Effect of Selection of Design Parameters on the Optimization of a Horizontal Axis Wind Turbine via Genetic Algorithm

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Abstract. The effect of selecting the twist angle and chord length distributions on the wind turbine blade design was investigated by performing aerodynamic optimization of a two-bladed stall regulated horizontal axis wind turbine. Twist angle and chord length distributions were defined using Bezier curve using 3, 5, 7 and 9 control points uniformly distributed along the span. Optimizations performed using a micro-genetic algorithm with populations composed of 5, 10, 15, 20 individuals showed that, the number of control points clearly affected the outcome of the process; however the effects were different for different population sizes. The results also showed the superiority of micro-genetic algorithm over a standard genetic algorithm, for the selected population sizes. Optimizations were also performed using a macroevolutionary algorithm and the resulting best blade design was compared with that yielded by micro-genetic algorithm.

1. Introduction

Wind power is generated by the aerodynamic forces developing on the blades of wind turbines. Therefore, aerodynamic design of the blades is very important to maximize the energy capture [1]. In [2], [3] wind turbine design was performed using gradient based search algorithms. These algorithms however, are successful for smooth search spaces containing a single extreme [4]. Gradient-free metaheuristic optimization methods [5], on the other hand are very suitable for multi-parameter optimization problems like wind turbine blade design. Being gradient-free they are very insensitive to the presence of local extremes in the search space [4]. Genetic algorithms is one of these methods [4], [6] where, a group of turbines called a population is generated and each member of the population is ranked according to its fitness function which may the power output of the turbine. Examples of wind turbine design using genetic algorithms can be found in [7] - [13]. Power output at a given wind speed strongly depends on the blade parameters like chord length and twist angle distributions along the blade span [1]. The way these distributions are defined may affect the output of the optimization. In [7][8]and[13] chord and twist distributions along the span were defined using second order polynomials with three uniformly distributed stations, while they were defined using fourth order polynomials with five evenly distributed points in [11]. Reference [9] used linear chord and nonlinear twist distributions which were obtained using inverse design software PROPID [14] and a genetic algorithm software PROPGA [15] while a third order polynomial for chord distribution and a spline function for the twist distribution were used in [10]. An alternative way was presented in [12] where these distributions were specified by keeping the chord length and twist angle values at a given station randomly between the predefined minimum and maximum values for that station. It is clear that many different ways had been employed in the literature to describe the chord and twist distributions along

the blade. In order to see the effect of using different ways to specify these distributions on the optimization results, studies were performed by using different number of control points on the blade span and different interpolation techniques to define the chord and twist angle distributions. Here, optimizations were performed for a two-bladed, stall regulated turbine with a diameter of 10.6m. These characteristics are same with those of NREL Phase VI experimental wind turbine [9]. A genetic algorithm code was used for the computations which maximized the annual energy production (AEP) of the turbine. Here AEP was calculated using blade element momentum theory (BEMT) which can yield quick aerodynamic load predictions [1], [16]. Despite its weaknesses for high wind speeds, unsteady conditions and yaw error, BEMT can yield good predictions for steady wind conditions [16]. This makes it a very suitable tool for preliminary calculations performed to rank the individuals in the population [11]. Wind characteristics of a wind turbine site are also very crucial for the AEP of the turbines located there. Here, aerodynamic optimization of a 10.6 m diameter horizontal axis wind turbine was performed for Gökçeada location in Turkey for which the wind speed characteristics were obtained by using the Weibull distribution [1].

Optimizations were performed using genetic algorithm with and without the micro approach [17] and using different population sizes. During the computations same random number seeds were used so that the changes were purely due to chord length and twist angle distributions. In order to compare the capabilities of the employed genetic algorithm with a different metaheuristic optimization approach, resulting optimizations were also compared to those obtained using a macroevolutionary algorithm [18].

2. Methodology

Aerodynamic optimization of a 10.6m diameter, stall regulated and constant speed wind turbine was performed for Gökçeada, Turkey using a micro-genetic algorithm. For this purpose, the free version of the genetic algorithm code written by David L. Carroll was used [19]. Here the code was modified so that it used annual energy production (AEP) as the fitness function. Computations were performed for population sizes of 5, 10, 15 and 20, and the maximum number of generations was taken to be 5000.

In order to calculate AEP, the variation of power generated with wind speed and the wind characteristics of the turbine site were needed. The latter was obtained using Weibull distribution of wind [1] for Gökçeada location [13]. For the calculation of the power output at different wind speeds, the BEMT solver WT_Perf [20] was used. This solver was developed by National Renewable Energy Laboratory (NREL), operated by the Alliance for Sustainable Energy, LLC for the U.S. Department of Energy. During the computations, drag force was included in the axial and tangential induction factor calculations. Prandtl hub and tip loss corrections [1] were included along with swirl effects. The rotor was assumed to have no precone angle, shaft tilt or yaw error.

BEMT requires the aerodynamic data of the airfoil used at a segment on the blade at different Reynolds numbers [1]. The airfoil database which was created in [7] was also used in this study. The airfoils in the database can be seen in Table 1. The root section extended up to 0.4R, the primary portion covered the region between 0.4R and 0.9R, and the tip region constituted the rest of the blade. Here R was measured from the rotation axis. The aerodynamic data of the airfoils were extrapolated to -180 ° to 180° angle of attack range using preprocessor program AirfoilPrep [21], which was developed at NREL. BEMT predictions were obtained using 64 spanwise segments on each blade. This number was obtained from a segment independence study performed in [7].

Table 1. Airfoil Database

Portion	Airfoils
Root	FFA-W3-241, FFA-W3-301, NACA 63-430, S814, S823
Primary	FFA-W3-211, FFA-W3-241, FX-66-S196, NACA 63-218, NACA 63-221, NACA 64-421, NACA 65-421, S809, S822, S834
Tip	Airfoils for primary portion + SD2030, NACA 63-215, NACA 64-415, NACA 65-415, FX-63-137, E387.

The AEP for a turbine was calculated using equation (1) [22]:

$$AEP = \sum_{i=1}^{N-1} \frac{1}{2}\left(P(V_{i+1}) + P(V_i)\right)\left(\exp\left(-\left(\frac{V_i}{c}\right)^k\right) - \exp\left(-\left(\frac{V_{i+1}}{c}\right)^k\right)\right)8760 \qquad (1)$$

Where $P(V_i)$ is the power generated by the turbine at a wind speed of V_i, and c and k are the Weibull parameters. During the calculations the cut-in and cut-off speeds were taken to be 4 m/s and 25 m/s, respectively. The velocity increment was taken to be 1 m/s so that the value of N in equation (1) was 22. For the AEP calculations, all individuals were operated at their optimal tip speed rations [7].

The optimization parameters for blade design were selected as chord length and twist angle distributions along the blade span, the pitch angle of the blades and airfoil profiles for the root, primary and tip portions of the blades. Preliminary optimizations were performed using five different ways to define twist angle and chord length distributions. The first three cases used three equally spaced stations on the blade and employed a 2nd order interpolating polynomial, cubic spline interpolation and a Bezier curve, respectively. The remaining two cases used seven equally spaced stations and employed cubic spline interpolation and a Bezier curve, respectively. Preliminary analysis showed that different approaches used for defining the distributions considerably affected the optimization results.

2.1. Genetic Algorithm

In the genetic algorithm code [19] the values of the design parameters in their specified range are defined using a prescribed number of binary digits (bits). These bits, also called alleles [6], are initialized randomly for each individual in the population. After this the fitness function for each individual was calculated using equation (1). The optimization process was performed for turbines with rated power of 20 kW. Therefore, if the power output of a turbine exceeds 10% of this rated power its fitness was set to zero. The parents that would be used to generate the next generation were selected using tournament selection [6] with a tournament size of 2. The off-springs were obtained using uniform cross-over [6] with a probability of 0.5 [23]. The best individual was carried on to the next generation using elitist strategy, while the other individuals were replaced by the off-springs.

Majority of the optimizations were performed using the micro-genetic algorithm technique [17] which allows small population sizes. In this technique mutation was not applied; instead the convergence of the population was checked. This was done by counting the number of alleles different from the alleles of the best individual, and if this number was less than 5% of the total number of the bits then population was assumed to converge. When this happened, all the individuals except the best one were regenerated randomly [17]. Optimization performed using this strategy, however, was shown to lead to the premature convergence of the best individual [7]. Therefore, the regeneration process was performed every ten generations regardless of the convergence, as it was done in [7].

Computations were also performed without using this micro approach. Here, regeneration process was replaced with mutation [6]. In this study jump mutation was applied with a probability of 0.1.

2.2. Macroevolutionary Algorithm

Optimizations using macroevolutionary algorithm was performed by following the procedure described in [18]. Unlike a genetic algorithm where new individuals (off-spring) are created by combinations of old individuals (parents); in macroevolutionary algorithm a species (which may be an individual) is eliminated (becomes extinct) or carried on to the next generation (stays alive) through some inter-species relationships. These relationships are defined using a so called connectivity matrix [18] and if a species becomes extinct, it is replaced by a new species, which is created either randomly or by attracting the extinct species towards one of the surviving species [18]. Experiments performed in this study showed that, best results were obtained if the best individual was selected as the one

towards which an extinct species was attracted. Also, in order to avoid premature convergence, the regeneration process described in the previous section was performed every ten generations.

An in-house computer code was developed for the computations and was coupled with the WT_Perf software in order to maximize AEP.

3. Results and Discussion

In this section, optimization results obtained by using different techniques to describe chord length and twist angle distributions of the blades of a two-bladed, stall regulated horizontal axis wind turbine with a rotor diameter of 10.6m were presented. Once a number of control points are selected on the span of a blade, different techniques can be used to define a distribution of a quantity along the span using its values specified on these control points. Three of these techniques are polynomial interpolation [24], spline interpolation [24] and a Bezier curve [25]. In order to see the effect of using these different techniques, initial optimizations were performed using five different ways to define twist angle and chord length distributions. The first three cases used three equally spaced stations on the blade and they employed a 2nd order interpolating polynomial, cubic spline interpolation and a cubic parametric Bezier curve, respectively. The remaining two cases used seven equally spaced stations and employed cubic spline interpolation and a Bezier curve, respectively. The optimizations were performed using micro-genetic algorithm approach with 5 individuals. Same random number seeds were used during the optimizations so that the changes were purely due to chord length and twist angle distributions. This preliminary analysis showed that using different approaches for defining the distributions considerably affected the optimization results and using seven stations (cases 4 and 5) yielded higher AEP values.

When the resulting chord and twist distributions of cases 4 and 5 are examined from Figure 1, it was observed that cubic spline interpolation used in case 4 led to highly wavy distributions for both parameters. Although the resulting design led to high AEP value, the blades may be difficult to manufacture. In this study, the maximum and minimum values for twist angle and chord length at the control points were decreased along the spanwise direction. However, the ranges were allowed to overlap. Figure 1 clearly showed that, unless a monotonic distribution constraint is enforced, polynomial and spline interpolation methods might yield oscillatory distributions with sharp changes as the number of control points increased. Therefore, Bezier curve was used for the rest of the study. Although this approach cannot be considered as the ultimate solution to this problem, it was preferred because it yielded smooth chord length and twist angle variations ever with high number of control points.
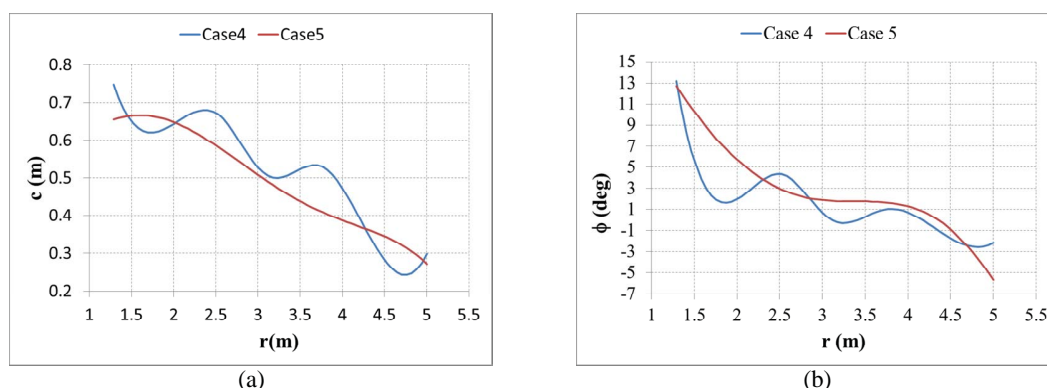

Figure 1 Chord length (a) and twist angle (b) distributions yielded by cases 4 and 5

Figure 2 displays the evolution of AEP obtained using 3, 5, 7 and 9 control points along the span of the blade using populations composed of 5, 10, 15 and 20 individuals. It is clear from this figure that changing the number contol points affected the optimization results considerably. For 3 and 5 points,

highest AEP values were achieved for a population with 10 individuals. However, this size was 15 and 5 for 7 and 9 points, respectively. Unfortunately, the results were not very conclusive about the optimum number of control points and population size for the optimizations. Nevertheless the overall best performance was achieved by using 3 points on the surface for a population size of 10. The best AEP values obtained for each case was given in Table 2.

Chord and twist angle distributions of the best blade designs obtained using different number of control points were displayed in Figure 3. Distributions were found to be in agreement with highest discrepancies observed in the vicinity of the root and tip regions. Here, the design, which employes 9 points yielded wavy distirbutions while the best profile obtained using 3 points yielded a blade whose twist angle is almost contant toward the tip and relatively thicker at the inboard stations.

Table 2. Best AEP values

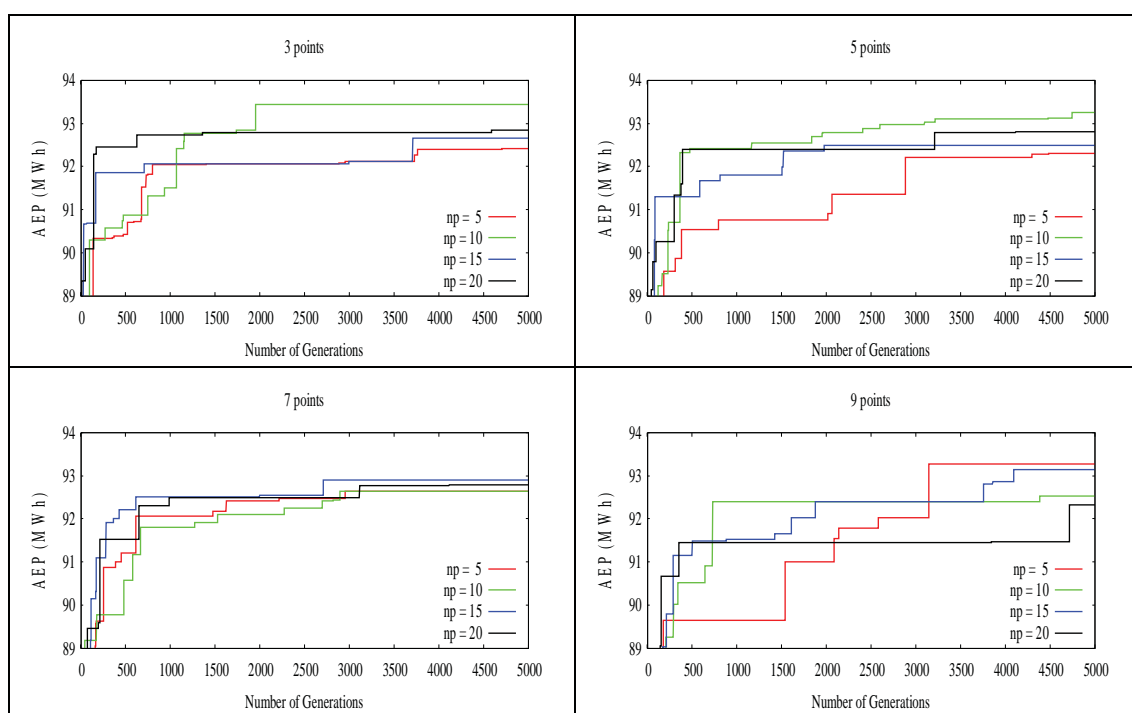| Number of Control Points	AEP (kWh)
3	93444
5	93256
7	92879
9	93270

Figure 2 Evolution of AEP for different number control points on the blades using different population sizes.

In order to compare the performance of micro-genetic algorithm approach with that of a standard genetic algorithm, optimizations were repeated with a standard genetic algorithm using 3 control points and different population sizes. Evolution of AEP for populations composed of 5, 10, 15, 20 individuals were displayed and compared with micro-genetic algorithm predictions in Figure 4. Analysis of this figure revealed that the micro genetic algorithm outperformed the latter for all population sizes, and performance differences were considerable for population sizes of 10 and 15. Although a standard genetic algorithm requires much larger population size than 20 for optimum

performance, population size had to be kept low due to high computational cost of fitness function evaluation.
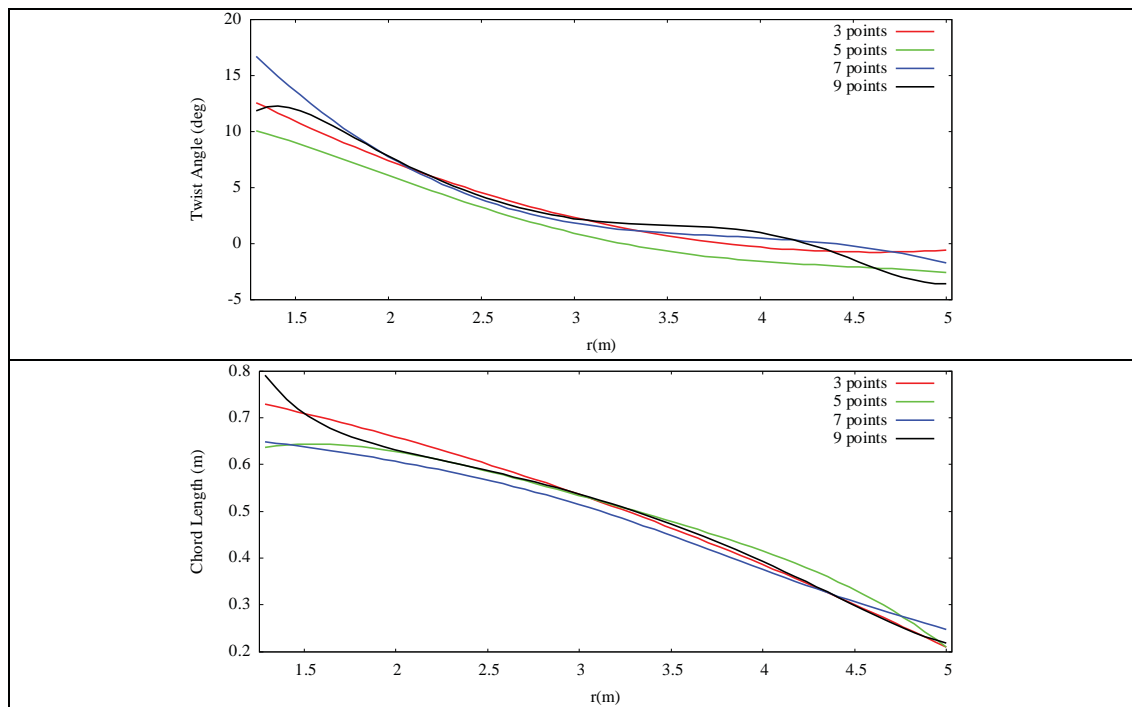

Figure 3 Twist angle (top) and chord length (bottom) distributions of best blade designs for different number of control points.

Optimizations performed using macroevolutionary algorithm were displayed in Figure 5. Here the computations were done using two population sizes, 5 and 20. For 3 and 5 control points, smaller population yielded slightly better results, while for 7 and 9 control points, using larger population was clearly more beneficial.

Chord and twist angle distributions of the best blade designs obtained using different number of control points were displayed in Figure 6. Here, using seven points also led to wavy chorld length and twist angle distributions. The best blade again had a convex twist angle and concave cord length distributions similar to the micro-genetic algorithm output.

The highest AEP value, 92972 kWh, obtained with 5 points and 5 individuals, was slightly lower than 93444 kWh, which was obtained by micro-genetic algorithm. In order to compare the blade designs yielded by these two algorithms, twist angle and chord length distributions of the best blades found by micro-genetic algorithm and macroevolutionary algorithm were displayed in Figure 7. Both designs had a nearly constant twist angle distribution towards the tip region while macroevolutionary algorithm design was more twisted with a non-monotonic distribution. Compared to micro-genetic algorithm design, macroevolutionary algorithm design was thicker at the outboard and thinner at the inboard spanwise stations.

Power coefficient versus tip speed ratio (TSR) plots of both designs were shown in Figure 8. The curves were almost identical with micro-genetic algorithm design produced slightly higher power between TSRs of 5 and 6. The optimum TSR was found to be 6 for designs.
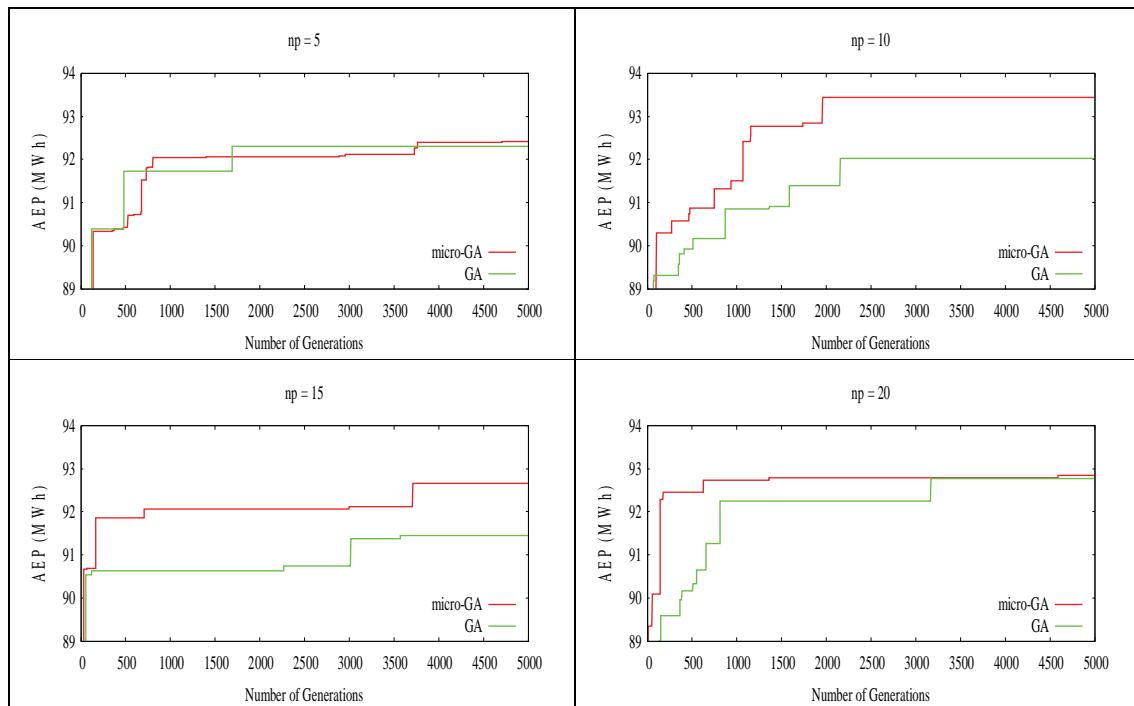
Figure 4 Evolution of AEP for genetic algorithm with and without micro approach using different population sizes.
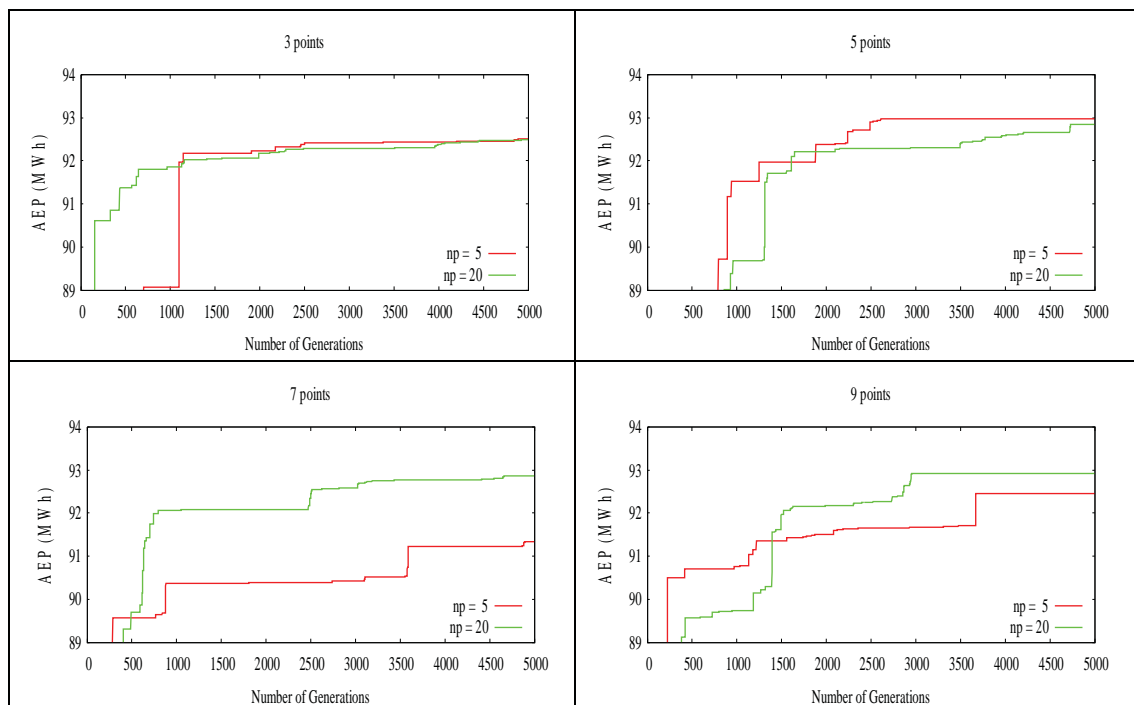

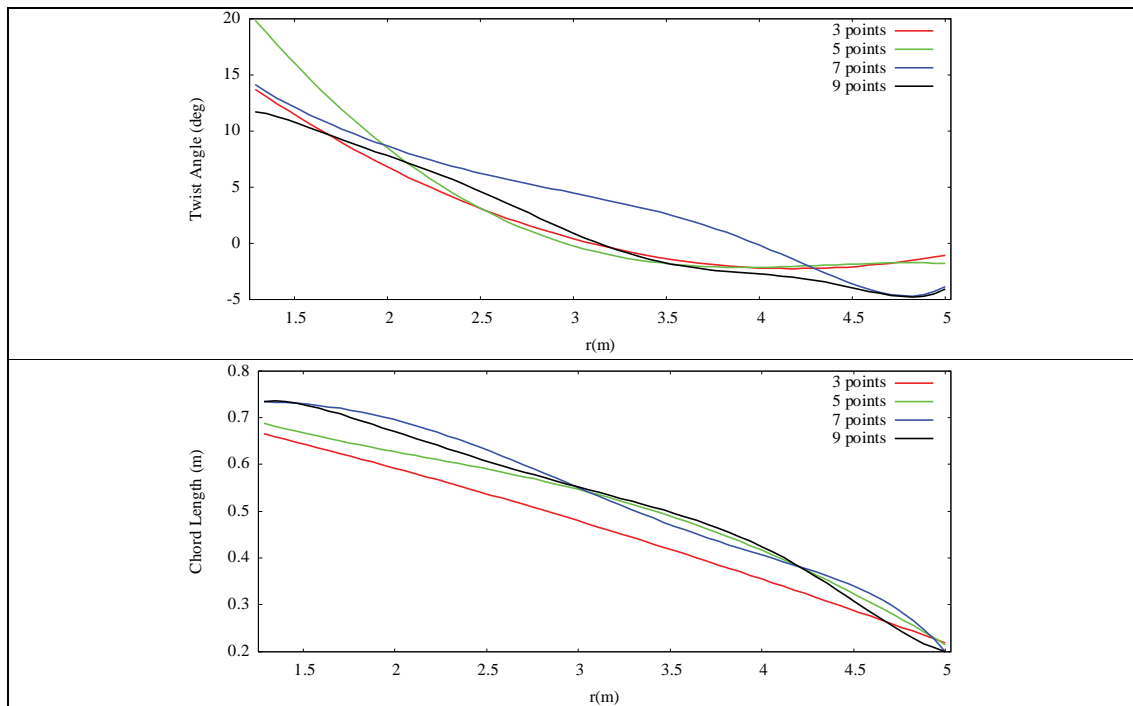Figure 5 Evolution of AEP obtained using macroevolutioary algorithm with different population sizes.

Figure 6 Twist angle (top) and chord length (bottom) distributions of best blade designs for different number of control points.
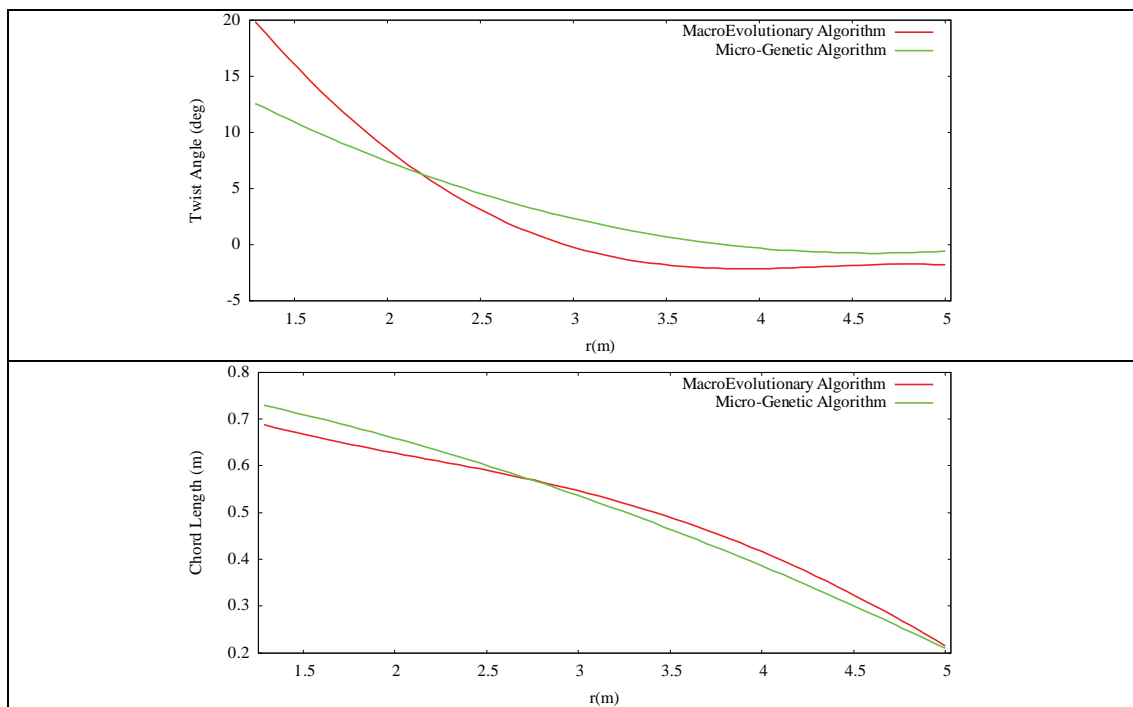

Figure 7 Twist angle (top) and chord length (bottom) distributions of best blade designs obtained using micro-genetic algorithm and macroevolutionary algorithm.
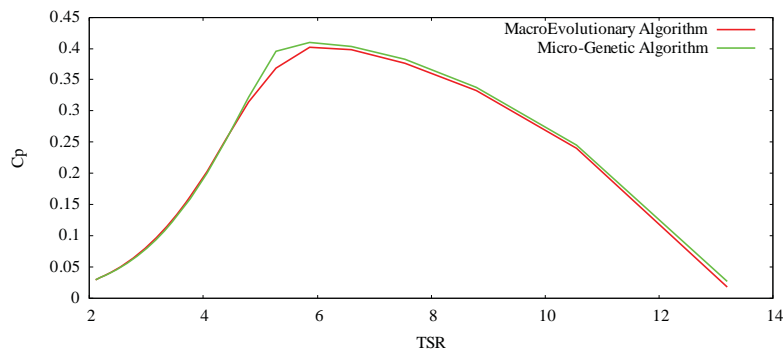
Figure 8 Power coefficient vs. tip speed ratio of the turbines optimized using micro-genetic algorithm and macroevolutionary algorithm.

4. Conclusions

Aerodynamic optimization of the blades of a two-bladed, stall regulated, horizontal axis wind turbine was performed using micro-genetic algorithm and macroevolutionary algorithm. Optimizations were performed by maximizing the annual energy production, which was calculated using blade-element momentum theory. Chord length and twist angle distributions along the blade span, the pitch angle of the blades and airfoil profiles for the root, primary and tip portions of the blades were selected as design parameters. Throughout the study twist angle and chord length distributions were defined using Bezier curve and different number control points uniformly distributed along the span. Here, Bezier curve selected over polynomial and spline interpolation techniques in order to avoid oscillatory distributions that might be obtained for large number of control points. Computation performed for different population size showed that the number of control points affected the evolution of annual energy production. Using different number of control points led to different outcome for different population sizes, hence the results were not conclusive, however, highest annual energy production values was obtained using 3 control points with micro-genetic algorithm and 5 control points with macroevolutionary algorithm. Hence, one might not need too many control points to define an optimum distribution for twist angle and chord length.

When the micro-genetic algorithm was compared with a standard genetic algorithm, the former outperformed the latter for all the population sizes considered. The highest annual energy production value yielded by macroevolutionary algorithm was also slightly lower than that yielded by micro-genetic algorithm. When the best blade designs obtained by these two algorithms were compared, macroevolutionary algorithm yielded a non-monotonic twist distribution with the outboard parts of the blade twisted towards feather.

In this study, a pseudo random number generator with same seed was used for all the cases studied so that the changes would be purely due to the design parameters and the optimization algorithm. When the optimizations were repeated with a different seed, similar outcomes were observed however, with slightly different AEPs and final optimization parameters. Therefore, optimizations should be repeated with more random number seeds. All the optimization methods studied yielded a different design (albeit slightly) when the random number seed was changed. This indicated that the exploitation/exploration balance [26] of the algorithms may be poor. All of the optimization algorithms employed in this study had constant parameters. Adaptation of these parameters [26] might be necessary to provide a better exploitation/exploration balance.

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