Struct Multidisc Optim (2015) 52:791–801
DOI 10.1007/s00158-015-1269-1

RESEARCH PAPER

Stacking sequence optimization of horizontal axis wind turbine blade using FEA, ANN and GA

P. Emmanuel Nicholas[1] · K. P. Padmanaban[2] · D. Vasudevan[1] · T. Ramachandran[1]

Received: 29 December 2014 / Revised: 4 April 2015 / Accepted: 15 May 2015 / Published online: 19 June 2015

Abstract The requirements for wind energy are significantly increasing for the sources of non-renewable energy is censoriously shortened and the awareness on green energy is emergent. The required energy from the wind turbine can be increased by optimally varying the aerodynamic considerations like aerofoil section, chord length, angle of attack, twist angle and the rotor diameter. However the blade may structurally fail, for the aerodynamic considerations are generally against the structural requirements. For example, the coefficient of lift can be increased with the reduced thickness but the structure may fail due to lacking of bending and torsional strength. Similarly, when the wind turbine blade radius is increased, the structure will have poor buckling strength. As the outer shape of a wind turbine blade and the thickness are determined based on the aerodynamic considerations, they are kept constant in this work and the buckling strength of the wind turbine structure is improved by optimally varying the ply orientations and stacking sequences at each section of the wind turbine blade. The difficulty due to high computational cost in the stacking sequence optimization of wind turbine blade is overcome by replacing finite element analysis using artificial neural network.

Keywords Stacking sequence optimization · Horizontal axis wind turbine blade · Artificial neural network · Genetic algorithm · Finite element analysis

✉ P. Emmanuel Nicholas
p.emmanuelnicholas@gmail.com

[1] Department of Mechanical Engineering, PSNA College of Engineering and Technology, Dindigul 624622, India

[2] Department of Mechanical Engineering, SBM College of Engineering and Technology, Dindigul 624005, India

1 Introduction

The requirements for wind energy are significantly increasing for the sources of non-renewable energy is critically shortened and the awareness on green energy is emergent. Cai et al. (2013) stated that the required energy can be increased by optimally varying the aerodynamic considerations, like aero foil section, chord length, angle of attack, angle of twist and the rotor diameter. However the aerodynamic considerations are generally against the structural performances of the wind turbine blade. For example, with the reduced thickness the coefficient of lift can be increased but the structure may fail due to lacking of bending strength and torsional strength. Froyd and Dahlhaug (2011) cited that the turbine rotor is increased so as to get maximum energy from the wind turbine. Lanting (2012) mentioned that the structure will have poor buckling strength when the wind turbine blade size becomes very large. As the radius of wind turbine blade is increased more than 70 m and the possibilities are there for the failure due to buckling and resonance, many researchers have optimized the wind turbine blade parameters to improve their structural performances.

Many researchers have optimized the design variables of the wind turbine blade to improve its structural and aerodynamic performances. Wang et al. (2011) referred that the optimization of wind turbine blade comprises many disciplines like aerodynamics, structural mechanics and aeroacoustics. Liao et al. (2012) optimally varied the thickness and the location of layers of spar caps in order to minimize the weight of the wind turbine blade. Vasjaliya Naishadh and Gangadharan (2013) optimized the shape parameters, twist angle, pitch angle and the thickness of composite layers of SERI-8 wind turbine blade to maximize its aerodynamic efficiency as well as to minimize the blade mass and cost. The tip deflections and the in-plane stresses were set as design constraints. Initially, the aerodynamic design variables like chord length, angle of attack and twist angle were optimized to improve the aerodynamic efficiency. Later, finite element analysis was used to analyze the structure when the thickness of composite layers was optimized using design of experiments. Wang et al. (2011) have chosen the maximization of power coefficient and minimization of blade mass, between which distinct conflicts exist, are chosen as design objectives. They used modified BEM theory to calculate the maximum power coefficient and the aerodynamic loads acting on the blade. The chord length, angle twist and the thickness of the spar were set as the design variables. Grujicic et al. (2010) developed a multi-optimization procedure to design the horizontal axis wind turbine blades. The airfoil type, chord-length, twist angle, location of the shear webs and the thickness of layers were chosen as the design variables. Zhu et al. (2014) minimized the weight and cost of a commercial 1.5 MW wind turbine blade by using glass fiber reinforced plastic (GFRP) together with carbon fiber reinforced plastic (CFRP) materials. The width of the spar cap, number of layers, location of layers and position of the shear webs were used as the design variables. The strain limit, blade and tower clearance limit and vibration were taken as the design constraints. The blade was subject to flap-wise load and edge-wise load conditions.

Hu et al. (2012) carried out the multi objective optimization to minimize the cost and weight of the wind turbine blade. The types of composite material, thickness of each layer and orientation angle were optimized to enhance the structural performance. The glass fiber reinforced plastic (GFRP) and carbon fiber reinforced plastic (CFRP) materials were used. Ultimate strength, fatigue failure and critical deflection of the blade were chosen as the design constraints. For easiness, the orientation angles are limited to 0°, ±45° and 90°. Jureczko et al. (2005) formulated a multi-objective optimization procedure to minimize the blade vibrations, material cost and maximize the power generated. They selected the shell thickness, web thickness, number and the arrangement of stiffening ribs as design variables. Song et al. (2011) took 20KW horizontal axis wind turbine blade and optimized the blade's aerodynamic contour based on Wilson method. Cai et al. (2012) presented an optimization procedure for the structural design of horizontal-axis wind turbine blade using particle swarm optimization algorithm (PSO) and finite element method (FEM). The minimization of weight of the structure was chosen as the design objective while the number and the location of layers in the spar cap and the positions of the shear webs were used as the design variables. Sale et al. (2013) carried out optimization process to minimize the weight of the wind turbine blade subject to the constraints like maximum allowable stress, tip deflection, buckling strength, and natural frequencies. Width of the spar cap, thickness of spar cap and thickness of shear web were chosen as the design objectives. Gaudern and Symons (2010) stated that buckling is one of the significant failures in wind turbine blade when its radius is increased. Zhu et al. (2014) and Lund (2009) mentioned that the buckling is the critical failure in wind turbine blades as they are modeled as thin walled structures and are subjected to flapwise bending load. Lund and Stegmann (2005) stated that the outer shape of a wind turbine blade and the thicknesses of the shell structures were usually determined based on the aerodynamic considerations and so they should not be subject to change. The blade is generally made up of glass fiber and carbon fiber reinforcement composites and so the buckling strength of wind turbine blade can be improved by optimally varying the stacking sequence itself.

The literature review evidently shows that the structural optimization on wind turbine blade is performed either by optimally varying the thickness of the material, material type and or the location of shear web. Though the structural performance of the composite structure highly depends on the ply orientation, the ply orientation having the reduced intervals is not considered as the design variable in the field of wind turbine blade. As the thickness is decided based on the aerodynamic considerations, the mass of the structure is kept constant in this paper and the buckling strength is maximized by optimally varying the ply orientation and the stacking sequence at each section of the wind turbine blade. Further the effect of dispersed layer angles over conventional layer angles is studied.

Table 1 Aerodynamic details of wind turbine blade Butterfield et al. (2009)

S. no	Radius (m)	Chord (m)	Twist (Deg.)	Type of airfoil
1	2	3.542	0	Cylinder
2	2.867	3.542	0	Cylinder
3	5.6	3.854	0	Cylinder
4	8.3333	4.167	0	Cylinder
5	11.75	4.557	13.308	DU40
6	15.85	4.652	11.48	DU35
7	19.95	4.458	10.162	DU35
8	24.05	4.249	9.011	DU30
9	28.15	4.007	7.795	DU25
10	32.25	3.748	6.544	DU25
11	36.35	3.502	5.361	DU21
12	40.45	3.256	4.188	DU21
13	44.55	3.01	3.125	NACA64
14	48.65	2.764	2.31	NACA64
15	52.75	2.518	1.526	NACA64
16	56.1667	2.313	0.863	NACA64
17	58.9	2.086	0.37	NACA64
18	61.6333	1.419	0.106	NACA64
19	62.9	0.7	0	NACA64

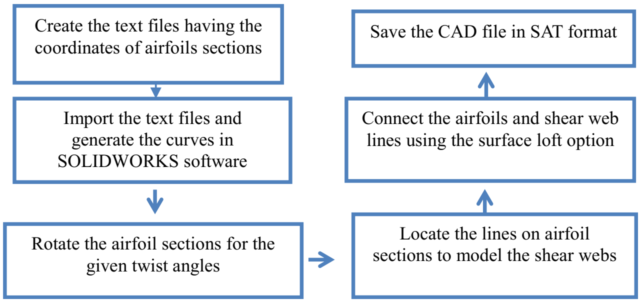


Fig. 1 Modelling of wind turbine blade

Le Riche and Haftka (1993) and Park et al. (2001) used genetic algorithm to maximize the strength of the laminated composites in which the design variables are discontinuous. Vincenti et al. (2013), Iyengar and Vyas (2011), Gurdal et al. (1994), Messager et al. (2002) and Todoroki and Ishikawa (2004) used GA to maximize the buckling strength of the laminated composites. Almeida and Awruch (2009), Rajendran and Vijayarangan (2001) and Gantovnik et al. (2002) used GA to reduce the weight of the laminated composites. Ghiasi et al. (2009) stated that GA can widely be used in all kind of applications, as it has a very simple and flexible procedure. The genetic algorithm, one of the most successful optimization techniques in discrete optimization technique is used to optimize the structure. The wind turbine blade has complex geometry and different numbers of layers. This increases the computational cost of the optimization technique and it is minimized in this paper by replacing the time consuming finite element method using artificial neural network.

2 Problem definition and formulation

2.1 Structural geometry of the blade

The aerodynamic factors like airfoil type, chord length and twist angle along the span of the wind turbine blade are obtained by using blade element momentum (BEM) theory. Butterfield et al. (2009) developed the specifications the

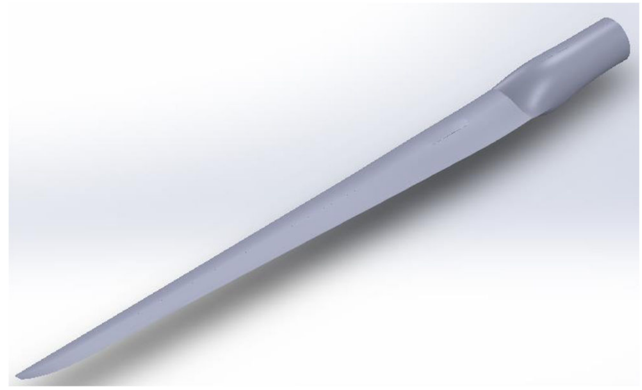


Fig. 3 CAD model of wind turbine blade

NREL offshore 5-MW baseline wind turbine to be used as a reference wind turbine by the researchers throughout the world. Many researchers (Sieros et al. (2012), Bazilevs et al. (2012) and Schlipf et al. (2013)) have used their proposed blade as the reference blade in their research works. As this work concerns only with the structural design of wind turbine blade, the aerodynamic factors proposed by Butterfield et al. (2009) are used to model the geometry of the blade. The blade is made up of a total length of 63 m in which the hub is 2 m long. In the remaining 61 m length of blade, different airfoil types are selected as follows. The bottom most portion of the blade is made with circular cross section as the maximum bending stress is acting on these portions. From the root of the blade to the tip of the blade the airfoil's type, chord length, twist angle and the thickness are gradually modified by considering the aerodynamic effects as shown in the Table 1. In Table 1 "DU" denotes to Delft University and "NACA" denotes to the National Advisory Committee for Aeronautics. The complex wind turbine structure is modelled as a shell using the commercial CAD software SOLIDWORKS. The step by step procedure of modelling of wind turbine blade is shown in Fig. 1.

The coordinates of each airfoil section is generated as text files based on the data provided in Table 1 and are imported in SOLIDWORKS. The generated airfoil section is later twisted for the given twist angle. The isometric and front views of the airfoil sections after twisting are shown in Fig. 2a and b.

Fig. 2 **a** 2D airfoil sections-isometric view **b** 2D airfoil sections-front view

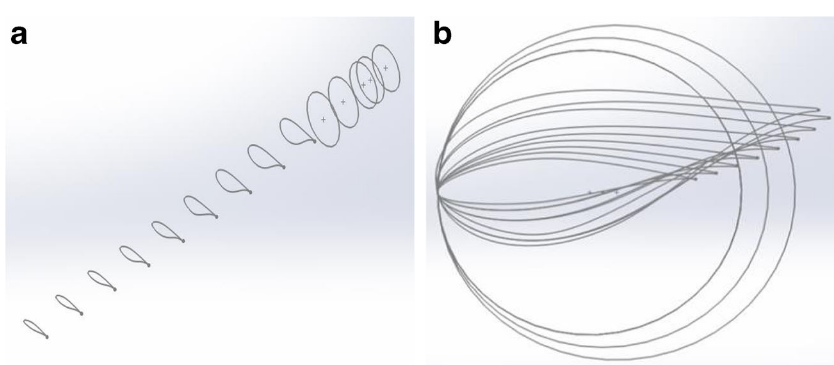
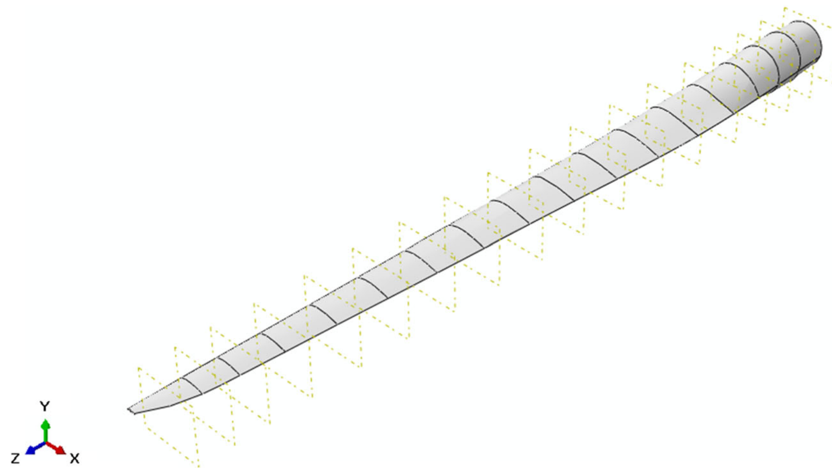


Fig. 4 Partitioned wind turbine blade sections



The lines are drawn on the airfoils to model the shear webs at the specified locations of shear webs. The surfaces modelling of wind turbine blade is obtained by joining all the airfoil sections and shear web lines using the surface loft option available in SOLIDWORKS. The 3D CAD model of the wind turbine blade is shown in Fig. 3.

2.2 Finite element model of the blade

The complex shape of the wind turbine blade requires finite element method to analyze them. Jensen et al. (2006) employed non-linear finite element analyses to predict the failure of a 34 m composite wind turbine blade under flap-wise loading. Lund et al. (2005) used finite element analysis to compute the stiffness of the wind turbine blade. Kong et al. (2005) proposed a specific configuration for the composite structure like wind turbine blade which can carry aerodynamic, hygrothermal and mechanical loads. They used finite element method to evaluate the complex composite structure. Maheri et al. (2007) evaluated the blade twist of the wind evaluation using the finite element analysis. Jureczko et al. (2005) analyzed the dynamics of the blade using finite element method. Zhu et al. (2014) analyzed a 1.5 MW wind turbine blade subject to the flapwise load using the finite element software ANSYS. Gaudern and Symons (2010) carried out finite element analysis to find the buckling strength of the blade using the ABAQUS. "S4R" shell elements were used to mesh the structure.

In this paper, the buckling strength of the wind turbine structure is analyzed using the finite element analysis software ABAQUS. The CAD model in SAT format is imported in ABAQUS software and is partitioned into 17 sections in order to assign different thickness and ply orientation from base to tip of the blade. The partitioned wind turbine structure is shown in Fig. 4.

The material properties listed in Table 2 are assigned to the wind turbine model. The material lay-up consists of a surface gel coat, lining materials, tri-axial laminate and uni-axial laminate (C120) as it is listed in Table 3. The gel coating is applied at the outer and inner most layers of the wind turbine blade in order to protect the blade from corrosion and to reduce the aerodynamic drag. The lining is applied following the gel coating to guard the load carrying laminas. The thicknesses of the gel coating and the lining material are kept constant throughout the structure. The FRP composite material of a thickness of 0.5 % of the chord length is applied throughout the blade to increase the buckling strength of the blade.

The shear webs are placed to resist the shear forces under flap wise deflection, however it also improves the strength of the blade under edgewise and torsional loading. In this work the webs are modeled with the same material lay-up and thickness. Though the location of webs have the influence on the structural performance of the blade, it is kept constant in this work so as to study the effect of fiber orientation and stacking sequence of the FRP composites. They are positioned at 15 and 50 % of the chord length. Once the material properties and

Table 2 Summary of material properties

Property	Gel coat	Random-mat laminate	Glass fiber	Balsa core
E_{11} in GPa	3.44	9.65	34.412	2.07
E_{22} in GPa	3.44	9.65	6.531	2.07
G_{12} in GPa	1.38	3.86	2.433	0.14
ν_{12}	0.3	0.3	0.217	0.22
Density, ρ in kg/m^3	1230	1670	2000	144

Table 3 Material lay-up sequence of wind turbine blade

S. no	Region	Material	Thickness of ply (in m)	Number of layers	Stacking sequence
1	Entire Blade	Gel	0.000128	4	fixed
2	Entire Blade	Random-mat laminate	0.000095	4	fixed
3	Entire Blade	Balsa core	0.000635	4	fixed
4	Set-1	Glass Fiber	0.00127	64	to be optimized
5	Set-2	Glass Fiber	0.00127	84	to be optimized
6	Set-3	Glass Fiber	0.00127	84	to be optimized
7	Set-4	Glass Fiber	0.00127	64	to be optimized
8	Set-5	Glass Fiber	0.00127	60	to be optimized
9	Set-6	Glass Fiber	0.00127	56	to be optimized
10	Set-7	Glass Fiber	0.00127	48	to be optimized
11	Set-8	Glass Fiber	0.00127	40	to be optimized
12	Set-9	Glass Fiber	0.00127	16	to be optimized
13	Entire Blade	Random-mat laminate	0.000095	4	fixed
14	Entire Blade	Gel	0.000128	4	fixed

layer angle with the thickness are specified, the structure is divided into finite elements using S4R elements. The finite element model of the wind turbine blade is shown in Fig. 5.

The blade is fixed at the root end. The flap-wise bending load is considered for this work and the wind load pressure acting on various sections of the wind turbine blade are obtained using the Eq. (1). These flap-wise bending loads are applied on the blade from the pressure side towards the suction side.

The Fig. 6 shows the forces acting on the airfoil section. The average wind velocity is taken as V∞ at an angle of attack of α. The lift force (L) and drag force (D) are always acting perpendicular and parallel to the wind velocity irrespective of the dimensions and orientation of the airfoil section. However, the normal force (N) and axial force (A) have to be measured with respect to the orientation and geometry (chord length) of the airfoil. In wind turbine blade, the normal load (N) is known as flap wise load and the axial load (A) is known as edge wise load. These loads can be calculated using the following Eq. (1).

$$\begin{aligned} F_n &= \frac{1}{2}\rho V^2 c C_d \\ F_a &= \frac{1}{2}\rho V^2 c C_l \end{aligned} \tag{1}$$

where ρ, V, c, C_d and C_l are air density of air (1.293 kg/m3), velocity of wind, coefficient of drag and coefficient of lift respectively. In this work only the flap wise load is considered and the value of Cd is varying based on the airfoil type and the angle of attack. Generally the coefficient of drag is 1.8 at the root and 1.6 at the tip of the blade (Zhang et al. (2011)). The blade is fixed at its root and the pressures of different values are applied at the different sections of the blade. The loading and boundary conditions are shown in Fig. 7.

3 Optimization procedure

3.1 Design objective

Gaudern and Symons (2010) stated that buckling is one of the significant failure modes in the field of design of large size wind turbine blades. Zhu et al. (2014) and Lund (2009) cited that the wind turbine blade is modelled as a thin walled structure and subjected to large flapwise bending moments. So the surface panels near the blade root of the blade are predominantly vulnerable to elastic instability which may cause failure due to buckling. As the wind turbine blade is modelled here for more than

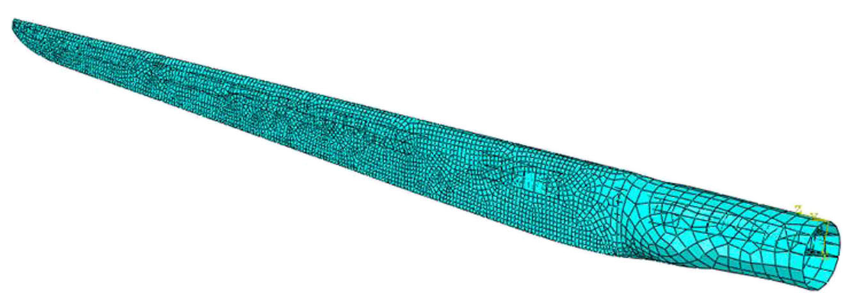


Fig. 5 Finite element model of wind turbine blade

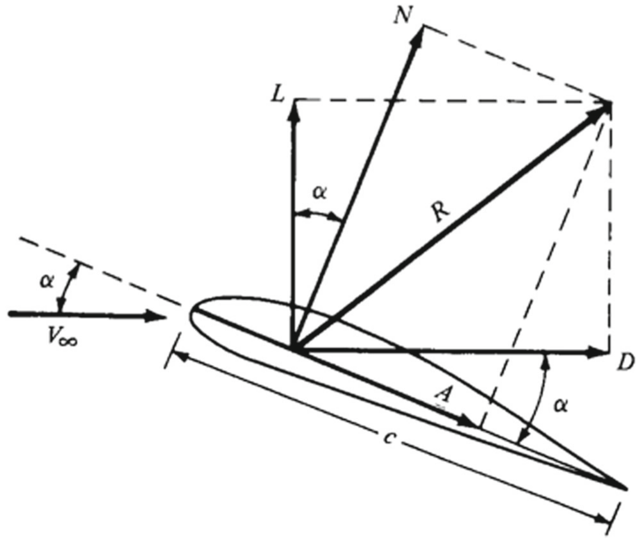


Fig. 6 Various loads acting on airfoil section

60 m and buckling is one of the critical failures in these cases, maximization of buckling strength of the wind turbine blade is chosen as the design objective.

3.2 Design variables

Lund (2009) stated that the outer shape of a wind turbine blade is decided based on the aerodynamic considerations and so they cannot be adjusted while the structure is optimized for the structural performances. As the blade is made of FRP composites for which the performances can be by tailoring the stacking sequences, the buckling strength of the structure is improved here by optimally varying the stacking sequences at various sections of the wind turbine blade.

3.3 Design constraints

The structural enactments like stiffness, strength, mass and vibrations are to be considered while the blade is designed.

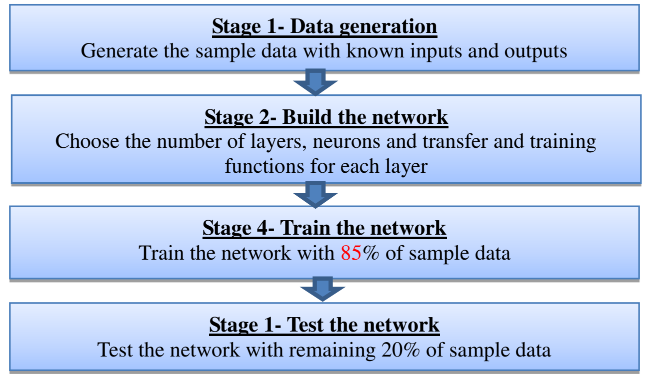


Fig. 8 Various stages in ANN construction

In order to make the optimization process simple and single objective, any one of these (most important) parameters is chosen as design objective and the other desired characteristics are considered as design constraints. In this paper, the maximum tip deflection is set as the design constraint. Hu et al. (2012) and Todoroki and Kawakami (2007) stated that generally the load is applied onto the windward face of the blade and it causes flapwise tip deflection. Generally the value of tip deflection must be lesser than 7 % of the blade length. The design constraint used in his work is given in Eq. (2).

$$Tip\ deflection,\ d \leq 0.07R = 4.41m \tag{2}$$

3.4 Optimization procedure

The optimization method proposed by the authors in their previous work (Emmanuel Nicholas et al. (2014)) has been considered here to optimize the ply orientations at each section of the wind turbine blade. The time consuming finite element method is replaced by the artificial neural network (ANN). Usually ANNs are used as a prediction tool for the applications in which the existing methods consume high computational time. As the geometry of the blade is more complex and FEA is required to analyze the structure, ANN is proposed here to

Fig. 7 Loading and boundary conditions of wind turbine blade

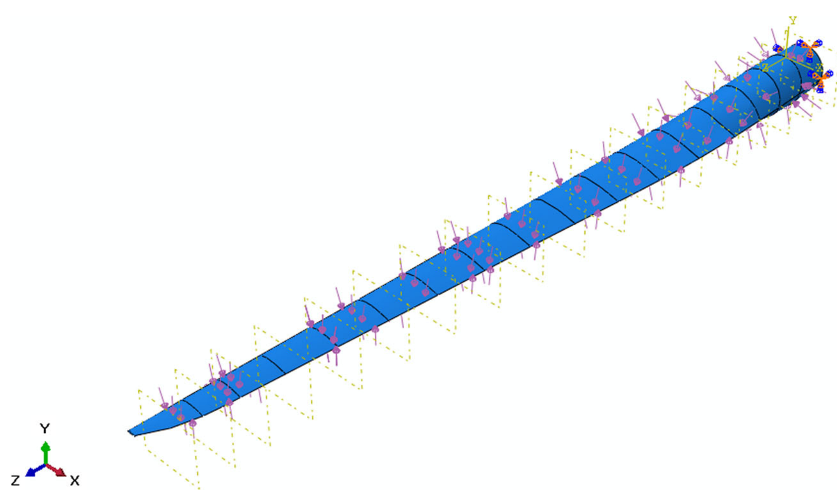


Table 4 Architecture of ANN

Ply angle interval	Neurons in each layer	Transfer function	Training algorithm
45°	9-25-3	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm
30°	9-25-3	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm
15°	9-25-3	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm
10°	9-25-3	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm
5°	9-25-3	Tansig-Tansig-Linear	Fletcher-Reeves conjugate gradient algorithm

predict the fitness value in genetic algorithm based optimization. A multilayer feed-forward back-propagation neural network is used. The various stages in the construction of neural network is Shown in Fig. 8. First, the sample data with their known outputs are generated randomly. Next, the network objects like number of layers, neurons in each layer, transfer function and the training algorithm of the network are chosen based on the trial and error method. The network is trained in the stage three with 85 % of the samples generated in first stage. Finally the network is tested with the remaining samples.

The performance of neural network during the training and after the training depends upon the choice of numbers of hidden layers, neurons, training algorithm and transfer function. Yuen and Lam (2006) mentioned that these parameters have to be decided based on the experience or rule of thumb only. Tomislav et al. (2014) have obtained the network structure by optimally varying these parameters. In this paper, the network objects are decided by trial and error method as Kermanshashi and Iwamiya (2002) and Chakraborty (2005) have done in their work. The network is constructed with three layers in which the first layer is an input layer followed by a hidden layer and an output layer. The inputs and the targets are normalized between −1 and 1. Tan-sigmoid transfer function is used for the first two layers and linear transfer function is used for the last layer. Fletcher-Reeves conjugate gradient training algorithm is used for this network which updates weight and bias values based on conjugate gradient back-propagation.

Usually the network will memorize the training and testing samples and function well during the training but when the same network is used for the newly generated data, there may be possibilities of over fitting. In order to improve the generalization of the network, the regularization method suggested by Demuth et al. (2009) is used in this work. In this method, the mean square error performance function is modified and added with the mean squared weights and biases of the network. The various objects of network obtained by trial and error method are shown in Table 4.

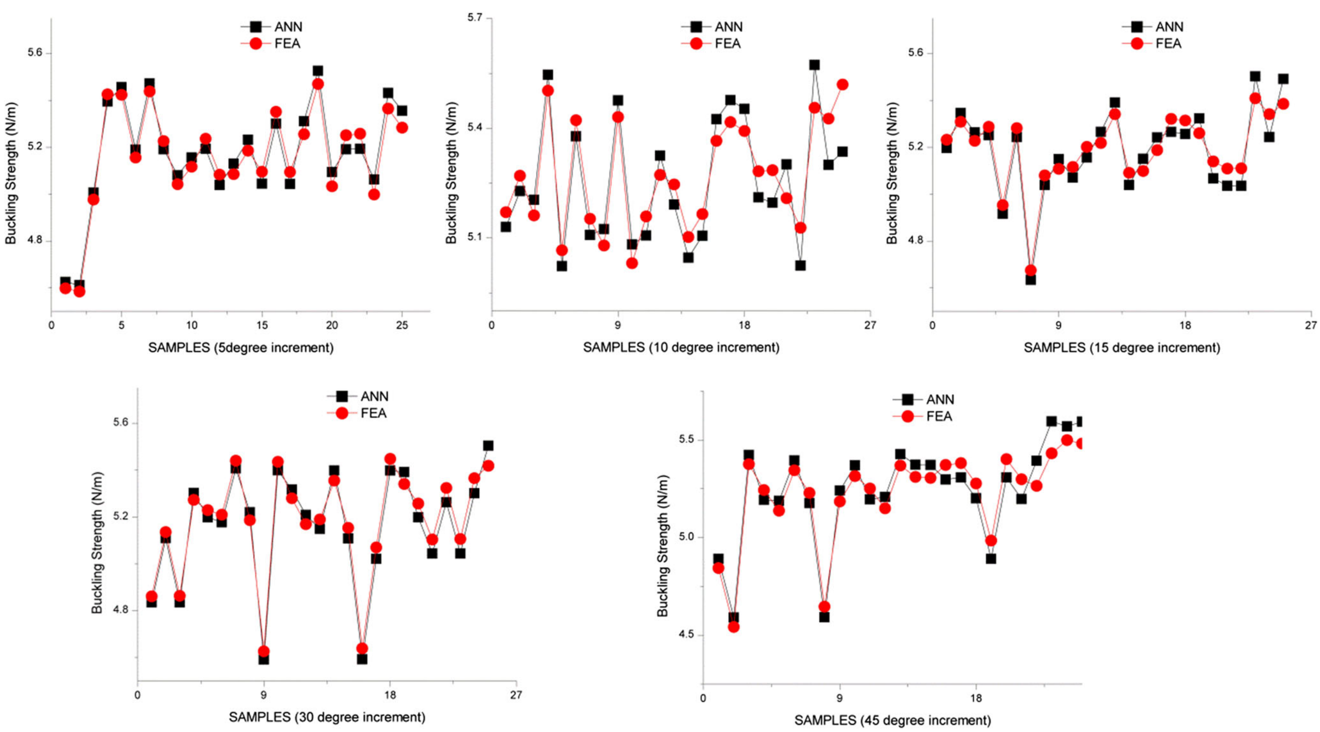


Fig. 9 Predictions of ANN Vs actual results

Table 5 The maximum buckling strength for the blade having same ply angles

S. no.	Angle of ply	Buckling strength in N/m	Maximum tip deflection in m
1	45°	5.1065	3.76
2	−45°	5.0472	3.79
3	90°	4.865	3.89
4	0°	4.887	3.84

Table 6 Optimum results

Ply angle interval	Optimum stacking sequence	Buckling strength (N/m)		Tip deflection (m)	
		ANN	FEM	ANN	FEM
45°	$[-45_{64}/90_{84}/45_{84}/0_{64}/45_{60}/-45_{56}/0_{48}/90_{40}/45_{16}]$	5.549	5.595	3.49	3.54
30°	$[90_{64}/90_{84}/-60_{84}/90_{64}/-60_{60}/30_{56}/-60_{48}/90_{40}/60_{16}]$	5.544	5.561	3.48	3.44
15°	$[-75_{64}/75_{84}/90_{84}/0_{64}/45_{60}/45_{56}/15_{48}/-75_{40}/45_{16}]$	5.610	5.58	3.46	3.57
10°	$[-80_{64}/90_{84}/-80_{84}/-80_{64}/90_{60}/-80_{56}/-80_{48}/-80_{40}/40_{16}]$	5.593	5.571	3.60	3.42
5°	$[80_{64}/-15_{84}/-85_{84}/10_{64}/-50_{60}/-50_{56}/-30_{48}/-70_{40}/45_{16}]$	5.623	5.655	3.61	3.493

Genetic algorithm, which has been proved as the preeminent optimization tool by many researchers in the field of optimization of laminated composite, is chosen for this work. It works with the genetic operators known as selection, crossover, and mutation. At first, the initial population of size 'N' is generated randomly and their fitness values are evaluated. The succeeding generations are fashioned by picking the parents from the current population based on their ranks and subsequently applying the genetic operators. Roulette wheel selection is used as the selection operator to pick the healthy chromosomes to accomplish crossover and mutation in order to yield the offspring. The crossover operator is used to combine two parent chromosomes to produce the new chromosomes called offspring. After the crossover, mutation takes place to avoid the population from stagnating at any local optima. Since the design variable is a discrete one in this work, a real coded genetic algorithm is used. The uniform crossover and mutation operators are applied. The uniform crossover operator permits the parent chromosomes, to be mixed at gene level rather than the segment level. The uniform mutation operator used here interchanges the value of the selected gene with a uniform random value selected between the upper and lower limits for that gene.

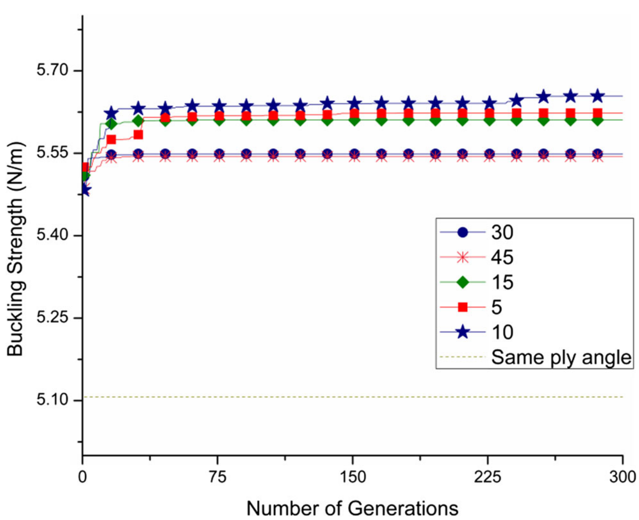


Fig. 10 Optimum results Vs number of generations

4 Numerical results and discussions

4.1 Construction of ANN

The optimization is carried out for each ply angle interval by optimally varying the stacking sequences at various sections of the wind turbine blade. The material properties and the loading conditions discussed in section 2 are applied. The stacking sequences are generated randomly for which the buckling strength and the tip deflection are computed using FEA later these samples are used to train the network. The choice of reduced ply angle intervals increases the design space from 4 to $37e^9$ and so 1000 samples are generated randomly for each ply angle interval and their desired targets are obtained. The python script written for ABAQUS software is used to analyze the structure. The networks with the architecture mentioned in Table 4 are trained using 85 % of these samples and then tested using the remaining samples. The efficiency of the trained network is shown in Fig. 9 where each network has been tested with newly generated 25 samples. The results show that the prediction of ANN is very close to the actual targets.

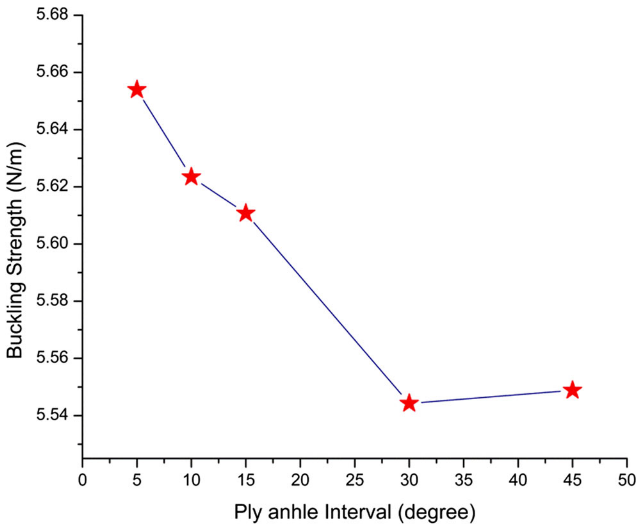


Fig. 11 Optimum results in each ply angle interval

4.2 Stacking sequence optimization of wind turbine blade

The effect of ply orientation on the structural performance of wind turbine blade is investigated here. The computational cost of the optimization technique is reduced by replacing the finite element analysis using trained neural network. Initially, the plies having same angle have been used from root to tip of the blade and the buckling strengths are calculated using FEM. The buckling strengths obtained for various conventional ply angles are given in Table 5 along with their corresponding maximum deflection. The results show that the blade has a maximum buckling strength of 5.1065 N/m when 45° ply angles have been used at all sections of the blade.

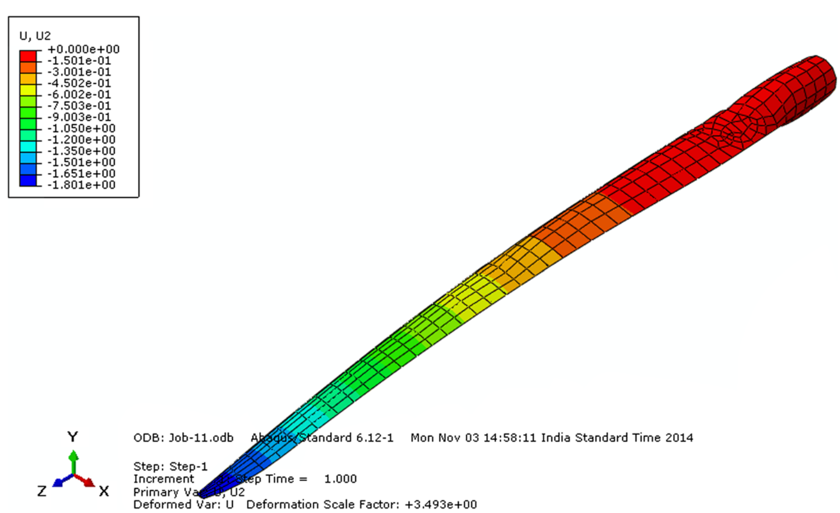
As wind turbine blade has different airfoil section and thickness from root to tip of the blade and the magnitudes of the wind load also vary from section to section, the ply angles at each section of the blade are optimized. As the structure of the blade has been divided into nine groups during the material layup, the angles of plies used in these nine sections are to be optimized.

The maximum buckling strength is found to be 5.1065 N/m when the same ply angles have been used in all sections of the wind turbine blade. However, it is found that the maximum buckling strength has been increased from 5.1065 to 5.65 N/m, when the ply angle at each section of the blade is optimized using the concept of ply angles with reduced intervals. The solutions of the optimum designs obtained in all ply angle intervals are compared using FEM and are given in Table 6 which proves that the predictions of ANN are prodigious. It is also proved that the buckling strength of the blade is increased by 10.64 % by just optimally varying the ply angle itself at each section of the blade whereas the aerodynamic factors and the thickness of the blade are kept unchanged. The Fig. 10 divulges that the results have been converged even after 275 generations (for 5° ply interval) where each generation has 60 populations. If FEA would have been used to predict the objective function, the optimization procedure would consume more than 400 h for each run of FEA takes 1.5 min approximately. However this problem has been resolved in this proposed method with the choice of artificial neural network with which the optimization procedure consumes less than 5 min to find the optimum stacking sequence. As GA is one of the Stochastic Optimization (SO) methods, it must be run several times in order to ensure that there is no possibility for the optimization algorithm to get stuck in any local optima. As GA has to be run several times to ensure for the global optima, the optimization process in which FEM has been used to evaluate the fitness function is highly complex due to the computational time. However, when ANN is used to predict the fitness value, its weights and biases can be stored and used in future at any number of times without any further training to the network.

The optimum results obtained in each ply angle interval is compared in the Fig. 11 which shows that the buckling strength can be further increased about 2 % with the choice of reduced ply angle intervals.

The deflection of wind turbine blade due to the flap wise wind load is plotted in Fig. 12 for the optimum stacking sequence. The

Fig. 12 Maximum tip deflection of blade



maximum deflection is occurred at the tip of the blade with the value of 3.49 m which is within the permissible limit.

5 Conclusions

The horizontal axis wind turbine blade has been optimized to improve the buckling strength of the structure. As the aerodynamic factors and the thickness of the structure are decided based on the aerodynamic considerations, they have been kept constant. The blade is generally made of FRP composites and so the structural performance of the blade has been improved by just optimally varying the ply orientations at each section of the blade. One of the main difficulties involved in stacking sequence optimization of the wind turbine blade is very high computational cost and this problem has been overcome in this paper by using the proposed optimization technique in which neural network has been used to replace the finite element analysis. The numerical results show that the prediction of networks are very close to the actual targets and so the network can be used to predict the fitness value for the genetic algorithm based optimization technique. The optimization has been carried out using various ply angle intervals and it has been found that the buckling strength can be increased about 10.64 % by just varying the stacking sequences of the wind turbine blade. In addition, it has been shown that the buckling strength can be further increased to 2 % with the choice of reduced ply angle interval. The results also show that the computational cost has been significantly reduced by using artificial neural network.

References

Almeida FS, Awruch AM (2009) Design optimization of composite laminated structures using genetic algorithms and finite element analysis. Compos Struct 88(3):443–454

Bazilevs Y, Hsu MC, Scott MA (2012) Isogeometric fluid–structure interaction analysis with emphasis on non-matching discretizations, and with application to wind turbines. Comput Methods Appl Mech Eng 249:28–41

Butterfield S, Musial W, Scott G (2009) Definition of a 5-MW reference wind turbine for offshore system development. National Renewable Energy Laboratory, Golden

Cai X, Zhu J, Pan P, Rongrong G (2012) Structural optimization design of horizontal-axis wind turbine blades using a particle swarm optimization algorithm and finite element method. Energies 5(11):4683–4696

Cai X, Pan P, Zhu J, Rongrong G (2013) The analysis of the aerodynamic character and structural response of large-scale wind turbine blades. Energies 6(7):3134–3148

Chakraborty D (2005) Artificial neural network based delamination prediction in laminated composites. Mater Des 26(1):1–7

Demuth H, Beale M, Martin H (2009) Neural network toolbox user’s guide. The Mathworks, Natick

Emmanuel Nicholas P, Padmanaban KP, Vasudevan D (2014) Buckling optimization of laminated composite plate with elliptical cutout using ANN and GA. Struct Eng Mech 52(4):815–827

Froyd L, Dahlhaug O (2011) Rotor design for a 10 MW offshore wind turbine. In Proceedings of the Twenty-first International Offshore and Polar Engineering Conference 19–24

Gantovnik VB, Gürdal Z, Watson LT (2002) A genetic algorithm with memory for optimal design of laminated sandwich composite panels. Compos Struct 58(4):513–520

Gaudern N, Symons DD (2010) Comparison of theoretical and numerical buckling loads for wind turbine blade panels. Wind Eng 34(2):193–206

Ghiasi H, Pasini D, Lessard L (2009) Optimum stacking sequence design of composite materials part I: constant stiffness design. Compos Struct 90(1):1–11

Grujicic M, Arakere G, Pandurangan B, Sellappan V, Vallejo A, Ozen M (2010) Multidisciplinary design optimization for glass-fiber epoxy-matrix composite 5 MW horizontal-axis wind-turbine blades. J Mater Eng Perform 19(8):1116–1127

Gurdal Z, Haftka RT, Nagendra S (1994) Genetic algorithms for the design of laminated composite panels. SAMPE J 30(3):29–35

Hu W, Han I, Park SC, Choi DH (2012) Multi-objective structural optimization of a HAWT composite blade based on ultimate limit state analysis. J Mech Sci Techol 26(1):29–135.

Iyengar NGR, Vyas N (2011) Optimum design of laminated composite under axial compressive load. Sadhana 36(1):73–85

Jensen FM, Falzon BG, Ankersen J, Stang H (2006) Structural testing and numerical simulation of a 34 m composite wind turbine blade. Compos Struct 76(1):52–61

Jureczko MEZYK, Pawlak M, Mężyk A (2005) Optimisation of wind turbine blades. J Mater Process Technol 167(2):463–471

Kermanshashi B, Iwamiya H (2002) Up to 2020 load casting using neural nets. Electr Power Energy Syst 24:789–797

Kong C, Bang J, Sugiyama Y (2005) Structural investigation of composite wind turbine blade considering various load cases and fatigue life. Energy 30:2101–2114

Lanting Z (2012) Research on structural lay-up optimum design of composite wind turbine blade. Energy Procedia 14:637–642

Le Riche R, Haftka RT (1993) Optimization of laminate stacking sequence for buckling load maximization by genetic algorithm. AIAA J 31(5):951–956

Liao CC, Zhao XL, Xu JZ (2012) Blade layers optimization of wind turbines using FAST and improved PSO. Renew Energy 42:227–233

Lund E (2009) Buckling topology optimization of laminated multi-material composite shell structures. Compos Struct 91:158–167

Lund E, Stegmann J (2005) On structural optimization of composite shell structures using a discrete constitutive parametrization. Wind Energy 8(1):109–124

Lund E, Kuhlmeier L, Stegmann J (2005) Buckling optimization of laminated hybrid composite shell structures using discrete material optimization. 6th World Congress on Structural and Multidisciplinary Optimization

Maheri A, Noroozi S, Vinney J (2007) Combined analytical/FEA-based coupled aero structure simulation of a wind turbine with bend–twist adaptive blades. Renew Energy 32:916–930

Messager T, Pyrz M, Gineste B, Chauchot P (2002) Optimal laminations of thin underwater composite cylindrical vessels. Compos Struct 58(4):529–537

Park JH, Hwang JH, Lee CS, Hwang W (2001) Stacking sequence design of composite laminates for maximum strength using genetic algorithms. Compos Struct 52(2):217–231

Rajendran I, Vijayarangan S (2001) Optimal design of a composite leaf spring using genetic algorithms. Comput Struct 79(11):1121–1129

Sale D, Aliseda A, Motley M, Li Y (2013) Structural optimization of composite blades for wind and hydrokinetic turbines. Proceedings of the First Marine Energy Technology Symposium, Washington

Schlipf D, Schlipf DJ, Kühn M (2013) Nonlinear model predictive control of wind turbines using LIDAR. Wind Energy 16(7):1107–1129

Sieros G, Chaviaropoulos P, Sorensen JD, Bulder BH, Jamieson P (2012) Upscaling wind turbines: theoretical and practical aspects and their impact on the cost of energy. Wind energy 15(1):3–17

Song F, Ni Y, Tan Z (2011) Optimization design, modeling and dynamic analysis for composite wind turbine blade. Procedia Eng 16:369–375

Todoroki A, Ishikawa T (2004) Design of experiments for stacking sequence optimizations with genetic algorithm using response surface approximation. Compos Struct 64(3):349–357

Todoroki A, Kawakami Y (2007) Structural design for CF/GF hybrid wind turbine blade using multi-objective genetic algorithm and kriging model response surface method. AIAA Conference and Exhibit, California

Tomislav B, Ukic S, Peternel I, Kusic H, Bozic AL (2014) Artificial neural network models for advanced oxidation of organics in water matrix-comparison of applied methodologies. Indian J Chem Tech 21(1):21–29

Vasjaliya Naishadh G, Gangadharan SN (2013) Aero-structural design optimization of composite wind turbine blade. PhD diss., PhD thesis, Embry-Riddle Aeronautical University

Vincenti A, Vannucci P, Ahmadian MR (2013) Optimization of laminated composites by using genetic algorithm and the polar description of plane anisotropy. Mech Adv Mater Struct 20(3):242–255

Wang L, Wang T, Luo Y (2011) Improved non-dominated sorting genetic algorithm (NSGA)-II in multi-objective optimization studies of wind turbine blades. Appl Math Mech 32:739–748

Yuen K-V, Lam H-F (2006) On the complexity of artificial neural networks for smart structures monitoring. Eng Struct 28(7):977–984

Zhang C, Wang S, Xie H (2011) Static structural analysis of parked composite wind turbine blades. Proceedings of the 8th International Conference on Structural Dynamics, Leuven

Zhu J, Cai X, Pan P, Rongrong G (2014) Multi-objective structural optimization design of horizontal-axis wind turbine blades using the non-dominated sorting genetic algorithm II and finite element method. Energies 7(2):988–1002