Stability of Electronic Circuits Based on Complex Neural Network Theory

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Abstract. In recent years, with the widespread application of power electronic equipment in various fields of the national economy, the problem of insufficient stability of power electronic equipment has brought a greater negative impact on the application and promotion of new technologies and the development of the national economy. Therefore, to carry out the stability research of power electronic circuits and find suitable methods to reduce the failure rate of power electronic circuits is of great significance for improving the stability of power electronic circuits and promoting the development of power electronic technology and social progress. The purpose of this article is to study the stability of electronic circuits based on the theory of complex neural networks. In this paper, in order to realize the effective use of power grid electricity, during the low period of power consumption, the energy storage battery is operated in the charging state to store the excess energy in the grid; during the peak period of power consumption, the energy storage battery is operated in the discharged state to the load side of the grid powered by. This paper adds a multi-agent system to the power system and uses the linear time-invariant consistency protocol of the multi-agent system to obtain the net active power of the grid. Then, according to the size of the net active power and the working state of the energy storage battery, it is determined whether switch the working status of the energy storage battery. By calculating the changes in the network efficiency value of the circuit weighted network model when the failure rate of each component in the power electronic circuit changes, find the weak points in the power electronic circuit, and prove that the component's stability to the power electronic circuit is not only related to the failure of the component itself the rate is related to the position of the component in the circuit. Experimental studies have shown that the resistance of current or control signal transmission becomes smaller, especially when the component D1 or D4 is short-circuited, the circuit network efficiency value increases by about 15%.

Keywords: Power Electronic Circuits, Complex Networks, Frequency Synchronization, Circuit Stability

1. Introduction
The stability of the power system is a necessary condition for the safe operation of the power system [1, 2], and it is closely related to the stable development of the national economy and policies. When the system frequency drops significantly, the stability of the entire power grid will be destroyed [3, 4], and even "frequency collapse" or "voltage collapse" may occur, which may eventually cause the entire system to collapse [5, 6]. After clean energy is connected to the grid, the dynamic performance of the grid will become more complex and changeable, which will be a severe test for power quality. Therefore, in this case, the study of frequency synchronization of the power system has very important applications and economic value [7, 8].

In the research on the stability analysis of electronic circuits based on the theory of complex neural networks, many scholars have studied them and achieved good results. For example, Fortuna L assumes that each vibrator in the network only interacts with its neighboring vibrators. And ignore the amplitude change of the vibrator, thus simplifying the synchronization problem of the network to the problem of studying the phase change of the vibrator in the network [9]. Park HG proposed that under the same coupling strength, when the network is fully connected and the coupling strength is sufficiently large, the Kuramoto model can achieve stable global synchronization for any initial value [10].

This paper sets an index vector and decision vector for each agent, and then calculates the net active power of the entire grid through a consensus protocol. When the energy storage node meets the state transition conditions, the agents make a decision and finally realize the charge and discharge transition of the energy storage node. This paper presents a critical value of the output power adjustment range of traditional generator sets before and after the clean energy and energy storage batteries are connected to the grid to balance the grid power. Set an index vector and decision vector for each agent, and then calculate the net active power of the entire grid through a consensus protocol.

2. Stability of Electronic Circuits Based on the Theory of Complex Neural Networks

2.1. Charge and Discharge Control of Energy Storage Node Based on Multi-Agent System

(1) Calculation of net active power of power system

Assuming that, except for the transformer bus, an agent system is set up on each of the remaining buses, then the topology of the multi-agent system is the same as the topology of the power grid (we ignore the transformer bus when analyzing the topology of the power grid). The graph \( \mathbf{G} = (\mathbf{V}, \mathbf{E}, \mathbf{A}) \) is used to represent the topological structure of the power grid and multi-agent system, \( \mathbf{V} = \mathbf{n}, \mathbf{E} = \mathbf{m} \). Each agent system only knows the local information on the bus, such as the node type and node power connected to the bus.

Assuming that at the initial moment when the power grid is working normally, there are a total of \( N \) agents, each agent is given an index value, and an index vector of length \( N \) is set. For agent \( i \), except for the value of the \( i \)-th element in the index vector, all other elements are 0. The index vectors of \( N \) agents are shown in equation (1):

\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 2 & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & N-1 & 0 \\
0 & 0 & 0 & N
\end{bmatrix}
\]

(1)

(2) Decision vector

Each agent can know the energy storage node that meets the conversion condition in the current state according to its own decision vector, and for the agent connected to the energy storage node that meets the conversion condition, it can decide whether to treat itself according to the known priority. The energy storage node performs state transition: among all energy storage nodes that meet the transition conditions, when its own energy storage node has the highest priority, the state transition is performed, otherwise the transition is abandoned. When each agent completes the action according to the decision vector, it clears the decision vector to prepare for the next state transition.
2.2. Charge and Discharge Control of Energy Storage Battery Based on Multi-Agent System

For ease of analysis, it is assumed that all energy storage nodes are working in the discharge state at the initial moment, the decision vectors of all agents are all zero vectors, all agents are working normally, and the grid scale is fixed. The specific control strategy is as follows:

1. First calculate the net active power of the grid. When calculating the net active power of the grid, it is necessary to calculate the average net active power and the number of normal working agents.

2. The agent connected to the energy storage node makes a decision. In practical applications, the power shortage seriously affects the stable operation of the power system, and we should try to avoid power shortages.

When the net active power of the grid is greater than twice the power of the energy storage node, changing the state of the energy storage node will not cause a power shortage. That is, when the energy storage node is working in the discharging state and the net active power of the grid is greater than zero and greater than twice the energy storage node power, the energy storage node is considered to meet the conditions for transition from the discharging state to the charging state. Finally, the agents connected to the energy storage nodes make decisions based on the above conditions, and through the consensus protocol, each agent knows the energy storage nodes that meet the conversion conditions.

3. According to the decision vector and the known priority, the agent connected to the energy storage node decides whether to perform state transition on its own energy storage node: among all energy storage nodes that meet the transition conditions, the priority of its own energy storage node. When it is the highest, the state transition is performed, otherwise the transition is abandoned. When each agent makes a decision based on the decision vector, it clears the decision vector.

2.3. Negative Dynamic Model of Clean Energy Nodes and Energy Storage Nodes Based on Droop Control

When clean energy and energy storage batteries are connected to the grid, it is necessary to convert DC power or non-power frequency AC power into power frequency power through a converter. Here, the commutation technology based on droop control is used to establish the dynamic model of clean energy and energy storage battery. Frequency-based droop characteristic formula. If let: \( D_i = \frac{1}{n_i} \), we can get:

\[
D_i f_i = D_i f_0_i - P_i \tag{2}
\]

Next, use \( \theta_i \) to denote \( f_i \), and \( P_{d,i} \) to denote the controller's nominal power \( D_i f_0_i \), then equation (2) can be equivalently expressed as:

\[
D_i \dot{\theta}_i = P_{d,i} - (E_i G_{t11} + \sum_{j=1}^{n} E_i G_{1j} \sin (\theta_i - \theta_j)) \tag{3}
\]

Equation (3) is the kinetic model of clean energy and energy storage battery under discharge. In addition to the discharging state, the energy storage battery can also work in the charging state. At this time, the energy storage battery is the load node. Therefore, its dynamic model is the dynamic model of the load node described by the equation.

3. Experimental Research on the Stability of Electronic Circuits Based on Complex Neural Network Theory

3.1. Experimental Research on Undirected Graph and Adjacency Matrix

The calculation of complex network characteristic parameters is based on the actual network equivalent model. If you want to use the knowledge of complex network theory to analyze the stability of power electronic circuits, you must first establish an equivalent network model corresponding to the actual circuit. According to the undirected graph modeling method in graph theory, the components in
the power electronic circuit (such as resistors, power supplies, diodes, inductors, capacitors, transformers, switch tubes, control chips, etc.) are equivalent to the nodes of the network to connect the electrical connection lines between the various components are equivalent to undirected edges, and the unweighted network model of the power electronic circuit can be obtained.

3.2. L6562 Unweighted Network Experimental Model and Parameter Collection of Power Factor Corrector

There are many components in the L6562 power factor corrector and the connection relationship between the components is more complicated. In order to obtain the unweighted network diagram of the L6562 power factor corrector and the centralization parameters of each component more efficiently, the Protel and pajek interfaces are used here. The software can obtain the adjacency matrix of the unweighted network model of the L6562 power factor corrector, and then use Pajek software to read the adjacency matrix, and draw the unweighted network model of the L6562 power factor corrector

4. Experimental Research and Analysis of Electronic Circuit Stability Based on Complex Neural Network Theory

4.1. Stability Analysis of L6562 Power Factor Corrector When the Component is Open

Suppose that each component of the L6562 power factor corrector has an open circuit fault, and use the written network efficiency value calculation software to calculate the network efficiency value of the L6562 power factor corrector unweighted network model when each component is separately open, and each component has an open circuit. The network efficiency value of L6562 power factor corrector unweighted network model at the time of failure is shown in Table 1.

Table 1. Network efficiency value changes when each component in the L6562 power factor corrector has an open circuit fault

| Element | Test result one | Test result two |
|---------|----------------|----------------|
| C1      | 0.064          | 0.067          |
| C2      | 0.056          | 0.055          |
| C3      | 0.051          | 0.049          |
| C4      | 0.048          | 0.044          |
| C5      | 0.043          | 0.046          |

Figure 1. Network efficiency changes when each component in the L6562 power factor corrector has an open circuit fault
As can be seen in Figure 1, when a component in the L6562 power factor corrector has an open circuit failure, the network efficiency value in the unweighted network model will show a certain degree of decline, and when the component C2 or C3 is open, the network efficiency value the decline is larger. This indicates that when a component breaks down, the connectivity between circuit components will decrease, and the difficulty of transmitting or propagating current or circuit control signals in the circuit will increase, especially when component C2 or C3 is open. The efficiency value of the circuit network has decreased more obviously, which proves that the components C2 and C3 are the key components of the L6562 power factor corrector. When these two components break down, the circuit will be more destructive.

4.2. Stability Analysis of L6562 Power Factor Corrector When Components are Short-Circuited

Assuming that each component of the L6562 power factor corrector has a short-circuit failure, use the written network efficiency calculation software to calculate the network efficiency value of the L6562 power factor corrector unweighted network model when each component is short-circuited, and each component has a short-circuit failure. The network efficiency value of L6562 power factor corrector unweighted network model is shown in Table 2.

Table 2. Network efficiency value change curve when each component in the L6562 power factor corrector has a short-circuit fault

| Element | Test result one | Test result two |
|---------|----------------|----------------|
| D1      | 0.063          | 0.065          |
| D2      | 0.075          | 0.072          |
| D3      | 0.072          | 0.076          |
| D4      | 0.074          | 0.071          |
| D5      | 0.069          | 0.073          |

![Figure 2](image_url)

Figure 2. The network efficiency value change curve when each component in the L6562 power factor corrector has a short-circuit fault

It can be seen from Figure 2 that when a short-circuit fault occurs in a component of the L6562 power factor corrector, the network efficiency value of the circuit unweighted network model will show a certain degree of increase, and when the component D1 or D4 is short-circuited, the network efficiency the increase in value is greater. This shows that when a short-circuit fault occurs in a component, the electrical connection between the components of the circuit will become closer, and the resistance of current or control signal transmission will decrease, especially when the component...
D1 or D4 is short-circuited, the circuit network efficiency value will increase. About 15%, this also proves that components D1 and D4 are the key components of the L6562 power factor corrector. When these two components are short-circuited, they will be more destructive to the circuit.

5. Conclusions
This paper establishes an unweighted network model and a weighted network model of power electronic circuits, and quantitatively analyzes the importance of each component in the power electronic circuit, searches for key components in the circuit, and analyzes the stability of power electronic circuits. Finally, the circuit stability design is carried out according to the relevant conclusions obtained from the stability analysis of power electronic circuits.

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