Localization of Sub/super-synchronous Oscillation Sources in Wind Power Systems Based on Deep Adaptation Network

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***Abstract*—When persistent sub/super-synchronous oscillations occur in a wind power system, timely and accurate localization of the wind turbine that causes the oscillations is the first and foremost task to suppress the oscillations precisely. However, the scarcity of actual system oscillation data causes a serious data bottleneck in the research of localization based on data-driven technology. Based on this, this paper proposes an online localization method of oscillation source based on deep adaptation network. Through the transfer and generalization between data, the problem of scarcity and difficulty in obtaining the oscillation data of the actual system is solved. The analysis of examples shows that the oscillation source localization method proposed in this paper has better performance in terms of model training speed as well as localization accuracy.**

Keywords—sub/super-synchronous oscillation, wind turbine, oscillation source location, deep adaptation network(DAN)

I. Introduction

The feed-in of a high proportion of new energy intensifies the power electrification of the power system, and the complex coupling between the new energy field stations and the grid induces sub/super-synchronous oscillations with a wider frequency band, which seriously threatens the safe and stable operation of the power system. Considering the increasing scale of wind power, in order to take more effective measures to suppress the sub/super-synchronous oscillations, it is urgent to quickly and accurately identify and locate the source of oscillations among many wind turbines.

The present methods for oscillation source localization based on traditional mechanism modeling mainly include traveling wave detection method [1], energy method [2]-[4], and so on. The travelling wave detection method is limited by the mounting position of the voltage measuring unit, This method fails when the oscillation source is close to the measurement unit [5]. The energy method is widely used in the low-frequency domain, and broadband adaptability is yet to be demonstrated [6]. On the other hand, with the diversification of power system structure and the strong nonlinearization of dynamic characteristics, it is increasingly difficult to carry out the research of sub/super-synchronous oscillation localization and identification from the perspective of physical mechanism. Machine learning has been introduced to the field of oscillation source localization due to its powerful ability to deal with nonlinear problems. Reference [7], [8] implements forced oscillation source localization based on KNN deep learning algorithm. Reference [9] breaks through the communication bandwidth limitation of data transmission in wide-area power system by signal compression based on self-encoder, and proposes an oscillatory source localization method based on long short-term memory network. However, the main factor limiting the development of machine learning in the field of oscillation source localization is the difficulty of obtaining training data. Machine learning is dependent on a large amount of valid data, but the actual oscillation data in the power system is very scarce, so the lack of actual system oscillation data has become an urgent problem to be solved. The development of transfer learning offers an important idea to solve the problem. Reference [10], [11] attempts to alleviate the problem of data scarcity using migration learning for sub-synchronous frequency band oscillations. In this paper, a large number of samples are formed by adjusting the control parameters in the simulation system to stimulate the sub/super-synchronous

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oscillations, which constitute two data domains with a small number of sub-synchronous oscillation samples in the actual system, and the sub-synchronous oscillation source is localized by migration learning between the two domains. However, in the sub-synchronous/hypersynchronous frequency bands, it is also difficult to form a large number of available oscillation samples by adjusting the control parameters in the simulation system, and at the same time, the above study does not consider the coupling problem of the oscillation frequency, but only the sub-synchronous frequency oscillations are taken into account.

In view of the above problems, this paper proposes a new oscillation source localization method based on deep adaptation network for sub/super-synchronous oscillations. A large number of effective samples are acquired by directly adding sub/super-synchronous oscillation perturbation sources to form sub/super-synchronous forced oscillations in the simulation system, and then generalized to the field of sub/super-synchronous oscillations of the actual system by using migration learning to solve the issues of the scarcity of samples of the actual oscillations and the difficulty of acquiring the samples. Finally, a validation analysis is carried out, and the results show that the proposed sub/super-synchronous oscillation source localization method can obtain more accurate localization results in a relatively short period of time.

II. Deep Adaptation Network

The sub/super-synchronous frequency band forced oscillation excited by adding the perturbation source and sub/super-synchronous oscillations in real turbines due to control parameters and other issues have a significant difference in the generation mechanism, that is, there are large differences between the two data domains, so the source domain samples can not be directly expanded to the use of the target domain, and therefore we propose to adopt transfer learning for transfer generalization between two domains.

In migration learning, let D_s and D_t represent the source domain and target domain, respectively [12]. The source domain has a large number of samples and is the migratable generalization domain, which is the forced oscillation domain in this paper. The target domain is the data domain that lacks samples, i.e., the object that needs to be given migration knowledge, which is the actual sub/super-synchronous oscillation in this paper. Each domain consists of a feature space X as well as a probability distribution $P(X)$, i.e., $D_s = \{X_s, P(X_s)\}$ and $D_t = \{X_t, P(X_t)\}$. The learning task of the domain consists of the labeling space and its corresponding prediction function, i.e., $T = \{Y, f\}$. where Y is the label space composed of samples corresponding to labels, and f is the function mapping relationship between samples and labels, which reacts to the data, i.e., represents the conditional probability of the data distribution, i.e., $Q_s(Y_s \mid X_s)$, $Q_t(Y_t \mid X_t)$. Then the learning task in the source domain and target domain can be expressed as $T_s = \{ Y_s, f_s\}$, $T_t = \{ Y_t, f_t\}$. When the spatial distributions of the samples in the source domain and target domain are the same, the prediction function in the source domain will be equally applicable to the target domain task.

In the problem of oscillating source localization faced in this paper, both domains have the same labeling space for oscillating source fan labels. Therefore, the task of migration learning in this paper is to find a mapping φ that maps the source domain and the target domain onto another potential feature space, on which $P(X_s) = P(X_t)$, $Q_s(Y_s \mid X_s) = Q_t(Y_t \mid X_t)$ are satisfied. At this point, the prediction function f_s obtained by supervised learning of the source domain samples and sample labels can then be fully generalized and adapted to the target domain task T_t.

In order to make the designed models have the use of commonality, this paper adopts the feature-based transfer learning method. By designing different adaptation layers in the neural network, based on the regular term of domain metrics, the distance between the two domains is measured and brought closer to realize the distribution alignment between the source domain and target domain. Therefore, the core of feature-based migration learning is the design of the adaptation layer: selecting the appropriate migration regular term for the measurement of the distribution difference between the two domains.

In the adaptive domain, the maximum mean discrepancy (MMD) is the most classical discrepancy measure. In MMD, the concept of k kernel is very important, which is defined as the inner product of the mapping, as shown in (1).

$$k(\boldsymbol{x}_{\mathrm{s}}, \boldsymbol{x}_{\mathrm{t}}) = \langle \phi(\boldsymbol{x}_{\mathrm{s}}), \phi(\boldsymbol{x}_{\mathrm{t}}) \rangle \tag{1}$$

where $\varphi(\cdot)$ denotes the mapping of the data from the original data space to the producing kernel Hilbert space (RKHS).

However, in MMD, the k kernel can only be singularly chosen to be a linear or Gaussian kernel, which is not guaranteed to achieve the best results. Therefore, Multi-kernel MMD (MK-MMD) is defined based on MMD, where the total kernel is constructed by using multiple kernels weighted jointly to achieve the best fitness [13], at which time the kernel is defined as:

$$\mathrm{K} \triangleq \left\{ k = \sum_{u=1}^{m} \beta_u k_u : \beta_u \geq 0, \forall u \right\} \tag{2}$$

where β_u is the weight of different kernel k_u.

At this point, the difference between the two domains can then be calculated using MK-MMD as shown in the following equation.

$$d_k^2(p,q) \triangleq \left\| E_p(\phi(\boldsymbol{x}_{\mathrm{s}})) - E_q(\phi(\boldsymbol{x}_{\mathrm{t}})) \right\|_H^2 \tag{3}$$

where p, q are the probability distributions of the source domain and target domain, respectively; E_p and E_q are the mathematical expectations of the data in the source domain and target domain, respectively; H denotes RKHS.

The deep adaptation between the source domain and target domain is accomplished by establishing a multilayer adaptation layer and utilizing the above MK-MMD for multiple approximations between the distances of the two domains. The overall structure of the deep adaptation network (DAN) is shown in Fig. 1:

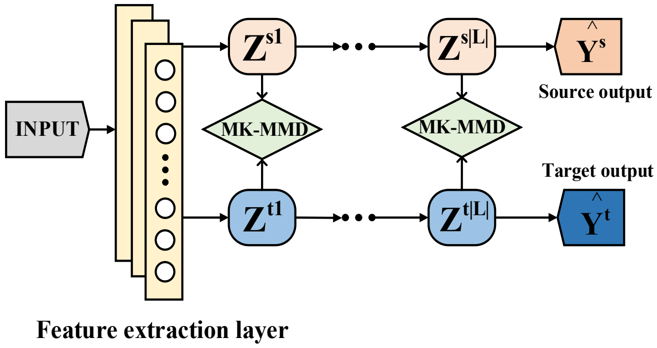


Fig. 1. DAN model structure diagram.

In summary, the model optimization objective consists of two parts: classification loss function and distribution distance. In this paper, the classification loss is calculated with the cross-entropy function, so the model can be expressed as shown in (4).

$$f = \min_{f} \frac{1}{n}\sum_{i=1}^{n} J(f(\boldsymbol{x}_i), \boldsymbol{y}_i) + \lambda \sum_{l=1}^{L} d_{k,l}^{2}(p,q) \tag{4}$$

III. Specific Process of DAN-based Sub/super-Synchronous Oscillation Source Localization Method

The specific implementation process of the sub/super-synchronous oscillation source localization method proposed in this paper can be roughly divided into three major parts: data processing, offline training and online application. As shown in Fig. 2.

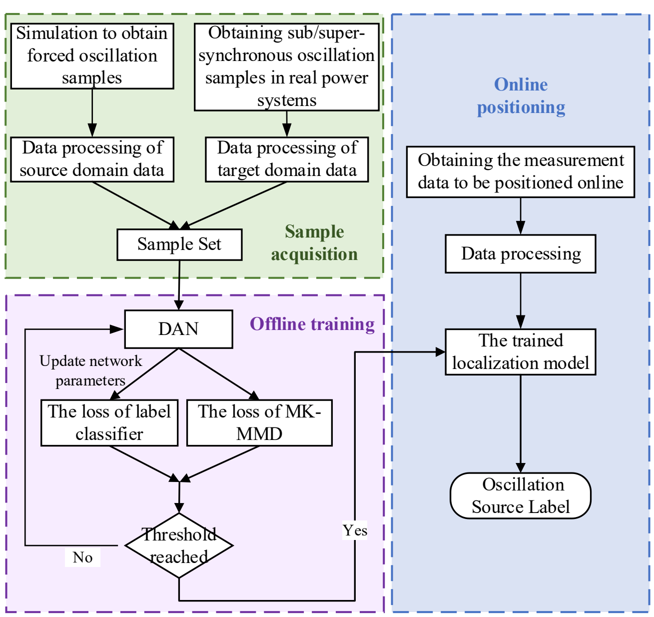


Fig. 2. Flow diagram of oscillation source localization method based on deep migration learning

1) Construct a time-domain simulation system based on the actual system, and generate source-domain samples by excitation of forced oscillations in the simulation system; obtain the sub/super-synchronous oscillation history data in the actual system to form target-domain samples. The source and target domain data are preprocessed to obtain usable samples and form a sample set. The samples are divided into training samples and test samples.

2) Multiple attempts are made to obtain the optimal learning rate and other hyperparameters to train the model. The accuracy of the model is measured using the ACC metric, which is defined as shown in equation (5). It is worth noting that the accuracy rates referred to in this paper are all the accuracy rates of the test samples that do not participate in training.

$$\mathrm{ACC} = \frac{TN_1 + TN_2 + TN_3 + \cdots + TN_n}{N} \times 100\% \tag{5}$$

where N is the total number of samples in the test set, n is the total number of turbines, and TN_m is the number of test samples in which both the predicted and actual are turbines m which are oscillating sources.

If the accuracy of the test sample does not reach the threshold, update the network parameters. If the threshold is reached, stop training and save the network. The network obtained at this point is the final sub/super-synchronous oscillation localization model.

3) Online application of the sub/super-synchronous oscillation localization model. That is, the measurement data of the oscillation source to be localized by the system are obtained on-line and input into the model to obtain the label of the oscillation source.

IV. Example Analysis

A. Construction of the Example Dataset

A model of two direct-drive wind turbines connected to the grid via a weak AC grid is constructed on PSCAD/EMTDC as an experimental example to verify the effectiveness of the proposed method, and the model structure is shown in Fig. 3:

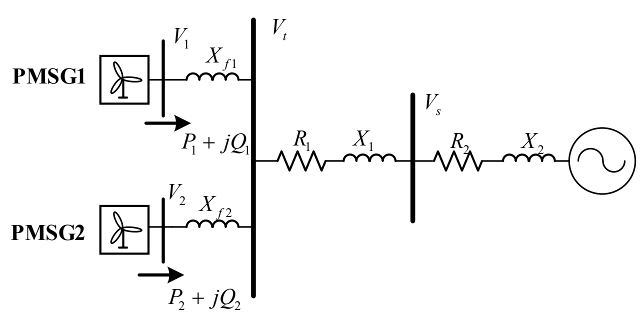


Fig. 3. Structural diagram of two direct-drive fans connected to the grid via a weak AC grid

1) Target domain sample acquisition: In this paper, a simulation system is used to generate a small number of target domain training samples and test samples by simulating the occurrence of sub/super-synchronous oscillations in the actual

system. Set two wind turbines as oscillation sources, adjust the control parameters of the oscillation source coupled with the AC system to generate sub/super-synchronous oscillations[14], adjust the rated output of each unit in the range of 0.5 to 1, and obtain a number of different operating points to simulate the actual system operation. In this example, the harmonic frequency of the system varies from 20 to 25 Hz and 75 to 80 Hz with the change of the operating point. The power, voltage and current signals at the outlet buses of the two turbines are collected (sampling frequency of 2 kHz, sampling time of 0.5 s), and the oscillating samples x_t=[P_1, Q_1, U_1, I_1, P_2, Q_2, U_2, I_2] in the target domain are formed. The invalid samples that the system trend does not converge are eliminated, and 400 valid training samples in the target domain are obtained after data preprocessing. Valid test samples are 200.

2) Source domain sample acquisition: Periodic disturbances (20-25Hz and 75-80Hz in this example) are injected at the buses on the outlet side of the two turbines, respectively, causing forced oscillations in the sub/super-synchronous frequency band of the system. The turbine output case is varied (0.5 to 1) and the perturbation amplitude (0.01 to 0.05) is injected to simulate a number of operating points in actual operation. According to Section 2.1, the electrical quantities at the outlet bus of each turbine at the time of oscillation are recorded (sampling frequency of 2 kHz and duration of 0.5 s) to form the source domain samples x_s=[P_1, Q_1, U_1, I_1, P_2, Q_2, U_2, I_2], and the corresponding labeled dataset Ys is formed according to the method shown in Section 2.1. The invalid samples such as stable and non-convergence of the tidal currents are rejected. After data preprocessing, 2930 valid training samples in the source domain and 500 test samples in the source domain were obtained.

B. *Model Training Results*

During the offline training of the model using the training samples generated in the previous section, the model training parameters are shown in Table I.

TABLE I. NETWORK TRAINING PARAMETERS SETTING

Parameter Name	*Parameter Value*
Learning rate	0.0005
Batch size	40
Transfer loss weights	0.5
Optimizer	Adam
Feature extractor activation function	ReLU
Adaptation layer activation function	ReLU
Label classifier activation function	Softmax

The graph of the model accuracy evaluation metric ACC changing with the number of training sessions during the training process is shown in Fig. 4.

Observing the curve, it can be seen that with the increasing number of training times, the model training is gradually deepened, and the model accuracy shows an overall trend of elevation. When the number of training times reaches 400 times, the model accuracy has reached a high level of more than 90%. After the convergence of the model, the final accuracy can reach 92.5%, which meets the accuracy requirements of oscillation source localization in practical applications.

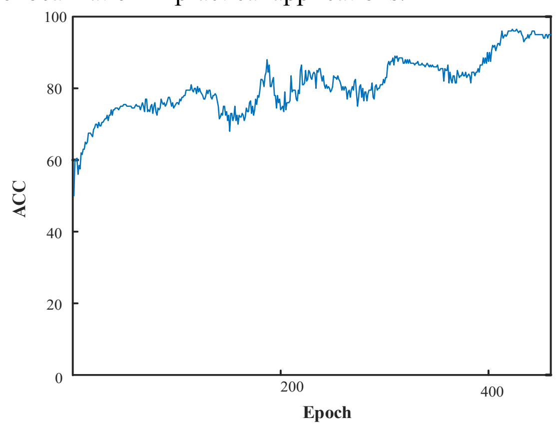
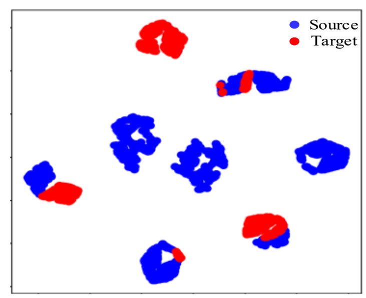
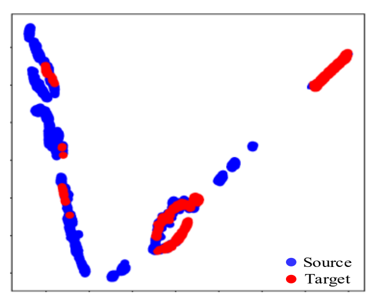


Fig. 4. Graph of model accuracy versus training times

In order to reflect the intrinsic domain adaptation effect of the proposed transfer learning method, the t-SNE dimensionality reduction algorithm is utilized to carry out the analysis of the feature spatial distribution before and after the training of the two-domain samples, as shown in Fig. 5. Where red color indicates the target domain sample and blue color indicates the source domain sample.



(a) pre-domain adaptation



(b) after domain adaptation

Fig. 5. The distribution of data characteristics of the two domains before and after DAN

As can be seen from the above figure, before going through the model proposed in this paper, the gap between the spatial distribution of samples in the two domains is large; after going through the learning network, the data in the two domains basically overlap, i.e., the spatial distribution of features in the two domains at this time is basically the same. It shows that the built migration network completes the migration generalization of the forced oscillation samples to the actual system sub/super-synchronous oscillation samples. At the same time, it can be seen that after the localization model, the sample data are more obviously divided into two sets, completing the classification of labels, i.e., the localization of the oscillation source.

In summary, the above examples fully verify the localization accuracy and effectiveness of the oscillation source localization method proposed in this paper. Through the migration generalization between the forced oscillation and the actual oscillation, the problem of the scarcity of the actual system oscillation data is solved.

C. Comparison with Traditional Deep Learning Localization Models

This section designs deep learning models adapted to oscillatory source localization based on convolutional neural networks. Data from forced oscillations in the source domain are used for training to investigate the adaptation of the source domain model to the actual oscillatory domain before migration.

The data of forced oscillations in the source domain are used to train the localization model, and when the test accuracy of the source domain reaches 99%, the model is saved to obtain an oscillating source localization model adapted to forced oscillations. When the model is used for real oscillations, the localization accuracy is only 67.5%. That is, without transfer, the localization model trained in the source domain is not applicable to the target domain, and the forced oscillation samples in the simulation system can not be directly expanded with the actual oscillation sample set. The accuracy of the final localization model can reach 92.5% after the feature migration of the two domains using the model proposed in this paper. The above shows that the migration learning can effectively realize the feature generalization between the two domains, realize the migration between the forced oscillation and the actual oscillation。

D. Comparison with Single Kernel Transfer Learning Models

In this section, an oscillatory source localization model is designed based on ordinary single kernel transfer learning. It is compared with the effect of MK-MMD proposed in this paper. The experimental results are shown in Table II:

TABLE II. COMPARISON OF EXPERIMENTAL RESULTS

transfer model	***accuracy***
MMD	83%
MK-MMD	92.5%

The above results show that the MK-MMD used in this paper has a better transfer effect than the single kernel transfer model.

V. CONCLUSION

In this paper, a sub/super-synchronous oscillation source localization method based on deep adaptation network is proposed for the scenario of direct-drive wind turbines connected to the grid via a weak AC grid. The effectiveness of the method is verified by simulation.

(1) The method implements data transfer for forced oscillations based on transfer learning, which solves the problem of scarcity and difficulty in obtaining oscillatory data for real systems.

(2) In this paper, by performing MK-MMD improvement, the total kernel is constructed jointly using multiple kernel weighting, which provides better fitness than single kernel.

(3) The proposed method does not require numerical modelling and achieves online localization of sub/super-synchronous oscillation sources in wind power systems by means of offline training of data and online application.

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