The Global Shape Optimization for 1MW Class Wind Turbine Blade under Variable Pitch Control Using Pattern Search Algorithm

1. Introduction

2. Frameworks

2.1 HARP\_Opt Code

The design of a horizontal-axis wind turbine blade is optimized based on the HARP\_Opt (Horizontal Axis Rotor Performance Optimization) code which was developed by NREL (National Renewable Energy Laboratory) (Sale *et al* 2009). Current available HARP\_Opt version is utilizing the genetic algorithm (GA) to obtain global optimization results and also to obtain the Pareto solution in the case of multi objective optimization problem. The HARP\_Opt code utilizes the WT\_Perf (Wind Turbine Performance evaluation) code which was also developed by NREL to evaluate the performance of wind turbine blades using blade element momentum method (Buhl, 2009). Therefore the HARP\_Opt is an integrated code combining WT\_Perf and GAs to optimize the horizontal axis wind and hydrokinetic turbines using artificial intelligence without the aid of human experts.

2.2 Objective Function and Constraint Equations

HARP\_Opt can handle the annual energy production (AEP) and also the generation efficiency as an objective function and the AEP can be more preferable one when the probability density function (PDF) of wind at an installation site is available for more economical and practical design. The AEP can be obtained as follows,

 (1)

where  and  are the power output curve and PDF of wind for , respectively. And 8750 is a constant to convert the hourly energy production to the annual energy production. The AEP is used as an objective function in the pattern search method and as a fitness value as a form of negative AEP in the genetic algorithms. And also the following constrains are imposed to obtained more practical results.

 (2)

 (3)

where ,  and  are the chord length, pretwisting angle and % thickness values, respectively, and  and  represents the lower bound and the upper bound for each variable, respectively, ,  and  are the numbers of control points for the chord length, pretwisting angle and % thickness values, respectively. Upper three inequality equations are for specifying the boundaries (which can be easily implemented in GAs) and the lower three inequalities are for specifying the monotonically decreasing characteristics of design variables. Therefore this problem is categorized as in the constrained nonlinear optimization problem.

2.3 Control theory

HARP\_Opt can handle the following four different control strategy to obtain maximum power efficiency: (1) fixed-speed and fixed-pitch (passive stall regulation), (2) fixed-speed and variable-pitch (active feather regulation), (3) variable-speed and fixed-pitch (active stall regulation), (4) variable-speed and variable-pitch (active feather regulation). From the previous research by Sale and Li (2010), the VSVP control is found as the most preferable control methodology owing to the maximized power output and the minimized torque and thrust, and it means that the overall performance and economic benefits can be optimized by adopting the VSVP control algorithm.

3. Theoretical Backgrounds

3.1 Blade Element Momentum Theory and Several Correction Ways

To evaluate the performance of wind turbine blades, HARP\_Opt utilizes the WT\_Perf, which is a modernized and enhanced BEM code by NREL based on the PROP developed by Oregon State University, and WT\_Perf is recently widely utilized for this purpose. WT\_Perf evaluates the performance of turbine blade using BEM theory based on the information on blade shape, and aerodynamic characteristics including lifting and drag force according the airfoil (Buhl, 2009). BEM theory, which is originally attributed by Betz and Glauert (1935), assumes that (1) blades can be divided into small elements that act independently of surrounding elements and operate aerodynamically as two-dimensional airfoils, and (2) the loss of pressure or momentum in the rotor plane is caused by the work done by the airflow passing through the rotor plane on the blade element. In practice, BEM theory is implemented by dividing the blades of a wind turbine into many elements along blade span as shown in Figure 1. From this BEM theory, each blade element is modeled as a two-dimensional airfoil as shown in Figure 2(a) and the resultant aerodynamic forces and their components perpendicular and parallel to the rotor plane are shown in Figure 2(b) (Moriarty and Hansen, 2005).

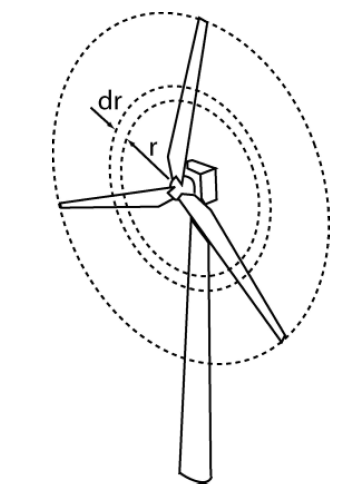


Figure 1. Annular plane used in blade element momentum theory (Moriarty and Hansen, 2005)

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| (a) Local element velocities and flow angles | (b) Local elemental forces |
| Figure 2. Two-dimensional blade element and resultant forces (Moriarty and Hansen, 2005) | |

From Figure 2, we can obtain the following equations,

 (4)

where  is the local inflow angle,  and  are the inflow velocity and tip speed, respectively, and  is the tip speed ratio. And if the blade motion is not neglectible then the local velocities are included as follows,

 (5)

This equation hold for all elements of the blade along the span, although typically the inflow angle changes with element location. The induced velocity components in Equation 1 and 2 are a function of the forces on the blades and we use BEM theory to calculate them. From BEM and Figure 2(b), the thrust distributed around an annulus of width dr is equivalent to

 (6)

And the torque produced by the blade elements at the annulus is equivalent to

 (7)

More details about BEM theory can be found in references including Moriarty and Hansen (2005). To correct the results obtained from BEM by considering three-dimensional effects, WT\_Perf utilizes several empirical correction method including Stall-Delay model to consider the presence of span wise flow2 and (Selig and Du, 1998; Egger and Digumarthi, 1992) and Prandtl tip loss correction to consider the number of blades and vortex shedding effects at the end of blades (Glauert, 1935).

3.2 Pattern Search Method

Pattern search (PS) method is a kind of “direct search” methods which use only the function value itself and don’t compute nor approximate the gradient information of the objective function. Therefore, the PS method can be successfully applied to the optimization problems even with a high level of discontinuities and nonlinearity in the feasible searching space. PS method was first introduced by Hooke and Jeeves in 1961 with the introduction of a concept of “direct search” method (Hooke and Jeeves, 1961) and then many researches had been carried out to enhance the performance of PS method and to investigate its convergence characteristics. For example, the mesh size controlling technique was proposed by Fermi and Metropolis who utilized the PS method to find optimal fitting parameters for experimental data set using Los Alamos Maniac (Lewis et al., 2000). Also, the convergence of PS method was investigated using positive basis method by Dolan et al (Dolan et al, 2003).

The PS can be also easily integrated with any commercial or in-house engineering codes in which the gradient or sensitivity information is usually not available and so it would be very difficult to compute or approximate the gradient and to integrate with well-known elaborate gradient-based optimization methods. Many studies were carried out using engineering codes combining the PS method to minimize engineering cost values. Alsumait *et al* (2007) applied PS method to solve the power system economic load dispatch problem and they found that the PS had very reliable convergence characteristics and robustness. Wetter *et al*. (2003) utilized the PS method and GAs (Genetic Algorithms) to minimize the annual primary energy consumption of office buildings in three different locations with 13 design parameters and a cost function with large discontinuities in searching space. They found that the PS was better in convergence point of view, and the solutions from GA were relatively better those obtained from PS.

As mentioned earlier by Hooke and Jeeves, the direct search methods should describe the sequential testing rule of trial solutions with comparison of each trial solution with the “best” obtained up to that time and strategy how to determine the next trial solution(s) (Hooks and Jeeves, 1961). PS method utilizes the “exploring move” to find better solution in the next iteration step, and there is a specific pattern, such as one can move just in one direction of all the possible directions which can improve the current solution, and this “exploring move” was obtained from heuristic and engineering insights. Therefore the PS method can be considered as one of heuristic optimization techniques like GAs, simulated annealing (SA) and tabu search (TS). In spite of heuristic characteristics, the PS is inherently deterministic while GAs and TS are stochastic and random; therefore the convergence characteristics of PS are usually better than those of GAs, SA and TS. When the PS method is compared with simplex search method (Nelder and Mead 1965; Lagarias *et al*. 1998) which is one of most popular deterministic direct search methods, the simplex search method is much easier to be trapped in local minimum during searching operation, while the PS method probably finds a global or near-global minimization solution even when the optimization problem does have a certain level of discontinuities and nonlinearities in searching space like GAs and TS because the simplex searching method tends to concentrate on the path to improve the solution using the geometrical trial solution set called as “simplex” while the PS method allows to search more larger space by introducing expansion even the better solution was found in the trial solution set. However, the PS requires more time to find the optimal point than simplex search method.

Consider the following optimization problem,

Minimize  (4)

where ,  and  denotes the -dimensional real search space, i.e., the number of design variables is specified as . And the basic operations of PS method consist of (1) selection of pattern vectors, (2) polling, and (3) “exploring move” with expansion and contraction. Pattern vectors which represent the directions of the trial solution set, can be selected using the unit Cartesian vectors in . Generally the minimal and maximal pattern vectors are utilized in most cases as follows (see Figure 1),

* Minimal pattern vectors with  unit vectors,

 (5)

* Maximal pattern vectors with 2*n* unit vectors,

 (6)

where  denotes the -th unit Cartesian vector. Using the pattern vectors (’s) and current solution (), one can generate the trial solution set (’s) with mesh size, , as follows,

 (7)

where  and  denote the current solution and the -th point in the trial solution set at -th iteration step, respectively, and  denotes the mesh size and  is the -th pattern vector in pattern vector set. Then, the polling operation, which represents how to decide the next solution using the trial solution set, can proceed. During poll, the function values for trial solution set are computed and compared with the function value of the current solution, and there are two types of poll operation available; (1) complete poll if function values for all the trial solution set are evaluated and compared, and (2) incomplete poll if some of trial set just compared and stop once the better solution is found. After polling, the exploring move proceeds, and the next solution and trial set move with expansion and contraction. When the polling was successful, i.e. there exists a better solution in the trial solution sets (as shown in Figure 2(a) and 2(b)), the mesh size will be increased as

 (8)

Or, the poll was unsuccessful (as shown in Figure 2 from (b) to (c) and from (c) to (d)), i.e. there is no better solution, the mesh size can be reduced as

 (9)

Herein, the expansion and contraction factors, 2 and 0.5, can be adjusted by the users, even they usually used as 2 and 0.5 in many studies. The procedure for PS is summarized in Figure 2 and Chart 1.

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| (a) Minimal pattern vectors | (b) Maximal pattern vectors |
| Figure 1. Minimal and maximal pattern vectors for the case with 2 design variables | |

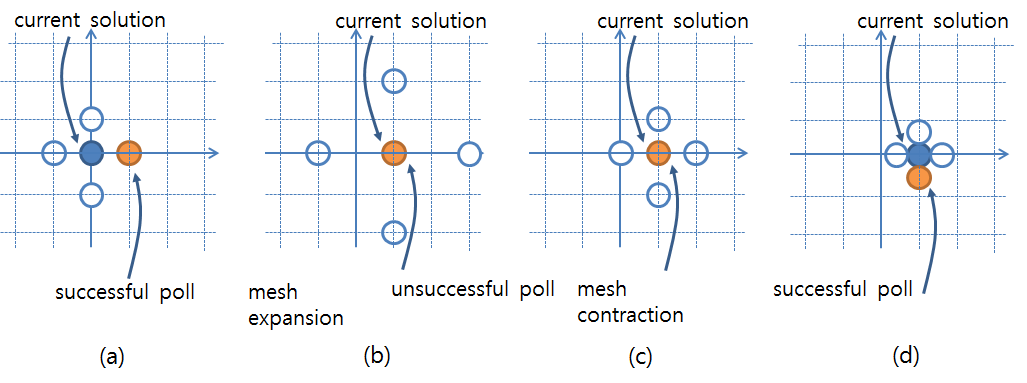


Figure 2. Example of pattern search operation for the case with 2 design variables

Chart 1. Procedure for Pattern Search Algorithm

1: Choose the set of pattern vectors, ,

- 2*n* vectors: 

- *n*+1 vectors: 

2: Choose  and 

3: For  Do

4: if there exist  such that  then

5: Set 

6: Set 

7: else

8: Set 

9: Set 

10: if 

11: PS has converged and terminate.

12: end if

13: end if

14: end for

**3.3 Genetic Algorithms**

The genetic algorithms (GAs) were initiated by observing the mechanism of natural evolution and natural genetics (Holland, 1975; Goldberg, 1989; Michalewicz, 2012). It is characterized by a parallel search with multiple solutions called “population” while a point-by-point search is carried out by the conventional optimization methods. An “individual” in the population is a string of symbols called “genes” and each string of genes is referred to as “chromosome” in a binary-coded GA. The chromosome can be converted to a design variable in a physical system. In the case of a real-valued problem, the decimal-coding or grey-coding can be utilized to convert the chromosome into the real design variable. Even though the binary-coded GA has been successfully applied for the real-valued problem (Maity and Tripath 2005, Kim *et al* 2007), it still has some drawbacks such as a weak local tracking performance near the optimal point. To overcome the limitation of the binary-coded GA for real-valued problems, a real-coded GA was derived to handle the continuous variables efficiently. In the real-coded GA, the concept of a gene disappears and the chromosome is a minimal unit and works as a design variable. The fundamental steps of a real-coded GA are the same as those of a simple binary-coded GA as shown in Figure 3.



Figure 3. Basic steps of genetic algorithm

Genetic operations with continuous variables can be carried out in the same way except for the crossover and mutation during reproduction. The crossover and mutation in a real-coded GA were derived by looking into the operation of a binary-coded GA (Kim and Yang 1995). Many researches related the real-code GAs have been reported in many engineering fields including Hadi and Arfiadi (2001), Kim and Ghaboussi (2001), Chou and Ghaboussi (2001). So the details about the real-code GA can be found the references. On the other hand, the micro GAs which uses the minimum number of populations such as 10-20, while the conventional GAs usually use many individuals up to several hundreds. The micro GAs is known as a good method to reduce the calculation time owing to the small number of population and function evaluations for each generation step. The references about the micro GAs can be found in the references by Au *et al*. (2003) and Park *et al*. (2007).

4. Example Study

4.1 Layout of 1MW-class wind turbine

In this study, the PS method was applied to the shape optimization problem on the 1MW-class wind turbine blades and the optimization performance of the PS method was compared with those of GAs and micro GAs, which are very popular stochastic direct search method. It can be noted that the simplex search method and the quasi-Newton method were applied also, but unfortunately they were not able to converge to the reasonable solution due to high level of discontinuities and nonlinearity in searching space and hence were not included in this paper.

The following basic conditions were considered for optimization of wind turbine blades as in Table 1. About the wind condition, the operational wind speed was considered in the range of 2 - 26m/sec, and the probability distribution for annual wind speed was assumed to follow the Rayleigh distribution with mean flow speed of 7.5 m/sec as shown in Figure 4. On the rotor control, the rotor speed and blade pitch controls are followed by VSVP (Variable-Speed and Variable-Pitch) control.

Table 1. Design condition for 1MW-class wind turbine blades

|  |  |  |  |
| --- | --- | --- | --- |
| Parameters | Values | Parameters | Values |
| Number of blades | 3 | Rated Power | 1,000kW |
| Rotor diameter | 50m | Airfoil Shapes | FFA-W3-301, 241, 211 |
| Hub diameter | 2m | RPM range for Rotor | 4 - 32.5 RPM |
| Design Wind speed | 2 - 26 m/sec | Wind PDF | Rayleigh Distribution |

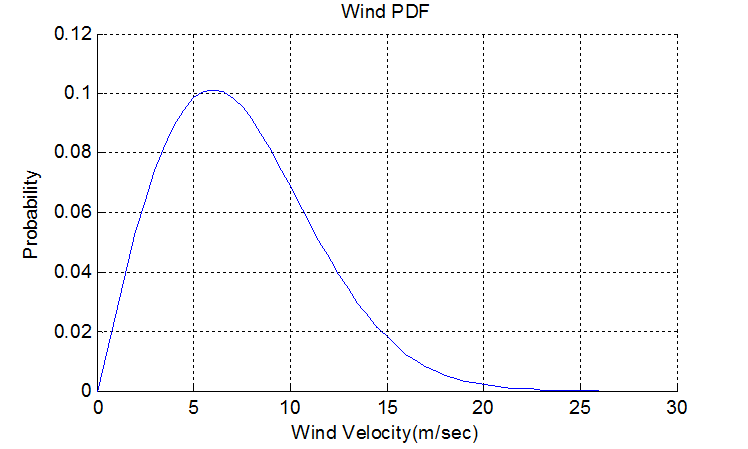


Figure 4. Probability distribution function of wind (=7.5m/sec)

4.2 Parameter Setup for Optimization

It is not rational to specify the chord length and pre-twisting angle at many points along the blade span, therefore the chord length and pre-twisting angles were represented by Bezier curves using design values at five control points along the blade span while the percent thickness was interpolated by Bezier curves using design values at three control points (Sale and Li, 2010). Therefore 13 design parameters were considered; i.e. 5 for pretwisting angles, 5 for chord and 3 for thickness. The initial values for 13 design variables for GAs and micro GAs are not given because the initial feasible individuals could be randomly generated, while the initial design variables for PS should be specified and they were determined by choosing the mean values of lower and upper bound values. The basic parameters for GAs and PS are shown as in Table 1. It is noteworthy that the mutation probability can be assigned as a very low uniform value in the usual unconstrained optimization problems, but the adaptive feasible mutation function was utilized to prevent unwilling and unfeasible mutation operation in this constrained optimization problem (Mathworks, 2011).

Figure 5 shows the initial curves for chord length, twisting angle and thickness along the blade span, and the Figure 6 shows the curves for power outputs and power coefficients and for rotor speeds and blade pitch angles obtained using the initial blade design. The power coefficients under design wind speed of 2 – 27 m/sec were calculated lower than 10 % and also the values for AEP (annual energy production) and CF (capacity factor) are calculated as 499,574 kWh and 5.7 %, respectively. And these values are also very low and undesirable results and it is natural because the blade shape is not optimized yet.

Table 2 Parameters for GAs and PS methods

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Genetic Algorithms | | | Pattern Search method | |
| Parameters | GAs | microGAs | Parameters | Values |
| Number of Population | 100 | 10 | Number of Iteration | 1000 |
| maximum Generation | 100 | 100 | Pattern Generation | maximal, 2N |
| function Tolerance | 1×10-6 | 1×10-6 | Polling Method | Incomplete Polling |
| Crossover probability | 0.8 | 0.8 | Mesh Size Tolerance | 1×10-6 |
| Mutation probability | adaptive | adaptive | Expansion factor | 2.0 |
| Elitism | Yes | Yes | Contraction factor | 0.5 |

Table 3 Control Points and Lower and Upper Boundary Values for Chord Length and Twisting Angles

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Control Point (m) | | 6.25 | 7.677 | 11.74 | 17.82 | 25 |
| Chord Length  (m) | LBVs | 0.5 | 0.1 | 0.1 | 0.1 | 0.1 |
| UBVs | 1.5 | 1.5 | 1.0 | 1.0 | 0.25 |
| Twisting Angle  (deg) | LBVs | -10 | -10 | -10 | -10 | -10 |
| UBVs | 40 | 40 | 40 | 40 | 40 |

|  |  |  |
| --- | --- | --- |
|  |  |  |
| (a) Initial chord length | (b) Initial pretwisting angle | (c) Initial thickness |

Figure 5 Initial design curves for pattern search method (\*: Upper and lower boundary values, 🞏: initial values)

|  |  |
| --- | --- |
|  |  |
| (a) Power output and efficiency w.r.t. wind speed | (b) Rotor speed and blade pitch angle w.r.t. wind speed |
| Figure 6 Power Output and Efficiency and Control Parameters for the initial design | |

4.3 Optimization results and comparison with the results from GAs and micro GAs

GAs are stochastic and random, therefore one may obtain a different solution for each trial even though GAs are known as global optimization algorithm. To investigate the repeatability of GAs, 20 times of executions were exercised using GAs and also using micro GAs, and the mean and coefficient of variations (COVs) were compared with the result obtained from the PS method. The optimized blade shapes obtained from GAs, micro GA and PS, are summarized in Figure 7, 8 and 9, respectively in three curves for pre-twisting angle, chord length and thickness. It can be observed that the results for micro GAs were more disturbance than others, which represents that the solutions may be trapped into the local minima due to the small number of population in micro GAs. The results from GAs and PS look quite similar to each other.

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| (a) Pretwist angle | (b) Chord Length | (c) Thickness |
| Figure 7 The results obtained from 20 trials of Genetic Algorithms | | |

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| --- | --- | --- |
|  |  |  |
| (a) Pretwist Angle | (b) Chord Length | (c) Thickness |
| Figure 8 The results obtained from 20 trials of micro Genetic Algorithms | | |

|  |  |  |
| --- | --- | --- |
|  |  |  |
| (a) Pretwist Angle | (b) Chord Length | (c) Thickness |
| Figure 9 The results obtained from 5 Trials of Pattern Search | | |

To analyze quantitatively and in detail about the consistency of the results, the optimized results are compared as shown in Table 4, because the optimized shapes are reproduced ones from the optimal values for design variables by use of Bezier curve. As summarized in Table 4, the mean of standard deviation (STD) of the results obtained from PS method is lower than those from Gas and micro Gas. In the case of pretwisting angles, the STD values are in the range of 0.140-0.621 with mean of 0.402 in the case of PS, while the STD values are in the range of 0.277-0.983 with mean of 0.596 and in the range of 0.428-2.832 with mean of 1.307. The results for the chord length and % thickness are found to be similar to the results for the pretwisting angle. It can be concluded that the PS was the best and the micro Gas was the worst in the view point of consistency.

Table 4. Mean and STD values for the optimized values from Gas, mGAs and PS

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Design Parameters | C.P. | GAs | | mGAs | | PS | |
| Mean | STD | Mean | STD | Mean | STD |
| Pretwisting angle | 6.25 | 16.146 | 0.677 | 16.355 | 2.832 | 16.449 | 0.6099 |
| 7.68 | 3.406 | 0.983 | 4.894 | 1.761 | 1.685 | 0.6208 |
| 11.74 | 0.614 | 0.554 | 0.377 | 0.903 | 0.955 | 0.3137 |
| 17.82 | -0.692 | 0.488 | -1.372 | 0.613 | 0.656 | 0.3267 |
| 25.00 | -4.203 | 0.277 | -3.719 | 0.428 | -4.886 | 0.1405 |
| **Mean** | **-** | **0.596** | **-** | **1.307** | **-** | **0.4023** |
| Chord Length | 6.25 | 1.468 | 0.026 | 1.460 | 0.048 | 1.497 | 0.0069 |
| 7.68 | 1.419 | 0.043 | 1.387 | 0.082 | 1.495 | 0.0075 |
| 11.74 | 0.970 | 0.015 | 0.973 | 0.022 | 0.999 | 0.0013 |
| 17.82 | 0.931 | 0.035 | 0.947 | 0.032 | 0.999 | 0.0014 |
| 25.00 | 0.226 | 0.017 | 0.233 | 0.020 | 0.248 | 0.0010 |
| **Mean** | **-** | **0.027** | **-** | **0.041** | **-** | **0.0036** |
| % Thickness |  | 0.274 | 0.017 | 0.278 | 0.022 | 0.252 | 0.0011 |
|  | 0.529 | 0.018 | 0.532 | 0.029 | 0.505 | 0.0058 |
|  | 0.587 | 0.049 | 0.608 | 0.076 | 0.505 | 0.0058 |
| **Mean** | **-** | **0.028** | **-** | **0.042** | **-** | **0.0042** |

Figures 10 and 11 show typical convergence curves for the fitness values for the best individuals and the distance between individuals in GAs and micro GAs with respect to the generation number, and Figure 12 shows the convergence curves for the solutions and the mesh size with respect to the iteration number. In the case of GAs with 100 populations, the fitness value (i.e. AEP) for the best individual in the first generation was about 2.2×106 kWh, which implies that one can obtain the best individual whose fitness value with over 2.2×106 kWh just with 100 random samples. But in the case of micro GAs, it took about 25 generations (it is equivalent to 250 function evaluations) to obtain the best individual with its fitness value over 2.2×106 kWh. Hence, it can be said that the best way to obtain better individual in the early generation is just trying a number of random samplings such as 100 random samples. In contrast, the objective function (i.e. AEP) of the PS method with the initial design values was just around 0.4×106 kWh and it is very low relatively to the optimal values around 3.0×106 kWh, but the solution was improved very quickly in early iteration stage and the solution was almost converged to the final solution after 200 iterations.

|  |  |
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|  |  |
| (a) Convergence of best individual | (a) Convergence of distance between populations |

Figure 10. An example of Convergence of Gas

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| --- | --- |
|  |  |
| (a) Convergence of best individual | (b) Convergence of distance between populations |

Figure 11. An example of Convergence of micro GAs

|  |  |
| --- | --- |
|  |  |
| (a) Convergence of best individual | (b) Convergence of mesh size |

Figure 12. An example of Convergence of PS

Figure 13 shows the comparison results on the AEPs and computational time (herein the computational time is compared in a term of the number of function evaluations) of 20 trials of GAs, 20 trials of micro GAs and 5 trials of PS. And Table 5 summarizes the mean and COV for the results from GAs, micro GAs and PS. In the view point of AEPs, the results obtained from PS with 5 different initial design variables have similar AEP values and also look most reasonable because the values for mean and COV for AEPs are calculated as 2.994×106 kWh and 0.21%, respectively. However the mean value of AEPs is not so significantly higher than those of GAs and micro GAs. The mean values from GAs and micro GAs are also very high as 2.942×106 and 2.928×106 kWh, respectively. The mean value of PS is just higher as amount of 1.76% than GAs and 2.25 % than micro GAs. But the COVs for AEPs are very lower as 0.206 in the case of PS, while the COVs form GAs and micro GAs are calculated as 0.709 and 1.135, respectively. It is concluded that the PS has higher AEP values and also more consistent than GAs and micro GAs in a view point of AEPs.

In the another view point of calculation time, i.e. the number of function evaluations, the GAs require much longer calculations of 6000 – 12000 counts for convergence (the values for mean and COV are 8985 and 18.4%, respectively), while the micro GAs just require 1200 – 2500 counts (the values for mean and COV are 1968 and 20.0%, respectively). It can be observed that the calculation time was significantly reduced by adopting micro GAs up to 78% from 8985 counts to 1968 counts. In the case of PS, the number of function evaluations was about 5400 – 6000 (the values for mean and COV are 5970 and 25.7%, respectively). Therefore PS method requires less time than conventional GAs and more time than the micro GAs.

Table 5 Comparison between AEPs and number of total function evaluation of GAs, mGAs, and PS

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Parameters | GAs | mGAs | PS |
| AEPs | Average (kWh) | 2.942 | 2.928 | 2.994 |
| COV (%) | 0.709 | 1.135 | 0.206 |
| Number of function evaluations | Average (Count) | 8985 | 1968 | 5970 |
| COV (%) | 18.4 | 20.0 | 25.7 |

|  |  |
| --- | --- |
|  |  |
| (a) AEP(Annual Energy Production) | (b) Number of Function Evaluations |

Figure 7. Comparison of AEPs and number of function evaluations for convergence

(Trials 1-20: GAs, Trials 21-40: mGAs, Trials 41-45: PS)

Figure 14 compares the AEPs and the number of function evaluations for all 45 cases, and it can be easily observed that the results from the PS were the best in the aspect of AEPs and also they were in the reasonable range in the aspect of the computation time. In contrast, the results from micro GAs were worst in AEPs, however they were the best in calculation time aspect, and the conventional GAs were worse than the micro GAs and PS in both of AEP and computational time aspects. Even though the results obtained from the conventional optimization techniques including the quasi-Newton method (one of gradient-based methods), and simplex search method (one of direct-search methods) were not reported herein, but they were able to find the reasonable optimized solution because of the high level of discontinuities and significant level of errors on numerically-obtained gradients by finite difference concept on this problem. Therefore, the GAs and micro GAs can be still good candidate for blade shape optimization even though their shortcomings in the AEPs and the computation time.

It is also noteworthy that the large amount of calculation time doesn’t guarantee better results as shown in Figure 9. And it can also be found that the GAs don’t guarantee the global and unique optimal solutions in real practical applications even though the GAs are well-known as one of global optimization techniques.



Figure 14. AEPs vs the number of function evaluations

4.4 The optimal design from PS method

Figure 15 shows the optimal design of 1MW wind turbine blade for the design condition including wind characteristics considered in this study, and it is obtained from the PS method with the initial values as the mean of upper and lower boundary values, and the Figure 16 shows the curves for power output and coefficients and for the rotor speed and blade pitch angle, and the values for initial design is also indicated in gray lines for comparison. As indicated in the Figure 16, the rated power is achieved at the wind speed of about 12 m/sec, which is then rated velocity. And the power coefficient are over 0.4 under low wind velocity (lower than 10 m/sec) and the power coefficients are getting smaller to maintain the power output to the rated power by adjusting the blade pitch angle as shown in Figure 16(b) above rated velocity. Before rated velocity, power coefficient is maximally maintained by adjusting rotor speed to get high efficiency and to operate it with optimal tip speed ratio.

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| --- | --- | --- |
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| (a) Chord length | (b) Pretwisting angle | (c) Thinkness |

Figure 15. Optimized blade shapes along span wise obtained from PS method

(solid lines: optimized values, dotted lines: initial values)

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| --- | --- |
|  |  |
| (a) Power output and efficiency w.r.t. wind speed | (b) Rotor speed and blade pitch angle w.r.t. wind speed |
| Figure 16. Power Output and Efficiency and Control Parameters for the initial design  (solid lines: optimized values, dotted lines: initial values) | |

5. Conclusion

References

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