Stability Evaluation Method of Grid Transient State Based on Deep Learning Technology

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Abstract. At present, with the size increase and complication of the grid, it has brought greater challenges to the stable operation of the grid; the author proposes a stability evaluation model of grid transient based on deep learning technology, which has high recognition speed and accuracy after being verified by practical examples.

1. Introduction
With the complication of the grid operation, various external factors that affect its operational stability are growing day by day; in addition, China's electrical power system basically adopts unified dispatch and management, and finds weak points in the power grid system through simulation, calculation and analysis, then make corresponding countermeasures. But this method can only be applied to not very complicated situations. In the large power failure accident, the power grid monitoring system cannot accurately and timely provide early warning information for the steady state vector, so there is no smart monitoring goal that can truly achieve grid operation. Therefore, this paper introduces deep learning algorithm into the transient evaluation of electrical power system in order to enhance the safe operation capability of the grid.

2. Overview of Influencing Factors of Transient Voltage Stability

2.1. Transmission capacity of transmission grid
In general, the stability problem of transient voltage occurs when the line is heavily loaded, because the transmission power is relatively large when the line is heavily loaded, the transmission line cannot transmit reactive power to weak areas, once a large disturbance occurs, and the voltage will collapse. Therefore, only when the reactive power supply is close to its load point can the local balance of reactive power be realized.

2.2. Load dynamic characteristics
Dynamic load is the main factor which affects the stability of transient voltage. In more complex power grids, the drop of load voltage will cause reactive power and current to increase in a very short period of time, thus leading to insufficient reactive power at the load point, and eventually cause the load voltage to drop.

2.3. Voltage support of receiving end
The generator is the main reactive power source of the grid, when the system is subject to large disturbances, the generator will trip, which will cause the reactive power of receiving end to decrease,
this requires the external system to transmit reactive power more systematically, but due to the far transmission distance and low efficiency, it will cause the reactive power balance of the system to be broken, resulting in a voltage drop in a short time.

3. **Principle of Deep Learning**

Deep learning technology is derived from artificial neural networks; its core idea is derived from the human brain's hierarchical process mode for visual information, starting from the input information, it gradually sample learns features through multiple hidden layer structures, and finally enhances the accuracy of classification, its structure is shown below:

![Deep learning model of transient voltage stability identification](image)

**Figure 1.** Deep learning model of transient voltage stability identification

The emergence of deep learning solves problems that machine learning technology cannot solve, such as overfitting problems and local optimization problem, etc. It has significant advantages in comparison with machine neural networks.

4. **Stability Evaluation of Transient State Based on Deep Learning**

4.1. *Establish the stability evaluation model of transient state*

This paper uses Tensor Flow build transient stability evaluation model of deep learning, this model directly inputs the data set from the bottom layer, extracts sample features through multi-layer neural networks, and establishes the non-linear mapping relationship among stable categories to obtain the final evaluation result. The model is mainly divided into the following three parts:

1. **Input layer**
   
   The main task of the input layer is to select input features and make physical meaning of selected data clear. The author uses k-fold cross validation (K-CV) to determine the index of the classifier. Namely the samples are randomly divided into k groups, and each group is set to have an equal number of samples, and the test set and the training set are repeatedly extracted k times in order to obtain the average accuracy rate.

2. **Multiple hidden layer structure**

   This model uses 5 layers of fully connected neural network layers, of which the first 4 layers are processed ReLU function and the last layer is softmax function. The first setting four layers are mainly to consider that when training the neural network, lower learning efficiency can reduce the sample...
training speed. In order to further ensure inaccurate condition of conventional learning model classification, the author constructs an objective function that classifies samples more accurately:

$$H(y) = 2 - y_{i1} y_{i1} - ay_{i2} y_{i2}$$

The subscript 2 in the above formula represents the second of the vector, and the coefficient a represents the accuracy of sample classification.

Because the accuracy and speed of classification are the main indicators for evaluating classifiers, the author introduces the learning rate. In order to ensure that the objective function is minimized, the minimum step and the minimum value need to approach. Therefore, the learning rate decays with the number of iterations, the formula is:

$$LG = I_{r_{\text{min}}} + (I_{r_{\text{max}}} - I_{r_{\text{min}}}) e^{-i/ds}$$

In the above formula, $I_{r_{\text{min}}}$ is set to 0.001, $I_{r_{\text{max}}}$ is set to 0.02, i is the number of iterations, and ds is the decay speed.

3) Output layer

The output layer is evaluation result of grid transient stability voltage of the model, the evaluation results are divided into stability and instability two cases, the one-hot coding is used, the stability is (1,0) and the instability is (0,1).

The evaluation criterion of stability is an empirical criterion, namely the voltage of the hub bus in the power system is lower than the minimum value 0.60p.u, and the duration is 1.5s.

4.2. Evaluation process

![Figure 2. Implementation process of grid transient state evaluation](image-url)
4.3. Example analysis

(1) Classification results of evaluation model

This paper takes 220-machine 789-node system and main grid system of State Grid 800KW as examples to verify the effectiveness and feasibility of this algorithm, the voltage change condition of nodes are used as input features. When the input sample is 1 cycle, the number of neurons in the connection layer in the deep learning model is 160, 70, 60, 20, 4, respectively, after inputting 1 cycle node voltage, the number of neuron samples is 400, 250, 70, 20, and 4. The number of iterations of the experiment is set to 800 and the initial speed of learning attenuation is 800, the experimental results obtained are shown in the following figure:

![Figure 3. Experimental result](image)

Among them, the blue curve represents the recognition accuracy of the training set, and the red curve represents the recognition accuracy of the test set. It can be seen from the above figure that the training set has a better learning effect, and the classification accuracy of the test set reaches 98.73% after 250 iterations, therefore, it can be seen that the node voltage is an excellent input feature of the evaluation model of transient stability.

In order to further study the recognition accuracy, this paper tests the recognition speed of the model when the failure occurs in the sample manufacturing process. It can be found from analysis of the sample data that after the majority of the instability occurs, the fault was removed within 0.2s, and the fault removal required 0.4s. This paper uses the stable data expansion method test the recognition speed, and the results are as follows:

| removal time after failure | sample accuracy |
|----------------------------|-----------------|
| 0.1                        | 94.35%          |
| 0.2                        | 94.35%          |
| 0.3                        | 96.28%          |
| 0.4                        | 98.87%          |
| 0.5                        | 1005%           |

It can be seen from the above table that the increase of the fault removal rate has greatly improved the recognition accuracy rate, and the recognition accuracy is the best after the failure occur 0.5s.

5. Conclusion

In summary, deep learning technology is of great significance in the transient evaluation of power grids, and it can achieve rapid evaluation of the transient stability of the grid.
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