

Adaptive Emergency Control of Power Systems Based on Deep Belief Network

Junyong Wu, *Senior Member, IEEE*, Baoqin Li, *Student Member, IEEE*, Liangliang Hao, Fashun Shi, and Pengjie Zhao

Abstract—Emergency control is an essential means to help system maintain synchronism after fault clearance. Traditional “offline calculation, online matching” scheme faces significant challenges on adaptiveness and robustness problems. To address these challenges, this paper proposes a novel closed-loop framework of transient stability prediction (TSP) and emergency control based on Deep Belief Network (DBN). First, a hierarchical real-time anti-jitter TSP method using sliding time windows is adopted, which takes into account accuracy and rapidity at the same time. Next, a sensitivity regression model is established to mine the implicit relationship between power angles and sensitivity. When impending instability of the system is foreseen, optimal emergency control strategy can be determined in time. Lastly, responses after emergency control are fed back to the TSP model. If prediction result is still unstable, an additional control strategy will be implemented. Comprehensive numerical case studies are conducted on New England IEEE 39-bus system and Northeast Power Coordinated Council (NPCC) 140-bus system. Results show the proposed method can detect instability of system as soon as possible and assist in maintaining reliable system synchronism.

Index Terms—Deep learning, emergency control, power system, sensitivity, transient stability prediction.

I. INTRODUCTION

IN recent years, as the scale of power grids has continued to expand, a high proportion of new energy sources and high proportion of power electronic devices have been contained in power systems broadly [1]. Due to continuous increase of power systems’ complexity, it is more and more challenging to ensure grids run in a stable condition. Several large blackouts occurred around the world [2], [3]. After fault clearance, if the dispatch control center cannot assess stability and make effective interventions in time, fault will be further expanded, which will cause catastrophic social impact and economic losses [4]. Therefore, it is vital to evaluate stability and make

a real-time decision according to disturbed information of the power system.

Traditional transient stability analysis approaches include time-domain simulation (TDS) [5], transient energy function (TEF) method [6] and extended equal area criteria (EEAC) [7]. However, due to requirements of real-time, there are significant challenges to apply these methods to post-fault systems. Thanks to continuous progress of artificial intelligence (AI) technology, machine learning based transient stability prediction (TSP) has been widely studied, such as support vector machine (SVM) [8], [9], multilayer perceptron (MLP) [10], random forest (RF) [11] and decision tree (DT) [12]. In these studies, a large number of samples are obtained through TDS, and the mapping relationship between system’s responses and transient stability is established in offline stage. When response information is obtained online by phasor measurement units (PMUs), the mapping relationship can be utilized to get an evaluation result in advance. However, in most research, a fixed response time of the post-fault system is employed, which cannot effectively utilize the time-series data of power systems. Some researchers have carried out studies on time-adaptive TSP. In [13], a time-adaptive ensemble model is proposed to evaluate stability accurately and rapidly. In [14], a TSP model is developed based on long short-term memory network (LSTM). An anti-jitter dynamic model is proposed in [15], which can make good use of time-series data. An integrated learning model based on neural network with random weight is constructed to realize short-term voltage stability assessment [16]. Time-series data in a period of time after fault is taken as input feature, so the model can learn fault information more fully [17]. In [18], a missing-data tolerant method is proposed for post-fault short-term voltage stability assessment.

TSP based on machine learning has achieved a lot, but its further application in emergency control is relatively rare. Emergency control schemes of power systems are divided into three types, including “offline decision-making, real-time matching”, “online decision-making, real-time matching” and “real-time decision-making, real-time control” [19]. Offline decision-making is to generate a large quantity of designated look-up tables for presumed fault scenarios. Online decision-making is to generate a look-up table in an ultra-short-term stage. Real-time decision-making is to calculate a control strategy directly according to scenarios of the system. Because there may be a mismatch between offline look-up table and actual contingency scenario, real-time decision-making is more

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J. Wu, B. Li (corresponding author, email: 19117011@bjtu.edu.cn), L. Hao, F. Shi, and P. Zhao are with the Department of Electrical Engineering, Beijing Jiaotong University, Beijing 100084, China.

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in line with real situation in a practical system, so effect of control is better.

To help post-fault system recover stability, the most commonly used control measures are generator tripping and load shedding. Most meaningful research on generator tripping and load shedding have been done, which mainly include heuristic algorithm, phase plane trajectory method, EEAC and so on [20]–[22]. The heuristic algorithm is to make a control decision by a small number of simulation calculations. The phase trajectory method guides emergency control through slope of phase plane trajectory, avoiding a large number of iterative calculations. The EEAC method utilizes multi-machine system equivalence to determine amount of control according to acceleration and deceleration area. All the methods mentioned above have clear physical meanings, but the calculation process is complicated and cannot fully consider limitations of multi-dimensional factors. Because more and more measurement data of power systems are accumulated by wide area measurement system (WAMS), emergency control measures based on AI have attracted more and more attention. In [23], an innovative adaptive emergency control scheme using deep reinforcement learning is developed. A novel model-free control-based emergency frequency control scheme is presented in [24].

However, most existing studies separate transient stability prediction and emergency control. To fill the gap of existing research and give full play to ability of feature extraction and data mining of deep learning, a novel closed-loop framework of TSP and emergency control based on DBN is proposed. The main contributions are summarized as follows:

1) An anti-jitter adaptive TSP model based on sliding windows is adopted, which can effectively balance trade-off between evaluation accuracy and response time. Reliability of evaluation results is greatly improved.

2) A method for identifying severely disturbed generators is proposed, which can quickly calculate and sort the disturbed severity of generators at initial stage of fault occurrence and provide alternative action space for subsequent emergency control.

3) Sensitivity prediction models are constructed to evaluate contributions of tripping different generators and loads. In addition, responses after emergency control are fed back to the TSP model. When prediction result is still unstable, an additional emergency control strategy will be implemented.

The rest of this paper is organized as follows. Deep belief network employed in this paper is briefly introduced in Section II. Section III presents identification of severely disturbed generators and construction of emergency control optimization model in detail. Section IV gives proposed closed-loop scheme for adaptive TSP and emergency control. Comprehensive case studies in Section V verify effectiveness of the proposed method. Conclusions are given in Section VI.

II. OVERVIEW OF DEEP BELIEF NETWORK

DBN consists of several layers of restricted Boltzmann machine (RBM) and a BP layer. It has strong ability of data mining and feature extraction. DBN can be utilized to solve classification problems or regression problems.

A. Brief Introduction of RBM

RBM is composed of visible layer and hidden layer. Fig. 1 shows structure of RBM. Each node has two states: 0 or 1. 0 and 1 represent nodes that will be selected in model training. 0 means node is not activated, and 1 means activated. Activation probability of nodes is determined by joint probability distribution.

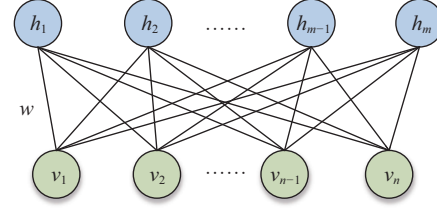


Fig. 1. Structure of RBM.

RBM is an energy-based model [25]. For a given set of states, (v, h) , joint probability distribution of visible layer and hidden layer is calculated by

$$E(v, h|\theta) = -\sum_{i=1}^n a_i v_i - \sum_{j=1}^m b_j h_j - \sum_{i=1}^n \sum_{j=1}^m v_i w_{ij} h_j \quad (1)$$

where $\theta = \{w = (w_{ij})_{n \times m}, a = (a_i)_{1 \times n}, b = (b_j)_{1 \times m}\}$, and θ is parameter of RBM. i_{th} visible layer's state is v_i and bias is a_i . j_{th} hidden layer's state is h_j and bias is b_j . w_{ij} represents weight between i_{th} visible layer and j_{th} hidden layer; n and m are number of visible and hidden layer' neurons, respectively.

Activation probability of j_{th} hidden layer is calculated by the following formula:

$$P(h_j = 1|v, \theta) = \sigma\left(b_j + \sum_i w_{ij} v_i\right) \quad (2)$$

Because of particularity of RBM structure, RBM belongs to bidirectional connection. The visible layer can also be activated by hidden layer, which is expressed as follows:

$$P(v_i = 1|h, \theta) = \sigma\left(a_i + \sum_j w_{ij} h_j\right) \quad (3)$$

where σ is activation function. The sigmoid activation function is adopted in this paper, $\sigma(x) = \frac{1}{1+\exp(-x)}$, which is used to limit output amplitude of neurons.

For hidden layers, when a set of input data are assigned to the visible unit, activation probability can be calculated according to formula (2). u is randomly selected as threshold, which is between [0, 1]. Neurons whose activation probability is larger than threshold are activated, otherwise not activated.

$$h_j = \begin{cases} 1, & P(h_j|x) \geq u \\ 0, & P(h_j|x) \leq u \end{cases} \quad (4)$$

Training process of RBM is to update these parameters (w_{ij} , a_i , and b_j) constantly. Contrast divergence CD-K algorithm is used to optimize these parameters through network reconstruction [26].

B. The Structure of Deep Belief Network

Structure of DBN is shown in Fig. 2. Top layer is used as label layer to output result of classification or regression, and other middle layers completes feature extraction.

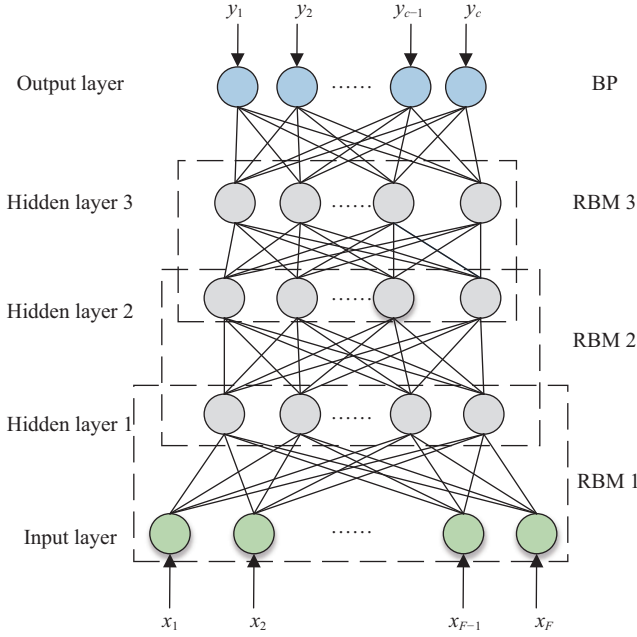


Fig. 2. Structure of DBN.

Hinton *et al.* proposed DBN first in reference [27]. Since the deep structure of DBN is not easy to train, a two-stage learning method of “pre-training and fine-tuning” is proposed. First stage is pre-training. It is an unsupervised training procedure from bottom layer to top. This procedure is realized by reverse reconstruction of RBM. Only input features are needed, then RBM is trained layer by layer. Unsupervised training method is used to initialize network, which effectively reduces optimization space of parameters. However, the main problem is parameters can only reach local extremum, not global optimal value. Therefore, the fine-tuning process for parameters is introduced in the second stage. Traditional method is to optimize these parameters by gradient descent algorithm for error of output layer. In this paper, Adam replaces the conventional algorithm [28]. Adam has a more independent adaptive learning rate and shows better performance.

III. EMERGENCY CONTROL OPTIMIZATION MODEL

A. Identification of severely disturbed generators

In most cases of system instability, power angles of one or several generators fly off track, which means power angles of one or several generators increase or decrease obviously relative to others. Therefore, power angles of a few severely disturbed generators can reflect instability due to fault. Identification of severely disturbed generators can be used as an alternative action space for subsequent emergency control. This study considers identification of severely disturbed generators from the following three aspects:

1) At initial stage of fault occurrence, generator corresponding to maximum value of relative kinetic energy is severely disturbed generator. That is $\max(M_i \tilde{w}_i^2/2)$, M_i is inertia constant, $\tilde{w}_i$ is angular velocity deviation of i_{th} generator under inertia center coordinate, $\tilde{w}_i = w_i - w_{coi}$, w_i is deviation from synchronous speed, and w_{coi} is equivalent speed of system inertia center.

2) At the initial stage of fault occurrence, generator corresponds to maximum value of normalized initial acceleration power. That is $\max(\Delta P_i/P_{mi})$, $\Delta P_i = P_{mi} - P_{ei}$, is acceleration power of i_{th} generator at moment of fault occurrence, P_{mi} is mechanical power, P_{ei} is electromagnetic power.

3) At the initial stage of fault occurrence, the generator corresponding to maximum value of relative acceleration reflects an instability trend. That is $\max(\alpha_i - \alpha_{coi})$, α_i is acceleration of i_{th} generator, α_{coi} is central acceleration of system inertia.

Average value of these three indexes is used as identification criteria of severely disturbed generators. Identification results can be obtained in early period of fault occurrence, and there is no need to predict complex disturbed track trend. In addition, the process is algebraic value calculation, which is very fast and can meet requirements of online real-time.

B. Construction of Optimization Model

1) Objective Function

Emergency control belongs to optimization problem. When system has sufficient reserve capacity to balance cut-off power, there is no need to shed load. On the contrary, when remaining generators group is overloaded, it is necessary to consider load shedding measures. Buses of emergency control are taken as optimization variables. Minimum amount of generator tripping and load shedding is taken as optimization objective to minimize cost of emergency control. The objective function is:

$$\min \left(\sum_{i=1}^{n_G} \Delta P_{G,i} u_i + \sum_{j=1}^{n_L} \Delta P_{L,j} u_j \right) \quad (5)$$

where n_G represents those buses of generators that can be tripped, n_L represents those buses of loads that can be shed, $\Delta P_{G,i}$ is amount of i_{th} generator tripping, $\Delta P_{L,j}$ is amount of j_{th} load shedding. u_i is a control variable, the whole generator is often out of operation in engineering, so value of u_i is 0 or 1. On the premise of maintaining voltage stability constraint and considering demand of power supply reliability, load can be shed based on a certain proportion according to voltage drop caused by fault, so value of u_j is a continuous one within $[0, 1]$. $\sum_{i=1}^{n_G} \Delta P_{G,i} u_i$ represents overall control amount of n_G generators, and $\sum_{j=1}^{n_L} \Delta P_{L,j} u_j$ represents overall control amount of n_L loads.

2) Constraint Conditions

a) *Transient stability constraints*: Transient stability constraint is the fundamental constraint utilized to estimate stability level of post-fault system after emergency control. A reasonable and effective emergency control strategy can help impending unstable system maintain synchronism, and stability degree is greater than a preset threshold. Transient stability constraints can be converted into linear constraints by using sensitivity, as shown in (6).

$$TSI_0 + \sum_{i=1}^{n_G} S_{G,i} u_i + \sum_{j=1}^{n_L} S_{L,j} u_j > TSI_{\text{stable}} \quad (6)$$

where $S_{G,i}$ is sensitivity of i_{th} generator tripping, $S_{L,j}$ is sensitivity of j_{th} load shedding, and TSI_{stable} is threshold of transient power angle stability, $TSI_{\text{stable}} > 0$. $\sum_{i=1}^{n_G} S_{G,i} u_i$ represents increase value of transient stability index by generator tripping, and $\sum_{j=1}^{n_L} S_{L,j} u_j$ represents increase value of transient stability index by load shedding.

b) *Static security constraints*: Premise of generator tripping and load shedding control are all system variables are within a reasonable variation range, as shown in formula (7).

$$\begin{cases} P_{\min} < P < P_{\max} \\ Q_{\min} < Q < Q_{\max} \\ U_{\min} < U < U_{\max} \\ f_{\min} < f < f_{\max} \end{cases} \quad (7)$$

where P is active power, Q is reactive power, U is bus voltage, and f is frequency.

C. Sensitivity

Transient stability index (TSI) is selected to measure stability of post-fault system.

$$TSI = \frac{360^\circ - |\Delta\delta_{\max}|}{360^\circ + |\Delta\delta_{\max}|} \quad (8)$$

where $\Delta\delta_{\max}$ represents maximum power angle difference. TSI indicates stability of power system. If $TSI > 0$, system is stable, and larger the TSI , the higher the stability degree of system. Otherwise, system is unstable.

Transient stability will be affected by generator tripping and load shedding. TSI is employed to define sensitivity of control variables, as shown in formula (9), to seek optimal emergency control strategy. If sensitivity is greater than 0, it indicates this control variable is effective. The greater the sensitivity, the greater the contribution of control variable to system stability. In practical engineering applications, generators and loads with high sensitivity should be considered first.

$$\begin{cases} S_{G,i} = \frac{\partial TSI}{\partial P_{G,i}} \approx \frac{TSI_{G,i} - TSI_0}{\Delta P_{G,i}} \\ S_{L,j} = \frac{\partial TSI}{\partial P_{L,j}} \approx \frac{TSI_{L,j} - TSI_0}{\Delta P_{L,j}} \end{cases} \quad (9)$$

where $S_{G,i}$ and $S_{L,j}$ are influence on system stability after i_{th} generator tripping and j_{th} load shedding respectively, which is defined as sensitivity. TSI_0 is initial transient stability degree of system, $TSI_{G,i}$ is stability of system after i_{th} generator is tripping at amount of $\Delta P_{G,i}$, and $TSI_{L,j}$ is stability of

system after j_{th} load is shedding at amount of $\Delta P_{L,j}$. It is worth noting in the process of calculating sensitivity, only a single control variable is changed, and other variables in the alternative action space keep unchanged.

D. Implementation Time of Emergency Control

There is a period between emergency control implementation time and fault clearing time. This period includes sampling time T_s , data transfer time T_t , decision time T_{cal} and implementation time T_{im} . Sequence diagram is shown in Fig. 3. Considering the practical situation, T_s in this study is 60 ms (3.6 cycles), data transfer time T_t is 40 ms (2.4 cycles), and decision time T_{cal} refers to prediction time of post-fault system stability, which is 3 cycles. Implementation time T_{im} includes prediction time of sensitivity and solution time of optimal emergency control strategy, which is 4 cycles. $T_s + T_t + T_{\text{cal}} + T_{\text{im}} = 13$ cycles. Therefore, implementation time of emergency control is 13_{th} cycle after fault is cleared. Tripping time is 13_{th} cycle after fault is cleared.

IV. ANTI-JITTER TRANSIENT STABILITY PREDICTION MODEL AND CLOSED-LOOP EMERGENCY CONTROL

At present, one of the main reasons why emergency control cannot make real-time decisions is it is impossible to predict stability of the system after generator-tripping and load-shedding in real-time stage. Therefore, this paper constructs an integrated framework of anti-jitter TSP model and closed-loop emergency control.

A. Anti-jitter Transient Stability Prediction Model

Existing research [29]–[33] usually selected input features with fixed response time to train TSP model. To

take into account rapidity and accuracy and take advantage of time-series data of power systems, a hierarchical anti-jitter TSP method using sliding time windows is employed. Fig. 4 shows anti-jitter TSP model. DBNs are trained with input features of different response times. In the process of TSP, samples that are most difficult to distinguish are often those close to stable boundary. Stability or instability characteristics of those samples are not sufficient at initial stage after fault clearance, and it is difficult for TSP model to identify its actual label, which leads to different results predicted at different response times. This condition is defined as jitter phenomenon. For the purpose of determining real label of samples close to stable boundary reliably and quickly, when predicted labels of three continuous response times are consistent, the model will output the final result (stable or unstable). Otherwise, window

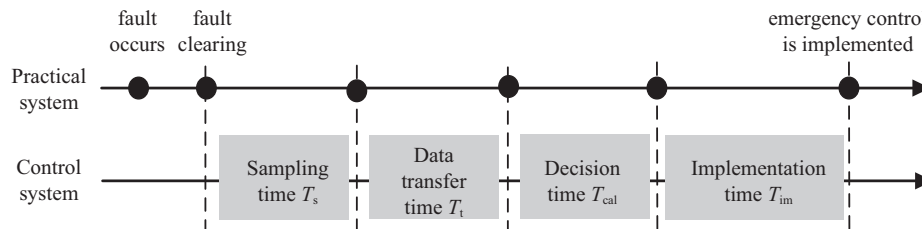


Fig. 3. Sequence diagram of emergency control.

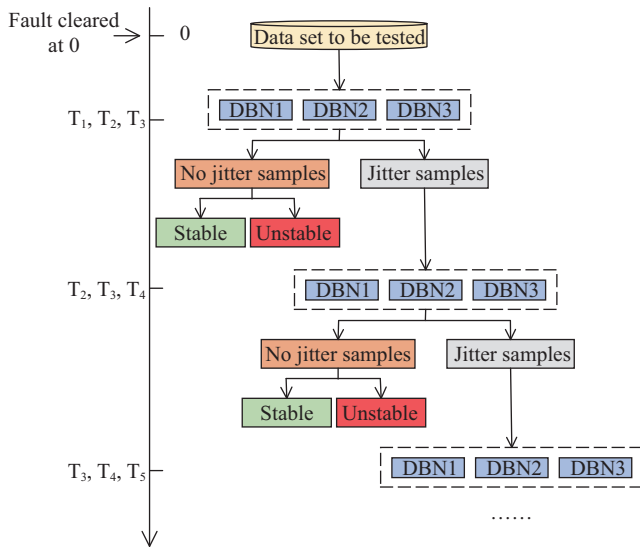


Fig. 4. Hierarchical anti-jitter prediction framework based on DBN.

continues to slide backward until the three predicted labels are consistent.

Using hierarchical prediction method, prediction results for these samples far from stable boundary will be output as soon as possible. For these samples with jitter, they often correspond to samples close to stable boundary. The model temporarily classifies them as uncertain samples and waits for next time-layer to get more information. Hierarchical prediction method can give predicted results early after fault clearance, to ensure rapidity. For these jitter samples, waiting for next time-layer to get more information, the model can output more accurate predicted results, to ensure accuracy.

Stability of power systems can be clearly and accurately reflected by geometric characteristics of generators' power angle. In addition, input dimension does not expand with expansion of system scale. Therefore, for the TSP model, 27 power angle trajectory cluster characteristics are chosen as input features [15], including basic cluster features, gradient and curvature features, acceleration features. Detailed calculation and description of input features are shown in Table AI of Appendix A. For TSP model, it is corresponding to the classification problem. Output has two categories. If post-fault system is stable, label is (1, 0). Otherwise, label is (0, 1).

B. The Process of Closed-loop Emergency Control Process

Sensitivity is critical for emergency control optimization decision-making. For sensitivity of generator-tripping, it not only determines amount of generator-tripping, but also decides which generator should be tripped first if system is foreseen to lose stability. In order to further evaluate sensitivity, this paper establishes a sensitivity regression model based on DBN. Input features are the trajectory cluster features after implementation time of emergency control, and output is sensitivity. Although dynamic responses after implementation time of emergency control cannot be measured by PMUs, response information can be obtained by algebraic jump [34]. Sensitivity model of load-shedding is similar to generator-tripping.

The process of transient stability prediction and emergency control based on DBN is displayed in Fig. 5, including offline and online stages. Steps of DBN offline training are as follows:

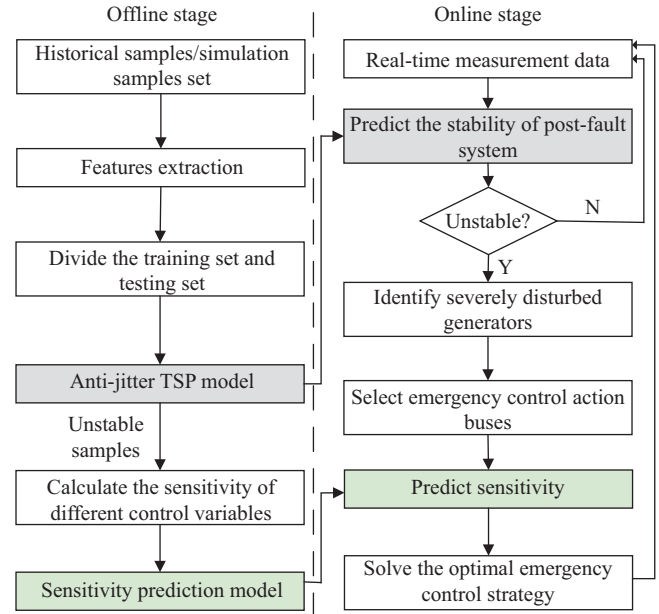


Fig. 5. The process of transient stability prediction and emergency control based on DBN.

Step 1: Obtain samples under different operating conditions by collecting historical data or time-domain simulation, and extract power angle trajectory cluster at different response times.

Step 2: Preprocess input features using maximum and minimum normalization method. Samples are proportional to make input features of DBN within range of [0, 1], to decrease numerical difference.

Step 3: Divide samples set into training set and test set on basis of preset proportion randomly. TSP model is trained by sample sets of two categories (stable or unstable), and generator-tripping sensitivity regression model and load-shedding sensitivity regression model are respectively, trained to use samples after emergency control. Performance of model is evaluated by test set. Specific training process of DBN is as follows:

1) Unsupervised pre-training: Input of DBN is trajectory cluster features of training set. RBM is trained layer by layer from bottom to top, and parameters of DBN are initialized by continuously reducing reconstruction error.

2) Fine-tuning parameters: Taking 27 features as input of DBN after pre-training, and corresponding label as the output. Anti-jitter TSP model corresponds to classification problem. Labels are (1, 0) or (0, 1), corresponding to stable or unstable, respectively. Sensitivity prediction model corresponds to regression problem, and label is sensitivity.

In online application, once predicted result is unstable, severely disturbed generators are identified quickly first. Then sensitivity of generator-tripping for the top 3 generators of severely disturbed generators are predicted by sensitivity regression model. Finally, NSGA-II [35] optimization algorithm is employed to obtain optimal emergency control strategy.

In order to help post-fault system maintain synchronism reliably, dynamic responses after emergency control are continuously input into TSP model. If predicted result is still unstable, additional emergency control measures are implemented, to realize a closed-loop process of stability prediction and emergency control. This process will be continued until system reliably recovers stability. Framework of closed-loop TSP and emergency control is shown in Fig. 6.

C. Evaluation Indices

1) Evaluation Indices of Classification Model

TSP is a typical non-equilibrium classification problem. The confusion matrix shown in Table I is adopted to evaluate effect of anti-jitter TSP model. Evaluation indices include Acc , η_{SR} , η_{UR} , and O_{mean} . Specific process of calculation is shown in formulas (10)–(13).

$$Acc = (U_s + U_{us}) / (U_s + U_{us} + R_s + R_{us}) \quad (10)$$

$$\eta_{SR} = U_s / (U_s + R_{us}) \quad (11)$$

$$\eta_{UR} = U_{us} / (R_s + U_{us}) \quad (12)$$

$$O_{mean} = \sqrt{\eta_{SR} \times \eta_{UR}} \quad (13)$$

2) Evaluation Indices of Regression Model

For the purpose of analyzing sensitivity regression model's performance, prediction absolute error (AER) and prediction mean square error (MSE) are employed in this paper. Specific definition and calculation are shown in formulas (14)–(15).

$$AER = |\hat{y}_i - y_i| \quad (14)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i|^2 \quad (15)$$

where $\hat{y}_i$ represents sensitivity of DBN regression model to predict i_{th} sample, and y_i means actual sensitivity of i_{th} sample. N represents total number of test samples.

TABLE I
CONFUSION MATRIX

Confusion matrix	Stable (predicted)	Unstable (predicted)
Stable (practical)	U_s	R_{us}
Unstable (practical)	R_s	U_{us}

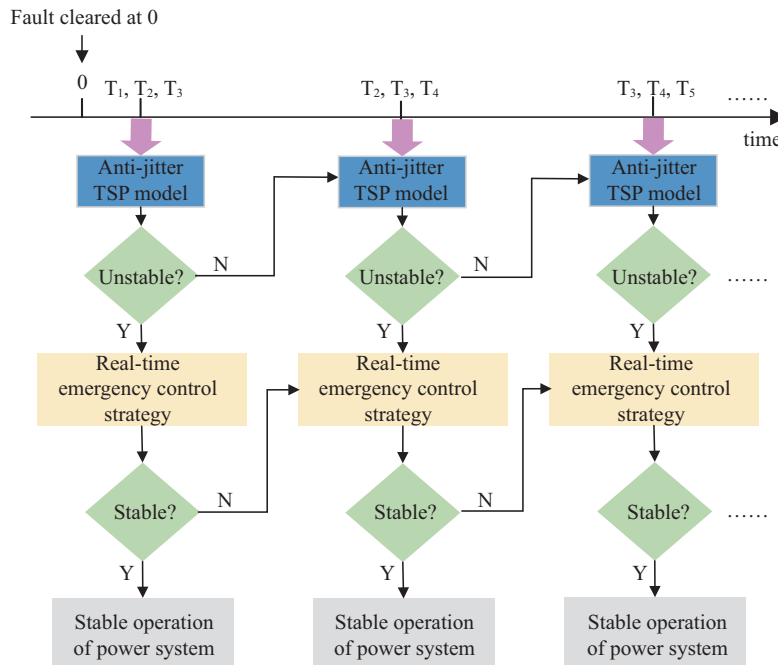
V. CASE STUDIES

To test effectiveness of the closed-loop TSP and emergency control method, DBN is built in Tensorflow 1.13, programming language is python. Comprehensive experiments are implemented on IEEE 39-bus system and NPCC 140-bus system.

A. Samples Generation of IEEE 39-bus System

Considering various operating conditions, samples are generated by TDS using Matlab Toolbox Power System Tool (PST3.0). Load levels are set 90%, 100%, 110%, respectively. Three-phase short circuit fault is set to be located at 0%, 10%, ..., 90% of AC lines. Fault clearing time of 1st cycle (0.0167s) to 11th cycle (0.1837s) after fault is set, respectively. Rated frequency of system is 60 Hz and simulation time is 5 s. 7343 samples are generated, including 3236 stable samples and 4107 unstable samples. Training set and test set are randomly divided according to ratio of 3:1.

For 4107 unstable samples, severely disturbed generators are identified. Based on the above fault settings, generator-tripping and load-shedding are implemented after fault clearance. For generator tripping, there are 10 possible settings, which are arranged from small to large according to number of generator buses, but severely disturbed generators for different unstable samples are different. Total number of generator-tripping samples generated is 12,321, and sensitivity of generator tripping are calculated according to (9) as labels. Considering importance of loads, some loads are selected as alternative



control objects, including buses 3, 4, 8, 15, 20, 24, and 28. A total of 28,749 samples for load-shedding are generated, and their sensitivity indexes are calculated as labels, respectively. Training set and test set are randomly divided in ratio of 3:1. Then sensitivity regression models of generator-tripping and load-shedding are trained separately using their respective training sets.

B. Performance of Anti-jitter TSP Model

Table II shows results of anti-jitter TSP. Number of uncertain samples and time system gets unstable of certain unstable samples are shown in Table III. Two tables reveal hierarchical anti-jitter TSP model can quickly identify these samples far from stable boundary, and Acc , η_{SR} , η_{UR} , O_{mean} indices are 100%. For these samples close to stable boundary, TSP model can wait until next time layer to obtain more information, to realize accurate and reliable prediction of their real categories. In addition, by counting average instability time of unstable samples, it can be found anti-jitter TSP model can always give accurate predicted results before scenario really gets unstable, so leaving sufficient and valuable time for subsequent emergency control. Maximum look-ahead time is 4950 ms, and minimum is 370 ms, which is still a considerable ahead-time. Therefore, anti-jitter TSP model ensures accuracy and rapidity at the same time, and provides an excellent priori condition for emergency control.

C. Effectiveness of Severely Disturbed Generators Identification

To test effectiveness of identification indices of severely disturbed generators, identification results are compared with dominant unstable generators among unstable samples. Since there is often more than one leading unstable generator in practice, statistical method is adopted for verification. If statistical distribution of the severely disturbed generators obtained is based on the three indices is close to statistical distribution of dominant unstable generators, it shows the identification method is statistically effective.

Disturbed power angle curve is observed, and make statistics on distribution number of dominant unstable generators. In an unstable scenario, if power angle data of one or several generators are removed, remaining power angles are in a stable state after criterion calculation according to Eq. (8), removed generators are dominant unstable generators. Traverse all unstable samples and count serial number of dominant unstable generators. Statistical quantity of generator serial number is taken as a random variable to fit its statistical distribution. Distribution fitting curve of severely disturbed generators of top three levels and practical dominant unstable generator are shown in Fig. 7.

Figure 7 indicates among unstable samples, samples with dominant unstable generator No.6 accounted for the vast majority, which is similar to statistics of ranking of severely

TABLE II
RESULTS OF HIERARCHICAL ANTI-JITTER TSP MODEL

Cycles	State	Stable (predicted)	Unstable (predicted)	Acc	η_{SR}	η_{UR}	O_{mean}
T ₁ , T ₂ , T ₃	Stable	768/768	0/768	100%	100%	100%	100%
	Unstable	0/1051	1051/1051				
T ₂ , T ₃ , T ₄	Stable	1/1	0/1	100%	100%	100%	100%
	Unstable	0/3	3/3				
T ₃ , T ₄ , T ₅	Stable	3/3	0/3	100%	100%	100%	100%
	Unstable	0/3	3/3				

TABLE III
THE TIMELINESS ANALYSIS OF PREDICTION RESULTS

Cycles	Unstable case No.	Uncertain rate	Average instability time	Range of early prediction advantages	The range of instability time
T ₁ , T ₂ , T ₃	16	0.87%	1.35 s	370 ms–4950 ms	0.42 s–5 s
T ₂ , T ₃ , T ₄	12	0.65%	3.44 s	2363 ms–4863 ms	2.43 s–4.93 s
T ₃ , T ₄ , T ₅	6	0.33%	3.56 s	2897 ms–4933 ms	2.98 s–5 s

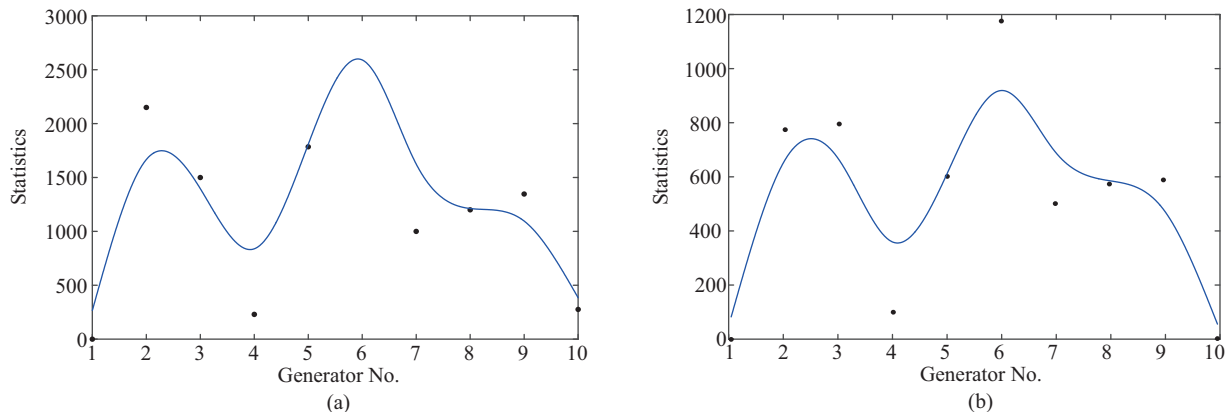


Fig. 7. Fitting curve according to different methods. (a) Statistics distribution of severely disturbed generators. (b) Statistics distribution of practical dominant unstable generators.

disturbed generators identified. If statistical quantity of generator serial number is taken as a random variable, probability density function of random variable is fitted. Fitting function curve obtained by superposition of statistical distributions of top three severely degrees is shown in Fig. 7(a). Fitting curve of statistical distribution of actual dominant unstable generators is shown in Fig. 7(b). By comparing two curves, it can be seen trends of the two probability density curves are very similar. So, in the sense of probability and statistics, it can be considered statistical distribution of severely disturbed generators identified according to the three indices is similar to dominant unstable generators, which verifies effectiveness of using the three indices to identify disturbed generators.

D. Performance Analysis of Sensitivity Regression Model

After identification of severely disturbed generators, it is necessary to predict sensitivity of generator tripping for severely disturbed generators. Predicted value of sensitivity determines which generator should be tripped first and amount to trip. Therefore, there are strict requirements for performance of sensitivity regression model. This paper tests accuracy and generalization ability of generator tripping sensitivity regression model.

1) Accuracy

Input unit of DBN is 27. Number of hidden layers neurons are searched layer by layer, and number of hidden layers is gradually increased. Ultimately, optimal structure of DBN is [27, 200, 100, 50, 30, 1]. MLP adopts the same structural parameters as DBN. Kernel function of SVM is radial basis function. DT adopts C5.0 algorithm.

MSE of DBN, MLP, SVM, DT and RF is compared in Fig. 8. Fitting error of DBN is 0.0045 lower than of MLP. Structure and parameters of DBN and MLP are consistent, but fitting error is different, which shows the unsupervised method of DBN effectively pre-trains parameters of network and improves performance of model. MLP adopts the method of random initialization parameters, which is difficult to effectively optimize parameters, and fitting error is large. Therefore, unsupervised training can provide a better initial value for supervised training and make fitting error of DBN converge effectively. Fitting error of DBN is 0.0081, 0.0025,

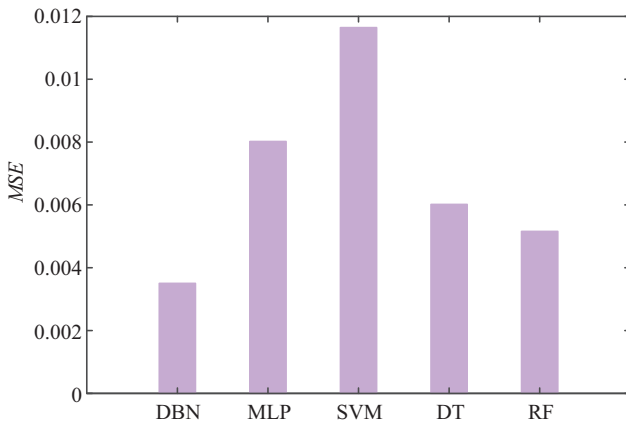


Fig. 8. Comparison of regression prediction performance of different models.

and 0.0017 lower than SVM, DT, and RF, respectively. It reveals deep architecture can better mine features of data. Because traditional machine methods only relies on supervised learning to train the model, and lacks the ability to mine and extract deep features of original data, so fitting error of them is large.

DBN realizes accurate fitting of sensitivity through strong feature extraction and data mining capabilities, and provides a good reference value for formulating an emergency control strategy. Sensitivity regression model is trained in offline stage. Sensitivity indices of test samples are predicted by pre-trained model, and compared with real sensitivity value of each instance. In training stage, average prediction error *AER* is 0.0246. In test stage, average *AER* is 0.0258. Distribution of *AER* is further analyzed, as shown in Fig. 9. In *AER* more than 90% samples are less than 0.047, and more than 80% samples are less than 0.026. The above results further show DBN regression model has an excellent performance in fitting sensitivity.

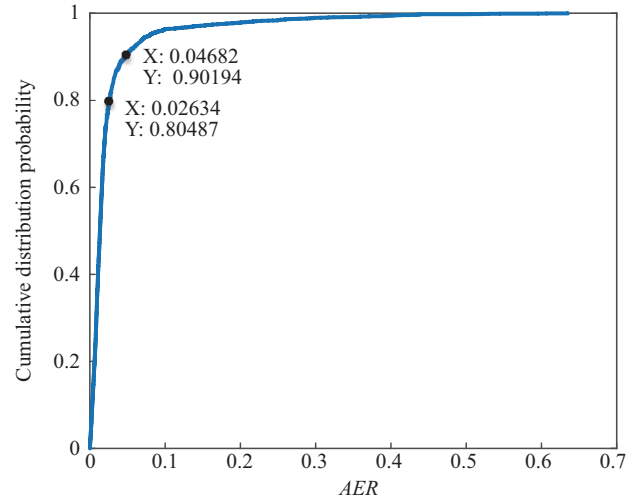


Fig. 9. Cumulative distribution probability of *AER* of sensitivity.

2) Generalization Ability

In this paper, offline training samples of sensitivity model include three load levels of 90%, 100%, and 110%, and different fault locations, fault lines and fault clearing time are set, respectively. Due to continuous fluctuation of load level in practical operation, it is essential to use sensitivity regression model to predict and analyze samples under different load levels and evaluate generalization ability.

Load levels are set as 75%, 85%, 95%, 105% and 115%, respectively. For each load level, 50 test samples are collected randomly, and sensitivity is predicted using pre-trained generator tripping sensitivity regression model. Prediction error of *AER* is shown in Fig. 10, and prediction error of *MSE* is 0.0182. According to statistics, *AER* of 91.2% samples is between 0~0.025, that of 7.2% samples is between 0.025~0.25, and that of the remaining 1.6% samples is between 0.25~0.3. Therefore, for fault of load levels other than initial sample set, the DBN with good generalization ability can accurately predict sensitivity, and further solve emergency control strategy.

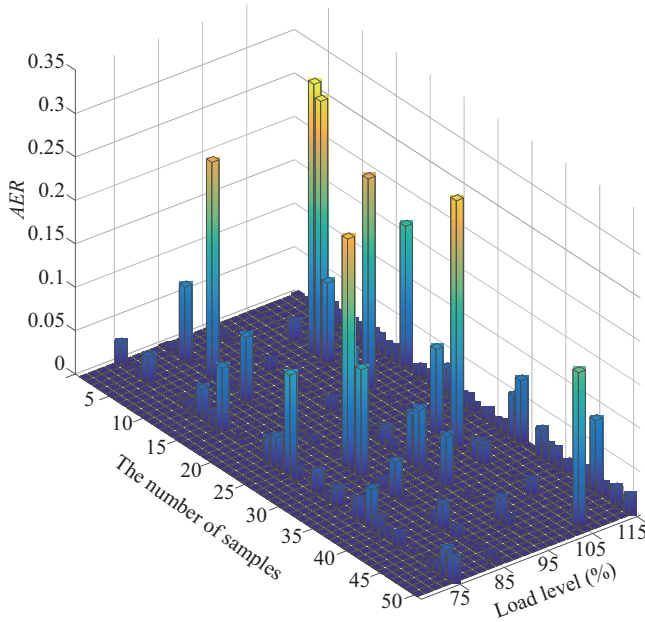


Fig. 10. Prediction performance of sensitivity model when load level changes.

E. Effectiveness Analysis of Closed-loop Emergency Control Strategy

Generator tripping objects of emergency control are generators in the top 3 of severely disturbed generators. Considering importance of loads, some loads are selected as alternative control objects, including buses 3, 4, 8, 15, 20, 24, and 28. Beyond that, in practice, it is impossible to trip part of

a generator, and generator tripping is implemented by tripping one or multiple units in power plants. To simulate tripping of some generators and recover stable operation of the system at minimum cost, it is assumed each generator bus is connected with five generators with the same scale parameters, and the upper limit of generators that can be tripped from each generator plant is four. Load shedding is in proportion, and impact on transient stability to shed of unit load is same. Emergency control strategies in three scenarios are investigated.

1) *Disturbance-I: Load Level is 0.9, Three-phase Short Circuit Fault Occurs at The Head of Line 2–1, and The Fault Clearing Time is 0.05 s.*

This scenario is predicted as a certain unstable one in the first layer of hierarchical anti-jitter transient stability prediction, that is, third cycle after fault clearance. System instability is shown in Fig. 11(a). Three identification indices of severely disturbed generators introduced in Section 3.1 are calculated and ranked, and values are shown in Table IV. Sensitivity values of generators in the top 3 are predicted in turn, as shown in Table V. Transient stability level can be improved by tripping off G6, G8 and G9, and sequence sensitivity of generator tripping from large to small is G9, G8, and G6. DBN regression model is used to fit sensitivity value. Table V indicates DBN regression model can effectively fit sensitivity, and ranking is consistent with real value. The developed emergency control strategy is adopted, TSI_{stable} is set to 0.2, and range of frequency fluctuation is less than 0.2 Hz. It can

TABLE IV
IDENTIFICATION INDICES OF SEVERELY DISTURBED GENERATORS

Generator No.	Relative kinetic energy	Acceleration power	Relative acceleration	Average value	Rank
G1	0.775	−12.856	−0.257	−4.113	10
G2	0.180	−7.577	0.305	−2.364	9
G3	0.004	0.206	0.383	0.198	7
G4	0.00007	0.839	0.315	0.385	6
G5	0.017	6.007	0.365	2.130	4
G6	0.058	6.876	0.469	2.468	3
G7	0.022	4.174	0.331	1.509	5
G8	0.003	20.763	0.608	7.125	1
G9	0.158	11.288	0.458	3.968	2
G10	0.024	−1.323	1.000	−0.010	8

TABLE V
COMPARISON BETWEEN ACTUAL VALUE AND PREDICTED VALUE OF SENSITIVITY

Generator No.	The amount of generator tripping (p.u.)	Actual sensitivity	Predicted sensitivity
G6	5.20	1.1741	1.1728
G8	4.32	1.1743	1.1731
G9	6.64	1.1807	1.1826

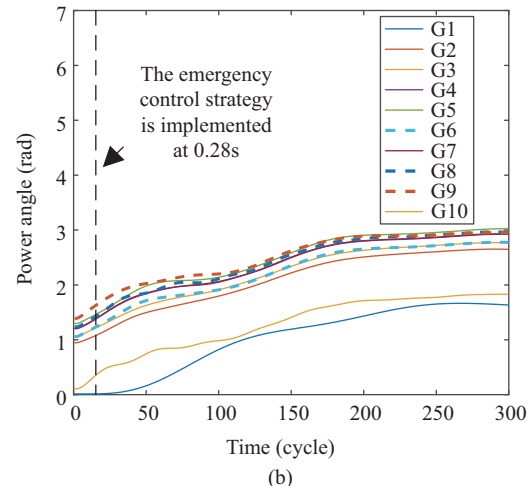
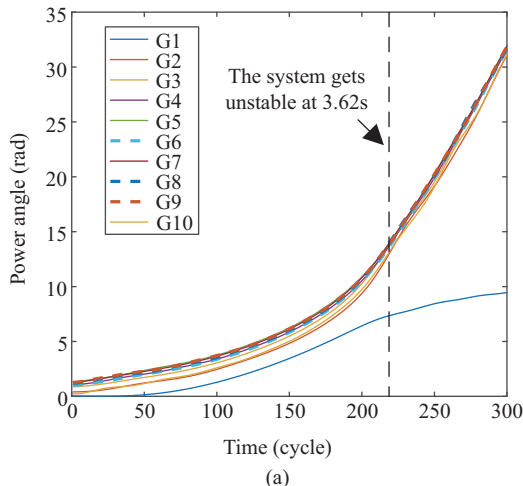


Fig. 11. Generators' power angle curve before and after emergency control of disturbance I. (a) Before emergency control. (b) After emergency control.

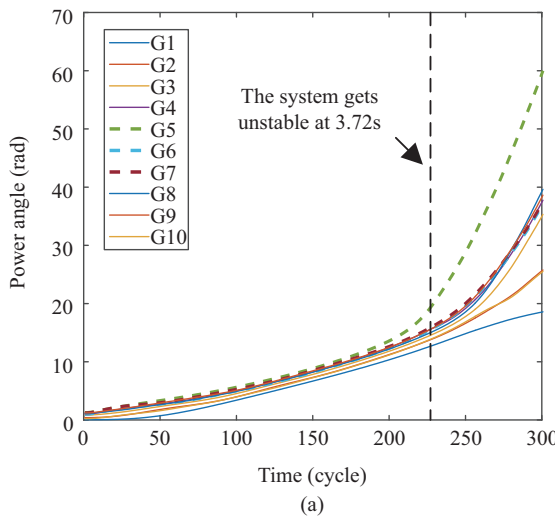
be obtained optimal strategy is to trip off 1.66 p.u. of G9. Because this scenario is foreseen as an unstable one in the first layer of TSP. Considering time cost of data transmission and decision-making in actual online applications, emergency control is implemented on the 13th cycle after fault clearance. Power angle of generators after emergency control is shown in Fig. 11(b). Response characteristics after emergency control are fed back to the anti-jitter TSP model, and prediction result is stable, which is in line with the TDS result.

2) *Disturbance-II: Load Level is 1.0, Three-phase Short Circuit Fault Occurs at Head of Line 24–16, and Fault Clearing Time is 0.1 s.*

Scenario is predicted as a certain unstable one in the first layer. System instability is shown in Fig. 12(a). Through identification of severely disturbed generators, top three generators are G5, G6 and G7, respectively. It is found that only sensitivity of G5 is greater than 0, which is conducive to recovery of system stability. On the contrary, when G6 and G7 are tripped, sensitivity values are less than 0, which means tripping generators of these two power plants is not conducive to the recovery of system stability. Therefore, object of generator tripping is G5. At this time, it is found system cannot satisfy requirements of transient stability threshold and is still unstable. Therefore, load shedding strategy is considered, and sensitivity of load shedding is calculated, loads of buses 3, 4, 8 and 20 and G5 are able to improve transient stability level effectively. Solving optimization model, optimal emergency control strategy is shown in Table VI. At 13th cycle after fault clearance, optimal emergency control is implemented. Fig. 12(b) shows power angle of generators. At this time, system recovers synchronization operation and keeps stable.

TABLE VI
THE OPTIMAL EMERGENCY CONTROL STRATEGY

Bus No.	The amount of generator tripping or load shedding (p.u.)
G5	4.064
4	0.5
8	0.261



Dynamic responses of the system are fed back into the anti-jitter TSP model, and predicted result is also stable, which is consistent with the practical situation.

3) *Disturbance-III: Load Level is 1.1, Three-phase Short Circuit Fault Occurs at 10% of Line 9–8, and The Fault Clearing Time is 0.0501s.*

The scenario is predicted as unstable in the first layer of hierarchical anti-jitter transient stability prediction. Three indices of severely disturbed generators are calculated and ranked first. The generators in the top 3 are G2, G3 and G6. The sensitivity regression model is used to fit sensitivity and solve emergency control optimization model. It is concluded emergency control strategy is to trip the G6 1.3 p.u. At the 13th cycle after fault clearance, emergency control is implemented, anti-jitter TSP is started again to predict the transient stability to build a closed-loop. But the predicted result is still unstable, indicating this strategy is not enough to recover stability of the system. Therefore, optimization model is continued to solve, and additional emergency control strategy is to trip G2 1.0416 p.u. Considering time cost of data transmission and decision making of dynamic process, additional control action is added in the 13th cycle after the implementation of the first emergency control. Fig. 13(a) shows power angle curve of generators before emergency control, and Fig. 13(b) shows the curve after control. It depicts, the impending instability state can be predicted as soon as possible for implementing emergency control, the power angles converge in the process of emergency control and post-fault system recovers stability. This also indicates practical operation conditions, when the system after fault clearance is predicted to be unstable, only once emergency control measure sometimes cannot recover the stability of the system, but the responses are fed back to the TSP model to build a closed-loop emergency control to safeguard the system. It can dramatically make the system operate in a safe and stable state.

F. NPCC 140-bus System

For the purpose of further analyzing the effectiveness of the closed-loop framework of TSP and emergency control

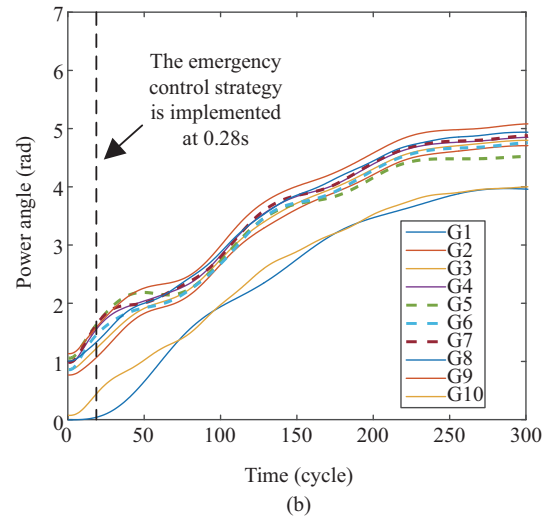


Fig. 12. Generators' power angle curve before and after emergency control of disturbance II. (a) Before emergency control. (b) After emergency control.

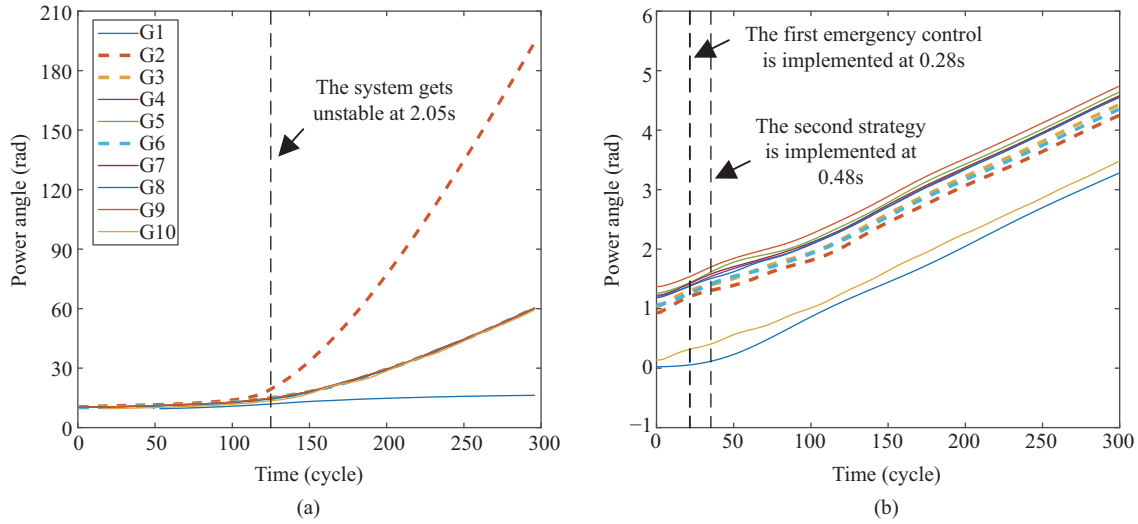


Fig. 13. Generators' power angle curve before and after emergency control of disturbance III. (a) Before emergency control. (b) After emergency control.

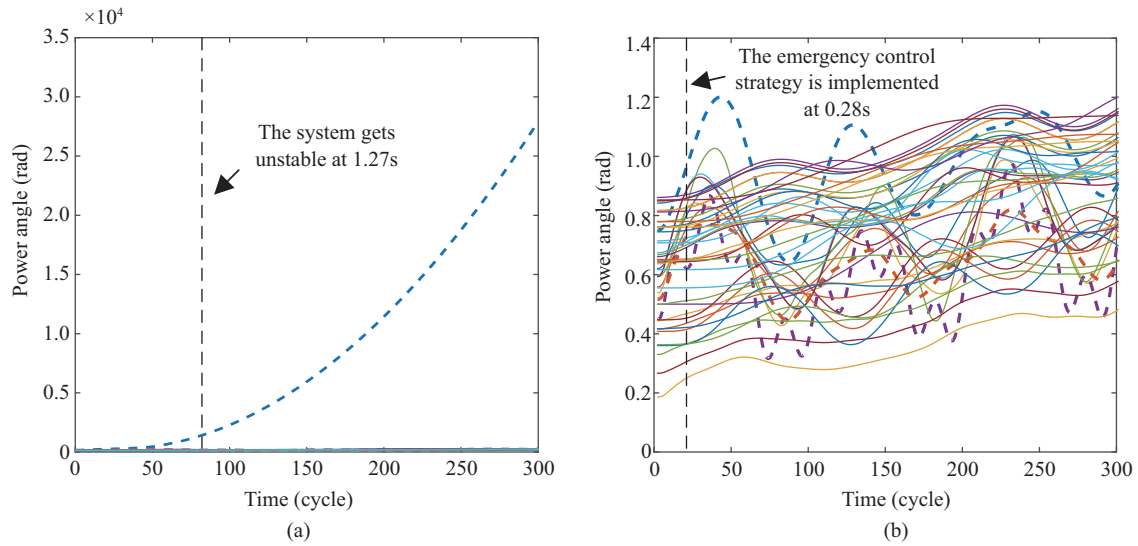


Fig. 14. Generators' power angle curve before and after emergency control in NPCC 140-bus system. (a) Before emergency control. (b) After emergency control.

based on DBN, a larger NPCC 140-bus system is analyzed. This system represents the backbone of the northeast of the interconnected power grid in the eastern United States. It contains 48 generators, 233 branches, and 140 buses.

The load level is set to change between 75%~120% of basic load level, and change step is 5%. There are 10 kinds of different load levels in total. Output of generators should

be set differently according to the load levels. Three-phase short circuit faults are set on the lines. The fault clearing time is 5 cycles (0.08 s) or 9 cycles (0.15 s). Total number of samples generated is 25,045. The ratio of training set and test set is 3:1. The anti-jitter TSP model is trained by using the training set, severely disturbed generators are identified first. According to the arrangement, the top 3 levels of severely disturbed generators are tripping in turn, 12048 samples of emergency control are generated. Then the sensitivity regression models including generator tripping and load shedding are trained separately.

A three-phase short-circuit is applied to line 18–17 at 0.0167s. Then fault is cleared by tripping line at 0.08 s. The generator power angles for this fault are shown in Fig. 14(a). The system gets unstable at 1.27 s, and anti-jitter TSP model predicts this scenario as a certain unstable one at the first time-layer. At the initial stage of the fault clearance, top three severely disturbed generators are G8, G9, G4. The sensitivity index is predicted, and optimization algorithm is solved. The optimal emergency control measure is to trip G8 4.432 p.u. Emergency control is implemented at the 13th cycle after fault clearance. Fig. 14(b) shows the power angles after control. It indicates post-fault system is stabilized via the proposed emergency control method.

Performance comparison between the proposed method and reference [34] is shown in Table VII. The different characteristics considered for comparison are: (1) type of instability, (2) real-time TSP, (3) features dimensions for TSP, (4) real-time emergency control (5) closed-loop of TSP and emergency con-

TABLE VII
PERFORMANCE COMPARISON OF PROPOSED METHOD WITH
REFERENCE [34]

Method	Proposed	Reference [34]
Type of instability	Angle	Angle
Real-time TSP	Yes	No
Features dimensions for TSP	27	15
Real-time emergency control	Yes	Yes
Closed-loop of TSP and emergency control	Yes	No

trol. As shown, the proposed method realizes the closed-loop of TSP and emergency control. When predicted result is still unstable, additional emergency control will be implemented, and security of the power system is guaranteed significantly.

VI. CONCLUSION

In this paper, a novel closed-loop framework of transient stability prediction (TSP) and emergency control based on DBN is proposed. It can realize the rapid prediction of the transient stability for post-fault system and implement effective emergency control. Comprehensive case studies are performed on New England 39-bus system and NPCC 140-bus system. The main conclusions are summarized as follows:

1) The proposed hierarchical anti-jitter TSP method can quickly determine samples are far away from stable boundary. For these samples near stable boundary, reliable and accurate prediction can be achieved by waiting for the next time-layer, so rapidity and accuracy can be taken into account simultaneously.

2) The severely disturbed generators can be quickly identified at the initial stage of the fault occurrence by the proposed method, which is similar to the statistical distribution of the practical dominant unstable generators and provide alternative action space for emergency control. In addition, the sensitivity regression model can accurately fit the sensitivity of generator-tripping and load-shedding, which has a certain generalization ability and robustness. Data-driven TSP and real-time emergency control optimal strategies can be implemented online.

3) The closed-loop TSP and emergency control strategy realize continuous evaluation and emergency control for post-fault system. When the predicted result is still unstable, additional emergency control will be implemented, and security of the power system is guaranteed significantly.

When topology or operation conditions changes greatly, performance of TSP and sensitivity prediction model may deteriorate. Combining with transfer learning to update the pre-trained models will be the focus in future work.

APPENDIX

A. Basic Cluster Features

The trajectory cluster is represented by $\{x_{ij}\}_{m \times n}$, where m represents the number of trajectories and n represents the number of cycles of the sample.

$$\text{Arithmetic mean: } C_j = \frac{1}{m} \sum_{i=1}^m x_{ij}$$

$$\text{Degree of dispersion: } d_j = \frac{1}{m} \left[\sum_{i=1}^m |x_{ij} - C_j|^2 \right]$$

TABLE AI
FEATURES DEFINITION OF TRAJECTORY CLUSTER

Description	No.	Description
	1	Arithmetic mean
	2	Degree of dispersion
	3	Upper envelope
	4	Lower envelope
	5	Mid-range
Basic cluster features	6	Difference between the upper envelope and arithmetic mean
	7	Difference between the lower envelope and arithmetic mean
	8	Envelope height
	9	Difference between the arithmetic mean and mid-range
Gradient and curvature features	10	Gradient of the arithmetic mean
	11	Gradient of dispersion
	12	Gradient of the upper envelope
	13	Gradient of the lower envelope
	14	Gradient of the arithmetic mean
	15	Gradient of the envelope height
	16	Trajectory curvature
	17	Curvature of the arithmetic mean
	18	Curvature of dispersion
	19	Curvature of the upper envelope
	20	Curvature of the lower envelope
	21	Curvature of the mid-range
Acceleration features	22	Arithmetic mean variation acceleration
	23	Dispersion variation acceleration
	24	Upper envelope acceleration
	25	Lower envelope acceleration
	26	Mid-range variation acceleration
	27	

Upper envelope: $\{\max\{x_j\}\}$, $j = 1, 2, \dots, n$

Lower envelope: $\{\min\{x_j\}\}$, $j = 1, 2, \dots, n$

Mid-range: $m_{cj} = \frac{1}{2}(\max(x_j) + \min(x_j))$, $j = 1, 2, \dots, n$

B. Gradient and Curvature Features

Gradient: $r_j = \frac{1}{h}|x_{j+1} - x_j|$, $j = 1, 2, \dots, n-1$

where h is the time sampling interval.

Curvature:

$$C_j = \frac{1}{h^2} \left[\sum_{i=1}^m x_{i,j-1} - 2x_{i,j} + x_{i,j+1} \right]^2 \Bigg)^{1/2},$$

$$j = 2, 3, \dots, n-1$$

C. Acceleration Features

$$a_{cj} = \frac{1}{h}[r_{c,j+1} - r_{c,j}], \quad j = 1, 2, \dots, n-2$$

where r_c is the gradient of the trajectory cluster.

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Junyong Wu received B.S., M.S., and Ph.D. degrees from Huazhong University of Science and Technology, Wuhan, China, in 1987, 1989, and 1993, respectively. From 1998 to 2004, he was a Postdoctoral Researcher at the University of Tokyo, Tokyo, Japan. He currently serves as a Professor, Ph.D. Supervisor, and the Department Head, in the School of Electrical Engineering, Beijing Jiaotong University, Beijing, China. His research interests include power system analysis and automation, the Big Data and AI technology in power system.



Baoqin Li received the B.S. degree in Electrical Engineering from Beijing Jiaotong University, Beijing, China, in 2018. Currently, she is a Ph.D. student with the department of Electrical Engineering. Her research interests include transient stability assessment of power system based on deep learning, emergency control and data augment.



Liangliang Hao received the Ph.D. degree from the Tsinghua University, Beijing, China, in 2012. Currently, he is an Associate Professor in the department of Electrical Engineering at Beijing Jiaotong University, Beijing, China. His research interests include fault analysis and protection in power system, and excitation control.



Pengjie Zhao received the B.S. degree in Electrical Engineering from Taiyuan University of Technology, Taiyuan, Shanxi, China, in 2018. He is currently pursuing the Ph.D. degree at Beijing Jiaotong University, Beijing, China. His research interests include deep reinforcement learning, data mining and deep learning.



Fashun Shi received the B.S. degree in Electrical Engineering from North China University of Water Resources and Electric Power, Zhengzhou, China, in 2019. He is currently pursuing the Ph.D. degree at Beijing Jiaotong University, Beijing, China. His research interests include transient stability analysis and control of power system, and deep learning.