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A hybrid multi-objective evolutionary algorithm for wind-turbine blade optimization

M. Sessarego\textsuperscript{a\ast}, K.R. Dixon\textsuperscript{b}, D.E. Rival\textsuperscript{a} and D.H. Wood\textsuperscript{a}

\textsuperscript{a}Department of Mechanical and Manufacturing Engineering, University of Calgary, 2500 University Dr. NW, Calgary, Alberta, Canada, T2N 1N4; \textsuperscript{b}Wind R&D Center, Siemens Energy Inc., 1050 Walnut Street, Suite 303, Boulder, CO 80302, USA

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A concurrent-hybrid non-dominated sorting genetic algorithm (hybrid NSGA-II) has been developed and applied to the simultaneous optimization of the annual energy production, flapwise root-bending moment and mass of the NREL 5 MW wind-turbine blade. By hybridizing a multi-objective evolutionary algorithm (MOEA) with gradient-based local search, it is believed that the optimal set of blade designs could be achieved in lower computational cost than for a conventional MOEA. To measure the convergence between the hybrid and non-hybrid NSGA-II on a wind-turbine blade optimization problem, a computationally intensive case was performed using the non-hybrid NSGA-II. From this particular case, a three-dimensional surface representing the optimal trade-off between the annual energy production, flapwise root-bending moment and blade mass was achieved. The inclusion of local gradients in the blade optimization, however, shows no improvement in the convergence for this three-objective problem.

Keywords: hybrid multi-objective evolutionary algorithm; multi-objective optimization; blade element momentum theory; beam theory

1. Introduction

For conventional upwind horizontal-axis wind turbines (HAWTs), studies have found that the flapwise root-bending moment ($M_{\text{flap,root}}$) and blade mass ($m_{\text{blade}}$) grow with rotor radius at $R^3$ and $R^{2.1}$, respectively, while the rotor power grows only with $R^2$ (Griffin 2001; Griffith and Ashwill 2011; Steele et al. 2012). Future development of larger wind turbines with higher power extraction capabilities requires reducing the rate of growth for $M_{\text{flap,root}}$ and $m_{\text{blade}}$ as much as possible. In addition to improvements in the design process, wind-turbine blade optimization can be used to reduce the above-mentioned growth rate. When applying an optimization method, blade element momentum (BEM) theory and beam theory are commonly used in the preliminary stages of blade design for quickly approximating the aerodynamic and structural performance.

The simultaneous optimization of wind-turbine blades with respect to aerodynamic and structural performance is, however, a challenging task. In contrast to a single-objective optimization where a single optimal solution is obtained, a multi-objective problem will typically give rise to a set of optimal trade-off (or Pareto-optimal) solutions. An optimization problem with conflicting objectives, numerous variables and nonlinear constraints cannot be solved using analytical methods.
methods. Even when considering the aerodynamics alone, analytical methods for optimizing blades are limited. For example, Wilson and Lissaman (1974) presented a method of deriving the optimum wind-turbine blade parameters for the single objective of maximum power coefficient ($C_P$). The disadvantage of Wilson and Lissaman’s method is that it requires a prescribed design tip speed ratio ($\lambda$) and the annual energy production (AEP) should be considered rather than $C_P$ (Fuglsang et al. 2002; Xudong et al. 2009; Selig and Coverstone-Carroll 1996; Benini and Toffolo 2002). The drag and tip-loss effects were also neglected in the analysis. As a consequence, researchers have resorted to gradient and non-gradient based numerical techniques to optimize wind-turbine blades for both single and multi-objective cases (Fuglsang et al. 2002; Xudong et al. 2009; Selig and Coverstone-Carroll 1996; Benini and Toffolo 2002; Lee et al. 2010; Giguère and Selig 2000; Wang, Wang, and Luo 2011).

Gradient-based examples can be found in Fuglsang et al. (2002), Xudong et al. (2009) and Lee et al. (2010). In Fuglsang et al. (2002) and Xudong et al. (2009), two objectives of maximum annual energy production (AEP) and minimum cost were converted into a single-objective problem by minimizing the cost of energy (COE). Instead of using COE, Lee et al. converted the objectives of maximum capacity factor ($C_F$) and minimum cost by using a weighted-sum of objectives. Here, a distinct Pareto-optimal solution was obtained by running the optimization each time with a different value of the weight factor.

Selig and Coverstone-Carroll (1996) were the first to implement a non-gradient based genetic algorithm (GA) for optimizing the AEP of stall-regulated wind-turbine rotors. Their work was later improved in Giguère and Selig (2000) to handle two objectives from a choice of three: minimum COE, maximum AEP or $C_P$, and minimum rotor thrust or torque. In Benini and Toffolo (2002), the AEP per square metre of wind park and the COE were optimized using a multi-objective evolutionary algorithm (MOEA) based on evolution strategy. Wang, Wang, and Luo (2011) optimized the NREL 5 MW wind-turbine blade for maximum $C_P$ and minimum $m_{blade}$ using an improved non-dominated sorting genetic algorithm (NSGA-II) (Deb et al. 2002).

For the current study, the goal is to obtain a set of optimal solutions for a benchmark pitch-regulated and variable-speed HAWT blade optimization in as few objective-function evaluations as possible. Furthermore, a reasonable distribution (or spread) of solutions must be obtained. The number of objective-function evaluations needed for an algorithm to converge to the optimal set largely determines the computational time, and reducing this number is crucial if more detailed and time-consuming models are to be implemented. In an attempt to achieve this goal, a hybridized gradient and non-gradient based algorithm is developed and applied for the first time, to the authors’ knowledge, on a multi-objective wind-turbine blade design optimization problem. It is postulated that the optimal set could be achieved in fewer objective-function evaluations using a hybrid MOEA than using a conventional MOEA. The reason is that gradient-based algorithms are the fastest in optimizing continuous single-objective optimization problems. Conversely, evolutionary algorithms have certain advantages over gradient-based methods when determining the Pareto-optimal set in multi-objective problems and tend to be better suited to design space exploration rather than exploitation. Evolutionary algorithms are more likely to find global-optimum solutions, are less sensitive to local minima, and are capable of determining multiple Pareto-optimal solutions in a single optimization run (Deb 2001).

In the present multi-objective optimization study on large-scale wind-turbine blades, the authors consider a three-dimensional surface that represents the optimal trade-off between the AEP, $M_{flap,root}$ and $m_{blade}$. This three-objective problem is considered to be the minimum number of objectives that captures the majority of the first-order physics involved in a typical blade design. In reality, many more objectives, constraints and other physical phenomena must be considered, often requiring simulations using computationally intensive high-fidelity models. The computational cost of solving the full design problem is not practical within the scope of this work, and therefore this study focuses on lower-fidelity methods that approximate the complete
problem to facilitate design space exploration and the development of a hybrid method for this purpose.

This article begins with relevant concepts on multi-objective optimization and subsequently describes the hybrid algorithm. The wind-turbine simulation codes are presented and then followed by the optimization results, some discussion and finally conclusions.

2. Multi-objective optimization concepts

The authors consider a multi-objective optimization problem of the form

\[
\begin{align*}
\min/\max & \quad f_1(x), f_2(x), \ldots, f_q(x) \\
\text{subject to} & \quad x \in S \\
& \quad g_c(x) \leq 0, c = 1, \ldots, N_c \\
& \quad x^L_k \leq x_k \leq x^U_k, k = 1, \ldots, n
\end{align*}
\]

with \( q \geq 2 \) conflicting objective functions. The vector of objectives \( f(x) = (f_1(x), f_2(x), \ldots, f_q(x)) \) is called an objective vector and the vector of design variables \( x = (x_1, x_2, \ldots, x_n) \) a decision vector. The decision vector \( x \) is an element of the \( n \)-dimensional real numbers \( x \in \mathbb{R}^n \) that satisfy all constraints. The function \( g_c(x) \) is an inequality constraint and the design variables \( x_k \) are bounded by upper \( x^U_k \) and lower \( x^L_k \) values. Altogether, \( x \) belongs to the feasible region \( S \).

In the field of multiple criteria decision making, see e.g. Miettinen (1999), multi-objective optimization problems are treated in a single-objective sense by using scalarization functions. Among the numerous different scalarization functions available in the literature, an achievement scalarizing function (ASF) (Miettinen 1999; Wierzbicki 1986) is common and the one implemented in the hybrid algorithm.

3. Concurrent-hybrid NSGA-II

The hybrid algorithm developed is based on the concurrent-hybrid NSGA-II (hybrid NSGA-II) due to Sindhya, Deb, and Miettinen (2011). The hybridization is composed of a non-gradient based MOEA and a gradient-based local search. In Sindhya, Deb, and Miettinen (2011), the NSGA-II is chosen as the MOEA and the sequential quadratic programming (SQP) method is chosen for the gradient-based local search. The local search entails solving the differentiable version of the ASF (Miettinen 1999) and is applied according to a predefined probability function (Sindhya, Deb, and Miettinen 2011). In this work, an alternative MOEA could be used instead of the NSGA-II; however, the NSGA-II is selected for the same reasons as stated in Sindhya, Deb, and Miettinen (2011). For the gradient-based local search, the MATLAB\textsuperscript{R} R2011a \texttt{fminimax} command is used since it reformulates the ASF into its differentiable form and applies the SQP method automatically (The MathWorks 2014).

The selection, crossover and mutation operators in the NSGA-II are the main constituents of a GA and several different types exist for each. A commonly used selection operator is binary tournament selection. The type of operators chosen for solving a particular optimization problem will have the most significant effect on the performance of an MOEA. In addition, each operator includes parameter settings that also influence the GA’s performance. Further explanation of the three operators can be found in one of many available textbooks on the topic, e.g. Deb (2001). For examples of crossover and mutation operators see Table 1.
Table 1. Summary of algorithms and parameter settings for the DTLZ2 test function.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Hybrid NSGA-II</th>
<th>NSGA-II</th>
<th>gamultiobj</th>
<th>gamultiobj (default)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size (N_{\text{pop}})</td>
<td>200</td>
<td>200</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>Selection</td>
<td>binary tournament</td>
<td>binary tournament</td>
<td>binary tournament</td>
<td>binary tournament</td>
</tr>
<tr>
<td>Crossover</td>
<td>scattered(^a)</td>
<td>binary tournament</td>
<td>scattered(^a)</td>
<td>intermediate</td>
</tr>
<tr>
<td>Crossover fraction</td>
<td>0.9(^b)</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>Mutation</td>
<td>polynomial</td>
<td>polynomial</td>
<td>adaptive feasible</td>
<td>adaptive feasible</td>
</tr>
<tr>
<td>Mutation probability</td>
<td>0.001(^b)</td>
<td>0.001</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Mutation index</td>
<td>20(^b)</td>
<td>20</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Pareto fraction</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.35</td>
</tr>
<tr>
<td>Spread maintenance</td>
<td>clustering approach</td>
<td>clustering approach</td>
<td>crowding routine</td>
<td>crowding routine</td>
</tr>
</tbody>
</table>

\(^a\) Also known as uniform.
\(^b\) As suggested by Sindhya, Deb, and Miettinen (2011).

4. Verification using analytical test function

Before applying the hybrid algorithm for wind-turbine blade optimization, its performance on analytical test functions from the ZDT (Zitzler, Deb, and Thiele 2000) and DTLZ (Deb et al. 2005) test suites was investigated. For brevity, the results for only the DTLZ2 test function will be shown here. DTLZ2 is scalable in both the number of objectives and the number of variables, and does not contain any equality or inequality constraints. The number of objectives and variables chosen are \(q = 3\) and \(n = 20\), respectively, which matches comparatively to the wind-turbine blade optimization problem. The Pareto front for the three-objective DTLZ2 is shown in Figure 1.

In the current study, the performance of an algorithm for multi-objective optimization is focused on convergence. Hence, the generational distance (GD) (Van Veldhuizen and Lamont 2000) metric is used to compare different algorithms. The GD metric measures the average Euclidean distance in the objective-function space between each solution resulting from the algorithm and its nearest Pareto-optimal solution in the true Pareto front \(\text{PF}_{\text{true}}\). The \(\text{PF}_{\text{true}}\) shown in Figure 1 was derived from 441 perfectly spread Pareto-optimal solutions. When the solutions from an algorithm lie exactly on the Pareto-optimal solutions of \(\text{PF}_{\text{true}}\), the GD will have the optimal value of zero. This seldom occurs because the heuristics prevent a perfectly-spread and fully-converged set of solutions. As shown for two MOEAs in Figure 2, the solutions are unevenly distributed and are situated at varying distances from \(\text{PF}_{\text{true}}\). Therefore, the aim is to attain the minimum GD value in as few objective-function evaluations as possible rather than achieving \(\text{GD} = 0\). When assessing the convergence, it is common practice to calculate the average GD based on multiple runs to account for the heuristic effects. Furthermore, since the accuracy of the GD is dependent on the resolution of \(\text{PF}_{\text{true}}\), a large number (i.e. \(|\text{PF}_{\text{true}}| = 10,000\)) should be used for GD calculations.
Figure 1. Three-objective DTLZ2 Pareto front ($|PF_{true}| = 441$ shown for clarity).

Figure 2. Comparison of computed results between hybrid (left) and non-hybrid (right) NSGA-II at 10,000 objective–function evaluations ($|PF_{true}| = 441$ shown for clarity).

The average GD versus the number of objective-function evaluations\(^1\) from 10 runs is plotted for four algorithms in Figure 3. Two of the four algorithms consist of the NSGA-II as described in Section 3 with and without the gradient-based local search. The NSGA-II embedded in the MATLAB\(^\text{®}\) R2011a `gamultiobj` command with improved and default parameter settings comprise the remaining two algorithms. Attempts were made to determine the parameters (such as the crossover and mutation operators) that resulted in the best possible convergence for `gamultiobj`. Accordingly, identical parameters were used for the hybrid and non-hybrid NSGA-II whenever possible for a fair comparison. A summary of the algorithms and parameter settings is given in Table 1.

Figure 3 shows that the hybrid NSGA-II outperforms all other algorithms with respect to the GD metric. The inclusions of gradient-based local search have reduced the number of objective-function evaluations needed to reach the minimum GD value by approximately 50% in comparison with the regular NSGA-II. Figure 2 displays the objective vectors obtained from the hybrid and non-hybrid NSGA-II at 10,000 objective-function evaluations. Although the hybrid produces solutions closer to $PF_{true}$, the difference in the GD values between the two algorithms
is small. It is observed from Figure 2 that the reduction in objective-function evaluations is attributed to the fine-tuning capabilities of gradient-based local search that the regular NSGA-II lacks. For this particular test function, executing `gamultiobj` using its default settings yields poor convergence. Similar results for the four algorithms have been obtained for other ZDT and DTLZ test functions. Based on these results, it is in the authors’ interest to achieve the same reduction in objective-function evaluations for the wind-turbine blade optimization problem as well.

5. Wind-turbine simulation codes

5.1. Aerodynamic model

The widely-used BEM method (see for example Hansen [2008]) is implemented as the aerodynamic model. In the BEM method, the aerodynamic forces are obtained by analysing the flow over a discretized blade (blade elements—BEs) and momentum theory. An in-house steady-state BEM code was developed that includes Prandtl’s tip-loss factor and a correction by Buhl (2005) for the thrust coefficient at high values of the axial induction factor. The code was validated against WT_Perf (Buhl 2012) by the National Wind Technology Center (NWTC), see Sessarego (2013).

Two objective functions\(^2\) are obtained from the BEM code:

\[
\begin{align*}
\text{maximize} & \quad \text{AEP} = 8760 \int_{V_{\text{cut-in}}}^{V_{\text{cut-out}}} P(V, \theta, \lambda) f(V) \, dV; \\
\text{minimize} & \quad M_{\text{flap,root}} = \int_{r_{\text{hub}}}^{R} r p_{\text{norm}}(r) \, dr.
\end{align*}
\]

In Equation (2), 8760 is the number of turbine operating hours per year, \( P(V, \theta, \lambda) \) is the rotor power obtained from the power curve (Figure 4(a)), and \( f(V) \) is the probability density function of the wind speed. Although not difficult to incorporate, site-specific wind speed data is not considered here and the simple Rayleigh probability density function was chosen for \( f(V) \) with a mean wind speed of 7.5 m/s. Deriving the power curve for a pitch-regulated and variable-speed HAWT involves running the BEM code for a range of \( \theta \) and \( \lambda \), and subsequently extracting
the pitch (Figure 4(b)) and RPM (Figure 4(c)) schedules. The operational schedule consists of constant (optimal) $\lambda$ up to the rated rotor speed, followed by pitch regulation.

The aerodynamic load per length of blade normal to the rotor plane, $p_{\text{norm}}(r)$, in Equation (3) is taken from the maximum $M_{\text{flap,root}}$ experienced between $V_{\text{cut-in}}$ and $V_{\text{cut-out}}$. The thrust curve (Figure 4(d)) is used to obtain the maximum $M_{\text{flap,root}}$ and hence $p_{\text{norm}}(r)$. The load $p_{\text{norm}}(r)$ is also fed into the structural model described in the following section along with the tangential aerodynamic load per length of blade $p_{\text{tang}}(r)$. Centrifugal forces, which affect the blade deflections and overall loads, are not included.

5.2. Structural model

The structural model is based on simple Euler–Bernoulli beam theory as described by Hansen (2008). A box-type structural lay-up common to many blade designs is selected as the baseline (Figure 5). The lay-up includes a shell composed of multiple skins, two shear webs, fore and aft panels, and two spar caps of equal thickness. In practice, wind turbine blades are made with composite anisotropic materials and classic laminate theory or finite-element based approaches are used to predict blade structural performance (see for example Damiani [2012] and Yu, Hodges, and Ho [2012]). For the current study, the complexity of the structural analysis is reduced by treating all materials isotropically. Approximate dimensions for the skins, webs and panels are obtained from TPI Composites (2002). The only variable is the thickness of the spar caps between the blade root and tip (Figure 6(a)). The spar-cap thickness (SCT) variable is not included in Section 6.2 because it is determined through an optimization scheme internal to the code. The internal optimization minimizes $m_{\text{blade}}$ while satisfying the constraints described in Section 6.3.

Following blade discretization, a simple scheme involving Green’s theorem and a weighted-sum approach is implemented to estimate the primary structural properties of each blade element: linear mass ($\mu$) and effective bending stiffness (EI) aligned with the principal axes (EI1 and EI2) and centred at the tension centre (TC), see Figure 5 and Sessarego (2013). The bending moments $M_{\text{flap}}$ and $M_{\text{edge}}$ due to the aerodynamic loads are also calculated, and are rotated to
align with the principal axes to give $M_1$ and $M_2$. The element bending stiffness ($EI_1$ and $EI_2$) and bending moment ($M_{\text{flap}}$ and $M_{\text{edge}}$) distributions for an arbitrary blade are given in Figures 6(b) and 6(c), respectively. The code was compared with PreComp by the NWTC (Damiani 2012), see Sessarego (2013).

Given $EI_1$, $EI_2$, $M_1$ and $M_2$, the maximum strain occurring at each blade element and the tip deflection (Figure 6(d)) can be determined. The maximum strain is calculated using Equations (4) and (5):

$$
\varepsilon_1 = \frac{|M_1|}{|EI_1|} \max[|y'_\text{max}|, |y'_\text{min}|],
$$

$$
\varepsilon_2 = \frac{|M_2|}{|EI_2|} \max[|x'_\text{max}|, |x'_\text{min}|]
$$

where $x'_\text{max}$, $x'_\text{min}$, $y'_\text{max}$ and $y'_\text{min}$ are the approximate locations of maximum strain defined in the $x'$–$y'$ coordinate system as shown in Figure 5.
In beam theory, the effect of each strain component (i.e. $\varepsilon_1$ and $\varepsilon_2$) on a blade element should be aggregated based on the principle of superposition. Here, $\varepsilon_1$ and $\varepsilon_2$ are treated separately and whether $\varepsilon$ is in compression ($-$) or tension ($+$) is not considered. The flapwise deflection, $\delta_{\text{flap}}$, is obtained by integrating the blade curvature twice and applying boundary conditions of zero slope and zero deflection at the root.

The objective function calculated from the structural model is then

$$\text{minimize } m_{\text{blade}} = \int_{r_{\text{hub}}}^{R} \mu \, dr.$$  \hfill (6)

5.3. **Simplified aero-structural approach**

For a coupled aero-elastic computation, the blade velocity and deflection obtained from a structural model should be fed into the aerodynamic model and the loads recalculated. This process is repeated until convergence is achieved. Here, a quasi-static computation is employed where the BEM code and structural model are each executed once only per blade. The multi-objective blade optimization involves the simultaneous optimization of a set of solutions. Depending on the size of solutions, the computational cost will be orders of magnitude larger than optimizing a single solution. Executing quasi-static simulations, as opposed to dynamic load cases using an aero-elastic model, is necessary to reduce the overall computing time. Since the aero-structural approach used is simple and the only load case considered is the steady maximum $M_{\text{flap,root}}$, the current framework can only be used as a means to explore the design space and identify regions of interest for further investigation. The framework provides the opportunity to explore trade-offs between various objectives and derive trends in the parameters describing the blade’s shape. After selecting a candidate blade from the Pareto-optimal set, a full set of load cases should be conducted using higher-fidelity models to continue the blade design process. In the present work, operating conditions in turbulent wind, extreme and emergency situations including gusts, storm events and faults have been neglected. Constraints on the blade natural frequencies to avoid resonant conditions as well as buckling limits are also not considered.

To illustrate the differences between the quasi-static approach and an aero-elastic model, results from the wind-turbine simulation codes are compared with FAST (Jonkman 2013). The predicted blade deflections from both approaches for the NREL 5 MW blade (Jonkman et al. 2009) and a steady wind of 11.4 m/s are shown in Figure 7. The computations from FAST include precone and tilt angle effects, centrifugal stiffening, gravitational and inertial loads, as well as dynamic stall and wake models. In Figure 7, the relative change between the quasi-static method and FAST for the flapwise and edgewise tip deflections are 6.65 and 0.36%, respectively.

6. **Wind-turbine blade optimization**

6.1. **Objective functions**

Following the suggestions in Hjort et al. (2009), Equations (2), (3) and (6) are used in the objective vector $f(x)$. For Equation (3), it is assumed that minimizing the peak $M_{\text{flap,root}}$ will also minimize the equivalent fatigue loads. This assumption is based on Fuglsang and Madsen (1995), where equivalent fatigue loads have been found to vary linearly with the mean blade root flapwise moment for a stall-regulated machine. The current framework takes advantage of this linear correlation as a method to avoid time consuming aero-elastic computations required for fatigue analysis. The aspect of fatigue is also implicit in the value chosen for maximum allowable strain in Equation (9). Since the competitiveness of wind energy against other energy sources depends
strongly on cost, minimizing the cost (or COE) has typically been considered as an objective function (Fuglsang et al. 2002; Xudong et al. 2009; Benini and Toffolo 2002; Lee et al. 2010; Giguère and Selig 2000). However, the cost of a turbine is difficult to calculate and assumptions are often made for simplification. In Xudong et al. (2009), Benini and Toffolo (2002) and Lee et al. (2010), the cost depends on the blade (or rotor) only. When determining the blade cost, mass is used as a parameter (Xudong et al. 2009; Benini and Toffolo 2002). For Equation (6), a cost model is not included and $m_{\text{blade}}$ is assumed to be well correlated to blade cost instead. Minimizing the peak $M_{\text{flap,root}}$ also partially accounts for the cost of other turbine components (e.g. nacelle, tower, etc.) required to sustain the transmitted loads.

Having introduced the objective vector in problem (1) for the blade optimization, the decision vector will be presented in Section 6.2, and the inequality and boundary constraints in Section 6.3.

### 6.2. Design variables and parameterization

Bézier curves that are manipulated by control points (CPs) define the blade twist, chord ($c$) and relative thickness ($t/c$) distributions (Figure 8(a)–8(c)). Between the hub and maximum chord position, the relative thickness is also defined by a cubic B-spline. In Figure 8(b), the root chord is iterated such that a monotonically-decreasing dimensional thickness is obtained, as shown in Figure 8(d). The dimensional thickness is the product of the relative thickness and the chord. The CPs and distributions are shown in Figure 8 for an arbitrary blade.

The methodology used to define the blade shape follows that of Sale’s HARP_Opt code (Sale 2010) closely with two main exceptions: (1) the number of CPs for the twist, chord and relative thickness distributions outboard of the maximum chord position is adjustable, and (2) a Bézier curve is used instead of a piecewise-linear distribution for the relative thickness. Exception (1) provides the user with a choice of the number of CPs used and (2) generates a smoother blade shape. The reader is referred to Sale (2010) for a detailed description of the optimization variables.

The decision vector $x$ is given by

$$x = (\text{CP}_1, \text{twist}, \text{CP}_2, \text{twist}, \ldots, \text{CP}_{N_x}, \text{twist}, \text{CP}_1, \text{chord}, \text{CP}_2, \text{chord}, \ldots, \text{CP}_{N_x}, \text{chord}, \text{CP}_1, \text{rel.thick}, \text{CP}_2, \text{rel.thick}, \ldots, \text{CP}_{N_x}, \text{rel.thick})$$

(7)

Figure 7. Comparison of predicted flapwise (left) and edgewise (right) blade deflections between the quasi-static approach and FAST for the NREL 5 MW blade and a steady wind of 11.4 m/s.
where the number of CPs for the twist, chord and relative thickness are $N_u$, $N_c$ and $N_w$, respectively.

### 6.3. Constraints

There are two types of constraints involved in the present optimization of the wind-turbine blade. The first are nonlinear inequality constraints and the second are boundary constraints, which are given by Equations (8) to (11) and Equations (12) to (14), respectively. In Equation (8), $\delta_{\max}$ is equal to 50% of the initial blade tip clearance, which is the allowable tip deflection under normal turbine operation for a quasi-static analysis in the GL guidelines (Germanischer Lloyd 2012):

$$\frac{(\delta_{\text{flap}} - \delta_{\max})}{\delta_{\max}} \leq 0. \quad (8)$$

The maximum allowable strain ($\varepsilon_{\max}$) shown in Equation (9) is a value used typically in blade design and is not associated to specific material and safety factor choices. The value of $\varepsilon_{\max}$ is also constant from the blade root to tip. The tip deflection and strain are computed as discussed in Section 5.2. The strain constraint is given by

$$\frac{(\max[\varepsilon_1, \varepsilon_2] - \varepsilon_{\max})}{\varepsilon_{\max}} \leq 0. \quad (9)$$

The remaining set of inequality constraints given by Equations (10) and (11)

$$\frac{(f_{i,\min}(x) - f_i(x))}{f_{i,\min}(x)} \leq 0 \quad (10)$$

$$\frac{(f_i(x) - f_{i,\max}(x))}{f_{i,\max}(x)} \leq 0 \quad (11)$$

prevents a multi-objective optimization algorithm from searching an excessively large region of the objective-function space. In other words, the authors are only interested in blade designs that are in the vicinity of the original. For the blade optimization considered here, $\text{AEP}$, $M_{\text{flap,root}}$ and $m_{\text{blade}}$ are constrained to be within $\pm5$, $\pm40$ and $\pm40\%$ from the original, respectively. All
inequality constraints (Equations 8 to 11) are normalized to prevent bias from any particular constraint. The boundary constraints involve limiting the CPs for the twist, chord and relative thickness as shown by Equations (12) to (14)

\[
\begin{align*}
CP_{\text{min}, \text{twist}} & \leq CP_{u, \text{twist}} \leq CP_{\text{max}, \text{twist}} & (12) \\
CP_{\text{min}, \text{chord}} & \leq CP_{v, \text{chord}} \leq CP_{\text{max}, \text{chord}} & (13) \\
CP_{\text{min}, \text{rel.thick}} & < CP_{w, \text{rel.thick}} < CP_{\text{max}, \text{rel.thick}} & (14)
\end{align*}
\]

where \(u = 1, \ldots, N_u\), \(v = 1, \ldots, N_v\) and \(w = 1, \ldots, N_w\).

In terms of the hybrid NSGA-II, nonlinear inequality constraint violation is minimized and removed by using the selection-based constraint-handling approach described in Deb et al. (2002) for the NSGA-II and the method in the \textit{fminimax} SQP routine for the gradient-based local search. In addition to applying the hybrid NSGA-II for wind-turbine blade optimization, \textit{gamultiobj} is also used for comparison. However, \textit{gamultiobj} does not include nonlinear inequality constraint-handling capabilities and therefore a simple penalty approach is used instead. In the penalty approach, when a candidate blade design violates one or more constraints, the objective vector \(f(x)\) is set to the worst possible values (i.e. \(\text{AEP} = -10^{50}\) and \(M_{\text{flap, root}} = m_{\text{blade}} = 10^{50}\)). Using this method allows the algorithm within \textit{gamultiobj} to discard unfeasible blade designs without having to modify the coding, which is necessary for the selection-based approach. The crossover and mutation operators in the NSGA-II and \textit{gamultiobj} as well as the \textit{fminimax} SQP routine always satisfy the boundary constraints.

6.4. Blade optimization results and discussion

The NREL offshore 5 MW wind-turbine blade is selected as a baseline design for optimization and its basic properties are shown in Table 2 (Jonkman et al. 2009). The structural lay-up and material properties are not provided in Jonkman et al. (2009), thus a structural lay-up described in Section 5.2 and material properties from Griffin (2001) are applied instead. For the elastic modulus, \(E\), the flapwise component is chosen from Griffin (2001). The material properties used in the structural model are summarized in Table 3. The twist, chord and thickness distributions for the NREL 5 MW blade are displayed in Figure 9. For the results given in the following section, 30 blade elements and 18 design variables \((N_u = 5, N_v = 6\) and \(N_w = 7)\) were used.

In contrast to test functions such as those discussed in Section 4, \(PF_{\text{true}}\) cannot be derived for the wind-turbine blade optimization problem. As a result, before determining the convergence of the algorithms, an approximation of \(PF_{\text{true}}\) is necessary to calculate the GD metric. This can be achieved by executing a multi-objective optimization that results in a well-spread and fully-converged Pareto-optimal set. An accurate GD calculation also requires that the size of the Pareto-optimal set is large. In an attempt to meet these requirements using the computational

<table>
<thead>
<tr>
<th>Table 2. Basic NREL 5 MW wind-turbine properties.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating (MW)</td>
</tr>
<tr>
<td>Number of blades</td>
</tr>
<tr>
<td>(R) (m)</td>
</tr>
<tr>
<td>(V_{\text{cut-in}}) (m/s)</td>
</tr>
<tr>
<td>(V_{\text{cut-out}}) (m/s)</td>
</tr>
<tr>
<td>Rated tip speed (m/s)</td>
</tr>
<tr>
<td>Airfoils</td>
</tr>
</tbody>
</table>
Table 3. Material properties used in the structural model.

<table>
<thead>
<tr>
<th>Property</th>
<th>[0°] A260</th>
<th>[±45°][0°] CDB340</th>
<th>Random mat</th>
<th>Balsa</th>
<th>Gel coat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elastic modulus, $E$ (GPa)</td>
<td>31.0</td>
<td>9.65</td>
<td>2.07</td>
<td>3.44</td>
<td></td>
</tr>
<tr>
<td>Density, $\rho$ (kg/m$^3$)</td>
<td>1700</td>
<td>1670</td>
<td>144</td>
<td>1230</td>
<td></td>
</tr>
</tbody>
</table>

Figure 9. Blade element twist (a), chord (b), and thickness (c) and (d) distributions for the NREL 5 MW blade and a Pareto-optimal (PO) solution.

resources available, $PF_{true}$ is approximated by executing the algorithm described in Section 3, without the gradient-based local search, for as many ($l = 110$) iterations as possible and with a large population size ($N_{pop} = 1000$). The result of the approximation is shown in Figure 10.

In Figure 10, an arbitrary Pareto-optimal solution (PO-* ) and the NREL 5 MW blade (filled circle) are also plotted. The PO has a 1.4% increase in AEP, 8.8% decrease in $M_{flap,root}$ and 0.8% decrease in $m_{blade}$ with respect to the NREL 5 MW turbine. Consequently, not only has the algorithm optimized the initial design for more than one objective, but it has also provided a complete set of optimal trade-off solutions as illustrated by the surface in Figure 10. As discussed in Section 6.3, the Pareto-optimal set is, however, bounded by the inequality constraints on the objective-function space (Equations 10 and 11). Figure 11 displays the NREL blade on the AEP–$M_{flap,root}$ and $M_{flap,root}$–$m_{blade}$ planes where $m_{blade}/m_{NREL} = 1$ and AEP/AEP$^{NREL} = 1$, respectively. Pareto-optimal solutions on the AEP–$m_{blade}$ plane where $M_{flap,root}/M_{NREL}^{flap,root} = 1$ do not exist, and hence are not shown. As illustrated in Figure 11 for increasing $M_{flap,root}$, AEP also increases while $m_{blade}$ decreases.

Figure 12 shows the change in optimum (or constant) power coefficient, $C_{P,\text{opt}}$, and tip-speed ratio, $\lambda_{\text{opt}}$, at the variable-speed region as a function of the objectives. In Figure 12(a), the AEP correlates well with $C_{P,\text{opt}}$, where an increase in $C_{P,\text{opt}}$ results in an increase in AEP. The diagonal transition from $C_{P,\text{opt}} = 0.46$ (bottom-left corner) to $C_{P,\text{opt}} = 0.50$ (top right) illustrates that the trade-off for increasing AEP is an increase in $M_{flap,root}$ and $m_{blade}$. In Figure 12(b), a rotor operating at $\lambda_{\text{opt}} = 10.5$ (top left) will have a large $m_{blade}$ with low AEP and $M_{flap,root}$. In the bottom-right corner of the Pareto front where $\lambda_{\text{opt}} = 8.5$, the rotor will have a small $m_{blade}$ with high AEP and $M_{flap,root}$.
Comparisons of the twist, chord and thickness distributions for the NREL 5 MW blade and PO are shown in Figure 9. It is observed that the twist (Figure 9(a)) and chord (Figure 9(b)) near the root section for PO both approach their maximum allowable values set by the boundary constraints in Equations (12) and (13). Conversely, there is a decrease in relative thickness near...
the root but an increase at about $r/R = 0.75$ instead (Figure 9(c)). A decrease in chord also occurs between the mid-span and blade tip. Although the optimized blade yields improved performance, the results are based on a number of simplifying assumptions in the models. As mentioned in Section 5.3, a full aero-elastic simulation and design load case set must be conducted using higher-fidelity methods to continue the blade design process.

Figure 13 displays the power and thrust curves, as well as the pitch and RPM schedules for the NREL 5 MW and PO. In Figure 13(a), PO produces more power for all wind speeds up to approximately the rated power. The increase in power is attributed to PO’s improved $C_{P,\text{opt}} = 0.50$ in comparison with $C_{P,\text{opt}} = 0.48$ of the NREL 5 MW blade. Figures 13(b) and 13(c) reveal that $C_{P,\text{opt}}$ for PO corresponds to a lower pitch angle ($\theta = -0.8^\circ$) and higher tip-speed ratio ($\lambda = 8.6$) than the NREL 5 MW ($\theta = 0^\circ$ and $\lambda = 7.8$). In Figure 13(d), the peak thrust for PO is lower than the NREL 5 MW as well. The local $C_P$ at the variable-speed region and $C_T$ at peak $M_{\text{flap,root}}$ are plotted for both blades in Figure 14. The increase in $C_{P,\text{opt}}$ for PO is the result of increasing the twist and chord, and using an improved aerodynamic profile between $r/R = 0$
and $r/R = 0.25$. Decreasing the chord and increasing the relative thickness towards the tip (i.e. $r/R > 0.5$) reduces the flapwise loads that largely determine $M_{\text{flap,root}}$.

Comparisons of the structural properties and performance between the two blades are presented in Figure 15. In Figure 15(a), the increase in the relative spar-cap thickness is the consequence of reducing the chord towards the tip region, resulting in a dimensional spar-cap thickness similar to that of the NREL design. While the flapwise bending stiffness decreases slightly towards the blade root, the edgewise component increases because of the increase in chord as shown in Figure 15(b). The reduced value of $M_{\text{flap,root}}$ for PO is illustrated by the lower $M_{\text{flap,PO}}$ distribution compared to $M_{\text{flap,NREL}}$ in Figure 15(c). Lastly, the edgewise bending moments and flapwise deflections are nearly identical in Figures 15(c) and 15(d).
Table 4. Summary of algorithms and parameter settings for the three-objective NREL 5 MW blade optimization.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Population size</th>
<th>Selection</th>
<th>Crossover</th>
<th>Crossover fraction</th>
<th>Mutation</th>
<th>Mutation probability</th>
<th>Mutation index</th>
<th>Pareto fraction</th>
<th>Spread maintenance</th>
<th>Constraint handling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hybrid NSGA-II</td>
<td>200</td>
<td>binary tournament</td>
<td>scattered</td>
<td>0.9</td>
<td>polynomial</td>
<td>0.001</td>
<td>20</td>
<td>1</td>
<td>clustering approach</td>
<td>selection based</td>
</tr>
<tr>
<td>NSGA-II</td>
<td>200</td>
<td>binary tournament</td>
<td>scattered</td>
<td>0.9</td>
<td>polynomial</td>
<td>0.001</td>
<td>20</td>
<td>1</td>
<td>clustering approach</td>
<td>selection based</td>
</tr>
<tr>
<td>gamultiobj</td>
<td>200</td>
<td>binary tournament</td>
<td>scattered</td>
<td>0.9</td>
<td>adaptive feasible</td>
<td></td>
<td></td>
<td>1</td>
<td>crowding routine</td>
<td>penalty based</td>
</tr>
</tbody>
</table>

Figure 16. Algorithm convergence for the three-objective NREL 5 MW blade optimization.

6.5. Algorithm results and discussion

Having computed a well-defined Pareto-optimal set that approximates \( \text{PF}_{\text{true}} \), it is now possible to apply the algorithms and measure their convergence. Table 4 summarizes the parameter settings used for three algorithms, which are based on the studies performed on the ZDT and DTLZ test functions. As shown on the last row of Table 4, the wind-turbine blade optimization problem differs from the DTLZ2 test case in the addition of constraint handling. The three algorithms used are the hybrid and non-hybrid NSGA-II, and \( \text{gamultiobj} \). Figure 16 displays the GD results for the three algorithms. Due to the high computational cost involved in the wind-turbine blade optimization, each algorithm is executed once only (as opposed to 10 runs for DTLZ2) for calculating the average GD. Consequently, the GD results in Figure 16 may be subject to uncertainties for the same reason as described in Section 4. Furthermore, the approximation of \( \text{PF}_{\text{true}} \) used to calculate the GD may also introduce some additional uncertainty.

As shown in Figure 16, the hybrid fails to provide the significant reduction in objective-function evaluations anticipated from the ZDT and DTLZ test-function studies. For the first 20,000 objective-function evaluations, the NSGA-II results in the best convergence while the hybrid and \( \text{gamultiobj} \) perform less efficiently. The effect of the penalty constraint-handling approach in \( \text{gamultiobj} \) is seen by the GD values, which exceed the upper limit of the y-axis on
the plot. As discussed in Section 6.3, this occurs because the objective vector is set to the worst possible values for unfeasible blade designs, which are abundant during the early stages of the optimization. Past the 1200 objective-function evaluations mark, the convergence for `gamultiobj` approaches that of the other two algorithms.

There are a few potential factors that might explain the hampered performance of the hybrid NSGA-II on the wind-turbine blade optimization problem. The most likely one is due to the substantial increase in complexity of the objective and constraint functions in comparison with the simple analytical ZDT and DTLZ test cases. Like all other gradient-based methods, `fminimax` requires that the objective and constraint functions be continuous. If the design space contains multiple local minima, then a gradient-based optimizer will encounter a number of obstacles that prevent it from performing efficiently. For illustration, the ASF values from a local search performed on an individual from the DTLZ2 and wind-turbine blade optimization problems are shown in Figure 17. When the value of the ASF decreases as the number of objective-function evaluations increases, then the objective and constraint functions of the individual chosen for local search are being minimized (or improved) as expected. This is shown for the DTLZ2 in Figure 17 but is not the case for the three-objective wind-turbine blade optimization. In
Figure 17, the ASF values for the three-objective wind-turbine problem are not decreasing below the ASF = 0 mark.

For a two-objective wind-turbine blade optimization however, an improvement in the ASF is observed independent of whichever one of the three objectives is removed. The unevenness of the design space is reduced and the gradient-based optimizer encounters fewer (although still some) obstacles when minimizing the merit function. The local minima are seen in Figure 18, which depicts the ASF as a function of the first and second normalized CPs for the chord. The maximum (\(|CP_{1,\text{chord}}| = 1\)) and minimum (\(|CP_{1,\text{chord}}| = 0\)) correspond to the boundaries \(CP_{\text{max},\text{chord}}\) and \(CP_{\text{min},\text{chord}}\), respectively. To justify the hybrid method in a multi-objective wind-turbine blade optimization, it is essential to have a merit function that is as continuous as possible. This indicates that the aerodynamic and structural models must be nearly as continuous as the analytical test functions. If a sufficient level of continuity for the merit function cannot be achieved, then the number of dimensions in the problem can be reduced to yield better results.

7. Conclusions

A hybridized gradient and non-gradient based multi-objective evolutionary algorithm, the hybrid NSGA-II, has been applied to the simultaneous optimization of the AEP, \(M_{\text{flap,root}}\) and \(m_{\text{blade}}\) of the NREL 5 MW wind-turbine blade. To justify the potential of hybridization, a study on convergence to the Pareto-optimal set was performed. The convergence metric used required prior knowledge of the true Pareto front, which was approximated using the non-hybrid NSGA-II. From this approximation, a three-dimensional surface representing the optimal trade-off between the AEP, \(M_{\text{flap,root}}\) and \(m_{\text{blade}}\) was achieved. Despite the promising results obtained for the hybrid NSGA-II on analytical test functions, no significant improvement in convergence was achieved for the three-objective wind-turbine blade optimization problem. The obstacles encountered by the merit function in the uneven design space impedes the progress of the gradient-based optimizer. By reducing the dimensional space to a sufficient level or providing objective and constraint functions that are almost as continuous as analytical test functions, the hybrid method may yield improved convergence in comparison with conventional MOEAs.

Funding

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Notes

1. The evaluation of all objective functions in the objective vector is considered as one objective-function evaluation.
2. A maximization of the AEP is performed by minimizing the negative value of its objective function.

References
