Dynamic equivalence of doubly-fed wind turbines based on parameter identification and optimization

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Abstract. The dynamic equivalence and modeling of large-scale wind farms is the basis for studying the problem of multi-temporal and spatial scale wind farms grid connection, and the establishment of a high-precision equivalence model is a key issue among them. This paper takes doubly-fed wind turbines as the research object. Aiming at the problem of large dynamic errors in direct aggregation of equivalents into a single unit, an equivalent model combined with particle swarm optimization algorithm is established to improve the accuracy of dynamic equivalents. The electrical parameters, reactive power reference values, active power controller parameters, and active DC voltage controller parameters are optimized using particle swarm optimization. The research results show that the equivalent model after optimizing the parameters of the active power and DC bus voltage controller is the closest to the detailed model in describing the dynamic characteristics of multiple machines.

1. Introduction
In order to deeply reveal the interaction mechanism between wind farms and power systems, and to lay a theoretical foundation for the safe and stable operation of power systems under the new energy structure, it is necessary to simulate and model large wind farms. At present, there are two main ideas for modeling large-scale wind farms. The first is to establish a detailed wind turbine model and superimpose the output results of each model as the wind farm output. The second is to use a single or fewer wind turbines to characterize the entire wind farm, then solve the model results of these several representative wind turbines and superimpose them as the overall output result. The results obtained by the first way of thinking can most accurately express the impact of the entire wind farm on the power system, but it is difficult to solve and not very adaptable to parameter changes. It requires high computer performance and has a large workload for model modification. Although the second way has some errors in describing the overall system, the model is simple and easy to modify, the physical problems can be simplified while accurate conclusions can be drawn, thus of great significance in studying the impact of wind farms on the power system.

In the past research, there are many literatures on the equivalence problem of wind farms. Literature[1-4] focuses on clustering indicators, including wind speed, active power, and wind turbine state vector[1], rotation speed during fault removal[2], three-dimensional correlation coefficient matrix of wind speed, wind direction, and wind turbine number[3], 13 state variables obtained from wind speed, nameplate parameters, and power curve[4]. Literature[5-7] focuses on parameter aggregation methods. Most parameter aggregation methods use capacity weighting, or use simplex and genetic optimization algorithms to optimize parameters on this basis[5][6]. Literature[8-10] began to try to apply the idea of parameter identification to wind farm equivalence. Literature[8] verified that the short-
circuit fault disturbance data can effectively identify the electrical parameters of the wind turbine, and the gust disturbance data can effectively identify the mechanical parameters of the wind turbine. Literature[9] proposed the identification of the electrical parameters of doubly-fed wind turbines based on particle swarm optimization, and improved the algorithm's deficiencies. Literature[10] uses the particle swarm optimization algorithm to adjust the voltage/reactive power reference value of the equivalence unit, and uses a single unit to equalize the entire wind farm, which effectively solves the equivalence problem of doubly-fed generator wind farms with large input wind speed differences.

The output characteristics of multiple doubly-fed units as accurately as possible with the least number of equivalent units is described in this paper. First, multiple doubly-fed units are equalized into a single unit using the capacity weighting method, and electrical parameters, reactive power reference values, active power controller parameters, active power and DC bus voltage controller parameters are optimized using particle swarm algorithm. Then, by comparing the optimized equivalent model and the active output curve of the original detailed model in turn, it is verified that the equivalent model obtained by optimizing the active power and DC bus voltage controller parameters after the capacity-weighted equivalent is used to form a single machine is the closest to the dynamic characteristics of the original detailed model, when a three-phase short-circuit fault occurs at the grid connection point of the wind farm.

2. Mathematical model of doubly-fed wind turbine

The state equation of the doubly-fed wind turbine under the synchronous rotating coordinate axis considers the mechanical dynamics, stator and rotor dynamics at the same time. The motor voltage equation under the synchronous rotating coordinate system is as follows.

\[
\begin{align*}
    u_{ds} &= \frac{d\psi_{ds}}{dt} - \omega\psi_{qs} + R_s i_{ds} \\
    u_{qs} &= \frac{d\psi_{qs}}{dt} + \omega\psi_{ds} + R_s i_{qs} \\
    u_{dr} &= \frac{d\psi_{dr}}{dt} - (\omega_s - \omega_r)\psi_{qr} + R_r i_{dr} \\
    u_{qr} &= \frac{d\psi_{qr}}{dt} + (\omega_s - \omega_r)\psi_{dr} + R_r i_{qr}
\end{align*}
\]

(1)

Where \(u_{ds}, u_{qs}, u_{dr}, i_{ds}, i_{qs}, i_{dr}, i_{qr}\) are \(d\)-axis, \(q\)-axis stator and rotor winding voltage and current respectively. \(\psi_{ds}, \psi_{qs}, \psi_{dr}, \psi_{qr}\) are \(d\)-axis, \(q\)-axis stator and rotor winding flux linkage respectively. \(R_s, R_r\) are the stator and rotor winding resistance respectively. \(\omega_s, \omega_r\) is the rotational angular velocity of the coordinate system and is equal to the synchronous speed and the rotational angular velocity of the rotor.

The corresponding flux linkage equation is shown below.

\[
\begin{align*}
    \psi_{ds} &= (L_s + L_m)i_{ds} + L_m i_{dr} \\
    \psi_{qs} &= (L_s + L_m)i_{qs} + L_m i_{qr} \\
    \psi_{dr} &= (L_s + L_m)i_{dr} + L_m i_{ds} \\
    \psi_{qr} &= (L_s + L_m)i_{qr} + L_m i_{ds}
\end{align*}
\]

(2)

Where \(L_s, L_{ir}\) are the leakage inductance for each phase of stator and rotor respectively. \(L_m\) is mutual inductance.

The generator is equivalent to a transient impedance \(Z' = R_s + jX'\), a transient voltage source \(E' = E_d' + jE_q'\) in simplified DFIG third-order model. Ignoring the transient process of stator flux, a simplified third-order dynamic model can be obtained.
\[
\begin{align*}
\frac{d\psi_{qs}}{dt} &= 0 \\
\frac{d\psi_{ds}}{dt} &= 0
\end{align*}
\]  

(3)

Finally, the DFIG third-order dynamic model composed of the stator and rotor voltage equations and the rotor motion equations is as follows.

\[
\begin{align*}
\frac{dE_d}{dt} &= \frac{R_r}{L_r} [E_d + \omega_s (L_s L_r)(i_{q_s})] + \omega_s E_q \omega_1 L_{mr} U_{qr} \\
\frac{dE_q}{dt} &= \frac{R_r}{L_r} [E_q \omega_1 (L_s L_r)(i_{d_s})] \bar{\omega}_s E_d + \omega_1 L_{mr} U_{dr} \\
T_j \frac{d\omega_s}{N_p dt} &= T_m T_e
\end{align*}
\]  

(4)

Where \( L_s \) is stator transient inductance. \( E_d, E_q \) are the potential \( dq \)-axis component within the DFIG equivalent. \( \omega_s = \omega_1, \omega_1 \).

3. Capacity weighting method parameter aggregation

The capacity weighting idea considers that a certain parameter of the equivalent unit is equal to the parameter in the single unit multiplied by the weight. But in fact, the situation that the overall characteristics of each wind turbine are completely equal to the superposition of the characteristics of a single wind turbine must be based on specific assumptions, such as the same speed.

From the perspective of the wind turbine to the grid side, the parameters that need equivalent values mainly include: moment of inertia (there is also a model corresponding to the inertia time constant), damping coefficient, stator resistance, stator leakage inductance, rotor resistance, rotor leakage inductance, stator and rotor mutual inductance, proportional and integral constants of each PI controller, DC bus capacitance connecting the rotor side and grid side converter, impedance parameter between the grid-side converter and the grid-connected point, box-type transformer parameters at the outlet of the wind turbine.

In the case where the speed of each wind turbine is different, the input wind speed needs to be equivalent. Usually, the equivalent wind speed is the wind speed of each unit multiplied by the capacity weighting coefficient of the corresponding unit. The equivalent formula of each parameter is as follows.

3.1. Equivalent moment of inertia

\[
J_{eq} = \sum_{i=1}^{n} J_i
\]  

(5)

In the formula, the subscript \( eq \) represents the parameter of the equivalent unit, the subscript \( i \) \((i=1,2,...,n)\) represents the parameter of the equivalent unit, and \( n \) is the number of units required to be equivalent in the wind farm.

3.2. Equivalent inertia time constant

\[
H_{eq} = \frac{J_{eq} \omega_1^2}{S_{eq}}
\]  

(6)
In the formula, \( \omega_m \) is the standard value of the mechanical speed of the wind turbine, that is, the corresponding mechanical speed when the generator rotor is at the synchronous speed. \( S_{eq} \) is the equivalent wind turbine capacity, which is the algebraic sum of the unit capacity to be equivalent. For wind turbines with the same moment of inertia and the same capacity, the inertia time constant of the equivalent unit is equal to the inertia time constant of each unit. Damping coefficients mostly appear in the form of per unit value in wind turbine parameters, and the equivalent damping coefficient is the damping coefficient of each unit multiplied by the corresponding capacity weighting coefficient.

3.3. Equivalent generator impedance parameters

\[
R_{eq} + jX_{eq} = \sum_{i=1}^{n} \frac{S_i}{S_{eq}} R_i + j\sum_{i=1}^{n} \frac{S_i}{S_{eq}} X_i
\]  

(7)

Where \( R_i, X_i, S_i \) are the resistance, reactance, and wind turbine capacity of the \( i \)-th unit.

3.4. Equivalent impedance parameter between grid-side converter and grid connection point

\[
\frac{K_{eq}}{S_{eq}} = \sum_{i=1}^{n} \frac{K_i}{S_i}
\]  

(8)

The equivalence of each PI controller parameter in the rotor-side converter and the grid-side converter follows the principle of equal standard unit value, and the proportional and integral constants are proportional to the multiples of the equivalent unit and the unit to be equivalent. In the formula above, \( K_i \) is the nominal value of the proportional and integral constants of each PI controller.

3.5. Equivalent DC bus capacitance between the converters on both sides

\[
C_{eq} = \sum_{i=1}^{n} C_i
\]  

(9)

The equivalent analogy of the impedance parameters of the box transformer from the outlet of the wind turbine to the grid connection point is the equivalent of the impedance parameters of the generator, and the capacity of the box transformer after the equivalent value is equal to the sum of the box transformer capacity of each wind turbine.

4. Particle swarm parameter identification equivalent method

When a three-phase symmetrical short-circuit fault occurs in a wind farm, the stator and rotor currents all contain DC transient components, AC components, and steady-state components\(^{[11]}\). The AC components of the stator and rotor are respectively related to the power frequency and the rotor angular frequency, and the steady-state component is related to the depth of the voltage drop. Through simulation, it is found that when a three-phase short-circuit fault occurs at the grid connection point of the wind farm, the dynamic error during the fault process is not large. That is because most of the faults set in the simulation are metallic ground faults, the voltage is close to zero, and the transient current has little effect on the active power curve. However, in the process of fault recovery, the dynamic error between the single-machine equivalent model obtained by the capacity weighting method and the detailed model is very large. The fault recovery process is similar to the instantaneous grid connection process of wind turbines, and is related to factors such as the phase angle of the wind turbine grid-connected point voltage and the speed of the wind turbine when the fault is removed.

Because the transient power of the grid connection process is difficult to quantitatively describe, the current literature mostly focuses on the grid connection control strategy of doubly-fed wind turbines. It is difficult to quantitatively express the dynamic errors of the detailed model and the equivalent model during the fault recovery process. Therefore, the output characteristics of the
equivalent model and the detailed model can be similar by optimizing some parameters that affect the dynamic characteristics of the doubly-fed wind turbine.

The method of using identification methods to obtain accurate values of physical component parameters has been widely used in synchronous generators and electric loads \cite{12}. The parameter identification method also has certain advantages in the dynamic equivalence of doubly-fed wind turbines. It only needs to know the electrical and mechanical parameters of each wind turbine when it leaves the factory as an optimal initial value. And then through the iterative optimization algorithm, it can achieve equivalent values for the dynamic characteristics of the entire wind farm. Appropriate initial value selection and appropriate algorithm are conducive to quickly find the optimal solution and improve simulation efficiency. However, the difficulty of parameter identification lies in the need to obtain disturbance data, which is difficult to obtain under normal conditions. The parameter identification method in this paper is only carried out in a simulation environment for the time being.

The particle swarm optimization algorithm has the characteristics of good overall performance and fast convergence speed, and is widely used in power systems and other engineering fields. In each iteration of the particle swarm algorithm, the particle tracks two extreme values, one is the optimal solution found so far by the particle itself, and the other is the optimal solution found so far by the entire population. The flow chart of the basic particle swarm algorithm in the parameter identification of the doubly-fed fan is as follows.

- Set the disturbance, simulate the disturbance data corresponding to the real parameters and store it.
- Set the population size, number of particles, number of iterations, initial position and speed.
- Solve the particle fitness function in the initialized population to find the global optimum.
- Update the particle position, obtain the fitness function value and update the optimal fitness of the particle.
- Update the optimal fitness of the population and the corresponding particle position.
- Determine whether the maximum number of iterations or iteration accuracy is reached. If yes, end the process. If not, go back to the fourth step until the maximum number of iterations is reached or the iteration accuracy is reached.

Among them, the fitness function for parameter identification is as follows. It is used to find the optimal one and minimize the value of the fitness function.

\[
F(\theta) = \min \sum_{i=1}^{n} [y_{\text{real}} - y_{\text{sim}}(\theta)]^2
\]  

(10)

5. Dynamic equivalent optimization simulation using particle swarm identification algorithm

5.1. Capacity weighted equivalence model

The following is a simulation of the doubly-fed wind turbine model based on the MATLAB/Simulink platform. The schematic diagram of three 1.5MW double-fed wind turbines connected to the 120kV system is shown in Figure 1.
Taking the simulation start time as the timing starting point, at $t=1.2s$, a three-phase short-circuit fault occurs on the 25kV bus, and the fault will be removed after 0.05s. The parameters of each wind turbine and the box transformer at the outlet of the wind turbine are exactly the same, and the input wind speed of each wind turbine is 9m/s. It is assumed that the rotor crowbar loop action during the fault process is not considered, and the line protection action is also not considered. First, the capacity of three wind turbines is weighted and equalized into a single unit. The parameter aggregation method is shown in section 3. The transformer parameter aggregation means the capacity overlap. And the impedance parameter is based on the principle of consistent standard unit value. The mechanical, electrical parameters and controller parameters of the equivalent unit are shown in Tables 1 and 2 respectively. After intercepting the data within 0.6s after the fault occurs, the active and reactive dynamic curves of the capacity weighted equivalent model and the detailed model are shown in Figures 2 and 3, respectively.

Table 1. Mechanical, electrical parameters of DFIG.

| Parameters                      | Single | Equivalent |
|---------------------------------|--------|------------|
| rated power(MVA)                | 1.5/0.9| 5          |
| Stator terminal voltage(kV)     | 0.575  | 0.575      |
| Rated frequency(Hz)             | 60     | 60         |
| Inertial time constant(s)       | 5.04   | 5.04       |
| Mechanical damping coefficient  | 0.01   | 0.01       |
| Grid side resistance            | 0.0015 | 0.0015     |
| Grid side inductance            | 0.15   | 0.15       |

| Parameters                      | Single | Equivalent |
|---------------------------------|--------|------------|
| Stator resistance               | 0.00706| 0.00706    |
| Winding rotor resistance        | 0.005  | 0.005      |
| Magnetizing inductance          | 2.9    | 2.9        |
| Stator leakage inductance       | 0.171  | 0.171      |
| Rotor leakage inductance        | 0.156  | 0.156      |
| DC capacitor(μ F)               | 1000   | 3000       |
| DC bus voltage(kV)              | 1.2    | 1.2        |

Table 2. Controller parameters of DFIG.

| Proportional constant          | Single | Equivalent |
|--------------------------------|--------|------------|
| Rotor side inner ring          | 0.05   | 0.15       |
| Active outer ring on the rotor side | 0.16667 | 0.5       |
| Rotor side reactive power outer ring | 0.00833 | 0.025     |
| Network side inner ring        | 0.16667| 0.5        |
| Outer loop of grid-side DC voltage | 0.000333 | 0.001     |

| Integral constant              | Single | Equivalent |
|--------------------------------|--------|------------|
| Rotor side inner ring          | 1.5    | 4.5        |
| Active outer ring on the rotor side | 16.667   | 50         |
| Rotor side reactive power outer ring | 0.8333   | 2.5        |
| Network side inner ring        | 16.667 | 50         |
| Outer loop of grid-side DC voltage | 0.00833  | 0.025     |
When the failure recovery process reaches the steady state again, the dynamic characteristics of the capacity-weighted equivalent model and the detailed model have large errors. Therefore, the particle swarm optimization algorithm is used to optimize the electrical parameters, reactive power reference values, active power controller parameters, and DC bus voltage controller parameters of equivalent units. Set the number of particles to 5, the number of independent variables to 5, 1, 1, 2, 2, the maximum number of iterations is 100, the learning factors 1 and 2 are both set to 2, and a constant inertia weight of 0.2 is used.

5.2. Comparison of particle swarm optimization models

5.2.1. Optimize electrical parameters. The grid-side fault can stimulate the fast dynamic mode of the electrical part of the wind farm\textsuperscript{[8]}, and electrical parameters also have a certain impact on the dynamic process of fault recovery. Based on the capacity-weighted aggregation parameters, the use of basic particle swarm optimization to optimize the electrical parameters of the equivalent unit can reduce the dynamic error in the fault recovery process.

5.2.2. Optimize the reactive power reference value. The reactive power characteristics of doubly-fed wind turbines affect the equivalent accuracy in the dynamic process. By superimposing a compensation quantity $\Delta Q$ on the reactive power reference quantity of the doubly-fed wind turbine, the particle swarm algorithm is used to find the optimal $\Delta Q$ to meet the minimum average relative error in the dynamic process. It is noteworthy that optimize the $\Delta Q$ can cause static error increases.

5.2.3. Optimize active controller parameters. In the converter of the doubly-fed unit, if the rotor side adopts the stator flux-oriented control strategy, the electrical quantity related to the active output characteristic is mainly $I_{dq}$. By optimizing the active controller parameters, the $I_{eq, \text{ref}}$ of the equivalent unit and the detailed model is consistent, which effectively reduces the dynamic error.

5.2.4. Optimize active power and DC bus voltage controller parameters. The main parameter related to active power in the grid-side converter of the doubly-fed wind turbine is the DC bus voltage $U_{dc}$. After optimizing the parameters of the active controller, optimizing the parameters of the $U_{dc}$ controller can further reduce the dynamic error.

5.2.5. Comparison. The final optimization results of each optimization model parameter are shown in Table 3. The electrical parameters and reactive power parameters in the table are in p.u., and the controller parameters are dimensionless. The optimized active power controller parameters $k_p$ is 0.0512, and $k_i$ is 6.011. The DC voltage controller parameter optimization value $K_p$ is 0.0005618 and $K_i$ is 0.00167.
Table 3. Optimization Results of model parameters.

| Model        | $R_s$  | $R_r$  | $L_m$ | $L_p$  | $L_n$  |
|--------------|--------|--------|-------|--------|--------|
| 1a           | 0.00270| 0.0126 | 0.262 | 0.291  | 2.061  |
| 2b           | $\Delta Q$ | 0.243  |
| 3c           | $k_p$  | $k_i$  | 0.0512| 6.011  |
| 4d           | $P_{-k_p}$ | $P_{-k_i}$ | $U_{dc-k_p}$ | $U_{dc-k_i}$ |
|              | 0.0512 | 6.011  | 0.0005618 | 0.00167 |

The 15 iteration errors of each optimization model and the active dynamic curve within $t=1.1-1.7s$ are shown in Figure 4 and Figure 5. It can be seen from the figure that the dynamic error between the model after optimizing the parameters of the active power and DC bus voltage controller and the detailed model is the smallest. The effect of reactive power reference value optimization and DC bus voltage controller parameter optimization is less obvious than electrical parameter optimization and active power controller parameter optimization.
In order to establish a high-precision equivalent model of wind farms, whether static or dynamic, the input wind speed of the equivalent unit can be obtained by optimizing the input wind speed in the static state firstly, then build a stand-alone equivalent model based on the capacity weighting method. Finally, by optimizing the parameters of the active power controller and the DC voltage controller, higher accuracy in the dynamic process is obtained, and the equivalent model with the overall static and dynamic performance closest to the detailed model is obtained.

6. Conclusion
This article first aggregates multiple wind farm units into one unit using the capacity weighting method. Because of the large dynamic error between the capacity weighted model and the detailed model in the case of a short-circuit fault, the period of large dynamic error is concentrated in the process from fault removal to restoration of steady state. The basic particle swarm algorithm is used to optimize the electrical parameters, reactive power reference values, active power controller parameters, and active DC voltage controller parameters. By comparing various equivalent models with detailed models, the dynamic equivalent errors of three-phase short-circuit faults are compared. The research results show that after optimizing the parameters of the active DC voltage controller, the dynamic error between the equivalent model and the detailed model is the smallest, and the dynamic process of the detailed wind farm model can be described more accurately.

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