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Power System Transient Stability Assessment based on Rough Set and Deep Belief Network

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Abstract

With the continuous expansion of modern power system scale, the difficulty of power system transient stability assessment is also increasing. A power system transient stability assessment method based on rough set and deep belief network (DBN) is proposed. Firstly, the simulation method is used to obtain part of the operation data of the power system during the fault period; Secondly, attribute reduction algorithm based on attribute importance is used to reduce the dimension of original data group; Finally, the dimension reduced data set is trained by deep belief network, and the trained network is used for evaluation test. Through the IEEE New England 10-machine 39-bus system simulation experiment, compared with other methods, this method has higher accuracy and lower miss rate.

Keywords

Power System; Transient Stability; Rough Set; Deep Belief Network; Feature Reduction.

1. Introduction

With the continuous expansion of modern power system, the harm of transient fault in power system is also increasing. To reduce the harm of transient instability, it is necessary to judge whether transient instability fault may occur in advance. The transient stability capability of power system is the ability to restore the original operation state or reach a new stable operation state when the power system is greatly disturbed [1]. At present, the main methods to analyze power system transient stability are time-domain simulation method [2] and Lyapunov method [3]. And all kinds of artificial intelligence methods. Because the power system is a large-scale dynamic system with strong nonlinearity, high dimension, and hierarchical distribution [4], the traditional analysis methods (time-domain simulation method and direct method) have limitations in dealing with the transient stability of power system. Therefore, there are many methods using artificial intelligence to study the transient stability.

The theoretical basis for the application of artificial intelligence method to the study of transient problems is that the causal data including physical mechanism usually also shows the external characteristics of data correlation [5]. When using artificial intelligence method to study power system transient stability, the research on the physical mechanism of the model can be simplified. It is not necessary to start with the complex physical mechanism of the system. A large amount of data can be obtained directly to establish a data model for transient stability assessment. The principle of this method is simply to establish the input-output mapping relationship between the characteristic data set and the transient stability results.

Commonly used artificial intelligence algorithms for evaluating transient stability problems include Support Vector Machine (SVM) [6,7], Decision Tree (DT) [8], Artificial Neural Network (ANN) [9], etc. Many researchers have used the above methods to study transient stability. However, because these algorithms are shallow learning networks, the complexity of power system is very high, and there is a deeper relationship between relevant data, these methods have shortcomings such as insufficient generalization ability [10]. With the development of deep learning technology, Convolutional Neural Network [11], Generative Adversarial Network [12], Deep Belief Network and Deep Residual Shrinkage Network [13] have been used to evaluate the transient stability of power system. Deep learning technology has strong feature extraction ability and better generalization performance. In this paper, Deep Belief Network is used to evaluate the transient stability of power system. Rough set [14] is used to preprocess the original data. To better reflect the advantages of the algorithm, this paper compares the DBN with several shallow networks. The simulation results show that the depth confidence network can have higher prediction accuracy, and rough set can further improve the performance of the evaluation model.

2. Deep Belief Network

2.1 Restricted Boltzmann Machine

DBN is a deep learning algorithm proposed by Hinton [15]. DBN is a multi-hidden layer generative structure graph model [16]. A general DBN consists of several Restricted Boltzmann Machines (RBM), and each RBM consists of a visible layer and a hidden layer. RBM network is a fully connected network between layers and not connected within layers. Compared with Boltzmann Machine (BM) which is also connected within layers, RBM network has faster training speed and does not have much loss in classification performance. Figure 1 is the structure diagram of the RBM network. The input layer has n units, and the hidden layer has m units.

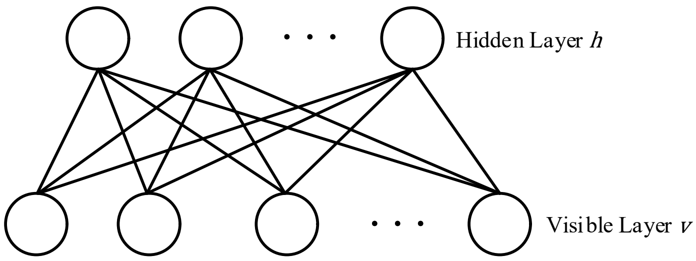

Figure 1. Structure diagram of RBM

The parameter of visible layer v is a_i. The parameter of hidden layer h is b_j. The connection weight between is w_{ij}, where $\boldsymbol{\theta} = \{w_{ij}, a_i, b_j\}$, and the system energy function can be written as:

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

Then the joint probability distribution function of v and h is as follows:

$$P(v,h\,|\,\boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta})} e^{E_1} \tag{2}$$

$$Z(\boldsymbol{\theta}) = \sum\nolimits_{v,h} e^{E_1} \tag{3}$$

Where $E_1 = -E(v,h|\boldsymbol{\theta})$. Then the marginal probability distribution of equations (2) and (3) can be written as follows:

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$$P(v \mid \boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta})} \sum\nolimits_h e^{E_1} \tag{4}$$

The activation function of the j hidden unit is:

$$P(h_j = 1 \mid v, \boldsymbol{\theta}) = \sigma(b_j + \sum\nolimits_{i=1}^{n} v_i w_{ij}) \tag{5}$$

Where $\sigma = \frac{1}{1+e^{-x}}$.
Similarly, the activation function of the i visible unit is:

$$P(v_j = 1 \mid h, \boldsymbol{\theta}) = \sigma(a_i + \sum\nolimits_{j=1}^{m} w_{ij} h_j) \tag{6}$$

Maximum likelihood estimation of $P\left(v^{(t)} \middle| \boldsymbol{\theta}\right)$:

$$\boldsymbol{\theta}^* = \arg\max_{\theta} \sum\nolimits_{t=1}^{T} \ln P(v^{(t)} \mid \boldsymbol{\theta}) \tag{7}$$

$$L(\boldsymbol{\theta}) = \sum_{t=1}^{T} (\ln \sum_h e^{E_2} - \ln \sum_v \sum_h e^{E_1}) \tag{8}$$

Where $E_2 = -E\left(v^{(t)}, h \middle| \boldsymbol{\theta}\right)$. Use the gradient rise method to find the maximum value of equation (8). The partial derivative of $\boldsymbol{\theta}$ is:

$$\frac{\partial L(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \sum_{t=1}^{T} (< \frac{\partial (E_2)}{\partial \boldsymbol{\theta}} >_{P_1} - < \frac{\partial (E_1)}{\partial \boldsymbol{\theta}} >_{P_2}) \tag{9}$$

Where $<*>_P$ is the mathematical expectation about P. $P_1 = P\left(h \middle| v^{(t)}, \boldsymbol{\theta}\right)$, $P_2 = P(v, h|\boldsymbol{\theta})$. By substituting equation (1) into equation (9):

$$\frac{\partial L}{\partial (w_{ij})} = \sum_{t=1}^{T} (< v_i h_j >_{data} - < v_i h_j >_{model}) \tag{10}$$

Where $data$ and $model$ represent $P\left(h \middle| v^{(t)}, \boldsymbol{\theta}\right)$ and $P(h, v|\boldsymbol{\theta})$ respectively. Then the update formula of parameter w_{ij} in RBM can be obtained as follows:

$$\delta w_{ij} = \rho(< v_i h_j >_{data} - < v_i h_j >_{recon}) \tag{11}$$

Where $<*>_{recon}$ is the distribution after one Gibbs sampling, and ρ is the learning rate.

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2.2 The Principle of Deep Belief Network

A DBN is generally composed of multiple RBMs stacked, and finally a feedback neural network (BP) is used to output the results. The training process of DBN includes two stages: the first stage is the unsupervised pre training stage, which is carried out from bottom to top, using the unsupervised greedy algorithm. RBM1 is trained first, and then the activation probability of RBM1's hidden layer is used as the input of RBM2, and so on until RBMk; The second stage is the reverse fine-tuning stage, in which the BP network at the output end is used to fine-tune the parameters from top to bottom. This completes the training of DBN network.

As can be seen from Figure 2, the training process of each RBM is unsupervised, while the fine-tuning of DBN parameters is supervised. Because each layer of RBM constructed previously can only ensure that the weight in its own layer is optimal for the feature mapping extraction of this layer, to ensure the optimality of the overall result, the common method is to set up BP network supervision training and learning before classification. The combination of the two ensures that the parameters are not easy to fall into local optimization and can make up for the disadvantage of long training time to a certain extent.

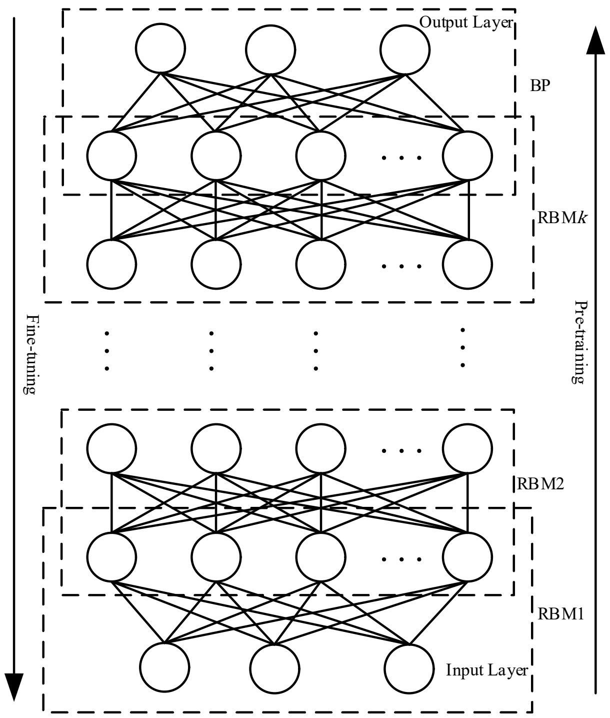

Figure 2. Structure of DBN

3. Attribute Reduction based on Rough Set

In the field of artificial intelligence, because the training data is very large and often contains some useless data or redundant data, it will lead to a series of problems such as the decline of network learning efficiency and low evaluation accuracy. Therefore, it is necessary to prepare the data for preprocessing in advance. This paper will use the attribute reduction algorithm based on attribute importance in rough set theory to preprocess the original data.

3.1 Basic Principles of Rough Set

U is a nonempty finite set of objects to be understood. Any subset $X \subseteq U$ in U is called a concept of U. Any subset cluster in U is called knowledge about U.

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Given a U and a cluster of equivalence relations S on it, $K=(U,S)$ is called a knowledge base or approximate space about U. If $P \subseteq S$, and $P \neq \emptyset$, then $\bigcap P$ is still an equivalent relationship on U, which is called the indistinguishable relationship on P, which is recorded as $\mathrm{IND}(P)$, and has,

$$\forall x \in U, [x]_{\mathrm{IND}(P)} = [x]_P = \bigcap_{\forall R \in P} [x]_R \tag{12}$$

The core basis of rough set theory and application is upper approximation and lower approximation. Given the knowledge base $K=(U,S)$, when there is an equivalent relationship $R \in IND(K)$ on $\forall X \subseteq U$ and U, define the lower approximation and upper approximation of subset X with respect to knowledge R as follows:

$$\underline{R}(X) = \{x \mid (\forall x \in U) \wedge ([x]_R \subseteq X)\} \tag{13}$$

$$\overline{R}(X) = \{x \mid (\forall x \in U) \wedge ([x]_R \cap X \neq \varnothing)\} \tag{14}$$

Then there are:

$$bn_R(X) = \overline{R}(X) - \underline{R}(X) \tag{15}$$

$$pos_R(X) = \underline{R}(X) \tag{16}$$

$$neg_R(X) = U - R(X) \tag{17}$$

Equation (15) represents the R boundary domain of X, equation (16) represents the R positive domain of X, equation (17) represents the R negative domain of X, the following conclusion:

$$\overline{R}(X) = pos_R(X) \cup bn_R(X) \tag{18}$$

Figure 3 is a schematic diagram of upper and lower approximation and boundary of rough set.

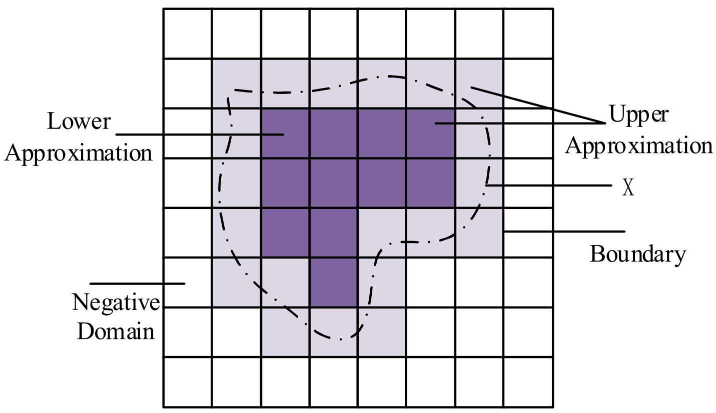

Figure 3. Schematic diagram of rough set

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3.2 Knowledge Reduction and Kernel

Knowledge reduction is a process of deleting some unnecessary knowledge on the premise of maintaining the classification ability of the system. In this paper, knowledge reduction is used to delete unnecessary features in the original data used for training to improve the performance of the algorithm. The following introduces the concepts of reduction and kernel in rough sets.

Given a knowledge base$K=(U,S)$and an equivalence relation family $P\subseteq S,\forall R\in P$, if:

$$\mathrm{IND}(P)=\mathrm{IND}(P-\{R\}) \tag{19}$$

Then knowledge R is an unnecessary knowledge in P, and even if it is deleted, it has no great impact on the classification performance.

In the above knowledge base, if for any $Q\subseteq P$, if Q is independent and $\mathrm{IND}(Q)=\mathrm{IND}(P)$, then Q is a reduction of P. generally, the reduction is not unique. In the above, for any $R\in P$, if:

$$\mathrm{IND}(P-\{R\})\neq\mathrm{IND}(P) \tag{20}$$

Then R is called the necessary knowledge in P. deleting r will have a great impact on the classification ability of the system. The set composed of all necessary knowledge in P is the kernel of P.

3.3 Reduction based on Attribute Importance

This paper adopts the attribute reduction algorithm based on attribute importance [17]. In rough set theory, the measurement of attribute importance only needs to express the data provided by the system itself without additional auxiliary information. Attribute importance measures the classification ability of attributes to information systems. If an attribute is deleted in a knowledge expression system, the greater the change in the classification ability of the knowledge expression system, the greater the importance of the deleted attribute.

If an information system $IS=(U,C,V,f),\forall B\subseteq C$ and $\forall\alpha\in C-B$ are given, define:

$$sig(\alpha,B;C)=\frac{card(U/\mathrm{IND}(B\cup\{\alpha\}))-card(U/\mathrm{IND}(B))}{card(U)} \tag{21}$$

This is the importance of attribute α to attribute set B, where $card(*)$ represents the cardinality of the set. Calculate the importance of all attributes through the above formula, and then eliminate redundant attributes through the ranking of importance.

4. Transient Stability Assessment Model

4.1 Basic Principles of Transient Stability

Transient stability of power system refers to the ability of power system to return to the original operation state or reach a new acceptable operation state after large disturbance deviates from the equilibrium point in a certain operation state (equilibrium point).

4.2 Sample Feature Selection

In feature selection, easy to obtain features are mainly selected, so that they can be evaluated more efficiently in practical use. By referring to relevant literature [18,19], and considering the convenience of obtaining features and the usefulness to transient stability assessment, this paper finally selects a total of 32 relevant original features for initial data acquisition. The 32 features are listed in Table 1,

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where t_{cl} time represents the time of fault removal, t_f represents the time when the fault occurs, t_0 represents the time when the fault has not occurred.

Table 1. Original feature set

Label	Features
1	Average value of rotor acceleration at t_{cl}
2	Maximum difference between mechanical power and output active power at t_{cl}
3、4	Maximum and minimum value of active impact on a single generator at t_{cl}
5	Average mechanical power at t_{cl}
6	Maximum rotor angular velocity at t_{cl}
7	Difference between maximum and minimum relative rotor angle at t_{cl}
8	Difference between maximum and minimum rotor kinetic energy at t_{cl}
9	System total energy adjustment at t_{cl}
10	Average value of rotor kinetic energy at t_{cl}
11	Difference between maximum and minimum rotor acceleration at t_{cl}
12	Average value of rotor angular velocity at t_{cl}
13、14	Average and maximum output active power at t_{cl}
15、16	Average value and maximum value of generator power angle at t_{cl}
17	Average value of output reactive power at t_{cl}
18	Average value of rotor acceleration at t_f
19	Maximum difference between mechanical power and output active power at t_f
20	Average mechanical power at t_f
21	Maximum rotor angular acceleration at t_f
22	Difference between maximum and minimum relative rotor angle at t_f
23	Difference between maximum and minimum rotor kinetic energy at t_f
24	System total energy adjustment at t_f
25	Average value of rotor kinetic energy at t_f compared with t_0
26	Difference between maximum and minimum rotor acceleration at t_f
27	Average value of rotor angular velocity at t_f
28、29	Average and maximum output active power at t_f
30、31	Average value and maximum value of generator power angle at t_f
32	Average value of output reactive power at t_f

4.3 Model Evaluation Indicators

In this paper, the maximum power angle difference between any two generators is calculated to judge whether the system is transient stable. The criteria for judging whether the system is transient stable can be written in the following form:

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$$T = 360^\circ - |\Delta\delta_{\max}| \tag{22}$$

Where, $|\Delta\delta_{\max}|$ is the maximum power angle difference of any two generators. If the maximum power angle difference of the generator is greater than 360°, T is greater than 0, and the system is unstable. Otherwise, it is transient stability.

Accuracy is usually used as the index of transient stability assessment, but because the probability of transient instability is low and there are few transient instability data in the sample, only accuracy cannot be used as the evaluation index to evaluate the performance of the model, and transient instability will bring actual losses, Therefore, in the transient stability assessment, we are more concerned about the instability, so the missed judgment rate is also used as the index to judge the stability. To better analyze the performance, this paper uses the confusion matrix, as shown in Table 2.

Table 2. Confusion matrix

	Predictively stable	Predictively unstable
Stable	ss	su
Unstable	us	uu

According to the given in Table 2, the accuracy f_0, misjudgment f_1 and missed judgment f_2 of the evaluation model can be calculated.

$$f_0 = \frac{ss + uu}{ss + su + uu + us} \tag{23}$$

$$f_1 = \frac{su}{ss + su} \tag{24}$$

$$f_2 = \frac{us}{us + uu} \tag{25}$$

5. Case Study

5.1 Case Introduction

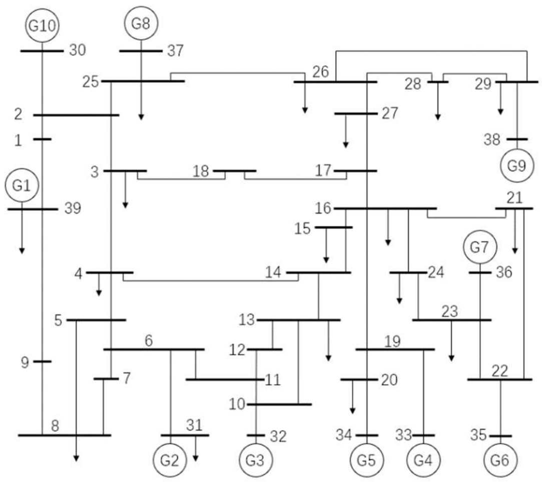

Figure 4. New England 10-machine 39-bus system

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This paper adopts the New England 10-machine 39-bus system [20]. The system has a total of 10-machine 39-bus. The capacity reference value of the system is 100MVA and the frequency is 60Hz. Figure 4 shows the topology of the system.

5.2 Sample Data Set Acquisition

The 10-machine 39-bus power system model is established by using the Simulink toolbox of MATLAB. A total of six different failure time intervals and seven different load rates are set. The failure time intervals are 0.05s, 0.15s, 0.2S, 0.25s and 0.3s respectively; The load rates are 70%, 80%, 90%, 110%, 120% and 130% respectively. Then a three-phase short-circuit fault is set at each transmission line of the model in turn. Since the system has a total of 39 buses, a total of 39 three-phase short-circuit fault points are set, and a total of 1638 groups of data can be generated. Each group of data has 32 features, so the original data set is a 32×1638 matrix.

Figure 5 is a two-dimensional scatter diagram drawn according to feature 1 and feature 2 in Table 1 after simulation. In the legend, ‘0’ represents unstable sample and ‘1’ represents stable sample.

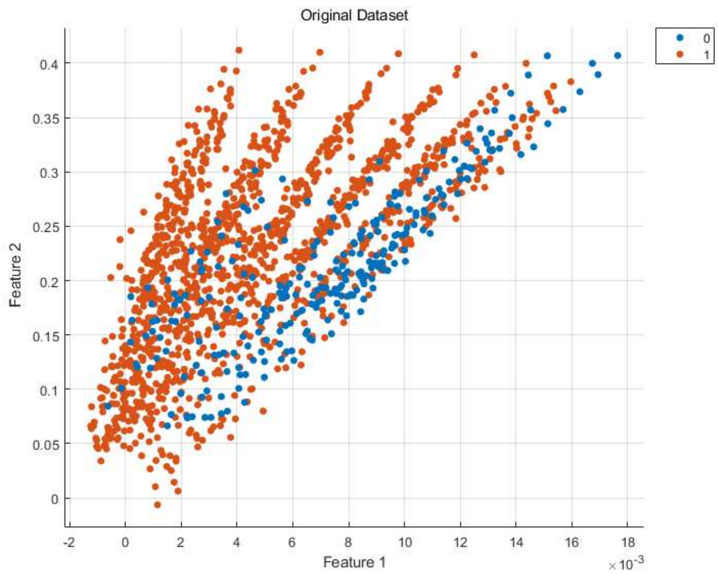

Figure 5. Distribution diagram of sample stability

5.3 Experimental Results and Evaluation

To verify the effectiveness of the method proposed in this paper, this paper uses eight algorithms for comparative experiments, namely DBN, BP, decision tree, SVM and the method of adding rough set to these four algorithms.

The first algorithm adopts the DBN+RS method proposed in this paper. Firstly, the original data of 32×1638 is simplified by rough set algorithm to obtain a reduced data set of 21×1638, and then the data set is used as the input of DBN network. In this paper, a RBM hidden unit is set, the data batch for one training is 21 groups of data, three RBM layers are set, each layer includes 16, 8 and 4 nodes respectively, the number of iterations is 500, the learning rate of the network is 0.1, the output layer of the last layer is BP network, the number of iterations is also set to 500, and 21 groups of data are output per batch. All stable samples are marked as ‘1’, unstable samples are marked as ‘2’, 1260 groups of data are used as training data, and the remaining 378 groups of data are used as test data sets. Finally, the test result of each group of data is ‘1’ or ‘2’. Compare it with the original mark of this group of data to judge the accuracy of the result. The confusion matrix in Tab.2 is used to evaluate performance.

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The second algorithm only uses a separate DBN algorithm to evaluate the transient stability of the power system for test. The setting of DBN and the division of sample set in this method are the same as the first algorithm.

The third algorithm adopts BP neural network. In this method, the BP neural network is set as a single hidden layer structure. The hidden layer contains four neurons. The gradient descent algorithm is adopted, and the learning rate is 0.1. In this method, the division of training set and test set is the same as the first algorithm.

The fourth method uses the combination of BP neural network and rough set. The reduced data set shown in the first algorithm is used as the input of BP network.

The fifth algorithm adopts the method of SVM. The kernel function used is a linear kernel function.

The sixth algorithm adopts the method of SVM+RS, and the kernel function and data processing are the same as above.

The seventh algorithm adopts the method of decision tree (DT). Several experiments were carried out and the average value was selected.

The eighth algorithm adopts the method of decision tree + RS, and the data processing is the same as above.

Before network learning, the original data set is reduced using the method based on attribute importance. The reduced feature set contains 22 groups of features.

According to the above eight algorithms, the results shown in Table 3 can be obtained. It can be seen from Table 3 that the accuracy of the eight algorithms is relatively high, among which the accuracy of BP+RS is the highest. However, for transient stability assessment, the index of missed judgment rate of the model is very important, and the missed judgment rate of this method is not the lowest. Similarly, although the accuracy of SVM+RS and DT+RS methods is also high, the missed judgment rate is higher than that of DBN+RS algorithm. The miss rate of DBN+RS method is the lowest, while the miss rate of DBN method alone is higher. All the eight methods have a low misjudgment rate. From the comparison of the eight algorithms, the shallow artificial intelligence algorithms have a high miss rate. From the comparison of all eight kinds, rough set can reduce the missed judgment rate of the network and improve the accuracy of prediction results. For some relatively simple networks, the improvement of rough set is not obvious. After synthesizing several indexes, the method based on rough set and DBN proposed in this paper has good performance for the evaluation of power system transient stability.

Table 3. Test result

Algorithm	f_0%	f_2%	f_1%
DBN	95.4	12.7	2.9
DBN+RS	95.6	8.9	3.5
BP	94.8	16.9	2.8
BP+RS	96.1	12.3	1.9
SVM	95.6	19.3	1.3
SVM+RS	95.5	18.9	1.5
DT	95.4	13.6	2.8
DT+RS	95.6	12.5	2.7

The main reason for the high miss rate is that the number of transient unstable samples in the sample set is relatively small, and the network will tend to run in the direction of low overall error rate. For the underlying network, even if all the results are judged as transient stability, a high overall accuracy will be obtained, because there are too few unstable samples, the relative weight is very low, and the influence of missed judgment on the accuracy is too little.

According to the above speculation, the influence of adding weight to SVM and DT model is tested, and the results are shown in Table 4. It can be seen from the table that increasing the cost of missed judgment can indeed reduce the missed judgment rate of the model, but it may also increase the false judgment rate, adversely affect the accuracy of the model, and the result is not as good as DBN.

Table 4. Test results of some algorithms after adding weight

Algorithm	f_0%	f_2%	f_1%
SVM+RS	94.6	11.4	4.1
DT+RS	95.7	11.4	2.8

6. Conclusion

In this paper, use rough set and deep belief network to evaluate transient stability of power system. Through the simulation of New England 10 machine 39 node system, DBN network has better feature extraction ability and generalization ability than traditional machine learning algorithms; Rough set can reduce the dimension of data and preprocess the data first, which can further improve the accuracy of the algorithm and the rapidity of evaluation. Using depth confidence network can effectively reduce the probability of missing judgment of evaluation results.

In this paper, the method of deep learning combined with rough set is used to evaluate the transient stability, and good results are obtained, which provides a new idea for the research of this subject. With the development of deep learning technology, how to apply new theories and methods to transient stability assessment is the main research direction in the next stage.

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