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SURROGATE MODELS FOR STALL REGULATED WIND TURBINES FOR IMPROVED PERFORMANCE PREDICTIONS

Donald Harby, **Isaac Ofuafor**, **Ziaul Huque**, **A.B. Mahmud Hasan and Raghava Kommalapati**

Center for Energy and Environmental Sustainability (CEES), Prairie View A&M University, USA

ABSTRACT

Nowadays the Blade Element Momentum theory is used to determine a given element's airfoil section performance coefficient. The objective of this work is to improve the current method of determining the airfoil section performance coefficients and to determine these coefficients where little or no experimental data exists such as angles of attack of stall, post stall and at very low Reynolds numbers. Kriging method is used to develop surrogate models that can supply high quality airfoil sectional lift and drag coefficients over a wide range of angle of attacks and Reynolds numbers. One wind turbine blade (FX63137) is analyzed using BEM theory and the surrogate models. It is found that the predicted performance from the BEM theory and the Kriging method is very sensitive to the angle of attack and Reynolds number of the elemental airfoil sections and the performance predictions can be improved by using the developed surrogate models.

Keywords: Wind Turbine, Surrogate Model, Kriging Method, Airfoils.

1. INTRODUCTION

Amidst rising oil prices, it is very important to reduce the US crude oil import by one-third by 2025 through expanded exploration of crude oil and natural gas and investment in alternative energy sources including nuclear energy, biofuels and wind energy. The volatility in crude oil prices has led to renewed drive for renewable energy sources. Wind power is a renewable energy source that is clean, environmentally friendly and helps the US meet its energy needs and also provide economic benefits.

Currently, wind power accounts for 3% of electricity generated in the US with individual turbine capacity of around 4MW. In spite of these developments, it is still expensive to analyze the aerodynamic characteristics and performance parameters of wind turbine rotors through wind tunnel experiments or practical site experiments to improve the design and efficiency of wind turbine rotors. It is imperative that less costly means be devised to analyze the aerodynamic and performance parameters of the wind turbine blades.

Wind tunnel experiments have limitations on getting data on minimum Reynolds numbers (Re) and angle of attacks (α). Figure-1 shows necessary angle, forces and torque that works in an airfoil. The objective of this work is to use surrogate models of blades to analyze performance characteristics at untried angle of attacks and Reynolds number for wind turbine blade designs. There are various types of surrogate models such as data fit type (single data, multiple data, and global data), model hierarchy type, and reduced order modeling. The current work uses global data fit type. The Kriging model is used to approximate the lift and drag coefficients of the wind turbine blades (FX63137) from wind tunnel experimental data.

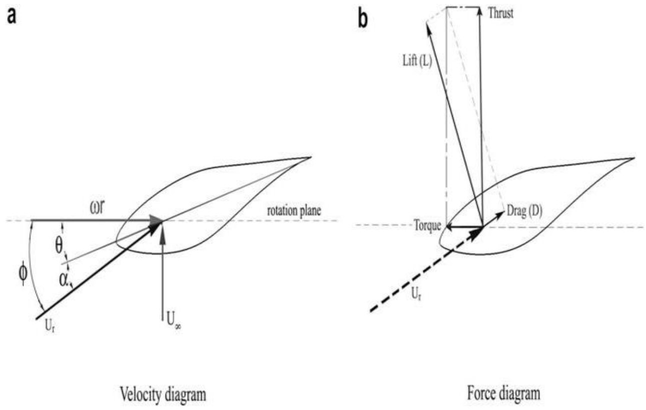

Fig 1. (a) Velocity and, (b) Force diagram showing angle of attack (α), Drag, Thrust, Lift forces and torque directions [1].

2. LITERATURE REVIEW

The Blade Element Momentum (BEM) theory is a mathematical model and also one of the most commonly used models in engineering for the fluid dynamics design of rotor blades and evaluation of wind turbine performances. In designing the wind turbine blade this model enables the choosing of geometric characteristics of the turbine such as the aerodynamic airfoils, rotor radius, chord length, pitch and twist angles. This also includes the evaluation of the forces acting on the blade, the torque and power at the rotor shaft. The mathematical model also enables turbine performance evaluation at wide ranges of wind speeds.

The experimental data used by this paper has a small range of angle of attack from-11^o to 20^o because of wind tunnel limitations. The flat plate theory enables the calculation of the peak post-stall data using the Viterna and Corrigan method [2]. The combined experimental and flat plate theory data when modeled using the Kriging method could be used to simulate the blade design parameters and thus, the power coefficient (C_p), torque and normal and tangential forces acting on the blade. The peak rotor power and post-peak power is important in the predictive design of constant-speed and variable speed stall-regulated rotors.

Coefficient of power (C_p) is calculated using the equation:

$$C_p = \frac{P}{\frac{1}{2}\rho_\alpha A U_\alpha^2} \quad (1)$$

Here, P =Power, ρ_α =Free stream flow density, A=Cross-sectional area of the blade, U_α =Free stream velocity.

Experimental studies lack a method for determining the blade's angle of attack (α) distribution so that normal and tangential force coefficients (C_n and C_t) acquired from chord-wise pressure measurements can be converted into lift and drag coefficients (C_l and C_d) for engineering calculations.

By definition, 'stall' means a particular angle of attack when the blade does not produce any lift force, therefore we do not get any power from wind turbine. The region just after stall condition is known as 'post-stall'.

References [3-5] have concentrated on the determination of the angle of attack distribution from experimental data. Under the sponsorship of the National Renewable Energy Laboratory (NREL) the Lifting-Surface Wind Turbine (LSWT) performance-prediction methodology [6], provided a unique capability for deriving angle of attack. From Unsteady Aerodynamic Experiment (UAE) data of C_n and C_t could then be converted into values of C_l and C_d using angle of attack distributions derived from LSWT. Through an iterative process, agreement was achieved between UAE measured and LSWT-predicted C_n and C_t radial distributions [2].

This agreement yielded angle of attack distributions compatible with the measured post-stall 3D aerodynamic characteristics. Unlike blade-element momentum (BEM) theory, the LSWT methodology accounts for the induced effects of the blade configuration and those from the span-wise distribution of trailing vorticity in calculating the angle of attack distribution [3].

After an angle of attack of 20^o the lift/drag ratio for the five radial locations at which pressure measurements were acquired essentially followed simple flat plate theory [7]. The difficulty of relating BEM-predicted angle of attack distributions to the post-stall 3-D aerodynamics and measured power are demonstrated in [3-5]. This finding pointed to the need for a global post-stall approach, as for instance, previously developed by Viterna [8] and [9] for generating post-stall C_l and C_d based on both airfoil and blade specific stall characteristics.

These generated post-stall data are combined with the experimental data to create surrogate models that are used to predict the lift and drag coefficients at untried location of the Reynolds number and angle of attack (untried sites) to predict peak power and other rotor performance characteristics.

The Kriging method is a good tool to provide good predictive values. The programs used are from the "Design Analysis of Computer Experiments (DACE) a Matlab Kriging Toolbox" for constructing Kriging approximation models based on data from computer experiments and to use this approximation model as a computer model [10].

3. GENERATING GLOBAL DATA

Since the experimental data of lift coefficient (C_l) and drag coefficient (C_d) are available for mainly pre-stall angle of attacks, flat plate theory was used to calculate the post-stall C_l and C_d from the given experimental data according to Viterna and Corrigan method [2,8]. Following are the set of equations used [3-9] to get global data:

Drag coefficient:

$$C_d = B_1 \sin^2\alpha + B_2 \cos\alpha \qquad \alpha = 15^o to 90^o \quad (2)$$

$$C_{d\,\max} = 1.11 + 0.018AR \qquad \alpha = 90^o \quad (3)$$

where: $$B_1 = C_{d\,\max} \quad (4)$$

$$B_2 = \frac{C_{dstall} - C_{d\,\max}\sin^2\alpha_{stall}}{\cos\alpha_{stall}} \quad (5)$$

Lift coefficient:

$$C_l = A_1 \sin 2\alpha + A_2 \frac{\cos^2\alpha}{\sin\alpha} \qquad \alpha = 15^o to 90^o \quad (6)$$

where:

$$A_1 = \frac{B_1}{2} \quad (7)$$

$$A_2 = (C_{lstall} - C_{d\max} \sin\alpha_{stall} \cos\alpha_{stall}) \frac{\sin\alpha_{stall}}{\cos^2\alpha_{stall}} \quad (8)$$

An initial angle of attack (α_{stall}) with its associated lift ($C_{l,stall}$) and drag ($C_{d,stall}$) coefficients with the blade aspect ratio (AR) is required. The C_l/C_d will not agree with the flat plate theory if the C_l/C_d at the initial angle of attack is not satisfied. These global C_l and C_d data are used to develop the surrogate models.

4. KRIGING MODEL CONSTRUCTION

In developing surrogate model by Kriging method the choice of correlation function should be motivated by the underlying phenomenon that is the function we want to optimize or the physical process we are modeling. If the underlying phenomenon is continuously differentiable, the correlation function will likely show a parabolic behavior near the origin, which means that the GAUSSIAN, CUBIC or the SPLINE function should be chosen. Conversely, when the physical phenomena shows a linear behavior near the origin the EXP, EXPG, LIN or SPHERICAL correlation would perform better.

In the present work we first choose the gauss correlation function. The model developed for FX63137 with gauss correlation function did not accurately represent the approximated points. This is one of the challenges to choose the model type to approximate the data. The exponential correlation function was chosen next to make the approximation model. Figure 2 below is the approximation model of the lift and drag coefficients of the FX63137 airfoil using the exponential correlation. The data points of the lift and drag coefficients are represented by the black straight lines. This is a reasonably good representation of the shape of the data points. This model now can be used for prediction at untried sites.

Figure 3 shows the Mean Square Errors (MSE) for the airfoil. From the figure it could be seen how areas with few design sites have high MSE values. In its simplest form, a Kriging estimate of the field at an observed location is an optimized linear combination of the data at the observed locations. The coefficients of the Kriging estimate and the associated error measure both depend on the spatial configuration of the data, the unobserved location relative to the data locations, and spatial correlation or the degree to which one location can be predicted from a second location as a function of spatial separation [12]. Essentially in the Kriging model, the data points between Reynolds numbers must be close together to have small Mean Squared Errors (MSE) between the untried sites. Where there are large differences in the Reynolds numbers there are high MSE.

There were no Reynolds number runs of the wind tunnel experiment at $2x10^5$ to $3.5x10^5$ and close to $5x10^5$. This does not preclude the surrogate model from making

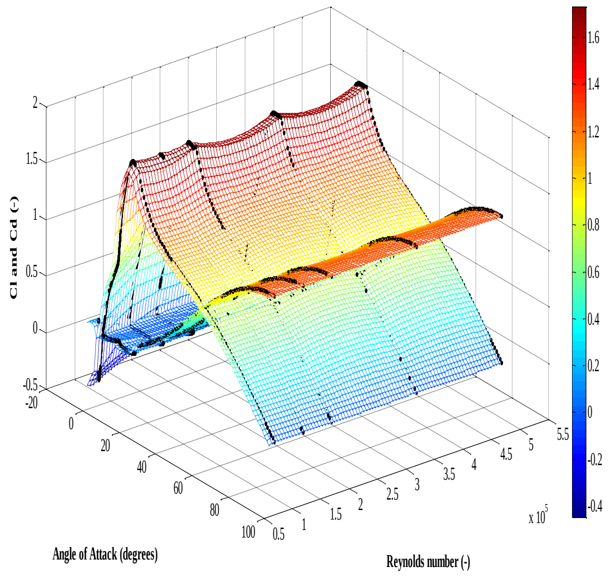

Fig 2. Kriging model of C_l and C_d of the FX 63137 airfoil

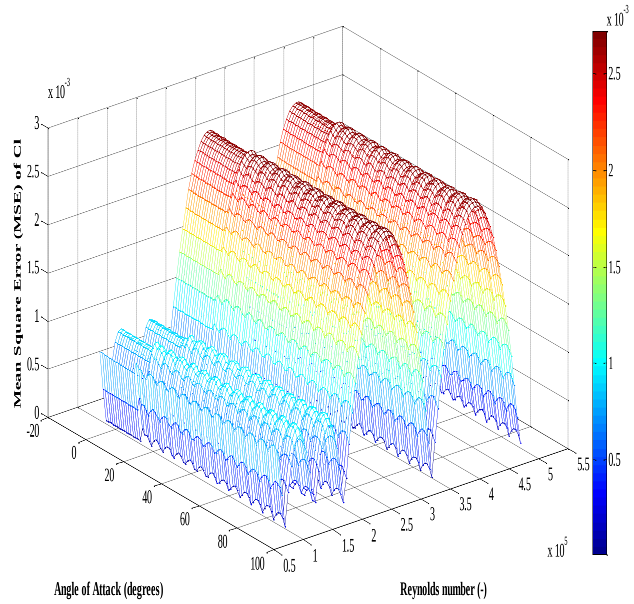

Fig 3. The MSE of C_l of the FX 63137 airfoil

accurate predictions at the untried site. For example to predict the lift and drag coefficients at Reynolds number $2x10^5$ and angle of attack of 10^o of the airfoil (which are untried points), the surrogate model predicted a C_l value of 1.2337 and MSE in the range of 0 to 0.0015. The drag coefficient C_d is predicted to be 0.0343 and the range of MSE is 0 and 0.012. Another useful performance characteristic of this approximation model is the estimated process variance which is $\sigma^2 = 0.0029$ for the C_l model and $2.18x10^{-4}$ for the C_d model.

5. COMPARISON OF PREDICTED OUTPUTS

MSE is one of several ways to measure the difference between values implied by an estimator and true values of the quantity being estimated. MSE is a risk function corresponding to the expected value of the squared error loss. Minimizing MSE is a key criterion in selecting estimators and MSE being the difference between experimental data and the response predicted by the model, it can be used to determine if the model fits the data.

The MSE of the Kriging model and the experimental data of the FX63137 airfoil were calculated and compared and was found to have a reasonably good fit. The coefficients of the Kriging estimate and the error depend on the spatial configuration of the data, the unobserved sites relative to the data sites and spatial correlation or the degree to which one point can be predicted from a second point as a function of spatial separation. This could be explained further by visual observation of the Kriging method. In Figure 2, there is sagging at the crest of the model of lift coefficient between the spatial separations and also depicted more vividly in Figure 3 where the MSE is highest at untried sites of the Reynolds numbers. The predicted C_l and C_d at untried sites are also presented in Table 1.

Table 1: Predicted C_l and C_d of the FX63137 airfoil at untried sites

FX63137 Airfoil							
				NEURAL NETWORKS			
		Kriging		Trainlm		Trainbfg	
Re	α	C_l	C_d	C_l	C_d	C_l	C_d
100000	13	1.7279	0.0521	1.7046	0.0615	1.6848	0.0633
100000	14	1.6968	0.0841	1.6878	0.0755	1.6884	0.0751
100000	15	1.6775	0.1374	1.6592	0.0917	1.6753	0.0891
100000	16	1.6019	0.1488	1.6212	0.1096	1.647	0.105
100000	20	1.3851	0.2005	1.4305	0.1875	1.4397	0.1814
200000	13	1.7123	0.052	1.7166	0.0582	1.7325	0.0559
200000	14	1.7031	0.071	1.7009	0.0734	1.7255	0.0695
200000	15	1.719	0.1216	1.673	0.0906	1.7031	0.085
200000	16	1.6735	0.1415	1.6354	0.1092	1.6667	0.1024
200000	20	1.4402	0.1934	1.4501	0.188	1.4435	0.1825
300000	13	1.6373	0.0744	1.7229	0.0554	1.7458	0.0554
300000	14	1.6364	0.0923	1.7052	0.0716	1.7355	0.0695
300000	15	1.6455	0.1354	1.6745	0.0896	1.7099	0.0855
300000	16	1.605	0.157	1.6341	0.1088	1.671	0.1033
300000	20	1.4062	0.2079	1.4434	0.1883	1.4471	0.1835
400000	13	1.6439	0.0771	1.7275	0.0557	1.7402	0.0586
400000	14	1.6457	0.0939	1.7054	0.0733	1.7253	0.0732
400000	15	1.6501	0.135	1.6697	0.0926	1.6956	0.0897
400000	16	1.61	0.1595	1.6248	0.1128	1.6535	0.1079
400000	20	1.4105	0.2104	1.425	0.1947	1.4279	0.1881

6. APPLICATION OF THE KRIGING METHOD TO BEM THEORY

In this work the BEM theory is used to predict the performance of wind turbines using Kriging method for untried sites of the wind tunnel experimental data. The performance of wind turbine is predicted using the BEM theory using the WT_Perf code [14] which was originally developed by Oregon State University as the PROP code, but has since been rewritten and modernized with added new functionalities and algorithms by the staff at National Wind Technology Center (NWTC). A hypothetical wind turbine is described below:

Blade radius is 5m, hub radius is 0.2m with no twist and no taper. The blade radius is divided into 20 dimensionless equal elements. With aerodynamic data assumed for standard temperature and pressure at sea level the air density is taken as 1.225kg/m^3 and kinematic viscosity is taken as 1.464x10^{-5} m^2/s. The simulations produced the power coefficient, torque coefficient, thrust coefficient, power, flap bending moment and the thrust of the rotor at incremental wind speed.

The power coefficient of the FX63137 airfoil using the design parameters above is 0.41 and conditions leading to this are 8 m/s wind speed and 100 rpm rotor speed as shown in Figure 4. Figure 5 shows the power generated when the airfoil was simulated with the wind turbine performance code across various wind speeds. The power is found to be fairly constant at 100 rpm at the various wind speeds.

From the blade element data of the performance output at maximum power coefficient condition, Figure 6 shows the distribution of the thrust coefficient (dF), torque coefficient (dT) and power coefficient (C_p) along the blade length while Figure 7 depicts the thrust and torque acting on the rotor blade. This is the distribution of the power, forces and torque on the rotor along the length of the blade. These parameters increase gradually along the rotor radius from the hub to the tip where there is dramatic drop as a result of tip loss.

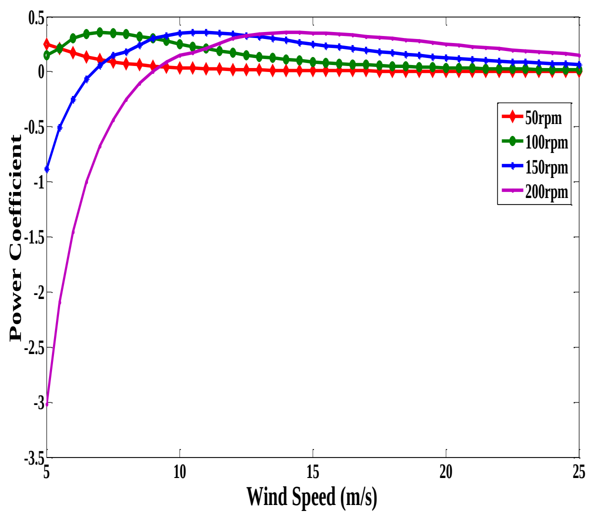

Fig 4. Power coefficient versus wind speed of the FX63137 airfoil

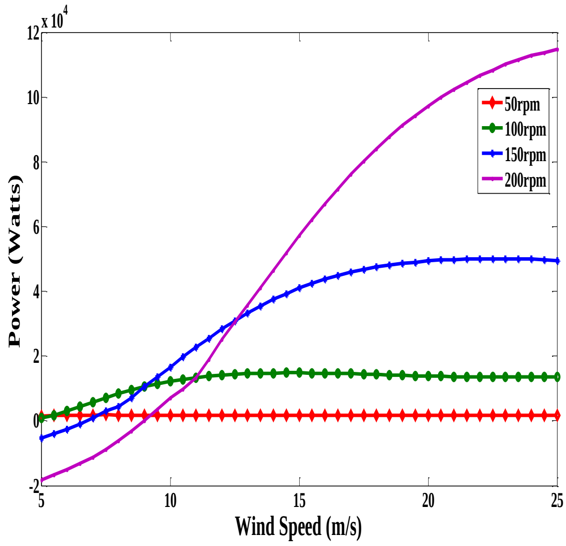

Fig 5. Power versus Wind speed

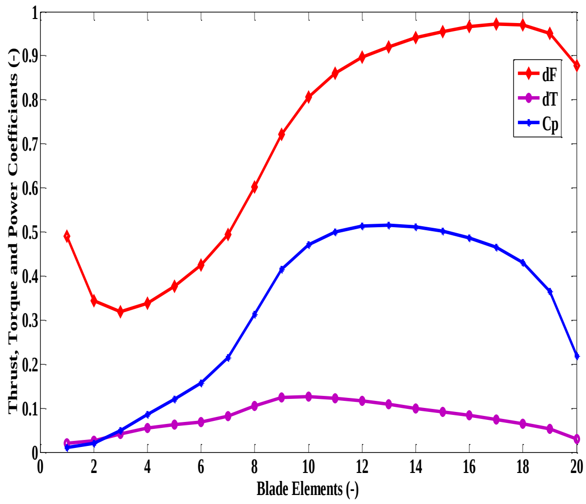

Fig 6. Plot of Thrust (dF), Torque (dT) and Power coefficients (C_p)

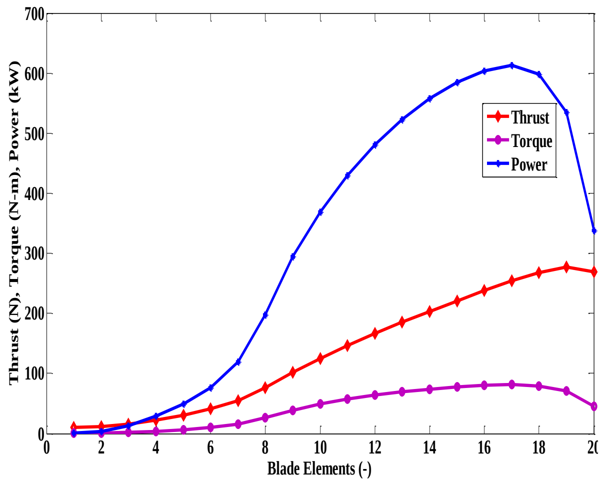

Fig 7. Plots of Thrust, Torque and Power

7. CONCLUSIONS

Several innovative techniques have been developed for predicting the lift and drag coefficients of wind turbine blades over a wide range of angle of attacks and Reynolds numbers. This unique Kriging method optimizes the target data and accurately predicts or simulates the lift and drag at untried sites. The Kriging model generates important design parameters such as the generalized least square estimate, correlation factors and the estimate of the process variance. With the right combination of learning and training parameters more could be done with designing wind turbine blades and simulating the performance parameters using Kriging method. The MSE and the Regression are important measurements of how the Kriging method fits the experimental data. Depending on the sensitivity of the experimental data Kriging method in this research produced close approximation models. The Kriging model gives an estimate of the process variance. The Kriging method increased the accuracy of the BEM theory through accurate prediction of the lift and drag coefficients**.**

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9. MAILING ADDRESS

Donald Harby
Center for Energy and Environmental Sustainability (CEES)
Prairie View A&M University
Prairie View, Texas 77446
USA