

Analysis of Power Grid Stability Based on Artificial Intelligence Methods

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Abstract: With the growth of global energy demand and the increasing complexity of the power market, the stable operation of the power grid is of utmost importance. This paper focuses on the artificial intelligence-based methods for power grid stability analysis. It details the basic principles, structural characteristics, and the error backpropagation algorithm of the fully-connected neural network, and explores the dynamic adjustment strategy of the learning rate to train a model with better performance. By testing the performance of models under different data partition widths, different numbers of neural network layers, and different activation functions, the results show that using the Sigmoid function as the activation function and medium- or wide - type neural networks contribute to improving the model performance. High-precision and high - recall models are trained to complete tasks with high requirements such as power system stability prediction.

Keywords: Power Grid Stability Analysis, Fully-Connected Neural Network, Error Backpropagation Algorithm

1. Introduction

With the continuous increase in global energy demand and the growing complexity of the power market, ensuring the stable operation of the power grid has become a crucial issue that needs to be addressed urgently in the current power system field[1]. The stability of the power grid is directly related to the safety and reliability of the power system. Factors such as large - signal interference and the control effect of energy storage devices can affect the power balance of the system, resulting in an imbalance between the input and output power of the DC bus and thus causing bus voltage fluctuations[2]. Therefore, in-depth research on power grid stability analysis has important theoretical significance and engineering value.

In recent years, with the rapid development of artificial intelligence technology, its application in the power system has gradually become a research hotspot. Artificial intelligence technology, with its powerful data - processing capabilities and non - linear modeling capabilities, provides new solutions for power grid stability analysis. For example, regarding the problem of improving the small - signal stability of micro - grids, the mainstream approach is to optimize system parameters through optimization algorithms to enhance the stability of the system. Such methods are usually based on eigenvalue analysis, and the system parameters are optimized by solving the objective function to achieve the stable operation of the micro - grid. [3]In addition, the multi - clustering algorithm proposed in Reference [4] is used to study the grid - connected stability of doubly - fed wind power systems under weak grids, and the method for predicting the critical value of the constant - power

load (CPL) in islanded DC micro - grids based on deep learning in Reference [5] demonstrates the potential of artificial intelligence in the analysis of complex power systems. At the same time, the application of the random forest algorithm in the static voltage stability assessment of power grids in Reference [6] further verifies the wide applicability of artificial intelligence technology in power system stability analysis.

As one of the most disruptive technologies at present, the new - generation artificial intelligence, combined with new theories and technologies such as big data and supercomputing, is profoundly influencing and changing the entire power and energy industry. [7] In the context of smart grids and the Energy Internet (EI), the application of artificial intelligence technology in power system stability analysis shows great potential. By using artificial intelligence technology, real - time monitoring of the power grid operation status, fault prediction, and stability assessment can be realized, providing strong support for the safe and stable operation of the power system.[8]

This paper aims to deeply explore the artificial - intelligence - based methods for power grid stability analysis, conduct systematic research using methods such as fully - connected neural networks, and explore their development trends, so as to build a solid theoretical and technical support system for the stable operation of future power systems. It is expected that through this research, a new path can be opened for solving power system stability problems, and it can strongly promote the power system to develop towards intelligence, high - efficiency, and sustainability, so as to better adapt to the changes in the global energy pattern and the complex requirements of the power market.

2. Fully - Connected Neural Network

The fully - connected neural network (FCNN) is a parallel distributed computing model composed of multiple layers of non - linear computing units. Its core design concept is derived from the mechanism by which neurons in the biological nervous system transmit information through synapses. The most basic component is the neuron model. Each neuron receives n weighted input signals. The total input value received is compared with the threshold, and the output is generated through the processing of the Sigmoid function. Multiple neurons are connected to form a certain hierarchical structure, that is, a neural network. Therefore, a neural network is essentially a set of several functions nested with each other. The learning process of a neural network is to dynamically adjust the weights between neurons and the thresholds of functional neurons according to the training data. In power grid stability analysis, neural networks provide a mathematical modeling tool for solving problems such as power oscillations, voltage instability, and multi - time - scale coupling by simulating the characteristics of complex non - linear dynamic systems.

2.1. Neuron Model

The basic unit of a neural network is the artificial neuron, and its mathematical model can be described as follows: Given an input signal $\mathbf{x} = (x_1, x_2, \dots, x_d)$, each neuron receives weighted input signals from all neurons in the previous layer and performs a non - linear transformation through an activation function. For the h -th hidden - layer neuron, its input calculation is:

$$\alpha_h = \sum_{i=1}^d v_{ih} x_i - \theta_h$$

where v_{ih} is the connection weight from the input layer to the hidden layer, and θ_h is the neuron threshold. The output is non - linearly mapped through the Sigmoid function $f(\cdot)$:

$$b_h = f(\alpha_h) = \frac{1}{1 + e^{-\alpha_h}}$$

The input of the j -th neuron in the output layer is obtained by the weighted summation of the hidden - layer outputs:

$$\beta_j = \sum_{h=1}^q w_{hj} b_h - \theta_j$$

Finally, the output is $\hat{y}_j = f(\beta_j)$. Through the nested combination of multiple layers of non - linear functions, a neural network can approximate any complex continuous function. This characteristic enables it to effectively represent the dynamic behaviors such as multi - variable coupling and time - varying non - linearity in the power grid.

2.2. Network Hierarchical Structure

A typical multi - layer feed - forward neural network includes an input layer, hidden layers, and an output layer. Its topological features are as follows:

Fully - connected feature: Neurons between adjacent layers are fully connected, while neurons in the same layer or across layers have no direct connection.

Hierarchical information processing: The input layer is only responsible for data reception. The hidden layers extract high - order features through non - linear transformations, and the output layer completes the final decision - making mapping.

Depth expansion ability: By increasing the number of hidden layers, a deep network can be constructed to enhance the model's ability to represent the high - dimensional dynamic characteristics of the power grid.

3. Error Backpropagation Algorithm and Parameter Optimization

The core of power grid stability analysis lies in constructing an accurate system dynamic model, and the optimization of neural network parameters is a key link to achieve this goal.

3.1. Principle of the Error Backpropagation (BP) Algorithm

Given a training sample set $\{(\mathbf{x}_k, \mathbf{y}_k)\}_{k=1}^m$, the mean - square error between the network output $\hat{\mathbf{y}}_k$ and the true value $\mathbf{y}_k$ is defined as:

$$E_k = \frac{1}{2} \sum_{j=1}^l (\hat{y}_j^k - y_j^k)^2$$

The BP algorithm adjusts the network weights layer by layer through the backpropagation of the error gradient to minimize the cumulative error $E = \frac{1}{m} \sum_{k=1}^m E_k$. The update amount of the weight w_{hj} is calculated as:

$$\Delta w_{hj} = \eta \cdot \delta_j \cdot b_h$$

where $\delta_j = (\hat{y}_j - y_j) \cdot f'(\beta_j)$ is the error term of the output layer, and $\eta \in (0,1)$ is the learning rate. Similarly, the update of the hidden - layer weight v_{ih} depends on the error term $\delta_h = (\sum_{j=1}^l \delta_j w_{hj}) \cdot f'(\alpha_h)$.

3.2. Dynamic Adjustment Strategy of the Learning Rate

In power grid dynamic modeling, the selection of the learning rate directly affects the model convergence speed and stability, which can be divided into two cases:

High learning rate ($\eta > 0.1$): It may cause excessive parameter update amplitudes, resulting in oscillations during the training process. Especially when dealing with sudden change conditions such as voltage sags, the model is prone to instability.

Low learning rate ($\eta < 0.01$): Although it can ensure the convergence stability, it will significantly extend the training time and is difficult to meet the real - time requirements of online stability analysis. In practical applications, adaptive learning rate algorithms (such as Adam, RMSProp) or learning rate decay strategies can be adopted. A larger learning rate is used in the initial stage of training to accelerate convergence, and the step size is gradually reduced in the later stage to improve accuracy.

4. Case Analysis

Draw the flow chart of the neural network in Matlab, simulate the functions of the neural network, and specify the data type and training algorithm.

Use the collected power grid operation data as the data set, and use a function to randomly divide it into a training set and a validation set. There are 7000 groups in the training set and 3000 groups in the validation set. This ratio has been proven to effectively balance the training and validation effects of the model in multiple experiments. The training set is used for the parameter learning of the model, and the validation set is used to test the generalization ability of the model to prevent overfitting. After each generation of training of the training set, the validation set is used to test the error (val fail). When the validation - set error rises continuously for multiple times, it is considered that the model may be overfitting, and the training is stopped at this time.

During the training process, combined with Figure 1, it is found through experiments that when the gradient is as small as possible within a certain limit and the damping factor (μ) is as large as possible, the model training effect is better. For example, in a certain round of training, when the gradient reaches 1.3996×10^{-5} , the model training is relatively stable.

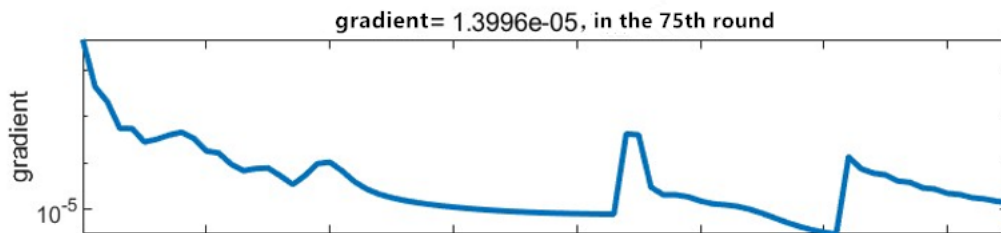


Figure 1: Gradient changes with the number of training rounds.

In addition, drawing the mean - square error graph, error histogram, and regression graph can more clearly reflect the model training effect. The closer the mean - square error is to the optimal value, the smaller the difference between the model prediction value and the true value. The closer the correlation coefficient of the regression graph is to 1, the better the fitting effect of the model. For example, in Figure 2, after a certain training is completed, the correlation coefficient R of the training set of the model reaches 0.96847, the R of the validation set is 0.97022, the R of the test set is 0.96403, and the overall R is 0.96809, indicating that the model has a good fitting effect on different data sets. The error histogram shows the distribution of prediction errors, and it can be intuitively understood the degree of error concentration. As shown in Figure 3, from the error histogram with 20 bins, it can

be seen that the error distributions of the training, validation, and test sets are relatively concentrated, indicating that the prediction results of the model are relatively stable.

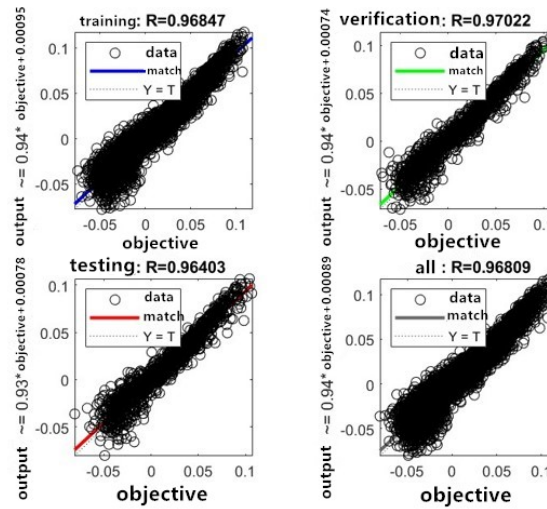


Figure 2: Regression diagram of a model training.

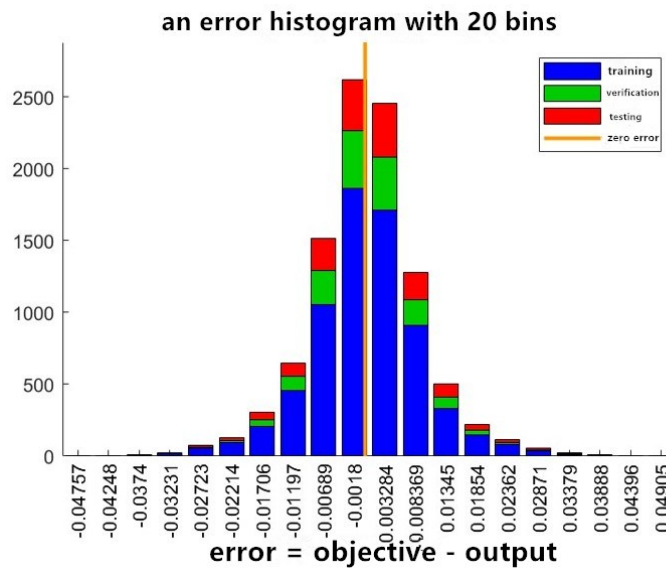


Figure 3: Histogram of error in training of a certain model.

Further increase the number of neuron layers, and verify the performance of the trained model according to the above method. After multiple iterations, a neural network with a more complex structure can be trained.

Table 1: Performance comparison between different models.

model number	model type	width	number of plies	activation function	accuracy (verification)	total cost (verification)	accuracy (testing)	total cost (testing)
1	neural network	10	1	ReLU	93.13%	68	94.50%	55
2	neural network	25	1	ReLU	96.06%	39	95.10%	49
3	neural network	100	1	ReLU	95.96%	40	95.70%	43
4	neural network	10	2	ReLU	95.86%	41	94.50%	55
5	neural network	10	3	ReLU	95.35%	46	94.80%	52
6	neural network	10	1	Sigmold	96.46%	35	97.20%	28
7	neural network	10	1	Tanh	96.67%	33	96.80%	32

Test the fitting effects of models under different data partition widths, different numbers of neural network layers, and different activation functions. The results are shown in Table 1. The comparison results show that using the Sigmoid function as the activation function has a significant effect on improving the model performance. Medium - or wide - type neural networks can ensure that each layer of the neural network learns rich features due to their sufficient width, which also has a certain effect on improving the model performance. However, the width should not be too large to avoid feature redundancy and an increase in the computational burden. It is especially pointed out that models with high precision and excellent recall rates are suitable for tasks with high requirements such as power system stability prediction. For example, Model 6 and Model 7, and Model 2 and Model 3 also have high stability and performance and can be used as sub - optimal choices.

5. Conclusion

This paper elaborates on the basic principles, structural characteristics of the fully - connected neural network, and the error backpropagation algorithm, and deeply analyzes the impact of the dynamic adjustment strategy of the learning rate on the model performance, providing a solid theoretical basis for subsequent research.

At the beginning of the experiment, the data set is divided, and the data is input into the fully - connected neural network to train and test neural network models with different parameters and structures. It is found that using the Sigmoid function as the activation function and medium - or wide - type neural networks have significant advantages in improving the model performance. At the same time, the relationship between factors such as the gradient, damping factor, and the model training effect is clarified. In the model evaluation stage, various means such as the mean - square error graph, error histogram, and regression graph are used to comprehensively evaluate the prediction ability and stability of the model. Excellent models with high precision and high recall rates such as Model 6 and Model 7, and sub - optimal models with stable performance such as Model 2 and Model 3 are screened out, providing diverse choices for different power system stability prediction scenarios.

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