

Research Article

Application of Extension Neural Network Type-1 to Fault Diagnosis of Electronic Circuits

Meng-Hui Wang

Department of Electrical Engineering, National Chin-Yi University of Technology, No. 35, Lane 215, Section 1, Chung-Shan Road, Taichung County, Taiping City 411, Taiwan

Correspondence should be addressed to Meng-Hui Wang, wangmh@ncut.edu.tw

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The values of electronic components are always deviated, but the functions of the modern circuits are more and more precise, which makes the automatic fault diagnosis of analog circuits very complex and difficult. This paper presents an extension-neural-network-type-1-(ENN-1-) based method for fault diagnosis of analog circuits. This proposed method combines the extension theory and neural networks to create a novel neural network. Using the matter-element models of fault types and a correlation function, can be calculated the correlation degree between the tested pattern and every fault type; then, the cause of the circuit malfunction can be directly diagnosed by the analysis of the correlation degree. The experimental results show that the proposed method has a high diagnostic accuracy and is more fault tolerant than the multilayer neural network (MNN) and the k -means based methods.

1. Introduction

In the real situation, there are certain errors in the electronic components. For example, the last color ring of electronic resistance is used to specify the range of errors. Therefore, every component would have errors when they are produced by the factory. This would result the shift of the circuit. As long as the errors are still in the acceptable range, the circuit is still normal. But when the value of the component is out of the error range, there would be faults. Therefore, the faults of circuit include two types: hard fault and soft fault [1]. Generally speaking, hard fault happens when the circuit is burned and cannot be operated, while soft fault happens when the value of the circuit is out of the acceptable range but can still work. The result of output is wrong and may destroy the output of the circuit. Compared with hard fault, soft fault is harder to detect [2, 3]. The value of the component which shifts less than 5% is normal and acceptable in the range of errors. The value of the component shifting from

5% to 50% is called soft fault [4]. As for the hard faults, they can result in short learning time that makes the circuit unable to work normally.

Recently, many papers contribute to lots of ways to diagnose faults, such as hierarchical fault diagnosis [5], neural networks [6], grey relation diagnosis [7], and fuzzy theory [8]. Hence, this paper proposed a new method using the extension neural network and develops a fault diagnosis scheme for soft fault of analog circuit. The proposed method can classify the fault types, and it calculates the correlation degree between characteristics and fault types. The ENN-1 has been proposed in my recent paper [9, 10] it uses an extension distance instead of using the Euclidean distance (ED) to measure the similarity between tested data and cluster domain. It can quickly and stably learn to categorize input patterns and permit adaptive process to significant new information. Moreover, the ENN-1 has shorter learning times and simpler structure than traditional neural networks. The proposed method has been tested on a practical analog circuit and compared with the multilayer-neural-network-(MNN-) based methods and k -means classification method. The application of this new method to some testing cases has given promising results.

2. Extension Neural Network Type-1

The extension neural network type-1 (ENN-1) introduced by this author is a new pattern classification system based on concepts from extension theory and neural networks. ENN-1 permits that clustering problems have a range of features, supervised learning, continuous input, and discrete output. This new neural network is the first combination of extension set theory and neural network. The extension theory provides a novel distance measurement for classification, and the neural network can embed the salient features of parallel computation power and learning capability. The ENN-1 is a relatively new neural network model and has been shown to be successful as a classifier using the well-known Iris dataset and the more complex problems [9, 10].

2.1. Structure of the ENN-1

ENN-1 has been successfully applied to fault diagnosis of 12 actual cases, the schematic structure of the ENN-1 is depicted in Figure 1. It comprises both the input layer and the output layer. The nodes in the input layer receive an input feature pattern and use a set of weight parameters to generate an image of the input pattern. In this network, there are two connection values (weights) between input nodes and an output node; one weight w_{kj}^L represent the lower bound for this classical domain of the features and the other weights w_{kj}^U represents the upper bound. This image is further enhanced in the process characterized by the output layer. Only one output node in the output layer remains active to indicate a classification of the input pattern. The learning algorithm of the ENN-1 is discussed in the next section.

2.2. Learning Algorithm of the ENN-1

The learning of the ENN-1 is a supervised learning. Before the learning, several variables have to be defined. Let training pattern set be $X = \{x_1, x_2, \dots, x_{N_p}\}$, where N_p is the total number of training patterns. The i th pattern is $X_i^p = \{x_{i1}^p, x_{i2}^p, \dots, x_{in}^p\}$ where n is the total

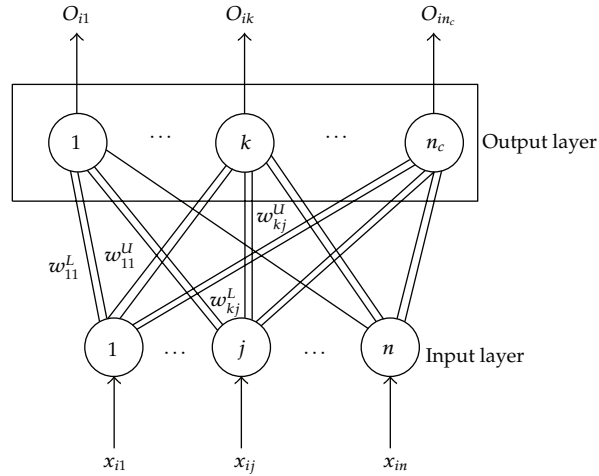


Figure 1: The structure of extension neural network (ENN-1).

number of the feature of patterns and the category of the i th pattern is p . To evaluate the clustering performance, the total error number is set as N_m , and the total error rate E_T is defined below:

$$E_T = \frac{N_m}{N_p}. \quad (2.1)$$

The detailed supervised learning algorithm can be described as follows.

Step 1. Set the connection weights between input nodes and output nodes according to the range of classical domains. The range of classical domains can be directly obtained from previous experience or determined from training data as follows:

$$\begin{aligned} w_{kj}^U &= \text{Max}_{i \in N_p} \{x_{ij}^k\}, \\ w_{kj}^L &= \text{Min}_{i \in N_p} \{x_{ij}^k\} \end{aligned} \quad \text{for } i = 1, 2, \dots, N_p; j = 1, 2, \dots, n; k = 1, 2, \dots, n_c. \quad (2.2)$$

Step 2. Calculate the weights of each feature median:

$$\begin{aligned} Z_k &= \{z_{k1}, z_{k2}, \dots, z_{kn}\}, \\ Z_{kj} &= \frac{(w_{kj}^L + w_{kj}^U)}{2}, \end{aligned} \quad \text{for } k = 1, 2, \dots, n_c, j = 1, 2, \dots, n. \quad (2.3)$$

Step 3. Read the i th training pattern and its cluster number p :

$$X_i^p = \{x_{i1}^p, x_{i2}^p, \dots, x_{in}^p\}, \quad p \in n_c. \quad (2.4)$$

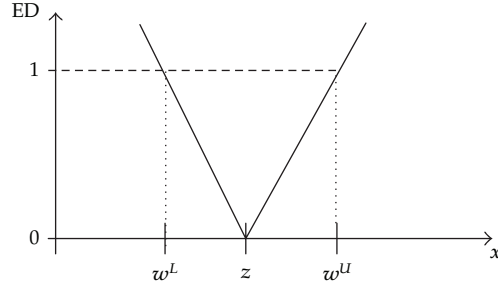


Figure 2: The proposed extension distance (ED).

Step 4. Use the extension distance (ED, Figure 2) to calculate the distance between the input pattern X_i^p and the k th cluster as follows:

$$ED_{ik} = \sum_{j=1}^n \left[\frac{|x_{ij}^p - z_{kj}| - (w_{kj}^U - w_{kj}^L)/2}{|(w_{kj}^U - w_{kj}^L)/2|} + 1 \right] \quad \text{for } k = 1, 2, \dots, n_c. \quad (2.5)$$

Step 5. Find the k , such that $ED_{ik} = \min\{ED_{ik}\}$. If $k = p$, then go to Step 7, otherwise go to Step 6.

Step 6. Update the weights of the p th and the k th clusters as follows:

$$\begin{aligned} w_{pj}^{L(\text{new})} &= w_{pj}^{L(\text{old})} + \eta \left(x_{ij} - \frac{w_{pj}^{L(\text{old})} + w_{pj}^{U(\text{old})}}{2} \right), \\ w_{pj}^{U(\text{new})} &= w_{pj}^{U(\text{old})} + \eta \left(x_{ij} - \frac{w_{pj}^{L(\text{old})} + w_{pj}^{U(\text{old})}}{2} \right), \\ w_{kj}^{L(\text{new})} &= w_{kj}^{L(\text{old})} - \eta \left(x_{ij} - \frac{w_{kj}^{L(\text{old})} + w_{kj}^{U(\text{old})}}{2} \right), \\ w_{kj}^{U(\text{new})} &= w_{kj}^{U(\text{old})} - \eta \left(x_{ij} - \frac{w_{kj}^{L(\text{old})} + w_{kj}^{U(\text{old})}}{2} \right), \end{aligned} \quad (2.6)$$

for $j = 1, 2, \dots, n_c$,

where η is a learning rate, set to 0.1 in this paper. From this step, we can clearly see that the learning process is only to adjust the weights of the p th and the m th clusters.

Step 7. Repeat Step 3 to Step 6; if all patterns have been classified, then a learning epoch is finished.

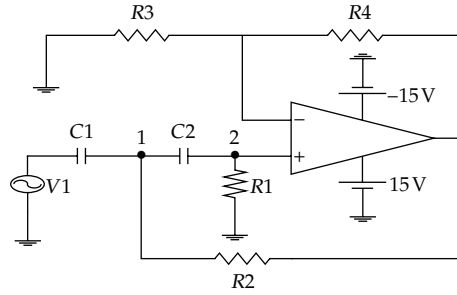


Figure 3: The second-order high-pass filter.

Step 8. Stop if the clustering process has converged, or the total error rate has arrived at a preset value, otherwise, return to Step 3.

2.3. ENN-1 Recognition Stage

After finishing learning ENN-1, we can classify or distinguish the fault types by the following steps.

Step 1. Read the weight matrix which is learned by extension neural network.

Step 2. Calculate each middle value, just like function (2.3).

Step 3. Read test sample:

$$X_t = \{x_{t1}, x_{t2}, \dots, x_m\}. \quad (2.7)$$

Step 4. Calculate distance between test sample and each group by extension distance if (2.5).

Step 5. Find out k^* , using $ED_{ik^*} = \min(ED_{ik})$, and set $O_{ik^*} = 1$ of the cluster categories.

Step 6. If all test samples have been classified completely, it stops; otherwise, turn back to Step 3.

3. The Proposed Fault Diagnosis Method

The tested circuit of this paper was the second-order high-pass filter as shown in Figure 3. Second-order high-pass filter is a signal filter that passes high frequencies well but attenuates frequencies lower than the filter cutoff frequency. The actual amount of attenuation for each frequency is a design parameter of the filter. For different filters, the attenuation level of each frequency signal is different. It is called a low-cut filter when it used in audio applications. In this paper, the DC gain of the filter is set to 1.586 and the cutoff frequency is set to 7.96 kHz. Nodes 1 and 2 are the testing node where voltage can be measured or simulated. A list of the nominal values of components is presented in Table 1.

Table 1: The nominal value of high-pass filter.

Components	Nominal values
R_1	1 k Ω
R_2	1 k Ω
R_3	1 k Ω
R_4	586 Ω
C_1	20 nF
C_2	20 nF

Table 2: The tolerance ranges of normal and soft faults for the circuit components.

Components	Nominal values	Variables $\pm 5\%$ normal	Variables $\pm 20\%$ soft faults
R_1	1 k Ω	1.05 k Ω 0.95 k Ω	1.2 k Ω 0.8 k Ω
R_2	1 k Ω	1.05 k Ω 0.95 k Ω	1.2 k Ω 0.8 k Ω
R_3	1 k Ω	1.05 k Ω 0.95 k Ω	1.2 k Ω 0.8 k Ω
R_4	586 Ω	615.3 Ω 556.7 Ω	703.2 Ω 468.8 Ω
C_1	20 nF	21 nF 19 nF	24 nF 16 nF
C_2	20 nF	21 nF 19 nF	24 nF 16 nF

3.1. The Various Situations of Analog Circuits

The circuit under test was simulated both at normal and all faulty conditions by using PSPICE software; the tolerance normal range was selected with deviation of about $\pm 5\%$ of the nominal values, and soft fault was deviation of about $\pm 20\%$. By analyzing sensitivity of the circuit under test, R_1 , R_2 , R_3 , R_4 , C_1 , and C_2 are selected to be the fault components; the preselected set of single faults of the test circuit are presented in Table 2.

The measurement point in the study is node 1 and node 2 which are transient voltage and phase spectrum as four test signals and simulate normal and various fault conditions. Figures 4, 5, 6 and 7 show the RMS value of transient voltage and phase spectrum by R_1 as the fault components to simulate the correct and soft fault on the node 1 and node 2. Using the Monte-Carlo method produces 30 training sets for each fault type in training phase; in addition, every fault type can build 11 matter element models. Figure 8 in this paper designs a user interface of fault diagnosis for this analog circuit by the LabVIEW, and Figure 9 shows a diagnostic fault in R_2 and also shows in the fault-displayed window a twinkling green light to alert user to in which the circuit element fault was happening.

3.2. ENN1-Based Fault Diagnosis Method

If the circuit components have fault, that can cause the function to change in a circuit. In this study, the circuit faults can be divided into 11 types (1 for normal, 10 for the soft fault), and using PSPICE software simulates various faults, and then we used the ENN-1 to diagnose the

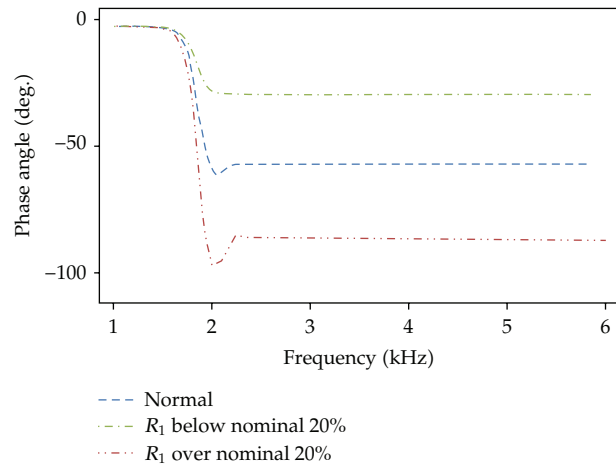


Figure 4: The phase spectrum between normal and soft fault at node 1.

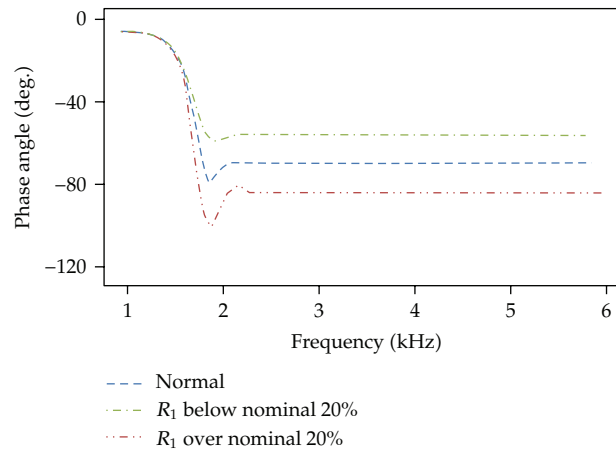


Figure 5: The phase spectrum between normal and soft fault at node 2.

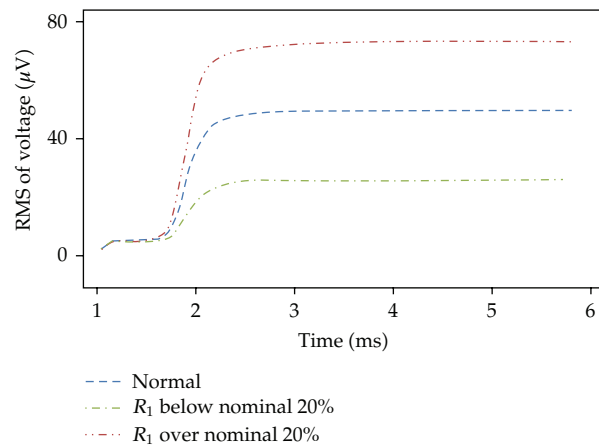


Figure 6: The RMS value of voltage between normal and soft fault at node 1.

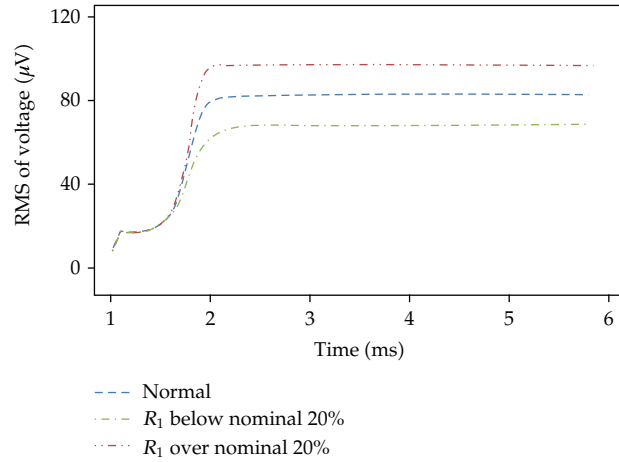


Figure 7: The RMS value of voltage between normal and soft fault at node 2.

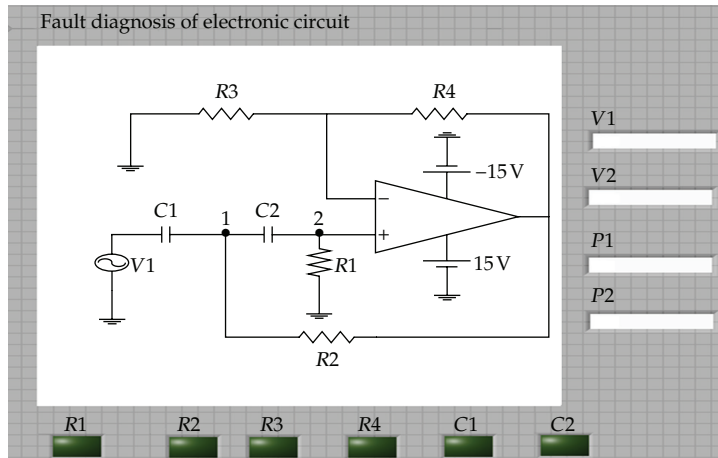


Figure 8: The window of the fault diagnosis system.

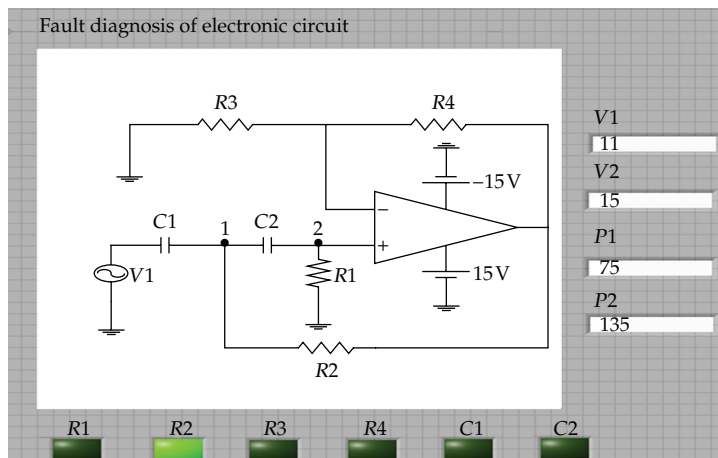


Figure 9: Diagnosing the fault in R_2 .

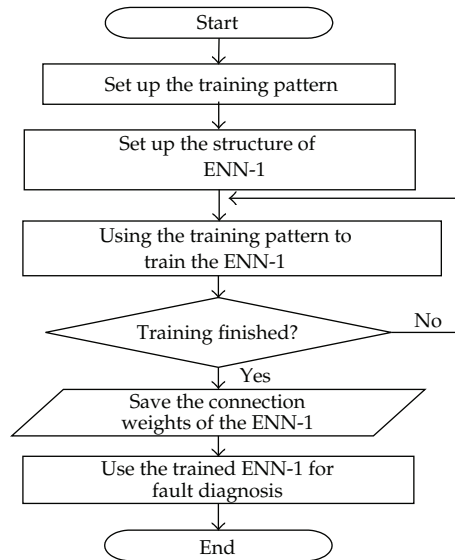


Figure 10: The overall operation flowchart of the proposed fault diagnosis method.

fault conditions of the testing circuit. The proposed fault has been successfully implemented using LabVIEW software for fault diagnosis of electronic circuit. The overall operation flowchart is shown in Figure 10. Using the proposed method can be simply described as follows.

Step 1. Set up the training pattern.

Step 2. Set up the structure of the ENN-1 that has 4 input nodes and 11 output nodes in this paper.

Step 3. Train the ENN-1 using the proposed learning algorithm in Section 2.2.

Step 4. Go to Step 3 if training process is not finished; otherwise go to Step 5.

Step 5. Save the weight vector of the trained ENN-1.

Step 6. Use the trained ENN-1 to diagnose the fault types of the electronic circuit.

Basically, the learning time of the proposed method is shorter than the traditional neural-based methods due to the fact that initial weights of ENN-1 can be directly determined from training data according to the upper bound and lower bound of input features of pattern.

4. Experimental Results and Discussion

The fault types are divided into 11 categories in this paper, every fault type has 30 sets and total 390 sets of the training data for the training stage. After completing the training stage, this diagnosis system can carry out the fault diagnosis. Table 3 shows the typical circuit signal

Table 3: The circuit data with different fault types (partial samples).

No.	V_1	V_2	P_1	P_2	Fault no.	Actual fault type
3	4.75	7.89	73	136	1	Normal
44	6.46	8.98	76	136	2	R_1 over nominal
75	3.95	6.88	69	135	3	R_1 below nominal
140	4.76	7.93	69	132	4	R_2 over nominal
195	4.95	8.02	77	139	5	R_2 below nominal
235	4.52	8.0	72	135	6	R_3 over nominal
268	5.21	7.89	75	138	7	R_3 below nominal
290	4.62	7.93	74	137	8	R_4 over nominal
315	5.11	8.02	71	134	9	R_4 below nominal
350	4.77	7.92	73	133	10	C_2 over nominal
385	4.91	8.01	72	138	11	C_2 below nominal

for 11 kinds of faults. The partial relation indexes of soft faults are shown in Table 4, the relation indexes of using ENN-1 to diagnose training sample. For example, the correlation index of the third data and first type in Table 4 is the smallest, so the circuit neither has a fault nor is normal. The proposed method cannot only diagnose the circuit fault type but also know the circuit potential failure factors by the correlation index and then in the future can early maintain the circuit to prevent more serious faults.

Table 5 shows the accuracy by using the multilayer neural network (MNN), k -means, and the proposed ENN-1-based method to diagnose the soft fault of tested circuit. There are total 390 sets of the new data for the testing diagnosis. The maximum testing accuracy is 89% in the MNN and 85% in the k -means-based method. The testing accuracy of proposed method is 97%. It is clearly shown that the proposed ENN-1 diagnosis method is better than the other methods in both the training and testing stages. The accuracy rates of the proposed ENN-1 based method are 99% and 97% in training and testing stages, respectively. It is obvious that the ENN has strong generalized capability. Moreover, the training times of proposed method are also less than the MNN. The input data of a diagnosis system would unavoidably contain some noise and uncertainties. The sources of error include environmental noise, transducers, human mistakes, and so forth, which could lead to data uncertainties. To take into account the noise and uncertainties, 390 sets of testing data were created by adding ± 5 to ± 15 of random, uniformly distributed error to the training data to appraise the fault-tolerant abilities of the proposed method. The test results using different amounts of errors added are given in Table 6. Usually, the error-containing data indeed degrade the diagnosis capabilities in proportion to the amounts of error added. Table 6 shows that the proposed methods all bear remarkable tolerance to the errors contained in the data. The proposed methods show good tolerance to added errors and have high accuracy rate of 71% in extreme error of ± 15 . Contrarily, the accuracy of the MNN-based method is only 39%, and the k -mean method is only 30% under the same conditions.

5. Conclusions

This paper presents a novel fault diagnosis method based on ENN-1 for analog circuits. Compared with other traditional AI methods, the proposed ENN-1-based method can

Table 4: Correlation indexes of the ENN-1 after diagnosis (partial results).

Data no.	Correlation indexes											Fault types of diagnosis results	Actual fault type
	1	2	3	4	5	6	7	8	9	10	11		
3	1	13	15	3.4	2.8	4	5	2	3.8	2.4	2.3	1	Normal
44	29	1	59	31	26	35	23	27	32	30	31	2	R_1 over nominal
75	13	19	1	12	12	11	16	12	13	13	13	3	R_1 below nominal
140	10	24	24	1	6.4	8	15	9	7.1	5.2	8.5	4	R_2 over nominal
195	4	8	14	3.8	1	7	3	3	5.7	3.8	2.8	5	R_2 below nominal
235	4.1	16	17	4.1	4.9	1	8	4	2.9	3.6	4.6	6	R_3 over nominal
268	4.3	11	19	5.6	3.1	8	1	3	6.4	4.9	3.5	7	R_3 below nominal
290	4	21	27	6.8	4.4	7	6	1	8	5	4.4	8	R_4 over nominal
315	3.4	10	15	2.9	3.8	3	5	5.1	1	2.6	3.8	9	R_4 below nominal
350	3	18	21	2.9	4.2	4	8	4.6	4	1	5.1	10	C_2 over nominal
385	4	17	24	5.3	3.6	7	6	4	5.4	5.5	1	11	C_2 below nominal

Table 5: Diagnosis performances of different methods.

Methods	Training time (Epochs)	Training accuracy (%)	Testing accuracy (%)
ENN-1	10	99%	97%
k -means	N/A	N/A	85%
MNN I (4-8-11)	1000	86%	83%
MNN II (4-9-11)	1000	90%	87%
MNN III (4-10-11)	1000	92%	89%

Table 6: Diagnosis performances of errors added.

Noise percentage (%)	ENN-1	k -means	MNN
± 0	99%	85%	92%
± 5	83%	55%	66%
± 10	75%	39%	45%
± 15	71%	30%	39%

achieve the higher accuracy. The calculation of the proposed diagnosis algorithm is also fast and simple. According to the simulation results, the proposed method has a significantly high degree of diagnosis accuracy and shows good tolerance to the errors added. This new approach merits more attention, because the ENN-1 deserves serious consideration as a tool in fault diagnosis or pattern recognition. We hope this paper will lead to further investigation for industrial applications.

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References

- [1] S. Yongkui, C. Guangju, and L. Hui, "Analog circuits fault diagnosis using support vector machine," in *Proceedings of the International Conference on Communications, Circuits and Systems (ICCCAS '07)*, pp. 1003–1006, July 2007.
- [2] M. Slamani and B. Kaminska, "Fault observability analysis of analog circuits in frequency domain," *IEEE Transactions on Circuits and Systems Part II*, vol. 43, no. 2, pp. 134–139, 1996.
- [3] Z. You, E. Sanchez-Sinencio, and J. Pineda de Gyvez, "Analog system-level fault diagnosis based on a symbolic method in the frequency domain," *IEEE Transactions on Instrumentation and Measurement*, vol. 44, no. 1, pp. 28–35, 1995.
- [4] M. Catelani and A. Fort, "Soft fault detection and isolation in analog circuits: some results and a comparison between a fuzzy approach and radial basis function networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 51, no. 2, pp. 196–202, 2002.
- [5] C. K. Ho, P. R. Shepherd, F. Eberhardt, and W. Tenten, "Hierarchical fault diagnosis of analog integrated circuits," *IEEE Transactions on Circuits and Systems. I*, vol. 48, no. 8, pp. 921–929, 2001.
- [6] L. Yuan, Y. He, J. Huang, and Y. Sun, "A new neural-network-based fault diagnosis approach for analog circuits by using kurtosis and entropy as a preprocessor," *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 3, pp. 586–595, 2010.
- [7] M. H. Zhang, S. J. Lv, D. H. Wang, Y. X. Song, and H. Liu, "Research on fault diagnosis methods with grey relation analysis," in *Proceedings of the IEEE International Conference on Grey Systems and Intelligent Services (GSIS '09)*, pp. 72–75, November 2009.
- [8] M. Catelani, A. Fort, and C. Alippi, "A fuzzy approach for soft fault detection in analog circuits," *Measurement*, vol. 32, no. 1, pp. 73–83, 2002.
- [9] M. H. Wang and C. P. Hung, "Extension neural network and its applications," *Neural Networks*, vol. 16, no. 5-6, pp. 779–784, 2003.
- [10] M. H. Wang and C. P. Hung, "Extension neural network," in *Proceedings of the International Joint Conference on Neural Networks*, vol. 1, pp. 399–403, July 2003.



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