838. Improved aerodynamic optimization for the design of wind turbine blades

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Abstract. A wind turbine rotor converts the kinetic energy of wind to drive a generator which in turn yields electricity. The aerodynamic analysis and the optimization of design parameters for the wind turbine blades are key techniques in the early stage of the development of wind turbine blades. In this study a computational procedure using artificial neural network and numerical optimization techniques was developed for three-dimensional blades design of a wind turbine. The procedure was applied for improving a previously studied wind turbine rotor design. Results showed that the aerodynamic performance of the new blade has remarkable improvement after optimization.

Keywords: wind turbine blade, neural network, aerodynamics, optimization.

1. Introduction

For everlasting life of human beings and protection of the Earth, a global awareness has led to reawakening of interest in renewable energy technologies in recent years. In efforts to reduce the dependence on fossil fuels, cleaner power generation methods are being searched in many fields. Wind power has no fuel problem, nor does it have harmful emissions such as radiation or carbon dioxide, is quite suitable to serve as an independent unit for supplementary electricity. According to the report of the Global Wind Energy Council, the total wind turbine capacity installed has reached 122GW in 2008 [1].The average growth rate in the past five years is about 25 %. It is expected that the total wind turbine capacity will reach 1,245 GW in 2020 and the small-medium sized wind turbines will share one-thirds of it. Wind power seems like a promising alternative for future power generation.

A wind-power generation system uses wind turbine blades to convert the kinetic energy of wind into electricity. It is beneficial in improving a wind turbine to increase the percentage of wind energy extraction. The aerodynamic performance of wind turbine blades has decisive effect on the cost benefit of the whole system. The factors that affect the efficiency of a wind turbine blade may include the shape of airfoil, twist angle, blade size, number of blades, etc. [2, 3]. Determination of these factor values plays an important role on improving efficiency of wind turbine rotor. To simplify the analysis, a three-dimensional blade is usually represented by several two-dimensional sections [4]. These two-dimensional sections are then blended or stacked up to form the three-dimension blade. Unfortunately, this approach was applied mostly to the structural optimization of wind turbine blades [5, 6]. Based on the previously established ability in managing aerodynamics optimization for two-dimensional airfoils [7], a computational procedure using artificial neural network and optimization techniques was established in this study for the design of three-dimensional blade such that the aerodynamic performance of the rotor is maximized. The establishment of the computational procedure may build up the ability in improving the quality and the speed of the development of wind power generation systems.

2. Formulation of the problem

2.1. General description

The wind turbine rotor is the main mechanism which interacts with the wind in order to convert wind energy into electricity. The ratio of the power conversion is called power coefficient of the wind turbine (C_p). The higher the C_p the better the wind blade is capable of extracting power from the wind. Theoretically, the maximum power coefficient, known as Betz limit, is 0.5926 (16/27) and would be lower as it will be affected by the tail flow, blade tip loss, aerodynamic frictional loss and others. A rotor with higher C_p value represents better aerodynamic performance. In this study, the rotor design is simplified as a single blade with several radial sections to reduce analysis time and complexity and the lift-to-drag ratio (C_L/C_D) is used as the measure of dynamic performance for each two-dimensional section. The solution strategy first regards to the optimization of two-dimensional airfoil profiles at the radial sections. The three-dimensional geometric features such as chord lengths, pitch angles are then calculated. The procedure is applied on the rotor design of a three-bladed 25 kW horizontal axis wind turbine (HAWT). The two-dimensional aerodynamic characteristics are calculated by using XFOIL and the three-dimensional aerodynamic performance are calculated by using the blade element momentum method (BEM) methods and an open design code YAWDYN [8]. The parameters to be determined include the variable airfoil shapes across the entire rotor, the chord distribution, twist angle and rotor pitch. The rotor radius (R) is 6.3 m with wing length 5.8 m, rated wind speed is 12 m/s. The base airfoil is chosen as NACA4412.

2.2. Design procedure

The two-dimensional stacked design concept is used as a tool for determining three-dimensional blade. The stacked design concept divides a three-dimensional blade into several discontinuous 2-D sections. The rotor blade is represented by an interpolation throughout the rotor span of these 2-D airfoils. The method proposed in this study essentially takes the concept of stacked design one step further, performing not only shape stacking, but shape optimization as well. The airfoil shape is optimized so that the lift-to-drag ratio is a maximum at each individual section. The parameters to be optimized include the leading edge radius scaling ratio, foil thickness, chamber and the attack angle that yields the maximum lift-to-drag ratio. The first three parameters determine the shape of an airfoil while the last parameter determines the orientation of the airfoil. The orientation of an airfoil is depicted in Fig. 1. Although XFOIL can be used to evaluate the aerodynamic properties of two-dimensional airfoils, the major difficulty of incorporating it into optimization code is that XFOIL might not converge under certain circumstances. Instead of using XFOIL directly, an artificial neural network concept is introduced to conquer this problem. The performance of the rotor is calculated by using blade element momentum method (BEM) as well as the open source design code YAWDYNE. The design procedures adopted from [9, 10] are modified and used for this work and are listed as follows.

1. The radius of the rotor of the wind turbine is calculated according to the predefined wind condition and required power. In this study, the required power output of the wind turbine is selected as 25 kW and the wind speed is 12 m/sec. Therefore a rotor with radius 6.3 m and length 5.8 m is used for this study.
2. In general, the tip speed ratio of wind turbine (λ) ranges from 4 to 10. In this study, the tip speed ratio 4 is selected, and therefore the rotational speed of the wind turbine is 72 RPM.
3. The number of blades (B) is selected as 3 for the inherent nature of better dynamic balance characteristics [10].

4. The rotor blade is divided into several sections on which the airfoil shape, twist and chord are defined. The distance between adjacent sections (Δr_j, $j = 1, B$) is determined accordingly. Then the position of mid-point of each element (r_j, $j = 1, B$) can be determined. The blade is divided into six sections and the positions, in this study, are:

$$[0.1, 0.16, 0.35, 0.55, 0.75, 0.95]\cdot R \tag{1}$$

where R is the radius of the rotor. The first section is circular and other five sections' shapes are optimized following the next step.
5. A base airfoil is selected (NACA4412 in the present study). Each individual airfoil is optimized to obtain the best aerodynamic performance, the maximum lift-to-drag ratio (C_L/C_D) in this study. The orientation related parameters such as the local rotational speed ratio ($\lambda_{r,j}$), the local angle of relative wind (φ_j), the local chord length (c_j) and local pitch angle (θ_j) can then be calculated by Eq. (2-5) [8]:

$$\lambda_{r,j} = \lambda(r_j / R) \tag{2}$$

$$\varphi_j = \frac{2}{3}\tan^{-1}(1/\lambda_{r,j}) \tag{3}$$

$$c_j = \frac{8\pi r_j}{BC_{L,j}}(1-\cos\varphi_j) \tag{4}$$

$$\theta_j = \varphi_j - \alpha_j \tag{5}$$

6. The power coefficient (C_p) and the power of the wind turbine can be calculated by using BEM and YAWDYN.
7. The three-dimensional model of the optimized wind turbine blade can be generated by blending the optimized airfoils at each section.

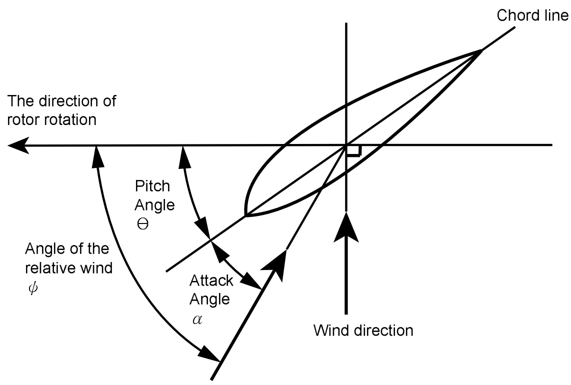


Fig. 1. Orientation of an airfoil

The major improvement of this procedure is that the C_L is maximized in each radial section such that the chord length calculated by Eq. (4) is a minimum. Therefore, the size of the blade can be reduced. This result is beneficial in structural design and cost reduction of rotor design.

2.3. Optimization model

As previously mentioned, the rotor blade is represented by six airfoil shapes and the five non-circular airfoils are optimized so that the lift-to-drag ratio is maximized. The design variables include the parameters defining the shape and orientation of the foil. These design variables are leading edge radius scaling ratio, thickness, camber and the attack angle. The following optimization statement demonstrates the objective function, side constraints and design variables for each section. The corresponding upper/lower bounds of design variables are listed in Table 1.

$$\min \quad f(x) = -\frac{C_L}{C_D} \quad \text{s. t.} \quad x_i^L \le x_i \le x_i^D \tag{6}$$

Table 1. 2-D airfoil deign variables and bounds

Design variables	Lower bound	Upper bound
LE radius scaling ratio	0.7	2.5
Thickness	0.07	0.21
Camber	0.00	0.09
Attack angle	-5	20

3. Optimization methods

3.1. Optimization architecture

The aerodynamic characteristic of wind turbine is a continuous nonlinear system. Gradient-based optimization methods, searching for the optimum design by defining a search direction using the derivatives of the objective function and constraints, are considered most efficient for this kind of problems. For a constrained design problem, the gradient-based optimization method can be separated into three levels, being strategy, optimizer and one-dimensional search [11, 12]. At each level, several options exist so that many possible combinations can be tried to give a better chance of obtaining the global optimum. The strategy level determines what technique is used to tackle the problem, for example, techniques that deal with the constraints directly or techniques that create a sequence of unconstrained minimizations by penalty concepts. Two strategies, the sequential unconstrained minimization technique with exterior penalty (SUMT-Exterior) and the Augmented Lagrange Multiplier Method (ALM) are tried in this study. The search direction is determined in the optimizer level. Various gradient-based algorithms are available. However, first-order methods are efficient and are considered most appropriate in the present study. The conjugate-direction method of Fletcher and Reeves and two variable metric methods, Davison-Fletcher-Powell (DFP) method and Broydon-Fletcher-Goldfarb-Shanno (BFGS), are selected for the optimizer level. Only one one-dimensional search method, the golden section method, is used.

3.2. Neural network models

As mentioned earlier, the XFOIL program cannot always get a converged solution and will cause unexpected termination of the optimization code. Therefore, a multilayer feedforward network (MLP) is used as a function approximator to replace the position of XFOIL in the optimization process. A three-layer network with the tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer is used [13]. The architecture of the network is shown in Fig. 2. The neurons of the input layer are used to receive the four design variables, i.e. LE radius scaling ratio, thickness, camber and the attack angle. The neuron of the output layer is used to send out the C_L/C_D, i.e. the lift-to-drag ratio**.** The input vector is normalized such that each input value is between [-1, 1]. A gradient-based training method, Levenberg-Marquardt algorithm (trainlm), is selected. This algorithm is designed to approach second-order training speed without having to compute the Hessian matrix. Training data are collected from the XFOIL analysis results and each training pair is composed of four inputs and one output.

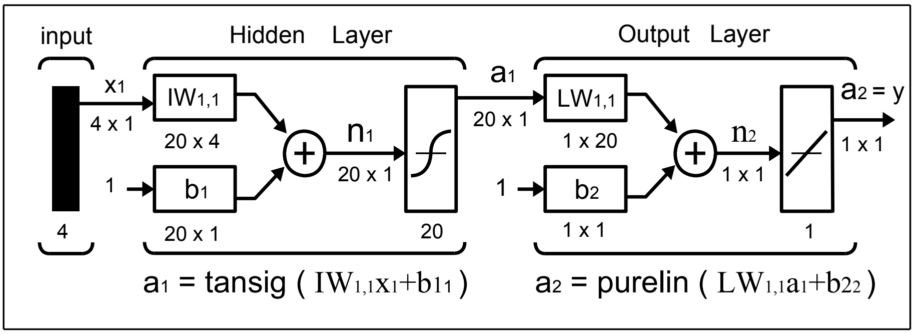


Fig. 2. Neural network architecture

The number of neurons in the hidden layer depends on how complicated the system is. By experiment, it is found that 40 neurons in the hidden layer can provide better prediction of C_L/C_D. During the training process, the average RMS error is reduced to about 0.00087 in 169 iterations.

4. Results and discussion

The airfoil profiles of the five sections are optimized using all possible combinations of methods at each optimization level. The best result obtained at each section and the corresponding methods used are listed in Table 2. Although some methods performed better than others, the difference is insignificant. The optimum C_L/C_D values for each section evaluated by XFOIL are also listed in Table 2. As can be seen from Table 2, the difference between the values predicted by the trained network and the XFOIL outputs are around 0.2 % ~ 1.0 %. This represents that the network is well-trained and is capable of making good predictions.

Table 2. Optimization results and corresponding methods

Sec.	Optimization method	Objective function and design variables	XFoil value (C_L/C_D)	Prediction error (%)
1	SUMT_F-R_Golden (exterior)	C_l/C_d = 151.0328 X = (2.5, 0.12, 0.08, 6.145)	149.475	1.042
2	SUMT_BFGS_Golden (exterior)	C_l/C_d = 165.1388 X = (2.5, 0.10, 0.09, 5.871)	164.026	0.678
3	SUMT_BFGS_Golden (exterior)	C_l/C_d = 191.2681 X = (2.5, 0.08, 0.09, 5.837)	189.838	0.753
4	ALM_F-R_Golden	C_l/C_d = 211.0682 X = (2.5, 0.06, 0.09, 4.268)	210.647	0.200
5	ALM_DFP_Golden	C_l/C_d = 219.8327 X = (2.5, 0.05, 0.09, 4.051)	219.214	0.282

The 2-D airfoil design parameters and aerodynamic performance are listed in Table 3 and the airfoil shapes are illustrated in Fig. 3. These parameters are then served as inputs to the BEM method and YAWDYNE to evaluate the three-dimensional aerodynamic characteristics. Fig. 4 shows the plots of C_L vs. attack angle, C_D attack angle and C_L/C_D vs. attack angle (α) of the five optimum 2-D foils.

Fig. 3 also shows that the foil is thicker near the root and is becoming thinner as it moves away from the rotor center and Table 3 shows that the outer airfoils have higher optimum lift-to-drag ratio. These facts have positive influence on the structural design of the blade. The rotational speed ratio ($\lambda_{r,j}$), the pitch angle (ϕ_j), the cord length and pitch angle calculated by Eq. (2-5) together with the optimum attack angle of each section are displayed in Table 4. A three-dimensional model of the wind turbine blade blended from the optimized airfoils is shown in Fig. 5.

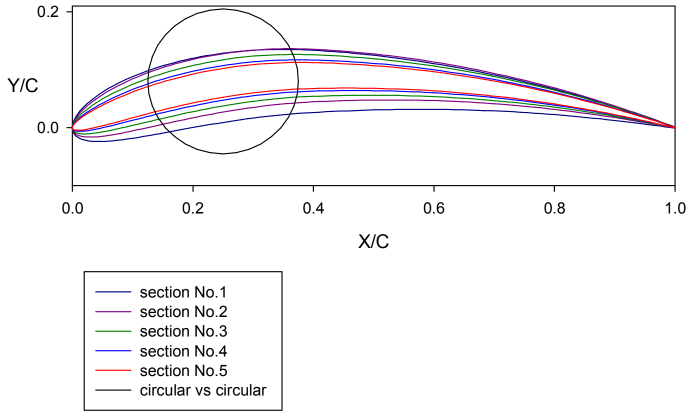


Fig. 3. Stack-up of the five optimum airfoils

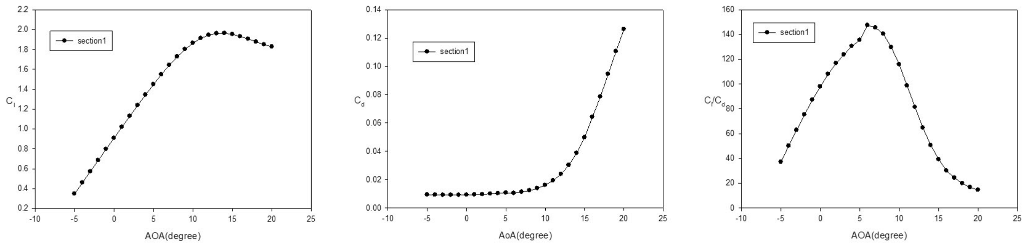
Table 3. Design parameters and aerodynamic performance of 2–D foils

Section	No. 0	No. 1	No. 2	No. 3	No. 4	No. 5
Location	0.1	0.16	0.35	0.55	0.75	0.95
R/L range	0.08~0.12	0.12~0.2	0.2~0.5	0.5~0.6	0.6~0.9	0.9~1
r/r_0	Circular	2.5	2.5	2.5	2.5	2.5
Thickness (chord)		0.12	0.1012	0.08	0.06	0.05
Camber		0.08	0.09	0.09	0.09	0.09
Attack angle		6.145	5.871	5.837	4.268	4.051
C_L		1.5656	1.6419	1.6478	1.5293	1.4512
C_D		0.01047	0.01001	0.00868	0.00728	0.00662
C_L/C_D		149.475	164.026	189.839	210.647	219.214

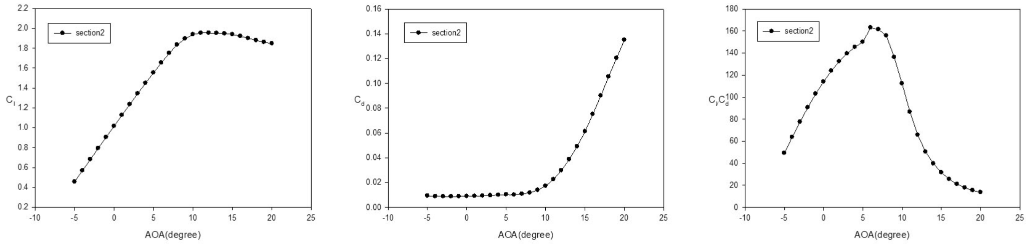
Both the original design and optimum design are evaluated by BEM and YAWDYNE code. The results are summarized in Table 5. As we can see from this table and Fig. 3, these two designs generate virtually the same power output. However, the foils of the optimized design are much shorter and thinner than the original NACA4412 design. This feature shows a great advantage when dealing with the structural design of the blade.

Table 4. Configurations of the optimum foils

Section	Location (R)	Rotational speed ratio	Relative wind angle (deg)	Attack angle (deg)	Chord (m)
1	0.16	0.633	38.4	6.1	1.169
2	0.35	1.385	23.9	5.9	0.963
3	0.55	2.177	16.4	5.8	0.721
4	0.75	2.969	12.4	4.3	0.605
5	0.95	3.760	9.9	4.1	0.517



(a)



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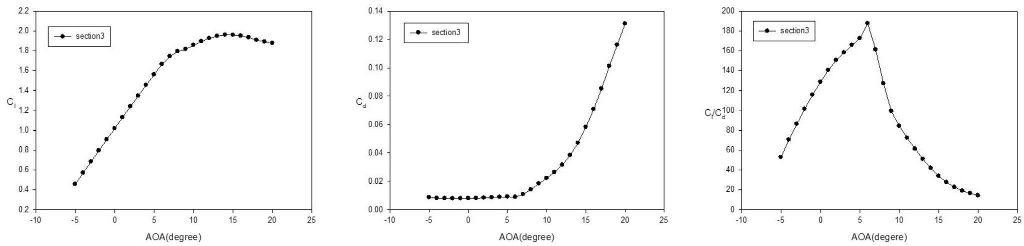

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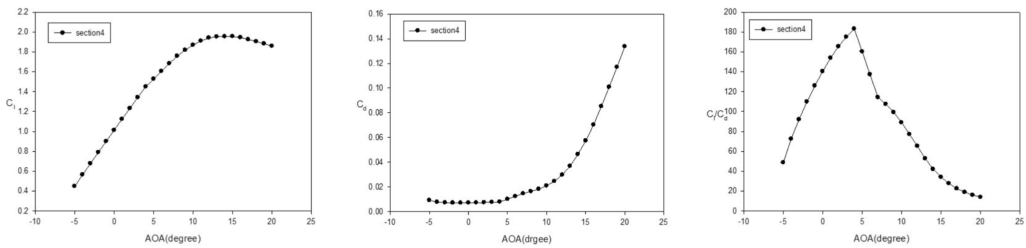
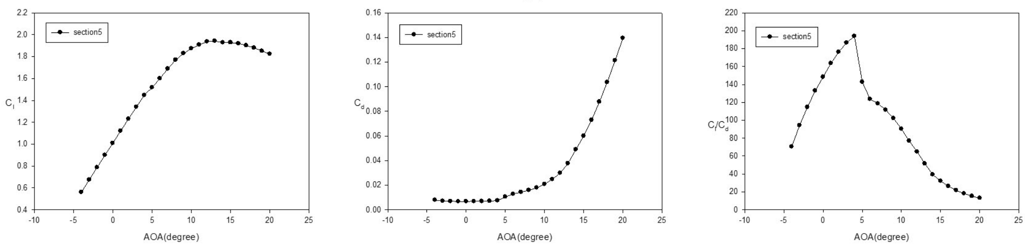


(d)



(e)

Fig. 4. C_L vs. attack angle, C_D vs. attack angle and C_l/C_D vs. attack angle:
(a) section 1, (b) section 2, (c) section 3, (d) section 4, (e) section 5

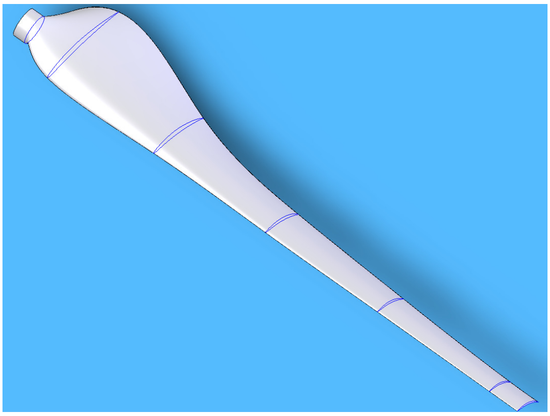


Fig. 5. 3-D model of the optimized blade

Table 5. Comparison of the original design and optimum design

NACA4412					
Location	Section 1 (root)	Section 2	Section 3	Section 4	Section 5 (tip)
Chord (m)	1.798	1.541	1.1607	0.903	0.7354
dP (kW)	1.503	14.434	7.845	31.446	9.704
P_{total} (kW)	BEM	64.932	NREL	63.752	
C_p	BEM	0.5090	NREL	0.4998	
NACA4412 (optimize OBJ = C_L/C_D maximum)					
Location	Section 1 (root)	Section 2	Section 3	Section 4	Section 5 (tip)
Chord (m)	1.169	0.963	0.721	0.605	0.517
dP (kW)	1.505	14.477	7.893	31.771	9.918
P_{total} (kW)	BEM	65.565	NREL	63.612	
C_p	BEM	0.5140	NREL	0.4987	

5. Conclusions

This research proposed an optimization process for blade design of wind turbine. The proposed method takes the concept of stacked design one step further, performing not only shape stacking, but shape optimization as well. With two strategies, three optimizers and one one-dimensioal search algorithms, six first-order optimization methods were developed. For the cases studied in this work, although some methods performed better than others, the difference is minor. A trained neural network is used in place of the XFOIL analysis to avoid unexpected termination of the optimization process due to the un-converged XFOIL run. The design obtained by the proposed method retains virtually the same power rating as the original design. However, the foils are much shorter and thinner. Therefore lighter and high performance wind turbine is achievable.

Acknowledgments

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