

Genetic Algorithm Based Modeling of Doubly-Fed Wind Farms

Yujia Gu¹, Yinfeng Wang², Xutao Li¹, Bei Tian¹, Feng Gao¹ and Chao Lu^{2,*}

¹Power Science Research Institute of State Grid Ningxia Power Co., Yinchuan, China 750011

²Tsinghua University, Beijing, China 100084

*Corresponding author

Abstract—Faced with the drawback of conventional doubly-fed wind farm models, which cannot reliably reflect the actual control law and dynamic characteristics, a method of complex characteristics modeling based on simulation is developed in this paper. The software MATLAB/Simulink platform is utilized to create a universal equivalent model, including structure characters and control modes. In order to make the parameters identification process of higher-order wind farm models simpler, trajectory sensitivity analysis method is used to select dominant dynamic parameters. Besides, a method melting the bright side of model simulation and the genetic algorithm is proposed to search the optimal parameter combination. The test results on the IEEE 9-bus system demonstrate the effectiveness of the proposed comprehensive method.

Keywords—doubly-fed wind farm; matlab/simulink; trajectory sensitivity analysis; model simulation; genetic algorithm

I. INTRODUCTION

In recent years, wind energy resources get the favor of people because of its advantages such as rich reserves, environmental protection and flexible application. However, the fluctuation and randomness features of wind power are especially evident, as increasement of wind power penetration in power system. Thus, establishing the model that can effectively reflect the actual characteristics of wind farms and reliably setting the model parameters are both important to analyze the impact of large scale wind power integration into power systems. Previously, in order to study the faults in a large-scale wind farm affected by complex relationship among those doubly-fed wind generators, the wind generators are classified by dynamic consistency and the aggregated to get the output features. Actually, the wind farms internal structure is complex and changeable. The overall output features have more influence on the system safe and stable operation in the engineering practice. Therefore, the research work of reliability modeling of large-scale wind farms carried out recently are more focused on the external response properties of overall wind farms.

In allusion to the difficulty that the high-order models are too complex to perform efficient parameter identification. The majority of modeling methods already proposed [1,2] would simplify the order of equivalent wind farm models according to different research problems. Although the model complexity is greatly decreased by this mean, some control laws and response characteristics of the wind farms may be lost. So the scope of those methods is restricted. In the process of wind farm modeling, there also has been a special

outpouring of concern for the model parameters selection methods that are commonly used in the daily analysis and calculation of dispatch and operation departments. Setting unified and typical parameters for all the wind farms in power system is unreasonable. The above conditions show that modeling and parameter identification based on measured data is imperative. To overcome such limitation, a modeling and optimized parameter identification method of doubly-fed wind farms based on MATLAB/Simulink is proposed in this paper. on the basis of G.E.'s 1.5/3.6MW doubly fed induction generator (DFIG) models [3], an equivalent model of wind farms is established in Simulink platform, which includes fundamental control links and response characteristics. In addition, the parameters with high trajectory sensitivities related to output active and reactive powers are treated as the dominant parameters. Genetic algorithm is embedded in the process of model simulation to obtain the optimized parameter combination, which avoids the cumbersome process of model simplification and offers an effective solution to the parameters optimization of complex models. A comparison between the simulation results with optimal and actual parameters in WECC 9-bus system is made to validate the effectiveness and reliability of the modeling methodology.

II. MODEL ESTABLISHMENT OF WIND FARMS

The model presented in this article describes the relevant dynamics of doubly-fed wind farms in the s domain, which consists of four parts: the equivalent shaft model, active power control model, reactive control model and grid interface model. The overall connectivity of this model can be observed in Figure I.

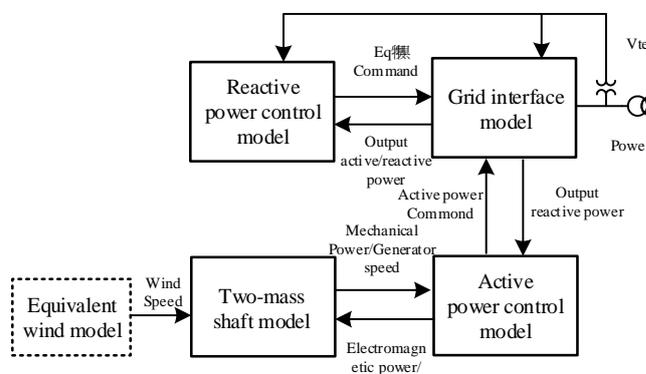


FIGURE I. DYNAMIC MODEL CONNECTIVITY OF DOUBLY-FED WIND FARMS.

constant power factor control. Similarity, Q_{ord2} represents the command value of constant reactive power.

D. Grid Interface Model

As it is indicated in the Figure IV, the whole wind farm is integrated into the power grid as a controlled current source. X_{eq} is the equivalent reactance of the whole wind farm. Active and reactive current are respectively controlled by active command and quadrature axis transient electromotive force. This model simulates the connection among the converter, generator stator and the power grid.

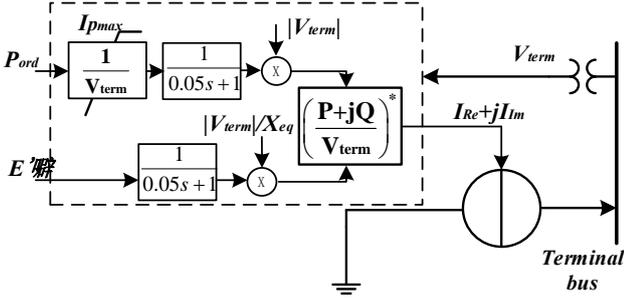


FIGURE IV. GRID INTERFACE MODEL DIAGRAM.

III. MODEL PARAMETERS IDENTIFICATION BASED ON SIMULATION

Few researchers have addressed the problem of parameters identification of the complex wind farm models. It's difficult to make a balance between the model's accuracy and the parameter identifiability. The purpose of this study is to optimize the parameter combination, which the simulation results based on correspond with the actual dynamic response results as possible.

A. Selection of the Domination Parameters

As mentioned previously, the main difficulty of parameter identification is too many parameters. The parameters of PI controller, saturation and rater limiter can be off-line set, without frequent exchange. The other parameters with clear physical meanings need to be identified, as listed in Table I.

TABLE I. PARAMETERS AND THEIR TYPICAL VALUES OF WIND FARM.

Parameter name	Symbol	Typical value (p.u.)
Equivalent reactance of the wind farm	X_{eq}	0.55
Innertial time constant of generator	T_g	1.14
Innertial time constant of wind turbine	T_{wt}	7.64
Rigidity coefficient of the shaft	K_{gt}	1.25
Damping coefficient of the shaft	D_{gt}	1.50

As we know, those parameters that are most sensitive to the output are more easily identified [4], [5]. So the trajectory sensitivity defined in (4), is used to analyze the identifiability of those parameter.

$$S_{\theta_i} = \lim_{\Delta\theta_i \rightarrow 0} \frac{y(t, \theta, \theta_{i0} + \Delta\theta_i) - y_0(t, \theta, \theta_{i0})}{\Delta\theta_i / \theta_{i0}} \quad (3)$$

Where S_{θ_i} is the trajectory sensitivity of the i th parameter θ_i related to the output variable y . y_0 is the initial value of y , as an observational variable. when the θ_i is given as θ_{i0} . $\Delta\theta_i$ is the variable quantity of the parameter θ_i . θ includes all the parameters except for θ_i .

The trajectory sensitivity is change over time in the dynamic process. For ease of comparison among those parameters, the average values can be calculated in the response time periods, as in (5).

$$\overline{S_{\theta_i}} = \frac{1}{t_1 - t_0} \int_{t_0}^{t_1} S_{\theta_i}(t) dt \quad (4)$$

Where the t_0, t_1 are separately the start and end times of the dynamic process. $S_{\theta_i}(t)$ is the trajectory sensitivity of parameter θ_i at time t . $\overline{S_{\theta_i}}$ is the average value. This equation can be also expressed as a discrete form.

Above all, the output active and reactive power of the wind farm model are selected as observational variables. The average trajectory sensitivities of those parameters related to the two observational variables are used to determine the dominant parameters.

B. The Optimization Algorithm Based on Simulation

The essence of the parameter identification is optimization under the limited conditions. For the wind model with complex structure and numerous control units, model simplification is meaningless to replicate the work of previous authors. So a method is timely developed in this section, which is not dependent on the model structure information, but the results of model simulation.

Firstly, an optimal model with constraint is built in (6). The optimization object is to minimize the error between the simulation value and the measured value of the model output. In addition, the parameters and the intermediate variables must vary in their limited ranges.

$$\begin{aligned} & \min \sum_{n=0}^N \left| \hat{Y}_n(u, \hat{\theta}) - Y_n(u, \theta) \right|^2 \\ & s.t. \quad \theta_{\min} \leq \hat{\theta} \leq \theta_{\max} \\ & \quad \quad x_{\min} \leq \hat{x}(\hat{\theta}) \leq x_{\max} \end{aligned} \quad (5)$$

Where $Y_n(u, \theta)$ is the n th measured value of the observational variable with input variable u and parameter combination θ . While the $\hat{Y}_n(u, \hat{\theta})$ is the n th simulated value with the estimated value $\hat{\theta}$. $\hat{x}(\hat{\theta})$ is the estimates of the intermediate variable. N is the number of samples.

In order to make full use of the output information of the wind farm model, and as far as possible to reduce dependence on the model, the genetic algorithm is applied in the model parameter identification process. On the one hand, model simulation provides data for optimization algorithm. On the other hand, optimization algorithm is employed to search for the optimal parameters in the feasible region of the parameters. And then the parameters passed to the simulation model. The flow chart is as follows, in Figure V.

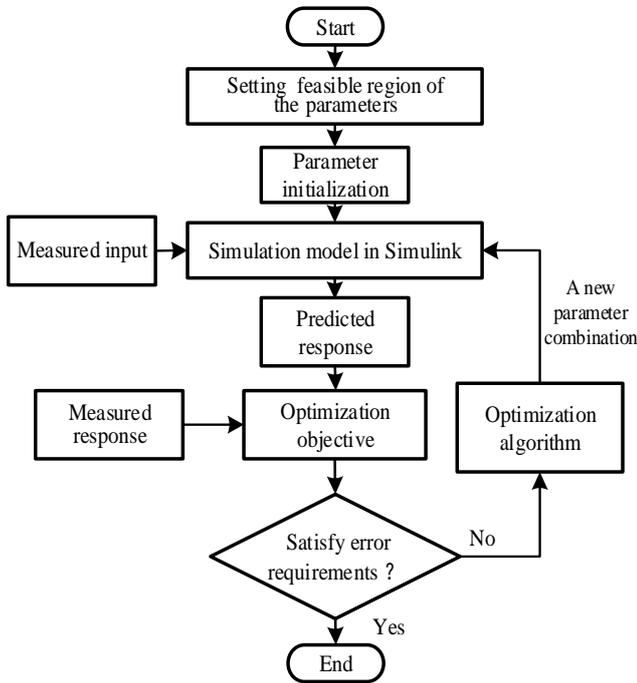


FIGURE V. THE FLOW CHART OF PARAMETER OPTIMIZATION.

The response data from the model simulation based on the current parameters is used to calculate the current value of objective function. The reciprocal of the objective function is set as double fitness, considering non-negative and minimization of the objective function. Furthermore, the ratios between the single fitness and the total fitness act as the selection probability of each combination. It is apparent that the combination with high fitness would have a high probability of heredity to the next generation. Genetic crossover operation and mutation operation are applied to produce new parameter combinations with higher fitness. Then the parameter combination with highest fitness is delivered back to the simulation model. Model simulation and parameter optimization algorithm are alternately conducted till the response results satisfy the error requirements.

IV. ALGORITHM VERIFICATION FOR THE WIND FARM MODEL

A test is carried out in the IEEE 9-bus system to demonstrate the effectiveness of the model and the algorithm, as in Figure VI. The generator GEN-1 is a slack generator, and the GEN-2 is a PV generator. While the GEN-3 is the doubly-fed wind farms, which includes 67 wind generators. The system standard capacity is 100MVA.

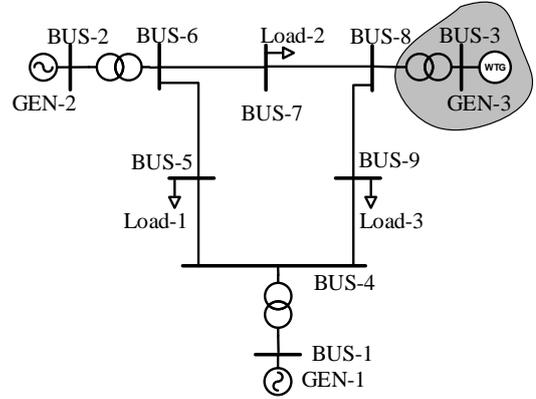


FIGURE VI. IEEE 9-BUS TEST SYSTEM.

The voltage of BUS-3 and the wind speed are selected as the input variables. The active power and the reactive power of the wind farm act as the observational variable. Two cases are studied in this test. The first one is that a three-phase short circuit fault is set at BUS-6 and continues 0.2 seconds. And the other is the gust disturbance from 2.0s to 12.0s. Simulation data is used to imitate the PMU data, restricted to the current conditions. The averages of trajectory sensitivity are summarized in Table II.

TABLE II. AVERAGES OF TRAJECTORY SENSITIVITY.

Disturbance	Observation variables	X_{eq}	T_g	T_{wt}	K_{tg}	D_{tg}
Short-circuit fault	P_g	0.187	0.020	0.006	0.012	0.001
	Q_g	0.558	0.104	0.056	0.030	0.003
Gust disturbance	P_g	0.002	0.050	0.041	0.039	0.001
	Q_g	0.159	0.049	0.043	0.240	0.001

The results in Table II show that the parameters (such as X_{eq}) with close links to the electrical parts have higher trajectory sensitivity under the fault disturbance. But on the contrary, the parameters (such as T_g , K_{wt} , K_{tg}) related to the mechanical parts are more sensitive under the gust disturbance. Certainly, there are some parameter that is difficult to identify, D_{tg} is the one in this two cases.

Based on the analysis above, those parameters are divided into two groups to identify. The X_{eq} is identified in the fault disturbance case. The others including T_g , K_{wt} , K_{tg} , are in the gust disturbance case. The response results of the measurement and simulation are compared in the Figure VII. There is only the comparison of active power owing to space reasons.

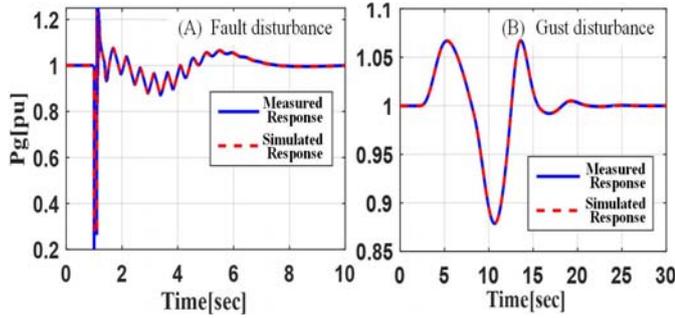


FIGURE VII. COMPARISON OF THE MEASURED RESPONSE AND MEASURED RESPONSE.

The parameter values of identification based on simulation almost corresponds to the actual values, which proves that the validity and practicability of the parameter identification method based on simulation, as detailed in the Table III.

TABLE III. COMPARISON OF PARAMETER ACTUAL VALUES AND IDENTIFIED VALUES.

Parameter	X_{eq}	T_g	T_{wt}	K_{tg}
Actual value	0.520	1.200	7.600	1.250
Identified value	0.518	1.183	7.511	1.267
Relative error	0.38%	1.42%	1.17%	1.36%

V. CONCLUSIONS

In summary, a new method based on simulation is presented to solve the modeling problem of doubly-fed wind farms in this paper. Dominant parameters and identifiability conditions are obtained by trajectory sensitivity analysis. Additionally, optimization algorithm is employed during the model simulation to search for the optimal parameter combination that can accurately reflect the dynamic characteristics of wind farms. Verification experiment in the IEEE 9-bus system provides compelling evidence of important application value of the method. Further work would focus on the improvement of computation efficiency of the method.

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