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Natural Computing Based Wind Turbine Blade Design Performance Optimization

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Abstract

In this paper, wind turbine blade design parameters chord length and local pitch angle have been optimized through dynamic particle swarm optimization and differential evolution optimization methods. The objective function of the optimization is to maximize the torque and hence rotor power coefficient. The possibility of any structural shape of blade has been given focus towards maximizing the torque as much as possible without physical constraint of wind turbine blade shape. Blade element momentum method has been applied to extract the fitness of solutions in terms of maximizing the torque. Other performance parameters such as power and rotor power coefficient are obtained from the torque value. Comparative performance analysis has been given between both algorithms. Performances obtained from differential evolution are better. The values obtained have not only shown more precision but are also robust. The proposed solutions have shown better exploration of solution space in terms of generating high torque.

Keywords: Wind Turbine Blade, Pitch Angle, Blade Element Momentum Theory, Particle Swarm Optimization (PSO) PSO, Differential Evolution (DE)

Nomenclature

a: Axial induction factor

a': Angular induction factor

B: Number of blades

c: Aerofoil chord length

CL: Lift coefficient

CD: Drag coefficient

CP: Power coefficient

D: Drag force

N : Number of blade elements

P: Power

r: radius and radial direction

R: Blade tip radius

T : Torque

V : Absolute velocity

Ω : Angular velocity of wind turbine rotor

σ :Solidity Ratio

ρ: Air Density

β: Relative flow angle onto blades

INTRODUCTION

The exponential growth within the rate of energy consumption is the main explanation for energy shortage, yet as energy resources depletion worldwide. Electricity shortage is incredibly common in most of the Asian countries wherever most of the population (i.e. over 40%) has no access to trendy energy services. On an average, electricity demand is anticipated to rise 7.4 % annually for next twenty five years. As per International Energy Agency, quite 28% share of the world's total energy is consumed in Asian countries and China by the year 2030. Therefore a major quantity of energy should return from renewable sources. The basic challenge is to satisfy the energy needs in a very proper type approach**.** One of the most effective offered choices in current situation is renewable energy sources. Thus it is needed to accentuate renewable energy and energy potency program. By moving towards renewable energy production, that is indigenous in nature and that has low generation price, we would be able to enhance energy security condition, scale back our import dependency, solve drawback of fuel value instability etc. Carbon dioxide chemical compound emissions are often reduced on an average by3.3 million tons in every year by adding 1 GW energy of renewable origin. Thus it'll facilitate to reduce the adverse effects of temperature change in India. Wind energy will emerge as an answer to most of these issues through its efficient nature and clean energy resource. This will scale back fuel demand and a lots of burden will reduce over fighting tools and process which are working against temperature change. The capital and operational investments in alternative energy may be reduced in varied ways. In fact, the wind energy trade is craving for novel ways to reduce prices. A sample of areas wherever the price may be reduced includes site choice for wind farms, layout style, and prognosticative maintenance. The location hand-picked and layout style of a powerhouse might extend the time period of turbines and increase wind energy production. The rotary engine stress level may be reduced, leading to a lesser load on mechanical elements, along with a casing, that is there to take care of and replace. Another way to cut back prices is to optimize the capture of energy from the wind with effective management methods. Such an optimization ought to be performed which does not have adverse result on the time period of rotary engine elements, e.g., the casing. Wind Turbine technology is comparatively new. There's lots of space to boost the performance of wind turbines within the presence of operations and maintenance constraints. Increasing the energy captured from the wind makes wind energy competitive within the overall energy portfolio.

In recent years, wind energy has made a significant contribution to the world’s energy supply mix. However, there is lot more to be done in all areas of the technology for it to reach its full potential. Currently, horizontal-axis wind turbines (HAWTs) are the most commonly used type of wind turbines. For wind energy to compete with other sources of alternate energy, the primary consideration must be to reduce the cost of energy from wind power. In current wind power researches, the method of minimizing the cost of a wind turbine per unit of energy is a significant task. Blade is the key element to capture wind energy and hence it plays an important role in the whole wind turbine. The geometrical shape of the wind turbine rotor blades plays a vital role in determining the overall aerodynamic performance. Thus, aerodynamic optimization of the blade shape is a very important step in the design of wind turbines. In this present research work, two natural computing algorithms, namely dynamic particle swarm optimization (DWPSO) and differential evolution (DE) are used for wind turbine blade design optimization. The performances of the two optimization methods are also compared.

RELATED WORK

An evolutionary computation approach for optimization of power factor and power output of wind turbine generator (WTG) has been discussed in [1]. Data-mining algorithms capture the relationships among the power output, power factor, and controllable and non-controllable variables of a 1.5 MW wind turbine. In order to satisfy the requirements of widely operational range of rotor speed, high nonlinearity and time variant characteristics in variable-speed wind turbines, a system with a fuzzy neural network controller based on mind evolutionary computation (MEC) optimization has been designed in [2]. An automatic design environment using evolutionary techniques has been presented in [3] for the designs of Horizontal Axis Wind Turbine (HAWT) blades taking into account both the aerodynamics and the structural constraints of the blades. This design environment is based on a simple, fast, and robust aerodynamic simulator intended for the prediction of the performance of any turbine blade produced as an intermediate individual of the evolutionary search process. The structural aspects of a long blade in an upwind, horizontal-axis wind turbine were developed in [4] for use in a high wind speed location. A hybrid composite structure using glass and carbon fiber plies was created yielding a light-weight design with a low tip deflection. Ducted wind turbine with multiple blades installed was believed to have a good wind power energy conversion effect. However, little information was available on how to design a good ducted wind turbine. In [5] the effects of blade number on a ducted wind turbine performance is studied. [6] has described the design of a wind turbine airfoil under various operating conditions through the use of a suitable combination of flow analysis and optimization techniques. The proposed method includes a parametric study on the influence of design variables and different design conditions on airfoil performance. The work in [7] has analyzed the link between the aspect ratio of a vertical-axis straight-bladed (H-Rotor) wind turbine and its performance (power coefficient). Incorporating controlled elitism and dynamic distance crowding strategies, a modified NSGA-II algorithm based on a fast and genetic non-dominated sorting algorithm are developed in [8]with the aim of obtaining a novel multi-objective optimization design algorithm for wind turbine blades. Airborne wind turbine (AWT) is a novel conceptual approach of enhancing the existing capabilities of capturing wind energy. AWT generates power from winds at altitudes of up to 1500 m. It uses a tethered structure with on board turbines, through a range of lift production methods. [9] has presented further AWT designs, which utilize readily available small-capacity wind turbines.The theory of inventive problem solution (TRIZ) is a systematic methodology for innovation. The design of a wind turbine system as an engineering example is illuminated in [10] to show the significance and approaches of applying TRIZ in getting the creative conceptual design ideas. Surrogate-assisted evolutionary algorithms has been used to design vertical-axis wind turbines wherein candidate prototypes are evaluated under fan-generated wind conditions after being physically instantiated by a 3D printer. [11] has presented the work by exploring alternative surrogate modeling and evolutionary techniques. [12] has optimized pitch angle, along wind turbine blade, based on an aerodynamic code. This aerodynamic code was able to accurately predict the aerodynamics of horizontal axis wind turbines.

BLADE ELEMENT MOMENTUM THEORY(BEM)

Before Blade element momentum theory is an iterative procedure that can be used to find the load on wind turbine and developed power under different conditions of wind speed, rotational speed and pitch angle. Considering that blade is made of N number of elements, in result each element will get the different flow because of difference in their rotational speed (W*r*), a different chord length (*c*) and a different twist angle (g). Blade element theory involves dividing up the blade into a sufficient number (usually between ten and twenty) of elements and calculating the flow at each one. Overall performance characteristics are determined by numerical integration along the blade span. Assuming that the drag C_D is zero and the tip loss correction Q is one, the equations to be solved are therefore represented as Eq.1 to Eq.3:

$$\tan\beta = \lambda r(1+a')/(1-a) \tag{1}$$

$$a/1-a = \sigma'[C_L \sin\beta]/(4\cos^2\beta) \tag{2}$$

$$a'/1-a = \sigma' C_L/(4\lambda r \cos\beta) \tag{3}$$

The algorithm for an iterative solution is as follows:

1. Guess a and a'

2. Calculate λr and β

3. Look up *CL* and *CD* for the appropriate incidence angle

4. Calculate a and a'again, if the error between iteration value for a and a' is more than tolerance value repeat the process from step 2.

As a first guess for the flow solution use the following equations. These are based on an ideal blade shape derived with wake rotation, zero drag and zero tip losses. Note that these equations provide an initial guess only. The equations (4-6) are given as follows:

$$\beta = 90 - \frac{2}{3}\tan^{-1}\left(\frac{1}{\lambda_r}\right) \tag{4}$$

$$a = 1 + 4\cos^2\beta/(\sigma' C_L \sin\beta)^{-1} \tag{5}$$

$$a' = (1-3a)/(4a-1) \tag{6}$$

NATURAL COMPUTING: SWARM AND EVOLUTIONARY PERSPECTIVE

A. PSO

Among the several natural computing approaches, swarm intelligence has shown its own benefits in terms of efficiency and performance. Not only that computational requirement is also lesser in compared to other format of natural computing. There is more interest under the swarm intelligence community towards the PSO. PSO is social influence based concept where a population shifts from one position to the other position by change in velocity values. The change in the position with addition of velocity happens under vector domain of the mathematical world. There are two influencing parameters

1. Influence from the global leader
2. Influence from individual best in past

Through this influencing factor, influencing difference decide to change in the value of velocity. PSO provides intrinsic parallel search through the individual member by exploring in their own way. In the population according to the fitness values, a leader decision takes place. Examples of systems like this can be found in nature, including ant colonies, bird flocking, animal herding, bacteria molding and fish schooling.

Velocity of each agent can be modified by the Eq.7:

$$V_i^{(k+1)} = \chi\left[wV_i^k + c_1 rand1 \times \left(pbest_i - s_i^k\right) + c_2 rand2 \times \left(gbest_i - s_i^k\right)\right] \tag{7}$$

Where V_i^k :Velocity of agent i at iteration k, w: Weighting function, $c_1 \& c_2$: Weighting coefficients, $rand1 \& rand2$ are the uniformly distributed random number between 0 and 1, S_i^k : Current position of agent i and at iteration k, $pbest_i$: pbest of agent i, gbest : gbest of the group, χ is the constriction factor.

The following weighting function is usually utilized in (8):

$$w = w_{max} - \frac{(w_{max} - w_{min})}{iter_{max}} \times iter \tag{8}$$

Where w_{max}: initial weight. w_{min}: final weight. $iter_{max}$: maximum iteration number. iter: current iteration number.

Using the above equation, a certain velocity, which gradually gets close to *pbest* and *gbest* can be calculated. The current position (searching point in the solution space) can be modified by the following Eq.9:

$$S_i^{(k+1)} = S_i^k + V_i^{k+1} \tag{9}$$

There is no exclusive exploration operator exist. In result sometimes there may be premature convergence take place.

B. Dynamic Particle Swarm Optimization(DWPSO)

In the Eq.7, weight factor w plays the central role in the convergence characteristics of PSO. High value of w makes PSO under the exploration stage. Low value will make the move towards the exploitation. It is very logical that at the beginning of iteration there is need of high level of exploration and as the iterations are increasing, level of exploration has to reduce. Mathematically in this work, this has been achieved by providing a reduced value of w as a function of iterations as given by Eq.8.

C. Differential Evolution

In the evolutionary computation algorithms, fundamentally GA evolutionary programming and evolutionary strategy play the central role. Functionally there are two approaches to generate the offspring. Through single parent or through bi-parental system. As like the GA, there are cross-over and mutation operations. DE is also carrying both the operators but it is a single parental system. The offspring is created through differences existing between two or more population members. This difference can provide the facility to exploit the solution more efficiently. There is all point cross over, which makes the solution move towards the maximum level of exploration and exploitation. The high level of exploration and exploitation makes the DE more valuable in terms of finding the global solution. There is less chance to converge the solution sub-optimally.

The population of the DE algorithm contains NP individuals and each has D-dimensional vector as according to D dimensions available in the problem. During one generation for each vector, DE employs mutations to produce a donor vector of dimension D. There are various strategies exist to define the donor vector. In this research, a strategy called DE/rand/1 as defined in Eq.10 hasbeen taken. The crossover operator under probabilistic environment has been applied to develop the trial vector as shown in Eq.11. CR is a crossover control parameter or factor within the range [0, 1] and represents the probability of creating parameters for a trial vector from the mutant vector. Index j_{rand} is a randomly chosen integer within the range [1, NP]. Then a greedy selection operation selects between the target and corresponding trial vectors to choose vectors for the next generation as according to Eq.12 where F represents a type of mutation factor in terms of comparing the fitness value through fitness function f.

$$V_i^{(G)} = X_{r1}^{(G)} + F * (X_{r2}^{(G)} - X_{r3}^{(G)}) \tag{10}$$

$$u_{ij}^{(G)} = \begin{cases} v_{ij}^{(G)} & if\ rand(0,1) \leq CR\ or\ j = j_{rand} \\ x_{ij}^{(G)} & otherwise \end{cases} \tag{11}$$

$$x_{ij}^{(G)} = \begin{cases} u_i^{(G)} & if\ f(u_i^{(G)}) \leq f(x_i^{(G)}) \\ x_i^{(G)} & otherwise \end{cases} \tag{12}$$

EXPERIMENTAL RESULTS

In this research spatial dependent chord length and local pitch angles optimization have been done to maximize the generated torque for horizontal axis wind turbine blade. The operating conditions of environment and other parameters have shown in Table1.BEM iterative procedure has been applied to evaluate the objective functions. Matlab environment has been opted to develop the solution. DWPSO and DE have been applied for same number of iterations with population size of 50 and allowed maximum number of iterations/generations are 100.Individual solutions in population carries 16 real numbers in which first half represent the chord value while other half represents the pitch angle. With the obtained torque, the other two performance parameters mechanical power and rotor power coefficient are estimated. 10 independent trials have been applied to estimate the statistical performances delivered by each algorithm. PSO parameters values are taken as C1=C2=0.5, χ=0.72. 'w' is decreased from 1.2 to 0.1 with iterations. In all experiments the DE parameters are assumed as F=0.4 and CR=0.5 respectively, where F is scaling factor and CR is cross over constant.

A. Objective Function Definition

The Torque on an element, *dT is* given by the Eq.13 and the power generated by the blade element is given by Eq.14

$$dT = 4a'(1-a)\rho V\Omega r^3 \pi dr \tag{13}$$

$$dP = \Omega dT \tag{14}$$

Integration of Eq.13 & Eq.14 will deliver the total torque (T) and total power (P) generated by the aerodynamic forces appearing on rotor. The rotor power coefficient (Cp) can be computed by total generated power by the wind kinetic power on the rotor plane as it given by Eq. 15

$$C_p = \frac{P}{\frac{\rho \pi R^2 V^3}{2}} \tag{15}$$

Objective function has defined as total generated torque as given in Eq.16 which has to maximize.

$$max\ T = \sum_{j=1}^{N} 4a'(1-a)\rho V\Omega r(j)^3\ \pi dr \tag{16}$$

Where N is the number of elements.

In Table2 explored final values delivered by DWPSO for chord and pitch angle have been shown while in each trial obtained torque, power and rotor coefficient have shown in

Table3. Similarly the obtained results in case of DE have been shown in Table4 and Table5.

Table I: Operating conditions and rotor design parameters

SI No.	***Parameter***	***Value***
1.	Wind velocity (m/s)	7
2.	No.of Blades	3
3.	Outer blade radius (m)	5
4.	Tip speed ratio	8
5.	Air density (kg/m^3)	1.23

Convergence characteristics in case of DWPSO are shown in Fig.1. From the figure, it can be observed that for all the different trails, significant difference exists in convergence characteristics under same working environment.

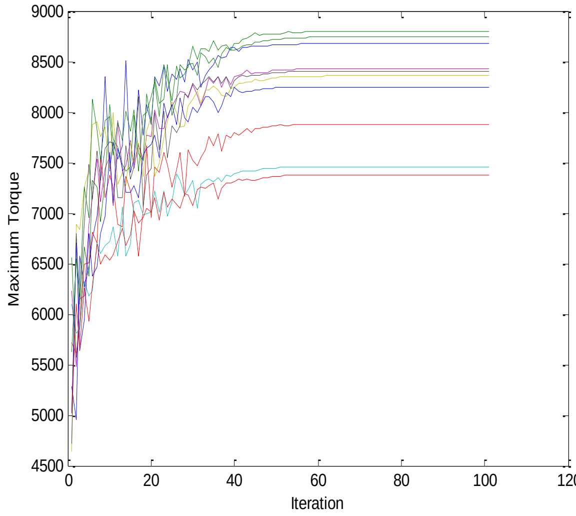

Figure 1: Convergence characteristics of torque for 10 trials in DWPSO

Table II.: Best Solution delivered by DWPSO for chord and pitch angle

BBLADE PARAMETERS	**Blade Chord length and Pitch Angle at different radius values**								
	Radius value	***0.2000***	***0.4000***	***0.6000***	***1.0000***	***2.0000***	***3.0000***	***4.0000***	***5.0000***
Local chord length	Trial 1	0.8740	0.6805	0.7276	0.7152	0.9367	0.8833	0.9973	0.9999
	Trial 2	0.9256	0.7671	0.8477	0.8778	0.8709	0.9443	0.9972	0.9999
	Trial 3	0.8238	0.7158	0.9357	0.9011	0.9251	0.8702	0.9958	0.9995
	Trial 4	0.7491	0.8728	0.8996	0.8464	0.9549	0.8763	0.9930	0.9988
	Trial 5	0.8510	0.7830	0.5210	0.9045	0.7880	0.9259	0.9938	0.9999
	Trial 6	0.8350	0.7818	0.7885	0.9206	0.6940	0.9861	0.9962	0.9985
	Trial 7	0.6737	0.8638	0.9014	0.7270	0.8143	0.9502	0.9954	0.9968
	Trial 8	0.6240	0.8253	0.7909	0.8735	0.6353	0.9045	0.9700	0.9997
	Trial 9	0.7123	0.7717	0.8114	0.8568	0.8958	0.9496	0.9952	0.9991
	Trial 10	0.7097	0.9251	0.7586	0.8440	0.7850	0.9842	0.9914	0.9994
Local Pitch Angle	Trial 1	91.1359	45.3724	67.2186	72.6589	91.9942	83.3288	98.2593	99.0030
	Trial 2	76.6098	40.4925	58.7811	87.6026	69.8632	90.3069	97.2999	99.8974
	Trial 3	80.9161	21.5593	78.8890	29.4029	55.9262	44.0753	95.8630	99.8013
	Trial 4	50.5390	26.0058	58.2517	71.1817	71.8200	81.7041	55.3565	99.9778
	Trial 5	85.1270	25.4066	68.7660	72.0223	81.5354	74.1554	95.6595	99.5749

BBLADE PARAMETERS	Blade Chord length and Pitch Angle at different radius values								
	Radius value	***0.2000***	***0.4000***	***0.6000***	***1.0000***	***2.0000***	***3.0000***	***4.0000***	***5.0000***
	Trial 6	32.5248	56.8535	62.1135	84.1972	72.6361	64.0060	98.5980	99.4961
	Trial 7	78.7157	30.8218	77.9471	53.9494	36.0802	88.2957	95.5997	99.9851
	Trial 8	72.9035	45.6924	71.6915	78.2982	42.1873	82.5623	96.1372	99.8959
	Trial 9	61.5543	49.8640	16.7784	63.8388	82.4151	89.1195	98.9294	99.8495
	Trial 10	34.1265	74.1759	31.0228	85.4263	41.5041	84.8972	54.3984	99.7467

Table III: Performance parameters using DWPSO

Trial No.	**Wind Turbine Performance Parameters**		
	Total Torque (kNm)	***Total Mechanical Power(kW)***	***Rotor Power Coefficient***
1.	8.6778	95.4553	5.7616
2.	8.7380	96.1185	5.8016
3.	7.8707	86.5778	5.2257
4.	7.4567	82.0233	4.9508
5.	8.4220	92.6418	5.5917
6.	8.3558	91.9137	5.5478
7.	8.4036	92.4399	5.5796
8.	8.2463	90.7094	5.4751
9.	8.7903	96.6929	5.8363
10.	7.3760	81.1364	4.8973

Table IV: Best Solution delivered by DE for chord and pitch angle

Blade Parameters	**Blade Chord length and Pitch Angle at different radius values**								
	Radius value	***0.2000***	***0.4000***	***0.6000***	***1.0000***	***2.0000***	***3.0000***	***4.0000***	***5.0000***
Local chord length	Trial 1	0.4973	0.7378	0.9657	0.9599	0.9819	0.9986	0.9992	0.9992
	Trial 2	0.1954	0.7231	0.8547	0.9257	0.9941	0.9945	0.9989	0.9994
	Trial 3	0.5634	0.7105	0.9380	0.9881	0.9894	0.9995	0.9977	0.9973
	Trial 4	0.7468	0.8971	0.9779	0.9187	0.9935	0.9930	1.0000	0.9994
	Trial 5	0.6757	0.8616	0.8969	0.8846	0.9985	1.0000	0.9999	0.9986
	Trial 6	0.7754	0.7836	0.8262	0.9827	0.9911	0.9983	0.9997	0.9981

Blade Parameters	**Blade Chord length and Pitch Angle at different radius values**								
	Radius value	***0.2000***	***0.4000***	***0.6000***	***1.0000***	***2.0000***	***3.0000***	***4.0000***	***5.0000***
	Trial 7	0.6445	0.8162	0.7084	0.9915	0.9858	0.9988	0.9983	0.9993
	Trial 8	0.3235	0.8205	0.9047	0.9748	0.9996	0.9839	0.9998	0.9993
	Trial 9	0.3187	0.3193	0.9219	0.9949	0.9982	0.9972	0.9985	0.9976
	Trial 10	0.4140	0.5616	0.9582	0.8981	0.9906	0.9974	0.9973	0.9999
Local Pitch Angle	Trial 1	76.5772	50.0000	54.3953	98.8107	99.5824	99.2644	99.7567	99.9221
	Trial 2	54.1769	44.7035	93.8351	90.6362	98.4505	99.9551	99.9502	99.8571
	Trial 3	54.9501	60.9114	99.8150	98.7217	98.9848	99.4670	99.8070	99.8165
	Trial 4	31.0976	44.1572	94.7179	98.9315	99.8152	99.4991	99.4452	99.8967
	Trial 5	51.1440	65.4543	87.1885	95.1612	99.2785	99.8787	99.8432	99.9414
	Trial 6	81.1950	60.8087	87.0164	94.8827	98.6694	99.9042	99.7822	99.8906
	Trial 7	52.8763	95.3440	93.7348	98.7940	97.9106	99.0975	99.8891	99.8443
	Trial 8	65.3016	99.4410	88.1457	99.7838	98.6742	99.2864	99.7747	99.7888
	Trial 9	76.3145	71.9790	88.5957	99.7844	99.5474	99.3243	99.6978	99.9373
	Trial 10	60.3278	74.9145	93.6992	95.7893	98.3476	99.8763	99.9002	99.8107

Table V: Performance parameters using DE

Trial No.	**Wind Turbine Performance Parameters**		
	Total Torque (kNm)	***Total Mechanical Power(kW)***	***Rotor Power Coefficient***
1.	9.2749	102.0239	6.1580
2.	9.2771	102.0479	6.1595
3.	9.2920	102.2121	6.1694
4.	9.2875	102.1626	6.1664
5.	9.2984	102.2821	6.1736
6.	9.2919	102.2105	6.1693
7.	9.2840	102.1240	6.1641
8.	9.2833	102.1166	6.1636
9.	9.2920	102.2123	6.1694
10.	9.2835	102.1185	6.1638

Convergence characteristics in case of DE are shown in Fig.2 for all 10 different independent trials and it can be observed that convergence characteristics are nearly similar for all trials. The statistical performance of both DWPSO and DE algorithms implemented in this present work is presented in Table 6.It can be observed that performance of DE is much better and more reliable. DE is able to reproduce the same results consistently over all the 10 trials carried out.

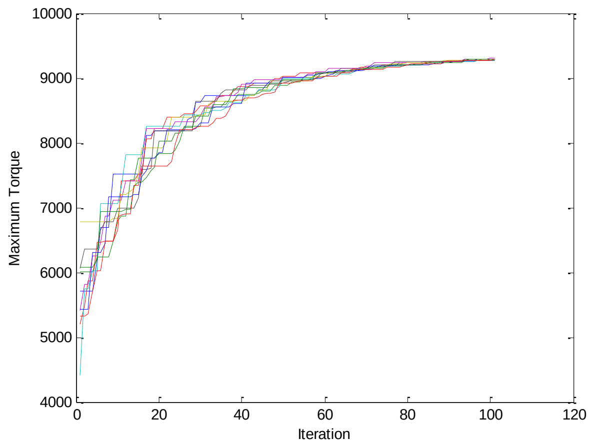

Figure 2: Convergence characteristics of Torque for 10 trials in DE

Table VI: Performance comparison between DWPSO and DE

	Wind Turbine Performance Parameters					
	Torque (kNm)		***Mechanical Power(kW)***		***Rotor Power Coefficient***	
	DWPSO	DE	DWPSO	DE	DWPSO	DE
Mean	8.2337	9.2865	90.5709	102.1511	5.4668	6.1657
Std. Deviation	0.5068	0.0073	5.5751	0.0803	0.3365	0.0048
Maximum	8.7903	9.2984	96.6929	102.2821	5.8363	6.1736
Minimum	7.3760	9.2749	81.1364	102.0239	4.8973	6.1580

CONCLUSION

A computational efficient methodology which is based on natural computing method such as swarm intelligence based method DWPSO and evolution based method DE have been applied. Both these methods are used to obtain the optimal values of chord and twist distributions in wind turbine blade in order to maximize the generated torque. BEM procedure has been applied as an integral part of solution process. It can be observed that rather than following the conventional shape if there is some irregularity in wind turbine blade geometry, there is significant improvement in aerodynamics and efficiency. At present because of feasibility of 3D printing it is possible to have such irregular shape blades in practice. From the algorithmic point of view, DWPSO has not provided the optimal exploration. But the performance of DE is more impressive.DE is simple, robust, converges fast and finds its optimum in almost every trial. DE is clearly and consistently superior compared to DWPSO both in terms of precision as well as robustness of the results (i.e. very similar results of repeated runs). Apart from superior performance, DE is very easy to implement compared to DWPSO algorithm used in this work

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