Static Voltage Stability Margin Prediction of Island Microgrid Based on Tri-Training-Lasso-BP Network

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***Abstract*—In this paper, neural network, semi-supervised training, integrated learning, and other techniques are applied to the prediction and analysis of static voltage stability margin of island microgrid power systems and an online prediction method based on the Tri-Training-Lasso-BP network is proposed. The network consists of Tri-Training, the least absolute shrinkage and select operator (Lasso) algorithm and the backpropagation (BP) neural network. The analysis results on an 115-node example show that the proposed method can reduce the requirement of the data volume of the training set, take advantage of the massive data collected during the daily operation of the power system, improve the prediction accuracy of the network and reduce manual intervention. Finally, this paper uses statistical methods to make a comprehensive and objective description of the performance of the method.**

***Index Terms*—ensemble learning; island microgrid; static voltage stability margin; Tri-Training-Lasso-BP network**

I. INTRODUCTION

In recent years, there have been many major blackouts [1], causing losses to the economic benefits of power companies and also having a serious impact on the development of social economy [2]. Researchers summarized these incidents and found that most of the large-scale shutdown of power systems is caused by the destruction of static voltage stability [3] and the voltage stability margin can provide intuitive information [4].

As a controllable system integrating distributed generators (DGs), loads and energy storage equipments, microgrid generally has two operation modes, which are grid-connected and island-isolated [5]. When the island is isolated, its own generators and energy storage equipments provide power. If any load in the microgrid has large fluctuations and the adjustment capability of itself cannot make the internal voltage of the microgrid constant, then voltage collapse may happen. The change of reactive load may cause destruction of voltage in the microgrid [6]. Therefore, the voltage stability of the island microgrid is a subject worth studying. Under the peer-to-peer control, there is no equilibrium node in the system, and there is a droop-controlled DG. The system frequency needs to be considered and the traditional calculation models of power flow is no longer applicable. Analysis on island microgrid requires a correction of the conventional power flow model.

The traditional estimation methods of voltage stability margin are based on continuous power flow calculation using power flow equation, and the process is slow. With the rapid development of microgrid, the traditional method of offline evaluation of voltage stability margin is difficult to meet the requirements of speed and accuracy for online real-time prediction [7]. In addition, most of the existing studies of voltage stability are targeted at transmission and distribution networks, yet less on microgrids.

At home and abroad, neural network, support vector machine [8] and other machine learning methods are used to realize the prediction of voltage stability margin. However, the methods used before all use offline simulation data to train neural network and the training samples established offline were limited, i.e. they could not completely cover all the operating states of the microgrid. Therefore, the model obtained has defects and deficiencies. At the same time, the actual operation states of the microgrid are various, and there are bound to be factors that are not considered in the offline training process. Consequently, it is necessary to use the system real-time operation data to update and optimize the network parameters online. In the conventional offline supervised training algorithm, changing of the parameters of the model can only be realized by retraining the model and putting the model online, causing low efficiency. With the development of power system automation, reducing manual intervention is becoming a major trend.

As a result, this paper introduces a semi-supervised regression method called *Tri-Training* to solve the problems mentioned above and studies voltage stability of the island microgrid. First, the power flow calculation model is modified according to the characteristics of the island microgrid. Then, for the prediction problem, the unlabeled data from state estimation in the system is pseudo-labeled and participates in the update of the parameters of the model. This can make up for the shortcomings such as insufficient sample coverage caused by training the network using offline simulation data, reduce the requirement on the number of samples in the training set, and lessen manual intervention in the training process. This method achieves better online prediction with a smaller offline training dataset and enables adaptive training.

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II. Static Voltage Stability Analysis Problem

A. Prediction Problem of Static Voltage Stability Margin

The static voltage stability margin is calculated as follow:

$$K_P = \frac{P_{\max} - P_0}{P_0} \times 100\% \quad (1)$$

where K_P is load margin of the system; P_0 is the active power of all loads in the current operating state of the system; $P_{\max}$ is the maximum active power of loads the system can carry [9].

The prediction problem of static voltage stability margin can be expressed as follow. It can be redefined as an optimization problem:

$$\begin{gathered} \min_{M} z = \left| \hat{P}_{\max} - P_{\max} \right| \\ \text{s.t.} \hat{P}_{\max} = M(X) \end{gathered} \quad (2)$$

where X is $[x_1,x_2,\ldots,x_{m-1},x_m]^T$ and $x_1,x_2,\ldots,x_{m-1},x_m$ are respectively m state variables describing the current state of the system, which may be voltage amplitudes, phase angles, active powers and reactive powers of all nodes of the system, or the sum of the active powers of all nodes of the system. The object is to find a good model which is able to minimize the error between the predict value and the true value of the maximum active power of loads that the system can carry. At the same time, the constrained equation need to be considered, which means that the predict value is generated using the model M.

The traditional continuous power flow method [10] is slow in calculation and difficult to meet the requirements of online real-time prediction of voltage stability margin. Therefore, the focus of this paper is to construct a computational model M. According to the characteristics of the prediction problem of static voltage stability margin, the input of model M is a m-dimensional vector X, and the output is a predicted value of $P_{\max}$. X is a set of U, θ, P and Q. U is a set of voltage amplitudes of all n nodes after the standardization. θ is a set of voltage phase angles of all n nodes in units of radians. P is a set of active powers of all n nodes and Q is a set of reactive powers of all n nodes. P and Q are all based on the reference capacity of power system S_{base} and the dimension of vector X is $m=4n$, in which n is the number of nodes.

B. Division of Training Samples

The Tri-Training-Lasso-BP network proposed in this paper is based on the neural network and needs to divide dataset S into training set and test set. There are k samples in the dataset S. Each sample is randomly generated within a certain range of values. It consists of the m-dimensional vector X and the maximum active power of loads $P_{\max}$ the system can carry. The entire dataset S is expressed as:

$$S = \left\{ \left(X_1, P_{\max,1}\right), \left(X_2, P_{\max,2}\right), \ldots, \left(X_k, P_{\max,k}\right) \right\} \quad (3)$$

The dataset S is divided into a labeled dataset A, an unlabeled dataset B, and a test dataset C. The number of samples in each dataset is k_A, k_B, k_C, respectively, and $k_A+k_B+k_C=k$. In the labeled dataset A, both the input argument X and the output response variable exist to participate in the offline training process. The unlabeled dataset B contains the input argument X but does not contain the output response variable. The test dataset C simulates the state of microgrid at a certain time in the future, which can be used to test the accuracy of the network and not participate in the training throughout the process.

C. Data Preprocessing

There are many factors that affect the static voltage stability margin of the power system. At the same time, the limit of load capacity cannot be expressed mathematically, so it is very difficult to choose suitable system state quantities to build an input vector. If all system state quantities are used, the speed of training and predicting will be affected. In order to solve this problem, the Lasso feature dimension reduction method [11] is introduced. The key features extracted from samples are used for network training and testing. It can improve the speed of the algorithm while making the accuracy of the it not greatly affected. The Lasso method uses the absolute value function of the model coefficients as a penalty to compress the model coefficients, and automatically compresses the coefficients with smaller absolute values to zero, thereby simultaneously achieving the selection of significant variables and the estimation of corresponding parameters [7]. It overcomes the shortcomings of the traditional method in the feature selection model, and its computational complexity is better controlled than other feature selection algorithms. Moreover, its time complexity is equivalent to the least square method [12].

For each sample in the dataset S describing the state of the system:

$$\left(X_i, P_{\max,i}\right), i = 1,2,\ldots,k \quad (4)$$

Where $X_i = \left[x_{i,1}, x_{i,2}, \ldots, x_{i,m-1}, x_{i,m}\right]^T$

Standardize $x_{i,j}$ to archive $\sum_i x_{i,j} / N = 0$ and $\sum_i x_{i,j}{}^2 / N = 1$ and use Lasso to extract key features to get sample being processed:

$$\left(X_i', P_{\max,i}\right), i = 1,2,\ldots,k \quad (5)$$

where $X_i' = \left[x_{i,1}, x_{i,2}, \ldots, x_{i,m'-1}, x_{i,m'}\right]^T$, m' is the dimension of the sample after dimensionality reduction and $m' \le m$. m' is automatically adjusted according to the size of the constraint parameter t in the Lasso algorithm. The smaller t is, the smaller the value of m' . Reasonably setting the value of t can control the dimensionality of the samples, thereby achieving the improvement of the training speed while ensuring the prediction accuracy.

III. Static Voltage Stability Analysis Based on Tri-Training-Lasso-BP Network

A. Structure of Tri-Training-Lasso-BP Network

The structure of Tri-Training-Lasso-BP network proposed in this paper is shown in Figure 1. The dotted line in the figure is based on offline supervised training. It first uses the labeled dataset A to train the neural network and then goes online for prediction. This part is commonly used in previous paper. In this paper, the online semi-supervised training module is added and the unlabeled dataset B can be pseudo-labeled to participate in the parameter update process. In order to evaluate the performance of the proposed method, the test dataset C is used. The test dataset C not participate in the network training process can simulate the random data in the actual running process to a certain extent and reflect performance of the model.

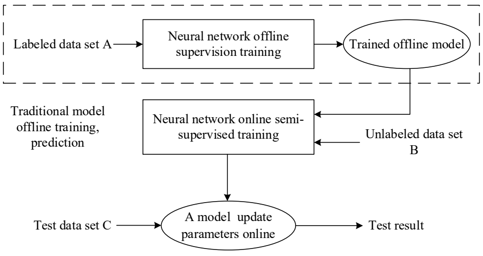

Fig. 1 Components of Tri-Training-Lasso-BP network

B. Online Semi-supervised Regression Training

On the basis of data preprocessing, each learner in semi-supervised training is constructed by one-hidden-layer BP neural network [13]. The resulting network is called Lasso-BP neural network [7].

The state estimation module in the microgrid system can generate a large amount of data describing the operating states of the system, i.e. the m-dimensional vector X mentioned above, and the maximum active power of loads $P_{\max}$ the system can carry is unknown, so the data belongs to the unlabeled dataset.

Semi-supervised training[14] is a method between supervised training and unsupervised training. It absorbs the characteristics of unlabeled data during the training process and trains with unlabeled data in the case of missing data features and less labeled data meeting the requirements. It can improve the prediction accuracy of the network, reduce the number of samples in the offline training set, and take advantage of the unlabeled data when there is less labeled data [15].

Literature [15] proposed Tri-Training, which combines the advantages of semi-supervised training and integrated learning to improve the performance of the model. The Tri-Training does not have stringent requirements for the dataset and does not require the use of different types of learners. In this paper, the conventional Tri-Training method for classification is improved for our regression problem. The specific implementation steps are as follows:

1） The labeled dataset A, the unlabeled dataset B, and the test dataset C are prepared, and their numbers of samples are k_A, k_B, k_C, respectively, and $k_A+k_B+k_C=k$.

2） Processing the labeled offline simulation dataset A: The labeled dataset A is repeated sampling for three times, and three subsets of A are obtained, denoted as A_1, A_2, and A_3. Then they are used to obtain three different Lasso-BP network learners, denoted as M_1, M_2, M_3.

3） Processing the unlabeled online state estimation dataset B: The learners M_1, M_2, M_3 are retrained using the unlabeled data. Here, the retraining process of the learner M_3 is taken as an example to introduce:

The learner M_1 and M_2 are used to predict the value of unlabeled data of the dataset B, and the confidence criterion of prediction results is:

$$\left| M_1(X_i') - M_2(X_i') \right| < \text{SURE\_ERR} \tag{6}$$

where $X_i' \in B$, SURE_ERR is a constant and can be adjusted according to the actual situation.

If equation 6 holds, then $(X_i', \hat{P}_{max,i})$ is added as a pseudo-labeled sample to the pseudo-labeled dataset π_3. $\hat{P}_{max,i}$ is the predicted value of the output response variable, which is calculated as:

$$\hat{P}_{\max,i} = \alpha M_1(X_i') + \beta M_2(X_i') \tag{7}$$

where $X_i' \in B$, $\alpha+\beta=1$.

If equation 6 does not hold, no action is taken.

4） Combine the pseudo-labeled dataset $\pi_3=\{(X_i', \hat{P}_{max,i})\}$, $X_i' \in B$ with the training dataset A_3 of the learner M_3 to obtain a new training dataset A_3':

$$A_3' = A_3 \cup \pi_3 \tag{8}$$

Replace A_3 with A_3' and retrain the learner M_3 with A_3. At this time, the retraining of learner M_3 is completed.

5） After all the three learners have performed steps 3) and 4), a Tri-Training process is completed. Repeat the Tri-Training process until the maximum number of repetitions *epoch_max* is reached and proceed to step 6), where *epoch_max* can be adjusted according to the actual situation.

6） The test dataset C is predicted using three learners M_1, M_2, and M_3. The predicted value of the maximum active power of loads the system can carry is:

$$\hat{P}_{\max,i} = \alpha M_1(X_i') + \beta M_2(X_i') + \gamma M_3(X_i') \tag{9}$$

where $X_i' \in C$, $\alpha+\beta+\gamma=1$.

As the algorithm runs, the data in the unlabeled dataset B is reduced and they are progressively labeled with pseudo-labels.

IV. Case Analysis

A. Evaluation Index of Performance

In order to exclude the impact of the magnitude of the results on the mean square error assessment index, measure the stability and robustness of the method and monitor occasional serious errors, this paper defines the average relative error e_{mean} and the maximum relative error e_{max} to evaluate the performance:

$$e_{\text{mean}} = \frac{1}{k_C} \sum_{i=1}^{k_C} \left| \frac{P_{\max,i} - \hat{P}_{\max,i}}{P_{\max,i}} \right| \tag{10}$$

$$e_{\max} = \max\left(\left| \frac{P_{\max,i} - \hat{P}_{\max,i}}{P_{\max,i}} \right| \right), i = 1, 2, ..., k_C \tag{11}$$

The algorithm performance problems to be studied in this paper correspond to independent samples, and there is no pair relationship or correlation between samples. Therefore, the Mann-Whitney U test is suitable for result assessment [16].

B. Experiment Background and Parameters Setting

The large-scale microgrid system in [17] is used as the test case. The system has 115 nodes and 118 branches, including 3 wind turbines, 2 photovoltaic cells and 8 gas turbines. Among them, the 71, 72, and 73 nodes where the wind turbine is located are regarded as PQ nodes, and the 49 and 50 nodes where the photovoltaic cells are located are regarded as PV nodes. The node where the gas turbine is located is considered to be a droop control node. When the droop node is running at no load, take ω_0=1.004 and U_{0i}=1.06. In the load model, the active and reactive power indices are from [18], and the static frequency characteristics are from [19].The system reference capacity S_{base} is 1 MVA and the reference frequency is 50 Hz.

After adding consideration of the droop nodes and the load characteristics in the microgrid[20][21] to the MATPOWER continuous power flow calculation program, 3000 sets of samples are generated as the dataset S in this paper. The specific method of generating samples of the power flow section [22] is: under the reference operating state, randomly initialize the operating state of the system, so that the power factor of each load node in the system is kept constant, and then the parameters of each node are randomly set according to Table I. Under the new operating state, the maximum active power of loads $P_{\max}$ the system can carry is obtained by the modified continuous power flow method, and the iteration step is 0.05. The programming language used in the paper is MathScript and the version of MATLAB is R2018b. The CPU used is Intel Core i7-8700 whose main frequency is 3.20GHz, and the available memory is 15.8G.

TABLE I. RANGE OF PARAMETER OF EACH NODE

Data Type of Node	Range of Parameter
Active power at each load node	Base value×(0.7~1.3)
Active power at generator node without droop control	Base value×(0.7~1.3)
Voltage amplitude at generator node without droop control	Base value×(0.97~1.03)

The original dataset of 3000 samples is divided into labeled dataset A, unlabeled dataset B and test dataset C according to the ratio of 0.40:0.45:0.15. The offline Lasso-BP network only uses A for training, C for testing; The proposed Tri-Training-Lasso-BP network is trained using A and B. Similarly it uses C for testing. The termination criterion of Lasso method is that iteration epoch reaches 10,000 or the convergence criterion is less than 1×10^{-7}. Three learners differ mainly in the process of resampling the labeled training set and the number of neurons in the hidden layer. In the online training process, part of the data that accounts for 80% of the original labeled data is used for training.

C. Results

The offline Lasso-BP network and the Tri-Training-Lasso-BP network proposed in this paper are tested for 10 rounds, and the performance test results are shown in Table II. The average and the maximum relative error distribution of each round are shown in Figure 2. The result shows that the Tri-Training-Lasso-BP network proposed in this paper can optimize the parameters using online unlabeled samples when the offline label samples are limited. The mean and standard deviation of the maximum and average relative errors are smaller than the offline Lasso- BP network's. The performance of the two networks was evaluated by the Mann-Whitney U test. The p value of average relative error is 0.0002(z=3.780) and the p value of maximum relative error is 0.0002(z=3.780), indicating that the results of the two algorithms are extremely statistically significant. Therefore, the Tri-Training-Lasso-BP network can be considered better than the traditional offline Lasso-BP network.

TABLE II. PERFORMANCE COMPARISON BETWEEN OFFLINE LASSO-BP NETWORK AND TRI-TRAINING-LASSO-BP NETWORK

Test System	Offline Lasso-BP network [7]		Tri-Training-Lasso-BP Network	
	e_{mean} (%)	$e_{\max}$ (%)	e_{mean}(%)	$e_{\max}$ (%)
115-node microgrid	1.42603	7.3429	0.85411	4.4769

The speed of the algorithm is evaluated when keeping the other test conditions as the same, and the time required is shown in Table III.

TABLE III. SPEED TEST RESULTS FOR THE TRI-TRAINING-LASSO-BP NETWORK

Test System	Preprocessing Time /s	Parameters Update Time /s
115-node microgrid	1.452	177.380

At present, the measurement devices used in microgrid systems are mainly PMU, RTU and AMI. The real-time data output delay of PMU is not greater than 30ms, which is a millisecond-level sampling device and its sampling period is defined as T_{PMU}. RTU is generally a second-level sampling device and its sampling period is defined as T_{RTU}. However, the sampling period of AMI is longer, which is generally 15 minutes, and the sampling period is defined as T_{AMI} [23][24]. The result shows that the Tri-Training-Lasso-BP network proposed in this paper is able to adapt to the actual needs of engineering practice. Considering that the calculation period of current state estimation is generally minute level, the method proposed can meet the requirements of online applications.

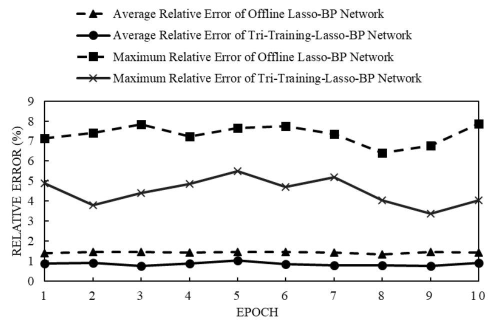

Fig. 2 Relative error of offline Lasso-BP network and Tri-Training-Lasso-BP network on 115-node microgrid test case

In actual applications, the number of labeled samples $\widetilde{k_A}$ and the proportion of labeled samples r_A used for offline training can be determined according to engineering needs, difficulty of obtaining labeled samples and the prediction accuracy level required. The number of unlabeled samples can be calculated as below:

$$\widetilde{k_B} = \frac{\widetilde{k_A}}{r_A}\left(1-0.15-r_A\right) \tag{12}$$

After the program goes online, it check whether the number of unlabeled samples collected reaches $\widetilde{k_B}$ every T period, where T=$k\cdot$lcm(T_{PMU}, T_{RTU}, T_{AMI}); k is a positive integer which can be set according to the actual requirements. If the number of unlabeled samples collected reaches $\widetilde{k_B}$, then a model parameter update process is performed.

V. CONCLUSION

The static voltage stability margin online prediction method based on Tri-Training-Lasso-BP network proposed in this paper can make full use of data features in unlabeled samples to update the parameters of the network when the label samples are limited. It not only reduces the requirement for the amount of data in the offline training set, but also improves the prediction accuracy of the conventional Lasso-BP network using only labeled samples for training.

In this paper, the concept of unlabeled samples is introduced in the field of static voltage stability margin prediction of microgrid and the power flow calculation model in microgrid is rebuilt. In engineering practice, unlabeled samples can be obtained in large quantities during actual system operation. This paper provides a way to utilize the measurement or pseudo-measurement data in the actual operation of the microgrid, which can improve the accuracy of the prediction model and reduce the manual intervention in the parameter update process. In addition, this paper embodies the idea of integrated learning, which can make full use of the advantages of learners of different structures, complement each other and improve prediction accuracy.

In the actual application of engineering, it is necessary to consider how to perform feature and sample screening on the massive operational data to participate in the update process of parameters.

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