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Research Paper

Sweep Blade Design for an Axial Wind Turbine using a Surrogate-assisted Differential Evolution Algorithm

Nantiwat Pholdee[1], Sumit Kumar[2], Sujin Bureerat[1], Weerapon Nuantong[3], Watcharin Dongbang[4]

[1] Sustainable and Infrastructure Research and Development Center, Department of Mechanical Engineering, Faculty of Engineering, Khon Kaen University, Khon Kaen, 40002, Thailand

[2] Australian Maritime College, College of Science and Engineering, University of Tasmania, Launceston, 7248, Australia

[3] Department of Mechatronics Engineering, Faculty of Engineering, Rajamangala University of Technology Isan, Khon Kaen Campus, Khon Kaen, 40000, Thailand

[4] Department of Energy Technology and Management, Faculty of Science, Energy and Environment, King Mongkut's University of Technology North Bangkok, Rayong, 21120, Thailand

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Corresponding author: W. Nuantong (weerapon.nu@rmuti.ac.th)

Abstract. This paper presents an optimal design of a sweep blade for the axial wind turbine using a hybrid surrogate-assisted optimizer. The design problem is defined to maximize the ratio of the torque coefficient to the thrust coefficient of a turbine blade at a low wind velocity of 10 m/s. Pitch angle and leading-edge blade curve are considered as the design variables. For the aerodynamic analysis of the wind turbine blade, computational fluid dynamics has been used as a high-fidelity simulation. While the surrogate models including, the Kriging model (KG), the radial basis function model (RBF), and the proposed hybrid of KG and RBF (HyKG-RBF) models are applied for function approximation or low-fidelity simulation. In this study, to obtain a set of sampling points and surrogate models development, an optimal Latin Hypercube sampling (OLHS) technique is utilized in the design of the experiment (DOE). A differential evolutionary (DE) algorithm is used to solve the proposed design problem. The performance of the proposed hybrid surrogate assisted optimization method is contrasted with two conventional surrogate assisted optimization techniques. Results demonstrate that the proposed hybrid surrogate model viz. HyKG-RBF is the most efficient surrogate-assisted optimization method for solving the sweep blade optimization problem.

Keywords: Evolutionary Algorithm, Meta Model, Blade Optimization Design, Hybrid Surrogate Model, Low-fidelity simulation.

1. Introduction

The design of the runner blade of the axial wind turbine includes various aspects such as aerodynamic efficiency, structural integrity, cost, etc. [1–4]. In terms of aerodynamic efficiency analysis, computational fluid dynamics (CFD) is a popular tool used to design the outer geometric shape that affects efficiency and propeller load [5–8]. The finite element method, whereas, is typically applied for structural analysis which is the internal structure design that affects the structural integrity [9–13].

Recently, the approach of numerical computation integration has gained popularity as a tool for fluid machinery or wind turbine blade design. For example, the technique of coupling CFD with surrogate assisted optimization for the optimal design of blade angles to maximize the efficiency of the hydro turbine and pump. Following this approach, the design of experiment (DOE) based on the Latin hypercube sampling (LHS) technique was initially used for generating a set of sampling points, and CFD is applied for real function calculation of the sampling points. Then, the surrogate model was constructed and a genetic algorithm (GA) was used to find optimum results based on the constructed surrogate model [14–15]. Also, the optimal design of twist angles and rotating axis positions on a chord length of the airfoils on an axial wind turbine blade, Kriging (KG) surrogate-based GA optimization with DOE using the optimum Latin hypercube sampling (OLHS) has been applied for maximizing the power coefficient of the wind turbine. The optimal results obtained were confirmed using CFD analysis [16]. Wang et al. [17] improved the wind turbine output by optimizing the local blade twist angle using the KG surrogate model. Lalonde et al. [18] applied six neural networks (NNs) in their surrogate aerodynamic blade model. The authors conducted the training and validation of a 5 MW wind turbine blade using 30 million data points at mean hub wind speeds ranging from 3 to 25 m/s. With average normalized root mean square errors of 0.66%, a time-dependent convolutional neural network (CNN) was found the most reliable surrogate model. Similarly, Sessarego et al. [2] applied NNs together with gradient-based optimization to design a curved wind turbine blade. As per the outcome, the power of a curved blade was found to increase by circa 1% with an 0.02% increase in mean thrust relative to the straight blade [2]. In another study to anticipate the power production of a wind turbine, Shetty et al. [19] developed a radial basis function neural network model (RBFNN). To improve the performance of RBFNN and to enhance the speed of learning authors examined a hybrid PSO-FCM algorithm and Extreme Learning Machine (ELM) algorithm respectively. The methodology yielded excellent results on testing, with 100% accuracy.

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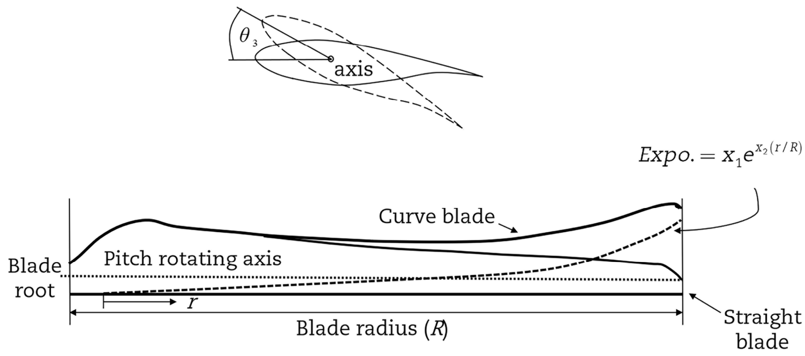


Fig. 1. Leading edge of straight and curved blades.

Considering the research reported above, numerical computation employing surrogate models-assisted optimization in conjunction with CFD was a popular and credible tool to boost the design efficiency of fluid machinery or wind turbines. However, the surrogate models presented for each work were a standalone surrogate model. As there are some reports in the literature that using a combination of multiple surrogate models leads to the improvement of the optimum results [20–21], implementation of multi-surrogate assisted optimization in fluid machinery or wind turbines, on the other hand, is rare. Investigation on such a research gab is interesting.

Therefore, this study presents an OLHS strategy together with a hybrid surrogate-assisted optimization to design the axial wind turbine blade. The objective function is defined to maximize the ratio of the torque coefficient (c_m) to the thrust coefficient of a turbine blade subjected to modifying the blade curve on leading-edge and pitch angle. Initially, the OLHS is applied to the DOE of the blade curve line on the leading edge and pitch angle. Then, the CFD is applied to analyze the aerodynamics of a wind turbine blade from sampling points. The KG, RBF, and the proposed HyKG-RBF surrogate models are applied to evaluate the objective function while the optimized design point is obtained by using the DE algorithm. In addition, the obtained optimum results are verified using CFD to compare the accuracy of the proposed methodology.

2. Numerical Formulation

2.1 Optimization Function Problem

An optimum design problem of a sweep blade is presented. The blade curve on the leading edge of each airfoil section positions and the pitch angle is adjusted to maximize the ratio of torque coefficient to thrust coefficient of a turbine blade as follows:

$$\text{Min: } f(x) = -\left[\frac{c_m - c_{m\_\max}}{c_{t\_\min} - c_t}\right] \tag{1}$$

subjected to

$$0.0001 \le x_1 \le 0.0005$$
$$1 \le x_2 \le 1.5$$
$$0^\circ \le \theta_3 \le 3^\circ$$

where $x = \{x_1, x_2, \theta_3\}$ is a set of design variables, f is the objective function to maximize the ratio of $(c_m - c_{m\_\max})/(c_{t\_\min} - c_t)$, which is a normalized value. The variables x_1 and x_2 are the coefficients of the exponential equation of blade curve on the leading-edge which can be expressed as follows:

$$Expo. = x_1 e^{x_2(r/R)} \tag{2}$$

where the r/R ratio is the airfoil section radial position on the blade. The variable θ_3 is the pitch angle on the runner blade. A runner blade on an exponential model is modified from a MEXICO blade [22]. The leading edge of the blade curve design has started a position of $0.15R$ to the blade tip on a straight blade as shown in Fig. 1. Note, the blade curve was expanded the bound from $0.8R$ as $0.15R$ to the blade tip that modified from the work of Sessarego et al. [2]. The θ_3 was improved to expand the pitch angle of the MEXICO blade [22].

2.2 Aerodynamics Analysis Tool of Wind Turbine Blade

CFD code under commercial software ANSYS/Fluent is used to analyze the aerodynamics of a wind turbine blade. Here, the steady Reynolds-averaged Navier–Stokes (RANS) with the turbulence model $k-\omega$ shear stress transport (SST) was applied. The air properties used a density of 1.225 kg/m^3 and a viscosity of 1.7894x10^{-5} kg/m-s for simulation of the fluid flow on an axial wind turbine blade.

As a boundary condition, the inlet wall is assigned a velocity and a static pressure is imposed on the outlet wall. The blade wall has been made movable while the other walls have remained stationary. The stationary domain and the rotating domain with the moving reference frame are defined as the two simulation fields of air. The radius of a rotating domain is taken as 2.5 m at a speed of 424.5 rpm. Both the stationary and revolving domains are connected through the domain interface. Here the CFD wind tunnel has been enlarged to lessen the turbulent flow influence of air on the rotating blade's local site. As illustrated in Fig. 2, the width and height of both the inlet and outlet walls were defined as 10D while the tunnel length is considered as 15D where D represents a rotor blade diameter of 4.5 m. The SIMPLE algorithm is used to calculate the velocity–pressure coupling in CFD analysis. The pressure, momentum, turbulent kinetic energy, and turbulent dissipation rates are calculated using the second-order upwind technique. For iteration, the residual values of the CFD code are defined as 10^{-5}.

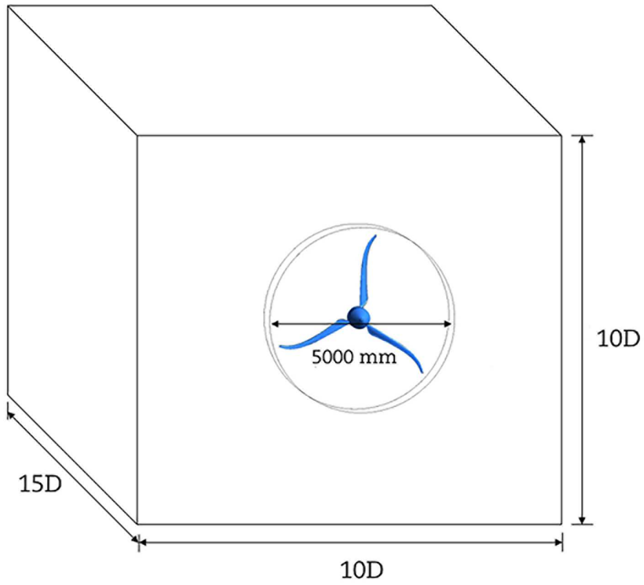


Fig. 2. Wind tunnel domains of CFD analysis.

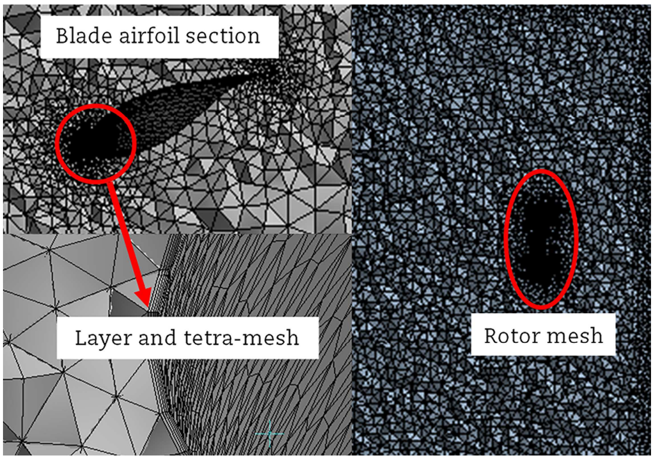


Fig. 3. Mesh elements of CFD wind tunnel.

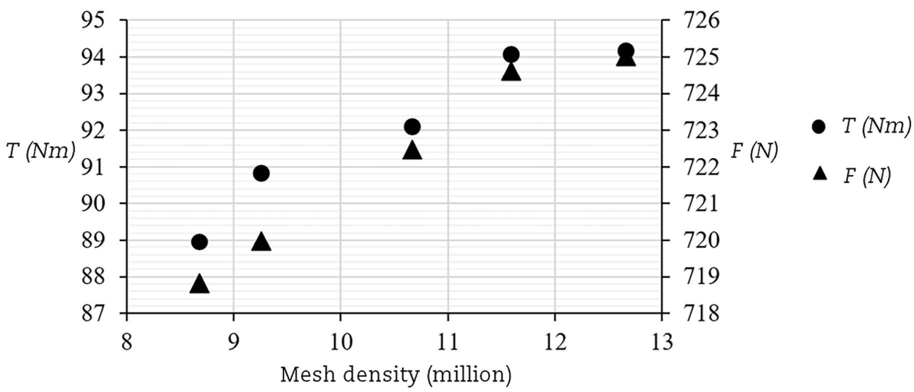


Fig. 4. Meshing uncertainty for CFD analysis.

The CFD model is meshed using tetrahedron elements to fit with the blade shape. The mesh thickness layer is defined with the five layers on the blade surface with the minimum size of $1x10^{-5}$ m as illustrated in Fig. 3. The mesh quality test is performed to find optimum mesh density while the error results of torque and thrust is validated as shown in Fig. 4. The optimum mesh quality is presented where the density of approximately 11.59 million elements with the relative errors of torque and thrust as 0.12%, 0.09% respectively, compared to that obtained from using 12.66 million elements. Therefore, the mesh density of 11.59 million elements was selected to analyze CFD so as to have more reliable results with reasonable computing time.

The CFD analysis of this study was validated by comparing the torque values of the rotor blade acquired from MEXICO wind turbine experimental data [22]. MEXICO blade detail [22] has been used to produce the wind turbine CFD analysis, which was compared to the empirical results at wind speeds of 10, 15, and 24 m/s. The CFD results were higher than the experimental results, which was due to the nature of the numerical technique, which prevents losses from occurring in the real system. The torque readings appeared consistent at 10 and 15 m/s, with error values of 0.15% and 0.1% respectively, however, the velocity at 24 m/s had a large error of 32.24%, as shown in Fig. 5. The wind turbine simulation with CFD utilizing the turbulence model $k-\omega$ (SST), may have incorrect implications when simulated at a velocity of 24 m/s. However, given the minimal error from the validation result above, this study is utilized to analyze the CFD for the wind turbine simulation at a velocity of 10 m/s. As a result, this CFD method based on the turbulence model $k-\omega$ (SST) is an effective tool for replacing the wind turbine experiment.

2.3 Surrogate models-assisted Optimization

The surrogate models-assisted optimization is applied to design the runner blade for an axial wind turbine while a CFD analysis is performed to simulate the blade aerodynamics. The proposed strategy used nine sampling points generated throughout the design domain using OLHS numerical scheme developed by Pholdee and Bureerat [23]. Then CFD simulation is performed following the sampling points as depicted in Table 1. Here the objective function values are predicted using surrogate models viz. KG, RBF, and HyKG-RBF.

The KG surrogate model is constructed using a Gaussian correlation function with a polynomial model following Kumar et al. [24]. The KG function can be written as:

$$f_{KG}(x) = g(x) + Z(x) \tag{3}$$

where, $f_{KG}(x)$ is the Kriging surrogate function, $g(x)$ is the polynomial function of the sampling points, and $Z(x)$ is the Gaussian random function. In this work, the MATLAB toolbox DACE is used for the Kriging surrogate model construction [25].

For the RBF, the approximate function can be represented as the following equation:

$$f_{RBF}(x) = \sum_{i=1}^{n} C_i \varnothing \left\| x - x^i \right\| \tag{4}$$

where $f_{RBF}(x)$ is the function of the RBF response, C_i is the interpolation coefficient, $\varnothing$ is a kernel function, and $\| x - x^i \|$ is distance between x and a sampling points x^i.

The parameters C_i can be obtained by solving linear equation system as follows:

$$\sum\nolimits_{i=1}^{n} C_i \varnothing \left(\left\| x^i - x^j \right\| \right) = f\left(x^j\right); \quad \text{for} \quad j = 1, \ldots, n \tag{5}$$

In this work, the linear kernel function is used for the RBF construction.

For the proposed hybrid HyKG-RBF, the weighted sum technique is used to combined KG and RBF functions, the function can be expressed as shown in Eq. (6),

$$F_{Hy}(x) = W_{KG}\left(f_{KG}(x)\right) + W_{RBF}\left(f_{RBF}(x)\right) \tag{6}$$

where, $F_{Hy}(x)$ is an approximated function obtained from the proposed HyKG-RBF, while W_{KG} and W_{RBF} are the weighting values of KG and RBF, respectively.

Finally, the DE optimizer is applied based on the surrogate models to search for the optimal design of a wind turbine blade. The optimal result obtained from optimizing a surrogate model is verified based on the CFD.

3. Results and Discussion

The surrogate models-assisted DE optimization was applied to design the parametric runner blade $(x = \{x_1, x_2, \theta_3\})$ with normalized objective function $(c_m - c_{m\_max}) / (c_{t\_min} - c_t)$. 9 sampling points obtained by OLHS are used for constructing three surrogate models (KG, RBF, and HyKG-RBF). The sampling points and their objective functions values are illustrated in Table 1. The optimal results were obtained from five runs of the DE optimizer for each surrogate model as illustrated in Table 2. The CFD tool was applied to verify the optimal results from the predicted functions of surrogate models (KG, RBF, and HyKG-RBF) as illustrated in Table 3. Note that, only the best result from five runs of each surrogate model was selected to verify by CFD.

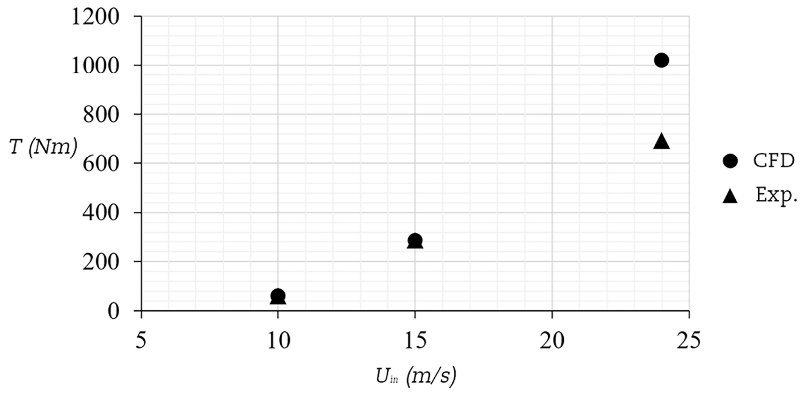


Fig. 5. Numerical validation.

Table 1. DOE and CFD results.

Variables		Samp.1	Samp.2	Samp.3	Samp.4	Samp.5	Samp.6	Samp.7	Samp.8	Samp.9
DOE	x_1	0.0002	0.0004	0.0001	0.0003	0.0002	0.0003	0.0005	0.0004	0.0002
	x_2	1.12	1.32	1.49	1.07	1.18	1.38	1.43	1.27	1.01
	θ_3	2.50°	2.93°	1.60°	1.85°	0.07°	0.51°	2.17°	1.18°	0.80°
CFD results	T	94.06269	89.17425	98.34719	96.20716	98.19587	106.0830	94.26808	104.0024	104.2185
	c_m	0.000758	0.000719	0.000793	0.000776	0.000792	0.000855	0.000760	0.000839	0.000840
	F	724.6126	687.2136	831.6824	799.1744	974.7204	940.4141	789.4272	872.3929	904.7175
	c_t	0.005842	0.005540	0.006705	0.006443	0.007858	0.007582	0.006364	0.007033	0.007294
	c_m / c_t	0.12981	0.12976	0.11826	0.12039	0.10074	0.11281	0.11941	0.11922	0.11520

Table 2. Optimal solution obtained based on surrogate-assisted DE.

Surrogate models	Run	x_1	x_2	θ_3	Min. Approx. Func.
KG	1	0.0005	1.2	2.9971	-1.04E+06
	2	0.0005	1.1536	2.9902	-2.51E+06
	3	0.0005	1.18	2.9852	-1.57E+05
	4	0.0004	1.0897	2.9449	-1.03E+05
	5	0.0002	1.4755	2.9931	-2.38E+08
RBF	1	0.0004	1.32	2.93	-1.23E+09
	2	0.0004	1.32	2.93	-2.10E+09
	3	0.0004	1.32	2.93	-1.04E+09
	4	0.0004	1.32	2.93	-2.04E+09
	5	0.0004	1.32	2.93	-7.62E+09
HyKG-RBF $W_{KG} = 0.8, W_{RBF} = 0.2$	1	0.0001	1.0828	2.8373	-3.74E+05
	2	0.0005	1.1305	2.9868	-5.26E+04
	3	0.0002	1.4811	2.9987	-1.95E+08
	4	0.0001	1.3882	2.9406	-2.71E+07
	5	0.0002	1.2561	2.9202	-2.90E+04
HyKG-RBF $W_{KG} = 0.6, W_{RBF} = 0.4$	1	0.0001	1.4686	2.9682	-5.24E+11
	2	0.0003	1.3422	2.9612	-9.31E+03
	3	0.0002	1.4653	2.9994	-4.36E+07
	4	0.0002	1.4885	2.9924	-1.37E+08
	5	0.0005	1.1658	2.9971	-1.54E+07
HyKG-RBF $W_{KG} = 0.3, W_{RBF} = 0.7$	1	0.0004	1.1857	2.9474	-9.17E+03
	2	0.0002	1.4436	2.9704	-1.65E+07
	3	0.0002	1.4319	2.9802	-1.27E+07
	4	0.0002	1.462	2.9836	-4.34E+07
	5	0.0003	1.4034	2.9917	-2.00E+05

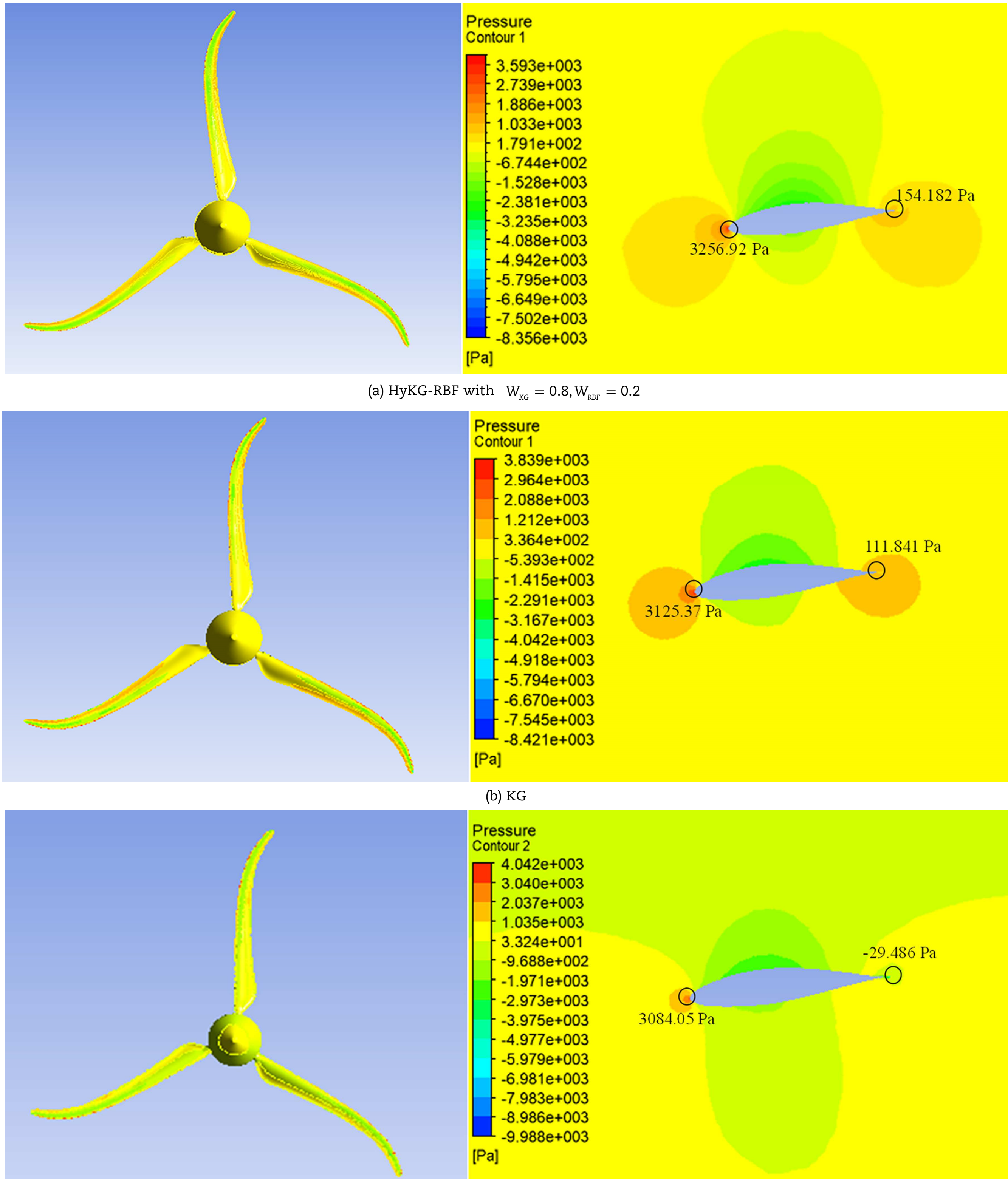
Table 3. CFD results for the best optimal solution from each method.

Parameters		KG	RBF	HyKG-RBF $W_{KG} = 0.8, W_{RBF} = 0.2$	HyKG-RBF $W_{KG} = 0.6, W_{RBF} = 0.4$	HyKG-RBF $W_{KG} = 0.3, W_{RBF} = 0.7$
Optimal design	x_1	0.0002	0.0004	0.0002	0.0001	0.0002
	x_2	1.4755	1.32	1.4811	1.4686	1.462
	θ_3	2.9931°	2.93°	2.9987°	2.9682°	2.9836°
CFD results	T	88.01348	89.17425	90.16016	89.93314	89.72086
	c_m	0.0007096	0.000719	0.000727	0.000725	0.000723
	F	676.55049	687.21369	671.00809	676.43196	674.79700
	c_t	0.0054547	0.0055406	0.0054100	0.0054537	0.0054405
	c_m / c_t	0.13009	0.12976	0.13437	0.13295	0.13296

From Tables 2 and 3, for the KG-assisted DE optimization, the design variables x_1, x_2 and θ_3 from the best run are 0.0002, 1.4755, and 2.9931°, respectively, while the maximum c_m / c_t value of 0.13009 are obtained from the CFD analysis. The design variables x_1, x_2 and θ_3 that obtained the best run of the original the RBF-assisted DE optimization are 0.0004, 1.32, and 2.93°, respectively while the maximum c_m / c_t value of 0.12976 is evaluated from the CFD analysis. For the proposed HyKG-RBF assisted DE optimization, the best weighting factor, W_{KG} and W_{RBF} are 0.8 and 0.2, respectively while the design variables x_1, x_2 and θ_3 realizes the optimal values of 0.0002, 1.4811, and 2.9987°. The maximum c_m / c_t obtained from CFD analysis are 0.13437 which is the best result obtained in this study.

Figure 6 shows the best optimal blade shapes and the results obtained by CFD analysis of the HyKG-RBF, KG and RBF. The runner blade's torque and axial force obtained from HyKG-RBF (Fig. 6a) were around 90.16016 Nm and 671.00809 N, respectively while the runner blade's torque and axial force obtained from KG (Fig. 6b) were 88.01348 Nm and 676.55049 N. For the results obtained from RBF, the runner blade's torque and axial force obtained displayed in Fig. 6c were 89.17425 Nm and 687.21369 N respectively.

In addition, Figs. 6a-6c present static pressure at the leading and trailing edge of airfoil. Note that the airfoil section was cut at 0.75R of blade radius to show the example of fluctuating pressure. From the figure, the proposed HyKG-RBF (Fig. 6a) obtained static pressure at the local of leading and trailing edge of 3256.92 Pa and 154.182 Pa while the KG (Fig. 6b) obtained static pressure at the local of leading and trailing edge of 3125.37 Pa and 111.841 Pa. The optimum blade shape from RBF gained static pressure at the local of leading and trailing edge of 3084.05 Pa and -29.486 Pa respectively. Based on the results obtained from Fig. 6, the proposed HyKG-RBF is said to be the most efficient method based on this study. Based on the static pressure, the proposed HyKG-RBF gained better optimum blade shape than the original KG and RBF for about of 27.46% and 119.12% respectively.

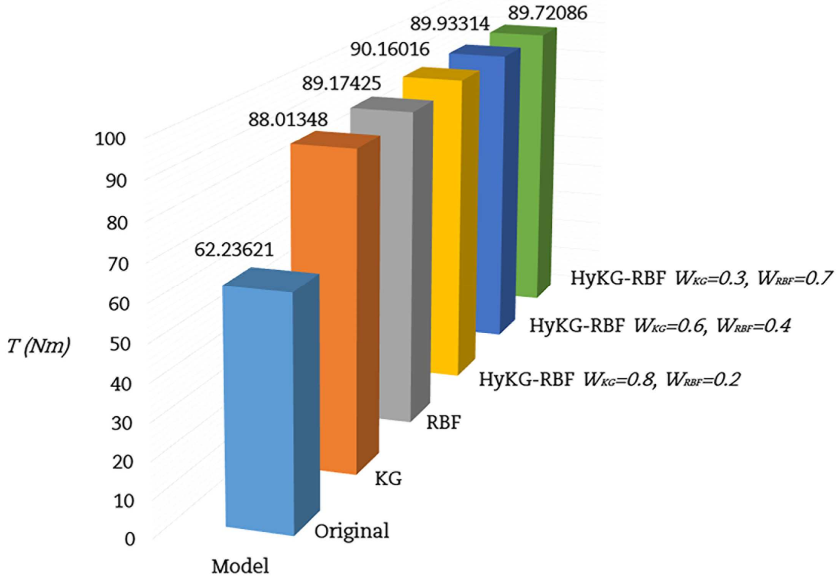


(a) HyKG-RBF with $W_{KG} = 0.8, W_{RBF} = 0.2$

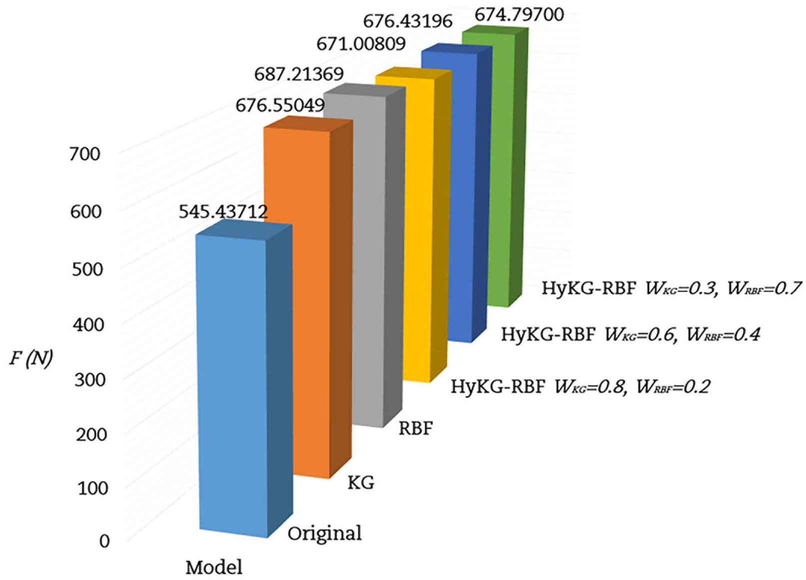
(b) KG

(c) RBF

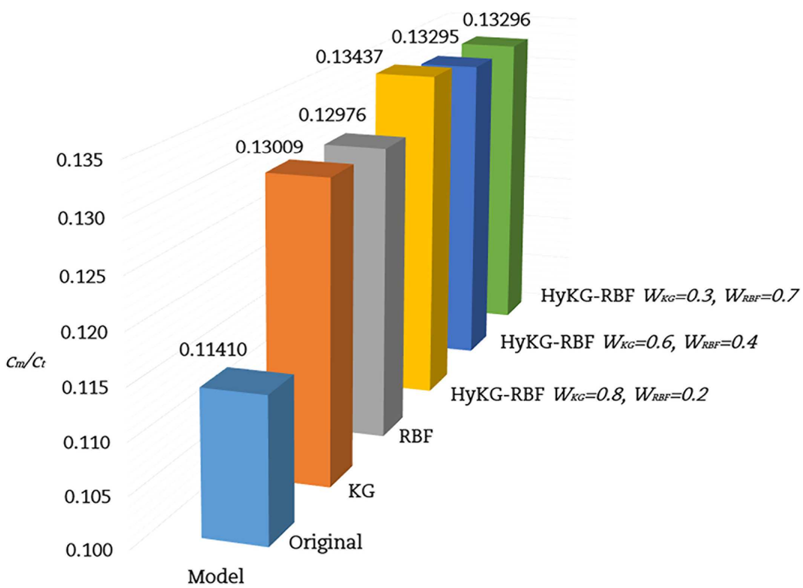
Fig. 6. Optimal design of wind turbine blade using HyKG-RBF, KG and RBF.



(a) Torque values



(b) Thrust values



(c) c_m/c_t values

Fig. 7. Results of CFD analysis from optimal blade shape by comparing with the original model.

Figures 7a-7c show the quantities of torque, thrust and c_m / c_t obtained from CFD analysis. The optimal results from all the methods are compared with the original model of the MEXICO blade [22]. From the figures, it is indicated that all of the optimal results give the better performance than the original design. The HyKG-RBF surrogate-assisted DE optimization is revealed as the best performer for the blade design with weighting factors, W_{KG} and W_{RBF} of 0.8 and 0.2, respectively while the values of torque, thrust and c_m / c_t are improved approximately 30.97%, 18.71% and 15% from the original design.

4. Conclusion

The HyKG-RBF surrogate-assisted DE optimization technique was successfully proposed for the optimal design of the wind turbine runner blade. The design problem was defined to maximize the ratio of the torque coefficient to the thrust coefficient of a turbine blade at a low wind velocity of 10 m/s. The pitch angle and leading-edge blade curve are considered as the design variables. For the aerodynamic analysis of the wind turbine blade, computational fluid dynamics has been used as a high-fidelity simulation. While the surrogate models including, the Kriging model (KG), the radial basis function model (RBF), and the proposed hybrid of KG and RBF (HyKG-RBF) models were applied for function approximation or low-fidelity simulation. The results obtained shown that the optimum blade shape obtained from HyKG-RBF with weighting factors of 0.8 and 0.2 is the most efficient for the proposed sweep blade design problem. The optimal blade design revealed that the values of torque, thrust and c_m / c_t are improved approximately 30.97%, 18.71% and 15% from the original design, respectively. For future work, the more efficient surrogate-assisted optimization method such as infill sampling technique and multifidelity modelling should by applied and investigated.

Author Contributions

N. Pholdee suggested the experiments, and examined the theory validation; S. Kumar conducted in proofreading the manuscript; S. Bureerat provided the technical interpretation of numerical analysis results; W. Nuantong planned the scheme, initiated the project, conducted the experiments, and analyzed the empirical results; W. Dongbang suggested the experiments; all authors contributed in writing and approved the final version of the manuscript.

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Conflict of Interest

The authors declared no potential conflicts of interest concerning the research, authorship, and publication of this article.

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Data Availability Statements

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Nomenclature

C_i	Interpolation coefficient	W_{KG}	Weighting value of Kriging
c_m	Torque coefficient	W_{RBF}	Weighting value of radial basis function
c_{m_max}	Maximal torque coefficient	x	Set of design variables
c_t	Thrust coefficient	x^i	Sampling points
c_{t_min}	Minimal thrust coefficient	$Z(x)$	Gaussian random function
D	Rotor blade diameter (m)	θ	Pitch angle (degree)
F	Thrust (N)	$\varnothing$	Kernel function
f	Objective function	Approx.	Approximate
$g(x)$	polynomial function	Exp.	Experimental
R	Blade radius (m)	*Expo.*	Exponential equation
r	Radial position (m)	func.	Function
T	Torque (Nm)	Min.	Minimum
U_{in}	Velocity (m/s)	Samp.	Sampling

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ORCID iD

Nantiwat Pholdee https://orcid.org/0000-0002-4370-5241
Sumit Kumar https://orcid.org/ 0000-0003-3042-3779
Sujin Bureerat https://orcid.org/0000-0002-6332-1202
Weerapon Nuantong https://orcid.org/0000-0003-3663-3136
Watcharin Dongbang https://orcid.org/0000-0002-3066-3396

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