On the Improvement of Convergence Performance for Integrated Design of Wind Turbine Blade Using a Vector Dominating Multi-objective Evolution Algorithm

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Abstract. A novel multi-objective optimization algorithm incorporating evolution strategies and vector mechanisms, referred as VD-MOEA, is proposed and applied in aerodynamic-structural integrated design of wind turbine blade. In the algorithm, a set of uniformly distributed vectors is constructed to guide population in moving forward to the Pareto front rapidly and maintain population diversity with high efficiency. For example, two- and three-objective designs of 1.5MW wind turbine blade are subsequently carried out for the optimization objectives of maximum annual energy production, minimum blade mass, and minimum extreme root thrust. The results show that the Pareto optimal solutions can be obtained in one single simulation run and uniformly distributed in the objective space, maximally maintaining the population diversity. In comparison to conventional evolution algorithms, VD-MOEA displays dramatic improvement of algorithm performance in both convergence and diversity preservation for handling complex problems of multi-variables, multi-objectives and multi-constraints. This provides a reliable high-performance optimization approach for the aerodynamic-structural integrated design of wind turbine blade.

1. Introduction
The design of large-scale wind turbine blade is a complicated optimization problem involving many variables, objectives and constraints among which conflicts may exist \[^{[1, 2]}\]. Meanwhile, wind turbine operates in a complex circumstance; therefore thousands of design load cases need to be evaluated according to the design standards, resulting in such a huge computational overhead that optimal efficiency becomes one of the key indicators to be considered.

In recent years, Multi-objective Evaluation Algorithms (MOEA), such as NSGA-II \[^{[3-6]}\], SPEA2 \[^{[7-8]}\] and PSO \[^{[9, 10]}\] and their variants \[^{[11, 12]}\], are widely used in the design of wind turbine and its components. In multi-objective optimizations, there is no single solution that is optimal (global minimum or maximum) with respect to all the optimization objectives contrast to single-objective one and only acceptable non-dominated solutions exist, which is the so-called Pareto optimal solutions. However, these algorithms are poor efficiency, and usually thousands of generations of evolution are needed in order to obtain the satisfied optimal solutions. Moreover, the performance of the algorithms will severely degrade and even invalid as the number of objectives increases, the main reason is that increasing the number of objectives causes most solutions to be non-dominated to each other using the usual dominance relation. Since the non-dominated solutions occupy most of the population members, any elite-preserving operator faces a difficulty in accommodating adequate number of new solutions in the population \[^{[13]}\]. This slows down the search process considerably. Also an implementation of a...
diversity-preservation operator (such as the crowding distance or clustering operator) becomes a computationally expensive operation. At present, the multi-objective designs of the wind turbine blade or the whole machine are carried out mainly based on the two-objective schemes and very few extend to the three-objective cases. Yet developing a new method with high efficiency and being suitable for high dimensional optimization will strongly support to carry out the more complex designs of wind turbine.

In this paper, a new multi-objective optimization algorithm incorporating vector mechanisms and evolution strategies is proposed, followed by its critical operators and algorithm procedures to be described elaborately. As examples, two- and three-objective designs of 1.5MW wind turbine blade are accomplished and analyzed to investigate the basic features of the algorithm. The performance of the new algorithm is also provided by comparison with the classical algorithm.

2. Proposed Algorithm
A new multi-objective evolutionary algorithm characterized by vector projection and vector diversity preservation in order to improve the efficiency and convergence is presented, named Vector Dominant Multi-objective Evolutionary Algorithm (VD-MOEA). This algorithm retains the basic frameworks of evolution algorithm and in particular constructs a Utopia reference system consisting of anchor points, Utopia plane, Utopia plane points and Utopia vectors, similar to the traditional Normal-boundary intersection methods. In VD-MOEA, population individuals are firstly related to Utopia vectors one by one, then are guided to advance along the vector directions, and finally converged to the intersections of the projection vectors and the Pareto optimal front. The procedures and main operator introduction of VD-MOEA are described as follows:

(1) **Parameter input**: Define the size of algorithm population $N_p$ and external archive population $N_e$. Set maximum iteration number $T$. Set upper and lower bounds for the variables one by one;

(2) **Utopia reference system construction**: Define the divisions of each objective axe $N_S$. Construct Utopia reference system in normalized $M$-dimensional space including anchor points, Utopia plane, Utopia plane points and Utopia vectors, as shown in Fig.1. Utopia points $u_i$ are a set of evenly spaced points generated by reasonably schematizing weight vectors $w$, given by

$$u_i = \sum_{i=1}^{M} w_i \cdot \mu_i$$

Where

$$0 \leq w_i \leq 1, \quad \sum_{i=1}^{M} w_i = 1$$

The total number of Utopia points $N_U$ in an $M$-objective optimization space can be calculated by:

$$N_U = C_{N_S}^{N_U}$$

(3) **Population initialization**: Generate Initial population $P_0$. Evaluate the fitness value of all individuals in $P_0$. Copy all individuals of $P_0$ to the external archive population $P_E$;

(4) **Genetic and evolutionary operation**: Carry out neighbourhood selection, SBX crossover and polynomial mutation to the external archive population $P_E$. Generate the next generation $P_t$;

(5) **Population recombination**: Evaluate fitness and constraint values of each individual in the population $P_t$. Generate combined population $Q_t$ by mixing current population and external archive population, expressed as:

$$Q_t = P_t \cup E_t$$

Therefore, the size of the combined population is $2N_p$;

(6) **Strength non-dominated delamination**: Strength non-dominated delamination strategy in the algorithm originates from SPEA2 where each individual in the combined population is compared with other individuals on the basis of the strength Pareto optimal principles to find Pareto non-dominated rank. Thus the Pareto optimal solutions of the $t$th generation are identified and of which every individual is assigned to a Pareto non-dominated rank.
(7) **Population fitness normalization**: Analyze the Pareto optimal solutions from the combined population \( Q \), to find the minimum and maximum fitness in every objective direction, and then make up the Nadir point \( f^N \) and Utopia point \( f^U \). For the individual \( i \), its original fitness \( f(x) \) is transformed to the dimensionless fitness \( F \) by adopting following formula:

\[
F_j(x) = \frac{f_j(x) - f_j^U}{f_j^N - f_j^U} \quad j = 1, 2, \ldots, M
\]

Accordingly, the combined population \( Q \) can be normalized as the new combined population \( \overline{Q} \).

![Figure 1. Normalized Utopia reference system for a three objective case](image)

(8) **Association operation**: Until now, Utopia vectors and normalization population \( \overline{Q} \) have been completely built. In this step, the association operation that each member of \( \overline{Q} \) is classified and subordinated to a vector is launched. For the purpose, the Euclidean distance of each individual of \( \overline{Q} \) with each of the vectors is calculated, and a vector is then found to be associated with every individual according to the shortest distance rule. After finishing this process, every vector has a subset \( Z_a(j) \) normally including one or more members.

(9) **Aggregation fitness assignment**: Each individual of \( \overline{Q} \) includes three key parameters, i.e. Pareto non-dominated rank (PR), Euclidean Sorting (ES) ranking according to the Euclidean distance in subset \( Z_a(j) \) of the associated vector, and Reference Number (RN). Based on these, a new fitness assignment method defined by serial connection with PR，ES and RN is proposed, named aggregation fitness. Thereby, the aggregation fitness of an individual is expressed as:

\[
VF_i = \{PR \cup ES \cup RN\}
\]

The aggregation fitness artfully forms a real value that can be used for comparison between each other, well preparing for the upcoming elite preservation and parent selection for the next generation.

(10) **Elite preservation strategy**: All individuals in \( Q \) are sorted in ascending order according to the aggregation fitness, and frontal \( N_E \) individuals are truncated to the external archive population forming a new generation.

(11) **Termination**: If \( t > T \) or other stopping principles are satisfied, storage the external archive population as the ultimate optimal solutions; otherwise, set \( t = t + 1 \), go back step 4 and continue iteration process of the next generation.

### 3. Modelling of Wind Turbine Blades

Figure 2 introduces the flow chart of the design of wind turbine blades, and the parametric modelling of the wind turbine blade, optimization objectives and constraints will be described in detail below.
3.1. Design variables

Design variables of a wind turbine blade can be categorized as aerodynamic shape variables and structural layer variables. The aerodynamic shape variables are used to describe the geometrical features of the blade including the distributions of chord, twist, relative thickness, and pre-bending. These variables determine the blade aerodynamic performance. In this study, third-order spline fitting is applied for chord distribution, twist distribution, and relative thickness distribution. More specifically, five variables are designed at the locations of 0.2R, 0.4R, 0.6R, 0.8R, and 0.96R in the spanwise direction (R represents the blade length). The relative thickness is fixed as 100% at the root. The pre-bending distribution is fitted by exponential functions with two variables.

The blade used in this study has a conventional structure consisting of two webs and I-beam, as shown in Figure 3. The sophisticated structure of the blade is simplified based on engineering experience to allow optimization. Herein, parameters, locations, and materials of the skins, webs, and leading-edge reinforced layer are aligned with a counterpart sample, the AeroDyn-1.5MW blade\cite{17,18}, while the relative thickness distributions of the spar cap and the trailing-edge reinforced layer are designed with optimization variables. The relative thickness distribution of the spar cap set eight variables. Linear and curve fitting are conducted for the part before the location of the maximum chord length and the part from the location of the maximum chord length to the blade tip. The relative thickness distribution of the trailing-edge reinforced layer is obtained using the method reported previously\cite{19}, and four different variables are used. Therefore, a total of 29 design variables are set up in this design (Table 1).

3.2. Optimization objectives

Maximum annual energy production (AEP), minimum blade mass, and minimum root thrust, among which distinct conflicts exist, are chosen as three optimization objectives to validate the developed optimization algorithm.

3.2.1. Maximum AEP. Annual energy generation is calculated under the given wind farm conditions using AeroDyn codes, as follows:
\[ f_1 = \max_{V_{\text{in}}} \int_{V_{\text{in}}}^{V_{\text{out}}} P(V) f\left(\frac{V}{V_{\text{avg}}}\right) Td\left(\frac{V}{V_{\text{avg}}}\right) \]

where, \( V_{\text{in}} \) and \( V_{\text{out}} \) are the cut-in wind speed and cut-out wind speed, respectively. \( V_{\text{avg}} \) is the annual average wind speed. \( P(V) \) is the output power at the wind speed \( V \). \( f \) is the Weibull distribution function. \( T \) is the annual hours.

3.2.2. Minimum blade mass. To obtain blade mass, mass distribution of the blade is firstly calculated by applied classic beam theory. The total mass of the blade is then calculated by integration as follow:

\[ f_2 = \min \int_{r=R_{\text{hub}}}^{r=R} m_i dr \]

In the formulas above, \( R_{\text{hub}} \) is the hub radius, \( R \) the radius of wind rotor and \( m_i \) the mass per unit spanwise length at the \( i \)th section.

3.2.3. Minimum extreme root thrust. The FAST codes are used to simulate the aeroelastic properties of the wind turbine[]. The design load cases (DLCs) are set according to ICE 61400-1 standard; and DLC1.3, DLC1.4, DLC1.5, DLC6.1, and DLC6.3, recommended by the reference [20], are used to evaluate the extreme loads. Hence, the objective function for minimum extreme root thrust is obtained using the following equation:

\[ f_3 = \min \{ \max \{ F_x(i) \} , i = \text{DLC}_1, \text{DLC}_2, \ldots, \text{DLC}_8 \} \]

where \( F_x(i) \) is the blade root thrust of the \( i \)th DLC.

| Description                              | Fitting method       | Parameters |
|------------------------------------------|----------------------|------------|
| Chord distribution                       | Three order spline   | 5          |
| Twist distribution                       | Three order spline   | 5          |
| Relative thickness distribution          |                      | 5          |
| Pre-bending distribution                 | Exponential function | 2          |
| Spar cap thickness distribution          | Linear and three     | 5          |
| Trailing edge reinforced layer thickness | Trapezoid            | 4          |

3.3. Constraints
The distributions of the chord, twist and relative thickness decrease gradually from the locations of maximum chord length to the blade tip. In addition, the strength and stiffness of the blade are also restricted.

3.3.1. Strength constraint. the safety factor (SF), defined as the ratio of the maximum stress allowed in the local area (\([\sigma_j]\)) to the stress at the location \( i (\sigma_i) \), must be greater than one on the entire blade, as in the following:

\[ SF = \min \frac{[\sigma_j]}{\sigma_i} > 1 \]
3.3.2. Deflection constraint: the deflection of blades must be controlled to avoid striking the tower. According to the IEC standard, the minimum clearance \( D_{c,\text{min}} \) of the blade is greater than 30\% of the initial clearance \( D_{c} \), as in the following:

\[
D_{c,\text{min}} \geq 0.3 \cdot D_{c}
\]

In addition, the constraints of fatigue life are also indispensable for the design of wind turbine blades in the real engineering applications. Fatigue life of the blade can be evaluated by using the engineering analytical approaches of blade fatigue according to the fatigue DLCs from IEC; however, it is neglected in order to reduce the difficulty of the optimization design in this paper. We emphasize that our purposes are not to design a blade containing all engineering requirements. Instead, our main goal is the development of a new high-performance optimization algorithm for wind turbine complex multi-objective designs, and still the evaluations of its basic characteristics.

4. Results

In this section, two- and three-objective designs of 1.5MW wind turbine blade employing maximum AEP, minimum blade mass, and minimum blade root thrust as the optimization objectives are presented, respectively. The blade design relies on a wind turbine platform of upwind, variable-speed variable-pitch, doubly-fed generator. The basic parameters set in terms of the AeroDyn-1.5MW blade are given in Table 2.

| Parameters                  | Value |
|-----------------------------|-------|
| Wind field                  | 3A    |
| Rated power/(MW)            | 1.5   |
| Numbers of blade            | 3     |
| Radius of rotor (m)         | 40.3  |
| Rated rotate speed/(RPM)    | 17.4  |
| Rated power/(MW)            | 1.5   |
| Cut-in wind speed/(m/s)     | 3     |
| Cut-out wind speed/(m/s)    | 25    |
| Height of tower/(m)         | 78.1  |
| Airfoil families            | DU/NACA 63 |

4.1. Two-objective designs

During the two-objective optimization, the maximum AEP and minimum blade mass are chosen as the objectives, the population size is 20 (typical small population optimization), and the evolution generation is 500.

Figure 4 shows the distributions of Pareto optimal solutions in objective space obtained using the VD-MOEA and NSGA-II algorithms. As can be seen, approximately uniformly distributed optimal solutions are achieved using the VD-MOEA algorithm, indicating that the population diversity is effectively maintained. The approximate Pareto front (PF) fitted by the optimal solutions divides the objective space into two parts. Part I is an infeasible region which cannot be reached under the design conditions, while part II is a feasible solution region. The monotonicity of approximate PF shows that the blade mass increases with AEP increasing, indicating that the two design goals have a certain degree of conflict. It cannot be said which point in the Pareto-optimal solutions set is much better than others in theory, because they are all optimal with different combinations of power output and blade mass, respectively. This illustrates that there is no a single point at which all objectives are optimal in the multi-objective optimization problems of wind turbine design. Slight population aggregations (see Figure 3b) are seen for the optimal solution set obtained by optimization using the NSGA-II algorithm; complete convergence to approximate PF is not achieved. Therefore, it is concluded that the VD-
MOEA algorithm successfully generates uniformly distributed optimal solutions; furthermore, the vectors constructed in objective space can effectively reduce the search range of each individual, and guide the search process, leading to better convergence efficiency.

![Figure 4](image)

**Figure 4.** Distributions of optimal solutions using VD-MOEA and NSGA-II in two-objective designs

### 4.2 Three-objective designs

Figure 5a shows the Pareto optimal solutions and distributions that meet the maximum AEP \(f_1\), the minimum blade mass \(f_2\) and the minimum root thrust \(f_3\) of the wind turbine simultaneously. In this design, the maximum iterations are set as 1000, the divisions of each objective axe \(N\) are prudentially defined as 11 to get a balance between convergence and efficiency, and thus the population size is calculated to be 78. The auxiliary surface to which the optimal solutions are attached in the figure is fitted using five order polynomial functions. It can be seen that the Pareto optimal solutions constitute a continuous curved surface with evident boundaries and complicated polygon characteristics, which are formed under the comprehensive influences of the variables, objectives and constraints. The optimal solutions in three-dimensional space achieve good convergence and their distribution is very uniform, meaning that the performance of VD-MOEA in the multi-objective optimization of wind turbine blade is excellent. All the points in the Pareto optimal set are the optimal solutions for the design conditions, and no one is superior to the others. With a set of optimal solutions, the multi-objective optimization design provides more flexible selections for designers than the conventional scheme of a single optimal solution.

For the purpose of comparison, another group of Pareto optimal solutions obtained using conventional NSGA-II in the same design conditions are displayed in the Fig.4b. Severe aggregation of the solutions occurs and, as can be seen, these solutions are distributed in irregular patterns. Therefore, accurate PF is not achieved and it is suggested that the NSGA-II algorithm is ineffective for three-objective designs of wind turbine blades.

![Figure 5](image)

**Figure 5.** The distribution of Pareto optimal solutions in three-dimensional space
For clarity, the distribution of Pareto optimal solutions obtained using VD-MOEA is projected to the two-dimensional planes of \((f_1-f_2)\) and \((f_1-f_3)\) presented as shown in Fig.5. The solutions are also found satisfactorily spreading and uniform in the two-dimensional spaces.

To better illustrate the features of Pareto optimal front, three blade designs marked in the figure 5 are selected to be analyzed. The AEPs, masses and ultimate root thrust of the blades A, B, C and together the counterpart blade are listed in Table 3, respectively. Let us look at the blades A and B firstly. The AEP of Blade A is a little higher than that of Blade B just by about 1.6% and, correspondingly, the root thrust of Blade A is a little higher than that of Blade B just by about 2.0%. From common point of view, it seems that the Blade A should be heavier than Blade B. From the multi-objective optimization design, however, the mass of Blade A is lower than that of Blade B by a margin of about 5.4% on the contrary. To explain the causes of forming this kind of complex objective combinations, there is not yet enough information acquired just from Fig.3 and Fig.4. This is only made by additional comparison of aerodynamic characteristics of different blade designs. Fig.5 shows the distributions of chord, relative thickness and absolute thickness for these three blades. From the figure, the solidity of Blade A is obviously larger than that of Blade B, which produces increased load of Blade A. This is the main reason why the root thrust and AEP of Blade A are a little larger. However, it can be seen from Fig.7 that the relative thickness of the blade B is lower and therefore has higher lift coefficient, also resulting in both higher aerodynamic performance and higher thrust. By these compromises, the differences in both AEP and blade mass between the blades A and B are not remarkable. Meanwhile, because Blade A has higher stiffness owing to a larger absolute thickness resulted from thicker airfoil and wider chord, it may need thinner bearing layout to resist the load and meet the deflection constraints, and thus the blade mass is effectively reduced.

![Pareto optimal solutions in \((f_1-f_2)\)](image1)

![Pareto optimal solutions in \((f_1-f_3)\)](image2)

**Figure 6.** Pareto optimal solutions in the two-dimensional projection space

**Table 3.** Performance comparisons of the different blades

(Percentages are values compared to Aerodyn-1.5MW blade)

| Blade | AEP MWh/a | Mass kg | Extreme root thrust kN |
|-------|-----------|---------|------------------------|
| A     | 5682.4 (-2.5%) | 5398 (-9.1%) | 143.1 (-11.6%) |
| B     | 5594.4 (-4.0%) | 5705 (-4.0%) | 140.3 (-13.4%) |
| C     | 6063.5 (4.1%)  | 5859 (-1.4%) | 154.9 (-4.4%) |
| Aerodyn-1.5MW | 5828.26 | 5943 | 162 |

The blade C produces higher AEP than the blade B because the chord of the blade C is wider than that of the blade B. On the other hand, the absolute thickness of the blade C is larger than that of the blade B, which is helpful to decrease the blade mass. The relative thickness of the blade C is the least among the three designs, which is also beneficial to improve the aerodynamic efficiency, resulting in the
highest AEP. In summary, the AEP, mass and root ultimate thrust cannot simultaneously be optimal. Nevertheless, good blade aerodynamic performance is generally acquired at the cost of high load on the blade, thus resulting in blade mass increase. By comparing the blades A, B and C, as well as Aerodyn-1.5MW blade, it can be seen that the AEP, mass and root ultimate thrust of the blade C are increased by 4.1%, -14% and -4.4%, respectively, than the Aerodyn-1.5MW blade, demonstrating that the blade C has good performance in all the three-objective directions and seems to be a more desirable result than the other two blades.

Figure 7. Distributions of blade chord, twist and thickness distributions

5. Conclusions
A new vector dominant multi-objective optimization algorithm, referred as VD-MOEA, incorporating basic evolution strategies and vector mechanism, has been proposed and applied in the field of aerodynamic-structural integrative design of wind turbine blades. A set of virtual vectors, which are used to guide optimal solutions in advancing to the Pareto optimal front with high efficiency, are elaborately constructed in the method. In comparison with the conventional methods, VD-MOEA can obtain a complete optimal solution set of uniform distributions through a single process, and shows the significant advantages in both population diversity preservation and convergence. The proposed algorithm is then used to design 1.5MW wind turbine blades with two and three conflicting optimization objectives, and a set of optimized blades has been obtained. At least one blade has higher performance, less mass and less root ultimate thrust than the reference Aerodyn-1.5MW blade without any design inputs changed. VD-MOEA can be used as a general high-performance approach in multi-objective optimization design of wind turbine blade.

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