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Simulation-based optimization of lattice support structures for offshore wind energy converters with the simultaneous perturbation algorithm

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Abstract. Support structures for offshore wind turbines are contributing a large part to the total project cost, and a cost saving of a few percent would have considerable impact. At present support structures are designed with simplified methods, e.g., spreadsheet analysis, before more detailed load calculations are performed. Due to the large number of loadcases only a few semi-manual design iterations are typically executed. Computer-assisted optimization algorithms could help to further explore design limits and avoid unnecessary conservatism.

In this study the simultaneous perturbation stochastic approximation method developed by Spall in the 1990s was assessed with respect to its suitability for support structure optimization. The method depends on a few parameters and an objective function that need to be chosen carefully. In each iteration the structure is evaluated by time-domain analyses, and joint fatigue lifetimes and ultimate strength utilization are computed from stress concentration factors. A pseudo-gradient is determined from only two analysis runs and the design is adjusted in the direction that improves it the most.

The algorithm is able to generate considerably improved designs, compared to other methods, in a few hundred iterations, which is demonstrated for the NOWITECH 10 MW reference turbine.

1. Introduction

Today, the design of wind turbine support structures is to a large extent a manual process. It requires a lot of experience on the designer's part, and the design tools are often based on simplified methods, e.g., preliminary sizing with spreadsheets. As larger structures are being developed and installations move to larger water-depths, multi-member support structures (such as the OWEC Quattropod® jacket) become increasingly interesting, but present specific challenges, e.g., the possibility of local vibrations [2]. These structures consist of a large number of members, which increases the need for efficient and accurate design-tools. Simulation-based optimization [6] is a promising technique that can help to automate this process.

Support structures for offshore wind turbines are typically fatigue-dominated, but an accurate assessment of fatigue lifetimes is time consuming and computationally costly. Therefore only a few design iterations are typically performed, and current designs might contain a considerable amount of convervatism. On the other hand, optimization of such designs has to be performed in an extremely efficient way, since analyses are so costly.

Figure 1. The NOWITECH 10MW reference turbine. Preliminary drawing.

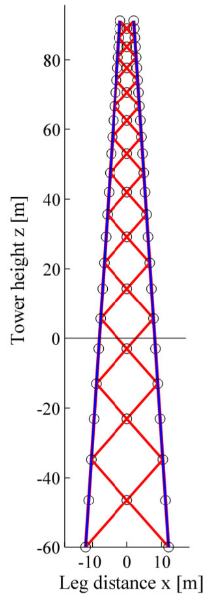

Figure 2. Geometry of the full-height lattice tower.

In this study Spall's simultaneous perturbation stochastic approximation (SPSA) algorithm [11, 12, 14] was used to automatically optimize thickness and diameter of the members in an offshore wind turbine support structure. The method utilizies a pseudo-gradient based on only two function evaluations per iteration, which allows for a computationally efficient process. Each evaluation of the design consisted of 2 min time-domain simulations of the complete wind turbine in Fedem Windpower (Fedem Technology AS, Trondheim), a flexible multibody solver that has recently been extended with functionality for aerodynamic and hydrodynamic loads.

Subsequently, rainflow counting was performed and joint lifetimes were calculated with stress concentration factors. The utilization of both ultimate and fatigue limit states is reported for each joint. Tower weight was chosen as an indicator of cost, and an objective function comprising variables for weight and joint lifetimes was defined. The method has shown promising results, and is able to find viable designs, even when starting from highly unacceptable starting points.

Some of the major challenges when using SPSA for multi-member support structures were the choice of the objective function and of the parameters governing the behavior of the algorithm. Existing guidelines [13] were followed when doing this calibration, but for an efficient search the parameters had to be modified. We report the results of a full calibration for the 10 MW NOWITECH reference turbine on a full-height lattice tower [10], which should provide a useful basis for application to other turbine sizes and water-depths.

2. Methods

All analyses were performed with Fedem Windpower software (pre-release version) and custom-written Matlab (The Mathworks, Inc.) functions.

2.1. Wind turbine model and environment

A preliminary version of the NOWITECH 10MW reference turbine was used (Fig. 1). The blades have been developed during the past two years [5] and the support structure is a novel concept that continues the typical jacket support structure up until the rotor-nacelle-assembly (Fig. 2), thereby avoiding the need for a complicated and costly transition piece [10]. Apart from its intrinsic interest, this structure was chosen since it consists of a large number of members and thereby poses a challenge for optimization algorithms.

The target water depth is 60m, and the preliminary tower design features a total height of 151m achieved with 12 sections, 4 legs spaced with 24m bottom-distance and 4m top-distance, for a total of 240 members (beam elements) in the basic computer model. This results in a total of 48 design parameters for the sizing problem: all combinations of 12 sections, both legs and braces, and the sizing of both diameters and thicknesses.

Only one loadcase was considered for this study, corresponding to power production at a wind speed of $U = 13.5\,\mathrm{m/s}$ and turbulent fluctuations with a turbulent intensity of 0.16. The seastate was taken to be irregular linear waves from a JONSWAP spectrum, with significant wave height $H_s = 4\,\mathrm{m}$ and peak period $T_p = 9\,\mathrm{s}$. A simple PID controller was employed.

2.2. Analysis

The wind turbine was analysed by 2 min time-domain simulations with Fedem Windpower. Time series of stresses were saved, and hot spot stresses were obtained by rainflow counting and using stress concentration factors according to DNV guidelines [3]. The results were normalized to the design lifetime of 20 years, such that a joint utiliziation of 1.2, e.g., reflects an estimated joint lifetime of 24 years.

2.3. Stochastic simultaneous perturbation algorithm

Standard gradient-based search algorithms for design optimization [1] need to evalute changes in each parameter independently, resulting in $2n$ analyses for n design parameters, in order to obtain an estimate of the gradient (design sensitivity) by finite-differences.

If θ_k denotes the n-dimensional vector of design parameters at the k-th step of the iteration, such methods evaluate an objective function f to obtain the values $f(\theta_k + c_k e_i)$ and $f(\theta_k - c_k e_i)$, where e_i denotes the i-th unit vector and c_k the current *perturbation width*. The sensitivity $\frac{\partial f}{\partial x_i}$ is thereby approximated by the finite difference

$$\frac{\partial f}{\partial x_i} \approx \frac{f(\theta_k + c_k e_i) - f(\theta_k - c_k e_i)}{2c_k} \quad \text{for each} \quad i = 1, \dots, n. \tag{1}$$

In contrast to this, the SPSA algorithm calculates a pseudo-gradient from only two function evaluations at $\theta_k^+ = \theta_k + c_k\Delta_k$ and $\theta_k^- = \theta_k - c_k\Delta_k$. The perturbation vector Δ_k consists of a random sample generated independently for each component from a zero-mean probability law with finite variance. Typically a Bernoulli distribution (with values $+1$ or -1 with equal probability) is chosen, and this example was followed here as well. The perturbation vector is chosen anew at each iteration of the algorithm.

Next the pseudo-gradient is calculated as

$$\hat{g}_k(\theta_k) = \frac{f(\theta_k^+) - f(\theta_k^-)}{2c_k} \begin{bmatrix} \Delta_{k,1}^{-1} \\ \Delta_{k,2}^{-1} \\ \vdots \\ \Delta_{k,n}^{-1} \end{bmatrix} \tag{2}$$

Finally, the design parameters are updated using a *gain sequence* a_k, according to

$$\theta_{k+1} := \theta_k - a_k \hat{g}_k \tag{3}$$

The gain sequence a_k and perturbation width c_k are typically given in terms of a few additional parameters a, c, A, α and γ:

$$a_k = \frac{a}{(1 + A + k)^\alpha}, \qquad c_k = \frac{c}{k^\gamma} \tag{4}$$

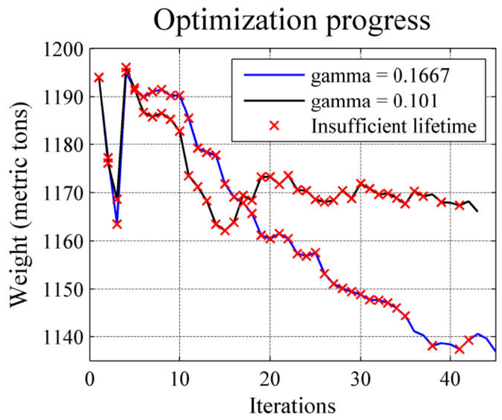

Figure 3. Dependence of optimization on perturbation width parameter γ.

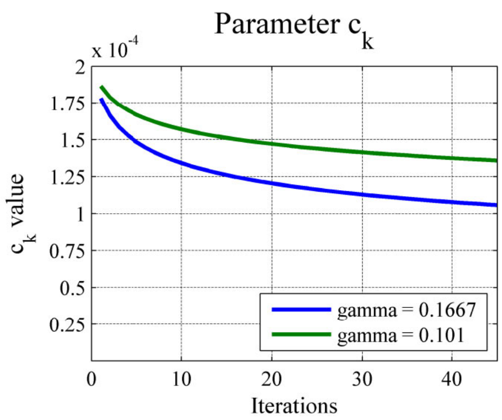

Figure 4. Perturbation width during optimization.

Default values are $\alpha = 0.602, \gamma = 0.101$. The parameter A is useful to reduce very large initial stepsizes and needs to be individually chosen. The following results were obtained with values of $a = 0.000025$, $c = 0.0005$ and $A = 15$, unless noted otherwise.

3. Results

3.1. Choice of objective function and algorithm parameters

The objective function controls the behavior of the algorithm and needs to be carefully chosen. Lower values represent a "better" design. Here we simply used structural steel weight as an indicator of cost, which shall be minimized. However, the design has to conform to the constraints given by the ultimate limit state (ULS) and the fatigue limit state (FLS). Designs that underperform have to be avoided. Various techniques exist for such constrained optimization problems, typically involving mirroring of parameters back into design space when a lifetime or strength constraint is violated.

We pursued a different and much simpler approach here: the objective function was extended by an additive term that quantifies how strongly a design violates the given design constraints, balancing the gain due to weight reduction. After some experimentation the following objective function was chosen:

$$\left(\frac{\text{weight} - 1200\,\text{t}}{50\,\text{t}}\right) + \sum_{L_i<1} \left((L_i - 1.25)^2 + (L_i - 1.10)^{20}\right), \tag{5}$$

where the sum on the right side runs over all joints whose normalized lifetime L_i does not fulfill the design limits.

This objective function leads to a substantial number of infeasible designs, but due to the stochastic nature of the algorithm (with only two directions to choose from at each iteration), the algorithm does intermittently find suitable designs (confer Fig. 3).

During testing, additional constraints were implemented: the minimum allowed member diameters were set to 5mm. If thicknesses became equal or larger than half the element diameters the diameters were slightly increased to avoid unphysical situations. Braces were also constrained to remain thicker than the corresponding sections of the legs.

Algorithm parameters were varied, within certain limits. The γ parameter controls the decrease of the perturbation width during the progress of the optimization. Too small a value slows the optimization process down, and an acceptable choice was obtained with $\gamma = 0.1667$

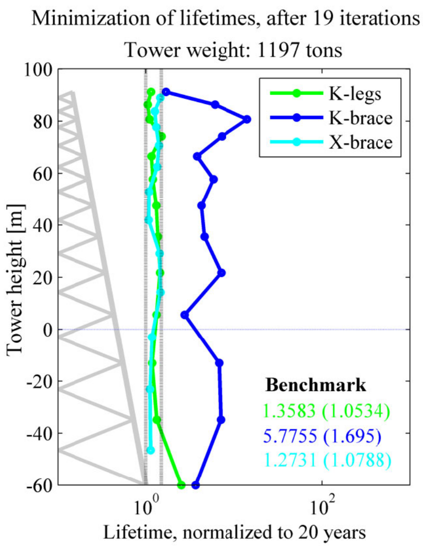

Figure 5. Performance of optimum design achieved by minimization-of-lifetimes method. Benchmark numbers refer to worst and average (in brackets) utilization of joints.

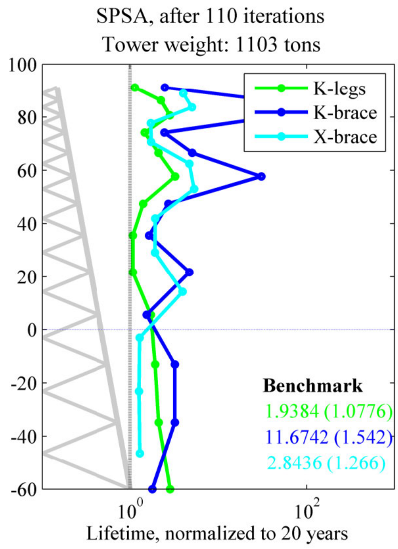

Figure 6. Performance of optimum design achieved by SPSA. Benchmark numbers refer to worst and average (in brackets) utilization of joints.

(Fig. 3). This leads to a relatively strong initial decrease of the perturbation width that then slowly levels out (Fig. 4).

Since in general the step size had a tendency to drop quicker than desired, the step size parameter α was taken at the lowest value recommended by Spall, $\alpha = 0.602$. Also the parameter A controlling the initial decrease in gain was set to 15, speeding up the optimization considerably.

In order to deal with variables with large differences in magnitude (e.g., diameters versus thicknesses) each component of the a_k and c_k values was scaled with a factor of 20 if it corresponded to a thickness parameter. Thereby all design variables showed approximately the same *relative* changes during an iteration.

3.2. Comparison with optimization-of-lifetimes method

The *optimization-of-lifetimes* method was introduced recently [15] to quickly perform an "optimal" sizing of a wind turbine support structure. It consists of a number of iterations where the present design utilization is evaluted. Then each member is sized independently of all the other members, weakening or strengthening the member until the utilization (assuming the exact same member forces as before) lies within 1.0–1.1. The analysis in the next iteration then typically leads to further redistribution of member dimensions, and the process is stopped if all joints perform within 1.0–1.5 utilization. The method converges quickly (Fig. 5). In contrast, the SPSA algorithm needs at least a factor of 10 more iterations (Fig. 6). However, although SPSA results in fewer feasible designs and takes significantly longer, it potentially results in better designs (Fig. 7).

This was confirmed by a restart simulation in which the best design obtained with the optimization-of-lifetimes method was used as starting point for the SPSA algorithm. A further reduction in weight of more than 90 tons was achieved (Fig. 8). Interestingly, the geometry of the final design was highly nontrivial, with alternating variations in leg diameters between sections that a human designer would not consider so quickly (Fig. 9).

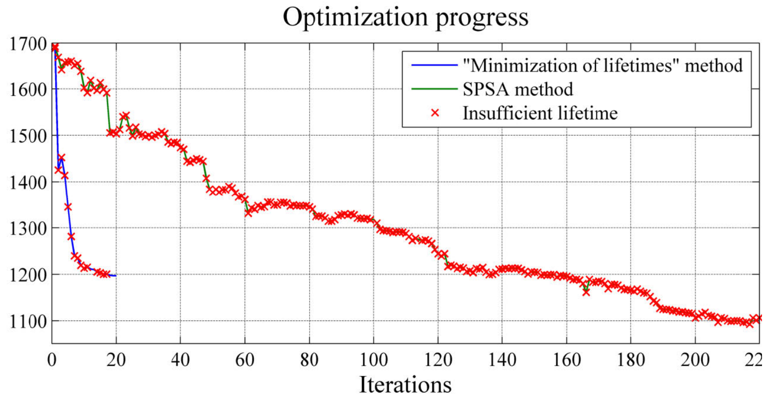

Figure 7. Comparison of minimization-of-lifetimes method and SPSA.

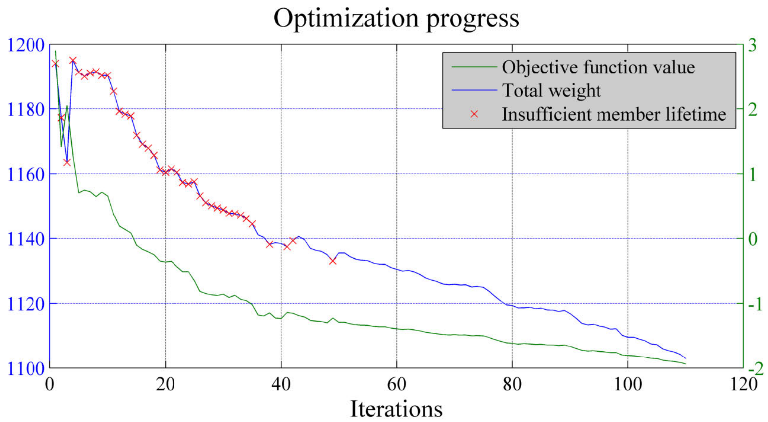

Figure 8. Optimization with SPSA from the best design obtained by the minimization-of-lifetimes method.

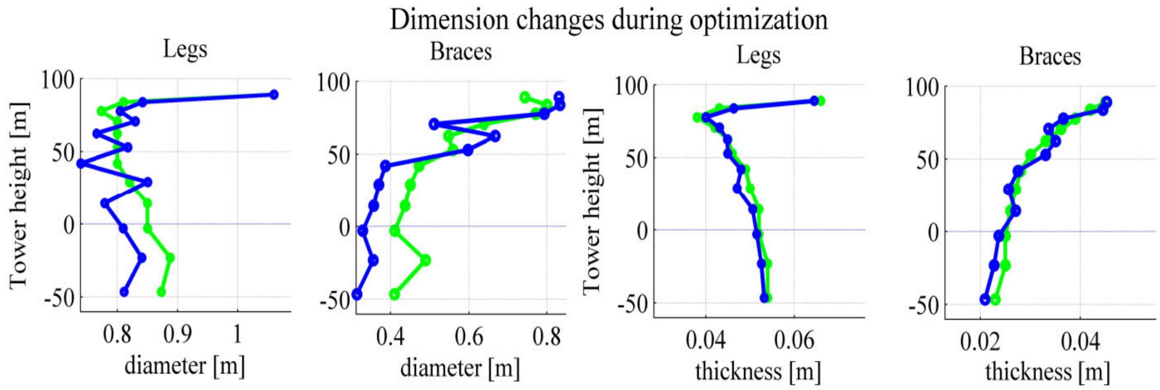

Figure 9. Geometry of the design optimized by SPSA. Green: original design (minimization-of-lifetimes method). Blue: optimized design after another 110 iterations.

3.3. A full optimization example

Starting from a design with constant member diameters and thicknesses, SPSA was run unsupervised for more than 300 iterations. During the process a number of interesting, feasible designs were obtained (Fig. 10) with weights similar to the above. The geometry of the design with 1132t mass (Fig. 11) differs markedly from the one previously obtained (Fig. 9). This illustrates the property that gradient-based algorithms (and therefore also pseudo-gradient based algorithms such as SPSA) will only lead to local optima. Different starting points and, for a

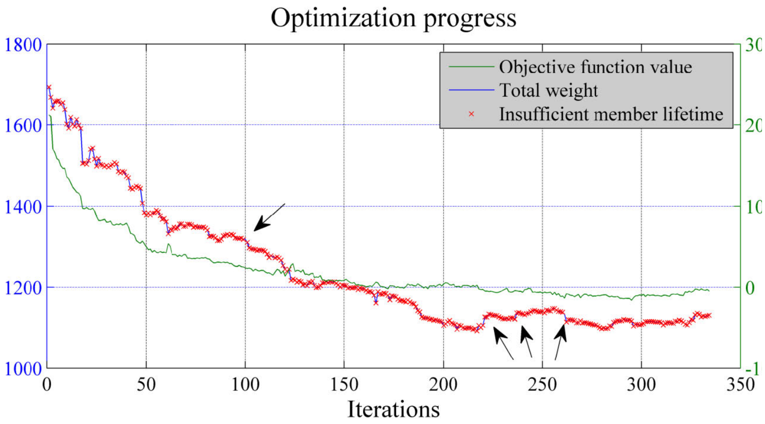

Figure 10. Full optimization example, using SPSA for an initial design with constant member dimensions.

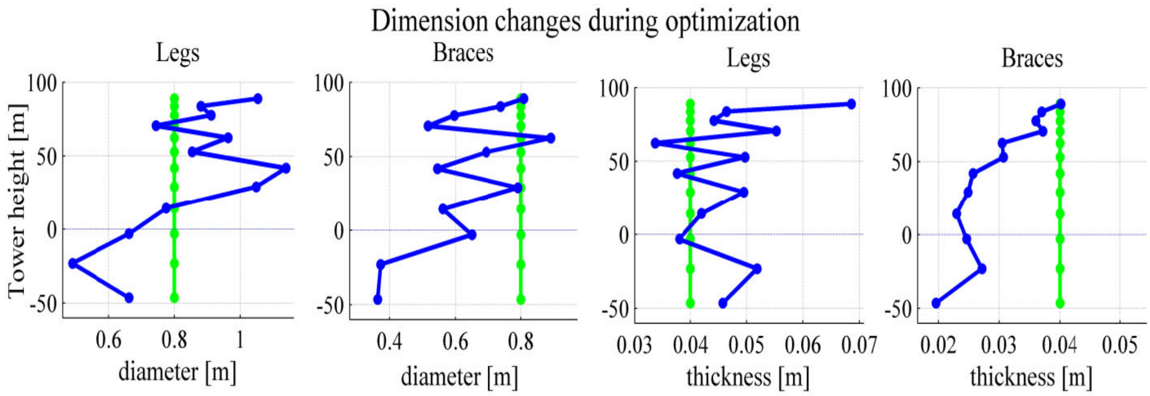

Figure 11. Geometry of the 1132t design optimized by SPSA. Green: original design (constant member dimensions). Blue: optimized design after 250+ iterations.

stochastic method such as SPSA, different perturbation vectors (random numbers) will generally lead to different results. Under certain conditions SPSA is actually provably able to find global optimal solutions [9], but these conditions are difficult to realize in practice.

4. Discussion

Optimization of offshore wind turbine support structures is a difficult problem, since fatigue lifetimes need to be estimated accurately. This typically necessitates a large number of loadcases (confer the loadcase tables in the relevant standards, e.g., [7]) with time-consuming time-domain simulations. SPSA has been designed for simulation-based optimization, where the evaluation of the objective function is computationally very expensive and should be attempted as few as possible.

The method was studied only with a single loadcase here. Moreover, no frequency (servicability) constraints were imposed and evalued for the designs, and the lifetime constraints were handled in a very simple manner. Nevertheless, the results demonstrate the potential of SPSA for automatic optimization of support structures. Further studies should focus on its application when multiple loadcases contribute to the value of the objective function. Also the effect of topology changes (e.g., differing the heights of sections) could be explored. Of course a better cost model taking into account manufacturing (welding) costs should be considered [4], as well as manufacturing constraints (e.g., discrete diameters and thicknesses for all tubular members).

Combined with a further approximation of fatigue lifetimes (e.g., using response-surface modeling [8]) that reduces the loadcases needed for fatigue estimation, the SPSA method seems a promising candidate for an automatic optimization algorithm.

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References
[1] Belegundu A D and Chandrupatha T R 2011 *Optimization concepts and applications in engineering* (New York: Cambridge University Press)
[2] Böker C 2009 *Load simulation and local dynamics of support structures for offshore wind turbines* (Hannover: Institut für Stahlbau, Gottfried Wilhelm Leibniz Universität Hannover)
[3] Det Norske Veritas 2010 *Fatigue design of offshore steel structures* Recommended practice DNV-RP-C203 (Høvik: DNV)
[4] Farkas J and Jármai K 2008 Cost comparison of a ring-stiffened shell and a tubular truss structure for a wind turbine tower *Design and optmization of metal structures* (Westergate: Horwood Publishing) 225–43
[5] Frøyd L and Dahlhaug O G 2011 Rotor design for a 10 MW offshore wind turbine *Proc. 21st Int. Offshore Polar Engng. Conf. (Maui, Hawaii)* 327-34
[6] Gosavi A 2003 *Simulation-based optimization* (New York: Springer)
[7] International Electrotechnical Commission 2009 *Wind turbines. Part 3: Design requirements for offshore wind turbines* International standard IEC 61400–3 (Geneva: IEC)
[8] Khuri A I and Cornell J A 1996 *Response surfaces: designs and analyses* (New York: Marcel Dekker)
[9] Maryak J L and Chin D C 2008 Global random optimization by simultaneous perturbation stochastic approximation *IEEE Trans. Automatic Control* **53** 780–3
[10] Muskulus M 2012 The full-height lattice tower concept *Energy Procedia* **23** 371–7
[11] Spall J C 1992 Multivariate stochastic approximation using a simultaneous perturbation gradient approximation *IEEE Trans. Automatic Control* **37** 332–41
[12] Spall J C 1998 An overview of the simultaneous perturbation method for efficient optimization *John Hopkins APL Technical Digest* **19** 482–92
[13] Spall J C 1998 Implementation of the simultaneous perturbation algorithm for stochastic optimization *IEEE Trans. Aerospace Electr. Systems* **34** 817–23
[14] Spall J C 2003 *Introduction to stochastic search and optimization* (Hoboken: John Wiley & Sons)
[15] Zwick D, Muskulus M and Moe G 2012 Iterative optimization approach for the design of full-height lattice towers for offshore wind turbines *Energy Procedia* **24** 297–304