Robust Optimization of Wind Turbine's Airfoil Under Geometric Uncertainty using Surrogate-Assisted Memetic Algorithm

Yohanes Bimo Dwianto, Pramudita Satria Palar, Lavi Rizki Zuhal

ABSTRACT--- Robust optimization was conducted for wind turbine's airfoil under geometric uncertainty in subsonic region. Since the performance of a wind turbine is highly affected by the aerodynamic characteristics of the blade's airfoil, aerodynamic efficiency is considered as the optimization objective. More exactly, the mean and standard deviation value of lift-to-drag ratio are the objective functions in this work. By utilizing an advanced optimization framework of Single-Surrogate Multi-Objective Memetic Algorithm (SS-MOMA), some airfoil shapes which are insensitive to geometric uncertainty were obtained. By observing the physical shape of some solutions, it was found that airfoil with higher leading edge radius, maximum upper curve thickness, and curvature tend to produce higher mean of lift-to-drag ratio, while thinner airfoil with sloping curvature tend to produce lower standard deviation of lift-to-drag ratio.

Keywords: robust optimization, geometric uncertainty, surrogate-assisted memetic algorithm, airfoil shape optimization, SS-MOMA

I. INTRODUCTION

Wind turbine is a popular technology in obtaining alternative form of energy, apart from organic fuel. By utilizing wind velocity to rotate a turbine, the system allows a conversion of kinetic energy produced by the rotation into potential energy. Then, the potential energy can be converted into other types of energy such as electrical energy, for daily activities purpose. Its performance is highly affected by the performance of the turbine blades. The blades should produce as high aerodynamic efficiency as possible with limited wind velocity from the surrounding area. For this sake, optimization of the blade's shape has been conducted in many ways.

The aerodynamic efficiency of the blade is highly affected by the aerodynamic efficiency of its airfoil shape. Research in [1] – [6] are some works which study the shape of the airfoils with main concern in aerodynamic efficiency optimization. Besides of two-dimensional airfoil shape design and optimization, direct full blade shape optimization can also be performed to obtain a complete performance of the blade ([7]). However, direct full blade optimization can be highly computationally expensive, hence, one can resort to airfoil shape optimization for performance improvement in conceptual or preliminary design phase.

Aside from the shape of the airfoil, another thing which needs to be considered is the uncertainty in the geometry of the airfoil. Due to some circumstances, it is very difficult to build a blade shape which is perfectly similar to the design. While it is a benefit to obtain some optimized designs from the optimization, it will be meaningless if the wind turbine cannot maintain its performance when geometrical error occurred. A work in [8] has attempted to consider the geometric uncertainty on the leading edge radius in the optimization process. When the uncertain conditions or parameters are considered, the optimization becomes robust optimization, in which the main goal is to find optimized designs which are also robust in the presence of uncertainties. Within the framework of probability theory, there are at least two objective functions to be optimized simultaneously (mean and standard deviation).

In this paper, a robust optimization of airfoil aerodynamic efficiency for wind turbine under geometrical uncertainty was conducted. To simulate random geometries, the airfoil design variables were subjected to small perturbation.

We start by defining and explaining the problem that we want to solve in this paper. After that, the computational tool, which mainly focus on the optimization method, is explained. The result and discussion of the optimization process are then given. Finally, the paper is concluded in the last section.

II. PROBLEM DEFINITION

The robust optimization is conducted for the shape of wind turbine's airfoil, as it greatly affects the aerodynamic efficiency of wind turbine. The objective of the optimization is to

$$\text{Minimize: } -\mu(L/D),\ \sigma(L/D)$$

where $L/D = C_l/C_d$, is the aerodynamic efficiency and a function of airfoil's geometry. The airfoil was represented by PARSEC parameterization, which has 11 parameters from the physical shape of the airfoil [9]. The aerodynamic characteristics were solved using XFOIL [10], a panel method coupled with boundary layer equation. The design conditions are set as follows: Reynolds number (Re) = 1.72 x 10^6, Mach number (M) = 0.1, and angle of attack (α) = 7^o.

The mean (μ) and standard deviation (σ) of the aerodynamic efficiency were solved using Monte Carlo Simulation (MCS) method, a robust and powerful tool to calculate the mean and standard deviation. The samples for μ and σ calculations are generated using Sobol sequence [11], a quasi-random method to generate space-filling sample points in high number of dimension.

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A commonly used airfoil for wind turbine, the FFA-W3-211 airfoil (See Fig. 1), was selected as the datum shape for the robust optimization. The PARSEC parameters of FFA-W3-211 airfoil are shown in Table 1. The decision variables for the optimization were the PARSEC parameters of the datum subjected to ±20% perturbation. To model the randomness of the airfoil shape, the uncertainty variations are applied directly to the PARSEC parameters. It is assumed that there is a maximum ±5% uncertainty in the airfoil shape, as calculated using coefficient of variation (CoV) equation, for each PARSEC parameter. The number of MCS samples (N_s) is set to 300.

The optimization algorithm is single-surrogate multi-objective memetic algorithm (SS-MOMA) [12], which is to be explained in the next section.

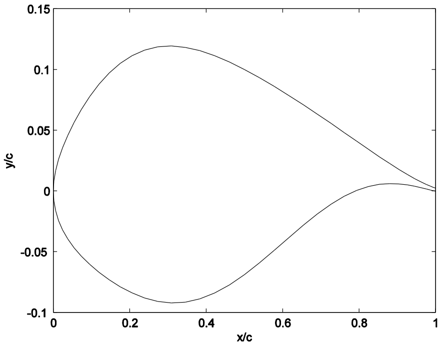

FIGURE 1. FFA-W3-211 Airfoil

TABLE 1. PARSEC parameters of FFA-W3-211 Airfoil

Parameters		**Value**
Leading edge radius,	R_{LE}	0.0223
Absis of Y_{UP},	X_{UP}	0.3047
Maximum upper thickness curve,	Y_{UP}	0.1193
Curvature of upper thickness curve at X_{UP},	Y_{XXUP}	-1.3995
Absis of Y_L,	X_L	0.3149
Maximum lower thickness curve,	Y_L	-0.0922
Curvature of lower thickness curve at X_L,	Y_{XXL}	1.4350
Trailing edge thickness,	Y_{TE}	0.0010
Gap of trailing edge,	Y_{off}	0.0026
Camber curve angle at trailing edge,	α_{TE}	-0.0946
Thickness curve angle at trailing edge,	β_{TE}	0.0300

III. OPTIMIZATION SETUP

The optimization module utilizes SS-MOMA, an optimization framework based on combination of genetic algorithm and surrogate modeling. The non-dominated sorting genetic algorithm (NSGA-II) works as the main optimization framework while surrogate modeling acts as the accelerator to exploit the locality near the offspring solution.

The complete framework of SS-MOMA is shown in Algorithm 1, where PP and OP are the parent and offspring population, respectively, while LP is a population created by individuals produced from local search process.

ALGORITHM 1: SS-MOMA

BEGIN:
Generate initial PP of N individuals
Evaluate all individuals in PP with true fitness and constraint function $f_i(\mathbf{x})$ and $g_k(\mathbf{x})$, respectively
Put all non-duplicated individuals to database
Sort PP using non-dominated sorting and crowding distance
While function evaluation budget is not exhausted
  Do selection, crossover, and mutation to generate OP consist of N individuals
  Evaluate all individuals in OP with $f_i(\mathbf{x})$ and $g_k(\mathbf{x})$
  Put all non-duplicated individuals to database
  LOCAL SEARCH SCHEME
  For each individual $\mathbf{x}$ in OP
    Generate surrogate model $\hat{f}_{sc}(\mathbf{x})$ and $\hat{g}_k(\mathbf{x})$ from m nearest neighbors extracted from database
    Search a locally optimum solution $\mathbf{x}_{opt}$ from $\hat{f}_{sc}(\mathbf{x})$ and $\hat{g}_k(\mathbf{x})$ using SQP
    Evaluate $\mathbf{x}_{opt}$ with $f_i(\mathbf{x})$ and $g_k(\mathbf{x})$ and put it in database if $\mathbf{x}_{opt}$ is different with other individuals in database
    Put $\mathbf{x}_{opt}$ and $f_i(\mathbf{x}_{opt})$ in LP
  end for
  END OF LOCAL SEARCH
  Combine PP, OP, and LP to get combined population CP with size of 3N
  Sort CP using non-dominated sorting and crowding distance
  Select N individuals with best non-dominated front and crowding distance from CP to become new PP
end while
END

Linear splines radial basis function is utilized to build approximation functions $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$ from $f(\mathbf{x})$ and $g(\mathbf{x})$. For a function $y(\mathbf{x})$, linear splines RBF build an approximation function $\hat{y}(\mathbf{x})$ with the following expression:

$$\hat{y}(\mathbf{x}) = \mathbf{w}^T \boldsymbol{\psi} = \sum_{i=1}^{n} w_i \psi\left(\left\|\mathbf{x} - \mathbf{c}^{(i)}\right\|\right) \quad (1)$$

where $\mathbf{c}^{(i)}$ is the center of basis function, ψ is linear spline radial basis kernel, $\mathbf{w}$ is weight vector determined from $\mathbf{w} = \boldsymbol{\Psi}^{-1}\mathbf{y}$, where $\boldsymbol{\Psi}$ is a Gram matrix defined as $\boldsymbol{\Psi}_{i,j} = \psi\left(\left\|\mathbf{x}^{(i)} - \mathbf{x}^{(j)}\right\|\right)$. In the local search scheme, the fitness functions $f_i(\mathbf{x})$ are scalarized into one function $f_{sc}(\mathbf{x})$ with achievement scalarizing function method [15], as follows,

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$$\hat{f}_{sc}(\mathbf{x}) = \max\left(\mathbf{w}\left(\hat{\mathbf{f}}(\mathbf{x}) - \mathbf{z}_{ref}\right)\right) \quad (2)$$

where w = 1/(z_{nadir} - z_{ideal}) is a weight vector and z_{ref} is a reference vector. Both z_{nadir} and z_{ideal} are maximum and minimum of Pareto-optimum values, respectively, while z_{ref} is the current individual x. $\hat{\mathbf{f}}(\mathbf{x})$ is a vector of approximation functions for each fitness function generated by RBF. The value of z_{nadir} and z_{ideal} are estimated with maximum and minimum of offspring fitness values in the offspring population. The parameters of SS-MOMA used for optimization in this paper are shown in Table 2.

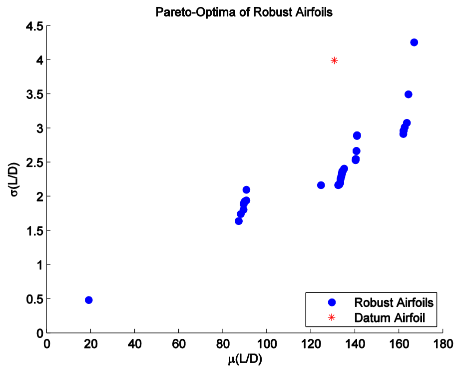
TABLE 2. Parameters of SS-MOMA

Parameter	Setting
Number of individual, N	100
Number of design variable, N_{var}	11
Number of neighbors, m	200
Evaluation budget	2100
Crossover Method	SBX
Mutation Method	Polynomial mutation
Local Search Method	SQP
Crossover probability	0.9
Mutation probability	$1/N_{var}$

IV. RESULT AND DISCUSSION

The result of the robust optimization is depicted in Fig. 2 (upper) which shows the final non-dominated solutions consisting of 36 distinct designs of the airfoil. Within this set of designs, users can select the most proper airfoil shape based on their own necessity. For example, by selecting the two extreme solutions: Airfoil_MAX_MEAN for extreme solution with maximum $\mu(L/D)$ and Airfoil_MIN_STD for extreme solution with minimum $\sigma(L/D)$, a geometric comparison can be made with datum airfoil as depicted in Fig. 2 (lower).

Airfoil_MAX_MEAN produces a very high $\mu(L/D)$ with higher $\sigma(L/D)$ compared to the datum, which means that the shape is more sensitive to geometrical error than the datum airfoil, although its mean aerodynamic efficiency is better. Moreover, the shape of Airfoil_MAX_MEAN is practically not feasible to be built because of its fish-tail shape towards the trailing edge. Therefore, Airfoil_MAX_MEAN should be excluded from the consideration. Meanwhile, Airfoil_MIN_STD generates a very low sensitivity to the geometrical error. However, the insensitivity is significantly traded-off with the aerodynamic efficiency due to pressure reduction caused by the big bump towards the trailing edge. Noticing that the aerodynamic efficiency reduction is too significant, Airfoil_MIN_STD should also be excluded from the consideration.



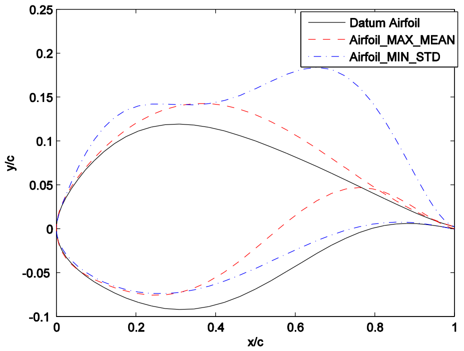


FIGURE 2. Pareto-Optima Airfoils of Robust Optimization (upper) and the Extreme Solution Airfoils Geometry Comparison with Datum Airfoil (lower)

As the extreme solutions are excluded, only the solutions between them are now considered. Now that the remaining robust airfoils have lower $\sigma(L/D)$ than datum airfoil, all of them are more insensitive to the geometrical error. For more detailed observation, three airfoils are selected from the remaining solutions, say: Airfoil 1, Airfoil 2, and Airfoil 3. The selected airfoils' parameters are presented in Table 3 and their shapes are shown in Fig. 3. By analyzing the selected robust airfoils, we can see that airfoil with lower thickness and sloping curvature tend to have lower $\sigma(L/D)$. It is most likely due to that if the geometrical errors leads to increased thickness and sharper curvature, the shape of airfoil will become closer to bluff body. Therefore, the separation process becomes easier and the reduction of L/D becomes more significant.

As for $\mu(L/D)$, it seems that an increase of leading edge radius, maximum upper curve thickness, and upper curvature contribute to the increase of $\mu(L/D)$. Their increase leads to higher velocity on the upper surface. This produces lower pressure on the upper surface of airfoil and increases the lift quite significantly. Since it is likely that the separation has yet occurred, their increase produce a high aerodynamic coefficient. As long as the leading edge radius, maximum upper curve thickness and upper curvature are still high (more negative for the upper curvature), the $\mu(L/D)$ will also be high, even with geometrical errors in those parameters.

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TABLE 3. Objective and PARSEC Parameter Values of Datum and Selected Robust Airfoils

Objective	Datum Airfoil	Airfoil 1	Airfoil 2	Airfoil 3
$\mu(L/D)$	130.70	164.21	140.61	87.15
$\sigma(L/D)$	3.99	3.50	2.67	1.64
Parameter	**Datum Airfoil**	**Airfoil 1**	**Airfoil 2**	**Airfoil 3**
R_{LE}	0.0223	0.0268	0.0250	0.0181
X_{UP}	0.3047	0.3655	0.3188	0.3656
Y_{UP}	0.1193	0.1431	0.1142	0.0954
Y_{XXUP}	-1.3995	-1.6176	-1.2107	-1.1776
X_L	0.3149	0.3426	0.3286	0.3317
Y_L	-0.0922	-0.0737	-0.0762	-0.0851
Y_{XXL}	1.4350	1.7067	1.6030	1.6262
Y_{TE}	0.0010	0.0009	0.0010	0.0009
Y_{off}	0.0026	0.0022	0.0025	0.0030
α_{TE}	-0.0946	-0.1111	-0.0948	-0.1098
β_{TE}	0.0300	0.0348	0.0320	0.0303

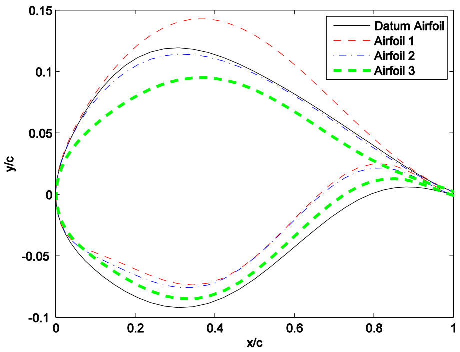

FIGURE 3. Geometry Comparison between Datum and Selected Robust Airfoils

V. CONCLUDING REMARKS

A robust optimization of FFA-W3-211 airfoil for wind turbine purpose has been conducted in subsonic region, producing some airfoil shapes which are more insensitive to geometrical error than the datum. In addition, some of the generated robust airfoils also have better aerodynamic efficiency, depending to their shapes. Airfoils with high leading edge radius, maximum upper curve thickness, and sharper curvature tend to produce high mean of aerodynamic efficiency in regards to the geometrical error. On the other hand, thinner airfoils with sloping curvature tend to be more insensitive when geometrical error occurred. In the process, there is also an extremum robust solution with impractical shape such as fish-tail shape at the trailing edge. The other extreme is a solution with very low aerodynamic efficiency, which is a significant decrement from the datum airfoil.

In the future, it is necessary to conduct a three dimensional modeling for the wind turbine so that the geometrical uncertainty can be applied more properly. It is also necessary to apply a RANS-based solver so that the effect of turbulence can be considered.

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