Power System Transient Stability Analysis Based on Artificial Intelligence Method

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Abstract

According to the characteristics of transient stability analysis problem, the transient stability evaluation is carried out based on the decision tree classifier based on genetic algorithm. According to the characteristics of the power grid system, the characteristics of the stable operation state of the power system are selected, and the genetic algorithm and the decision tree algorithm are combined to complete the dimensionality reduction of the original features and the improvement of the classification accuracy. The simulation results of IEEE39 node system show that the improved decision tree algorithm is higher in accuracy than other commonly used machine learning algorithms.

Keywords

Decision tree; machine learning; transient stability; artificial intelligence.

1. Introduction

With the rapid development of the economy, the level of interconnection of power systems continues to increase, and the power grid is developing in the direction of long-distance and ultra-high voltage. The scale of the power system in operation will become more complicated, and its operating state is getting closer to its stability limit. With the increasing importance of electrical energy in the modern economic society, the importance of the stable operation of the power system has become increasingly prominent. Therefore, it is necessary to study the transient stability assessment method.

The traditional power system system transient stability analysis is mainly the time domain simulation method and the direct method. However, because the time domain simulation evaluation method requires a large amount of calculation and takes a long time, the demand for the online application is difficult to meet. The direct method is difficult to establish an energy function for a specific grid. At the same time, these two methods cannot effectively utilize the massive data of the wide-area measurement system. With the continuous development of computer technology and artificial intelligence algorithms in recent years, the evaluation of power system transients based on machine learning algorithms has received more and more attention. The algorithm model based on machine learning algorithm generally includes the extraction and optimization of features, and the four steps of training set and test set, classifier training and classifier performance evaluation.

At present, the machine learning algorithms studied at home and abroad mainly include support vector machines[1], artificial neural networks[2] and decision trees[3]. Moreover, researchers have introduced deep learning algorithms into transient stability evaluation, which is mainly reflected in the extraction of input features, and has obtained certain research. Results. These methods have their own characteristics for the processing and analysis of data. The neural network algorithm has high complexity, large computation and long time. The expression of related knowledge in the support vector machine algorithm is more complicated. The decision tree algorithm was proposed by Breiman in the 1980s and has the characteristics of simple algorithm, easy understanding and strong interpretability.

Based on the characteristics of power system transient stability assessment, the decision tree classifier based on genetic algorithm is adopted. Through the advantage of genetic algorithm in optimization, the classification accuracy rate is used as the fitness function to select the optimal feature and improve the accuracy.

2. Transient stability feature construction

Data and features determine the upper limit of machine learning, while models and algorithms only approximate this upper bound, so feature engineering is very important. The data collected by the PMU in the power system is high-dimensional time series, and as the size of the power system increases, the amount of data increases. The higher the speed of the algorithm is, the more it is necessary to construct the feature quantity for the original data.

The following principles should be followed to construct the feature quantity: 1) the feature quantity can reflect the transient stability well; 2) the feature quantity has nothing to do with the power system scale; 3) the feature quantity calculation should ensure the time rapidity. Firstly, according to the change of the operating state in the power system before and after the fault, and referring to the experience of other researchers in feature selection [4], 21 features are selected in Table 1.

Table1 Original input feature

feature	description
f1	Maximum value of rotors acceleration at t0
f2	Maximum value of rotors kinetic energy at tc
f3	Difference of max.and min.generator rotor angle at tc
f4	Average value of all rotor kinetic energy at tc
f5	Kinetic energy of generator that has largest rotor angle at tc
f6	Total system ’energy adjustment’
f7	Difference of max.and min.generator angular velocity at tc
f8	Sum of generator rotor mechanical power at t0
f9	Root mean square error of rotors acceleration at t0
f10	Rotor angle of generator that has largest acceleration at t0
f11	Maximum reactive power impact of generator at t0
f12	Difference of max.and min.kinetic energy at tc
f13	Average value of all rotor acceleration at t0
f14	Sum of the absolute values generator angular velocity
f15	Maximum generator angular velocity
f16	Maximum active power impact of generator at t0
f17	Minimum generator relative acceleration at t0
f18	Rotor angle of generator that has largest kinetic energy at tc
f19	Minimum active power impact of generator at t0
f20	Minimum reactive power impact of generator at t0
f21	Impact level of fault to the system

3. CART classification decision tree and genetic algorithm

The CART algorithm is a classification prediction method that sorts out ordered regular expressions from the disorganized sample data through the form of a binary tree. It was first proposed by Leobreiman in 1984 and has been widely used in the field of statistics. The algorithm first finds the attribute as the root node based on the Gini index, and then builds the tree recursively from top to bottom until each sample set after the partition is pure, then the tree is stopped. The leaf node of the decision tree displays the category information of the sample, and from the root node, it goes down the branch and reaches the leaf node, and each path corresponds to a rule. A complete binary tree corresponds to a set of rules.

3.1 Gini indicator

The Gini indicator is used to measure the impurity content of a sample. The smaller the value, the lower the impurity level of the sample and the purer the sample. For set D, the Gini formula is expressed as follows:

$$Gini(D) = 1 - \sum_{i=1}^{N} p_i^2$$

Where: N is the number of class labels; the probability of classifying as class i

If the set D is divided into a sum under the A condition, then the split Gini indicator is expressed as follows:

$$Gini_{split(A)}(D) = \frac{D_1}{D} Gini(D_1) + \frac{D_2}{D} Gini(D_2)$$

3.2 Classification decision tree establishment

The establishment of the classification decision tree is a non-parametric process. In view of the fact that the binary tree is not easy to generate fragments and the accuracy is higher than that of the multi-fork tree, the statistician adopts the binary division, in which the root node contains all samples, and the root node is divided into Left and right 2 child nodes, and then continue to divide the child nodes in a recursive manner until they can no longer be divided. The specific building steps of the classification decision tree are given below:

(1) Create a root node Root.

(2) If all the samples in the training set belong to the same category T, then T is the root node and ends.

(3) If the condition attribute is discrete, the arbitrary condition attribute has m kinds of values, and the data set is divided into m subsets according to different attribute values, and the Gini value of the divided sample is calculated according to formula (2).

(4) If the condition attribute is continuous, the optimal division threshold is first selected, the data is discretized, and then the same operation as in step (3) is performed.

(5) Select the condition attribute with the smallest Gini value as the best split attribute of the root node Root.

(6) According to the best split attribute, the root node is divided into two parts of the left and right subtree.

(7) Recursively invoke steps (2) - (6) to continue dividing the left and right subtrees until all samples are classified into corresponding leaf nodes.

3.3 Genetic algorithm

The genetic algorithm originated from the research of computer-based biological systems [5-7], which is a kind of random search algorithm derived from the evolutionary law of the biological world (the survival of the fittest, the genetic mechanism of the survival of the fittest). Its main feature is to directly operate on structural objects, there is no limitation of function continuity and derivation; it has inherent hidden parallelism and better global optimization ability. The probabilistic optimization method can automatically acquire and guide the optimized search space, adaptively adjust the search direction, and does not require certain rules.

The genetic algorithm operates on the encoding of the parameters, not the parameters themselves. For example, for a function that requires a maximum value in the interval, it is required to be accurate to six decimal places. The coding method of the genetic algorithm is to divide the interval into parts, so that the number of the interval is encoded into a binary string with 22 bits, where [0000000000000000000000] represents -1, and [1111111111111111111111]represents 2.The genetic algorithm simultaneously uses the search information of multiple search points, that is, the genetic algorithm starts the search process of the optimal solution from an initial group composed of many individuals; the genetic algorithm directly uses the objective function as the search information; wherein the algorithm selects the cross mutation and other operations It is carried out in a probabilistic way; the genetic algorithm is basically unlimited for the function to be searched, and can be operated in parallel, so it is suitable for the optimization of large-scale complex problems.

4. CART Decision Tree Classification Based on Genetic Algorithm

According to the actual problem analysis of the power system, the problem is mainly dealt with in three aspects: sample acquisition, feature extraction and classifier selection, combined with genetic algorithm in the process of optimization process and parallelism and decision tree. The algorithm has the advantages of fast speed and high accuracy, and combines the decision tree algorithm with the genetic algorithm. In the genetic algorithm, the encoding method of the parameters is similar to the binary encoding method. Therefore, the original 21-dimensional features of the power system are equivalent to 21 bits in the genetic algorithm, and [000000000000000000000] represents that all 21 feature values are not selected. 111111111111111111111] represents 21 features all selected. In the process of the iterative process of the genetic algorithm, the optimal combination of features is continuously sought, and the decision tree is generated through the training data. The test data set is judged on the generated decision tree, and the category of the judgment is compared with the category of the actual test data. The correct number is p, and the number of errors is q, so the fitness function is become

$$f = \frac{p}{p+q}$$

The termination condition of the genetic algorithm is to maximize the fitness function, thus combining the selection of features with the process of improving the accuracy of decision tree classification.

5. Case analysis

In order to analyze the performance of decision tree classifier based on genetic algorithm, six data sets of Heart, Haberman, Ionosphere, WDBC, WBC and Sonar in UCI are selected. These six data sets are all data sets with category number 2. The power system fault data set is also a two-category data set. At the same time, according to the characteristics of excessive initial characteristics of the power system fault data set, the accuracy of the algorithm on six different data sets and the change graph of the correct rate of the genetic algorithm in the iterative process are tested respectively. At the same time, the improved algorithm and The accuracy of the base classifiers Cart, Bayesian, KNN and SVM are compared. At the same time, after the optimal feature selection by the genetic algorithm is selected, the number of newly selected feature quantities is compared with the number of original feature quantities.

As shown in Figure 1 to Figure 6, the accuracy curve of the genetic algorithm in the optimization process is given on the six data sets.

As can be seen from the figure, in addition to the Wdbc data sets, the accuracy of the genetic algorithm in the other five data sets at the beginning of the iteration is very fast, especially the Sonar data sets, which has been reached in the second iteration. The global optimal solution is a good proof that the genetic algorithm has a good global search ability. It can be seen from the accuracy curves of the three data sets of Haberman, Heart and Ionosphere that the genetic algorithm also plays a certain role in local search. As the number of iterations increases, the classification accuracy of all data sets has increased to varying degrees.

As shown in Table 3, the comparison between the number of original features and the number of new features is given after the combination of genetic algorithm optimization

Tabel2 Six sets of standard data sets

Data sets	Number of Instances	Number of Features	Class
Heart	270	13	2
Ionosphere	351	32	2
WDBC	569	30	2
WBC	683	9	2
Haberman	306	3	2
Sonar	208	60	2

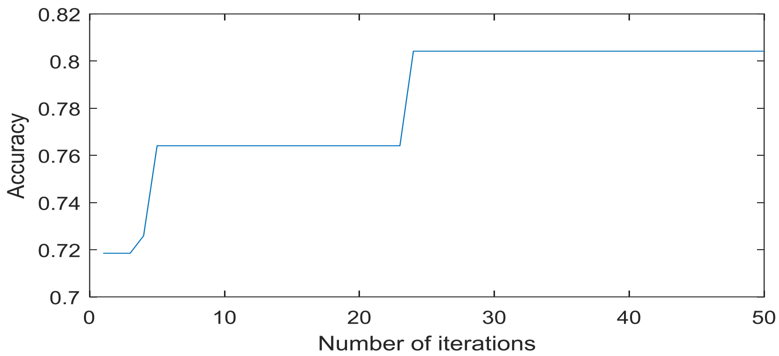

Figure1 Data sets of Haberman

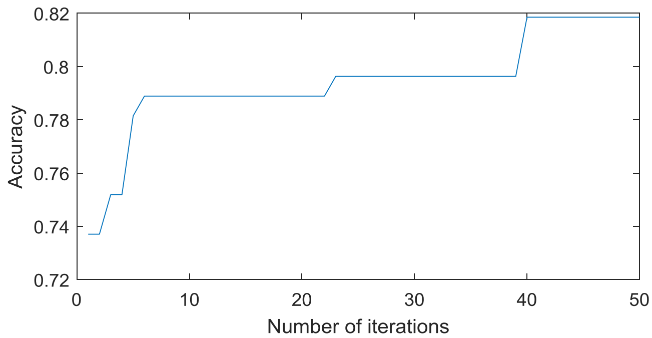

Figure2 Data sets of Heart

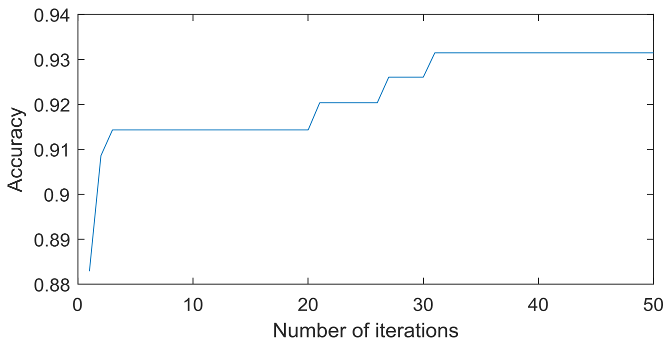

Figure3 Data sets of Ionosphere

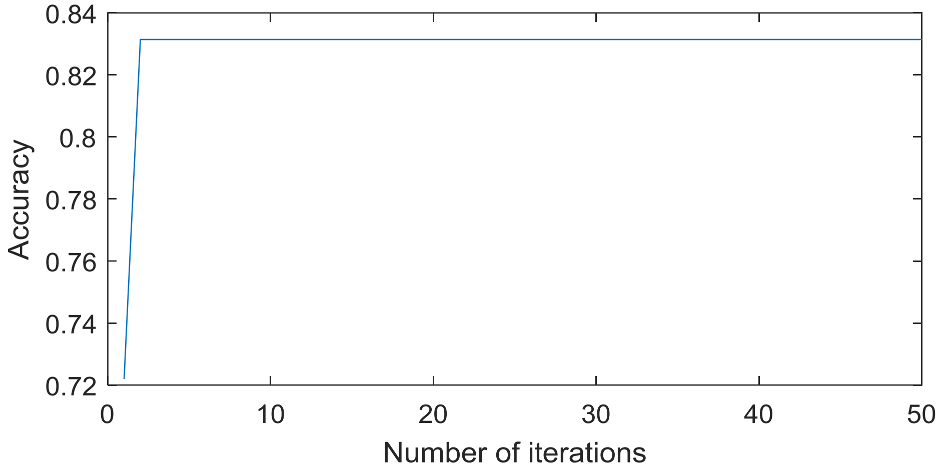

Figure4 Data sets of Sonar

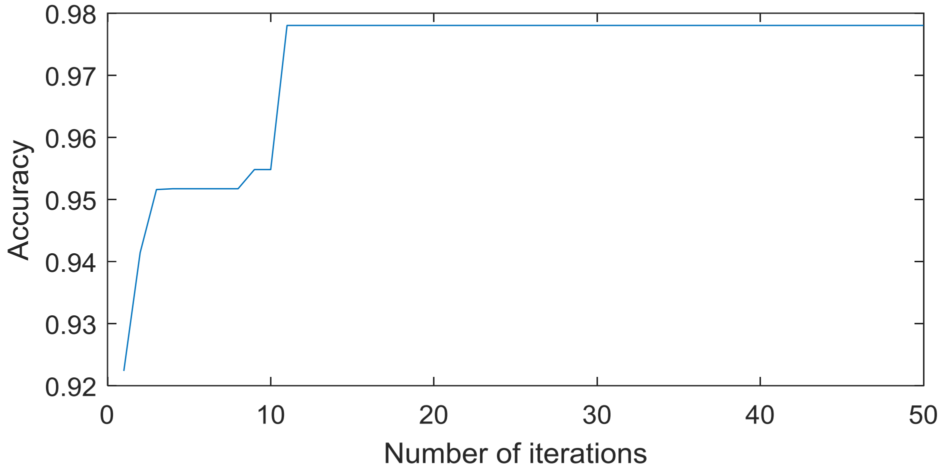

Figure5 Data sets of Wbc

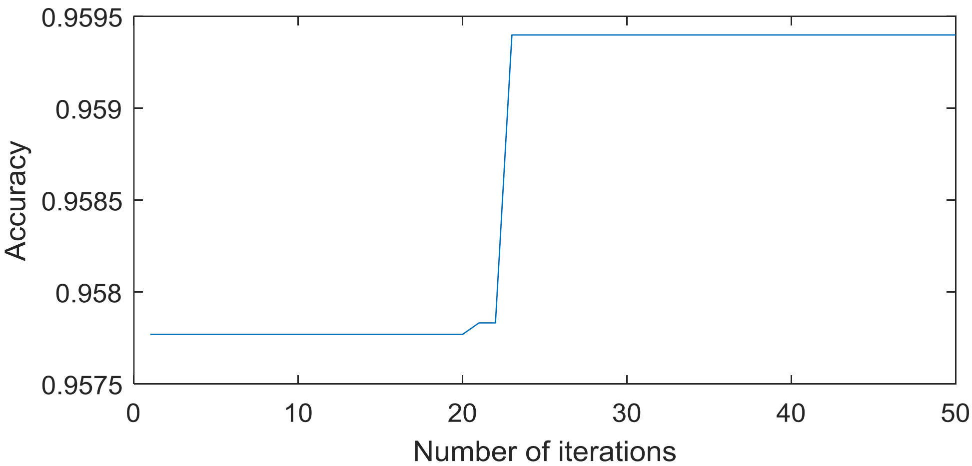

Figure6 Data sets of Wdbc

Tabel3 Characteristic change after genetic algorithm

Data sets	Original number	New number	Best times
Haberman	3	1	25
Wdbc	30	15	23
WBC	9	6	11
Heart	13	7	40
Ionosphere	32	13	31
Sonar	60	31	2

It can be seen from the table that the number of features of the six data sets has been reduced to different degrees after optimization by genetic algorithm, especially the three data sets of wdbc, ionosphere and sonar, the number of features are from the original 30 It fell to 15,32 to 13 and 60 to 31, indicating that many of the original features on the three datasets are characteristic of the outcome. The genetic decision tree algorithm is very good to delete these redundant features and extract useful features, which is beneficial to improve the computing speed of the computer.

Table 4 show the classification accuracy of the five classifiers on these six data sets.

Data sets	Cart	GA-Cart	NB	KNN	SVM
Heart	0.7551	0.8185	0.8296	0.6259	0.8296
Haberman	0.6891	0.8053	0.7295	0.6697	0.7273
Ionosphere	0.8858	0.9314	0.8261	0.8635	0.8574
Wdbc	0.9243	0.9593	0.9209	0.9122	0.9789
Wbc	0.9416	0.9780	0.9473	0.9402	0.9579
SONAR	0.6814	0.8314	0.6654	0.8190	0.7014

It can be seen from the figure that the GA-Gart algorithm has different degrees of improvement compared with the original Cart algorithm. For the three data sets with more original feature quantities, the accuracy of the improved algorithm compared with the original algorithm is from 68.14. %, 92.43%, and 88.58% increased to 83.14%, 95.93%, and 93.14%, respectively, indicating that the GA-Cart algorithm is not only conducive to good dimensionality reduction of the original features, but also has a great improvement in accuracy. . Compared with the other three base classifiers, the GA-Cart algorithm only has no SVM classifier on Wdbc. According to the graph analysis, although the genetic algorithm is very strong in global search ability, it has advantages in local search ability. Lack of, easy to fall into the local optimal solution. It can be seen from the Wdbc iteration accuracy graph that the GA-Cart algorithm finds the global optimal solution in the 23rd algorithm, and the correct rate remains at the 23rd accuracy rate, indicating that the algorithm is trapped at this time. Locally optimal situation. However, in general, the performance of the GA-Cart algorithm is still very good.

This example still uses the 10-machine 39-node system, and the 1200 sets of power system transient stability data collected by the Simulink model. The training data set and the test data set are still divided by a 10-fold crossover method. The optimal solution obtained by the result is the following parameter setting in the genetic algorithm of this paper, in which the number of iterations is 50, the crossover probability is 80%, and the mutation probability is 10%.

Figure 7 is a graph showing the classification accuracy and number of iterations of the power system data set after passing the GA-Cart algorithm. In the figure, the abscissa is the number of iterations and the ordinate is the accuracy. It can be seen from the figure that in the initial stage of the iteration, the accuracy rate has been improved to a large extent, indicating that the algorithm has a tendency to approach the global optimal solution at the beginning of the iteration, which embodies the good global search ability of the genetic algorithm. The number of iterations increased continuously. Finally, at the 45th iteration, the global optimal solution was found, and the accuracy rate reached 97.33%.

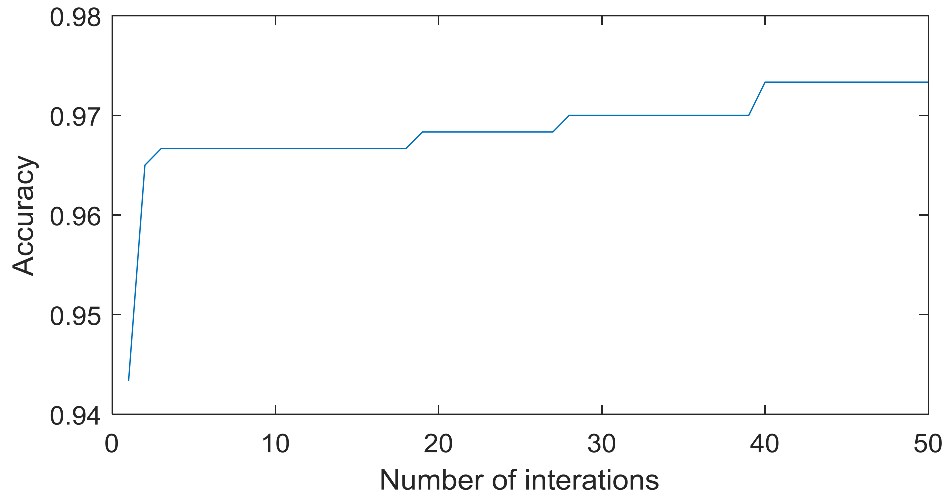

Figure 7 Relationship between classification accuracy and number of iterations

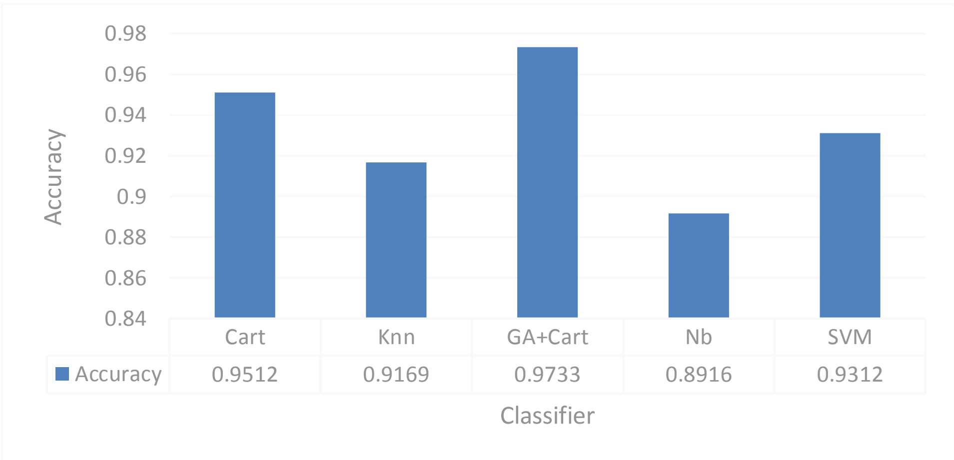

Figure8 Classification accuracy of different classifiers

As can be seen from Figure 8, compared with the Cart algorithm, the classification accuracy of GA-Cart is increased from 95.12% to 97.33%, and the GA-Cart algorithm has the highest classification accuracy compared with other base classifiers. . Therefore, the GA-Cart algorithm has a certain degree of improvement in the accuracy improvement and reduction feature dimensions.

6. Conclusion

This chapter first introduces the theoretical knowledge of genetic algorithms and Cart decision trees. Secondly, the process of combining the two algorithms is shown in the form of a flow chart. Finally, standard data sets and power system fault data sets are used to verify the effectiveness of the algorithm. Compared with the original Cart algorithm in the six standard data sets, the accuracy of the improved algorithm has been improved to some extent. At the same time, in terms of dimensionality reduction, the number of features on the standard dataset Sonar, Ionosphere, and Wdbc data sets were reduced from 60 to 31, 32 to 64 and 13 to 30 and reduced to 15. In the power system fault data set, the accuracy of the improved algorithm is also improved from 95.12% to 97.33% compared with the original algorithm, and the dimension is reduced from 21-dimensional to 9-dimensional.

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