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RESEARCH ARTICLE

Wind Turbine Clustering and Equivalent Parameter Identification in Multitime Scales Based on the Deep Migration of Multiview Features

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ABSTRACT To improve the precision of wind farm multi-machine equivalence and multi-scene generalization, this paper proposes a method for wind turbine clustering and equivalent parameter identification in multi-time scales based on the deep migration of multi-view features. The proposed technique carries out multi-machine equivalence by leveraging the multi-view information from each turbine in a wind farm. Specifically, a deep spatio-temporal Improved Auto-Encoder is designed, jointly trained with the target clustering layer. IAE is used for mining multi-view latent characteristics of wind turbines orienting to grouping turbines to improve the model's adaptability to multiple scenarios and divide turbines in an unsupervised manner. This method generates a visual heat map to represent the attended area of characteristics based on transfer learning and Class Activation Map to enable interpretability. In the next phase, this technique constructs a multi-objective optimization model by synthesizing the equivalent deviation of voltage, current, active power, and reactive power to further improve accuracy. It can identify the equivalent parameters of collector lines, the mechanical structure, and the control system at different time scales simultaneously via the black-box paralleled optimization method based on Bayes and Multi-arm Bandit. The proposed approach is evaluated on a typical double-fed wind farm with grid-side faults under various conditions of disturbing winds. Also, an ablation study is conducted to make analysis according to the two phases, i.e., turbine division and parameter identification. The results validate the accuracy and robustness of this method.

INDEX TERMS Big data, wind farm multi-machine equivalence, multi-view characteristics mining, joint training, deep spatio-temporal Improved Auto-Encoder, transfer learning, multi-objective and multi-time scale parameter identification.

NOMENCLATURE

IAE	Improved Auto-Encoder.
CAM	Class Activation Map.
DFIG	Doubly Fed Induction Generator.
PSO	Particle Swarm Optimization.
MRAS	Model Reference Adaptive System.
WSCM	Wind Speed Combination Model.
LVRT	Low Voltage Ride Through.
GCI	Generator Coherency Identification.
SH	Successive Halving.
TPE	Tree-structured Parzen Estimator.

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I. INTRODUCTION

Under the double pressure of environmental protection crisis and energy exhaustion, the renewable energy industry has developed rapidly and the scale of grid connection has been expanding. With the gradual increase of renewable energy permeability, the uncertainty and fluctuation of its output bring great influence on the safe and stable operation of power system. With the proposal of carbon peaking and carbon neutrality goals, the scales of wind farms are gradually increasing [1]. The scene of operation in wind farms has randomness and volatility contained with power electronic component, they are also sensitive to overvoltage and overcurrent with low inertia [2], and the law of operations and dynamic characteristics have a huge influence on the stability of electric power system after the combination of power grid [3], thus it is necessary and pressing to construct a model that accurately describes the actual operation characteristics [4], [5].

The stability of electric power system is divided into angle stability, voltage stability, and frequency stability, the time scale of relevant issues is millisecond to second [3]. Take the common DFIG as an example, due to the wide discrepancy in time constants of various components, its step response in the time scale includes microsecond power electronic dynamic state, millisecond electrical dynamic state, second level mechanical, and electrical dynamic state, mechanical dynamics of more than second and minute wind speed volatility etc. Reference [4], which endues it a strong nonlinearity on the time axis, thus DFIG is a multi-time scale dynamic system [6], moreover, dozens or even hundreds of DFIG constitute the wind farms in series and parallel by collector lines and link to external power grid, a number of time-window periods contained in the transient process of wind power high permeability power system are caused by the mutual coupling of multiple time scales in wind power system and power system. If the control system and collector lines of each turbine in a wind farm are modeled detailly, firstly, it has a complex structure and high dimensional data [7], while the capacity of it is generally much smaller than thermal power turbines, which not only increases the scale and time of real-time simulation analysis, but also brings severe challenges to its effectiveness and accuracy; Secondly, with the continuous promotion of power market reform, the whole machine suppliers are unable to provide the detailed internal structure of the grid-connected converter due to commercial confidentiality and other practical reasons, the control loop model, and the accurate parameters of other parts, making the wind power system information opaque; Thirdly, wind farms influence the dynamic behavior of power system through boundary nodes, it is necessary to pay attention to the variables of boundary nodes before and after equivalence, that is, the external characteristics at the points connected to the grid. Therefore, how to establish wind farm equivalent model with consideration of calculation accuracy and speed plays an important role in the security and stability analysis of wind power high-permeability new power system [8].

The precision of single-machine equivalence in large wind farms is usually difficult to meet the requirements [9], [10], [11], and multi-machine equivalence is required. Since the operating conditions of wind turbines are time-varying and different, how to classify wind turbines reasonably and effectively is the primary problem to solve. Therefore, the multi-machine equivalence problem of wind farms is decomposed into three steps: 1) Select the clustering index of the wind turbines; 2) Clustering wind turbines division; 3) Identify the equivalent parameters of the clustering wind turbines.

For step 1), [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22] selected the clustering index of the wind turbines. Reference [12] take wind speed similarity as a clustering index based on grouping turbines working areas. On this basis, [13] and [14] proposed a practical four-turbine equivalence method. Reference [15] also adopted the above method, and if there is a large voltage difference when DFIG working in the same area, it will cause obvious equivalent error due to different prying bar protection actions; [16], [17] regard rotor speed and pitch angle at fixed time as clustering indexes; [18], [19] takes the action of pitch angle controller and pry bar protection as a clustering principle; [20] and [21] chose multidimensional state variables as the clustering index; [22] classifies the wind conditions according to the most common wind conditions throughout the year. Therefore, the turbines clustering index should be more comprehensive and efficient in mining the operation characteristics of wind farms from a multi-temporal perspective.

For step 2), [20], [21], [22], [23], [24], [25], [26], [27], [28] divided wind turbine clusters. References [20] and [23] used clustering algorithms to divide wind turbine clusters, such as fuzzy C-means clustering and k-means clustering, among which k-means is widely used. Reference [24] improved k-means based on the sensitive initial center. References [25], [26], and [27] proposed a multi-stage clustering method, firstly, the wind turbines with similar operating status are divided into a group, and then further grouped by finer clustering index or optimization algorithm. Reference [28] provided an example for the application of advanced artificial intelligence ideas in wind turbine clustering based on transfer learning clustering, considering the operation characteristics and adaptability to multiple conditions theoretically, but in the numerical example, it shows only the migration from 16-turbine wind farms to 16-turbine wind farms, the principle of distribution similarity between source domain and target domain in transfer learning is blurred, therefore, the method proposed cannot achieve the knowledge migration in wind farms of different scales, and the clustering center of the source domain and degree of membership can be calculated directly, there is no need for knowledge transfer essentially, in the clustering of target domain, these two parameters are changed greatly, and the calculation results of source domain have little reference value. Therefore, it is necessary to design an efficient clustering algorithm combined with the characteristics of practical problems and advanced artificial intelligence.

For step 3), [29], [30], [31], [32] identified the equivalent parameters of the clustering wind turbines. References [29] and [30] used an effective wind power parameter identification framework which is generally based on (PSO) at the present stage, [29] took different wind speeds as excitation and identified equivalent wind turbine parameters through PSO, which is not accurate in the case of large power fluctuations, [30] comprehensively described the importance of wind power parameter identification for system security and stability, and demonstrated the superiority of PSO by comparing it with recursive least square method, however, parameter identification based on PSO can easily fall into local optimum. In addition, wind power parameter identification can also adopt Kalman filter [31], reference model self-adaptation [32], etc. Reference [32] investigated two different online parameter identification methods for doubly fed induction generators (DFIG). A model reference adaptive system (MRAS) and a new approach for estimation of the inductances are introduced. Lyapunov stability theory is applied to the adaptive law of the MRAS method. This method requires a test signal which excites all systems eigenvalues. Therefore, stator and rotor have to be excited by a test signal. However, not all eigenvalues are excited if the stator of the DFIG is directly connected to the grid.

Reference [33] has proposed a wind farm dynamic equivalence modeling framework that integrates analytical methods and identification methods, but its algorithm has poor accuracy and low efficiency, which cannot meet the actual engineering requirements. In [33], The acquisition of accurate parameter is one of the difficult problems in wind farm multi-machine equivalence. Based on the analytical method, the estimated value of each equal value parameter is obtained, which is taken as the initial value, and then the parameter is identified based on the actual disturbed trajectory. The parameter identification is carried out based on particle swarm optimization algorithm, and the parameter identification error is analyzed. Therefore, a more accurate and efficient method is needed to identify the equivalent parameters of wind turbine clusters.

By taking advantage of the slow-varying characteristics of the low-frequency components, accurate forecast of these components is readily obtained and incorporated into the developed dispatch planning procedure. The dispatchability of the wide-area wind generation is facilitated by the buffering actions offered by a centralized power dispatch energy storage system, operating under a proposed power flows control strategy. A wind speed combination model (WSCM) is established via K-means clustering from the sorted field-measured wind speed data, which can provide reasonable wind speeds for each WTG when aggregate modeling the wind farm. Subsequently, an improved two-step clustering method of the WTGs is proposed, by which the WTGs are initially clustered according to whether they enter low voltage ride through (LVRT) mode or not. An ''N-1 VS One'' aggregated model and the binary search algorithm were used to quickly and correctly predict whether a WTG in the wind farm enters LVRT mode under a grid fault.

To solve the above problems, this paper proposes an interpretable, unsupervised method for clustering wind turbines based on potential features from multiple perspectives, and carries out robust identification of multi-target black box with equivalent parameters, finally, data-driven wind farm multi-machine equivalence is achieved. Compared with traditional methods, three innovations are summarized as follows:

a) Define the index of fleet division at multi-view level: deep temporal and spatial IAE is trained layer by layer to capture the long-time dependence, short distance fluctuation and spatial correlation of active power, reactive power, terminal voltage, current, and rotor angular velocity, high-nonlinear mapping automatically embedded sequential data into low-dimensional space [34], data can retain effective information to the maximum extent while reducing dimension, which has high fitting accuracy and strong generalization ability [35]; The cite of joint training mechanism [36] is more conducive to obtain potential dimensions that express the segmentation of sequential unmarked data into multiple categories. This point has been stated in the third chapter.
b) Divide wind turbine clusters under unsupervised conditions: KL divergence is introduced and its gradient descent direction in k-means [37] is calculated, which does not rely on engineering prior knowledge and not require offline labeling data or manual determination of the number of turbines; Based on CAM and transfer learning knowledge, heat maps are generated which represent the attended area of wind turbine features from multiple perspectives, and they eliminate the ''black box'' nature of deep learning model and improve reliability. This point has also been stated in the third chapter.
c) Equivalent parameters of global search swarms: Calculate the initial equivalent parameters value of wind turbine according to physical properties, combine the Hyperband [38] parallel resource allocation method based on Multi-arm Bandit and the kernel density estimation modeling method in Bayesian optimization [39], build the BOHB black box parallel optimization framework, and identify the equivalent parameters of wind turbine clusters in different time scales. The proposed method is not only applicable to the equivalence of any wind turbine cluster in the multi-machine equivalence of wind farm, but also applicable to the equivalence of single wind farm. This point has been stated in the second chapter.

In the first chapter of this paper, a method of two-step equivalent parameter identification for wind turbine cluster is proposed; The second chapter transplants a method of GCI to divide the wind turbine cluster, it includes the selection of CID index and the division of wind turbine cluster, finally, the multi-machine equivalent step of wind farm is formed; The third chapter designs a ablation experiment, the effectiveness of this method is verified by using a doubly-fed wind farm in an area.

II. IDENTIFICATION OF EQUIVALENT PARAMETERS OF DOUBLY-FED WIND TURBINE CLUSTER

According to [9], the initial parameters are calculated first. After the grouping turbines in a doubly-fed wind farm are divided into multiple clusters, it is necessary to equate each grouping turbine to a single turbine and identify their equivalent parameters, the equivalent parameters of the turbine cluster system can be divided into operation parameters, structure parameters, and control parameters. Operating parameters include wind speed v, grouping turbine apparent power S_G, apparent power of terminal transformer S_T; Structural parameters include collector wire impedance Z_L, generator impedance Z_G, terminal transformer impedance Z_T, time constant of generator inertia H_g, time constant of inertia of wind turbine H_w, damping coefficient of shafting Ds, stiffness coefficient of shafting K_s; Control parameters include rotor-side speed regulator gain K_{p1} and $\mathrm{K}_{\mathrm{i}1}$, i parameter of the current regulator gain of the rotor-side converter K_{i2}, i parameter of the grid side voltage regulator gain K_{i3}, p parameter of the DC capacitor voltage regulator gain on the grid side K_{pdg}, p parameter of the current regulator gain of the grid side converter K_{pg}.

In this paper, the equivalent parameter identification of doubly-fed wind turbine cluster is divided into two steps, i.e., the calculation of the initial equivalent parameter of the grouping turbines and the optimization of the equivalent parameter.

A. CALCULATION OF INITIAL EQUIVALENT PARAMETERS OF WIND TURBINE CLUSTER

The parameters of generator, transformer, and shafting of equivalent sets are calculated by capacity weighting method; The equivalent wind speed is calculated based on the principle that the total input wind energy of each wind turbine cluster is equal before and after the equivalent wind speed; According to the equal power loss method, the trunk topology is converted to the radial topology, and then the equivalent parameters of the collector system are calculated; The control parameters are the original wind turbine parameters.

1) EQUIVALENT PARAMETERS OF GENERATOR AND TERMINAL TRANSFORMER

$$\begin{cases} S_{Geq} = \sum_{h=1}^{f} S_{Gh} \\ S_{Teq} = \sum_{h=1}^{f} S_{Th} \\ Z_{Geq} = \dfrac{Z_{Gh}}{f} \\ Z_{Teq} = \dfrac{Z_{Th}}{f} \end{cases} \tag{1}$$

In this equation, S_{Geq}, S_{Teq}, Z_{Geq}, and Z_{Teq} are the apparent power of the equivalent turbines, the apparent power of the terminal transformer, the impedance of the generator and the impedance of the machine end transformer; S_{Th} and Z_{Th} are the apparent power of terminal transformer of wind turbine h and the impedance of terminal transformer; f is the number of wind turbines included in equivalent turbines.

2) EQUIVALENT PARAMETERS OF SHAFTING

$$\begin{cases} H_{teq} = \sum_{h=1}^{f} H_{th} \\ H_{geq} = \sum_{h=1}^{f} H_{gh} \\ K_{eq} = \sum_{h=1}^{f} K_h \\ D_{eq} = \sum_{h=1}^{f} D_h \end{cases} \tag{2}$$

In this equation, H_{teq}, H_{geq}, K_{eq}, and D_{eq} are the inertial time constant, inertial time constant of generator rotor, shafting stiffness coefficient and shafting damping coefficient of equivalent turbines; H_{th}, H_{gh}, K_h, and D_h are the inertia time constant of wind turbine h, the inertia time constant of generator rotor, the stiffness coefficient of shafting and the damping coefficient of shafting.

3) EQUIVALENT PARAMETER OF WIND SPEED

$$\begin{cases} v_{eq} = \left(\dfrac{1}{Ac_{peq}} \sum_{h=1}^{f} A_h c_{ph} v_h^3 \right)^{\frac{1}{3}} \\ A = \sum_{h=1}^{f} A_h \\ c_{peq} = \dfrac{1}{f} \sum_{h=1}^{f} c_{ph} \end{cases} \tag{3}$$

In this equation, v_{eq}, A, and c_{peq} are the input wind speed, wind turbine sweeping area and wind energy utilization coefficient of equivalent wind turbine cluster; v_h, A_h, c_{ph} are the input wind speed, sweep area, and wind energy utilization coefficient of wind turbine h.

4) EQUIVALENT PARAMETERS OF THE COLLECTOR SYSTEM

There are two main topologies of collecting lines in wind farms: a) Radial topology; b) Trunk line topology. Each wind generator unit of radial topology is connected to PCC point through the line, the equivalent impedance of the collector system with this topology can be calculated directly by the equal power loss method. In the trunk topology, they are connected to the PCC point through the line except for the wind turbines in the first section, other wind turbines are connected to the end of the previous wind turbine through the line, the collector system of this topology is converted into a radial topology first, then the equivalent impedance is calculated by the method of equal power loss, the specific steps are as follows:

a) The equivalent impedance of each wind turbine on the main line is calculated by using the equal power loss method, then transformed into radial topology connection.

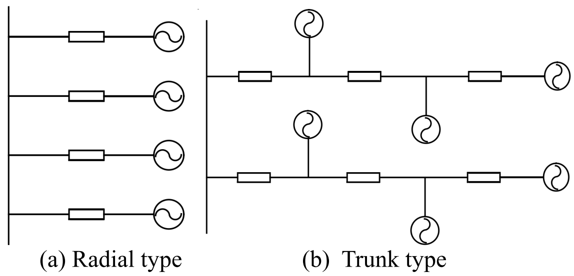

FIGURE 1. **Topology of wind farm collector lines.**

As shown in Fig. 1, there are n wind turbines on PCC point, which are connected by trunk topology, after being conversed into radial topology connection, the equivalent impedance of each wind turbine is calculated according to the following equation:

$$Z_{eqn} = \sum_{i=1}^{n} \frac{(P_1 + P_2 + \ldots + P_i)^2}{P_1^2 + P_2^2 + \ldots + P_i^2} Z_i \tag{4}$$

In this equation, n means any one wind turbine; Z_i is the line impedance at the exit of the ith wind turbine; Z_{eqn} represents the equivalent line impedance of wind turbine branch n.

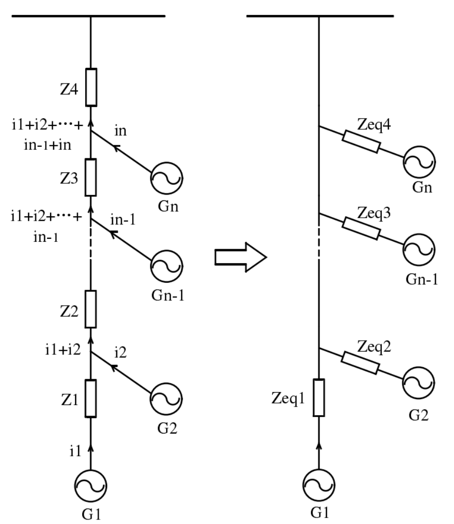

FIGURE 2. **Convert trunk topology to radial topology.**

b) According to the clustering results, the total equivalent impedance is calculated by using equal power loss method for all the wind turbines in each cluster, which is the equivalent impedance of the equal-value collector system. Assuming that wind turbine cluster 1 in the clustering result contains m turbines, and renumber them from 1 to m, the equivalent impedance of wind turbine cluster 1 is

$$Z_{eq} = \frac{\sum_{i=1}^{m} (P_i^2 Z_i)}{(P_1 + P_2 + \ldots + P_m)^2} \tag{5}$$

In this equation, Z_i represents the impedance on the branch of wind turbine i; P_i represents the power flowing through impedance Z_i; Z_{eq} represents the equivalent impedance of wind turbines 1.

The calculation method of equivalent impedance is based on the principle of equal losses before and after equivalence in collector networks, in the multi-machine equivalence modeling of wind farm, generally speaking, complex network transformation is needed to change the series-parallel hybrid topology into a pure-parallel network, then calculate the corresponding equivalent impedance if any wind turbine is aggregated into an equivalent wind turbine according to the principle of equal loss before and after equivalence, the calculation is complicated, and when there are many wind turbines in the wind farm, the error will also be large due to the approximation in the calculation process.

B. OPTIMIZATION OF EQUIVALENT PARAMETERS OF WIND TURBINE CLUSTER

The objective of wind turbine parameter identification is to find the parameters to be identified under the observed quantity, the errors between the disturbed trajectory and the measured trajectory based on this parameter can be minimized, its essence is an optimization problem, the steps of equivalent parameter optimization method for the wind turbine cluster designed in this paper are as follows:

1) The equivalent precisions of active power, reactive power, voltage, and current at the point connected to the grid of wind farm are selected to construct the objective function:

$$\min F(y) = \min_{y} \{f_P(y), f_Q(y), f_U(y), f_I(y)\} \tag{6}$$

In engineering applications, the effect of equivalent errors on power grid is not only evaluated by its value, therefore, the relative deviation value is used to represent the equivalent errors, the equation is as follows:

$$\begin{cases} f_P(y) = \dfrac{1}{M}\sqrt{\sum_{m=1}^{M}\left[\dfrac{\Delta P_{PCC}(m)}{P_b}\right]^2} \\ f_Q(y) = \dfrac{1}{M}\sqrt{\sum_{m=1}^{M}\left[\dfrac{\Delta Q_{PCC}(m)}{Q_b}\right]^2} \\ f_U(y) = \dfrac{1}{M}\sqrt{\sum_{m=1}^{M}\left[\dfrac{\Delta U_{PCC}(m)}{U_b}\right]^2} \\ f_I(y) = \dfrac{1}{M}\sqrt{\sum_{m=1}^{M}\left[\dfrac{\Delta I_{PCC}(m)}{I_b}\right]^2} \end{cases} \tag{7}$$

2) Determine the parameter y to be optimized, wind turbine cluster equivalent control parameters, structural parameters

in the length of the collector lines, and mechanical structure parameter (Generator inertia time constant H_g, Wind turbine inertia time constant H_w, damping coefficient of shafting D_s, Stiffness coefficient of shafting K_s) are included. Increase and decrease by 100% respectively based on the initial parameters, and take it as an optimization interval. The dynamic response is affected by the variation of parameters of the drive system and the doubly-fed induction generator, so the calculation of the objective function and response curve is dynamic, if there is a deviation within responses, it means the parameters are changed, they need to be adjusted dynamically, and minimizing objective function.

3) Aiming at the optimization problem of the parameters, a BOHB black box parallel optimization framework is established.

a) First, define the threshold b_{min}, b_{max}, and discard factor η for each parameter combination allocation of resources (number of iterations, amount of data, execution time, cache, etc.) by referring to Hyperband. Among them, η is greater than 1, the proportion of parameter combinations with large equivalent errors abandoned by SH strategy is $1/\eta$ in each round.

Define $s \in \{S_{max}, S_{max} - 1, \ldots, 0\}$, S_{max} is defined as $\lfloor \log_\eta (b_{max}/\, b_{min}) \rfloor$, a large number of experiments show that when η is set to 3 or 4, the effect has a better control, S_{max} is negatively correlated with η, the initial total resources are:

$$B = \eta^{-s} \cdot b_{\max} \tag{8}$$

b) Then, divide each s into a subset, different subsets of s use different threads to perform the following tasks, n parameter combinations were sampled from the parameter space based on Bayesian modeling method, where, $n = \lceil (S_{max} + 1)/(s+1)^* \eta^s \rceil$.

Assuming that the sample satisfies the Gaussian distribution with kernel function, at the beginning, $N_{min}+2$ parameter combinations are randomly selected (N_{min} is usually set to $d+1$, and d is the number of parameters), supposing the sample set is D $=\{(x_i, y_i)\}$, x_i is the parameter combination and y_i is the parameter optimization result under specified resources, then find the extremum point of the expectation of sampling function x_{i+1}.

Firstly, the TPE is used to fit the two density distributions with small and large equivalent errors respectively, i.e., $N_{b,l} = \max(N_{min}, qN_b)$ and $N_{b,g} = \max(N_{min}, N_b - N_{b,l})$. $N_b = \mid D_b \mid$, D_b are the set of observation points corresponding to budget b. the estimated probability density of the sample points of the parameter combination is:

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n} K\frac{x - x_i}{h} \tag{9}$$

In this equation, $K_h(x) = h^{-1}K(x/h)$ is a scaling kernel function; K is a kernel function (nonnegative, the integral in the real number field is 1, and the mean value is 0); The bandwidth h determined by minimizing the mean integral error is a non-negative smoothing parameter.

When $b = \operatorname{argmax}\{D_b{:}\mid D_b \mid \geq N_{min} + 2\}$, return to randomly generated combination of arguments, otherwise, go into exploitation; Define a probability density $l_{(x)}$, which can accelerate convergence in large scale problems (multiply the bandwidth of the density formed by the combination of parameters with an equivalent error less than the threshold by a factor to encourage more exploration around the known point), N_s parameter sample combinations are sampled from it, updated sample x returns the parameter combination that maximizes $l_{(x)}/g_{(x)}$ ($g_{(x)}$ is the density formed by the combination of parameters so that the equivalent error is more than the threshold), the mean and variance of Gaussian distribution with kernel function are updated until n parameter combinations are collected near x_{i+1}.

c) Lastly, according to the number of threads, n parameter sets are divided into subsets which contain the same number of parameter combinations for parallel calculation, the parameter combinations of $1/\eta$ ratio are eliminated under a given resource every time, therefore, the rest of the parameter combinations are available for more resources until the b_{max} resource is available for each parameter combination, comparing the optimal combination of parameters for each subset to obtain a global optimal solution of parameter combination.

4) The predicted curve of active power response is obtained by comparing the identified response with the actual response, whether the identified structural parameters can replace the actual parameters is determined according to the fitting degree of the two active power response curves.

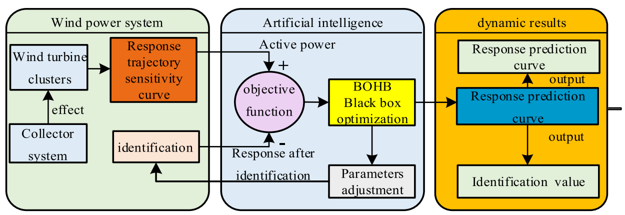

FIGURE 3. Parameter identification frame.

III. MULTI-MACHINE EQUIVALENCE OF DOUBLY-FED WIND FARM

Wind turbines in an actual wind farm usually come from the same manufacturer and are of the same model, if the spatial distribution of wind speed is not different, the wind turbine approximately has a same linearization model [40], [41]. Large scale wind farms and some small and medium scale wind farms cover large geographical spaces and wake effect is obvious, it can be divided into several wind turbine clusters composed of the same type of wind turbines without significant differences in operating conditions, and then make each wind turbine cluster equivalent respectively. This paper transplants the Generator Coherency Identification method proposed in document [42], i.e., structure IAE, including feature extraction layer, clustering layer, and visualization layer. Note that the Gaussian Mixed Model in IAE is replaced with k-means herein as k-means does not require a strong assumption on multivariate normality.

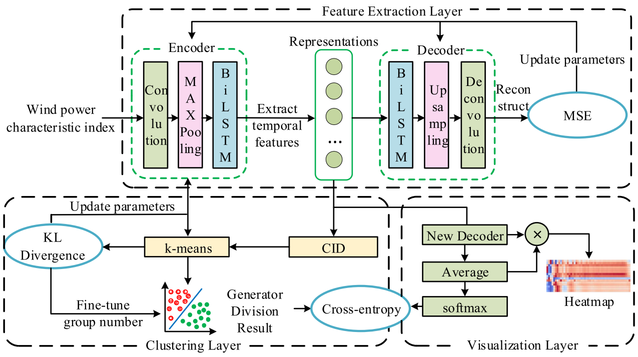

FIGURE 4. IAE to divide turbines and generate a visual heat map.

As shown in Fig. 4, it measures the active power, reactive power, terminal voltage, current, and rotor angular velocity of each doubly-fed wind turbine as the wind power characteristic index, and input the feature extraction layer, which is used to extract the division index of wind turbine cluster, the clustering layer divides the wind turbine cluster according to the index and reversely adjusts the index, the visualization layer represents the index of the timing attended area as a heat map.

The multi-machine equivalent method of doubly-fed wind farm in this paper is divided into five steps:

1) Input the active power, reactive power, terminal voltage, current, and rotor angular velocity of each doubly-fed wind turbine, the Auto-Encoder designed in this paper is used to mine its data features and calculate the CID of each wind turbine's timing features.

2) The CID of each wind turbine is input to k-means which update the mean by gradient descent based on KL divergence, the parameters of step 1) are reversely adjusted through the joint training mechanism, which makes step 1) tends to mine potential dimensions that characterize the segmentation of sequential unlabeled data into multiple wind turbine clusters, visual interpretation of the importance of feature time series interval is realized based on transfer learning and CAM, k-means finally outputs the result of cluster division and compares it with the control division result of wind turbine power.

3) According to the wind turbine cluster divided by step 2), the structure parameters, operation parameters, and collector network parameters of wind farm multi-machine equivalence are calculated based on capacity weighting method, equal input wind energy method and equal power loss method, the control parameter remains unchanged as the initial value of step 4).

4) Build BOHB black box parallel optimization framework, searching the optimal solutions of equivalent network parameters, mechanical structure parameters, and control parameters of wind turbine cluster in the optimization interval.

IV. THE EXAMPLE ANALYSIS

A. HARDWARE AND SOFTWARE PLATFORM CONFIGURATION

This algorithm is implemented by writing Python code, in terms of software configuration, this example uses TensorFlow framework and Visual Studio development environment (including code editor, compiler, debugger, etc.) [43]. The Linux server hardware used in the model training is configured with 2.3GHz eight core Intel Core i9 processor, 32GB 2667MHz DDR4 memory and Ubuntu 18.04 operating system.

B. CALCULATION EXAMPLE: A 16-TURBINE WIND FARM AND ITS SURROUNDING AREA

1) WIND FARM WIRING DIAGRAM AND EXPERIMENTAL DESIGN DESCRIPTION

This paper uses MATLAB /Simulink simulation platform to build a wind farm composed of 16 DFIGs with rated power of 1.5MW. The terminal rated voltage of DFIG is 575V, the unit connection mode of one machine and one change is used to boost the voltage locally to 25kV, it is transmitted to 25kV/220kV substation and external power grid through overhead lines, the altitude, length of collector lines, and topological structure of each DFIG are shown in the figure below.

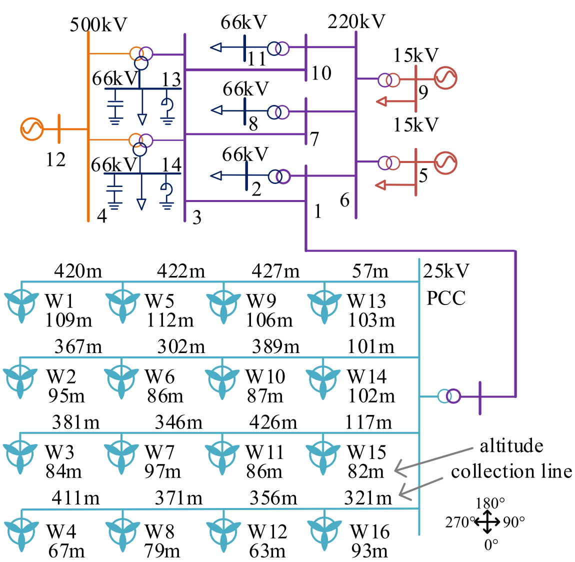

FIGURE 5. 16-Turbine wind farm wiring diagram.

The original parameters of each DFIG are shown in the table below.

The collector wire parameters are shown in the following table.

Set wind direction at 0°, the wind speed before reaching this wind field is 13m/s, according to the wind speed wake effect, the initial wind speed of each DFIG is calculated from the wind farm wiring diagram of this example, as shown in the table below:

TABLE 1. Original parameters of a single doubly-fed wind turbine.

Mechanical	Value	Electrical	Value	Control	Value
H_g	0.685s	S_G	1.5MVA	K_{p1}/K_{i1}	3/0.6
H_w	4.32s	Z_G	0.63Ω	K_{i2}/K_{i3}	8/20
D_s	1.5p.u.	S_T	1.75MVA	K_{pdg}	8
K_s	1.11p.u.	Z_T	0.55Ω	K_{pg}	0.83

TABLE 2. Collector lines parameter.

Sequence	Resistance(Ω/km)	Inductance(H/km)	Capacitance (F/km)
Positive	0.01273	$0.9337e^{-3}$	$12.74e^{-9}$
Zero	0.3864	$4.1264e^{-3}$	$7.751e^{-9}$

TABLE 3. The initial wind speed of each doubly-fed wind turbine.

WTG Number	Wind Speed (m/s)	WTG Number	Wind Speed (m/s)
1	13.0000	9	13.0000
2	12.3149	10	12.2824
3	11.8144	11	11.9069
4	10.7757	12	11.1397
5	13.0000	13	13.0000
6	12.2889	14	12.3851
7	12.0159	15	11.7793
8	11.4231	16	11.7355

The system dynamics excited by different disturbances may be different. Power grid side fault and input side wind speed change excitation are set respectively, perform the following experiments to obtain the active power, reactive power, voltage, current, and rotor angular velocity disturbance curves of the wind turbines.

Experiment One: Make the three-phase short circuit fault at the outlet of the wind farm occur within 12s, the fault lasts for 100ms, the voltage drops to around 0.0 p.u., take the data from 11s to 17s, and the step size is 50us.

Experiment Two:

a) Gust disturbance. Based on Experiment One, through the s_function module in Simulink function writing, a disturbance wind speed component of sinusoidal half wave is added to each basic wind speed to simulate the disturbance of gust, set the simulation time of 40s and the gust disturbance time of π s by varying the timing of the gust, three groups of data were measured successively for data analysis, as shown in the following table.

TABLE 4. Gust disturbance experiment disturbance component.

Group Number	Amplitude (m/s)	Time of Occurrence (s)
1	1	3π
2	1	2π
3	1	π

TABLE 5. Disturbance component parameter of progressive wind disturbance experiment.

Group Number	Amplitude (m/s)	Time of Occurrence (s)
1	1	6
2	1	12

b) Progressive wind disturbance. Truncate the basic constant wind speed, i.e., set the time of progressive wind, the progressive process is simulated with a positive proportional function, then make it to another constant wind speed after a certain time to complete the progressive wind simulation. Then set the occurrence time of progressive wind, and set the simulation duration to 40s and the progressive wind disturbance to 5s, two groups of data have been measured successively for analysis. As shown in the following table.

c) Comprehensive wind disturbance. Set the gust to occur at the time of 2s, maintain π s, and the amplitude is 1m/s; The progressive wind occurs at the 8th second and lasts for 5s.

2) EXPERIMENT ONE: CONSTANT WIND SPEED AND SHORT CIRCUIT AT THE POINT CONNECTED TO THE GRID

As a control group, based on the power control zoning characteristics, 16 DFIGs are divided into maximum power tracking regions(7 ∼ 12m/s), constant speed constant power area (12 ∼ 25m/s), i.e., the following two doubly-fed turbine clusters: {3,4,8,11,12,15,16}, {1,2,5,6,7,9,10,13,14}.

Input the active power, reactive power, voltage, current, and rotor angular velocity disturbance curves of 16 DFIGs from 11s to 17s, the power disturbed curve is shown in Fig. 6 and Fig. 7, it can be seen that the oscillation frequency of the disturbed track is high, about 2s after the fault, the system tends to be stable, it shows that the grid side fault excites the fast dynamic mode of the electrical part of the system, the sensitivity of electrical parameters is generally large at this time. And turbine group 4 has obvious outlier characteristics in line with the subsequent clustering results.

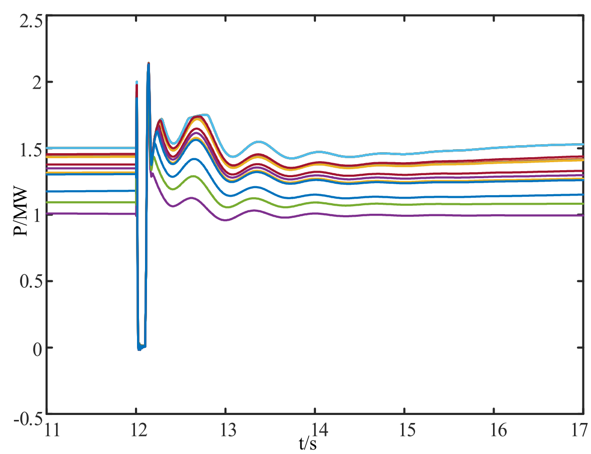

FIGURE 6. Active power curve of each turbine group.

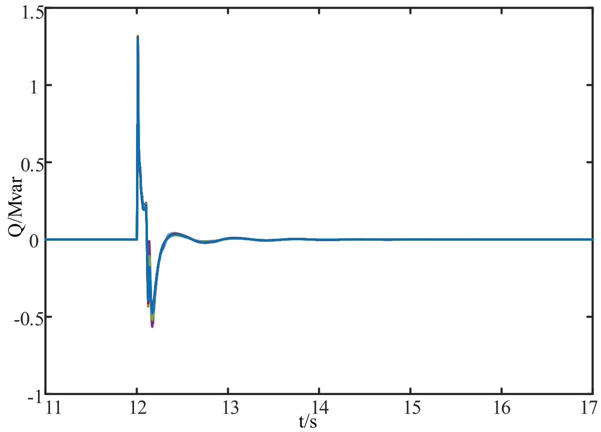

FIGURE 7. Reactive power curve of each turbine group.

TABLE 6. Equivalent parameters of model A and C.

Parameter	Maximum Power Tracking Area		Constant Speed and Constant Power Area	
	Model A	Model C	Model A	Model C
L	1.649km	0.037km	2.808km	0.512km
H_g	4.795s	4.315s	6.165s	7.896s
H_w	30.24s	31.72s	38.88s	66.87s
D_s	10.5p.u.	8.24p.u.	13.5p.u.	14.80p.u.
K_s	7.7p.u.	7.69p.u.	9.9p.u.	12.80p.u.
K_{p1}	3	2.2980	3	3.6568
K_{i1}	0.6	0.1962	0.6	0.1751
K_{i2}	8	5.1826	8	11.8675
K_{i3}	20	25.1496	20	16.9664
K_{pdg}	8	11.2918	8	5.0697
K_{pg}	0.83	0.5378	0.83	1.2027

The double-fed wind farm is divided into four turbine clusters by jointly training the spatio-temporal Auto-Encoder and probabilistic gaussian mixture model designed in this paper: {1,2,5,6,9,10,13,14}; {3,7,11,15,16}; {4}; {8,12}. At this time, the KL divergence of clustering loss function is 3.6877×10^{-9}, the characteristic loss function MSE is 1.81×10^{-4}, and the order of magnitude is very small, from the data point of view, it shows that the accuracy of turbine cluster division is very high and the feature loss is very small.

Build heat map based on CAM and learn from the idea of transfer learning, and represent the attended area of characteristics extracted in turbine cluster partition in Experiment One, the color represents the attention of the model to the characteristic, and the attention is normalized, the larger the value is, the more attention the model pays to regional characteristics, feature extraction from left to right along time series, from top to bottom represents wind turbines 1 to 16.

Wind turbine 4 with wind speed of 10.7757m/s shows the characteristic of being paid attention to by feature extraction layer after fault excision, it is obviously different from other wind turbines, which shows that the clustering characteristics of wind turbines cannot be simply divided by power control modes at different speeds, it is also affected by other physical conditions. Wind turbines 3,7,11,15 and 16 show the characteristics which are focused by the feature extraction layer

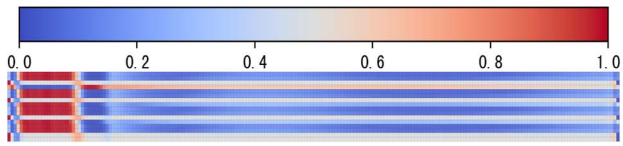

FIGURE 8. Characteristic heat map.

when the fault first occurs, then it soon falls out of the spotlight, it has obvious clustering characteristics, indicating that the wind speed of wind turbine 7 belongs to constant speed and constant power region, but its response characteristics are similar to wind turbines 3,11,15 and 16 in maximum power tracking area. Wind turbines 1,2,5,6,9,10,13,14 receive the same attention from the model at the same time, and only differ from wind turbines 8 and 12 at the moment when the fault is just removed, they are still keenly divided into two wind turbine clusters, it again shows that the clustering characteristics of wind turbines are not only determined by the power control method based on wind speed (rotational speed).

The initial calculation of equivalent parameters of multiple wind turbines is carried out based on the clustering results of the above two wind turbine clusters, i.e., the capacity weighting method is used to calculate the parameters of equivalent wind turbine generators, transformers and shafting; The equivalent wind speed is calculated based on the principle that the total input wind energy of each wind turbine cluster is equal before and after the equivalence, the trunk topology is transformed into radial topology by equal power loss method, then calculate the equivalent parameters of the collector system; The original wind turbine control parameters are used as equivalent control parameters. Starting from the position of the above initial parameters, the parameter identification problem is transformed into a nonlinear multi-objective hyperparametric optimization problem, **early stop** mechanism is introduced based on BOHB black box parallel optimization framework, iteration is stopped when the reduction of loss value between two iterations is less than the threshold (1e-10) for five consecutive times, the optimal equivalent parameters are solved.

To verify the causal relationship between the wind farm equivalent precision from the two aspects, the division of the wind farm clusters and the identification of the equivalent parameter in the wind farm mentioned in this paper, models A, B, C, and D are set to constitute the ablation study. The multiple wind turbine equivalent model based on power control zoning and initial calculation of steady-state parameters is abbreviated as model A, the equivalent wind speeds of equivalent wind turbines in maximum power tracking area and constant speed and power area are 11.52m/s and 12.6m/s respectively; The multiple wind turbine equivalent model based on clustering algorithm and initial calculation of steady-state parameters is abbreviated as model B, the equivalent wind speeds of wind turbine clusters 1 to 4 are 12.668m/s, 11.85m/s, 10.7757m/s, and 11.2831m/s,

TABLE 7. Equivalent parameters of model B and D.

Parameter	Wind Turbine Group		Wind Turbine Group		Wind Turbine Group		Wind Turbine Group	
	Model B	Model D	Model B	Model D	Model B	Model D	Model B	Model D
L	0.581km	0.161km	1.845km	1.010km	0.407km	0.995km	1.099km	0.587km
H_g	5.480s	6.593s	3.425s	3. 546s	0.685s	0.675s	1.37s	0.872s
H_w	34.56s	63.99s	21.60s	19.35s	4.32s	7.99s	8.64s	15.96s
D_s	12p.u.	11.26p.u.	7.5p.u.	7.99p.u.	1.5p.u.	1.07p.u.	3p.u.	3.49p.u.
K_s	8.88p.u.	11.13p.u.	5.55p.u.	6.14p.u.	1.11p.u.	0.85p.u.	2.22p.u.	1.27p.u.
K_{p1}	3	3.1028	3	3.3736	3	5.0130	3	0.9074
K_{i1}	0.6	0.2585	0.6	0.4527	0.6	1.3397	0.6	0.7002
K_{i2}	8	10.4987	8	7.3191	8	12.6685	8	2.2827
K_{i3}	20	19.4199	20	18.8800	20	11.8574	20	29.6930
K_{pdg}	8	7.7930	8	5.6414	8	10.8990	8	12.3698
K_{pg}	0.83	0.9578	0.83	0.7342	0.83	0.3120	0.83	0.9441

respectively; The multiple wind turbine equivalent model of comprehensive identification based on power control zones, equivalent control parameters of wind turbine cluster, length of collector lines, and mechanical structure parameters in structural parameters (generator inertia time constant H_g, wind turbine inertia time constant H_w, shafting damping coefficient D_s, and shafting stiffness coefficient K_s) is abbreviated as model C; The multiple wind turbine equivalent model of comprehensive identification based on clustering algorithm and length of collector lines and mechanical structure parameters in structural parameters is abbreviated as model D.

The above four equivalent wind farm models are built in simulink, and the relative equivalent deviations of voltage, current, active power, and reactive power at the point connected to the grid between the above four equivalent models and the original model are calculated by equation (7), as shown in the following table.

As can be seen from the above table, in the ablation study set in this paper, the equivalent deviations of voltage, current, active power, and reactive power at the point connected to the grid of model B and model C are significantly reduced compared with model A and model A, and verify the improvement of dynamic equivalent precision of wind farm by the clustering method and parameter identification method in this paper respectively. Finally, model D shows that the proposed model in this paper can more accurately simulate the dynamic characteristics of wind farm output, therefore, it is fully applicable to the interaction analysis between wind farm and power system, simultaneously, it can be used to analyze the stability of power system including wind power.

To verify the superiority of wind farm equivalence model in simulation efficiency, set the fixed step size to 50us, i.e., iterative calculation is performed once every 50us in the real wind farm, the average value is taken through 20 experiments, compare the time required for the original model and the equivalent model to iterate once in simulink and c++ environment based on gcc compiler.

TABLE 8. Dynamic equivalent relative deviation comparison.

Model	Voltage	Current	Active Power	Reactive Power
A	0.005921%	0.1216%	0.1100%	0.1600%
B	0.001491%	0.0287%	0.0299%	0.0292%
C	0.001020%	0.0007%	0.0382%	0.0830%
D	0.000356%	0.0002%	0.0039%	0.0215%

TABLE 9. Simulation efficiency comparison.

Environment	Original Model	Equivalent Model
simulink	2102.17us	485.24us
c++	8.79us	1.39us

3) EXPERIMENT TWO: WIND SPEED DISTURBANCE AND SHORT CIRCUIT AT THE POINT CONNECTED TO THE GRID

Due to the randomness of disturbed wind speed, the wind turbine clusters division in traditional wind farms shows uncertainty, the equivalent parameters of the wind turbine clusters need to be updated continuously by using the analytical method, while in practical engineering, it is necessary to obtain the clustering results which are generally applicable to various working conditions. On the other hand, the system dynamics excited by the change of wind speed is slow, i.e., the slow dynamic mode strongly related to the mechanical part is excited, the sensitivity of mechanical parameters is generally large at this time.

To obtain uniform clustering results applicable to the practical engineering application of multi-machine equivalence, three groups of experimental data under gust disturbance, two groups of experimental data under progressive wind disturbance and experimental data under comprehensive wind disturbance designed in Experiment Two are sequentially splice and input in a purely data-driven way in this paper, the unified clustering result is:

TABLE 10. **Equivalent relative deviation of model A in different scenarios.**

Experimental Group Number	Voltage	Current	Active Power	Reactive Power
Gust1	0.001148%	0.0223%	0.0216%	0.2834%
Gust2	0.001130%	0.0145%	0.0137%	0.2822%
Gust3	0.001171%	0.0100%	0.0095%	0.2848%
Progressive Wind 1	0.001216%	0.0145%	0.0144%	0.2902%
Progressive Wind 2	0.001188%	0.0177%	0.0169%	0.2876%
Comprehensive Wind	0.001235%	0.0110%	0.0107%	0.2891%

TABLE 11. **Equivalent relative deviation of model B in different scenarios.**

Experimental Group Number	Voltage	Current	Active Power	Reactive Power
Gust1	0.000399%	0.0105%	0.0102%	0.0970%
Gust2	0.000400%	0.0063%	0.0057%	0.0970%
Gust3	0.000464%	0.0044%	0.0039%	0.0971%
Progressive Wind 1	0.000458%	0.0057%	0.0060%	0.1000%
Progressive Wind 2	0.000429%	0.0090%	0.0087%	0.0972%
Comprehensive Wind	0.000486%	0.0047%	0.0042%	0.0973%

TABLE 12. **Equivalent relative deviation of model C in different scenarios.**

Experimental Group Number	Voltage	Current	Active Power	Reactive Power
Gust1	0.000326%	0.0008%	0.0187%	0.1873%
Gust2	0.000387%	0.0004%	0.0103%	0.1542%
Gust3	0.000455%	0.0004%	0.0076%	0.1601%
Progressive Wind 1	0.000479%	0.0005%	0.0088%	0.1537%
Progressive Wind 2	0.000387%	0.0006%	0.0093%	0.1432%
Comprehensive Wind	0.000348%	0.0004%	0.0085%	0.1695%

TABLE 13. **Equivalent relative deviation of model D in different scenarios.**

Experimental Group Number	Voltage	Current	Active Power	Reactive Power
Gust1	0.000178%	0.0003%	0.0020%	0.0826%
Gust2	0.000202%	0.0003%	0.0015%	0.0865%
Gust3	0.000287%	0.0003%	0.0012%	0.0801%
Progressive Wind 1	0.000382%	0.0004%	0.0017%	0.0792%
Progressive Wind 2	0.000315%	0.0004%	0.0022%	0.0785%
Comprehensive Wind	0.000211%	0.0002%	0.0015%	0.0813%

{1,5,9,13} {2,6,10,14} {3,7,11,15,16} {4,8,12}, among them, the equivalent wind speed and the length of collector lines from group 1 to 4 are 13 m/s, 12.31796m/s, 11.85124741m/s, 11.119141m/s, 1.05km, 0.8081243km, 3.05346177km, 3.287884655km. the equivalent deviation of the points connected to the power grid of the model defined in Experiment One in the 40s time window under various working conditions is shown in the table below:

The above experiments verify the proposed method of wind turbine clustering and equivalent parameter identification of wind turbine clusters in the wind farm under different wind speed scenarios, it has higher dynamic equivalence accuracy and strong robustness compared with traditional methods, and it is suitable for simulation of wind farm, interaction between wind power and power system and stability analysis in practical engineering.

V. CONCLUSION

This paper proposes a method for clustering wind turbines based on the deep migration of multi-view features, a multi-objective nonlinear multi-time scale model of wind turbine cluster equivalent parameter identification is constructed and solved it based on BOHB black box parallel optimization framework. According to theoretical analysis and ablation study, the conclusions are as follows.

1) In this paper, the constructed deep spatio-temporal Auto-Encoder and KL- k-means research are trained jointly, which achieves multi-view, unsupervised wind farm cluster division, compared to traditional methods, the equivalent deviations of voltage, current, active power, and reactive power at the point connected to the grid are reduced by 75%, 76%, 73%, and 82% under the experimental condition of constant wind speed, uniform clustering results can be obtained under variable wind conditions, it meets the requirement of equivalent value of wind farm in practical engineering, the equivalent deviation is reduced by 50% to 80% in all wind conditions, the accuracy and robustness are both high, and fully data-driven without the need to annotate data offline, the heat map of feature importance interval based on transfer learning and CAM also solves the problem of ''black box'' unexplainable, which makes it more reliable in practical engineering.

2) In this paper, according to the initial value of the equivalent parameters of the computer clusters of physical characteristics, a black box parallel optimization framework for the optimal value of equivalent parameters of identification turbine clusters are established based on BOHB, which can simultaneously identify the dynamic parameters of different time scales in wind turbines (Electrical, mechanical and control parameters), compared to traditional methods, the voltage, current, active power and reactive power deviations of wind farm equivalent are reduced about 83%, 99%, 65%, and 48% under constant wind speed, there is also 40% to 99% reduction in all wind conditions.

Compared with traditional methods, the proposed method of cluster division and parameter identification can reduce the voltage, current, active power, and reactive power deviation of wind farm equivalence about 94%, 99%, 96%, and 86% under the experimental condition of constant wind speed, the equivalent deviation in all kinds of working conditions is reduced by 80% to 99%, the accuracy and robustness are both high, it can simulate the dynamic characteristics of wind farm output more accurately, therefore, it is fully applicable to the interaction analysis between wind farm and power system, it can be used for the stability analysis of power system with wind power simultaneously, and it has the feasibility of extending to the equivalence of full power converter grid-connected wind turbines represented by permanent magnet direct drive wind turbines and photovoltaic power generation units.

REFERENCES

[1] X. Xiaoyuan, W. Han, and Y. Zheng, ''Overview of power system uncertainty and its solutions under energy transition,'' *Autom. Electr. Power Syst.*, vol. 45, no. 16, pp. 2–13, Jan. 2021.

[2] Y. Li, ''Research on multi-rate simulation of large scale renewable energy connected system based on time-frequency transformation and identification aggregation theory,'' Ph.D. dissertation, Shanghai Jiao Tong Univ., Shanghai, China, 2020.

[3] X. Xie, J. He, H. Mao, and H. Li, ''New issues and classification of power system stability with high shares of renewables and power electronics,'' *Proc. CSEE*, vol. 41, no. 2, pp. 461–475, 2021.

[4] G. Abad, J. Lopez, M. Rodriguez, L. Marroyo, and G. Iwanski, *Doubly Fed Induction Machine: Modeling and Control for Wind Energy Generation*. 2011.

[5] J. Ruan, Z. Lu, Y. Qiao, and Y. Min, ''Analysis on applicability problems of the aggregation-based representation of wind farms considering DFIGs' LVRT behaviors,'' *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4953–4965, Nov. 2016.

[6] Y. Jin, C. Lu, P. Ju, C. Rehtanz, F. Wu, and X. Pan, ''Probabilistic preassessment method of parameter identification accuracy with an application to identify the drive train parameters of DFIG,'' *IEEE Trans. Power Syst.*, vol. 35, no. 3, pp. 1769–1782, May 2020.

[7] P. Xueping, C. Zhang, P. Ju, F. Wu, and Y. Q. Jin, ''Coherency-based dynamic equivalence of wind farm composed of doubly fed induction generators,'' *Power Syst. Technol.*, vol. 39, no. 3, pp. 621–627, 2015.

[8] P. Wang, Z. Zhang, Q. Huang, N. Wang, X. Zhang, and W.-J. Lee, ''Improved wind farm aggregated modeling method for large-scale power system stability studies,'' *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6332–6342, Nov. 2018.

[9] Y. Ni, C. Li, Z. Du, and G. Zhang, ''Model order reduction based dynamic equivalence of a wind farm,'' *Int. J. Electr. Power Energy Syst.*, vol. 83, pp. 96–103, Dec. 2016.

[10] D. N. Hussein, M. Matar, and R. Iravani, ''A wideband equivalent model of type-3 wind power plants for EMT studies,'' *IEEE Trans. Power Del.*, vol. 31, no. 5, pp. 2322–2331, Oct. 2016.

[11] M. J. Mercado-Vargas, D. Gómez-Lorente, O. Rabaza, and E. Alameda-Hernandez, ''Aggregated models of permanent magnet synchronous generators wind farms,'' *Renew. Energy*, vol. 83, pp. 1287–1298, Nov. 2015.

[12] L. P. Kunjumuhammed, B. C. Pal, C. Oates, and K. J. Dyke, ''The adequacy of the present practice in dynamic aggregated modeling of wind farm systems,'' *IEEE Trans. Sustain. Energy*, vol. 8, no. 1, pp. 23–32, Jan. 2017.

[13] P. Chao, W. Li, X. Jin, J. Qi, and X. Li, ''An active power response based practical equivalent method for DFIG wind farms,'' *Proc. CSEE*, vol. 38, no. 6, pp. 1639–1646 and 1900, 2018.

[14] W. Li, P. Chao, X. Liang, J. Ma, D. Xu, and X. Jin, ''A practical equivalent method for DFIG wind farms,'' *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 610–620, Apr. 2018.

[15] P. Wang, Z. Zhang, Q. Huang, and W.-J. Lee, ''Wind farm dynamic equivalent modeling method for power system probabilistic stability assessment,'' *IEEE Trans. Ind. Appl.*, vol. 56, no. 3, pp. 2273–2280, May 2020.

[16] Z. Mi, X. Su, Q. Yang, Y. Wang, and T. Wu, ''Multi-machine representation method for dynamic equivalent model of wind farms,'' *Trans. China Electrotech. Soc.*, vol. 25, no. 5, pp. 162–169, 2010.

[17] Y. Jin, P. Ju, C. Rehtanz, F. Wu, and X. Pan, ''Equivalent modeling of wind energy conversion considering overall effect of pitch angle controllers in wind farm,'' *Appl. Energy*, vol. 222, pp. 485–496, Jul. 2018.

[18] Z. Mi, X. Su, Y. Yu, Y. Wang, and T. Wu, ''Study on dynamic equivalence model of wind farms with wind turbine driven doubly fed induction generator,'' *Autom. Electr. Power Syst.*, vol. 34, no. 17, pp. 72–77, 2010.

[19] P. Chao, W. Li, X. Liang, S. Xu, and Y. Shuai, ''An analytical two-machine equivalent method of DFIG-based wind power plants considering complete FRT processes,'' *IEEE Trans. Power Syst.*, vol. 36, no. 4, pp. 3657–3667, Jul. 2021.

[20] J. Zou, C. Peng, H. Xu, and Y. Yan, ''A fuzzy clustering algorithm-based dynamic equivalent modeling method for wind farm with DFIG,'' *IEEE Trans. Energy Convers.*, vol. 30, no. 4, pp. 1–9, May 2015.

[21] S. Chen, C. Wang, H. Shen, N. Gao, L. Zhu, and H. Lan, ''Dynamic equivalence for wind farms based on clustering algorithm,'' *Proc. CSEE*, vol. 32, no. 4, pp. 11–19 and 24, 2012.
[22] L. M. Fernández, C. A. García, J. R. Saenz, and F. Jurado, ''Equivalent models of wind farms by using aggregated wind turbines and equivalent winds,'' *Energy Convers. Manage.*, vol. 50, no. 3, pp. 691–704, Mar. 2009.
[23] Y. Mao and D. Juncheg, ''Study on characteristics of wind power fluctuation based on mixed distribution model,'' *Proc. CSEE*, vol. 36, no. S1, pp. 69–78, 2016.
[24] L. Lin, X. Pan, L. Zhang, and S. Zhao, ''The K-means clustering algorithm for wind farm based on immune-outlier data and immune-sensitive initial center,'' *Proc. CSEE*, vol. 36, no. 20, pp. 5461–5468, 2016.
[25] J. Han, S. Miao, Y. Li, W. Yang, and T. Zheng, ''A multi-view and multi-scale transfer learning based wind farm equivalent method,'' *Int. J. Electr. Power Energy Syst.*, vol. 117, May 2020, Art. no. 105740.
[26] Y. Zhou, L. Zhao, I. B. M. Matsuo, and W.-J. Lee, ''A dynamic weighted aggregation equivalent modeling approach for the DFIG wind farm considering the Weibull distribution for fault analysis,'' *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 5514–5523, Nov. 2019.
[27] Y. Zhou, L. Zhao, T.-Y. Hsieh, and W.-J. Lee, ''A multistage dynamic equivalent modeling of a wind farm for the smart grid development,'' *IEEE Trans. Ind. Appl.*, vol. 55, no. 5, pp. 4451–4461, Sep. 2019.
[28] J. Han, S. Miao, L. Li, W. Yang, and Y. Li, ''Wind turbines clustering in wind farm based on multi-view transfer learning and synthetic optimization of parameters in equivalent wind farm,'' *Proc. CSEE*, vol. 40, no. 15, pp. 4866–4881, 2020.
[29] Y. Zhou, L. Zhao, and W.-J. Lee, ''Robustness analysis of dynamic equivalent model of DFIG wind farm for stability study,'' *IEEE Trans. Ind. Appl.*, vol. 54, no. 6, pp. 5682–5690, Nov. 2018.
[30] C. Pan, Y. Xi, and Y. Hu, ''Grey-box parameter identification for drive-train system of large-scale wind turbine,'' in *Proc. Chin. Control Conf. (CCC)*, Jul. 2019, pp. 1512–1519.
[31] S. P. Azad and J. E. Tate, ''Parameter estimation of doubly fed induction generator driven by wind turbine,'' in *Proc. IEEE/PES Power Syst. Conf. Expo.*, Mar. 2011, pp. 1–8.
[32] S. Thomsen, R. Kai, and F. W. Fuchs, ''Online parameter identification methods for doubly fed induction generators,'' in *Proc. IEEE Power Electron. Spec. Conf.*, Jun. 2008, pp. 2735–2741.
[33] P. Xueping, Q. Xiangwei, L. Wei, Y. Established, D. Xinhu, L. Wei, and Z. Ling, ''Multi-machine equivalence and global identification of wind farms by combining model aggregation and parameter estimation,'' *Electr. Power Automat. Equip.*, pp. 1–9, Jun. 2021, doi: 10.16081/j.epae.202109004.
[34] G. E. Hinton and R. R. Salakhutdinov, ''Reducing the dimensionality of data with neural networks,'' *Science*, vol. 313, pp. 504–507, Jun. 2006.
[35] Y. LeCun, Y. Bengio, and G. Hinton, ''Deep learning,'' *Nature*, vol. 521, pp. 436–444, May 2015.
[36] N. S. Madiraju, S. M. Sadat, D. Fisher, and H. Karimabadi, ''Deep temporal clustering: Fully unsupervised learning of time-domain features,'' 2018, *arXiv:1802.01059*.
[37] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba, ''Learning deep features for discriminative localization,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016.
[38] L. Li, K. Jamieson, G. DeSalvo, A. Rostamizadeh, and A. Talwalkar, ''Hyperband: A novel bandit-based approach to hyperparameter optimization,'' *J. Mach. Learn. Res.*, vol. 18, no. 185, pp. 1–52, 2018.
[39] S. Falkner, A. Klein, and F. Hutter, ''BOHB: Robust and efficient hyperparameter optimization at scale,'' in *Proc. Int. Conf. Mach. Learn.*, 2018, pp. 1437–1446.
[40] D. Wenkai, D. Wenjuan, and W. Haifeng, ''Dynamic equivalent model of a grid-connected wind farm for oscillation stability analysis,'' *Proc. CSEE*, vol. 41, no. 1, pp. 75–87 and 399, 2021.
[41] Y. Xia, ''Research of equivalent modeling of large wind farm,'' Hefei Univ. Technol., Hefei, China, Tech. Rep., 2019.
[42] B. Li and F. Liu, ''A novel probabilistic framework with interpretability for generator coherency identification,'' *Int. J. Electr. Power Energy Syst.*, vol. 4, no. 1, pp. 13–17, 2022.
[43] F. Liu, Y. Li, B. Li, J. Li, and H. Xie, ''Bitcoin transaction strategy construction based on deep reinforcement learning,'' *Appl. Soft Comput.*, vol. 113, Dec. 2021, Art. no. 107952, doi: 10.1016/j.asoc.2021.107952.

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