



# 1 Structural optimisation of wind turbine towers based on finite

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# element analysis and genetic algorithm

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## 3 Abstract

### 4

5 A wind turbine tower supports the main components of the wind turbine (e.g. rotor, nacelle, drive train components, etc.). The structural properties of the tower (such as stiffness and natural frequency) can 6 7 significantly affect the performance of the wind turbine, and the cost of the tower is a considerable portion of the overall wind turbine cost. Therefore, an optimal structural design of the tower, which has a 8 9 minimum cost and meets all design criteria (such as stiffness and strength requirements), is crucial to 10 ensure efficient, safe and economic design of the whole wind turbine system. In this work, a structural 11 optimisation model for wind turbine towers has been developed based on a combined parametric FEA (finite element analysis) and GA (genetic algorithm) model. The top diameter, bottom diameter and 12 13 thickness distributions of the tower are taken as design variables. The optimisation model minimises the 14 tower mass with six constraint conditions, i.e. deformation, ultimate stress, fatigue, buckling, vibration and 15 design variable constraints. After validation, the model has been applied to the structural optimisation of a 16 5MW wind turbine tower. The results demonstrate that the proposed structural optimisation model is capable of accurately and effectively achieving an optimal structural design of wind turbine towers, which 17 18 significantly improves the efficiency of structural optimisation of wind turbine towers. The developed 19 framework is generic in nature and can be employed for a series of related problems, when advanced 20 numerical models are required to predict structural responses and to optimise the structure.

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# 22 **1. Introduction**

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24 Wind power is capable of providing a competitive solution to battle the global climate change and energy 25 crisis, making it the most promising renewable energy resource. As an abundant and inexhaustible energy resource, wind power is available and deployable in many regions of the world. Therefore, regions such as 26 Northern Europe and China are making considerable efforts in exploring wind power resources. According 27 to Global Wind Energy Council (GWEC, 2016), the global wind power cumulative capacity reached 432 28 29 GW at the end of 2015, growing by 62.7 GW over the previous year. It is predicted that wind power could reach a total installed global capacity of 2,000 GW by 2030, supplying around 19% of global electricity 30 31 (Council, 2015).

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32 A wind turbine tower supports the main components of the wind turbine (e.g. rotor, nacelle, drive train 33 components, etc.) and elevates the rotating blades at a certain elevation to obtain desirable wind characteristics. The structural properties of a wind turbine tower, such as the tower stiffness and natural 34 35 frequency, can significantly affect the performance and structural response of the wind turbine, providing adequate strength to support induced loads and avoiding resonance. Additionally, the cost of the tower is a 36 significant portion of the overall wind turbine cost (Aso and Cheung, 2015). Therefore, an optimal 37 structural design of the tower, which has a minimum cost and meets all design criteria (such as stiffness 38 39 and strength requirements), is crucial to ensure efficient, safe and economic design of the whole wind 40 turbine system. It also contributes to reducing the cost of energy, which is one of the long-term research 41 challenges in wind energy (van Kuik et al., 2016).

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43 The structural optimisation model of a wind turbine tower generally consists of two components, i.e. 1) a 44 wind turbine tower structural model, which analyses the structural performance of the tower, such as tower 45 mass and deformations; and 2) an optimisation algorithm, which deals with design variables and searches 46 for optimal solutions.

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Structural models used for wind turbine towers can be roughly classified into two groups, i.e. 1D (one-48 49 dimensional) beam model and 3D (three-dimensional) FEA (finite element analysis) model. The 1D beam 50 model discretises the tower into a series of beam elements, which are characterised by cross-sectional 51 properties (such as mass per unit length and cross-sectional stiffness). Due to its efficiency and reasonable 52 accuracy, the 1D beam model has been widely used for structural modelling of wind turbine towers (Zhao 53 and Maisser, 2006, Murtagh et al., 2004) and blades (Wang et al., 2014b, Wang et al., 2014a, Wang, 2015). 54 Although it is efficient, the beam model is incapable of providing some important information for the 55 tower design, such as detailed stress distributions within the tower structure, hence making such models incapable of capturing localised phenomena such as fatigue. In order to obtain the detailed information, it 56 57 is necessary to construct the tower structure using 3D FEA. In 3D FEA, wind turbine towers are generally constructed using 3D shell or brick elements. Compared to the 1D beam model, the 3D FEA model 58 59 provides more accurate results and is capable of examining detailed stress distributions within the tower structure. Due to its high fedility, the 3D FEA model has been widely used for modelling wind turbine 60 structures (Wang et al., 2015, Wang et al., 2016b, Stavridou et al., 2015). Therefore, the 3D FEA model is 61 62 chosen in this study to model the wind turbine tower structure.

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Optimisation algorithms can be roughly categorised into three groups (Herbert-Acero et al., 2014), i.e. exact algorithms, heuristic algorithms and metaheuristic algorithms. Exact algorithms, which find the best solution by evaluating every possible combination of design variables, are very precise because all possible combinations are evaluated. However, they become time-consuming and even infeasible when the number of design variables is large, requiring huge computational resources to evaluate all possible combinations. Heuristic algorithms, which find near-optimal solutions based on semi-empirical rules, are more efficient





70 than exact algorithms. However, they are problem-dependent and their accuracy highly depends on the 71 accuracy of semi-empirical rules, limiting their applications to some extent. Metaheuristic algorithms, 72 which are more complex and intelligent heuristics, are high-level problem-independent algorithms to find 73 near-optimal solutions. They are more efficient than common heuristic algorithms and are commonly 74 based on optimisation processes observed in the nature, such as PSO (particle swarm optimisation) 75 (Kennedy, 2011), SA (simulated annealing) (Dowsland and Thompson, 2012) and GA (genetic algorithm) 76 (Sivanandam and Deepa, 2007). Among these metaheuristic algorithms, the GA, which searches for the 77 optimal solution using techniques inspired by genetics and natural evolution, is capable of handling a large 78 number of design variables and avoiding being trapped in local optima, making it the most widely used 79 metaheuristic algorithm (Wang et al., 2016a). Therefore, the GA is selected in this study to handle the 80 design variables and to find the optimal solution.

81

This paper attempts to combine FEA and GA to develop a structural optimisation model for onshore wind turbine towers. A parametric FEA model of wind turbine towers is developed and validated, and then coupled with GA to develop a structural optimisation model. The structural optimisation model is applied to a 5MW onshore wind turbine to optimise the 80m-height tower structure.

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This paper is structured as follows. Section 2 presents the parametric FEA model of wind turbine towers.
Section 3 presents the GA model. Section 4 presents the optimisation model by combining the parametric
FEA model and GA model. Results and discussions are provided in Section 5, followed by conclusions in
Section 6.

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## 92 2. Parametric finite element analysis (FEA) model of wind turbine towers

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## 94 2.1. Model description

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96 A parametric FEA model of wind turbine towers is established using ANSYS, which is a widely used 97 commercial FE software. The parametric FEA model enables the design parameters of wind turbine towers 98 to be easily modified to create various tower models. The flowchart of the parametric model of wind 99 turbine towers is presented in Fig. 1.







- 100 101
- Figure 1. Flowchart of the parametric FEA model for wind turbine towers
- 102
- 103 Each step of the flowchart Fig. 1 is detailed below.
- 104

105 1) Define design parameters: In the first step, design parameters of the wind turbine towers, such as tower

106 top and bottom diameters, are defined.

107 2) Create tower geometry: The tower geometry is created based on the bottom-up approach, which creates

- 108 low dimensional entities (such as lines) first and then creates higher dimensional entities (such as areas) on 109 top of low dimensional entities.
- 110 3) Define and assign material properties: In this step, material properties (such as Young's modulus and
- 111 Poisson's ratio) are defined and then assigned to the tower structure.
- 4) Define element type and generate mesh: Due to the fact that wind turbine towers are generally thin-wall structures, they can be effectively and accurately modelled using shell elements. The element type used here is the shell element Shell281, which has eight nodes with six degrees of freedom at each node and it is well-suited for linear, large rotation, and/or large strain nonlinear applications. Additionally, a regular quadrilateral mesh generation method is used to generate high quality element, ensuring the computational accuracy and saving on computational time.
- 5) Define boundary conditions: In this step, boundary conditions are applied. The types of boundary
  conditions are dependent on the types of analyses. For instance, a fixed boundary condition is applied to
  the tower bottom for modal analysis.
- 6) Solve and post-process: Having defined design parameters, geometry, materials, element types, mesh and boundary conditions, a variety of analyses (such as static analysis, modal analysis and buckling analysis) can be performed. The simulation results, such as tower deformations and stress distributions, are then plotted using post-processing functions of ANSYS software.
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#### 126 **2.2. Validation of the parametric FEA model**

- 127
- 128 A case study is performed to validate the parametric FEA model of wind turbine towers. The NREL 5MW
- 129 wind turbine (Jonkman et al., 2009), which is a representative of large-scale of HAWTs is chosen as an





example. The NREL 5MW wind turbine is a reference wind turbine designed by NREL (National Renewable Energy Laboratory), and it is a conventional three-bladed upwind HAWT, utilising variablespeed variable-pitch control. The geometric and material properties of NREL 5MW wind turbine tower are presented in Table 1. The steel density is increased from a typical value of 7,850 kg/m<sup>3</sup> to a value of 8,500 kg/m<sup>3</sup> to take account of paint, bolts, welds and flanges that are not accounted for in the tower thickness data (Jonkman et al., 2009). The diameters and thickness of the tower are linearly tapered from the tower base to tower top.

137

138 Table 1. Geometric and material properties of the NREL 5MW wind turbine tower (Jonkman et al., 2009)

Properties	Values
Tower height [m]	87.6
Tower top outer diameter [m]	3.87
Tower top wall thickness	0.0247
Tower base outer diameter [m]	6
Tower base wall thickness [m]	0.0351
Density [kg/m <sup>3</sup> ]	8500
Young's modulus [GPa]	210
Shear modulus [GPa]	80.8

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140 The parametric FEA model presented in Section 2.1 is applied to the modal analysis of the NREL 5MW wind turbine tower. In this case, the tower is fixed at the tower bottom and free-vibration (no loads on the 141 tower), and tower head mass is ignored. A regular quadrilateral mesh generation method is used to generate 142 143 high quality elements. In order to determine the appropriate mesh size, a mesh sensitivity study is carried 144 out for the first 6 modal frequencies, of which the results are presented in Table 2. As can be seen from Table 2, the modal frequencies converge at a mesh size of 0.5m, with a maximum relative difference 145 (0.002%) occurring for the 2<sup>nd</sup> side-to-side mode when compared to further mesh refinement with a mesh 146 size of 0.25m. Therefore, 0.5m is deemed as the appropriate element size. The created mesh is presented in 147 148 Fig. 2, and the total number of element is 6,960.

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Table	2.	FEA	mesh	sensitivity	analysis
14010		1 12/1	meon	Sensitivity	unuiyon

Modal frequencies	2m sizing	1m sizing	0.5m sizing	0.25m sizing
1 <sup>st</sup> SS (Hz)	0.8781	0.8782	0.8782	0.8782
1 <sup>st</sup> FA (Hz)	0.8855	0.8855	0.8856	0.8856
2 <sup>nd</sup> SS (Hz)	4.2315	4.2305	4.2276	4.2275
$2^{nd}$ FA (Hz)	4.2463	4.2469	4.2429	4.2428

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(where SS refers to side-to-side; FA refers to force-aft)







1	5	2
1	5	3

Figure 2. Mesh of NREL 5MW wind turbine tower

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Table 3 compare the results from the present FEA model against the results from ADAMS software reported in Ref. (Jonkman and Bir, 2010).

157

158

Table 3. Mode frequencies of NREL 5MW wind turbine tower

Mode frequencies	ADAMS (Jonkman	Present FEA model	%Diff
	and Bir, 2010)		
1 <sup>st</sup> SS (Hz)	0.8904	0.8782	1.37
1 <sup>st</sup> FA (Hz)	0.8904	0.8856	0.54
2 <sup>nd</sup> SS (Hz)	4.3437	4.2276	2.67
$2^{nd}$ FA (Hz)	4.3435	4.2429	2.32

As can be seen from Table 3, the force-aft (FA) and side-to-side (SS) tower modal frequencies calculated from the present FEA model match well with the results reported in Ref. (Jonkman and Bir, 2010), with the maximum percentage difference (2.67%) occurring for the  $2^{nd}$  SS mode. This confirms the validity of the present parametric FEA model of wind turbine towers.

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## 165 **2.3. Application of parametric FEA model to a 5MW wind turbine tower**

166

167 The parametric FEA model is applied to FEA modelling of a 5MW wind turbine tower. The geometry and 168 material properties, mesh, boundary conditions used in the FEA modelling are presented below.

169

### 170 2.3.1. Geometry and material properties

171

The geometric and material properties of 5MW wind turbine tower are presented in Table 4. Again, the steel density is increased from a typical value of 7,850 kg/m<sup>3</sup> to a value of 8,500 kg/m<sup>3</sup>, taking account of paint, bolts, welds and flanges that are not accounted for in the tower thickness data. The tower height is 80m, and other geometric information (i.e. tower top diameter, tower bottom diameter and tower thickness

<sup>159</sup> 







- 176 distributions) are unknown and to be determined in this study. The 3D geometric model of the tower is
- presented in Fig. 3. 177
- 178
- 179

## Table 4. Geometric and material properties of the 5MW wind turbine tower

Properties	Values
Tower height [m]	80
Density [kg/m <sup>3</sup> ]	8500
Young's modulus [GPa]	210
Poisson's ratio	0.3



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- 181

Figure 3. 3D geometry model of the 5MW wind turbine tower

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#### 183 2.3.2. Mesh

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- The tower structure is meshed using structured mesh with shell elements. The element size is 0.5m, which 185
- 186 is based on the mesh sensitivity study results presented in Table 2 of Section 2.2. The mesh of the tower is
- 187 presented in Fig. 4.





190

Figure 4. Mesh of the 5MW wind turbine tower





193	2.3.3. Loads and Boundary conditions
194	
195	2.3.3.1. Loads
196	
197	The loads on the tower arise from three sources, i.e. 1) gravity loads; 2) aerodynamic loads on the rotor; 3)
198	wind loads on the tower itself, which are discussed below.
199	
200	Gravity loads
201	
202	The gravity loads due to the mass of the components on the tower top (such as the rotor and nacelle) and
203	the mass of the tower itself can significantly contribute to the compression loads on the tower structure.
204	These loads are usually taken into account by applying a point mass on the tower top.
205	
206	Aerodynamic loads on the rotor
207	
208	The aerodynamic loads on the rotor are transferable to the loads on the tower top. For example, the thrust
209	force on the rotor, $T$ , under a 50-year extreme wind condition with parked rotor is given by:
210	$T = \left(\frac{1}{2}\rho V_{e^{50}}^2\right) C_T \left(\pi R^2\right) $ (1)
211	where $\rho$ is air density with a typical value of 1.225 kg/m <sup>3</sup> , $V_{e_{50}}$ is the 50-year extreme wind speed, $c_{T}$ is
212	the thrust coefficient, and $R$ is the rotor radius.
213	
214	• Wind loads on the tower itself
215	
216	The wind load on the tower itself is given by:
217	$F_{d} = \frac{1}{2} \rho V(z)^{2} C_{d} D(z) $ <sup>(2)</sup>
218	where $F_{d}$ is the distributed wind load along the tower height per unit length; $v(z)$ is the wind velocity at
219	height $_z$ ; $_{C_a}$ is the drag coefficient for circular cross section, with a suggested value of 0.7 from IEC
220	61400-1 (Commission, 2005); $D(z)$ is the external diameter at height z as the tower is tapered.
221	
222	Due to wind shear, the wind velocity is varied along the tower height. $v(z)$ in Eq. (2) can be determined
223	by using the wind profile power law relationship:
224	$V(z) = V_{hub} \left(\frac{z}{z_{hub}}\right)^{\alpha} $ (3)
225	where $V_{hub}$ is the wind velocity at hub height; $z$ and $z_{hub}$ are the height above ground and hub height,
226	respectively; $\alpha$ is the power law exponent with a typical value of 0.2.
227	





228	2.3.3.2. Load cases

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Design standard IEC61400-1 (IEC, 2005) defines twenty-two load cases for the structural design of wind 230 231 turbines, covering all the operation conditions of a wind turbine, such as start up, normal operation, shut 232 down and extreme wind condition. The types of analyses of the twenty-two load cases can be categorised into two groups, i.e. ultimate and fatigue. For simplicity, the typical load case used in the structural design 233 of wind turbines is the ultimate load under 50-year wind condition (Cox and Echtermeyer, 2012, Bir, 2001) 234 235 and fatigue load (Schubel and Crossley, 2012).

236

237 In this study, both ultimate and fatigue load cases are considered. For the ultimate load case, the 50-year 238 extreme wind condition represents a severe load and therefore is taken as a critical load case. For the 239 fatigue load case, wind fatigue loads for the normal operation of wind turbines are considered. Table 5 240 presents the static ultimate loads under extreme 50-year extreme wind condition, and Table 6 lists the 241 fatigue loads. In this study, the two most significant components (i.e. thrust force  $F_{-}$  and bending moment 242  $M_{\perp}$ ) among the 6 components of force F and moment M are considered. Both ultimate and fatigue loads are taken from Ref. (LaNier, 2005) for WindPACT 5MW wind turbine, which is a reference wind turbine 243 244 designed by NREL (National Renewable Energy Laboratory). The fatigue loads in Table 6 were derived 245 through the DEL (Damage Equivalent Load) method, developed by NREL and detailed in Ref. (Freebury and Musial, 2000). It should be noted that the loads from Ref. (LaNier, 2005) are unfactored. In this study, 246 247 load safety factors for ultimate aerodynamic loads and fatigue loads are respectively taken as 1.35 and 248 1.00, according to IEC 61400-1 (Commission, 2005). Factored values of ultimate aerodynamic loads 249 taking account of a load safety factor of 1.35 are also presented in Table 5.

- 250
- 251

#### Table 5. Ultimate loads under 50-year extreme wind condition

Items	Unfactored aerodynamic	Factored aerodynamic loads
	loads (LaNier, 2005)	(safety factor of 1.35)
$F_x$ (kN)	578	780
<sub>M</sub> (kN-m)	28,568	38,567

252 253

Table 6. Fatigue load (LaNier, 2005)

Item	Values
$F_{x,f}$ (kN)	197
$M_{y,f}$ (kN-m)	3,687

(Note: subscript f denotes fatigue loads)

- 255
- 256
- 257





#### 258 2.3.3.3. Boundary conditions

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The loads given in Tables 5 and 6 are applied as concentrated loads on the tower top for static analysis and fatigue analysis, respectively. The wind turbine weight with a value of 480,076kg (LaNier, 2005) is taken into account by adding a point mass on the tower top. For ultimate load case, both gravity loads due to the weight of the tower itself and the wind loads due to wind passing the tower are taken into account as distributed loads on the tower. Additionally, for both load cases, a fixed boundary condition is applied to the tower bottom to simulate boundary conditions of onshore wind turbines.

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## **3. Genetic algorithm**

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269 GA is a search heuristic that mimics the process of natural selection. In GA, a population of individuals 270 (also called candidate solutions) to an optimisation problem is evolved toward better solutions. Each 271 individual has a set of attributes (such as its genotype and chromosomes) which can be altered and 272 mutated. The evolution generally starts with a population of random individuals, and it is an iterative 273 process. The population in each iteration is called a generation, in which the fitness of every individual is 274 evaluated. The fitness is generally the value of the objective function in the optimisation problem being solved. The individuals with higher fitness are stochastically chosen from the current population, and the 275 276 genome of each individual is modified (such as recombined and mutated) to form a new generation, which 277 is then used in the next iteration. Commonly, the GA terminates when either the current population reaches 278 a satisfactory fitness level or the number of generations reaches the maximum value.

279

280 Due to its capability of handling a large number of design variables, GA has been widely applied to 281 optimisation in renewable energy problems. Grady et al. (Grady et al., 2005) applied GA to obtain the 282 optimal placement of wind turbines in the wind farm, maximising production capacity while limiting the number of turbines installed. Lin et al. (Wang et al., 2016a) applied GA to the structural optimisation of 283 284 vertical-axis wind turbine composite blades, taking account of multiple constraints. The application of GA 285 to the optimisation of aerodynamic shape of wind turbine blades can be found in Refs. (Eke and Onyewudiala, 2010, Polat and Tuncer, 2013). Additionally, GA can also be applied to structural damage 286 287 detection (Chou and Ghaboussi, 2001) and structural health monitoring of wind turbines (Martinez-Luengo et al., 2016). 288

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GA generally requires a genetic representation of the solution domain and a fitness function to evaluate the solution domain. Each individual can be represented by an array of bits (0 or 1) or other types. Having defined the genetic representation and the fitness function, GA proceeds to initialise a population of candidate solutions and then to improve the population through repeatedly using mutation and crossover operators. The mutation and crossover used in the GA are presented below.





296 <b>3.1. Mutation</b> 297Mutation operator is analogous to biological mutation, and it alters one or more gene values in a chromosome from their initial state. For continuous parameters, the mutation is implemented by a polynomial mutation operation, as illustrated in the following equation.300 $C = P + (B_x - B_x) \delta$ 301 $C = P + (B_x - B_x) \delta$ 302where <i>c</i> is the child, <i>P</i> is the parent, $B_x$ is the upper bound of parameters, $B_z$ is the lower bound of parameters, $\sigma$ is a small variation obtained from a polynomial distribution.303 <b>3.2. Crossover</b> 306 <b>Crossover plays an important role in generating a new generation.</b> Crossover mates (combines) two chromosomes (parents) to generate a new chromosome (offspring). For continuous parameters, crossover operator linearly combines two parent chromosome vectors to generate two new offspring using the following two equations:311 $C_1 = b * P_1 + (1 - b) + P_2$ 312 $C_1 = b * P_1 + (1 - b) + P_2$ 313where $C_1$ and $C_2$ are children 1 and 2, respectively; <i>b</i> is a value between 0 and 1; <i>P</i> <sub>1</sub> and <i>P</i> <sub>2</sub> are parents 1 and 2, respectively.3141 and 2, respectively.315 <b>Convergence</b> validation: Initial population (candidate solutions) is randomly generated in this step.313 <b>Ordereste a</b> new opulation: This step, GA updates the design points in the new population.325 <b>Convergence</b> validation: The optimisation is not converged and the evolutionary process proceeds to the next step.314 <b>Design point update:</b> In this step, GA updates the design points in the new population.326 <b>Convergence</b> validation: The optimisation converged whe hav		
297298Mutation operator is analogous to biological mutation, and it alters one or more gene values in a chromosome from their initial state. For continuous parameters, the mutation is implemented by a polynomial mutation operation, as illustrated in the following equation.300 $\mathcal{C} = P + (B_r - B_r) \mathcal{S}$ (4)301 $\mathcal{C} = r + (B_r - B_r) \mathcal{S}$ (4)302where $c$ is the child, $P$ is the parent, $B_r$ is the upper bound of parameters, $B_r$ is the lower bound of parameters, $s$ is a small variation obtained from a polynomial distribution.303 <b>3.2. Crossover</b> 306 <b>3.2. Crossover</b> 307Crossover plays an important role in generating a new generation. Crossover mates (combines) two chromosomes (parents) to generate a new chromosome (offspring). For continuous parameters, crossover operator linearly combines two parent chromosome vectors to generate two new offspring using the following two equations:311 $C_1 = b * P_1 + (1 - b) * P_2$ (5)312 $C_1 = b + P_1 + b + P_2$ (6)313where $C_1$ and $C_2$ are children 1 and 2, respectively; $b$ is a value between 0 and 1; $P_1$ and $P_2$ are parents 1 and 2, respectively.315GA searches for optimal solutions through an iterative procedure, which is summarised below.3171) Define objectives, variables and constraints: The optimisation objectives, design variables and constraints are defined at the first step of GA.321) Initialise population: Initial population (candidate solutions) is randomly generated in this step.335) Convergence validation: The optimisation converged mutation and crossover.341 Design point update: In this step, GA updates the d	296	3.1. Mutation
Mutation operator is analogous to biological mutation, and it alters one or more gene values in a chromosome from their initial state. For continuous parameters, the mutation is implemented by a polynomial mutation operation, as illustrated in the following equation. $C = r + (B_{c} - B_{z})\delta$ (4) where <i>c</i> is the child, <i>r</i> is the parent, $B_{c}$ is the upper bound of parameters, $B_{z}$ is the lower bound of parameters, $\sigma$ is a small variation obtained from a polynomial distribution. 304 305 3.2. <b>Crossover</b> 306 307 Crossover plays an important role in generating a new generation. Crossover mates (combines) two chromosomes (parents) to generate a new chromosome (offspring). For continuous parameters, crossover 309 operator linearly combines two parent chromosome vectors to generate two new offspring using the 501 following two equations: 311 $C_{z} = b * P_{z} + (1 - b) * P_{z}$ (6) 312 $C_{z} = (1 - b) * P_{1} + b * P_{z}$ (6) 313 where $c_{z}$ and $c_{z}$ are children 1 and 2, respectively; <i>b</i> is a value between 0 and 1; $P_{1}$ and $P_{2}$ are parents 314 1 and 2, respectively. 315 316 GA searches for optimal solutions through an iterative procedure, which is summarised below. 317 318 1) Define objectives, variables and constraints: The optimisation objectives, design variables and constraints are defined at the first step of GA. 320 2) Initialise population: In this step, a new population is generated through mutation and crossover. 33 Generate a new population: In this step, a new population is not convergence eriteria. If 34 the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary 35 proceeds to the next step. 36 (5) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the 37 optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step 37 to generate a new population. 39 The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criter	297	
chromosome from their initial state. For continuous parameters, the mutation is implemented by a polynomial mutation operation, as illustrated in the following equation. $C = P + (B_x - B_z) \delta$ (4) where <i>c</i> is the child, <i>P</i> is the parent, $B_x$ is the upper bound of parameters, $B_z$ is the lower bound of parameters, <i>s</i> is a small variation obtained from a polynomial distribution. <b>3.2. Crossover</b> Crossover plays an important role in generating a new generation. Crossover mates (combines) two chromosomes (parents) to generate a new chromosome (offspring). For continuous parameters, crossover operator linearly combines two parent chromosome vectors to generate two new offspring using the following two equations: $C_1 = b + P_1 + (1 - b) + P_2$ (6) $C_2 = (1 - b) + P_1 + b + P_2$ (6) $C_2 = (1 - b) + P_1 + b + P_2$ (6) Where <i>c</i> , and <i>c</i> , are children 1 and 2, respectively; <i>b</i> is a value between 0 and 1; <i>P</i> <sub>1</sub> and <i>P</i> <sub>2</sub> are parents 1 and 2, respectively. GA searches for optimal solutions through an iterative procedure, which is summarised below. 1) Define objectives, variables and constraints: The optimisation objectives, design variables and constraints are defined at the first step of GA. 2) Initialise population: Initial population (candidate solutions) is randomly generated in this step. 3) Generate a new population: In this step, a new population is generated through mutation and crossover. 4) Design point update: In this step, GA updates the design points in the new population. 5) Convergence validation: The optimisation converges when having reached the convergence criteria. If the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary process proceeds to the next step. 6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step 3 to generate a new population.	298	Mutation operator is analogous to biological mutation, and it alters one or more gene values in a
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<ul> <li>2) Initialise population: Initial population (candidate solutions) is randomly generated in this step.</li> <li>3) Generate a new population: In this step, a new population is generated through mutation and crossover.</li> <li>4) Design point update: In this step, GA updates the design points in the new population.</li> <li>5) Convergence validation: The optimisation converges when having reached the convergence criteria. If the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary process proceeds to the next step.</li> <li>6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step 3 to generate a new population.</li> <li>The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been mat. Fig. 5 deniets the flowwheat of CA.</li> </ul>	319	constraints are defined at the first step of GA.
<ul> <li>3) Generate a new population: In this step, a new population is generated through mutation and crossover.</li> <li>4) Design point update: In this step, GA updates the design points in the new population.</li> <li>5) Convergence validation: The optimisation converges when having reached the convergence criteria. If</li> <li>the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary</li> <li>process proceeds to the next step.</li> <li>6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the</li> <li>optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step</li> <li>3 to generate a new population.</li> </ul>	320	2) Initialise population: Initial population (candidate solutions) is randomly generated in this step.
<ul> <li>4) Design point update: In this step, GA updates the design points in the new population.</li> <li>5) Convergence validation: The optimisation converges when having reached the convergence criteria. If</li> <li>the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary</li> <li>process proceeds to the next step.</li> <li>6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the</li> <li>optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step</li> <li>3 to generate a new population.</li> <li>The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been</li> </ul>	321	3) Generate a new population: In this step, a new population is generated through mutation and crossover.
<ul> <li>5) Convergence validation: The optimisation converges when having reached the convergence criteria. If</li> <li>the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary</li> <li>process proceeds to the next step.</li> <li>6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the</li> <li>optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step</li> <li>3 to generate a new population.</li> <li>The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been</li> <li>mat. Fig. 5 deniets the flowwheat of CA</li> </ul>	322	4) Design point update: In this step, GA updates the design points in the new population.
<ul> <li>the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary</li> <li>process proceeds to the next step.</li> <li>6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the</li> <li>optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step</li> <li>3 to generate a new population.</li> <li>The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been</li> <li>mat. Fig. 5 deniets the flowwhert of CA</li> </ul>	323	5) Convergence validation: The optimisation converges when having reached the convergence criteria. If
<ul> <li>process proceeds to the next step.</li> <li>6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the</li> <li>optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step</li> <li>3 to generate a new population.</li> <li>The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been</li> <li>mat. Fig. 5 deniets the flowwheat of CA.</li> </ul>	324	the convergence criteria have not yet been reached, the optimisation is not converged and the evolutionary
<ul> <li>6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the</li> <li>optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step</li> <li>3 to generate a new population.</li> <li>The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been</li> <li>mat. Fig. 5 deniets the flow hort of CA.</li> </ul>	325	process proceeds to the next step.
<ul> <li>327 optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step</li> <li>328 3 to generate a new population.</li> <li>329</li> <li>330 The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been</li> <li>321 met. Fig. 5 deniets the flowebert of CA.</li> </ul>	326	6) Stopping criteria validation: If the iteration number exceeds the maximum number of iterations, the
<ul> <li>328 3 to generate a new population.</li> <li>329</li> <li>330 The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been</li> <li>321 met Fig. 5 deniets the flowebert of CA.</li> </ul>	327	optimisation process is then terminated without having reached convergence. Otherwise, it returns to Step
329 330 The above Steps 3 to 6 are repeated until the optimisation has converged or the stopping criterion has been 321 mot. Fig. 5 deniets the flowebert of CA	328	3 to generate a new population.
met Fig. 5 deniets the flowebert of CA	329 220	The shows Stops 2 to 6 are repeated until the entimization has servered on the stopping with the hore
	330	The above steps 5 to 0 are repeated until the optimisation has converged of the stopping criterion has been met. Eig. 5 deniets the flowchart of GA











- where  $x_1$  is the diameter of the tower bottom;  $x_2$  is the diameter of the tower top;  $x_3$  to  $x_{18}$  are the 352
- thickness of 1st to 16th segment, respectively. Seg 16 Seg 15 Seg 14 Seg 13 Seg 12 Seg 11 Seg 10 Seg 9 Seg 8 Seg 7 Seg 6 Seg 5 Seg Seg 3 Seg 1 354 Figure 6. Schematic of tower structure 355 356 4.3. Constraints 357 358 In this study, the structural optimisation of wind turbine towers takes account of six constraint conditions, 359 360 i.e. deformation, ultimate stress, fatigue, buckling, vibration and design variable constraints. 361 362 **Deformation constraint** ٠ 363 364 In order to ensure the overall structural stability and to avoid the uncertainties introduced by large deformation, the maximum tower deformation  $d_{max}$  should not exceed the allowable deformation  $d_{max}$ . 365 This constraint is given by the following inequality: 366 (9) 367  $d_{\text{max}} \leq d_{allow}$ 368 369 According to Ref. (Nicholson, 2011), the allowable deformation  $d_{allow}$  can be determined using the 370 following empirical equation:  $d_{allow} = 1.25 \frac{L}{100}$ 371 (10)372 where L is the length of the wind turbine tower. 373 374 In this study, the tower length  $_L$  is 80m, and thus the allowable deformation  $_{d_{allow}}$  is 1m. 375
  - 13





376 **Ultimate Stress constraint** 377 The Von-Mises stress  $\sigma$  generated by the loads cannot exceed the allowable stress  $\sigma_{mbox}$ . This can be 378 expressed in the following inequality forms: 379  $\sigma \leq \sigma_{allow}$ 380 (11)381 382 The allowable stress  $\sigma_{allow}$  is given by: 383 (12) $\sigma_{allow} = \sigma_y / \gamma_m$ where  $\sigma_y$  is the yield strength and  $\gamma_m$  is the material safety factor. 384 385 Yield strength  $\sigma_{\mu}$  of Steel S355 is 345MPa (EN) for nomial thickness in the range of 16mm and 40mm. 386 The material safety factor  $\gamma_m$  is taken as 1.1 according to IEC 61400-1 (Commission, 2005). Thus, the 387 allowable stress  $\sigma_{allow}$  is 314MPa. 388 389 390 **Fatigue constraint** 391 392 Fatigue is particularly important in structures subject to significant cyclic loads. During the operation of 393 the wind turbine, every blade rotation causes stress changes in the wind turbine tower. The rated rotor 394 speed of the WindPACT 5MW wind turbine (the reference wind turbine used in this study) is 12.1rpm 395 (LaNier, 2005), resulting in a loading period of 4.96s. For a servie life of 20 years, the number of loading cycles  $N_d$  having a period of  $T_a$ , can be then estimated using: 396

$$397 N_{d} = \frac{20 \ [years]}{T_{p}[s]} = \frac{20 \ [years] \times 365 \ [day / year] \times 24 \ [h / day] \times 3600 \ [s / h]}{T_{p}[s]} (13)$$

398

The fatigue analysis in this study is based on S-N curve method, in which fatigue test results are presented as a plot of stress (S) against the number of cycles to failure (N). Based on the DEL (Damage Equivalent Load) developed by NREL and detailed in (Freebury and Musial, 2000), computational cost is reduced to an equivalent load case where the number of cycles to failure  $N_{DEL}$  can be obtained from an equivalent S-N curve. An appropriate S-N curve of slope m = 4 and intercept A = 13.9 was provided by Ref. (LaNier, 2005) with the DEL loads defined in Table 6 of Section 2.3.3.2.

405

406 The minimum fatigue safety ratio  $f_{sr,min}$  can be then derived by the ratio of the design stress range  $\Delta S_{detyn}$ 

407 that ensure a design number of cycles  $N_d$  over the maximum fatigue stress range  $\Delta S_{max}$  in the structure.

408 This safety ratio should be greater than the allowable fatigue safety ratio  $f_{allow}$ , i.e.:





409	$f_{sr,\min} \ge f_{allow}$ (14)
410	
411	$f_{allow}$ is equal to one times the material partial safety factor $\gamma_{m,f}$ for fatigue. According to IEC 61400-1
412	(Commission, 2005), the material partial safety factor for fatigue, $\gamma_{m,f}$ , should be not less than 1.1. In this
413	study, 1.1 is chosen for $\gamma_{m.f}$ , and thus $f_{allow}$ is equal to 1.1.
414	
415	Buckling constraint
416	
417	Wind turbine towers generally are thin-wall cylindrical shell structures and are subjected to considerable
418	compressive loads, making them prone to suffer from buckling failure. In order to avoid buckling failure,
419	the load multiplier $L_m$ , which is the ratio of the critical buckling load to the applied load on the tower,
420	should be greater than the allowable minimum load multiplier $L_{m,min}$ . This constraint can be expressed in
421	the following inequality form:
422	$L_m \ge L_{m,\min} \tag{15}$
423	In this study, an value of 1.4 is chosen for the minimum allowable load multiplier $L_{}$ , according to
424 425	design standard (GL, 2016).
426	The buckling analysis module in ANSYS software requires a pre-stress step (static structural analysis)
427	followed by the buckling analysis, and it outputs load multiplier. The critical buckling load is then given by
428	load multiplier times the applied load.
429	
430	Vibration constraint
431	
432	In order to avoid the vibration induced by resonance, the natural frequency of the tower should be
433	separated from harmonic vibration associated with rotor rotation, and it usually designed to be within the
434	range of 1P and 3P, which correspond to the frequencies of the rotor. This constraint can be expressed in
435	the following inequality form:
436	$f_{rotor} S_{f} \leq f_{tower} \leq 3 f_{rotor} / S_{f} $ (16)
437	where $f_{rotor}$ is the frequency associated with rotor rotation; $f_{tower}$ is the first natural frequency of the
438	tower; $s_{f}$ is the safety factor for frequency.
439	
440	In this study, the rotor rotational speed is 11.2 rpm, and thus the associated frequency $f_{rotor}$ is 0.187 Hz.
441	The frequency safety factor $s_{r}$ is taken as 1.05 according to GL standard (Lloyd and Hamburg, 2010).
442	Substituting $f_{rotor} = 0.187$ Hz and $S_f = 1.05$ into Eq. (16) yields:





443			0.196 Hz $\leq f_{tower}$	≤ 0.534 Hz	(17)		
444							
445	Design va	ariable constraint					
446	U						
447	The resultant	loads on the wind	turbine tower botto	om are general	ly greater than those on the tower top,		
448	requiring larger diameter on the tower bottom. Therefore, the diameter of the tower bottom is constrained						
449	to be larger than the diameter of tower top, which is expressed as:						
450			$x_1 - x_2 \ge$	0	(18)		
451							
452	Moreover, the thicknesses of the tower generally decrease from the tower bottom to tower top. This is						
453	ensured by the following constraint:						
454			$x_i - x_{i+1} \ge 0  i =$	3,4,,17	(19)		
455							
456	Additionally, each design variable is constrained to vary within a range defined by upper and lower bound						
457	This constraint can be expressed as:						
458	$x_i^L \le x_i \le x_i^U$ $i = 1, 2, \cdots, 18$ (20)						
459	where $x_i^L$ and $x_i^U$ are the lower bound and upper bound of the <i>i</i> <sup>th</sup> design variable, respectively.						
460							
461	Table 7 presents the lower and upper bounds of the design variables and the constraint conditions used						
462	the structural	optimisation of win	d turbine towers.				
463							
464	Table 7. Lower and upper bounds of the design variables and the constraint conditions						
	Item	Lower bound	Upper bound	Units	Variable definition		
	<i>x</i> <sub>1</sub>	5	7	m	Diameter of tower bottom		
	<i>x</i> <sub>2</sub>	3	6	m	Diameter of tower top		
	$x_{3} \sim x_{18}$	0.015	0.040	m	Thickness of tower segments		

1

314

\_

-

0.534

4	5:	5

 $d_{\text{max}}$ 

 $\sigma$ 

 $f_{sr,min}$ 

 $L_m$ 

 $f_{\scriptscriptstyle tower}$ 

466 **4.4. Parameter settings of genetic algorithm** 

-

-

1.1

1.4

0.196

467

m

MPa

\_

-

Hz

Deformation

Von-Mises stress

Fatigue safety ratio

Buckling load multiplier

Tower natural frequency





- 468 The GA presented in Section 3 is chosen as the optimiser to search for optimal solutions. The main
- 469 parameters used in GA are listed in Table 8.

470

- 471 Table 8. Main parameter settings of GA Parameter name Value Type of initial sampling Constrained sampling 180 Number of initial samples N Initial 50 Number of samples per iteration N Perlter Maximum allowable Pareto Percentage [%] 70 Convergence stability percentage [%] 2 40 Maximum number of iterations N MaxIer Crossover probability 0.82 0.01 Mutation probability 472 473 Each parameter in Table 8 is detailed below. 474 475 • Type of initial sampling 476 The initial samples are generally based on constrained sampling algorithm, in which the samples are constrained using design variable constraints defined in Eqs. (18), (19) and (20). 477 478 479 Number of initial samples ٠ 480 In this study, the number of initial samples N<sub>Ini</sub> is 180, which is 10 times the number of design variables 481 482 (Phan et al., 2013). 483 484 Number of samples per iteration •
- 485 In this study, the number of initial samples per iteration  $N_{Pertur}$  is 50.
- 486

## 487 • Maximum allowable Pareto percentage

488

The Pareto percentage, which is defined as the ratio of the number of desired Pareto points to the number
of samples per iteration, is a convergence criterion. The optimisation converges when the Pareto
percentage reaches the maximum allowable value (70% in this study).
Convergence stability percentage





495 Convergence stability percentage is a convergence criterion representing the stability of the population 496 based on its mean and standard deviation. The optimisation converges when this percentage (2% in this 497 study) is reached.

498

#### 499 • Maximum number of iterations

500

501 The maximum number of iterations  $N_{Maxlher}$ , which is defined as the maximum possible number of 502 iterations the algorithm executes, is a stop criterion. The iteration stops if this number (40 in this study) is 503 reached. The maximum number of iterations  $N_{Maxlher}$  also provides an idea of the absolute maximum 504 number of evaluations  $N_{Maxlher}$ , which can be calculated by:

$$N_{MaxEval} = N_{Ini} + N_{Perlter} \left( N_{Maxlter} - 1 \right)$$
(21)

506 where  $N_{Ini}$  is the number of initial samples,  $N_{Perler}$  is the number of samples per iteration.

507

#### 508 • Crossover probability

509

510 Crossover probability, which is the probability of applying a crossover to a design configuration, must be 511 between 0 and 1. A smaller value of crossover probability indicates a more stable population and faster 512 (but less accurate) solution. For example, if the crossover probability is 0, the parents are directly copied to 513 the new population. In this study, a typical value of 0.82 (Gandomkar et al., 2005) is chosen as the 514 probability of crossover.

515

#### 516 • Mutation probability

517

518 Mutation probability, which is the probability of applying a mutation on a design configuration, must be 519 between 0 and 1. A large value of mutation probability indicates a more random algorithm. For example, if 520 the mutation probability is 1, the algorithm becomes a pure random search. In this study, a typical value of 521 0.01 (Perez et al., 2000) is chosen as the probability of mutation.

522

## 523 **4.5. Flowchart of the optimisation model**

524

525 Figure 7 presents the flowchart of the structural optimisation model of wind turbine towers, which

526 combines the parametric FEA model (presented in Section 2) and the GA model (presented in Section 3).







531

527 528

529

530 **5. Results and discussions** 

The history of the objective function (mass of the tower) during the optimisation process is depicted in Fig. 8. As can be seen from Fig. 8, the mass of the tower oscillates in the first few iterations and then gradually converges, reaching the best solution with a mass of 259,040kg at the 11<sup>th</sup> iteration. A mass reduction of 6.28% is achieved when comparing the optimal tower design against the initial design, which has an initial tower mass of 276,412kg at 0<sup>th</sup> iteration.







- 537
- 538
- 539

Figs. 9 to 13 depict the history of the total deformation, maximum von-Mises stress, fatigue safety ratio, buckling load multiplier and first natural frequency of the tower, respectively. The associated allowable values (i.e. upper or lower bounds) are also presented in these figures to strengthen the illustration. As can be seen from Figs. 9 to 13, the fatigue safety ratio is quite close to the allowable values, while other constraint parameters have relatively large margins from the allowable values. This result indicates that the fatigue is dominant in the design in the present case.





Figure 9. History of maximum total deformation for ultimate load case





Figure 10. History of the maximum von-Mises stress for ultimate load case











564

Table 9. Optimised results of design variables

	1	e
Design variable	Optimal value [m]	Variable definition
<i>x</i> <sub>1</sub>	5.650	Diameter of tower bottom
<i>x</i> <sub>2</sub>	4.268	Diameter of tower top
<i>x</i> <sub>3</sub>	0.037	Thickness of Segment 1
<i>x</i> <sub>4</sub>	0.036	Thickness of Segment 2
<i>x</i> <sub>5</sub>	0.032	Thickness of Segment 3
<i>x</i> <sub>6</sub>	0.028	Thickness of Segment 4
<i>x</i> <sub>7</sub>	0.026	Thickness of Segment 5
x 8	0.025	Thickness of Segment 6
<i>x</i> <sub>9</sub>	0.025	Thickness of Segment 7
$x_{10}$	0.023	Thickness of Segment 8
<i>x</i> <sub>11</sub>	0.022	Thickness of Segment 9
$x_{12}$	0.021	Thickness of Segment 10
<i>x</i> <sub>13</sub>	0.020	Thickness of Segment 11
$x_{14}$	0.019	Thickness of Segment 12
<i>x</i> <sub>15</sub>	0.019	Thickness of Segment 13
$x_{16}$	0.018	Thickness of Segment 14
<i>x</i> <sub>17</sub>	0.017	Thickness of Segment 15
<i>x</i> <sub>18</sub>	0.016	Thickness of Segment 16

565

566 The tower deformations, von-Mises stress distributions, buckling analysis results, and first modal 567 frequency of the optimal tower are presented below.

568

#### 569 • Deformations

570

The total deformations of the tower is presented in Fig. 14. As can be seen from Fig. 14, the maximum total deformation is about 0.965m, observed at the tower top. This value is 4% lower than the alloable value of 1m, which indicates the present tower design is stiff enough and not likely to experience large deformations.







583 584

585

Figure 15. von-Mises stress distributions of the tower structure

#### 586 • Modal frequencies and shapes

7.4301e7 5.2539e7 3.0776e7 9.0143e6 Min

587

The modal analysis is used to calculate the modal frequencies and modal shapes of the tower. In this case, the tower is fixed at the tower bottom and free-vibration (no loads on the tower). Fig. 16 depicts the frequency and modal shape of the first model of the tower. As can be seen from Fig. 16 the first mode frequency is about 0.298 Hz, which is within the desired range of 0.196 Hz and 0.534 Hz.







592 593

Figure 16. Modal frequency and modal shape of the first mode of the tower

594

#### 595 • Buckling analysis results

596

The buckling analysis results of the tower are depicted in Fig. 17. As can be seen from Fig. 17, the load multiplier is about 3.3, which is 136% higher than the minimum allowable value of 1.4. This indicates the

599 present tower design is not likely to experience buckling failure.



600 601 602

Figure 17. Buckling load multiplier and buckling mode shape of the tower

## 603 6. Conclusions

604

605 In this work, a structural optimisation model for wind turbine towers has been developed by incorporating 1) a parametric FEA (finite element analysis) model, which offers high-fidelity evaluations of the structural 606 performance of the tower; with 2) a GA (genetic algorithm) model, which deals with design variables and 607 finds optimal solutions. The structural optimisation model minimises the mass of the wind turbine tower 608 609 with multi-criteria constraint conditions. The bottom diameter, top diameter of the tower and the thickness 610 of each tower segment are taken as the design variables. The optimisation model accounts for six 611 constraint conditions, i.e. deformation, ultimate stress, fatigue, buckling, vibration and design variable 612 constraints. The model has been applied to the structural design of a 5MW wind turbine tower. The 613 following conclusions can be drawn from the present study:





- 614 Good agreement (with maximum percentage difference of 2.67%) is achieved in comparison with the 615 modal analysis results of NREL 5MW wind turbine tower reported in the literature, which confirms the validity of the present parametric FEA model of wind turbine towers. 616 The structural optimisation model of wind turbine towers is capable of accurately and effectively 617 ٠ 618 determine the optimal thickness distributions of wind turbine towers, which significantly improves the 619 efficiency of structural optimisation of wind turbine towers. The mass of the optimal tower is 259,040kg, which is 6.28% lower than the initial design, which 620 ٠ indicates the tower mass can be significantly reduced by using the present optimisation model. 621 622 For the optimal tower, the fatigue safety ratio is quite close to the allowable values, while other 623 constraint parameters (i.e. deformation, maximum von-Mises stress, buckling load multiplier and 624 frequency) have relatively large margins from the associated allowable values. This indicates the 625 fatigue is dominant in the design in the present case. 626 627 Additionally, the present optimisation model can be used for any practice of structural optimisation of wind turbine towers, minimising the tower mass with multi-criteria constraint conditions. The proposed 628 629 framework is generic in nature and can be applied to a series of related problems, such as the optimisation 630 of offshore wind turbine foundations with complicated boundary conditions 631 References 632 633 634 ASO, R. & CHEUNG, W. M. 2015. Towards greener horizontal-axis wind turbines: analysis of carbon 635 emissions, energy and costs at the early design stage. Journal of Cleaner Production, 87, 263-274. 636 BIR, G. S. 2001. Computerized method for preliminary structural design of composite wind turbine blades. Journal of solar energy engineering, 123, 372-381. 637 638 CHOU, J.-H. & GHABOUSSI, J. 2001. Genetic algorithm in structural damage detection. Computers & 639 Structures, 79, 1335-1353. COMMISSION, I. E. 2005. IEC 61400-1: Wind turbines part 1: Design requirements. International 640 641 Electrotechnical Commission.
- 642 COUNCIL, G. W. E. 2015. Global wind energy outlook 2015. GWEC, November.
- 643 COX, K. & ECHTERMEYER, A. 2012. Structural design and analysis of a 10MW wind turbine blade. *Energy* 644 *Procedia*, 24, 194-201.
- 645 DOWSLAND, K. A. & THOMPSON, J. M. 2012. Simulated annealing. *Handbook of Natural Computing*.
   646 Springer.
- EKE, G. & ONYEWUDIALA, J. 2010. Optimization of wind turbine blades using genetic algorithm. *Global Journal of Research In Engineering*, 10.
- EN, B. 10025-2 (2004). Hot rolled products of structural steels, Part 2: Technical delivery conditions for nonalloy structural steels.
- FREEBURY, G. & MUSIAL, W. D. 2000. Determining equivalent damage loading for full-scale wind turbine
   blade fatigue tests, National Renewable Energy Laboratory.
- GANDOMKAR, M., VAKILIAN, M. & EHSAN, M. 2005. A combination of genetic algorithm and simulated
   annealing for optimal DG allocation in distribution networks. *CCECE/CCGEI, Saskatoon*, 645-648.
- 655 GL, D. 2016. DNVGL-ST-0126: Support structures for wind turbines.
- GRADY, S., HUSSAINI, M. & ABDULLAH, M. M. 2005. Placement of wind turbines using genetic
   algorithms. *Renewable energy*, 30, 259-270.
- 658 GWEC 2016. Global Wind Statistics 2015. Global Wind Energy Council.
- HERBERT-ACERO, J. F., PROBST, O., RÉTHORÉ, P.-E., LARSEN, G. C. & CASTILLO-VILLAR, K. K.
  2014. A review of methodological approaches for the design and optimization of wind farms. *Energies*, 7, 6930-7016.



662	IEC 2005 IEC 61400-1: Wind turbines part 1: Design requirements
663	IONKMAN I & BIR G 2010 Recent analysis code development at NRFL Sandia Blade Workshon
664	JONKMAN, J. M., BUTTERFIELD, S., MUSIAL, W. & SCOTT, G. 2009. Definition of a 5-MW reference
665	wind turbine for offshore system development. National Renewable Energy Laboratory Golden, CO,
666	USA.
667	KENNEDY, J. 2011. Particle swarm optimization. <i>Encyclopedia of machine learning</i> . Springer.
668	LANIER, M. W. 2005. LWST Phase I Project Conceptual Design Study: Evaluation of Design and Construction
669	Approaches for Economical Hybrid Steel/Concrete Wind Turbine Towers; June 28, 2002July 31,
670	2004. National Renewable Energy Lab., Golden, CO (US).
671	LLOYD, G. & HAMBURG, G. 2010. Guideline for the certification of wind turbines. Edition.
672	MARTINEZ-LUENGO, M., KOLIOS, A. & WANG, L. 2016. Structural health monitoring of offshore wind
673	turbines: A review through the Statistical Pattern Recognition Paradigm. Renewable and Sustainable
674	Energy Reviews, 64, 91-105.
675	MURTAGH, P., BASU, B. & BRODERICK, B. 2004. Simple models for natural frequencies and mode shapes
676	of towers supporting utilities. Computers & structures, 82, 1745-1750.
677	NICHOLSON, J. C. 2011. Design of wind turbine tower and foundation systems: optimization approach.
678	PEREZ, R. E., CHUNG, J. & BEHDINAN, K. 2000. Aircraft conceptual design using genetic algorithms. AIAA
679	Paper; 4938.
680	PHAN, D. T., LIM, J. B., SHA, W., SIEW, C. Y., TANYIMBOH, T. T., ISSA, H. K. & MOHAMMAD, F. A.
681	2013. Design optimization of cold-formed steel portal frames taking into account the effect of building
682	topology. Engineering Optimization, 45, 415-433.
683	POLAT, O. & TUNCER, I. H. 2013. Aerodynamic shape optimization of wind turbine blades using a parallel
684	genetic algorithm. Procedia Engineering, 61, 28-31.
685	SCHUBEL, P. J. & CROSSLEY, R. J. 2012. Wind turbine blade design. <i>Energies</i> , 5, 3425-3449.
686	SIVANANDAM, S. & DEEPA, S. 2007. Introduction to genetic algorithms, Springer Science & Business
687	Media.
688	STAVRIDOU, N., EFTHYMIOU, E. & BANIOTOPOULOS, C. C. 2015. Welded connections of wind turbine
689	towers under fatigue loading: Finite element analysis and comparative study. American Journal of
690	Engineering and Applied Sciences, 8, 489.
691	VAN KUIK, G., PEINKE, J., NIJSSEN, R., LEKOU, D., MANN, J., SØRENSEN, J. N., FERREIRA, C., VAN
692	WINGERDEN, J., SCHLIPF, D. & GEBRAAD, P. 2016. Long-term research challenges in wind
693	energy-a research agenda by the European Academy of Wind Energy. Wind Energy Science, 1, 1-39.
694	WANG, L. 2015. Nonlinear aeroelastic modelling of large wind turbine composite blades. University of Central
695	Lancashire.
696	WANG, L., KOLIOS, A., DELAFIN, PL., NISHINO, T. & BIRD, T. 2015. Fluid Structure Interaction
697	Modelling of A Novel 10MW Vertical-Axis Wind Turbine Rotor Based on Computational Fluid
698	Dynamics and Finite Element Analysis. EWEA 2015 Annual Event, France, Paris.
699	WANG, L., KOLIOS, A., NISHINO, T., DELAFIN, PL. & BIRD, T. 2016a. Structural optimisation of vertical-
700	axis wind turbine composite blades based on finite element analysis and genetic algorithm. Composite
701	Structures.
702	WANG, L., LIU, X., GUO, L., RENEVIER, N. & STABLES, M. 2014a. A mathematical model for calculating
703	cross-sectional properties of modern wind turbine composite blades. <i>Renewable Energy</i> , 64, 52-60.
704	WANG, L., LIU, X., RENEVIER, N., STABLES, M. & HALL, G. M. 2014b. Nonlinear aeroelastic modelling
705	for wind turbine blades based on blade element momentum theory and geometrically exact beam
706	theory. <i>Energy</i> , 76, 487-501.
707	WANG, L., QUANT, R. & KOLIOS, A. 2016b. Fluid structure interaction modelling of horizontal-axis wind
708	turbine blades based on CFD and FEA. Journal of Wind Engineering and Industrial Aerodynamics,
709	158, 11-25.
710	ZHAO, X. & MAISSER, P. 2006. Seismic response analysis of wind turbine towers including soil-structure
711	interaction. Proceedings of the Institution of Mechanical Engineers, Part K: Journal of Multi-body
712	Dynamics, 220, 53-61.