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Power System Operation Stability Assessment Method Based on Deep Convolutional Neural Network

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Abstract

INTRODUCTION: For the assessment of power system stability, a power system assessment method based on a deep convolutional neural network is studied.
OBJECTIVES: Through the improvement of the integrated convolutional neural network (CNN) network model, the impact of insufficient transient stability assessment caused by sample misjudgment and sample omission is effectively reduced.
METHODS: We adopt the hierarchical real-time prediction model to evaluate the stability and instability of the determined stable samples and unstable samples, thereby improving the timeliness and accuracy of transient evaluation.
RESULTS: Through experimental comparison, the integrated CNN network model in this study has obvious advantages in accuracy compared with the single CNN network. Compared with other algorithm reference models, this model has a higher evaluation accuracy of 98.39%, far exceeding other comparison models.
CONCLUSION: By further evaluating the model’ s accuracy, it is proved that the model can provide an effective reference for the follow-up power system stability prevention and has important application value.

Keywords: Convolutional neural network; Power system; Stability; Deep learning

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1. Introduction

With the process of economic globalization, the importance of the power system is growing. Its stability will also seriously affect the basic industries of the country and society. How to maintain the security and stability of the power system and avoid the impact of large grid disturbances, signal failures, and power short circuits is of great significance to social and economic stability [1]. Due to the high complexity of modern power systems, the traditional time-domain simulation and direct method can no longer meet the requirements of real-time monitoring of the current power system [2]. How to analyze the causes of power grid accidents and accurately assess the stability of the power system through the relevant data of the power grid is an important problem that needs to be solved urgently [3].

With the rapid development of artificial intelligence technology, the stability assessment of power systems through the construction of stability assessment models and the use of artificial intelligence has received the attention of researchers and achieved good results. L P Zhu et al. [4] studied the problem of unbalanced power data samples, and developed a new unbalanced learning machine to effectively solve the problem that it is difficult to extract the short-term features of the power system. The improved model can be effectively used for short-term stability assessment of the power system. However, due to the insufficient feature extraction ability of the shallow network in this method, the training data is over-fitted, which will seriously affect its ability to judge the stability of the power system. Chen H et al. [5] used the deep convolutional neural network method and the closed-loop detection method to effectively solve the short board problem of the neural network framework in the signal processing process. They improved the performance of the method in power system stability detection and proved its feasibility through actual measurement. Through the adoption of data mining technology, Zhu Qiaomu et al. [6] improved the mining ability of network deep data and proposed the power system stability assessment based on a deep confidence network. Through the adaptive ability training of the model, this method can effectively improve the stability assessment ability of the power system. Although the above methods can obtain the signal characteristics from a large amount of data, with the rapid growth of the amount of data and the continuous improvement of the complexity of the power system, the feature extraction ability of the above methods still needs to be strengthened. Besides, the evaluation efficiency of the power system’s stability still needs to be strengthened.

To improve the assessment efficiency of power system operation stability, this study adopts the strategy of integrating CNN network and makes good use of the hierarchical real-time transient stability prediction assessment method based on sliding time window, which improves the real-time and accuracy of power system transient stability assessment. Through experimental comparison, the effect of this study model is proved.

2. Power system stability assessment based on deep convolutional neural network

2.1. Convolutional neural network

Convolutional neural network (CNN) is a multi-layer perception feed-forward system with a neural perception mechanism, which can effectively complete the local connection work within the network, reduce the complexity and training amount of the network model, and improve the efficiency of the model [7].

For the CNN network, it mainly includes the input layer, feature layer and output layer [8]. The feature layer includes a convolution layer and a pooling layer. For the convolution layer of the network, it mainly includes a variety of feature matrices, which are learned by the convolution kernel [9]. Through multiple alternations between the convolution layer and the pooling layer, the feature extraction and abstract learning of the input data are realized, so that the stability assessment of the complex power system can be completed according to the architecture. Because the CNN network has good fault-tolerant ability, it can classify the feature data to abstract the feature of complex data reporting.

Multiple convolution kernels can obtain multiple data features. When the feature matrix obtained from the input layer is convoluted with the convolution kernel of the convolution layer, the final convolution feature matrix can be obtained through the correction processing of the bias function. The calculation method of the characteristic matrix can be expressed as:

$$h^{1,\alpha} = f(x * W^{1,\alpha} + b^{1,\alpha}) \tag{1}$$

In it, $h^{1,\alpha}$ represents the feature weight matrix of the convolution layer H_1 corresponding to the α th convolution surface; $W^{1,\alpha}$ represents the feature weight matrix of the convolution layer corresponding to the α th convolution kernel; $b^{1,\alpha}$ is the feature bias described above; f function is the activation function of the CNN network. The activation function used in this study is the sigmoid function.

The pooling layer in the CNN network is the sampling layer corresponding to the convolution layer [10]. In general, the structure of the pooling layer is also in one-to-one correspondence with the convolution layer, that is, it contains the characteristic matrix with the same structure, so the pooling layer is unique relative to the convolution layer. The pooling layer mainly includes multiple pooling matrices, and the commonly used pooling methods include maximum, mean and random. Considering the specific situation of power system data, the mean pooling method is mainly used in this study. The pooling layer can complete the down-sampling of the feature matrix of the previous layer and then extract the secondary features of the input data.

The output layer of the CNN network is mainly adopted to classify the data features learned by the network, which is generally represented by Softmax, and its expression is:

$$P(i) = \frac{e^{-\theta_i^T x_i}}{\sum_{i=1}^{k} e^{(-\theta_i^T x_i)}} \tag{2}$$

For the corresponding classification problem, the Softmax function calculates the result of P (i) to make it in the range of 0~1, and realizes its classification work according to the setting of the threshold situation. θ is the model parameter used to maximize the P (i) result.

For the multi-class case, the function expression of Softmax is:

$$P(y^{(0)} = n \mid x^{(0)}, W) = \begin{bmatrix} P(y^{(0)} = 1 \mid x^{(0)}, W) \\ P(y^{(0)} = 2 \mid x^{(0)}, W) \\ P(y^{(0)} = n \mid x^{(0)}, W) \end{bmatrix} = \frac{1}{\sum_{i=1}^{n} e^{\omega_j^T} x^{(i)}} \begin{bmatrix} e^{-\omega_1^T} x^{(i)} \\ e^{-\omega_2^T} x^{(i)} \\ \vdots \\ e^{\omega_n^T} x^{(i)} \end{bmatrix}$$

(3)

Where, P is the probability of the training sample, w_n^T is the output of the corresponding model input full connection, and n is the number of model sample categories.

2.2 Power system transient assessment model integrated with CNN

Considering the complex power system, a single input characteristic cannot accurately reflect the fault operation state of the whole system [11]. The existing evaluation methods are mostly aimed at some classification accuracy indicators and pay less attention to the stability of the sample. However, the unstable samples have a serious impact on the power grid state assessment. To assess the accuracy of the model, it is necessary to minimize the occurrence of sample omission and misjudgement in the model [12].

Similarly, it is impossible to achieve 100% accuracy by using a single assessment method to assess the stability of the power system. For high-dimensional power nonlinear systems, a single CNN cannot completely eliminate the overlap between samples. Moreover, it is difficult to achieve 100% accurate classification. In most cases, CNN with different parameters can obtain higher assessment accuracy. Therefore, this study combines multiple groups of CNN with the same structure and different parameters to realize the different selection of learning sub-classifiers and form a comprehensive transient stability assessment model, as shown in Figure 1.

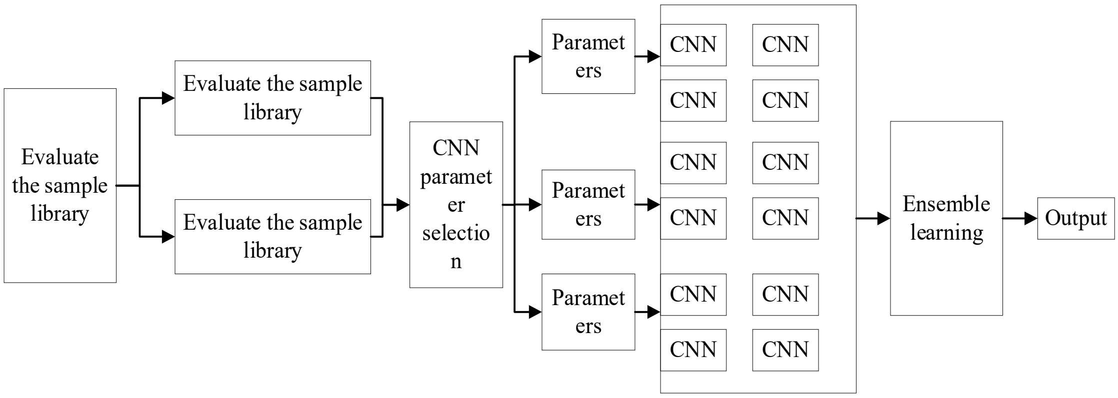

Figure 1. Transient stability assessment model

In Figure 1, for the multi-parameter CNN power system evaluation model, and for a variety of input features, each feature is trained with m groups of CNN with different parameters. Its feature set can be obtained. The stable classification probability and unstable classification probability of the sample can be obtained by inputting the feature sets into the CNN network and outputting the results. Then, the output probability of the whole model can be obtained.

The learning strategy of the entire integrated CNN network uses the average probability to describe the results, which is expressed by the output probability y formula as follows:

$$y = \left[P_E(C_1 \mid x), P_E(C_0 \mid x)\right] \tag{4}$$

In it, C_1 and C_0 represent the states of the model stable and unstable classes, respectively. We can get:

$$P_E(C_1 \mid x) = \frac{1}{M}\sum_{i=1}^{M} P_i(C_1 \mid x) \tag{5}$$

$$P_E(C_0 \mid x) = \frac{1}{M}\sum_{i=1}^{M} P_i(C_0 \mid x)$$

(6)

The output result can be defined by using the binary classification threshold δ, and the result of the integrated model can be transformed as follows:

$$Y_{pre}(x) = \begin{cases} 1, & P_E(C_1 \mid x) > \delta \\ 0, & P_E(C_1 \mid x) \le \delta \end{cases} \tag{7}$$

In general, δ is equal to 0.5 by default. When the result of $Y_{pre}(x)$ is 1, it means that the power system is in a stable state, and when the result is 0, it means that the system is in an unstable state.

2.3 Evaluation method of layered real-time transient stability prediction based on sliding time window

In order to realize the continuous evaluation of the system, this study mainly uses the form of sliding time window to sort out the input characteristics of the prediction model and make it become a sliding time window. Therefore, the prediction model of different response time is formed with the movement of the time window.

To make the whole model still have a high prediction effect in the case of a sample missing, we should define the credibility index R of the whole model, which is expressed by the formula:

$$R = \max\left\{P_E(C_1 \mid x), P_E(C_0 \mid x)\right\} \tag{8}$$

The reliability index R ranges from 0.5 to 1. It is mainly used to evaluate the accuracy and certainty of the prediction results. In order to improve the prediction effect of the model, the reliability thresholds of stable samples and unstable samples are set respectively, which are represented by R_1 and R_0 respectively. When the value of the credibility index R is greater than the corresponding credibility threshold, the prediction result of the model is regarded as a credible result. Further, the corresponding sample output is performed.

The whole credibility prediction model adopts a hierarchical real-time prediction method, and the specific structure is shown in Figure 2.

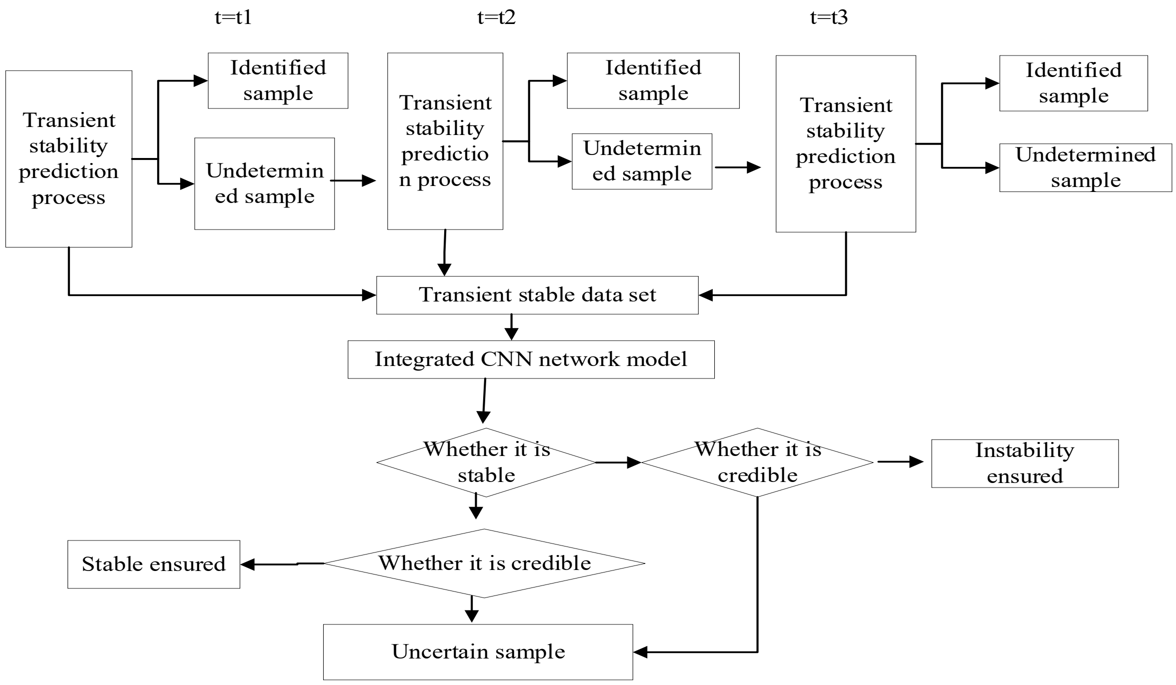

Figure 2. Flow chart of layered real-time prediction model

In Figure 2, for different time t, it is input into the temporary stability prediction process. Besides, the sample stability is evaluated to determine whether it is in a stable state. The input features with different response times are trained to obtain different integrated CNN network models, which constitute different levels of results of time-sharing prediction. For each layer of the model, after inputting the features, the credibility index of the prediction results can be obtained. Only the samples that meet the requirements are identified as stable. Then, they are output as stable samples. Samples with insufficient credibility need to be further judged to determine whether they are unstable samples. For uncertain samples, further judgment is needed.

This time-sharing prediction method can respond to the credibility index of the sample in a short time to ensure the rapidity of the prediction results. For uncertain samples, more input features are needed to make accurate judgments to ensure the certainty of the prediction results [13].

3 Experimental results and data analysis

3.1 Experimental parameter settings

In order to verify the reliability of the evaluation method in this study, we choose the Matlab toolbox to simulate the stability of the system. We also choose the New England 10-machine 39-point system as the research object to verify the validity of the model. Then, the steady-state/instability analysis is carried out. The system load is set to 75% ~ 120%. The step length is set to 5%, and the three-phase short circuit fault evaluation under these 10 load conditions is considered. The fault location is set at 10% ~ 90% of the AC line, and the location points are evenly distributed. Therefore, it is more difficult to set 10 kinds of faults. The duration of the fault is the duration of various faults from 1 cycle to 11 cycles.

The total number of simulation samples is 37400, which are divided into stable samples and unstable samples. The specific results are shown in Table 1. The samples are divided into training sets, validation sets and test sets according to the ratio of 3:1:1 to evaluate the performance of the system model.

Table 1. Sample composition of the test system

Test system	Data set	Total number of samples	Number of stable samples	Number of instability samples
New England 10 39-node system	Training set	22440	14973	7467
	Validation set	7480	4962	2518
	Test set	7480	4927	2553

The parameters of the CNN network model are shown in Table 2.

Network layer	Convolution kernel size/step	Number of filters
Network layer 1	(1) 3×3/1×1 (2) 5×5/1×1	32
Pool layer 1	(3) 5×5/1×1 2×2/2×2	32
Network layer 2	(1) 3×3/1×1	
	(2) 3×3/1×1 (3) 5×5/1×1	64
Pool layer 2	2×2/2×2	64
Fully connected layer	120	
Classification layer	2	-

3.2 Results of the experiment

(1) Contrast with single CNN model

The results of the integrated CNN evaluation model in this study are compared with those of the single CNN network model in the system stability test under the same conditions. The results are shown in Table 3.

Table 3. Test results of single optimal CNN model and integrated CNN model

Table 2. CNN network model parameters

Comparison of different models	Number of missed judgments	Number of misjudgments	Missed judgment rate (%)	Misjudgment rate (%)	Accuracy rate (%)
Single optimum CNN	88	76	3.38	1.57	97.79
Integration CNN	61	56	2.35	1.15	98.38

It can be verified that from the results in Table 3, for the integrated CNN network model, the accuracy of its evaluation is significantly improved compared with the single CNN network model with the accuracy improved by 0.59%. The rate of misjudgement decreased by 0.42% and the rate of missed judgment decreased by 1.03%. It also has great advantages in the number of missed and misjudged tests.

The integrated CNN network, because it integrates multiple CNN networks with different parameters, it can effectively eliminate the impact of the overlapping part of the samples in a single network on the evaluation performance. Thus, it can obtain a higher evaluation effect, which further proves that the integrated CNN model can improve the performance of the prediction model compared with the single CNN network.

(2) Performance comparison between this model and other machine-learning models

The basic CNN network model adopted in this study is compared with other models under the same conditions. The comparison results are shown in Table 4.

Table 4. Comparison of prediction results of different prediction models

Different models	Number of missed judgments	Number of misjudgments	Missed judgment rate (%)	Misjudgment rate (%)	Accuracy rate (%)
DBN	76	100	2.95	2.12	97.62
SVM	108	91	4.21	1.85	97.28
MLP	95	231	3.73	4.68	95.49
DT	155	147	6.35	2.97	95.89
KNN	158	293	6.12	5.94	93.94
Integrating CNN models	60	58	2.36	1.17	98.39

From the comparison results in Table 4, it is clear that compared with all the reference models, the model in this study has a higher evaluation accuracy of 98.39%, which is far higher than other comparison models. Among the comparison models, the DBN model has the highest evaluation accuracy of 97.62%. Besides, the KNN model has the lowest evaluation accuracy of 93.94%. In terms of misjudgement rate and missed judgment rate, the model of this study still has obvious advantages. The missed judgment rate of this study is 2.36%, and the misjudgement rate is 1.17%. It is still the lowest among all the comparative models, which further proves the advantages of the model in this study. It also verifies that there is a way to integrate the CNN network model in reducing the phenomenon of missed judgment and misjudgement in system stability evaluation.

(3) Missed/misjudged comparisons at different response times

For the power system after a fault, the real-time assessment of its transient stability can be evaluated and measured by the response time. The shorter the response time is, the longer the response time is left for operators before the system is unstable, so that emergency control can be implemented earlier to ensure the stability of the system [14].

In this study, different response time series are considered to evaluate the transient stability of the system input characteristics, and the response time is set as 0.1 s ~ 1s. In that case, evaluating the accuracy of the system evaluation is achieved. The evaluation results are shown in Figure 3 and Figure 4.

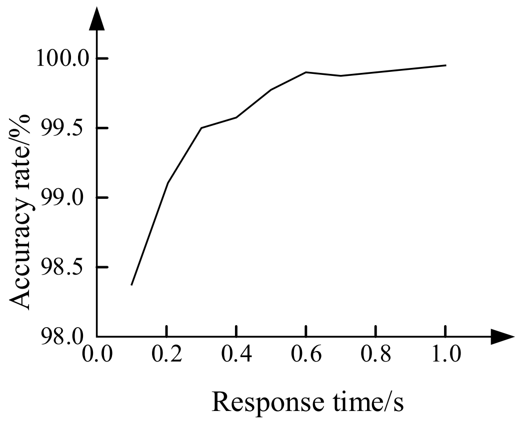

Figure 3. Accuracy of the model under different response times

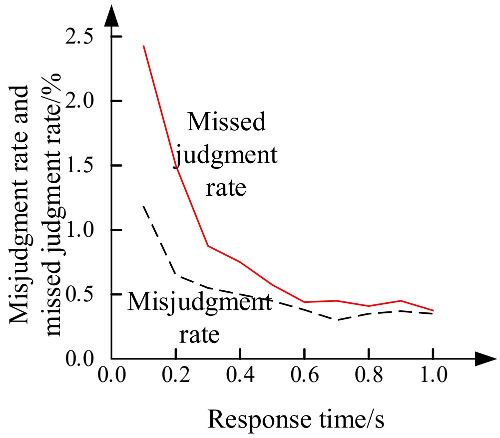

Figure 4. The rate of misjudgement and missed judgment of the model under different response times

It can be concluded from the results in Figure 3 and Figure 4 that as the response time gradually increases from 0.1s to 1s, the evaluation accuracy of the deep convolutional neural network model in this study also gradually increases. Besides, the accuracy gradually increases from 98.38% to 99.72%. The rate of misjudgement and the rate of missed judgment decrease gradually with a similar decreasing trend. When the response time increases from 0.1s to 0.3s, the rate of misjudgement and the rate of missed judgment both decrease rapidly. When the response time increases from 0.3s to 1s, the rate of misjudgement and the rate of missed judgment also decrease, but the decreasing rate slows down gradually. When the response time is 1s, the false positive rate and the false negative rate of the system decrease to 0.252% and 0.253%, respectively.

(4) Hierarchical dynamic prediction effect

To prove the effect of hierarchical prediction in this study, the number of samples and the prediction distribution under different layers are considered. The results are shown in Table 5. In Table 5, CS(Ti) represents the number of stable samples obtained by the prediction model in the current layer. M (Ti) respectively represent the number of unstable samples judged as stable samples by the current layer. M(T) represents the sum of the number of misjudgements that all corresponding unstable samples in the current layer are judged as stable samples. Similarly, CU(Ti) is the number of credible unstable samples corresponding to the output; F(Ti) and F(T) are the corresponding numbers of stable samples judged as unstable samples; A(Ti) and A(T) are the corresponding prediction accuracy; U(T) and Ur(T) are the corresponding numbers of uncertain samples and uncertain sample rate.

Table 5. Layered dynamic prediction results

	Judged to be stable			Judged to be unstable						
Number of layers	CS(Ti)	M(Ti)	M(T)	CU(Ti)	F(Ti)	F(T)	A(Ti)(%)	A(T)(%)	U(T)	Ur(T)(%)
1	3389	0	0	2578	104	104	98.27	98.27	1509	20.18
2	978	1	1	54	10	114	98.89	98.36	501	6.65
3	244	1	2	21	3	117	98.15	98.35	235	3.08
4	95	1	3	16	5	122	95.54	98.32	124	1.59
5	38	0	3	6	2	124	97.77	98.32	78	1.04
6	17	0	3	1	0	124	100	98.32	58	0.80

From the results in Table 5, we can see that the misjudgement rate of the model gradually decreases with the number of levels, and the final proportion of uncertain samples is only 0.8%. In the first layer, most of the samples were judged accurately, and the number of missed judgments and misjudgements was 0. With the increase in the number of layers, more and more samples are judged to be stable. Finally, a reliable prediction result is obtained after many times of judgments. As the response time gradually increases, the confidence of the prediction sample gradually reaches the threshold. As a result, the number of certain samples increases, and the number of uncertain samples decreases. With the further movement of the sliding time window, the model of this study gradually obtains the credible prediction results of the system data.

Figure 5 shows the statistics of the number of instability cases for different samples.

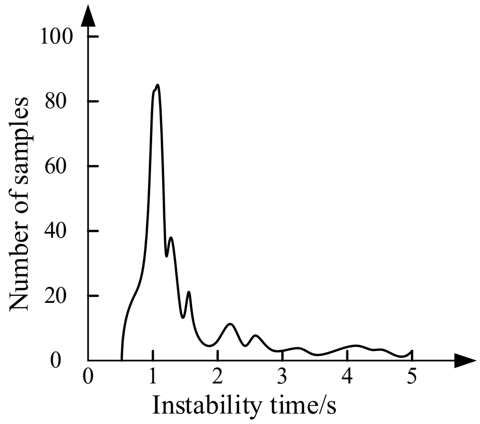

Figure 5. Statistics of the number of unstable conditions of different samples

In Figure 5, the occurrence time of the instability sample is mostly concentrated in the range of 0.5s~1.5s. As time goes on, the number of unstable samples gradually decreases, and the unstable samples are close to disappearing when the time is close to 5s.

To further prove the effect of the model in this study, the occurrence time and judgment time of the instability samples are counted respectively. The results are shown in Table 6.

Table 6. Statistics of instability occurrence time under different response time

Response time /s	Correctly identified instability sample instability occurrence time/s		Correctly judge the time when the leading instability occurs/s		Instability in an uncertain sample The time at which the sample instability occurred /s	
	Shortest	Longest	Shortest lead	Longest lead	Shortest	Longest
0.0167	0.4168	4.9855	0.4016	4.9634	1.6205	4.9855
0.1	1.6188	4.9855	1.5172	4.8867	2.2387	4.9855
0.2	2.2217	4.9855	2.0298	4.7867	2.4298	4.9476
0.3	2.4230	4.8587	2.1196	4.5623	2.6438	4.9132
0.4	2.6487	4.9855	2.2486	4.5826	4.0498	4.9132
0.5	4.0572	4.9375	3.5476	4.4532	4.3603	4.9132

In Table 6, we can conclude that the hierarchical real-time prediction method in this study can effectively make an accurate prediction before the system sample becomes unstable. It can also make an accurate judgment result as soon as about 0.5s before the system becomes unstable. The slowest pre-judgment time is 0.4016s before instability, which can effectively meet the requirements of transient stability of the power system for time and speed, and make a time guarantee for subsequent processing.

(5) Evaluation accuracy of the model in this study

To evaluate the evaluation accuracy of the model, the interference degree S of the sample is calculated and normalized to obtain the stability degree index Ms of the system, which is expressed by the formula:

$$M_s = \frac{S_{\max} - S}{S_{\max} - S_{\min}} \tag{9}$$

Where, S_{max} and S_{min} are the maximum and minimum values of the degree of interference for the stable epoxy boards in the sample set. It can be inferred that the larger S is, the smaller the stability index M_s is, and the lower the system stability is. On the contrary, the more stable the system is.

Similarly, in order to measure the instability degree of the model, the number T of all instability samples is calculated and normalized to obtain the instability degree index M_{us}, which is expressed by the formula:

$$M_{us} = \frac{T_{\max} - T}{T_{\max} - T_{\min}} \tag{10}$$

Where, T_{max} and T_{min} are the maximum and minimum values of the destabilized sample, respectively. It can also be inferred that the larger T is, the smaller the degree of instability is, and the greater the degree of developing instability is.

Table 7 shows the RMS error of the degree of system stability and instability with different response times.

Table 7. Root mean square error of stability and instability for different response time

Response time (s)	Stability assessment model MSE	Instability degree evaluation model MSE
0.0167	0.0059	0.0169
0.1	0.0048	0.0135
0.2	0.0042	0.0078
0.3	0.0030	0.0045
0.4	0.0026	0.0043
0.5	0.0024	0.0039
0.6	0.0022	0.0025
0.7	0.0020	0.0020
0.8	0.0018	0.0017
0.9	0.0016	0.0014
1	0.0014	0.0013

From the results in Table 7, it can be obtained that with the increase of the system response time, the root mean square error of the evaluation of the stability of the whole model team gradually decreases, from 0.0059 at 0.0167s to 0.0014 at 1s. The root mean square error of the instability degree evaluation model is similar to the stability degree, which gradually decreases from 0.0169 at 0.0167s to 0.0013 at 1s. It is verified that the evaluation accuracy of the model in this study will gradually improve over time.

For the actual operation of the power system, it is necessary to implement the corresponding measures according to the evaluation of the stability [15]. In case of serious instability, we should take emergency measures to correct it in time to avoid instability of the power system. In the case of low stability, there is also a need to take relevant measures to improve the system's stability. This model can predict the state of the power system, which is of great significance to improve the stability of the power system.

(6) Comparison of sensitivity under different fault types

The trained model is applied to power system faults such as harmonic fault, grounding fault, abnormal arc, voltage offset fault and other faults, and the actual judgment sensitivity results are shown in Table 8.

Table 8. Comparison of judgment sensitivity of different fault types

Different fault types	Single optimal CNN	Optimized model
Harmonic fault	94.5%	99.3%
Ground fault	95.3%	99.4%
Abnormal arc	92.1%	97.3%
Voltage offset fault	90.4%	98.2%
Other fault	89.8%	98.5%

Table 8 indicates that the improved system in this paper shows certain advantages in the judgment sensitivity of the above fault types, especially improving the judgment sensitivity of other faults with unknown fault causes, which is 8.7% higher than previous system.

4. Conclusion

In this study, in order to accurately evaluate the operation stability of a power system, especially the transient stability after fault, we study a power system operation stability assessment method based on the deep convolutional neural network. We assess the stability of the power system by integrating the CNN network model, especially in the case of considering the missed and misjudged samples.

Through the way of layered real-time prediction, the instability samples are judged in multiple steps to improve the accuracy of sample instability. Through the comparison of experimental data, it is proved that this model has a good advantage over a single CNN network and other networks and is far more sensitive to the judgment of different faults in the power system than initial model. As a result, the misjudgment of the data sample is reduced, and the influence of the misjudgment on the transient stability prediction of the system is also effectively reduced. Compared with all the reference models, the model of this study has a higher evaluation accuracy of 98.39%, far more than other comparison models. The prediction of the transient stability degree of the model samples under different response times is evaluated. Through the experimental results, we conclude that the evaluation accuracy of the model is significantly improved with the gradual increase of the response time, which suggests that the model can be used in evaluating the stability of the power system.

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