

Article

Impedance-Sensitivity-Based Equivalent Modeling of Distributed Direct-Drive Wind Turbine Groups in Microgrids for Sub/Super-Synchronous Oscillation Analysis

Jinling Qi ^{1,2,*}, Qi Guo ¹, Haiqing Cai ¹, Yihua Zhu ¹, Liang Tu ¹ and Chao Luo ¹

¹ Electric Power Research Institute, China Southern Power Grid, Guangzhou 510663, China

² School of Electrical Engineering, Dalian University of Technology, Dalian 116024, China

* Correspondence: qijl1@csg.cn

Abstract

Sub/super-synchronous oscillations induced by the interaction between wind turbines and the grid pose increasing challenges to the dynamic analysis of power-electronics-dominated power systems. For microgrids comprising a large number of distributed direct-drive wind turbines (DDWTs), detailed electromagnetic transient modeling becomes computationally prohibitive, while conventional single-machine equivalent models often fail to capture critical oscillatory characteristics. To address these issues, this paper proposes an impedance-sensitivity-based clustering and equivalent modeling method for DDWT groups in a microgrid. First, a frequency domain impedance model of DDWTs is established, and the impedance sensitivities of key control parameters are analyzed under various steady-state operating conditions. By jointly considering the absolute magnitude of impedance sensitivity and its variation across operating points, a sensitivity-informed criterion is developed to select physically meaningful clustering indices capable of distinguishing wind turbines with different operating conditions. Based on the selected indices, a *k*-means clustering algorithm is employed to group distributed DDWTs, and a multi-machine equivalent model is constructed accordingly. Simulation studies under impedance disturbances validate the effectiveness of the proposed equivalent model in accurately reproducing the oscillation characteristics of a microgrid with multiple DDWTs.

Keywords: distributed direct-drive wind turbine; microgrid; equivalent model; sub/super-synchronous oscillation

1. Introduction

In the context of the global energy transition, an increasing number of distributed direct-drive wind turbines (DDWTs) are being integrated into microgrids to enhance local renewable energy utilization and improve supply reliability [1–3]. DDWTs are connected to the grid through full-scale power converters, whose control loop interactions with grid impedance can excite resonances in the sub- and super-synchronous frequency ranges [4–6]. These resonances may cause shaft torsional vibrations, and even protective relay trips. Therefore, appropriate dynamic models are essential for analyzing these oscillations and assessing the stability of microgrids with numerous distributed DDWTs.

The modeling of individual DDWTs has been extensively studied, providing an important basis for analyzing converter dynamics and oscillation mechanisms. For example,

Academic Editor: Dorin Petreus

Received: 15 December 2025

Revised: 31 January 2026

Accepted: 3 February 2026

Published: 28 February 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

steady-state bi-directional converter models for hybrid AC/DC networked microgrids have been established in [7], and a variable speed direct-drive generator with power electronic interface is modeled for dynamic analysis in [8]. Based on these individual DDWT models, a detailed model of microgrids with numerous DDWTs can be constructed for system level oscillation analysis. However, such full-order models are computationally expensive. Therefore, it is necessary to develop an equivalent model for distributed DDWT clusters in microgrids [9,10].

At present, extensive research has been carried out on equivalent modeling of wind power generation for oscillation analysis. Some studies focus on reducing the state space order of detailed models to improve simulation efficiency while retaining the dominant oscillation modes [11–14]. However, these methods still involve high computational complexity, and the physical meaning of the system becomes unclear after model reduction [15]. Another approach is aggregation-based equivalent modeling, which can be classified into single-machine equivalent method and multi-machine equivalent method. In single-machine equivalent, all wind turbines are represented by an equivalent machine [16]. Although this approach is computationally efficient, it neglects differences in the operating conditions of individual wind turbines, which usually result in reduced equivalence accuracy. To improve modeling accuracy, parameter identification techniques have been applied to optimize the parameters of single-machine equivalent models [17]. However, the associated identification process introduces additional computational burden, which limits practical applicability in large-scale systems.

In multi-machine equivalent method, wind turbines are divided into several groups based on dynamic similarity, with each group represented by an equivalent machine. This approach better captures differences and spatially distributed dynamics. In [18], dominant mode eigenvalues of wind turbines are used to determine clustering and aggregation. In [19], wind turbines are clustered based on the participation factors of generalized short-circuit ratios. However, this method focuses on planning stage analysis under the idealized assumption that all wind turbines operate at rated conditions. In [20], doubly-fed induction generator (DFIG) wind turbines are clustered based on the similarity of their active power output. In [21], a clustering method based on index dimension reduction and weighted fuzzy C-means algorithm is proposed. In [22], rotor equivalent resistance is used as the cluster principle in a sub-synchronous frequency domain equivalent modeling method. In [23], dominant variables of the sub-synchronous oscillation (SSO) modes in a series-compensated DFIG-based wind farm are used for wind turbine clustering. In [24], key influencing factors of the dominant oscillation modes are chosen as clustering indices. These methods are developed for DFIG-based wind farms and are not directly applicable to DDWT-based wind farms due to differences in topology and dynamic characteristics. For DDWT-based wind farms, Ref. [25] uses participation factors of wind turbines in the dominant oscillation mode as clustering indices, and proposes a node-by-node aggregation method. However, the parameters of equivalent machines are obtained through relatively complex calculations. In [26], an equivalent modeling method is proposed in which the PI parameters of the phase locked loop (PLL), the current loop, and the filter inductance are selected as clustering indices. However, differences in operating points of wind turbines are not considered. In [27], dominant SSO-related parameters during and after the oscillation are used as clustering indices. This approach involves a large number of variables across multiple time instants, resulting in high computational complexity.

In summary, the existing equivalent modeling method of DDWT groups for oscillation analysis is insufficient. Some methods do not account for differences in the operating points of individual wind turbines when selecting clustering indices. Furthermore, some approaches rely on variables sampled during and after the oscillation period for clustering,

which are difficult to obtain before the oscillation occurs. Motivated by the above limitations, this paper proposes an impedance-sensitivity-based equivalent method for distributed DDWT groups. The main contributions are summarized as follows.

- (1) A frequency domain impedance model of DDWTs is established to perform impedance sensitivity analysis under multiple steady-state operating conditions, quantitatively revealing how key control parameters influence the sub/super-synchronous impedance characteristics and how such influence depends on the operating points.
- (2) A sensitivity-informed clustering strategy is proposed, in which control parameters that are both highly sensitive and strongly dependent on operating point are selected as clustering indices, and a k -means-based aggregation method is developed to divide the distributed DDWTs into several clusters, explicitly accounting for the difference in operating conditions.
- (3) An equivalent method is developed, where each cluster is aggregated into an equivalent machine. Case studies on microgrids with 20 distributed DDWTs demonstrate that the proposed method can accurately reproduce the oscillation characteristics of the detailed model while significantly reducing computational burden.

The rest of this paper is organized as follows. In Section 2, the frequency domain impedance model of the DDWTs is established. Section 3 presents the impedance sensitivity-based clustering indices selection criterion. The equivalent method of distributed DDWT groups is presented in Section 4. Section 5 validates the proposed equivalent method through case studies on a microgrid with 20 distributed DDWTs. The discussion and conclusion are presented in Sections 6 and 7, respectively.

2. Frequency Domain Impedance Modeling of Distributed DDWTs

Understanding the impedance characteristics of DDWTs is fundamental for analyzing their interactions with the grid and assessing the risk of sub/super-synchronous oscillations. Since the dominant oscillation mechanisms of DDWTs originate from the control dynamics of the full-scale power converter, particularly the grid-side converter (GSC), an accurate frequency domain impedance model is required to characterize the converter response to grid disturbances under different operating conditions. Therefore, a detailed impedance model is presented in this section.

2.1. Overall Structure and Control Architecture of a Distributed DDWT

A typical DDWT mainly consists of a wind turbine rotor, a drive shaft, a permanent magnet synchronous generator (PMSG), a machine-side converter (MSC), a dc link capacitor, a GSC, an ac filter, and the associated converter control system [8]. The mechanical power captured by the wind turbine is directly transmitted to the PMSG without a gearbox, which enhances system reliability and reduce mechanical losses. The PMSG generates three-phase electrical power, which is rectified by the MSC into dc power. A dc link capacitor is employed to stabilize the intermediate dc link voltage. Subsequently, the GSC converts the dc power into ac power and injects it into the grid through a filter. The overall configuration of the distributed DDWT is illustrated in Figure 1. In Figure 1, u_{dc} is the dc link voltage, u_{abc} is the three-phase terminal voltage of the DDWT, i_{abc} is the three-phase output current of the DDWT, C_{dc} denotes the dc link capacitance, and R_f and L_f represent the resistance and inductance of the filter, respectively. θ_e is the electrical angle of the PMSG, while θ_{pll} is the phase angle of the PLL.

The MSC regulates the PMSG to extract maximum available wind power, typically adopting a dual-loop control structure consisting of an outer loop and an inner loop. The maximum power point tracking (MPPT) module calculates the optimal aerodynamic power and generates the corresponding active power reference P_{mref} , which serves as the

reference for the outer loop. The outer power controller compares the MPPT power reference P_{mref} with the measured generator active power P_m . The resulting power error is processed by a PI controller to generate the q-axis current reference i_{mqref} , while the d-axis current reference i_{mdref} is typically set to zero to regulate the stator flux.

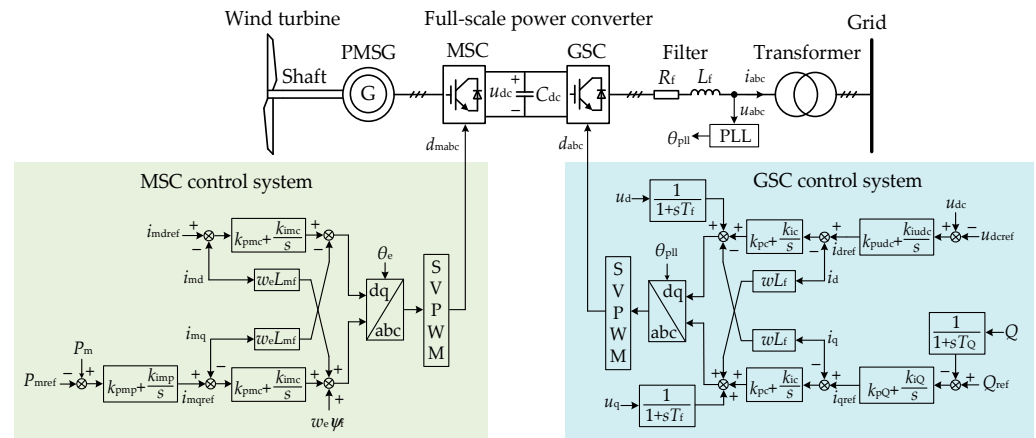


Figure 1. The schematic diagram and control block diagram of a distributed DDWT.

Accordingly, the current references (i_{mqref} and i_{mdref}) can be expressed as

$$i_{mqref} = k_{pmp} (P_m - P_{mref}) + k_{imp} \int (P_m - P_{mref}) dt \quad (1)$$

$$i_{mdref} = 0 \quad (2)$$

where k_{pmp} and k_{imp} are the proportional and integral coefficients of the MSC active power outer loop, respectively.

The three-phase generator currents are transformed into the synchronous dq reference frame to obtain the current components i_{md} and i_{mq} . The inner current control loop employs PI regulators with feedforward compensation to track the references i_{mdref} and i_{mqref} , and generates the corresponding dq-axis voltage references u_{mdref} and u_{mqref} , given by

$$\begin{cases} u_{mdref} = k_{pmc} (i_{mdref} - i_{md}) + k_{imc} \int (i_{mdref} - i_{md}) dt - \omega_e L_{mf} \\ u_{mqref} = k_{pmc} (i_{mqref} - i_{mq}) + k_{imc} \int (i_{mqref} - i_{mq}) dt + \omega_e L_{mf} + \omega_e \psi_f \end{cases} \quad (3)$$

where k_{pmc} and k_{imc} are the proportional and integral coefficients of the MSC current inner loop, respectively, ω_e is the electric angular speed of the generator, L_{mf} is the filter inductance of MSC, and ψ_f is the stator flux linkage.

The voltage references u_{mdref} and u_{mqref} are transformed into the abc frame through inverse Park transformation. Subsequently, space vector pulse width modulation (SVPWM) is applied to generate the switching signals d_{mabc} for the MSC semiconductor devices.

The GSC also adopts a dual-loop control structure consisting of the outer loops and inner loops. The outer loops include a dc link voltage control loop and a reactive power control loop. The dc link voltage loop regulates the dc link voltage and generates the d-axis current reference i_{dref} , which governs the active power exchange between the converter and the grid. Meanwhile, the reactive power loop produces the q-axis current reference i_{qref} , enabling independent reactive power regulation. The current references can be expressed as

$$i_{dref} = k_{pudc} (u_{dc} - u_{dcref}) + k_{iudc} \int (u_{dc} - u_{dcref}) dt \quad (4)$$

$$i_{qref} = k_{pQ} (Q_{ref} - Q) + k_{iQ} \int (Q_{ref} - Q) dt \quad (5)$$

where u_{dcref} is the dc link voltage reference, and k_{pudc} and k_{iudc} are the proportional and integral coefficients of the dc link voltage loop, respectively. Q_{ref} is the reactive power reference. k_{pQ} and k_{iQ} are the proportional and integral coefficients of the reactive power loop, respectively. Q_{f} denotes the filtered reactive power obtained by passing the measured reactive power Q through a first-order filter with the time constant T_{iQ} , which is described by $T_{\text{iQ}} \dot{Q}_{\text{f}} + Q_{\text{f}} = Q$.

The three-phase currents i_{abc} are transformed into the synchronous dq reference frame using the phase angle estimated by the PLL, yielding the current components i_{d} and i_{q} . These currents are compared with their references, and the resulting errors are processed by PI controllers with feedforward compensation to generate the dq-axis voltage references u_{gdref} and u_{gqref} , expressed as

$$\begin{cases} u_{\text{gdref}} = k_{\text{pc}}(i_{\text{dref}} - i_{\text{d}}) + k_{\text{ic}} \int (i_{\text{dref}} - i_{\text{d}}) dt - \omega L_{\text{f}} + u_{\text{df}} \\ u_{\text{gqref}} = k_{\text{pc}}(i_{\text{qref}} - i_{\text{q}}) + k_{\text{ic}} \int (i_{\text{qref}} - i_{\text{q}}) dt + \omega L_{\text{f}} + u_{\text{qf}} \end{cases} \quad (6)$$

where k_{pc} and k_{ic} are the proportional and integral coefficients of the GSC current inner loop, respectively, and ω is the grid angular frequency. u_{df} and u_{qf} denote the filtered voltage components in the dq frame obtained by passing the measured voltage components in the dq frame u_{d} and u_{q} through a first-order filter with the time constant T_{f} , which is described by $T_{\text{f}} \dot{u}_{\text{df}} + u_{\text{df}} = u_{\text{d}}$, $T_{\text{f}} \dot{u}_{\text{qf}} + u_{\text{qf}} = u_{\text{q}}$.

The voltage references u_{gdref} and u_{gqref} are transformed into the abc frame through inverse Park transformation. SVPWM is then applied to generate the switching signals d_{abc} for the GSC semiconductor devices. u_{d} and u_{q} are the grid voltage components in the dq frame, respectively.

2.2. Impedance Modeling of a DDWT

Following the modeling principles in [28], the dq domain admittance of the DDWT Y_{dq} can be expressed as

$$Y_{\text{dq}} = Y_{\text{dq4}} - Y_{\text{c}}(sC_{\text{dc}} + Y_{\text{dcM}} + Y_{\text{dc4}})^{-1}Y_{\text{d}} \quad (7)$$

where

$$Y_{\text{dq4}} = A^{-1}B \quad (8)$$

$$Y_{\text{c}} = A^{-1}C \quad (9)$$

$$Y_{\text{d}} = \frac{1.5}{u_{\text{dcn}}} \left(- \begin{bmatrix} u_{\text{d4s}} & u_{\text{q4s}} \end{bmatrix} Y_{\text{dq4}} + \begin{bmatrix} i_{\text{d4s}} & i_{\text{q4s}} \end{bmatrix} - \begin{bmatrix} i_{\text{d4s}} & i_{\text{q4s}} \end{bmatrix} \bullet \begin{bmatrix} R_{\text{f}} + sL_{\text{f}} & -\omega L_{\text{f}} \\ \omega L_{\text{f}} & R_{\text{f}} + sL_{\text{f}} \end{bmatrix} Y_{\text{dq4}} \right) \quad (10)$$

$$Y_{\text{dc4}} = -\frac{P_{\text{g}}}{u_{\text{dcn}}^2} - \frac{1.5}{u_{\text{dcn}}} \left(\begin{bmatrix} u_{\text{d4s}} & u_{\text{q4s}} \end{bmatrix} Y_{\text{c}} - \frac{1.5}{u_{\text{dcn}}} \begin{bmatrix} i_{\text{d4s}} & i_{\text{q4s}} \end{bmatrix} \right) \bullet \begin{bmatrix} R_{\text{f}} + sL_{\text{f}} & -\omega L_{\text{f}} \\ \omega L_{\text{f}} & R_{\text{f}} + sL_{\text{f}} \end{bmatrix} Y_{\text{c}} \quad (11)$$

$$Y_{\text{dcM}} = -\frac{P_{\text{m}}}{u_{\text{dcn}}^2} \quad (12)$$

$$A = \begin{bmatrix} R_{\text{f}} + sL_{\text{f}} & -\omega L_{\text{f}} \\ \omega L_{\text{f}} & R_{\text{f}} + sL_{\text{f}} \end{bmatrix} - \begin{bmatrix} 0 & -\omega L_{\text{f}} \\ \omega L_{\text{f}} & 0 \end{bmatrix} + H_{\text{c}} \bullet I - 1.5 H_{\text{c}} H_{\text{Q}} H_{\text{iQ}} \begin{bmatrix} 0 & 0 \\ u_{\text{iq4s}} & -u_{\text{id4s}} \end{bmatrix} \quad (13)$$

$$B = I + G_{upll} - \left(\begin{bmatrix} 0 & -\omega L_f \\ \omega L_f & 0 \end{bmatrix} - H_c \cdot I \right) G_{ipll} - H_f (I + G_{uipll}) + 1.5 H_c H_Q H_{fQ} \begin{bmatrix} 0 & 0 \\ i_{q4s} & -i_{d4s} \end{bmatrix} \quad (14)$$

$$C = -H_c \begin{bmatrix} H_{udc} \\ 0 \end{bmatrix} \quad (15)$$

where s is the Laplace operator, u_{dcn} is the rated dc-link voltage, and P_g is the active power of the DDWT. u_{d4s} and u_{q4s} are the steady-state d- and q-axis voltage components at the side of the GSC under the electrical coordinates reference frame, while i_{d4s} and i_{q4s} are the corresponding steady-state current components. u_{id4s} and u_{iq4s} are the steady-state d- and q-axis voltage components at the point of common coupling (PCC) under electrical coordinates reference frame. H_c is the transfer function of the current inner loop PI controller, given by $H_c = k_{pc} + k_{ic}/s$. H_{udc} and H_Q are the transfer function of the dc link voltage loop and reactive power control loop, respectively, expressed as $H_{udc} = k_{pudc} + k_{iudc}/s$ and $H_Q = k_{pQ} + k_{iQ}/s$. H_f is the voltage feedforward filter, expressed as $H_f = 1/(1 + sT_f)$, and T_f is the filter time constant. H_{fQ} is the transfer function of the first-order filter of the reactive power control loop, expressed as $H_{fQ} = 1/(1 + sT_{fQ})$, and T_{fQ} is the filter time constant.

In Equation (14), the PLL-related transfer functions G_{upll} , G_{ipll} , and G_{uipll} can be expressed as

$$G_{upll} = \begin{bmatrix} 0 & u_{q4s} G_{pll} \\ 0 & -u_{d4s} G_{pll} \end{bmatrix} \quad (16)$$

$$G_{ipll} = \begin{bmatrix} 0 & i_{q4s} G_{pll} \\ 0 & -i_{d4s} G_{pll} \end{bmatrix} \quad (17)$$

$$G_{uipll} = \begin{bmatrix} 0 & u_{iq4s} G_{pll} \\ 0 & -u_{id4s} G_{pll} \end{bmatrix} \quad (18)$$

where

$$G_{pll} = \frac{H_{pll}}{s + H_{pll} u_{id4s}} \quad (19)$$

where H_{pll} is the transfer function of the PLL, which can be expressed as $H_{pll} = k_{ppll} + k_{ipll}/s$, and k_{ppll} and k_{ipll} are the proportional and integral coefficients of the PLL, respectively.

The resulting dq domain admittance Y_{dq} of the DDWT is 2×2 transfer matrix

$$Y_{dq} = \begin{bmatrix} Y_{dd} & Y_{dq} \\ Y_{qd} & Y_{qq} \end{bmatrix} \quad (20)$$

To facilitate oscillation analysis in the sequence domain, Y_{dq} is further transformed into the positive sequence admittance Y_p using the standard transformation function [25]

$$Y_p = \frac{Y_{dd} + Y_{qq}}{2} + j \frac{Y_{dq} - Y_{qd}}{2} \quad (21)$$

Subsequently, the corresponding sequence impedance Z_p can be obtained as

$$Z_p = Y_p^{-1} \quad (22)$$

It should be noted that the dq-domain impedance model established above is derived based on the dq-transformation and small-signal linearization around a steady-state operating point. This modeling method assumes balanced three-phase conditions and sufficiently small perturbations, such that the system dynamics can be approximated as linear and time-invariant at each analyzed frequency. Under fast power variations or control

saturation, these assumptions may be violated, potentially leading to reduced modeling accuracy. Such limitations are inherent to small-signal dq-domain impedance modeling and define its applicable analysis scope.

To verify the correctness of the established impedance model, a simulation model of the DDWT is established in PSCAD/EMTDC. The main parameters are listed in Table 1. The PI control parameters of converter were selected based on standard bandwidth separation principles and typical industrial practice. Specifically, the current loop was designed with a bandwidth significantly higher than those of the dc-link voltage loop and the PLL. The outer loop control parameters were then tuned to achieve stable operation under the nominal operating condition.

Table 1. Main parameters of the distributed DDWTs.

Parameters	Values	Parameters	Values
Rated capacity	3.4 MW	k_{pudc}	1
Rated voltage	0.69 kV	k_{iudc}	50
DC link voltage	1.2 kV	k_{pQ}	0.6
DC link capacitance	60,000 μ F	k_{iQ}	0.98
Filter resistance	0.003 Ω	k_{pc}	0.13
Filter reactance	0.000125 H	k_{ic}	7.5
T_i	0.01	T_Q	0.005

A small amplitude sinusoidal voltage perturbation is injected at the voltage source, and the resulting current response is recorded. The impedance frequency sweep is performed from 2 Hz to 200 Hz. The starting frequency of 2 Hz is selected in accordance with common impedance scanning practices [29,30] and is used solely for impedance model verification, without implying a theoretical lower bound of the applicability of the proposed method. The proposed impedance modeling and clustering method remains valid below 2 Hz. The upper limit of 200 Hz is chosen to capture the dominant control-induced dynamics for sub- and super-synchronous oscillations, including the effects of the PLL, the dc-link voltage loop, and the major portion of the current loop. In contrast, higher frequency oscillations associated with switching harmonics, PWM modulation, and filter are beyond the scope of this study. Specifically, the current loop bandwidth is typically on the order of several hundred hertz but below the switching frequency, while the bandwidths of the dc-link voltage loop and the PLL are generally on the order of several tens of hertz, making 200 Hz sufficient to capture the oscillatory phenomena of interest. Based on the measured voltage and current, the sequence impedance Z_{p_sim} is computed and compared with the analytically derived impedance Z_p , as shown in Figure 2. Based on Figure 2, excellent consistency is observed in both magnitude and phase across the entire frequency range, thereby validating the accuracy of the established impedance model.

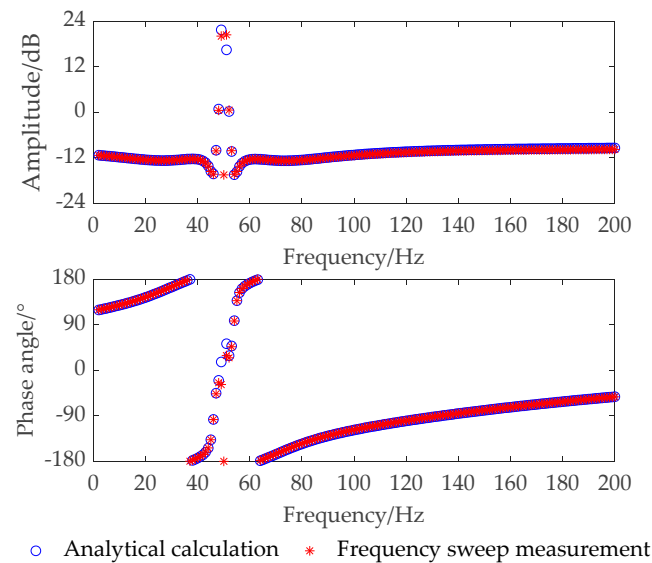


Figure 2. Comparison between the analytical impedance model and the frequency-sweep-based impedance measurement of the DDWT.

3. Impedance-Sensitivity-Based Criterion for Clustering Index Selection

For equivalent modeling of large-scale wind turbine groups, a key challenge lies in identifying wind turbines that exhibit similar dynamic behavior, so that they can be grouped and represented by appropriate equivalent machines. Since sub/super-synchronous oscillations are strongly influenced by the interactions between individual DDWTs and the grid, an effective clustering strategy must be able to reflect the dynamic and oscillatory characteristics of each wind turbine. In practice, DDWTs operate at different steady-state active power levels due to heterogeneous wind conditions. Such operating point differences lead to variations in the converter small-signal impedance, which in turn modify each wind turbine's contribution to oscillatory modes. Therefore, to establish physically meaningful clustering indices, it is necessary to explicitly quantify how the frequency domain impedance characteristics evolve with operating conditions. In this context, the impedance sensitivity analysis presented in this section provides a systematic tool for revealing the dependence of impedance characteristics on operating points. Section 3.1 formulates the impedance sensitivity with respect to key control parameters, while Section 3.2 develops sensitivity-based criteria for selecting clustering indices.

It should be noted that the clustering indices are selected based on the control parameters and operating points of individual DDWTs. The collector line impedance is not included as a clustering index. This choice is supported by prior studies, which indicate that the impedance of DDWTs is typically much larger than that of collector lines, even in the systems with massive DDWTs and long electrical distances to the PCC [26]. Moreover, the participation of individual wind turbines in oscillatory modes shows weak correlation with their geographical locations or electrical distance, but a strong dependence on operating points [25]. Therefore, the clustering index selection focuses on wind turbines' intrinsic impedance characteristics and operating conditions. The effect of collector lines is subsequently incorporated when constructing the aggregated equivalent network, ensuring that the frequency response of the original system is effectively captured.

3.1. Impedance Sensitivity Analysis

To quantitatively evaluate the influence of different control parameters on the impedance characteristics of a DDWT under varying operating conditions, an impedance sensitivity analysis is performed. The impedance of a DDWT, denoted as Z_p , is a function

of frequency f , the set of key control parameters $\theta = [k_{pudc}, k_{iudc}, k_{pQ}, k_{iQ}, k_{pc}, k_{ic}, k_{ppll}, k_{ipll}, T_f, T_Q]$, and the steady-state active power $P_{g,j}$. Since these control parameters differ significantly in physical units and numerical scales, direct comparison of their absolute sensitivity values is not meaningful. To enable a consistent and comparable comparison, a normalized impedance sensitivity index is adopted. The normalized impedance sensitivity of Z_p with respect to the i -th control parameter θ_i under a given steady-state active power P_g , denoted as $S_{\theta_i-P_{g,j}}$, is defined as

$$S_{\theta_i-P_{g,j}} = \lim_{\Delta\theta_i \rightarrow 0} \frac{(Z_p(\theta_1, \dots, \theta_i + \Delta\theta_i, \dots, \theta_m) - Z_p(\theta_1, \dots, \theta_i - \Delta\theta_i, \dots, \theta_m)) / Z_{p0}}{2\Delta\theta_i / \theta_i} \quad (23)$$

where $\Delta\theta_i$ represents a small perturbation applied to θ_i , Z_{p0} is impedance corresponding to the nominal parameter set, and m denotes the total number of considered control parameters.

To facilitate comparison over the entire frequency range, a scalar metric is further introduced by averaging the absolute sensitivity over the frequency range. The mean absolute sensitivity is defined as

$$A_{\theta_i-P_{g,j}} = \frac{\sum_{y=1}^{n_f} |S_{\theta_i-P_{g,j}}|}{n_f} \quad (24)$$

where $A_{\theta_i-P_{g,j}}$ denotes the mean absolute sensitivity of parameter θ_i under steady-state active power $P_{g,j}$, and n_f is the total number of frequency points within the calculated frequency range.

Based on the above definition, the mean absolute sensitivity $A_{\theta_i-P_{g,j}}$ of all control parameters is evaluated under several steady-state active power levels $P_{g,j}$. The corresponding results are illustrated in Figure 3.

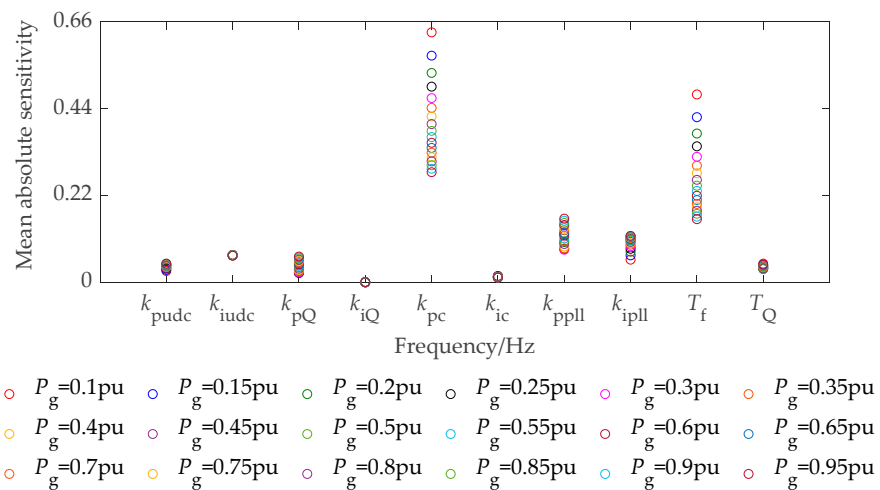


Figure 3. Mean absolute impedance sensitivity of each control parameter under different steady-state operating points.

It can be observed that the mean absolute sensitivities of different control parameters exhibit markedly different magnitudes as well as distinct dependencies on the operating point. Specifically, the current loop proportional gain k_{pc} presents the largest sensitivity magnitude and shows a pronounced variation across different operating conditions. This indicates that k_{pc} dominates the impedance shaping and is highly effective in reflecting operating-point-dependent dynamic behavior. The filter time constant T_f presents the sec-

ond largest sensitivity and also demonstrates a notable dependence on the operating condition, implying that the filter dynamics significantly influence both the magnitude and the operating point variation in the impedance. The PLL-related gains (k_{ppll} , k_{ipll}) maintain relatively high sensitivity values; however, their variation with respect to the operating point is comparatively moderate, suggesting a persistent but less operating-point-dependent influence on the impedance characteristics. The dc link voltage control gains (k_{pudc} , k_{iudc}), the reactive power loop proportional gain k_{pQ} , and the reactive power filter time constant T_Q present a medium sensitivity level. Among these parameters, k_{pudc} and k_{pQ} show noticeable operating point dependence, indicating that their influence on impedance characteristics becomes more pronounced at certain active power levels. In contrast, k_{iudc} and T_Q show nearly identical sensitivity values across different operating conditions, suggesting that its contribution to the impedance remains largely invariant and thus provides limited capability for distinguishing wind turbines operating at different steady-state power levels. The integral gain of the current loop k_{ic} , and the integral gain of the reactive power loop k_{iQ} display generally low sensitivity magnitudes, with minimal variation across operating points. This indicates that these parameters have only a minor impact on the impedance characteristics and provide limited discrimination capability under varying operating conditions. To clearly highlight the relative sensitivity levels and operating point dependencies discussed above, the key observations are summarized in Table 2. In summary, the results demonstrate that only a subset of control parameters effectively reflect impedance variations across different operating conditions, thereby providing a meaningful basis for subsequent clustering index selection and equivalent modeling.

Table 2. Impedance sensitivity and operating point dependencies of key control parameters.

Control Parameter	Sensitivity Magnitude	Operating Point Dependence
k_{pudc}	Medium	Moderate
k_{iudc}	Medium	Very small
k_{pQ}	Medium	Moderate
k_{iQ}	Small	Very small
k_{pc}	High	Significant
k_{ic}	Small	Very small
k_{ppll}	Relatively High	Relatively Significant
k_{ipll}	Relatively High	Relatively Significant
T_f	High	Significant
T_Q	Medium	Small

3.2. Sensitivity-Based Selection of Clustering Indices

Based on the sensitivity analysis presented in Section 3.1, this section describes the procedure for selecting clustering indices. The impedance sensitivities of different control parameters are evaluated under multiple steady-state operating points, thereby reflecting how variations in active power levels affect the converter dynamics. If the sensitivity corresponding to a given parameter exhibits noticeable variation as the operating point changes, it reflects differences in the oscillatory behavior of wind turbines operating under different active power conditions. Such a parameter is therefore capable of distinguishing wind turbines in terms of their impedance characteristics and can serve as a meaningful clustering index. Conversely, if the sensitivity remains nearly invariant across operating points, its contribution to the impedance characteristics is essentially constant, rendering it ineffective for differentiating wind turbines subjected to varying steady-state conditions.

However, sensitivity variation alone is insufficient for index selection. Parameters with extremely small absolute sensitivity may still exhibit relative variation, yet their overall influence on the impedance remains negligible. To avoid such cases, both the absolute

magnitude of impedance sensitivity and its operating point dependency must be jointly considered. Accordingly, the selection of clustering indices is based on the following two criteria:

- (1) A relatively large impedance sensitivity, ensuring that the parameter has a physically meaningful influence on the impedance characteristics.
- (2) A significant variation in sensitivity across operating points, ensuring that the parameter can effectively distinguish wind turbines operating at different steady-state active power levels.

To implement these criteria, the mean absolute sensitivity $A_{\theta_i-P_{g,j}}$ of each parameter θ_i under multiple active power levels $P_{g,j}$ is organized into a parameter-power sensitivity matrix.

$$M_{\theta-P_g} = \begin{bmatrix} A_{\theta_1-P_{g,1}} & \cdots & A_{\theta_i-P_{g,1}} & \cdots & A_{\theta_{10}-P_{g,1}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{\theta_1-P_{g,j}} & \cdots & A_{\theta_i-P_{g,j}} & \cdots & A_{\theta_{10}-P_{g,j}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{\theta_1-P_{g,n_p}} & \cdots & A_{\theta_i-P_{g,n_p}} & \cdots & A_{\theta_{10}-P_{g,n_p}} \end{bmatrix} \quad (25)$$

Threshold-based selection rules are then applied to objectively identify candidate parameters. First, the average sensitivity of each parameter across all operating points, denoted as A_{θ_i-avg} , is calculated to quantify its overall contribution. A_{θ_i-avg} is given by

$$A_{\theta_i-avg} = \frac{\sum_{j=1}^{n_p} A_{\theta_i-P_{g,j}}}{n_p} \quad (26)$$

where $A_{\theta_i-P_{g,j}}$ is the mean absolute sensitivity for parameter θ_i under active power levels $P_{g,j}$, and n_p is the total number of steady-state operating points considered.

A threshold for A_{θ_i-avg} is specified, denoted as A_{θ_i-th} . Parameters satisfying $A_{\theta_i-avg} > A_{\theta_i-th}$ are retained for further evaluation, while those with weak overall sensitivity are excluded.

Second, to characterize the operating point dependency of sensitivity, both the absolute range and the coefficient of variation are introduced. The sensitivity range across operating points R_{θ_i} is defined as

$$R_{\theta_i} = \max_{j=1,\dots,n_p} (A_{\theta_i-P_{g,j}}) - \min_{j=1,\dots,n_p} (A_{\theta_i-P_{g,j}}) \quad (27)$$

which reflects the absolute extent of variation. In addition, the coefficient of variation CV_{θ_i} is computed as

$$CV_{\theta_i} = \frac{\sqrt{\frac{1}{n_p} \sum_{j=1}^{n_p} (A_{\theta_i-P_{g,j}} - A_{\theta_i-avg})^2}}{A_{\theta_i-avg}} \quad (28)$$

which measures the relative fluctuation normalized by the average sensitivity.

Thresholds R_{θ_i-th} and CV_{θ_i-th} are specified for these two metrics. Parameters whose sensitivity variation range or coefficient of variation exceeds the corresponding threshold are retained. In this way, parameters exhibiting either pronounced absolute variations or significant relative fluctuations are identified as capable of capturing operating point dependent impedance differences. The parameters selected through this process constitute the initial candidate set of clustering indices.

To avoid either excessive or insufficient parameter selection, adaptive threshold adjustment and a top- N refinement strategy are further introduced. Specifically, the number

of selected parameters is constrained within a predefined interval $[N_{\min}, N_{\max}]$. If the number of candidates is smaller than $N_{\min}$, the thresholds of $A_{\theta_{i_th}}$, $R_{\theta_{i_th}}$, and $CV_{\theta_{i_th}}$ are gradually relaxed and the screening procedure is repeated until the constraint is satisfied. Conversely, if the number of candidates exceeds $N_{\max}$, the top $N_{\max}$ parameters ranked by sensitivity variation are retained as the final clustering indices. This procedure ensures that the selected indices are both physically interpretable and sufficiently discriminative.

4. Equivalent Modeling Method of Distributed DDWT Groups

4.1. DDWTs Clustering Method Based on the K-Means Algorithm

In this study, the k -means clustering algorithm is adopted to group all DDWTs based on the clustering index selection method described in Section 3.2. The k -means algorithm is chosen due to its wide application and computational simplicity. However, it is well known that the k -means algorithm has several limitations, such as implicit assumptions about cluster shape, the need to predefine the number of clusters, and sensitivity to initialization. These limitations are mitigated through specific measures implemented in the clustering procedure as follows.

First, regarding the assumption of cluster shape, the clustering space is constructed using impedance sensitivity indices that vary continuously with control parameters and operating conditions. In this context, the assumption of approximately convex cluster shapes does not invalidate the use of k -means.

Second, to address the requirement of predefining the number of clusters k , a clustering validity analysis is conducted. The average silhouette score is evaluated for different candidate values of k , and the optimal value is selected by maximizing the silhouette score.

Third, to reduce sensitivity to initialization, the k -means algorithm is executed multiple times with different random initial centroid selections [31]. The clustering result that yields the minimum within-cluster sum of squared distances is selected as the final solution, thus improving the robustness of the clustering result.

With these improvements, the k -means algorithm can effectively group DDWTs based on their impedance-related dynamic characteristics. Specifically, assume that there are N_w DDWTs to be clustered, each represented by a feature vector $\theta_{\text{index}, w} = [\theta_{w1}, \theta_{w2}, \dots, \theta_{wd}]$, which consists of d clustering indices. The k -means algorithm partitions the N_w wind turbines into k disjoint clusters by minimizing the within cluster sum of squared distances, which can be expressed as

$$\min_{\{C_k\}} \sum_{k=1}^K \sum_{\theta_{\text{index}, w} \in C_k} \|\theta_{\text{index}, w} - \mu_k\|^2 \quad (29)$$

where C_k denotes the k -th cluster, μ_k is the centroid of the k -th cluster.

4.2. Equivalent Model Parameters Calculation

Based on the clustering results obtained in Section 4.1, each cluster is aggregated into an equivalent machine, and then its parameters need to be calculated.

(1) Equivalent wind speed

For an equivalent machine representing n_w DDWTs, the total active power output P_{sum_w} is obtained as the sum of active power of all wind turbines in the cluster, which can be expressed as

$$P_{\text{sum}_w} = \sum_{i=1}^{n_w} g(V_{w,i}) \quad (30)$$

where $V_{w,i}$ is the wind speed of i -th DDWTs in the cluster, and $g(\cdot)$ represents the functional relationship between the input wind speed and the output active power of an individual DDWT.

The equivalent wind speed V_{weq} is then determined by inverting wind turbine active power and the wind speed relationship, given by [32]

$$V_{weq} = g^{-1} \left(\frac{P_{sum_w}}{n_w} \right) \quad (31)$$

where $g^{-1}(\cdot)$ is the functional expression relating output active power to input wind speed of an individual DDWT.

(2) Equivalent machine parameters

The electrical parameters of the equivalent machine are obtained by capacity-weighted aggregation of individual DDWTs within the same cluster. This aggregation method preserves the per unit electrical characteristics of wind turbine while scaling the absolute parameter values according to the total rated capacity of the aggregated DDWTs. The rated capacities of the equivalent converter and the equivalent transformer are scaled proportionally to the number of DDWTs contained in the cluster. For the circuit parameters, the aggregation follows the parallel relationships of the corresponding components [33]. As a result, the rated capacity and electrical parameters of the equivalent machine are given by [33]

$$\begin{cases} S_{cnv_eq} = n_w S_{cnv} \\ C_{dceq} = n_w C_{dc} \\ R_{feq} = \frac{R_f}{n_w} \\ L_{feq} = \frac{L_f}{n_w} \end{cases} \quad (32)$$

where S_{cnv} and S_{cnv_eq} are the rated capacity of the converter for an individual DDWT and the equivalent machine, respectively. C_{dceq} is the dc link capacitance of the equivalent machine, while R_{feq} and L_{feq} are the filter resistance and inductance of the equivalent machine, respectively.

Similarly, the rated capacity and impedance of the equivalent transformer can be calculated as

$$\begin{cases} S_{Teq} = n_w S_T \\ R_{Teq} = \frac{R_T}{n_w} \\ X_{Teq} = \frac{X_T}{n_w} \end{cases} \quad (33)$$

where S_T and S_{Teq} are the rated capacity of an individual transformer and the equivalent transformer, respectively. R_T and X_T are the resistance and reactance of an individual transformer, respectively, while R_{Teq} and X_{Teq} are the resistance and reactance of an equivalent transformer, respectively.

(3) Equivalent parameters of collector lines

Since the wind turbines within the same cluster are typically located at different distances from the PCC, their associated collector lines exhibit heterogeneous impedance characteristics. To derive the equivalent parameters of the collector lines, the wind turbines are first converted into a purely parallel structure using the equal voltage drop

method. Based on this equivalent structural representation, the equal power loss method is then employed to calculate the equivalent line parameters, such as the total active power and reactive power losses of the original collector network. The detailed calculation process can be found in [34].

4.3. Overall Procedures of the Proposed Equivalent Modeling Method

This section presents the complete workflow of the proposed equivalent modeling method, as shown in Figure 4.

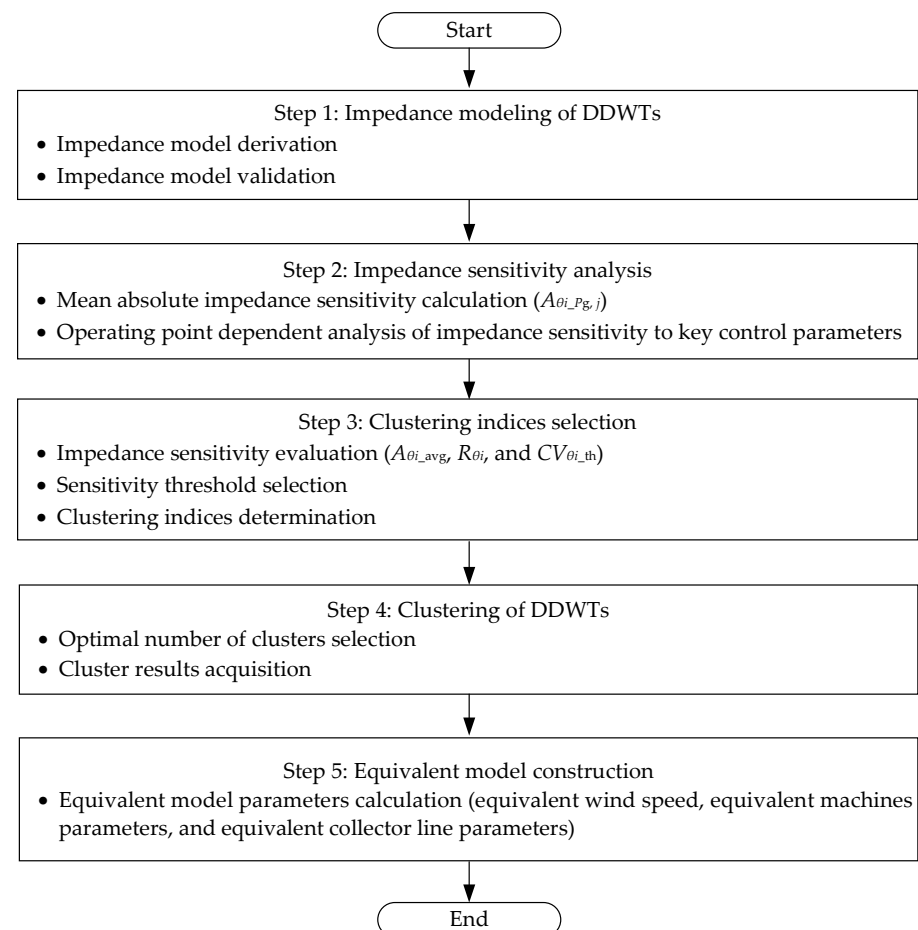


Figure 4. The flowchart of the proposed equivalent modeling method.

5. Simulation Results

To verify the effectiveness of the proposed clustering and equivalent modeling approach for distributed DDWTs, an electromagnetic transient simulation system of a microgrid with multiple distributed DDWTs is established on the PSCAD/EMTDC platform. The overall structure of the simulation system is illustrated in Figure 5. The system contains 20 wind turbines, identified as DDWTx in Figure 5, whose electrical configurations and control structures are identical to those described in Section 2. The operating points of individual wind turbines can be flexibly adjusted, enabling the construction of various steady-state operating conditions.

Based on this simulation system, extensive simulations are conducted. First, a representative operating condition is selected to demonstrate the complete implementation process of the proposed clustering and equivalent modeling methods. Following the sensitivity-based index screening and clustering procedures described in Section 3, the clustering indices are obtained, and the k-means algorithm is applied to derive the clustering

results. Subsequently, the equivalent wind turbine models and the corresponding equivalent collector network are constructed according to the clustering results. The dynamic responses of the equivalent models are then compared with those of the detailed model under the same operating condition. Quantitative evaluation indices, including output errors, are calculated to verify the accuracy of the proposed equivalent method. Furthermore, multiple additional operating conditions with different steady-state active power distribution scenarios are considered to evaluate the applicability of the proposed equivalent method. Through these comparative studies, the robustness of the proposed method under varying operating conditions is comprehensively assessed.

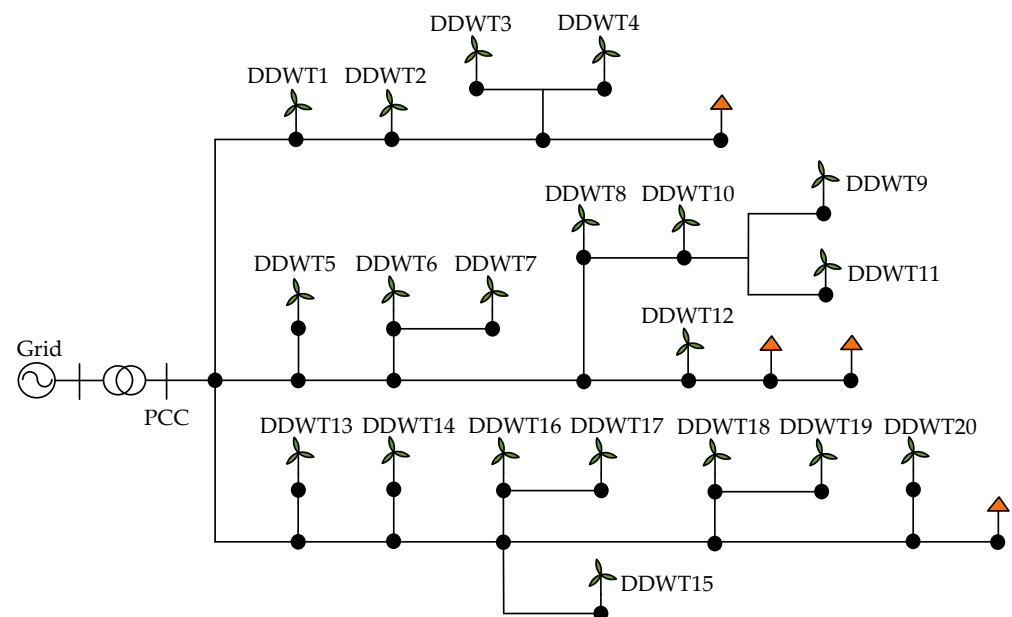


Figure 5. Schematic diagram of simulation system of a microgrid with 20 distributed DDWTs.

5.1. Application of the Clustering Method and Construction of the Equivalent Model

To illustrate the proposed clustering index selection and equivalent model construction procedure, a representative operating condition, denoted as case 1, is selected. The steady-state active power of all wind turbines under this case is shown in Figure 6.

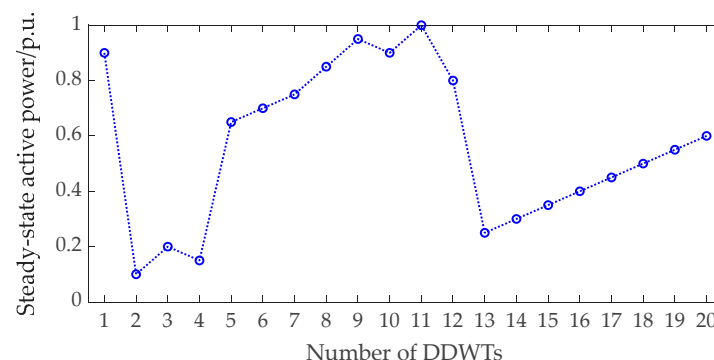


Figure 6. Steady-state active power of each DDWT in case 1.

5.1.1. Sensitivity Evaluation and Determination of Sensitivity Thresholds

First, the impedance sensitivities of each control parameter are evaluated under considered steady-state operating points. For each control parameter, $A_{\theta i_avg}$, $R_{\theta i}$, and $CV_{\theta i}$ are calculated. Control parameters showing both significant sensitivity and strong operating

point dependency are considered for clustering indices. To select clustering indices, three thresholds $A_{\theta i_th}$, $R_{\theta i_th}$, and $CV_{\theta i_th}$, are then specified as follows.

(1) Average sensitivity threshold $A_{\theta i_th}$

The calculated $A_{\theta i_avg}$ for different control parameters are shown in Figure 7, marked by the blue asterisks line. It can be observed that k_{pc} , T_f , k_{ppll} , and k_{ipll} show distinctly high sensitivity values. k_{iudc} , k_{pQ} , k_{pudc} , and T_Q show moderate sensitivity levels, while k_{ic} and k_{iQ} exhibit sensitivities close to zero. Based on this distribution, $A_{\theta i_th}$ is selected within the interval between the sensitivity of k_{ic} (approximately 0.015) and T_Q (approximately 0.05), and is set to 0.04 in this study, as indicated by the red dashed line in Figure 7. This choice effectively filters out parameters with insignificant influence while retaining those with moderate-to-high influence.

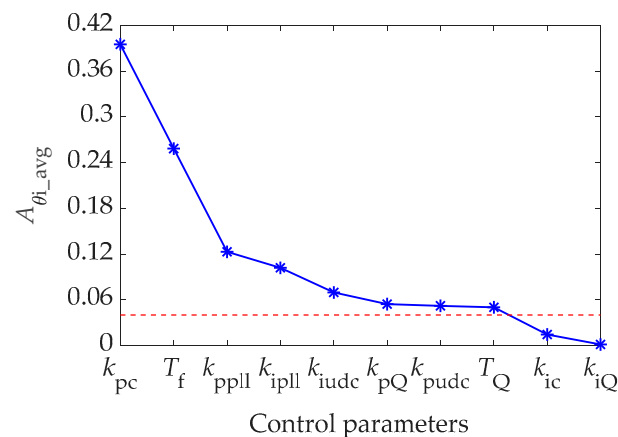


Figure 7. Average sensitivity $A_{\theta i_avg}$ of different control parameters.

(2) Sensitivity variation range threshold $R_{\theta i_th}$

The calculated $R_{\theta i}$ for different control parameters are shown in Figure 8, marked by the blue asterisks line. It can be observed that k_{pc} , T_f , k_{ppll} , k_{ipll} , and k_{pQ} show relatively large sensitivity ranges, whereas the remaining parameters rapidly approach zero. Accordingly, $R_{\theta i_th}$ is chosen between the values of k_{ic} (approximately 0.013) and k_{pQ} (approximately 0.04), and is set to 0.02 in this study, as indicated by the red dashed line in Figure 8.

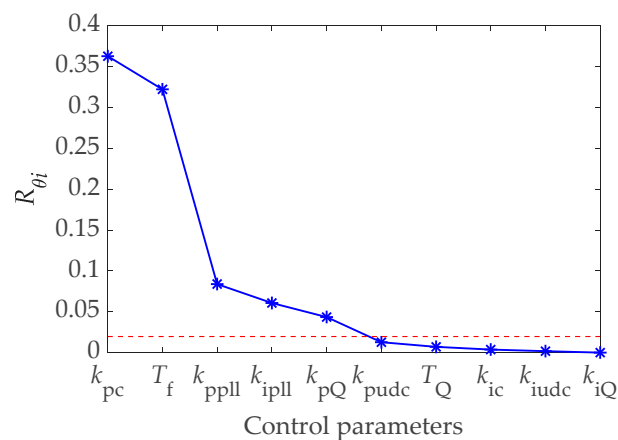


Figure 8. Average sensitivity range $R_{\theta i}$ of different control parameters.

(3) Coefficient of variation threshold $CV_{\theta i_th}$

The calculated $CV_{\theta i}$ for different control parameters are shown in Figure 9, marked by the blue asterisks line. Unlike $A_{\theta i_avg}$ and $R_{\theta i}$, the $CV_{\theta i}$ values exhibit a continuous decreasing trend without a distinct separation point. In this case, a moderate dispersion criterion is adopted, and $CV_{\theta i_th}$ is set to 0.2 (as indicated by the red dashed line in Figure 9), corresponding approximately to the upper portion of the distribution.

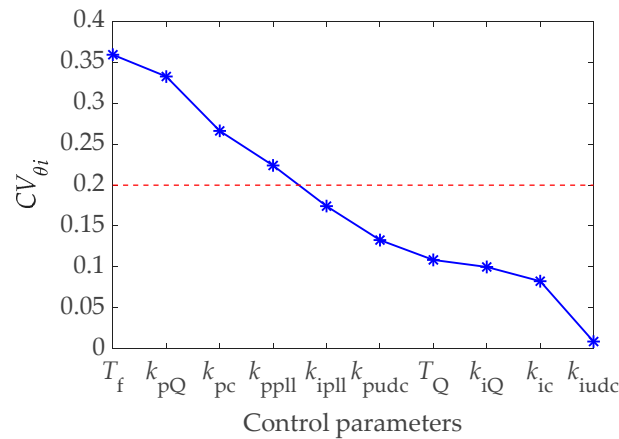


Figure 9. Coefficient of variation $CV_{\theta i}$ of different control parameters.

To further verify the rationality and robustness of the selected thresholds, a sensitivity analysis is conducted by perturbing $A_{\theta i_th}$, $R_{\theta i_th}$, and $CV_{\theta i_th}$ around their nominal values. For each threshold combination, the clustering index screening procedure is repeated, and the resulting selected indices are summarized in Table 3. It can be observed that the dominant clustering indices remain unchanged for most threshold variations, while only parameters near the threshold boundaries are occasionally added or removed. Specifically, increasing $A_{\theta i_th}$ by 40% excludes k_{pQ} , while decreasing $R_{\theta i_th}$ or $CV_{\theta i_th}$ by 40% introduces k_{pudc} . To further examine whether such threshold-induced variations in the selected indices lead to changes in the final clustering result, the k -means algorithm is applied to cluster the 20 DDWTs for each set of clustering indices. To ensure a fair comparison, the number of clusters is temporarily fixed to $k = 3$. The clustering results are compared in Table 4. It can be observed that the identical clustering results are obtained across all tested scenarios. This confirms that the proposed clustering index selection method does not rely on overly specific threshold tuning, and remains robust against reasonable threshold variations.

Table 3. Selected clustering indices under different threshold variations.

Threshold Variation	$A_{\theta i_th}$	$R_{\theta i_th}$	$CV_{\theta i_th}$	Selected Indices	Change
30%	$0.7A_{\theta i_th0}$	$R_{\theta i_th0}$	$CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged
	$1.3A_{\theta i_th0}$	$R_{\theta i_th0}$	$CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged
	$A_{\theta i_th0}$	$0.7R_{\theta i_th0}$	$CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged
	$A_{\theta i_th0}$	$1.3R_{\theta i_th0}$	$CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged
	$A_{\theta i_th0}$	$R_{\theta i_th0}$	$0.3CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged
	$A_{\theta i_th0}$	$R_{\theta i_th0}$	$1.7CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged
40%	$0.6A_{\theta i_th0}$	$R_{\theta i_th0}$	$CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged
	$1.4A_{\theta i_th0}$	$R_{\theta i_th0}$	$CV_{\theta i_th0}$	$k_{pc}, k_{ppll}, k_{ipll}, T_f$	k_{pQ} removed
	$A_{\theta i_th0}$	$0.6R_{\theta i_th0}$	$CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f, k_{pudc}$	k_{pudc} added
	$A_{\theta i_th0}$	$1.4R_{\theta i_th0}$	$CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged
	$A_{\theta i_th0}$	$R_{\theta i_th0}$	$0.6CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f, k_{pudc}$	k_{pudc} added
	$A_{\theta i_th0}$	$R_{\theta i_th0}$	$1.4CV_{\theta i_th0}$	$k_{pQ}, k_{pc}, k_{ppll}, k_{ipll}, T_f$	Unchanged

Note: $A_{\theta i_th0} = 0.04$, $R_{\theta i_th0} = 0.02$, $CV_{\theta i_th0} = 0.2$.

Table 4. Clustering results of case 1 based on different clustering indices.

Clustering Indices	Cluster Number	Number of DDWTs
$k_{pQ}, k_{pc}, k_{ppl}, k_{ipl}, T_f$	Cluster 1	2, 3, 4
	Cluster 2	13, 14, 15, 16, 17, 18, 19
	Cluster 3	1, 5, 6, 7, 8, 9, 10, 11, 12, 20
$k_{pc}, k_{ppl}, k_{ipl}, T_f$	Cluster 1	2, 3, 4
	Cluster 2	13, 14, 15, 16, 17, 18, 19
	Cluster 3	1, 5, 6, 7, 8, 9, 10, 11, 12, 20
$k_{pQ}, k_{pc}, k_{ppl}, k_{ipl}, T_f, k_{pudc}$	Cluster 1	2, 3, 4
	Cluster 2	13, 14, 15, 16, 17, 18, 19
	Cluster 3	1, 5, 6, 7, 8, 9, 10, 11, 12, 20

5.1.2. Determination of the Final Clustering Indices

To balance clustering effectiveness and computational efficiency, the number of clustering indices is constrained according to Section 3.2. In this study, impedance sensitivities of ten control parameters are evaluated. If too few parameters are selected, the clustering indices may be insufficient to distinguish DDWTs operating at different conditions. In this study, a minimum number of selected parameters is specified as $N_{\min} = 3$. Conversely, selecting an excessive number of indices may introduce redundancy without improving clustering performance. According to Figure 3, four control parameters exhibit both low sensitivity and weak operating point dependency. Accordingly, the upper bound is set to $N_{\max} = 6$. Following these criteria, the final set of clustering indices for case 1 is determined as $\theta_{\text{index}, w} = [k_{pQ}, k_{pc}, k_{ppl}, k_{ipl}, T_f]$, as shown in Table 5. While these indices are selected based on frequency-domain impedance sensitivity, their physical significance in the time domain is also analyzed in Appendix A.

Table 5. Selected clustering indices and justification based on sensitivity analysis.

Clustering Indices	Justification
k_{pQ}	Medium impedance sensitivity and moderate operating point dependence.
k_{pc}	High impedance sensitivity and strong operating point dependence.
k_{ppl}	Relatively high impedance sensitivity and relatively strong operating point dependence.
k_{ipl}	Relatively high impedance sensitivity and relatively strong operating point dependence.
T_f	High impedance sensitivity and strong operating point dependence.

5.1.3. Determination of the Optimal Number of Clusters and Cluster Results

The k -means algorithm is applied to cluster all wind turbines using the selected clustering indices. To determine the optimal number of clusters k , a clustering validity analysis is conducted using the silhouette score. The silhouette score measures both intra-cluster cohesion (how close the data points within a cluster are) and inter-cluster separation (how distinct the clusters are from each other). It ranges from -1 to 1 , where higher values indicate that the object is well matched to its own cluster and poorly matched to neighboring clusters. Specifically, values close to 1 correspond to well-separated clusters, values around 0 indicate overlapping clusters, and negative values suggest poorly defined clustering results. The silhouette scores for different candidate values of k are calculated to examine their variation trend. Typically, the silhouette score increases with the number of clusters up to a certain point, beyond which it may decrease or remain nearly constant. The optimal number of clusters is therefore selected as the value of k that maximizes the

silhouette score, representing the best balance between intra-cluster cohesion and inter-cluster separation.

In this study, since the objective of clustering is to reduce the complexity of the wind turbine group model, an excessively large number of clusters is unnecessary. Based on common practice in the literature, the number of clusters typically does not exceed eight. Accordingly, k is varied from 2 to 8. For each value of k , the k -means algorithm is applied and the corresponding average silhouette score is computed, as shown in Figure 10. It can be observed that the silhouette score reaches its maximum when $k = 3$. Therefore, $k = 3$ is selected as the optimal number of clusters. The detailed clustering results are summarized in Table 6.

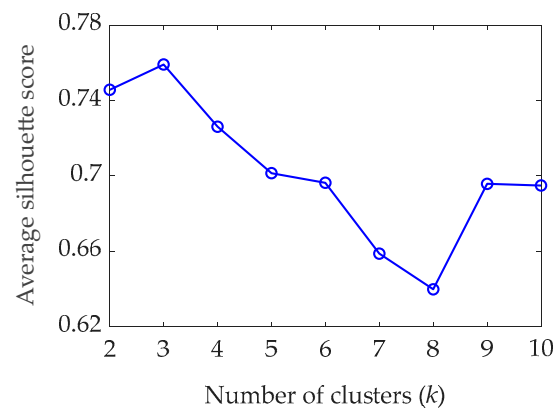


Figure 10. Average silhouette score of different number of clusters.

Table 6. Clustering results of proposed equivalent model for case 1.

Cluster Number	Number of DDWTs	Steady-State Active Power of Equivalent Machine
Cluster 1	2, 3, 4	1.633 MW
Cluster 2	13, 14, 15, 16, 17, 18, 19	10.164 MW
Cluster 3	1, 5, 6, 7, 8, 9 10, 11, 12, 20	29.403 MW

5.1.4. Equivalent Model Construction

After clustering, each wind turbine cluster is aggregated into an equivalent machine. The corresponding equivalent wind speed, equivalent machine parameters, and equivalent collection line parameters are calculated for each cluster. Based on these equivalent quantities, the three-machine equivalent model is constructed.

5.2. Time Domain Dynamic Verification Under Impedance Disturbance

After constructing the equivalent model, time domain simulations are conducted to validate its accuracy. A small impedance disturbance is applied at the PCC of the simulation system at $t = 4$ s. The response waveforms of the detailed model, the conventional single-machine equivalent model, the equivalent model based on [27], and the proposed equivalent model are compared, as shown in Figure 11.

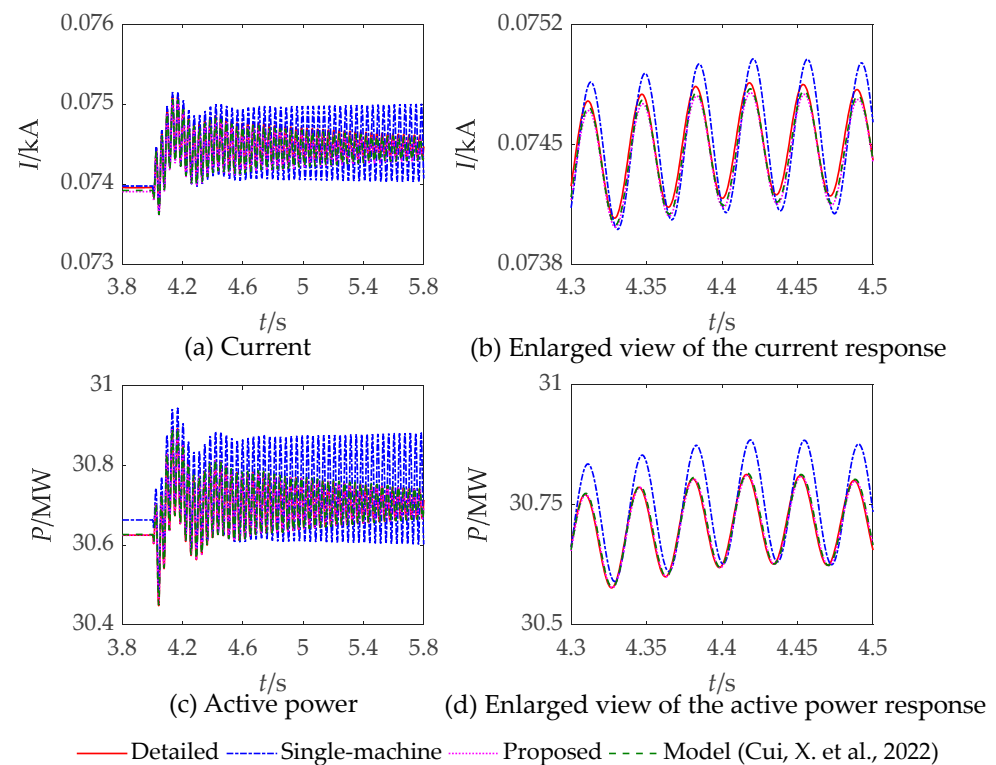


Figure 11. Response of different models of case 1 under impedance disturbance [27].

Prior to the disturbance, the system operates under a steady-state condition. After the disturbance, the detailed model exhibits oscillatory responses in current and active power, with a frequency of approximately 28 Hz. The oscillation amplitude gradually decays, indicating stable and convergent dynamic behavior. These responses are closely related to the impedance characteristics of individual wind turbines. Due to differences in operating conditions, wind turbines exhibit distinct dynamic responses, resulting in different contributions to the overall system damping when the impedance disturbance is applied. The single-machine equivalent model aggregates all wind turbines into an equivalent machine, neglecting these differences in impedance characteristics and dynamic interactions. Under impedance disturbances, such simplification leads to an inaccurate representation of the effective damping contribution. Therefore, the single-machine equivalent model produces current and active power oscillations with growing amplitudes after the disturbance, deviating significantly from the detailed model. The equivalent model based on [27], which clusters wind turbines using oscillation-related currents and voltages, reproduces the oscillatory frequency and damping behavior accurately. The proposed equivalent model clusters wind turbines according to their impedance sensitivity characteristics, ensuring that wind turbines with similar contributions to the system impedance are aggregated together. As a result, the key impedance features governing oscillatory behavior are preserved in the equivalent model. From a frequency domain perspective, system damping is primarily determined by the magnitude and phase angle of the aggregated model observed at the PCC. By maintaining these impedance characteristics in the frequency range of interest, the proposed equivalent model preserves the small-signal stability margin and effective damping of the detailed model. Consequently, in the time domain, the equivalent model reproduces oscillation frequencies and decay rates that are consistent with those of the detailed model under impedance disturbance conditions, leading to close agreement in oscillation attenuation and settling behavior.

To further quantify the modeling accuracy, performance indices are computed for selected outputs, such as the current and active power of DDWT clusters. The average

deviation e_X and maximum deviation $e_{\max,X}$ between the equivalent model and the detailed model are defined as

$$e_X = \frac{\sum_{i=N_{\text{start}}}^{N_{\text{end}}} |X_{\text{eq}}(i) - X_{\text{de}}(i)|}{N_{\text{end}} - N_{\text{start}} + 1} \quad (34)$$

$$e_{\max,X} = \max_{i=N_{\text{start}}, \dots, N_{\text{end}}} |X_{\text{eq}}(i) - X_{\text{de}}(i)| \quad (35)$$

where X_{eq} and X_{de} denote the variables of the equivalent model and the detailed model, respectively. N_{start} and N_{end} represent the first and last samples within the evaluation interval, respectively. The error is calculated over the time window from 4 s to 6 s, starting from the instant when the impedance disturbance is applied.

The error results for case 1 are summarized in Table 7. The comparison results in Figure 11 and Table 7 indicate that both the proposed equivalent method and the equivalent model based on [27] achieve significantly lower errors and more accurate damping reproduction than the conventional single-machine equivalent model. However, the equivalent model based on [27] requires extensive variables sampled during and after oscillation events for clustering. This requirement limits its practical applicability, as these variables are difficult to obtain prior to the oscillation occurrence. In contrast, the proposed equivalent model relies solely on clustering indices derived from impedance characteristics and operating conditions under normal operation, without requiring oscillation period data. As a result, the proposed method demonstrates both high fidelity and improved practicality, making it well suitable for equivalent modeling and stability assessment of large-scale DDWT groups.

Table 7. Errors of different equivalent models for case 1.

Model	e_P	$e_{\max,P}$	e_I	$e_{\max,I}$
Single-machine equivalent model	0.0739	0.1996	0.000231	0.000597
Equivalent model from [27]	0.0089	0.0188	0.000053	0.000099
Proposed equivalent model	0.0095	0.0194	0.000056	0.000100

In addition to the modeling accuracy, the proposed equivalent modeling method offers a clear advantage in terms of computational efficiency. In the full detailed model, each wind turbine is explicitly represented, resulting in a large number of state variables and differential equations to be solved. In contrast, the proposed method aggregates wind turbines with similar impedance sensitivity characteristics into a limited number of clusters, significantly reducing the model order. As a result, the number of units involved in the simulation is substantially decreased, leading to lower computational complexity and reduced simulation time. Importantly, as demonstrated by the above time domain responses, this reduction in model complexity does not compromise the simulation accuracy. This balance between computational efficiency and modeling accuracy highlights the practical advantage of the proposed methodology for dynamic analysis of power-electronics-dominated microgrids.

5.3. Performance of the Proposed Equivalent Modeling Method Under Multiple Operating Conditions

To further demonstrate the robustness and general applicability of the proposed equivalent method, additional operating conditions with different steady-state active power distributions are investigated. In this section, two representative operating conditions, denoted as cases 2 and 3, are selected for detailed analysis. These operating conditions are representative in that the steady-state active power outputs of individual wind

turbines span a wide range from 0 to 1 pu, resulting in substantially different power distributions and clustering results. Such variations effectively reflect practical operating scenarios under diverse wind conditions. The steady-state active power distributions for cases 2 and 3 are shown in Figure 12. For each operating condition, the wind turbine clustering and equivalent model construction are conducted. The thresholds $A_{\theta i_avg}$, $R_{\theta i_th}$, and $CV_{\theta i_th}$ are kept identical to those used in Section 5.1. The resulting clustering results and steady-state active power of each equivalent machine are summarized in Table 8.

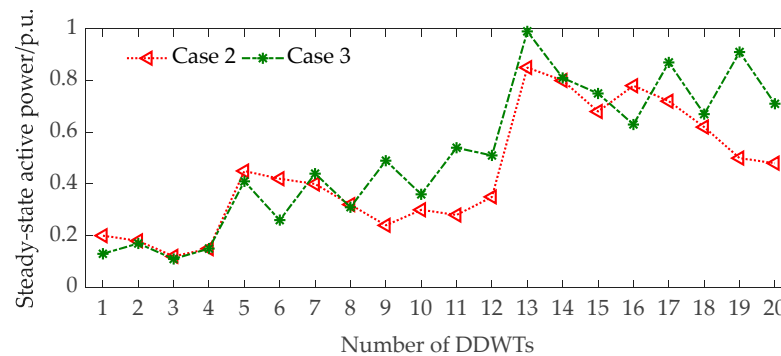


Figure 12. Steady-state active power of each DDWT of cases 2 and 3.

Table 8. Clustering results of proposed equivalent model for cases 2 and 3.

Case	Cluster Number	Number of DDWTs	Steady-State Active Power of Equivalent Machine
Case 2	Cluster 1	1, 2, 3, 4, 9	3.231 MW
	Cluster 2	5, 6, 7, 8, 10, 11, 12, 19, 20	12.705 MW
	Cluster 3	13, 14, 15, 16, 17, 18	16.154 MW
Case 3	Cluster 1	1, 2, 3, 4	2.033 MW
	Cluster 2	5, 6, 7, 8, 9, 10, 11, 12	12.052 MW
	Cluster 3	13, 14, 15, 16, 17, 18, 19, 20	23.014 MW

Figures 13 and 14 compare the dynamic responses of the detailed model, the single-machine equivalent model, the equivalent model based on [27], and the proposed equivalent model under impedance disturbances for cases 2 and 3, respectively. After the disturbance, the detailed model exhibits significant oscillatory behavior in both current and active power, with oscillation amplitudes gradually decaying over time. The equivalent model based on [27] and the proposed equivalent model closely reproduce the transient envelope of the detailed model for both operating conditions. In contrast, the single-machine equivalent model shows noticeable discrepancies, including inaccurate oscillation amplitudes and divergent responses.

Using the same performance indices defined in Section 5.2, the quantitative error results for cases 2 and 3 are calculated and summarized in Table 9. The results indicate that both the equivalent model based on [27] and the proposed equivalent model consistently yield significantly smaller waveform errors than the single-machine equivalent model under different operating conditions.

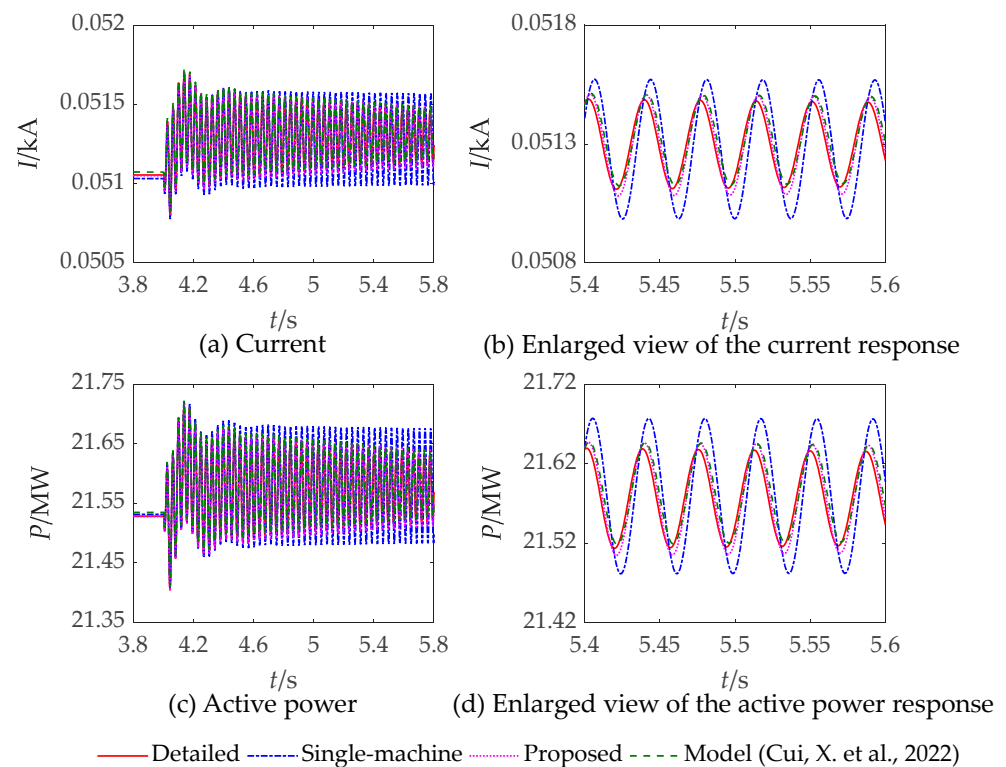


Figure 13. Response of different models of case 2 under impedance disturbance [27].

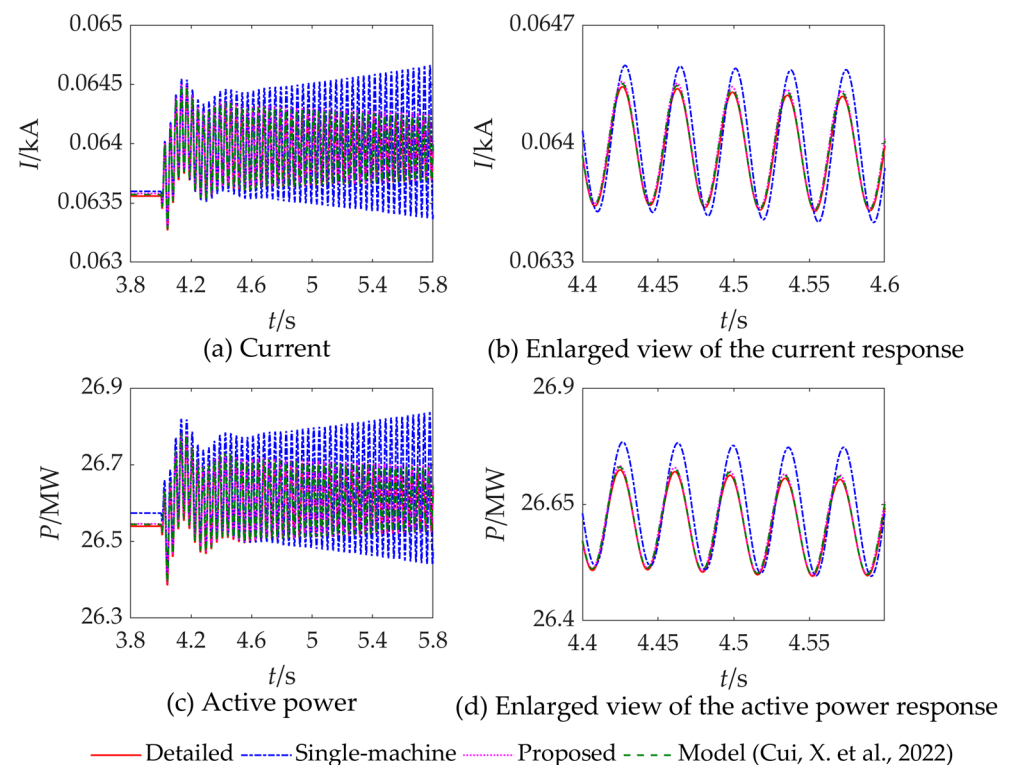


Figure 14. Response of different models of case 3 under impedance disturbance [27].

The above results demonstrate that the proposed impedance sensitivity-based equivalent modeling approach exhibits well robustness against changes in operating conditions. By adaptively selecting clustering indices based on impedance sensitivity characteristics, the equivalent model can reliably preserve dominant oscillatory dynamics across diverse

steady-state scenarios, while substantially reducing model complexity. This further validates the suitability of the proposed method for oscillation analysis of DDWT groups in practical applications.

Table 9. Errors of different equivalent models for cases 2 and 3.

Case	Model	e_P	$e_{\max,P}$	e_I	$e_{\max,I}$
Case 2	Single-machine equivalent model	0.0291	0.0809	0.000089	0.000255
	Equivalent model from [27]	0.0103	0.0280	0.000031	0.000084
	Proposed equivalent model	0.0075	0.0194	0.000022	0.000060
Case 3	Single-machine equivalent model	0.0749	0.2486	0.000223	0.000757
	Equivalent model from [27]	0.0068	0.0197	0.000017	0.000069
	Proposed equivalent model	0.0076	0.0208	0.000021	0.000071

6. Discussion

In Section 5, the proposed impedance sensitivity-based clustering strategy and equivalent modeling method has been verified under different operating conditions. In this section, several limitations related to the practical implementation of the proposed method are further discussed.

The proposed method is based on the frequency domain impedance model of wind turbines to perform sensitivity analysis and clustering index selection. Although impedance modeling techniques for wind turbines are well established in the existing literatures, the accuracy of the impedance model depends on the validity of the adopted modeling assumptions under practical operating conditions. Based on the established impedance model, the sensitivities of control parameters under different operating points are analyzed for the selection of clustering indices. To conduct the impedance sensitivity analysis, some control parameters of wind turbine converters are required. However, these parameters may not always be accessible in practical implementations. Additionally, it should be noted that the method assumes small-signal linearization, which may not be accurate under strongly nonlinear conditions or prolonged control saturation. In these scenarios, the linear assumptions could lead to reduced accuracy in the equivalent model. However, such conditions are outside the main focus of this work, and the proposed method remains reliable for operating scenarios with small disturbances.

Another consideration concerns the applicability of the proposed method to scenarios with higher technological heterogeneity, where the dispersion in control parameters and rated capacities of wind turbines is larger. The case study in this paper considers a microgrid with 20 distributed DDWTs sharing identical control parameters and rated capacities, which facilitates a direct comparison of impedance sensitivity characteristics. In practical systems, wind turbines may exhibit significant heterogeneity in terms of control parameter settings or rated capacities. This variation can lead to increased dispersion in their impedance characteristics and, consequently, greater difficulty in obtaining homogeneous clusters. If wind turbines with highly disparate parameters were directly clustered without any prior grouping, the impedance characteristics of each cluster would become less representative of individual wind turbines, thereby distorting the dynamic behavior of the aggregated model. This effect can degrade the accuracy of the equivalent model, particularly in terms of the contribution to system damping and oscillatory behavior. To mitigate this issue, the proposed method can be extended through a hierarchical grouping strategy. Wind turbines are first divided into several groups according to their

control parameters and rated capacities. Within each group, the proposed sensitivity-informed clustering strategy is then applied to identify clustering indices and perform aggregation using the k -means algorithm. In this manner, the proposed methodology remains robust and applicable to systems with higher technological heterogeneity, ensuring both modeling accuracy and computational efficiency.

In addition, the scalability of the proposed method is briefly discussed. The proposed sensitivity-informed clustering strategy is not explicitly dependent on the number of wind turbines, as it is based on impedance sensitivity characteristics rather than system scale. Increasing or decreasing the number of wind turbines does not change the clustering index selection procedure or the clustering method, but mainly affects the number of wind turbines contained in each cluster. When the number of wind turbines increases, the computational burden associated with impedance sensitivity analysis and clustering may increase accordingly. For microgrids with fewer wind turbines, the proposed method can be implemented with lower computational cost for wind turbine clustering.

7. Conclusions

This paper proposes an equivalent method for sub/super-synchronous oscillation analysis of DDWT groups in microgrids. Based on the frequency domain impedance model of the DDWT, the impedance sensitivities of key control parameters are systematically analyzed under multiple steady-state operating conditions. By jointly considering both the absolute magnitude of impedance sensitivity and its variation across operating points, a sensitivity-informed based clustering index selection criterion is proposed. This criterion ensures that the selected indices are not only dynamically influential, but also effective in distinguishing DDWTs operating under different active power levels. Using the selected indices, a k -means clustering algorithm is employed to aggregate the DDWTs with similar impedance-related dynamic characteristics, and a multi-machine equivalent model is subsequently constructed. Simulation studies under different operating conditions demonstrate that the proposed equivalent model can accurately reproduce the dominant oscillatory behavior of the detailed model, including damping characteristics and transient envelopes of output response. In contrast, the conventional single-machine equivalent model exhibits noticeable deviations in oscillation amplitude and convergence behavior, and fails to capture the correct dynamic characteristics under impedance perturbations.

The main advantage of the proposed method is that it accounts for the differences in impedance characteristics of individual wind turbines under varying operating points, ensuring that the clustering reflects the dynamic influence of DDWTs within each cluster. Meanwhile, the proposed method does not rely on variables sampled during or after oscillations for clustering. These features enable the proposed approach to accurately reproduce the oscillation frequency and damping behavior observed in the detailed model, while improving its practical applicability. Consequently, the method is particularly suitable for oscillation analysis, stability assessment, and control interaction studies in power-electronics-dominated power systems.

The principal limitation is that the proposed method relies on the availability of accurate impedance modeling and key control parameters, which may not always be accessible in practical implementations. In addition, when applied to systems with a large number of wind turbines, the computational cost associated with impedance sensitivity analysis and clustering could increase. For future research, the most immediate direction would be to develop control parameter identification methods for wind turbine converters, and design more efficient clustering algorithms suitable for large-scale wind turbine clustering.

Author Contributions: Conceptualization, J.Q., and Q.G.; methodology, J.Q.; software, L.T.; validation, J.Q., and Q.G.; formal analysis, Y.Z.; investigation, C.L.; resources, Y.Z.; data curation, Y.Z.; writing—original draft preparation, J.Q.; writing—review and editing, J.Q., Q.G., H.C.; visualization, C.L.; project administration, L.T. All authors have read and agreed to the published version of the manuscript.

Funding: The 2026 Routine Technical Service Project of the Electric Power Research Institute, China Southern Power Grid Co., Ltd. (SEPRI-A26M008).

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: Authors Jinling Qi, Qi Guo, Haiqing Cai, Yihua Zhu, Liang Tu, and Chao Luo were employed by the Electric Power Research Institute, China Southern Power Grid. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

In Section 5.1.2, the control parameters k_{pQ} , k_{pC} , k_{pPII} , k_{iPII} , and T_f are identified as clustering indices based on their sensitivity in the dq-domain impedance. To further illustrate how variations in these parameters are reflected in time-domain phenomena, simulations are conducted on a DDWT connected to the grid. For each selected control parameter, a $\pm 10\%$ variation around its initial value is applied, and the resulting active power and reactive power responses are compared. The schematic diagram of the simulation system is shown in Figure A1, and the main parameters of DDWT are listed in Table 1 of the manuscript. In Figure A1, the red frame highlights the DDWT, L_g denotes the grid side inductance, with $L_g = 0.000215$ H. At $t = 4$ s, switch s_1 is opened to insert an additional inductance L_{dis} to simulate a small-signal disturbance, where $L_{dis} = 5\%L_g$.

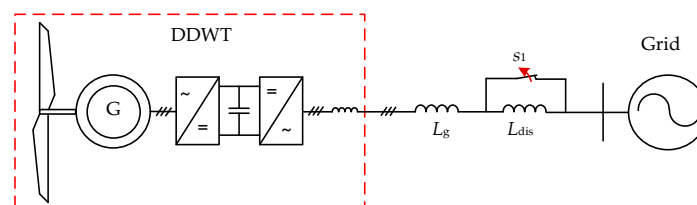


Figure A1. Schematic diagram of the simulation system of a DDWT connected to grid.

The reactive power loop proportional gain k_{pQ} mainly effects the dynamic regulation of reactive power, while also slightly influencing active power. Figure A2 shows the active power and reactive power responses under a $\pm 10\%$ variation in k_{pQ} . It can be observed that increasing k_{pQ} reduces the oscillation amplitude and enhances damping, accelerating the stabilization of both reactive power and active power.

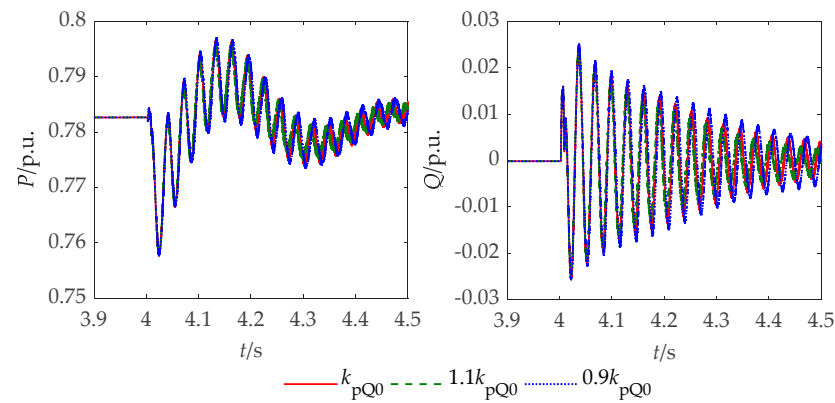


Figure A2. Active power and reactive power responses of the DDWT under a $\pm 10\%$ variation in k_{pQ} .

The proportional gain k_{pc} is directly related to the current loop control bandwidth. The active power and reactive power responses under a $\pm 10\%$ variation in k_{pc} are shown in Figure A3. Increasing k_{pc} improves current tracking and dynamic response, whereas decreasing k_{pc} reduces effective damping and increases overshoot, thereby raising the risk of oscillatory behavior.

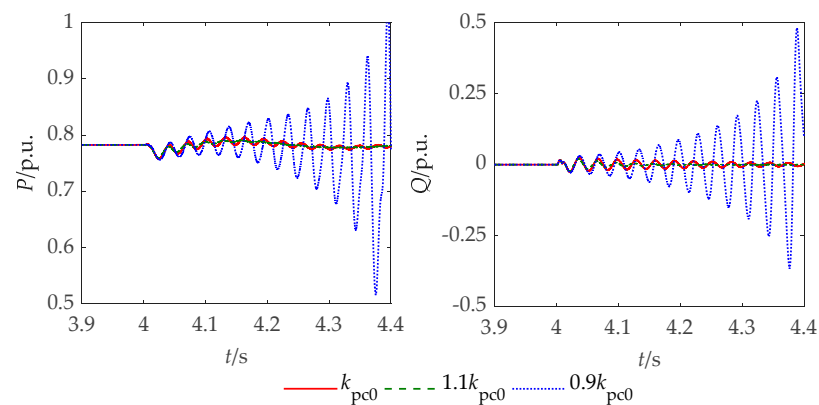


Figure A3. Active power and reactive power responses of the DDWT with $\pm 10\%$ variation in k_{pc} .

The proportional and integral coefficients of the PLL, k_{ppll} , and k_{ipll} affect the sensitivity of phase tracking to voltage disturbances, which are positively correlated with the PLL control bandwidth f_{pll} . Therefore, variations in f_{pll} are used to represent the corresponding changes in k_{ppll} and k_{ipll} for the purpose of analysis. Figure A4 shows the active power and reactive power responses under a $\pm 10\%$ variation in f_{pll} . It can be observed that increasing f_{pll} leads to larger oscillation amplitudes and a higher risk of oscillatory behavior.

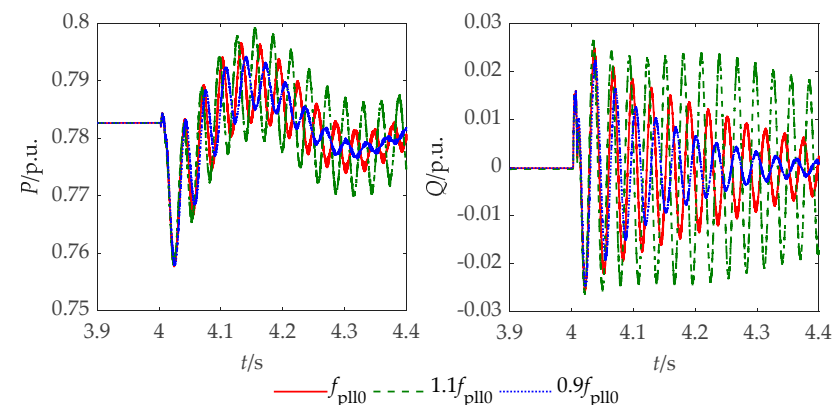


Figure A4. Active power and reactive power responses of the DDWT with $\pm 10\%$ variation in f_{pll} .

The voltage feedforward filter time constant T_f introduces a delay in the feedforward path. Figure A5 shows the active power and reactive power responses under a $\pm 10\%$ variation in T_f . An increased T_f attenuates high-frequency components, leading to smoother but slower dynamic responses, while decreasing T_f improves responsiveness at the cost of increased oscillatory behavior.

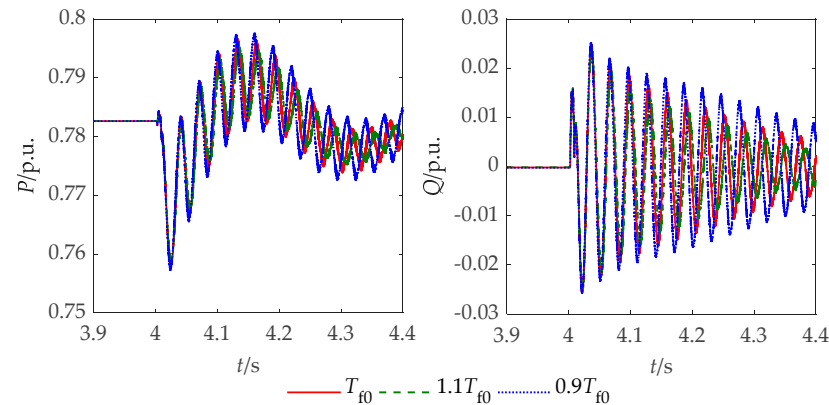


Figure A5. Active power and reactive power responses of the DDWT with $\pm 10\%$ variation in T_f .

In summary, although the clustering indices are identified based on frequency-domain impedance sensitivity, the time-domain simulations demonstrate that variations in these parameters produce clear and distinct effects on power response, oscillation amplitude, and damping. This validates that the selected clustering indices are not only mathematically significant but also physically meaningful in terms of dynamic performance.

References

1. Bagheri, A.; Mobayen, S.; Behzadi, S.; Osali, N. To capture curtailed renewable energies in smart distribution systems using a convex co-optimization of dynamic transformer rating and dynamic reconfiguration. *IEEE Trans. Power Deliv.* **2025**, *41*, 312–324. <https://doi.org/10.1109/TPWRD.2025.3642200>.
2. Roy, S.; Das, S.; Singh, B.; Panigrahi, B.K.; Bose, B. Synchronization of double fed induction generator-solar PV-BES based microgrid. *IEEE J. Emerg. Sel. Top. Ind. Electron.* **2025**, *7*, 137–148. <https://doi.org/10.1109/JESTIE.2025.3639920>.
3. Tripathi, S.M.; Tiwari, A.N.; Singh, D. Grid-integrated permanent magnet synchronous generator based wind energy conversion systems: A technology review. *Renew. Sustain. Energy Rev.* **2015**, *51*, 1288–1305.
4. Nasiri, M.; Milimonfared, J.; Fathi, S.H. A review of low-voltage ride-through enhancement methods for permanent magnet synchronous generator based wind turbines. *Renew. Sustain. Energy Rev.* **2015**, *47*, 399–415.
5. Zheng, Z.; An, Z.; Shen, C. Evaluation method for equivalent models of PMSG-based wind farms considering randomness. *IEEE Trans. Sustain. Energy* **2019**, *10*, 1565–1574.
6. Yan, G.; Wang, D.; Jia, Q.; Hu, W. Equivalent modeling of Dfig-based wind farms for sub-synchronous resonance analysis. *Energies* **2020**, *13*, 5426.
7. Liang, Z.; Chung, C.Y.; Zhang, W.; Wang, Q.; Lin, W.; Wang, C. Enabling high-efficiency economic dispatch of hybrid AC/DC networked microgrids: Steady-state convex bi-directional converter models. *IEEE Trans. Smart Grid.* **2025**, *16*, 45–61.
8. Kim, S.-K.; Kim, E.-S. PSCAD/EMTDC-based modeling and analysis of a gearless variable speed wind turbine. *IEEE Trans. Energy Convers.* **2007**, *22*, 421–430.
9. Du, W.; Dong, W.; Wang, H.; Cao, J. Dynamic aggregation of same wind turbine generators in parallel connection for studying oscillation stability of a wind farm. *IEEE Trans. Power Syst.* **2019**, *34*, 4694–4705.
10. Guo, Z.; Zhang, X.; Li, F.; Fu, X.; Han, F.; Wang, J. Double-machine equivalent method for evaluating plant- and unit-level stability of hybrid grid-connected renewable power plants. *CESS J. Power Energy Syst.* **2025**, *11*, 2102–2116.
11. Nan, D.; Lu, Z.; Qiao, Y.; Min, Y. Simplified equivalent models of large-scale wind power and their application on small-signal stability. *J. Mod. Power Syst. Clean Energy* **2013**, *1*, 58–64.
12. Du, W.; Dong, W.; Wang, H. A method of reduced-order modal computation for planning grid connection of a large-scale wind farm. *IEEE Trans. Sustain. Energy* **2020**, *11*, 1185–1198.

13. Shao, B.; Zhao, S.; Gao, B.; Yang, Y.; Blaabjerg, F. An equivalent model for sub-synchronous oscillation analysis in direct-drive wind farms with VSC-HVDC systems. *Int. J. Electr. Power Energy Syst.* **2021**, *125*, 106498.
14. Yan, G.; Wang, Y.; Fan, Y.; Yang, C.; Yue, L. Aggregation equivalence method for direct-drive wind farms based on the excitation–response relationship. *Electronics* **2024**, *13*, 2124.
15. Gu, T.; Yang, Q.; Lin, C.; Liu, M.; Gu, W.; Wu, H.; Zhang, Y.; Li, Y. A wind farm equivalent modeling method based on single-machine equivalent modeling and selection modal analysis. *Power Syst. Protection Control* **2021**, *41*, 75–87.
16. Dong, W.; Du, W.; Wang, H. Dynamic equivalent model of a grid-connected wind farm for oscillation stability analysis. *Proc. CSEE* **2021**, *41*, 75–87.
17. Feng, S.; Cui, H.; Lei, J.; Yang, H.; Tang, L. Data-driven time-frequency-domain equivalent modeling of wind farms for wide-band oscillations analysis. *IEEE Trans. Power Deliv.* **2023**, *38*, 4465–4475.
18. He, J.; Zhou, Y.; Kang, W.; Li, L.; Li, Z.; Xin, H. Self-adaptive equivalence method for wind farm with maintained dominant mode. *Autom. Electr. Power Syst.* **2021**, *45*, 28–36.
19. Zhou, Y.; Wang, G.; Wang, K.; Li, Z.; Li, L.; Hui, Y.; Xin, H. Structure-retained equivalent method for small signal stability analysis of wind farm. *Autom. Electr. Power Syst.* **2021**, *45*, 133–140.
20. Wang, D.; Jia, Q.; Hu, W.; Wang, J.; Liu, K.; Li, D. Aggregate modeling and analysis of subsynchronous resonance in DFIG group. *Renew. Energy Res.* **2021**, *39*, 1686–1692.
21. Zhang, Q.; Jin, X.; Zhang, F.; Yuan, H.; Zhou, B. Equivalent modeling and multi-parameter coupling optimization for DFIG-based wind farms considering SSO mode. *Front. Energy Res.* **2023**, *10*, 1–15.
22. Xu, Y.; Gao, T. Sub-synchronous frequency domain-equivalent modeling for wind farms based on rotor equivalent resistance characteristics. *Glob. Energy Interconnect.* **2022**, *5*, 293–300.
23. Han, P.; Wang, H.; Wang, X.; Cui, X.; Wu, J. Subsynchronous oscillation equivalence of doubly-fed wind farms based on index dimension reduction and collector system identification. *Proc. CSEE* **2022**, *42*, 8465–8474.
24. Wang, Y.; Du, T.; Liao, J.; Song, Y.; Zhu, L. Dynamic aggregation equivalence method for DFIG-based wind farm with maintained dominant oscillation mode. *Acta Energiae Sol. Sin.* **2024**, *45*, 518–529.
25. Zhou, P.; Li, G.; Sun, H.; Song, R.; Du, N. Equivalent modeling method of PMSG wind farm based on frequency domain impedance analysis. *Proc. CSEE* **2020**, *40*, 84–90.
26. Yuan, S.; Hao, Z.; Shu, J. Equivalent method of PMSG-based wind farm suitable for subsynchronous oscillation analysis. *Electr. Power Autom. Equip.* **2022**, *42*, 66–71.
27. Cui, X.; Wu, J.; Wang, X.; Xu, J.; Ye, S.; Xue, F.; Han, P. Equivalent modeling of direct drive wind farms for subsynchronous oscillation research. *Power Syst. Clean Energy* **2022**, *38*, 148–157.
28. Xue, T.; Lyu, J.; Wang, H.; Cai, X. A complete impedance model of a PMSG-based wind energy conversion system and its effect on the stability analysis of MMC-HVDC connected offshore wind farms. *IEEE Trans. Sustain. Energy* **2021**, *36*, 3449–3461.
29. NB/T 10651-2021; Technical Specification for Assessment of Impedance Characteristics of Wind Farm. National Energy Administration: Beijing, China, 2021.
30. NB/T 11344-2023; Technical Specification for Assessment of Impedance Characteristics of PV Power Station. National Energy Administration: Beijing, China, 2023.
31. Mao, J. K-Means Algorithm and Parallelization. Master Thesis, Chongqing University, Chongqing, China, 2003.
32. Shao, B.; Zhao, S.; Gao, B.; Yang, Y.; Blaabjerg, F. Adequacy of the single-generator equivalent model for stability analysis in wind farms with VSC-HVDC systems. *IEEE Trans. Energy Convers.* **2021**, *36*, 907–918.
33. Han, P.; Lin, Z.; Zhang, J.; Xia, Y.; Wang, L. Equivalent modeling of photovoltaic power plant based on factor analysis and correlation clustering. *IEEE Access* **2019**, *7*, 56935–56946.
34. Guo, C.; Gan, F.; Dy, D.; Guo, Y.; Cheng, H. Applicability evaluation of wind farm impedance models using different aggregation methods for high frequency oscillation analysis. *IEEE Trans. Power Deliv.* **2024**, *39*, 2231–2241.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.