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# Power Electronic Circuit Fault Diagnosis System Based on Optimal Neural Network

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**Abstract:** The fault diagnosis of power electronic circuit usually adopts the artificial neural network method, but with the deepening of application and the diversification of faults, this diagnosis method gradually presents a series of drawbacks, there is a problem of low detection accuracy, which needs to be further optimized and improved. This paper proposes a power electronic circuit fault diagnosis system based on optimal neural network, which integrates quantum mechanics into the neural network, improves the parallel processing capability of the system, and greatly improves the overall performance of the system.
**Keywords:** Optimal neural network; Quantum computing; Power electronic circuits; Fault diagnosis

In power electronic devices and systems, power electronic circuits play an important role, in the case of failure will lead to serious engineering accidents, resulting in serious economic losses. Realize the effective integration of artificial neural network and quantum computing, and build a new optimized neural network fault diagnosis system. By allocating uncertain data among various faults, it can effectively deal with massive information, process data sets quickly and efficiently, improve processing efficiency, enhance system reliability and stability, and accurately diagnose power electronic circuit faults. It has great value in practice and promotion [1].

## 1. Theoretical overview

Quantum neural network (QNNs) is a computational neural network model based on quantum mechanics. Compared with traditional neural computing, QNNS has strong stability, simple network topology, exponential recall speed and memory capacity, and can process information at a high speed to avoid pattern interference. Quantum neural networks have a wide range of applications in the field of machine learning, especially in pattern recognition.

In order to further improve the fault diagnosis efficiency of power electronic circuits, it is necessary to optimize the neural network. By integrating quantum computing theory with BP neural network and building fault diagnosis system based on optimizing three-layer quantum BP neural network, not only can the fuzziness of sampled data be automatically diagnosed, but also the categories of feature vectors (cross class boundary) can be divided, and the corresponding relationship between feature vectors and faults can be accurately mapped, so as to achieve accurate fault diagnosis [2]. Quantum BP neural network is the result of combining ordinary neurons and quantum neurons according to certain topological structure and connection rules, including input layer, output layer and hidden layer.Among them, the input layer includes $n$ a quantum neuron, the output layer includes $m$ a common neuron, and the hidden layer includes $p$ a quantum neuron. The neural network superimposed multiple excitation functions to form a hidden layer of quantum neuron excitation functions, and reasonably allocated the uncertain data of decision making to various fault modes to improve the diagnostic accuracy [3].

## 2. Second, power electronic circuit fault diagnosis system based on optimized neural network

When the power electronic circuit fault diagnosis system is constructed based on the optimized quantum neural network structure, the input layer can be set as $x=(x_1,x_2\cdots x_n)$, The output layer is $y=(y_1,y_2\cdots y_n)$, The hidden layer is subdivided into two parts: the first hidden layer and the second hidden layer. The transfer function between the layers of the network model applies Sigmoid, and the weights of the three layers are in turn $w1_{k,b}$ 、 $w2_{m,k}$ 、 $w3_{s,m}$ ,The number of faulty components in power electronic circuits to be detected is consistent with the quantum interval.

In this system, the learning algorithm of quantum BP neural network uses gradient descent method to calculate the neuron weight, and plays the advantage of additional momentum adaptive learning rate method to improve the training speed, improve the minimum accuracy, and obtain the local minimum. Based on the weight changes of the system before and after data training, the learning rate and momentum factors [4] are calculated. The steps of the optimized quantum BP neural network learning algorithm are as follows:

1) Conduct quantum state description analysis for input samples.

2) Initialize all network parameters, including phase parameters $\theta_{ji}$ 、 Number of units of each layer, connection weight $w_{k,j}$ 、 Threshold value $b_k$ 、 Rollover parameter $a_j$ 、 Defined error $\varepsilon$ 、 Learning rate $l_r$ 、 Momentum term $m_c$ 、 Limit number of iterations $m, f$ and $g$ Homologarithm $s$ Type activation function. Number of steps to the current iteration $t$ Set as $o$ .

3) According to the formula $h_j = \sin(\frac{\pi}{2} f(a_j) - \arg(\sum_{i=1}^{\pi} R(\theta_j k_i \succ)$ and $y_k = g(\sum_{j=1}^{p} w_{kj} h_j - b_k) = g(\sum_{j=1}^{p} w_{kj} \quad \sin(\frac{\pi}{2} f(\alpha_j) - \arg(\sum_{i=1}^{n} R(\theta_j)|\dot{x} \succ) \; - b_k)$ The output of each layer of the model is calculated, and the formula is used by gradient descent method

$$\Delta\theta_{ji} = \frac{\partial E}{\partial \theta_j} = -\sum_{k=1}^{m} (y_k - \hat{y}_k) g' w_{kj} \quad \cos(\frac{\pi}{2} f(\alpha_j) - \beta_j) - \frac{T_j}{1 + S_j^2}$$

$$\Delta\alpha_j = \frac{\partial E}{\partial \theta_j} = \frac{\pi}{2} \sum_{k=1}^{m} (y_k - \hat{y}_k) g' w_{kj} \quad \cos(\frac{\pi}{2} f(\alpha_j) - \beta_j) f'$$

$$\Delta w_{kj}' = -\frac{\partial E}{\partial w_{kj}} (y_k - \hat{y}_k) g' \sin(\frac{\pi}{2} f(\alpha_j) - \beta_j)$$

$$\Delta b_k' = -\frac{\partial E}{\partial b_k} (y_k - \hat{y}_k) g'$$

[6], Adjust the rules according to the parameters

$$\theta_{ji}(t+1) = \theta_j(t) + l r \Delta\theta_j(t)$$
$$a_j(t+1) = \partial_j + \Delta l r a_j(t)$$

, Adaptive learning rate and momentum factor gradient descent learning algorithm are used ,

$$\Delta w_{kj}(t) = m c * \Delta w_{kj}(t-1) + (1 - m c) * 1r * \Delta w_{kj}'(t)$$
$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj}(t)$$
$$\Delta b_k(t) = m c * \Delta b_k \; (t-1) + (1 - m c) * 1r * \Delta b_k' \; (t)$$
$$b_{kj}(t+1) = b_{kj}(t) + \Delta b_k \; (t)$$

Modify the network parameters. See Network performance size to

Learning rate Learning rate $l_r$ Make adjustments.

4) According to the formula $E = \frac{1}{2} \sum_{k=1}^{n} (y_k - \hat{y}_k) 2$ Calculated error $E$ .If $E$ 、 $\varepsilon$ Perhaps $t$ 、 $N$ ,Go to Step 5 to perform subsequent operations. If the rules are not met, $t + t + 1$ ,Go to Step 3 to continue the preceding operations.

5) To the parameters $\theta_{ji}$ 、 $a_j$ 、 Threshold value $b_k$ and $W_{kj}$ To save.

# 3. Analysis of experimental results

## 3.1 Experimental design

In order to verify the feasibility and effectiveness of the fault diagnosis system based on the optimized quantum BP neural network in this paper, the double-bridge 12-phase pulse rectifier circuit is taken as the fault detection object, and the open circuit thyristor is taken as an example. ORCAD simulation software is applied to simulate various faults existing in the circuit, obtain fault signals, and take fault signals as input samples. The corresponding fault type is used as the output data of the network model, the mapping relationship between the fault type and fault signal is established, stored in the neural network, and tested in the trained quantum BP neural network [5].

The sampling time of the test samples was 0.1ms, the single cycle time was 20ms, and the sample data of each group was 200. After data normalization, the samples were input into the system as samples. In view of the fact that the fault problem of the experimental object is mainly the non-conduction of single or two bridge arms, it covers seven categories of fault conditions, including normal trouble-free operation, which can be subdivided into 31 sub-categories of fault phenomena.With $Y_n$ Means,By numbering all kinds of faults, the corresponding fault codes of each group of characteristic signals can be known, and the obtained fault codes are the output samples of network targets.

## 3.2 Experimental results

In the power electronic circuit diagnosis system, there are 200 input nodes and 6 output nodes. The hidden layer of the optimized neural network model includes the first hidden layer and the second hidden layer, the selected layers are 80 layers and 100 layers respectively, and the activation function is expressed as $\sigma(t)=1(1+e^{-t})$, Set the initial weight randomly. In the process of detecting and optimizing the performance of the neural network fault diagnosis system, the training parameters can be set to compare the classical BP neural network and the optimized quantum BP neural network respectively in the number of training steps and the training error of the quantum neural network. The experimental results show that there is a certain difference in the number of training steps between the classical BP neural network and the optimized quantum BP neural network, the former is 26,745 steps, the latter is 10125 steps. In addition to the input of standard samples in the system, 3100 sets of data can also be added to the random noise to form a network test sample, and the accuracy of the optimized neural network fault diagnosis system for power electronic circuits can be tested. When the actual output of the system meets the standard of $\left|Y_S^P - \widehat{Y}_S^P\right| < 0.1$, the output is correct.Where, the target output of the network department is expressed as $\widehat{Y}_S^P$.

The number of fault diagnoses is set to 3100, and the fault error accuracy of classical neural network and optimized quantum BP neural network under random noise is compared and analyzed. The results are shown in the following table.

Table 1: Accuracy comparison

| Random noise（%） | Classical BP neural networks（%） | Quantum BP neural network（%） |
|---|---|---|
| 5 | 99.18 | 100 |
| 10 | 78.53 | 99.89 |
| 15 | 64.47 | 99.74 |
| 20 | 48.85 | 99.55 |

The number of fault diagnoses is set to 3100, and the fault misdiagnosis rate of classical neural network and optimized quantum BP neural network under random noise is compared and analyzed. The results are shown in the following table.

Table 2: Comparison of misdiagnosis rates

| Random noise（%） | Classical BP neural networks（%） | Quantum BP neural network（%） |
|---|---|---|
| 5 | 0.54 | 0 |
| 10 | 12.36 | 0.62 |
| 15 | 20.26 | 1.51 |
| 20 | 32.35 | 3.61 |

The comparison results show that the fault diagnosis accuracy of the optimized quantum BP neural network is significantly higher than that of the classical BP neural network, and the false diagnosis is also lower. The optimized quantum BP neural network has strong stability and anti-noise ability, and is not affected by random noise changes of the circuit, which has significant advantages in the fault diagnosis of power electronic circuits.

## 4. Conclusion

The classical BP neural network is optimized and improved, and the quantum computation is fused with the neural network to form the quantum BP neural network, which can get rid of the limitation and solve the problem of too long training time and local minimum. In this paper, a fault diagnosis system for power electronic circuits is constructed based on quantum BP neural network. The hidden quantum neuron excitation function can improve the accuracy of the training algorithm, form fuzziness, and further enhance the performance of the fault diagnosis system. Simulation experiments also show that the optimized neural network diagnosis system has good diagnostic efficiency, stability and practicability, and greatly reduces the misdiagnosis rate, and has a high application mechanism, which provides a new method for electronic circuit fault diagnosis.

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