Emergency control strategy of power system transient instability based on DBN

Ziyue Qiang, Junyong Wu, Baoqin Li, Ruoyu Zhang, Liuyun Qin

College of electrical engineering, Beijing Jiaotong University, Beijing, 100044, China
Type the corresponding author’s e-mail: 18121483@bjtu.edu.cn

Abstract. In order to satisfy the real-time emergency control decision-making after power system transient instability, an emergency control strategy based on deep belief network is proposed in this paper. Firstly, the DBN instability degree prediction model is established to fit the mapping relationship between generator power angle characteristics and transient stability coefficient; secondly, according to the fitting instability degree index, the sensitivity of generator tripping is solved to determine the generator tripping control action bus; finally, according to the emergency control optimization model and transient stability constraints, the optimal generator tripping strategy is solved and verified in New England 10-machine and 39-node system. The results show that the proposed method has high prediction accuracy and efficiency, which can make the unstable system quickly resume stable operation.

1. Introduction
With the development of smart grid construction, the scale of power grid is expanding, and the structure of power grid is becoming more and more complex. Once a natural or man-made fault causes a blackout accident [1], if the safety prevention and control cannot be carried out in time, it will cause serious economic losses and social losses. Therefore, it is of great significance to accurately evaluate the system stability and make real-time emergency control decisions based on the disturbance response information of power system.

Emergency control refers to the control measures taken by the power system to maintain the stable operation under the condition of large disturbance or fault, often using means such as generator tripping and load shedding. At present, the research on emergency control mainly includes heuristic algorithm and extended equal area method. For example, in reference [2], load shedding strategy is selected based on artificial neural network to realize power system transient stability. In reference [3], by fitting the electromagnetic power curve after fault clearing, the equivalent area method is used to solve the tripping quantity after instability.

The physical meaning of the emergency control method above based on the physical characteristics of power grid is clear, but it is difficult to calculate in complex power grid and cannot fully consider many factors. Thus in this paper, an emergency control method for transient instability based on data driven and real-time response solution is proposed. First, the DBN model is established to predict the degree of instability of the system. Then, the sensitivity is calculated according to the index of instability degree fitted by DBN, which is used as the basis for the selection of generator trip bus. Finally, according to the emergency control optimization model, the optimal strategy is solved.
2. Transient instability prediction based on DBN

The evaluation index of power system stability after disturbance should indicate both system stability and system stability margin. In order to save operation time, this paper selects transient stability index and uses the power angle value of each generator to measure the power system stability.

\[
TSI = \frac{360^\circ - |\Delta \delta_{\text{max}}|}{360^\circ - |\Delta \delta_{\text{max}}|}
\]

(1)

In the formula, \(\delta_{\text{max}}\) is the maximum power angle difference between any two generators in the system. When \(TSI > 0\), the system is stable; when \(TSI < 0\), the system is unstable, and the greater the \(TSI\) value, the higher the instability degree of the system.

The principle of deep belief network and its training process have been introduced in the previous research results \[4\], which will not be repeated here. The prediction of instability degree based on DBN belongs to regression problem. In this paper, the characteristics \[5\] of generator power angle trajectory cluster after disturbance are extracted and normalized to reduce the numerical difference of input characteristics. The sample label selects \(TSI\) value. The neuron activation function uses the ReLU function. The loss function uses the mean square deviation which is shown in formula (2). The Adam optimization algorithm is used to train, so that the mean square error between the predicted value and the real value is minimized.

\[
e_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}(i) - y(i))^2
\]

(2)

In the formula, \(N\) is the number of samples; \(\hat{y}(i)\) and \(y(i)\) are the predicted and true values of the \(i_{\text{th}}\) sample. The smaller the mean square error, the better the fitting effect of DBN.

3. Emergency control strategy based on DBN

3.1. Emergency control optimization model

Emergency control decision is an optimization problem. This paper considers that the system has enough reserve capacity to balance the power, so it is not necessary to cut off the load. The optimization objective is to minimize the power of the generator tripping, which is as follows:

\[
\min \sum_{i=1}^{N_g} \Delta P_{g_i} u_i
\]

(3)

In the formula, \(N_g\) is the number of nodes of the switchable generator; \(\Delta P_{g_i}\) is the cut-off capacity of generator node; \(u_i\) is the control variable. Its value is 0 or 1 since the whole generator should be cut off in practical project.

In addition, the basic constraints of safe and stable operation of power system, i.e. transient stability constraint \[6\], should be considered to judge the stability level of power system after generator cut-off:

\[
TSI_0 + \sum_{i=1}^{N_g} S_{g_i} u_i > F_{\text{stable}}
\]

(4)

In the formula, \(S_{g_i}\) is the sensitivity of the generator tripping; \(TSI_0\) is the transient stability degree of the system without any control strategy; \(F_{\text{stable}}\) is transient stability threshold and \(F_{\text{stable}} > 0\).

3.2. Generator tripping sensitivity

The transient stability of the system is affected by the control of generator tripping, and the combination of generator tripping strategies is not unique. In order to obtain the optimal emergency control strategy, this paper defines the cut-off sensitivity, as shown in equation (5). The higher the sensitivity is, the stronger the regulation ability of the control variable to the system stability is, and the units with high sensitivity are preferentially removed.

\[
S_{g_i} = \frac{\partial TSI}{\partial P_{g_i}} = (TSI - TSI_0)
\]

(5)
In the formula, $S_{gi}$ is the generator tripping sensitivity; $TSI_{gi}$ is the stability degree of the system after cutting off the generator with $\Delta P_{gi}$ capacity of the $i_{th}$ node.

3.3. Emergency control decision process

The emergency control decision process based on DBN is mainly composed of offline modelling and online decision-making.

![Emergency control decision flow chart.](image)

In the off-line stage, different input features are extracted from the measured data according to the requirements, and pre-processed as the sample set. The prediction model of instability degree based on DBN is trained. In the online stage, after the fault is cleared, the electrical data is extracted from the real-time measurement data as the input characteristics. Based on the previous research [4], if the system is predicted to be unstable, the sensitivity of the machine tripping is calculated based on the instability degree prediction model, and the action bus set of emergency control is selected. Finally, the control strategy is solved according to the emergency control optimization model, so that the system can resume stable operation.

4. Example

4.1. Generation of sample set

Using Matlab toolbox PST 3.0, the transient stability simulation of New England 10 machine 39 bus system is carried out. The system load level is set as 90% to 110% in 5% step. The most serious three-phase short circuit fault is set. The fault location is 10% to 90% of the AC line, and the fault clearing time is 1 cycle (0.0501s) to 8 cycles (0.167s) after the fault occurs. The simulation time is 5S and the frequency of the system is 60Hz. A total of 4263 instability samples were generated. In addition, on the basis of the above fault setting, the operation of cutting off the generator after fault clearing is added. The generator cut-off action is set in 10 ways from small to large generator nodes, and a total of 42630 samples were generated in the simulation. The TSI index is used as the label.

4.2. Prediction of DBN instability

The instability samples were randomly divided into training set and test set according to the ratio of 4:1, and the effect of regression prediction model of DBN instability degree was analysed. The learning rate of RBM reconstruction is set to 0.85, and that of NN is set to 0.001. The prediction performance of DBN model is compared with CNN, MLP, KNN and RF, as is shown in Table 1.

| Neural networks | DBN | CNN | MLP | KNN | RF |
|-----------------|-----|-----|-----|-----|----|
| Mean square error | 0.00940 | 0.00990 | 0.01021 | 0.01279 | 0.02621 |

The comparison shows that the mean square error of DBN model is the smallest, which shows better prediction performance. Compared with shallow learning as KNN and RF, the deep structure of DBN model can effectively mine the relationship between input characteristics and instability degree; compared with deep learning as CNN and MLP, the unsupervised training process of DBN can provide more accurate initial value for neural network and improve prediction performance.

The samples are arranged in ascending order of instability degree (i.e. $TSI$ descending order). The prediction results are shown in Figure 2, and the mean square error is 0.0094. It can be seen that DBN model has a good fitting effect on $TSI$, and can effectively predict the degree of instability.
4.3. Analysis of emergency control results

The object of emergency control of generator tripping is the unit whose sensitivity is greater than 0. Considering that a power plant may contain multiple generators, in order to simulate the effect of cutting off some generators to restore the transient stability of the system, this paper sets up 5 generators with identical parameters at each generator node.

When the load level is set at 1.0, the three-phase short circuit fault occurs at 40% of line 17-16, and the fault is cleared within 0.0835 s. The system instability is shown in Figure 3. The generator 2-9 is the critical cluster that firstly lose stability. The transient stability coefficient TSI based on DBN fitting is -0.7322, and the transient stability coefficient TSI of the system when different generators are cut off in turn is fitted. The sensitivity of generator tripping is shown in Table 2.

| Action bus | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 |
|------------|----|----|----|----|----|----|----|----|
| cutting capacity (p.u.) | 5.208 | 6.5 | 6.32 | 5.08 | 6.5 | 5.6 | 5.4 | 8.3 |
| sensitivity | -0.057 | -0.035 | 1.420 | 1.422 | 1.410 | 1.405 | -0.075 | -0.096 |

It can be seen that the generator with bus 33-36 cut off can improve the transient stability level of the system, and the generator can be cut off according to the order of sensitivity from high to low. The method of Section 3.3 is used to formulate the emergency control strategy, and the transient stability threshold $F_{stable} = 0.2$ is set. The frequency fluctuation range is set less than 0.2Hz. By solving the optimization model, the control strategy is to cut off the generator capacity of 3.048 (p.u.) on bus 34. The emergency control strategy is implemented 0.5s after the fault is cleared, and the generator power angle curve is shown in Figure 4. It can be seen that the generator power angle recovers synchronization and the system transient stability.

Considering the real-time performance of emergency control, the calculation time of the proposed method is mainly determined by DBN prediction time and solution time of emergency control optimization model. The time required for DBN to predict the TSI of a single sample is 0.857ms. The
The essence of solving the optimization model is to solve the linear optimization model, and the calculation time is usually within the range of milliseconds. The results show that the average instability time of all instability samples in this paper is 1.433 s. It provides enough time for emergency control decision-making and system restoration of transient stability, which has certain research significance for online application.

In addition, considering the different scenarios in the actual operation process, this paper investigates the generalization ability of the model under different operation level deviations. When the load level is changed to 93% and 107% respectively, the DBN model established in Section 4.2 is used for prediction, and the mean square error is 0.00969 and 0.00982 respectively. Compared with the initial data set, the prediction effect is not much different from the initial data set, and it still has certain adaptability to the load level deviation caused by load fluctuation.

5. Conclusion
Based on the application of deep learning to transient stability prediction and assessment, a DBN based emergency control method for transient instability is proposed in this paper.

The regression model of DBN instability degree can accurately fit the mapping relationship between system operation characteristics and TSI, and realize the prediction of instability degree, which meets the requirements of online evaluation. Combining with the TSI value fitted by DBN, the generator tripping sensitivity index can be obtained in real time, and a large number of simulation search can be transferred from the real-time stage to the offline stage. The data-driven method of emergency control optimization strategy is realized, which meets the requirements of online real-time control and makes the system recover transient stable operation. The focus of the next step of this paper is to comprehensively consider various factors that affect the safety of power grid operation, and update the models of the system in different operating modes online to improve the efficiency and accuracy of emergency control.

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