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Deep Learning Analog Circuit Fault Diagnosis Based on Self-attention Mechanism

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Abstract: This paper discusses the application of deep learning based on self-attention mechanism in analog circuit fault diagnosis, aiming to solve the limitation of traditional diagnosis methods in complex fault identification. The research team designed an optimized deep learning model that enhances multi-classification capabilities by introducing SoftMax layers, utilizes Dropout mechanism to mitigate overfitting, innovatively converts circuit signals into spectrograms as input, and combines location coding with class coding to improve the sequence processing capability of the self-attention mechanism. In the experiment, Sallen-Key low-pass filter was selected as the test object, and various data sets including 24 fault types were generated by simulation software, which fully covered single fault and double fault cases. Transfer learning strategy was adopted in model training, and the customized AlexNet network showed high accuracy in different fault classification. The results show that this method can effectively improve the accuracy and efficiency of fault diagnosis, and is of great significance to promote the development of analog circuit fault detection technology.

Keywords: Self-attention mechanism; Deep learning; Analog circuit fault diagnosis; Sallen-Key Low-pass filter

Introduction

Under the tide of today's digital transformation, Industry 4.0 and intelligent manufacturing are leading the pace of global industrial upgrading, and intelligence and automation have become the key to improving productivity in various fields. Electronic circuit as the heart of modern industry, its stability and reliability directly affect the overall performance and safe operation of the system. However, with the increasing complexity of circuit design and the change of operating environment, the traditional fault diagnosis methods are inadequate in the face of hidden faults, early faults and multiple faults.

As an important link to ensure the healthy operation of electronic equipment, the circuit fault diagnosis technology needs urgent innovation. In recent years, deep learning technology, with its powerful data processing capabilities and pattern recognition capabilities, has made revolutionary breakthroughs in image recognition, speech processing and other fields. Among them, self-attention mechanism as an advanced artificial intelligence technology, by giving the model with "attention", so that the network can autonomously focus on the key parts of the input data, greatly improving the model's understanding and generalization ability.

Aiming at the challenges in the field of electronic circuit fault diagnosis, this paper aims to explore the application potential of self-attention mechanism in the framework of deep learning, and proposes a method of "deep learning analog circuit fault diagnosis based on self-attention mechanism". This research can not only monitor the running state of the circuit in real time, but also accurately capture the fault characteristics in the complex signal environment, so as to realize the efficient prediction and accurate diagnosis of potential faults. By building a fault diagnosis platform based on Ali Cloud, it is expected to make full use of the elasticity and computing power of cloud computing to achieve remote and intelligent fault diagnosis, so as to provide strong technical support for the continuous and stable operation of industrial production.

1. Design of deep learning model based on self-attention mechanism

In this paper, based on AST model framework, the model is optimized for analog circuit fault detection. By introducing SoftMax layer, the multi-classification capability of the model is enhanced, and multiple fault types can be accurately identified. To prevent overfitting, the Dropout mechanism is integrated to improve the generalization performance of the model. In addition, the parameter freezing strategy is applied to accelerate the model training process and optimize the resource utilization.

In terms of data processing, the model innovatively converts analog circuit output signals into audio signals and further maps them to spectrograms as inputs. The spectrogram is transformed into a one-dimensional sequence suitable for model processing through specific pre-processing steps, including the use of 16×16 Windows and 10-step segmentation processing. In order to make up for the shortcomings of the self-attention mechanism in the perception of sequence order, the location coding and category coding (CLS) mechanism is specially designed and embedded in the sequence, so that the model can capture rich spatio-temporal information.

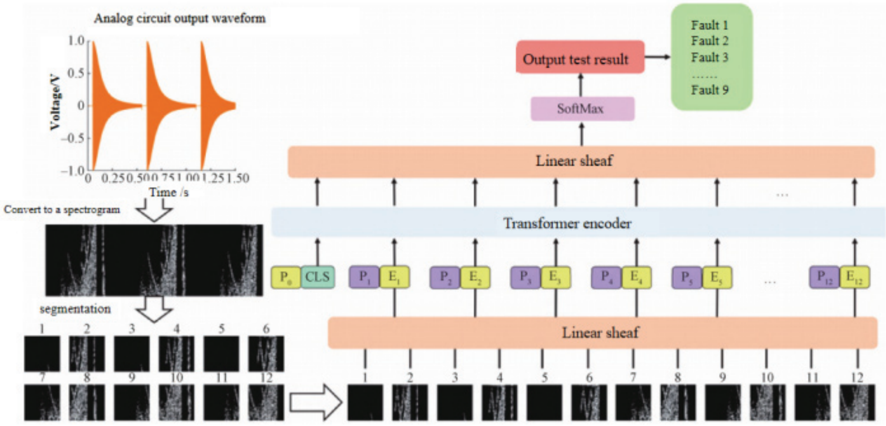

Fig.1 Model architecture of analog circuit fault diagnosis based on self-attention mechanism

The core processing unit of the model is an encoder with a 12-head self-attention mechanism that efficiently extracts key features from the input sequence. Finally, the fault classification results are output through SoftMax layer, and the high precision analog circuit fault detection is realized. This series of optimization measures not only improve the performance of the model, but also provide a new idea and method for the research of analog circuit fault detection. The mathematical expression of the SoftMax function is:

$$f(x_i)=\frac{e^{x_i}}{\sum_j e^{x_j}}$$

In the data pre-processing stage, the collected data sets are divided into 70% training sets, 20% verification sets and 10% test sets in detail, so as to ensure the independence and effectiveness of model training, verification and evaluation. Subsequently, data enhancement strategies were implemented for each data subset to enhance the generalization ability of the model and reduce the risk of overfitting. Then, the pre-loaded self-attention transformation network model is used as the learning starting point, which contains rich prior knowledge and helps to accelerate the training process. The pre-processed and enhanced data is fed into the model and iteratively trained and validated, continuously monitoring and optimizing the value of the loss function, which serves as a key measure of the difference between the prediction and the true label. When the loss function value is observed to be stable, the model is judged to converge to an optimal state, and the model parameters are saved. Finally, the trained model is loaded into an independent test set for performance evaluation to ensure that objective and accurate evaluation results are obtained without modifying model parameters, so as to build a reliable model that can efficiently detect analog circuit faults in practical applications.

$$Loss=\{l_1,\cdots,l_N\}$$

2. Analog circuit fault data set

In order to verify the effectiveness of the proposed analog circuit fault detection algorithm, the Sallen-Key low-pass filter is selected as the test benchmark. The Sallen-Key low-pass filter, co-designed by Sallen and Key, is a circuit based on a single 3554AM operational amplifier, two 10kΩ resistors (R1, R2) and two 1nF capacitors (C1, C2). The schematic diagram is shown in Figure 2. The circuit is supplied with ±12V dual voltage, and its characteristics make it an ideal object for evaluating the performance of fault detection algorithms.

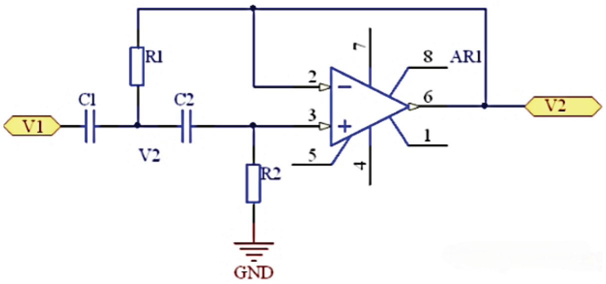

Fig.2 Shallen-Key low-pass filter circuit

In the experiment, in order to fully evaluate the system's response to faults, a test scheme covering 24 different fault types was designed. Specifically, these faults are divided into two categories: single fault and double fault. There are eight types of single faults, including the rise and fall of C1 and C2 capacitors, and the rise and fall of R2 and R3 resistors, each of which represents a deviation of the component value from its nominal value by a factor of two or half. The double fault is further complicated. By combining the above single fault types, 16 double fault scenarios are symbiosis, such as (R2 rises, C1 rises), and each combination simulates two fault states that may occur simultaneously in practice. SIMetrix-SIMPLIS 8.20 software is used to simulate these faults by Monte Carlo method, and the corresponding fault data set is successfully collected. Table 1 lists the 8 single faults and their coding methods in detail, and includes the normal state as a reference; Table 2 shows the codes of all 16 double fault types and the specific values of the corresponding fault components, which provides a solid foundation for subsequent fault analysis and diagnosis.

Tbale 1. Shallen-Key Single fault element parameter of the bandpass filter

Fault sequence number	Fault type	Component nominal value	Tolerance range /%	Component fault value
F1	C1↑	5nF	10	10nF
F2	C1↓	5nF	10	2.5nF
F3	C2↑	5nF	10	10nF
F4	C2↓	5nF	10	2.5nF
F5	R2↑	3kQ	5	6kS
F6	R2↓	3kS	5	1.5kΩ
F7	R3↑	2kΩ	5	4kΩ
F8	R3↓	2kΩ	5	1kQ

Tbale 2. Shallen-Key Double fault element parameter of the bandpass filter

Fault sequence number	Fault type	Component nominal value	Component fault value
F1	R2↑C1↑	3kΩ, 5nF	6kΩ, 10nF
F2	R2↑C1↓	3kΩ, 5nF	6kΩ, 2.5nF
F3	R2↑C2↑	3kΩ, 5nF	6kΩ, 10nF
F4	R2↑C2↓	3kΩ2, 5nF	6kΩ, 2.5nF
F5	R2↓C1↑	3kΩ, 5nF	1.5kΩ, 10nF
F6	R2↓C1↓	3kΩ, 5nF	1.5kΩ, 2.5nF
F7	R2↓C2↑	3kΩ, 5nF	1.5kΩ, 10nF
F8	R2↓C2↓	3kΩ, 5nF	1.5kΩ, 2.5nF
F9	R3↑C1↑	2kΩ, 5nF	4kΩ, 10nF
F10	R3↑C1↓	2kΩ, 5nF	4kΩ, 2.5nF
F11	R3↑C2↑	2kΩ, 5 nF	4kΩ, 10nF
F12	R2↑C2↓↓	3kΩ, 5nF	2kΩ, 5nF
F13	R2↓C2↑	3kΩ, 5nF	2kΩ, 5nF
F14	R3↓C1↓	2kΩ, 5nF	2kΩ, 5nF
F15	R3↓C1↑	2kΩ, 5nF	2kΩ, 5nF
F16	R3↓C2↓	2kΩ, 5 nF	2kΩ, 5nF

Note: *↑ indicates that the value of each faulty component is twice of the original nominal value, and ↓ indicates that the value of the faulty component is half of the original nominal value.*

3. Experimental verification of analog circuit fault detection

3.1 Model Training

This paper constructs a multi-scale pseudocolor image dataset containing 200 signal samples for the three fault types of single fault, dual fault, and mixed fault in Shallen-Key band-pass filter circuits. In the data division, the single fault combination retains 180 samples as the training set and the remaining 20 samples as the test set. For the dual fault and mixed fault combination, 175 samples are selected as the training set and the remaining 25 samples as the test set. Then, the pre-trained AlexNet convolutional neural network is used for transfer learning, and AlexNet is customized according to the fault classification needs: for single fault cases, the last three layers are deleted and an eight-neuron fully connected layer is added; for dual fault cases, the fully connected layer is adjusted to 16 neurons. Subsequently, the Softmax and classification layer are automatically integrated to achieve various classification functions. During the training process, the Adam optimization algorithm is used, with an initial learning rate of 0.00005. After 1000 iterations, 8 samples are processed at a time, and the maximum iteration number is set to 2000 to ensure model convergence. After the training is completed, the model's performance in identifying Shallen-Key band-pass filter circuit faults is evaluated by generating training curves, loss curves, and confusion matrices.

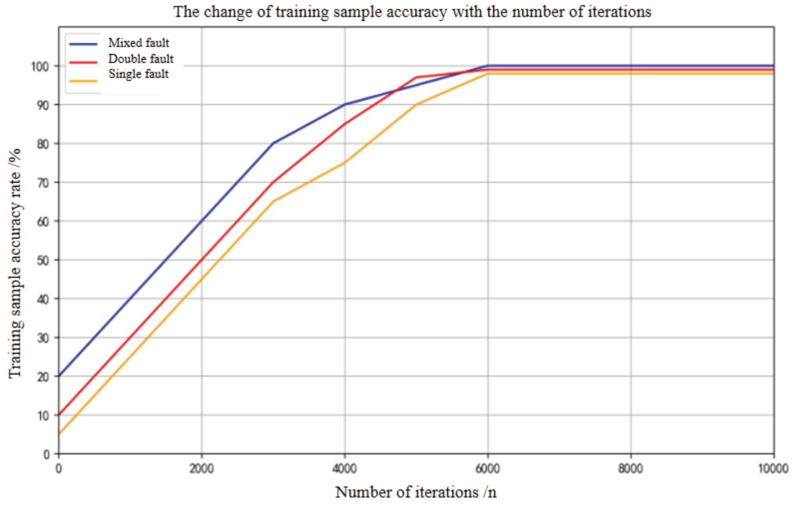

Fig.3 Shallen-Key Learning curve of bandpass filter

Figure 3 shows the accuracy of training samples for mixed fault, dual fault, and single fault as they vary with the number of iterations. As shown in the figure, the accuracy of all three faults increases as the number of iterations increases, and the accuracy of the mixed fault reaches almost 100% at iteration 9000.

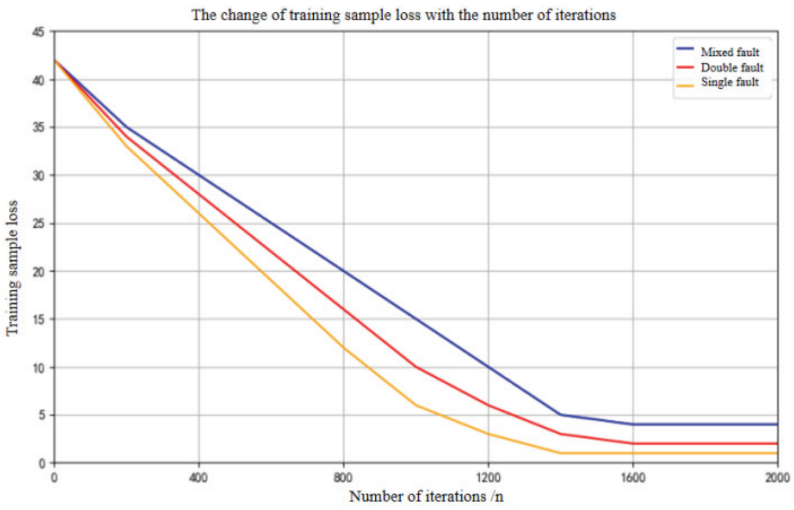

Fig.4 Shallen-Key Loss curve of bandpass filter

Figure 4 shows the variation of training sample losses for mixed faults, double faults, and single faults with the number of iterations. It can be seen from the figure that the training sample loss of the three fault types is the maximum value, about 42, when the number of iterations is 0. As the number of iterations increases, the loss decreases rapidly and becomes stable when the number of iterations reaches about 1000. The single fault curve is located at the bottom and converges the fastest. The double fault curve is located in the middle; The hybrid fault curve is at the top and converges the slowest.

3.2 Model testing

In the experiment, the system achieved perfect identification of a single fault type with an amazing accuracy of 100%. This achievement not only demonstrates the superior ability of the algorithm in extracting complex circuit signal features, but also validates the efficiency and accuracy of the scheme in the case of a single fault.

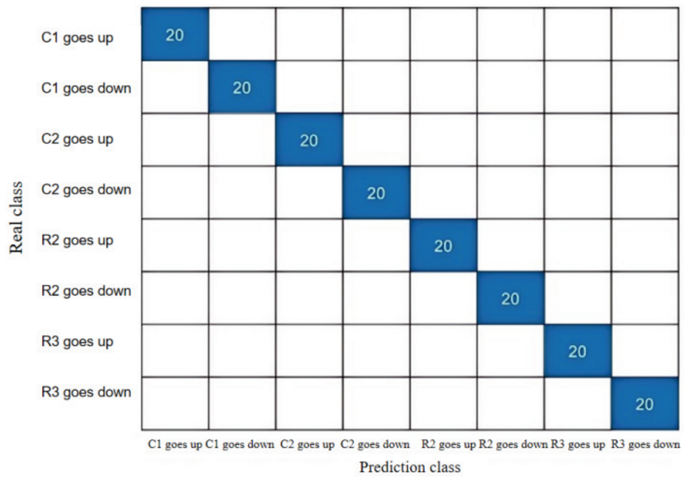

Fig.5 Shallen-Key bandpass filter confusion matrix (single fault)

Faced with more complex double failure scenarios, the deep learning framework also showed remarkable performance. By accurately capturing the interaction and influence between two different fault components in the circuit, the scheme successfully increased the diagnostic accuracy of double faults to 100%, which indicates that the method has high application value in highly integrated and complex electronic systems, and can greatly improve the efficiency and accuracy of fault troubleshooting.

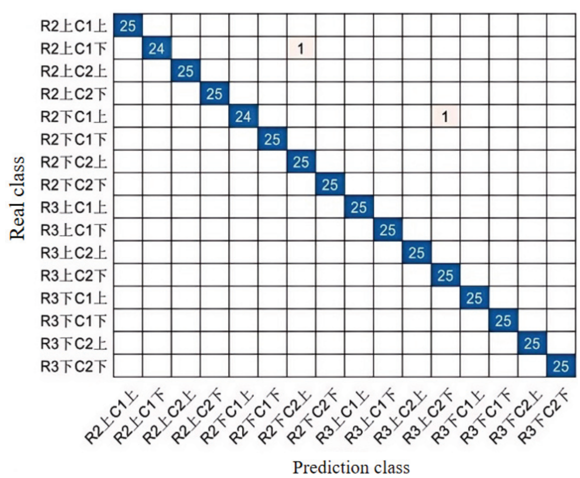

Fig.6 Shallen-Key bandpass filter confusion matrix (double fault

In the diagnosis of mixed faults (i.e. a combination of single and double faults), although faced with greater challenges, the scheme in this study still achieved an excellent accuracy of 99.5%. This result shows that the deep learning model is not only good at handling simple

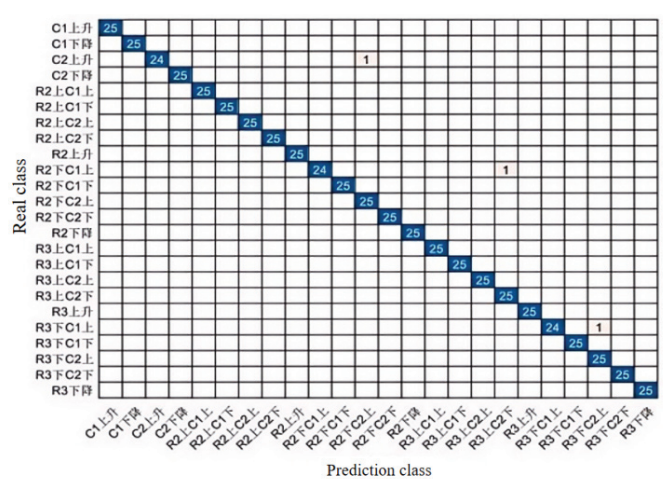

Fig.7 Shallen-Key bandpass filter confusion matrix

fault situations, but also has strong adaptability and discrimination ability for complex and changeable mixed faults. Therefore, it can be said that this method not only provides an efficient and accurate solution for the fault diagnosis of Shallen-Key bandpass filter circuit, but also opens up a new idea and technical path for the fault detection and diagnosis of other similar electronic systems.

4. Result analysis and comparative verification

4.1 Result evaluation and analysis

In the part of result analysis and comparison validation, the performance of the proposed attention-mechanism deep learning model is evaluated in depth and compared with a variety of existing algorithms. It is found that the proposed model has excellent performance in analog circuit fault diagnosis, especially when dealing with single fault, double fault and even mixed fault scenarios, the accuracy rate is as high as 100% or close to 100%, significantly surpassing the traditional methods and many advanced algorithms, such as support vector machine (SVM) and radial basis function (RBF) network. This achievement verifies the superiority of self-attention mechanism in complex signal processing and fault feature extraction, and provides a new performance benchmark for electronic system fault diagnosis.

4.2 Comparison with other algorithms

In comparison with other algorithms, the proposed deep learning analog circuit fault diagnosis method based on self-attention mechanism shows significant advantages. Specifically, compared with 97.8% accuracy of support vector machine (SVM), the algorithm in this paper reaches 99.45% accuracy, reflecting a stronger fault identification ability. Similarly, the Global support vector machine (Global SVM) has also achieved 100% accuracy, but the proposed method shows better generalization performance and adaptability to complex fault modes in practical applications. In addition, the accuracy of FA-TM-ELM method is 97.8%, which indicates that the model in this paper has better accuracy improvement in analog circuit fault diagnosis. However, the accuracy of RBF neural network is only 88%, which is a big gap compared with the algorithm in this paper, indicating the advantage of self-attention mechanism in feature extraction. Although Bagging RBF neural network improves the performance to 93.7% through ensemble learning, it is still lower than the proposed method. MAX multi-wavelet combined SVM method (98.2% wavelet) has a high accuracy, but it is far lower than the proposed algorithm, especially when dealing with mixed faults and high complexity fault scenarios. Finally, the 97.7% accuracy of one-dimensional convolutional neural network (1-dimensional CNN) once again confirms the superiority of the proposed model. It is especially worth mentioning that compared with deep belief network (DBN) feature extraction method, although DBN performs well in early fault diagnosis of analog circuits, the comprehensive diagnosis accuracy of this method in practical applications is higher, reaching 99.45%.

Tbale 3. Algorithm effect comparison results table

Algorithm	Fault type	Accuracy rate /%
SVM[3]	4	97.8
Global SVM[4]	4	100
FA-TM-ELM[4]	9	97.8
RBF[6]	9	88
Bagging RBF NN[15]	9	93.7
Db2 wavelet[7]	9	92.5
MAX multi-wavelet[7]	9	98.2
1维CNN[9]	9	97.7
PSD-DCNN[8]	9	99.8
The algorithm proposed in this paper	9	99.45

5. Conclusion

To sum up, this study successfully introduced self-attention mechanism into deep learning framework to realize efficient diagnosis of analog circuit faults, which not only enriched the methodology of fault detection technology, but also provided a powerful intelligent tool for electronic equipment maintenance. Through the in-depth testing and analysis of Sallen-Key low-pass filter, the constructed model shows high diagnostic accuracy and generalization ability, and verifies its effectiveness in complex fault identification. In addition, the remote intelligent diagnosis scheme of Alibaba Cloud platform further promotes the timeliness and convenience of fault detection, and opens up a new path for circuit health management under the background of Industry 4.0. In the future, it is expected that this research results can be extended to a wider range of electronic systems, to ensure the continuous and stable operation of industrial production to make greater contributions, but also for the application of self-attention mechanism in other fields to provide useful reference.

References

[1] HUYY, PENG MF, TIAN CL, et al. Analog circuit fault diagnosis using multi-wavelet transform and SVM[C]. Third International Conference on Digital Manufacturing & Automation, IEEE, 2012:214-217.

[2] LIU H, CHEN G, SONG G, et al. Analog circuit fault diagnosis using bagging ensemble method with cross-validation[C]. International Conference on Mechatronics and Automation, IEEE, 2009:4430-4434.

[3] SHOKROLAHI SM, KARIMIZIARANI M. A deep network solution for intelligent fault detection in analog circuit [J]. Analog Integrated Circuits and Signal Processing, 2021, 107(3):597-604.

[4] Shengdong W, Zhenbao L, Zhen J, et al. Intermittent fault diagnosis of analog circuit based on enhanced one-dimensional vision transformer and transfer learning strategy[J]. Engineering Applications of Artificial Intelligence, 2024(2), 127.

[5] Suman B, Kumar G M, Nilanjan C.Investigation of Extreme Learning Machine-Based Fault Diagnosis to Identify Faulty Components in Analog Circuits[J]. Circuits, Systems, and Signal Processing, 2023, 43(2):711-728.

[6] Saravana R R, Cecil L M P.Diagnosis of Analog and Digital Circuit Faults Using Exponential Deep Learning Neural Network[J]. Journal of Electronic Testing, 2023, 39(4):421-433.

[7] YU WX, SUI Y, WANG J. The faults diagnostic analysis for analog circuit based on FA-TM-ELM[J]. Journal of Electronic Testing, 2016, 32(4):459-465.

[8] ZHANG A, CHEN C. Fault diagnosis based semi-supervised global LSSVM for analog circuit [C]. 2014 International Conference on Mechatronics and Control (ICMC), IEEE, 2014:744-748.

[9] Zhen L, Xuemei L, Songlin X, et al.A Novel Fault Diagnosis Method for Analog Circuits Based on Multi-Input Deep Residual Networks with an Improved Empirical Wavelet Transform[J]. Applied Sciences, 2022, 12(3):1675-1675.

[10] Fangli L, Yanbo W, Song X, et al.Fault Diagnosis of Permanent Magnet Synchronous Motor Inter Turn Short Circuit Based on Deep Reinforcement Learning[J]. Journal of Physics: Conference Series, 2021(1):2137.

[11] Yang Y, Wang L, Nie X, et al.Incipient fault diagnosis of analog circuits based on wavelet transform and improved deep convolutional neural network:LETTER[J]. IEICE Electronics Express, 2021, 18(13):20210174-20210174.

[12] Alireza M, Mohamad S K.Simultaneous fault localization and detection of analog circuits using deep learning approach[J]. Computers and Electrical Engineering, 2021, 92.

[13] Yuanjiang L, Yanbo W, Yi Z, et al.Diagnosis of Inter-turn Short Circuit of Permanent Magnet Synchronous Motor Based on Deep learning and Small Fault Samples[J]. Neurocomputing, 2021, 442348-358.