analysis would not be able to recognize a logical distribution for the twist and chord.

CONCLUSIONAND FUTURE WORK

Using the evolutionary optimization algorithms has been one of the most popular methods in designing the optimal shape of MW wind turbine blades. This study examines two algorithms, GA and BA, in order to design the optimal shape of MW wind turbine blades. In order to propose a new algorithm, which is called GBBA, useful properties of these algorithms have been used. The results of performance analysis between original blade and our optimal results were similar.in this study, Different blade designs, twenty-one cases to be exact, were considered based on the length chord, twist angle and tip speed ratio using GA, BA and proposed Algorithms (GBBA).having examined the cases in this study, the findings emphasize that Genetic algorithm searches well in large spaces but it is inaccurate in finding the precise location of the optima. The results show that BA can be effective in locating global optima but has slow convergence in large spaces. The precision of the proposed algorithm in designing the optimal shape of MW wind turbine blades have been studied in comparison with GA and BA. The results suggest that the proposed algorithm is the best in terms of accuracy and convergence rate compared to either BA or GA. Future work concentrates on comparing the methods presented with other available tools. Optimizing of MW wind turbine blades can also be investigated with other hybrid intelligent optimization techniques like particle swarm optimization, ant colony algorithm and etc. The results of the different techniques could be compared with available methods.

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