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Wind Turbine Model Validation: Fusion of Simulation and Measurement Data

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Abstract: A new turbine model validation technique that is based on adaptation of look-up tables is described this paper. Simulation results from the VIDYN turbine simulation program and measurements from Big Glenn wind turbine, located outside Gothenburg, Sweden are used as an input to this new model validation technique. The models of the flapwise bending moment and power coefficient are validated for Big Glenn turbine. Measurement data are acquired during normal turbine operation. Verification results show good agreement between model outputs and measured data. The method allows prediction in a wide range of turbine operating variables, using only few measured points.

Keywords: Wind turbine, Model Validation, Table Update Method, Data Fusion

1. INTRODUCTION

A number of turbine quantities is estimated using look-up tables that describe mean value model of the turbine. For example, the steady-state operational loads (flapwise and edgewise bending moments) as well power coefficient can be presented as look-up tables with turbine speed, tip-speed ratio and pitch angle as input variables. Turbine output variables may be calibrated in a wide range of input variables using high fidelity simulation based on GH BLADED [1], FAST [2], VIDYN [3] and other programs. However, such models suffer from inaccuracies which are present even in the high fidelity simulation programs, and therefore may not be good enough for accurate predictions. The accuracy of simulation-based turbine models may be improved using measurement data. The data may be acquired during normal turbine operation. However, measurement data are often available in a certain operating region only. If the wind speed is below rated the data are available for tip-speed ratio that maximizes energy capture and zero pitch angle. The data which corresponds to a certain trajectory of pitch angle at optimal tip-speed ratio are available only, if wind speed is above rated. Besides, a measured data set should be properly selected in order to match the steady-state simulation data. For example, low variability in measured data that represents a certain quasi steady-state operating point is required. In addition, the data should be acquired over a relatively large time segment (several minutes) to ensure statistical consistency. Besides, a number of additional requirements may be added to the data selection method. For example, uniformity of the wind speed distribution across the rotor swept area is necessary for validation of the turbine load model. Therefore the data that corresponds to low tilt and yaw nacelle moments should be selected. Such selection

FIG 1. Big Glenn wind turbine located outside Gothenburg, Sweden. The turbine was manufactured by GE Wind Energy GmbH, and has rotor diameter 112.5 m with rated power of 4100 KW.

essentially reduces a set of measured data points. This motivates the development of a new turbine model validation technique that fuses simulation results with a small set of measured data which are available in a limited operating region.

Steady-state turbine behavior is usually described using look-up tables, and therefore model validation technique is associated with adaptation of look-up tables. Simulation results are used for pre-calibration of look-up tables and determination of priori dependencies between turbine variables. Statistical quantities of measured variables (mean values and standard deviations) are used for adaptation of look-up tables.

Adaptation algorithms of look-up tables were developed and successfully implemented in automotive applications for robustness enhancement [4] - [6]. However, adaptation algorithms described in [4],[5] and [6] do not allow prediction in a wide range of output variable using a sufficiently small new data set available in a certain operating region only. Algorithms that are suitable for adaptation of look-up tables, using data available in a limited operating region only were proposed in [7] and further developed in [8] and [9]. According to this concept the adaptation of look-up table is associated with a motion of the surface in three dimensional space. The position and the orientation of the surface in three dimensional space change only after adaptation, which in turn, allows for a prediction for a wide range of output variable. This prediction is possible with few measured points only by taking into account physical dependencies, which are present in the shape of the surface. An adaptation algorithm is constructed so that only the nodes of the look-up table are adapted, whereby the values of the output variable between the nodes are calculated using linear interpolation. Variability in measured data set is accounted via proper assignment of the weighting factors. This concept of adaptation of look-up tables is directly applicable to the turbine model validation.

A new method for turbine model validation that is based on look-up tables which are pre-calibrated using simulation results and adjusted according to measured data is the main contribution of this paper. Simulation results from VIDYN simulation program [3] are fused with measurements taken on Big Glenn wind turbine (see Figure 1) in this model validation method. The models of flapwise bending moment and power coefficient are validated for Big Glenn turbine. Verification results show good agreement between model output and measured data.

The paper is organized as follows. General adaptation algorithms of look-up tables are described in Section 2. Application of this technique to validation of the flapwise bending moment model is presented in Section 3. The paper ends with validation of the turbine power coefficient model in Section 4 and brief conclusions in Section 5.

2. GENERAL ADAPTATION ALGORITHMS OF LOOK-UP TABLES

Suppose that there is a look-up table describing output variable z as a function of two input variables x and y. The look-up table is presented as a number of nodes, where the output variable is defined. The values of the output variable between the nodes are calculated using linear interpolation. The problem of adaptation of the look-up table is reduced to calculation of an additive (or multiplicative) compensation term associated with a difference between new measured values of the operating parameter and output the look-up table. The values of this compensation term are added to the nodes of the look-up table. Therefore the problem of adaptation of the look-up table is reduced to the adaptation of the nodes.

Assume that new measured data x_{im}, y_{im}, z_{im} with the weighting factors w_{im} are available, where $i = 1, ..., N$. Notice, that the weighting factors w_{im} are assigned according to the accuracy of measured values of the operating parameter. Usually, the weighing factors are inversely proportional to the variances of the measurement noise.

The difference between a value of the parameter z_i calculated via a look-up table and new measured value of the parameter z_{im} is $\varepsilon_i = z_i - z_{im}$. Assume that ε can be approximated with a linear (with respect to parameters) function of two variables i.e.,

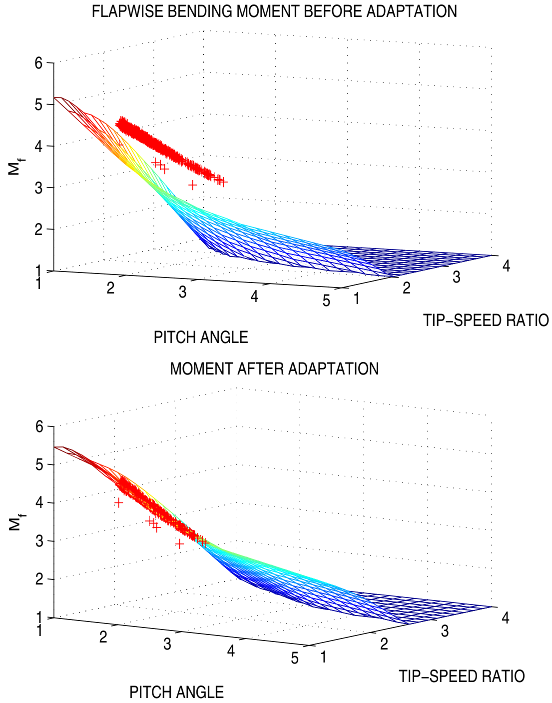

FIG 2. The flapwise bending moment as a function of tip-speed ratio and pitch angle for 15 [rpm]. Mean values of the flapwise bending moment measured on Big Glenn turbine are plotted with plus signs of a red color. All the variables are presented in normalized units.

$$\hat{\varepsilon} = \varphi^T \theta \tag{1}$$

where

$$\varphi^T = [1 \quad x \quad y \quad ...] \tag{2}$$
$$\theta = [a_0 \quad a_1 \quad a_2 \quad ...]^T \tag{3}$$

where $\hat{\varepsilon}$ is an estimate of ε. The parameters a_0, a_1 and a_2 correspond to adaptation of an offset and the slopes in x and y direction respectively. The model $\hat{\varepsilon}$ is constructed using a step-wise regression method, where the contribution of each term is reviewed, to ensure that it remains statistically significant. The residuals are compared using the *Test for Equal Variances*, see [9] for details. The coefficients (3) are calculated using least-squares method. As soon as the coefficients and the optimal order of the polynomial are found, the values of the compensation term are calculated and added to the values in the nodes of pre-calibrated look-up table.

3. VALIDATION OF THE MODEL OF FLAPWISE BENDING MOMENT

The steady-state flapwise blade root bending moment can be described as a sandwiched surface (for different turbine speeds) with the tip-speed ratio and blade pitch angle as input variables. Such a surface is pre-calibrated using VIDYN simulation program that describes the model of Big Glenn turbine, and it is plotted in the first subplot of

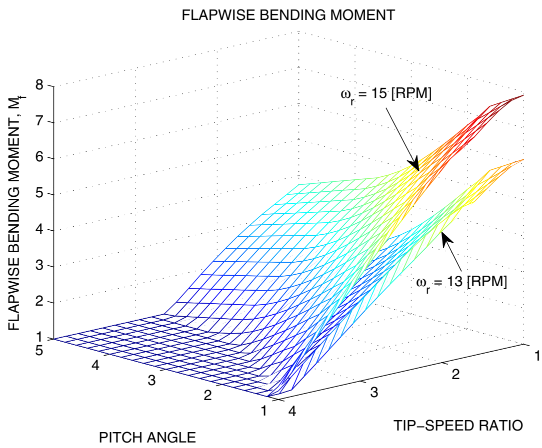

FIG 3. The flapwise bending moment as a function of tip-speed ratio and pitch angle for 13 [rpm] and 15 [rpm]. All the variables are presented in normalized units. Similar model of the flapwise bending moment was presented in [10].

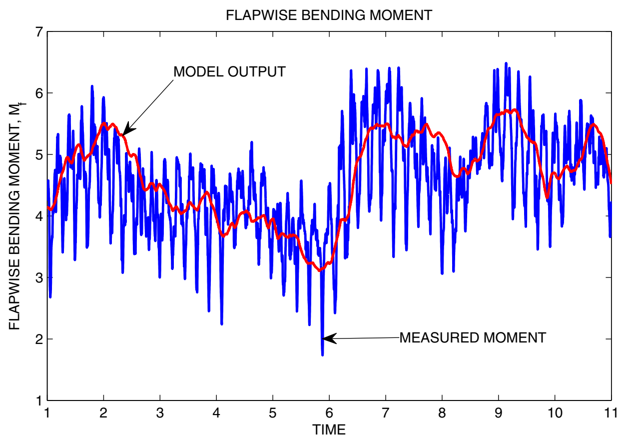

FIG 4. Verification of the model of the flapwise bending moment. Flapwise bending moment measured on Big Glenn wind turbine is plotted with a blue line. The output of the steady-state model of the flapwise bending moment is plotted with a red line. All the variables are presented in normalized units.

Figure 2 for the turbine speed of 15 [rpm]. The table is calibrated for a wide range of the values of tip-speed ratio and pitch angle. Measurements of the flapwise bending moment on Big Glenn turbine for the same turbine speed are plotted with plus signs of a red color. These measurements represent the values of the flapwise bending moment averaged over ten minute interval with low standard deviations. Notice that measurement data are available in a limited operating region only. Mismatch between pre-calibrated surface and measured data necessitates adaptation of the surface. The surface, presented in the first subplot of Figure 2 is adapted to the measured data, using adaptation technique described in Section 2. The slope in the pitch direction is adapted. The result of adaptation is illustrated in the second subplot of Figure 2, where it is shown that almost all measured points are located on

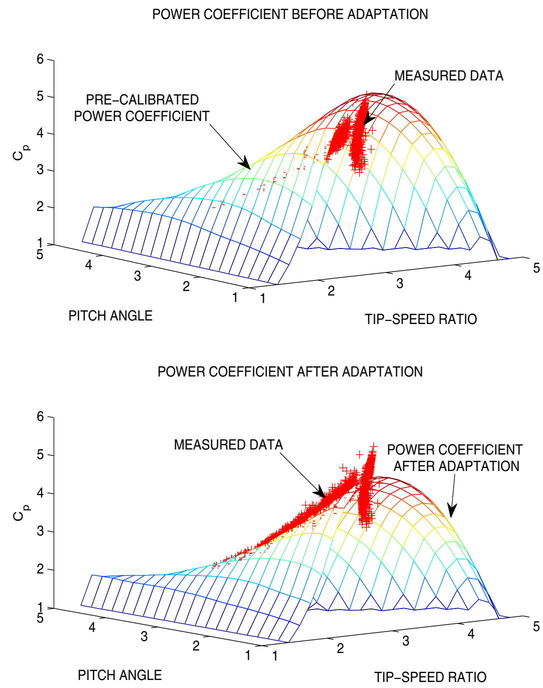

FIG 5. C_p surface before and after adaptation. Mean values of the power coefficient measured on Big Glenn turbine are plotted with plus signs of red color. All the variables are presented in normalized units.

the surface. In addition, the profiles of the flapwise bending moment for low turbine speeds and zero pitch angle are also adapted. Finally, the slope of all surfaces, which represent different turbine speeds is updated according to the slope of the surface for 15 [rpm]. Adapted surfaces which represent flapwise bending moment for 13 [rpm] and 15 [rpm] are plotted in Figure 3.
Verification of the model of the flapwise bending moment is presented in Figure 4. Flapwise bending moment which is measured on Big Glenn wind turbine is plotted with a blue line. The output of the model, which was adapted according to the procedure described above is plotted with a red line. This Figure shows that the model of the flapwise bending moment, presented as sandwiched surface is a mean value model that provides accurate prediction of the average values of the moment.

4. VALIDATION OF THE C_P SURFACE

Power coefficient describes the efficiency of wind turbine and it is presented as a C_p surface with tip-speed ratio and pitch angle as input variables. Power coefficient is pre-calibrated using steady-state VIDYN simulations and it is shown in the first subplot of Figure 5. Turbine power was measured on Big Glenn turbine and averaged over ten minute interval. Averaged values of the power coefficient, calculated using mean values of the turbine power with low variances are plotted in the same subplot with plus signs of a red color. This plot shows that the power coefficient is overestimated in VIDYN simulations. Notice that the power coefficient is calculated via turbine applied aerodynamic torque in the VIDYN steady-state simulations. Inaccuracies in estimation of aerodynamic torque have a direct impact on a quality of estimation of the power coefficient. The difference between pre-calibrated surface and measured data is minimized via adaptation. The C_p surface is adapted using algorithms described in Section 2. The result of adaptation is presented in the second subplot of Figure 5, which shows good agreement between measured data and adapted C_p surface.

5. CONCLUSION

A new method for turbine model validation based on both simulation and measured data was developed. Adaptation of the surfaces to measured data, which are acquired during normal turbine operation is the key idea of this novel model validation method. Validation of the flapwise bending moment and power coefficient for Big Glenn turbine is presented as an example. Good agreement between measured data and model output as a result of adaptation allows prediction of the turbine power and loads for a wide range of turbine operating variables. Validated models are simple enough to be used for control design and simulations.

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