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Aggregation Equivalence and Evaluation Method of Multiple Doubly-fed Wind Farms for Subsynchronous Oscillation Characteristics Analysis

Siqi Lyu[1,a], Huadong Sun[1,b,*], Ruihua Song[1,c], Yalou Li[1,d], Zutao Xiang[1,e], Bin Han[1,f], Bixing Ren[2,g], Peipeng Zhou[1,h]

[1]State Key Laboratory of Power Grid Safety (China Electric Power Research Institute), Beijing, 100192, China
[2]State Grid Jiangsu Electric Power Co., Ltd., Research Institute, Nanjing, Jiangsu Province, 210096, China
[a]lsqxinxi1101@163.com, [b]sunhdepri@126.com, [c]ssr1210@sohu.com, [d]liyalou@epri.sgcc.com.cn, [e]xzt@epri.sgcc.com.cn, [f]hanbin@epri.sgcc.com.cn, [g]renbixing@126.com, [h]zhoupeipeng@epri.sgcc.com.cn
[*]Corresponding author

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Abstract: The problem of subsynchronous oscillation (SSO) caused by large-scale wind farm integration seriously poses a threat to the safe and stable operation of high-proportion renewable energy power systems. To reduce the order of the system model and improve the simulation efficiency, this paper puts forward an aggregation equivalence and evaluation method of multiple doubly-fed wind farms for SSO characteristics analysis. Firstly, an aggregation equivalence method for multiple doubly-fed wind farms is proposed. The main influencing factors in the SSO analysis are taken as the clustering objects, and the simulated annealing (SA) algorithm and fuzzy c-means (FCM) clustering algorithm are combined to quickly obtain the wind farm clustering sets and equivalent model parameters. Secondly, the evaluation index of the wind farm equivalent models is proposed. The optimal equivalent scheme is selected by comparing the impedance characteristic curves of the equivalent model with that of the detailed model. Finally, taking the actual project as an example, the effectiveness of the proposed method for SSO characteristics analysis is verified.

1. Introduction

As the proportion of renewable energy power generation in the power system gradually increases [1], it brings about new changes to the stability characteristics of the power system [2]-[3]. Electromagnetic transient simulation is a fundamental approach for analyzing the stability issues of renewable energy grid-connected systems. When it comes to the simulation modeling of renewable energy stations, both precision and efficiency need to be taken into account, and equivalent processing is required. Common equivalent modeling methods include single-machine equivalence and multi-machine equivalence based on unit clustering. The equivalent methods for renewable energy stations, especially wind farms, have become one of the hot issues in related fields in recent years. However, even when the single-machine equivalent method [4]-[6] is adopted to establish a wind farm model, there may still be problems such as a large amount of calculation and low simulation efficiency due to an excessive number of power electronic models.

Currently, the research on the aggregation equivalence of doubly-fed wind farms mainly focuses on the units within the wind farms. However, few literatures have dealt with the aggregation equivalence of multiple doubly-fed wind farms. Based on the assumption that the linearized models of units within a wind farm are identical, Reference [4] proposed that a single-machine aggregation equivalence can be adopted for grid-connected wind farms and that the influence of the collection network can be neglected. Reference [5], on the basis of the single-machine equivalent aggregation model, applied the selective modal analysis method to equivalent the doubly-fed wind farm to a first-order model, effectively reducing the model order. Reference [6] took active power as the unit clustering index for analyzing the oscillation characteristics within the doubly-fed wind farm and recommended using the single-machine equivalent model to improve the simulation efficiency of SSO. Reference [7] put forward a power aggregation algorithm and defined a quantitative index for coherency discrimination based on the similarity in the oscillation modes among doubly-fed wind turbines. The above studies can provide certain references for the aggregation equivalence of multiple doubly-fed wind farms. However, Reference [8] pointed out that the impact of aggregation equivalence between stations on the subsynchronous modal characteristics is greater than that of aggregation equivalence within wind farms. Therefore, it is necessary to study how to conduct the aggregation equivalence of multiple doubly-fed wind farms without affecting the accuracy of SSO characteristics analysis, so as to further improve the simulation efficiency.

To solve this problem, this paper proposes an aggregation equivalence and evaluation method of multiple doubly-fed wind farms for SSO characteristics analysis. The main contributions are as follows:

1) The proportional gain and the integral time constan of the inner loop on the rotor side, and the line equivalent inductance are selected as the clustering objects. The simulated annealing (SA) algorithm and the fuzzy C-means (FCM) clustering algorithm are combined to conduct clustering for multiple doubly-fed wind farms. In this way, the equivalent model parameters corresponding to each clustering set and clustering center can be quickly determined, and then the equivalent model can be obtained.

2) A comprehensive evaluation index based on numerical evaluation and correlation evaluation is proposed, which comprehensively considers the overall error level and numerical similarity between the equivalent model of the wind farm and the detailed model, and provides a theoretical basis for the selection of the optimal equivalent scheme.

3) The established equivalent model takes into account both the analysis accuracy and the simulation efficiency, and the effectiveness of the proposed method is verified by an actual project.

The rest of this paper is organized as follows: Section 2 proposes an aggregation equivalence method for multiple doubly-fed wind farms; Section 3 presents the evaluation index of wind farm equivalent model; Section 4 verifies the rationality of the proposed method for SSO characteristics analysis using an actual project. Section 5 concludes the paper.

2. Aggregation Equivalent Method of Multiple Doubly-fed Wind Farms

2.1. Clustering objects

The modeling process of a single doubly-fed wind farm has been studied in detail in Reference

[9], and thus will not be reiterated in this paper. The difference between the aggregation equivalence of multiple wind farms and that of a single wind farm lies in the differences in unit parameters among wind farms and in the electrical distances between wind farms and substations of the power grid. Since the typical transmission structure of wind farms is that several stations are connected to the same collection station via lines with lengths ranging from several kilometers to hundreds of kilometers and then are connected to the power grid, this paper adopts the collection station as the fundamental unit to conduct the aggregation equivalence of multiple doubly-fed wind farms.

Regarding the dominant factors of the SSO characteristics for the doubly-fed wind farms connected to the grid, Reference [10] analyzed the sensitivity of doubly-fed induction generator (DFIG) parameters to wind turbine impedance, and the main influencing factors, namely K_{pr} and T_{ir} of the rotor-side converter (RSC), are considered. In addition, considering that the line equivalent inductance L_{Line} of the wind farm includes the step-up leakage inductance of the wind farm and the line inductance leading to the collection station, and given that the step-up leakage inductance of the wind farm is generally larger than the line inductance, L_{Line} can effectively reflect the electrical distance between the DFIG and the collection station.

In summary, this paper selects K_{pr}, T_{ir}, and L_{Line} as the clustering objects for multiple doubly-fed wind farms.

2.2. Clustering of Multiple Doubly-fed Wind Farms

FCM clustering algorithm is a widely used clustering algorithm, but sometimes it may converge to a local minimum and fail to obtain the global optimal solution. By establishing the objective function of the SA algorithm based on the FCM clustering algorithm, the global optimal solution can be quickly found and better clustering results can be achieved [11]. Therefore, the SA-FCM clustering algorithm is adopted to conduct clustering for multiple doubly-fed wind farms.

Let the data sample set be X={x_i (i=1,2,...,n)}, the clustering center set be V={v_k (k=1,2,...,c)}, and the corresponding clustering set be A={A_k (k=1,2,...,c)}. The fuzzy membership degree u_{ik} of sample x_i to class A_k and the clustering center v_k are as follows:

$$u_{ik} = \sum_{j=1}^{c} \left(d_{ik} / d_{jk} \right)^{-2/(b-1)} \tag{1}$$

$$v_k = \sum_{i=1}^{n} (u_{ik})^b x_i \Big/ \sum_{i=1}^{n} (u_{ik})^b \tag{2}$$

where d_{ik} represents the Euclidean distance, which is used to measure the distance between sample x_i and clustering center v_k; b is the fuzzy weighting index, and b≥1.

The FCM clustering method is utilized to determine the optimal clustering mode U, so that this clustering mode can generate the minimum value of the objective function J_b, which can be expressed as

$$J_b(U,V) = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^b d_{ik}^2 \tag{3}$$

where U=[u_{ik}] represents the fuzzy membership matrix; the smaller the value of J_b, the higher the fitness f of the data samples, which indicates a better clustering result. We can take f=1/J_b.

For the three-dimensional data sample set {($K_{pr,i}$, $T_{ir,i}$, $L_{Line,i}$)} composed of the clustering objects of each doubly-fed wind farm under the same collection station, the equivalent model of multiple doubly-fed wind farms can be established through the SA-FCM clustering algorithm. The steps of the method are as follows:

Step 1: Initialize the parameters, including the number of doubly-fed wind farms, the maximum number of evolutionary iterations, the crossover probability, the mutation probability, the initial annealing temperature, the temperature cooling coefficient, and the termination temperature T_{end}.

Step 2: Randomly initialize c clustering centers $\{(K_{pr,k}, T_{ir,k}, L_{Line,k})\}$, and calculate the fitness f of the data samples and the fuzzy membership degree to the clustering centers.

Step 3: Perform genetic operations such as selection, crossover, and mutation on the data samples [12], and calculate the fitness f' of the modified data samples and the fuzzy membership degrees to the newly generated clustering centers. If $f'>f$, replace the old clustering centers with the new ones; otherwise, accept the new clustering centers and discard the old ones based on the current temperature T with a probability $P = \exp((f - f')/T)$.

Step 4: Loop through Step 3 until the maximum number of evolutionary iterations M is attained. If $T<T_{end}$, then end the calculation and return the global optimal solution, specifically, the clustering centers and the corresponding clustering sets. Otherwise, we perform the temperature reduction operation $T' = kT$ and return to Step 3.

Step 5: We establish the equivalent model of the doubly-fed wind farms for each clustering set. The capacity of the equivalent model is the sum of the capacities of all wind farms in the clustering set. The parameters of K_{pr}, T_{ir}, and L_{Line} take the corresponding coordinate values of the clustering centers, and other parameters take the typical values under the same capacity.

3. Evaluation Index of Wind Farm Equivalent Model

The accuracy of the impedance amplitude and phase angle data of the doubly-fed wind farm equivalent model is evaluated from two aspects to select the optimal equivalence scheme, including numerical evaluation and correlation evaluation.

3.1. Numerical Evaluation Index

The data sequences of the impedance characteristic curves before and after the equivalence of the wind farm are respectively represented by $\{y_m\ (m=1, 2,\ldots,p)\}$ and $\{y'_m\ (m=1, 2,\ldots,p)\}$. The residual similarity φ is adopted as the numerical evaluation index to reflect the overall error level of the impedance characteristic curve after equivalence compared with that before equivalence [12], which is defined as follows:

$$\varphi = \left(\sum_{m=1}^{p} \gamma_m z_m \right) \times 100\% \tag{4}$$

where

$$\gamma_m = |y_m| \Big/ \sum_{m=1}^{p} |y_m| \tag{5}$$

$$z_m = 1 - |y_m - y'_m| / \max(|y_m|, |y'_m|) \tag{6}$$

Here, γ_m represents the weight of the m-th data point, that is, the ratio of the amplitude of the m-th data point to the sum of the amplitudes of all data points; z_m represents the similarity of the m-th data point.

3.2. Correlation Evaluation Index

The Theil inequality coefficient λ [13] is adopted as the correlation evaluation index to measure the similarity between the impedance characteristic curves before and after equivalence. The larger the value of λ is, the closer the impedance characteristics of the wind farm models before and after equivalence are. When λ is equal to 100%, it indicates that the impedance characteristics of the equivalent wind farm model are completely consistent with those of the detailed model. λ can be expressed as:

$$\lambda = \left(1 - \sqrt{\sum_{m=1}^{p} \left(y_m - y'_m \right)^2} \middle/ \sqrt{\sum_{m=1}^{p} y_m^2} + \sqrt{\sum_{m=1}^{p} y'^2_m} \right) \times 100\% \tag{7}$$

3.3. Comprehensive Evaluation Index

The comprehensive evaluation index D takes into account both numerical evaluation and correlation evaluation to characterize the accuracy of the impedance characteristic curve of the wind farm equivalent model, where:

$$D = \alpha\varphi + \left(1 - \alpha\right)\lambda \tag{8}$$

Here, α represents the weight coefficient.

For each clustering set, there will be a pair of D_a and D_b that respectively characterize the numerical accuracy of the impedance amplitude and phase angle. Therefore, the minimum value of the product of all clustering sets' D_{ak} and D_{bk} (k=1, 2,..., c) is taken as the comprehensive evaluation index F_k of the wind farm equivalent model under the scheme. For different numbers of cluster centers c, the clustering scheme and the corresponding F_k are different. The equivalent scheme with $F_k \geq 90\%$ and the smallest c is selected as the optimal equivalent scheme. F_k can be expressed as:

$$F_k = \min\left(D_{ak} \cdot D_{bk}\right) \tag{9}$$

4. Case Analysis

Figure 1 presents the schematic diagram of a large-scale wind power integration system. Specifically, seven doubly-fed wind farms are connected to Collection Station 1, three to Collection Station 2, and four to Collection Station 3.

For the groups of doubly-fed wind farms under each collection station, the clustering of multiple doubly-fed wind farms based on the SA-FCM algorithm is carried out respectively. For different numbers of clustering centers c, different equivalent schemes can be obtained, and then the equivalent models of doubly-fed wind farms under each equivalent scheme are established. Taking Collection Station 1 as an example, the clustering results of c=3 are depicted in Figure 2, where the symbol '○' represents the wind farms to be clustered, the symbol '▽' indicates the clustering centers, and the symbol '*' in different colors represent different clustering sets. It can be observed that the seven wind farms under Collection Station 1 are clustered into three sets {1, 6, 7}, {2,4} and {3,5}.

For different equivalent schemes, the comprehensive evaluation index F_k is adopted to evaluate the accuracy of the impedance characteristic curves of the wind farm equivalent models to select the optimal equivalent scheme. Here, α is set as 0.5. The calculated results of F_k for the three collection stations under different numbers of cluster centers c are presented in Table 1. The larger the value of c is, the closer F_k is to 100%. The scheme with $F_k \geq 90\%$ and the smallest c under each collection station is selected as the optimal equivalent scheme. That is to say, the optimal numbers of clustering centers for the three collection stations are 3, 1 and 2 respectively, and the corresponding clustering sets are {1,6,7}, {2,4}, {3,5}, {8,9,10}, {11} and {12,13,14}. Under this optimal equivalent scheme, the comparison results of the overall impedance characteristic curves of the wind farms connected to the power grid are presented in Figure 3. The impedance characteristic curves before and after equivalence are relatively close in the subsynchronous frequency band, indicating that the method proposed in this paper can be used for the reduced-order calculation for SSO characteristics analysis, improving the simulation efficiency while ensuring the calculation accuracy.

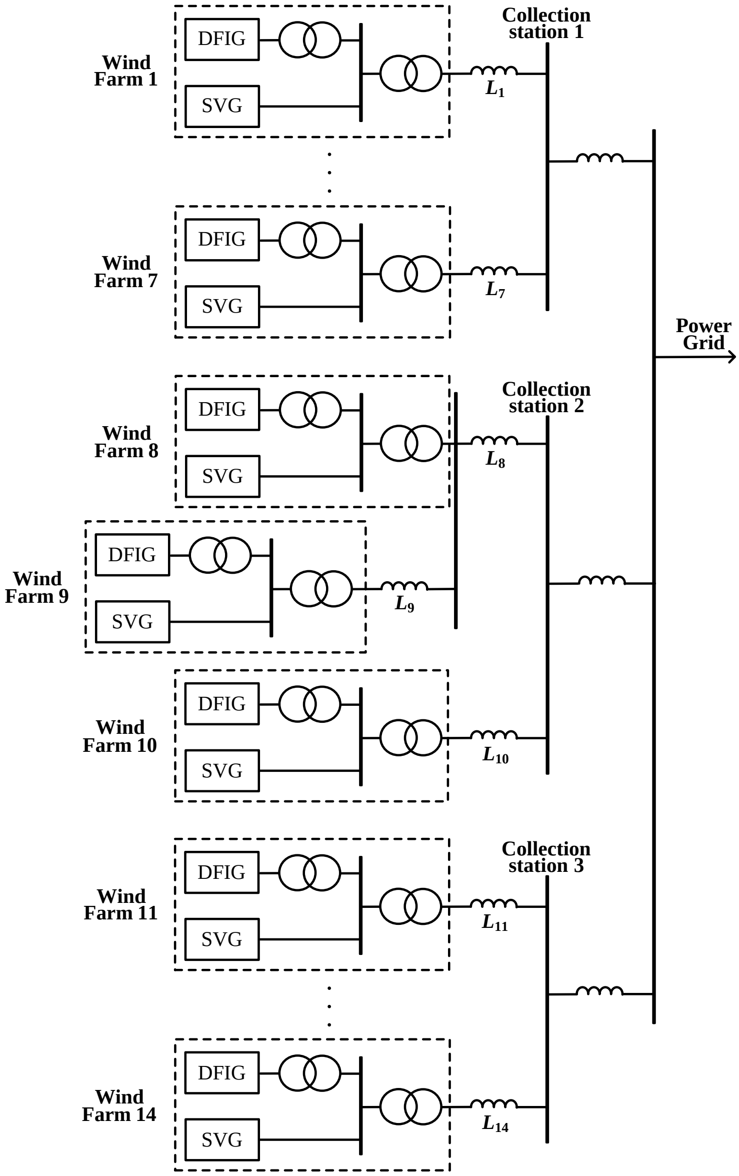

Figure 1: Schematic diagram of large-scale wind power integration system.

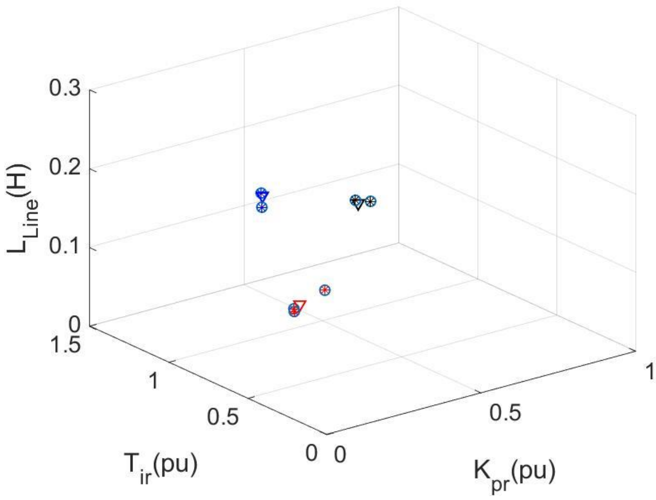

Figure 2: Clustering results of multiple doubly-fed wind farms under Collection Station 1.

Table 1: Calculation results of comprehensive evaluation index under different number of clustering centers.

c	Collection Station 1	Collection Station 2	Collection Station 3
1	70.9%	90.2%	86.8%
2	81.4%	94.3%	92.6%
3	90.5%	100%	96.4%
4	92.7%	—	100%
5	95.1%	—	—
6	97.9%	—	—
7	100%	—	—

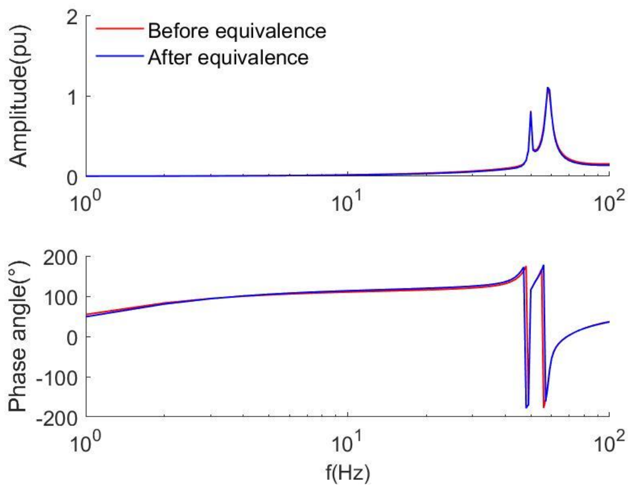

Figure 3: Comparison results of impedance characteristic curves of the wind farms connected to the power grid.

5. Conclusions

This paper proposes an aggregation equivalence and evaluation method of multiple doubly-fed wind farms for SSO characteristics analysis. The multiple doubly-fed wind farm aggregation equivalence method based on the SA-FCM clustering algorithm takes the main influencing factors for SSO characteristics analysis as the clustering objects and quickly determines the equivalent model parameters corresponding to each clustering set and clustering center. The comprehensive evaluation index of the wind farm equivalent model combining numerical evaluation and correlation evaluation is used to determine the optimal equivalent scheme by evaluating the accuracy of the impedance amplitude and phase angle of the wind farm equivalent model compared with those before equivalence. The effectiveness of the method has been verified by practical engineering cases. The method can also be applied to different types of wind farms or scenarios with lower renewable energy penetration rates. In the future, the applicability of the method for supersynchronous and medium-to-high frequency oscillation characteristics analysis will be further evaluated.

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