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Analog circuit fault diagnosis based on RBF

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Abstract. Analog circuit fault diagnosis is growing common using techniques based on artificial intelligence (AI). Among these, defect diagnosis based on radial basis function (RBF) has recently received attention and has demonstrated a respectable level of accuracy. This paper's goal is to demonstrate this method's thought process, methodology, and specific actions. Researchers can refer to the reference circuit diagram, experimental table, and analytic process in the publication to evaluate the efficacy of this approach. Additionally, the elements that can be changed and improved upon are highlighted, offering a path for future study.

Keywords: Analog Circuit, Fault Diagnosis, Radial Basis Function, Experiment.

1. Introduction

Recently, there has been a lot of research done on artificial intelligence, which is now widely used in a variety of industries. The diagnosis of analog circuit faults, on the other hand, is a constant concern in the field of electrical engineering because it can guarantee that the electronic system is in good operating condition before it is put to use and enables quick detection of the electronic system on the computer to confirm the running status. However, conventional categorization and diagnosis methods are unreliable and require a lot of work. Based on these two factors, it makes sense to use artificial intelligence to address the issue of fault identification. RBF offers a strong capacity for information parallel processing, a potent capacity for adaptive learning, and a capacity for nonlinear mapping, making it one of the greatest artificial intelligence and neural network methodologies.

The issue of radial basis function (RBF) fault detection of analog circuits will be covered in this study. The RBF model will be introduced together with its underlying theory and guiding principles after a brief summary of earlier efforts. In the third section, a specific circuit problem will be discussed and solved using the RBF method. After that, the procedures will be streamlined and enhanced, and the advantages and disadvantages will be reviewed. Next, a succinct conclusion will be given.

2. Literature review

RBF neural network is a type of local approximation network. Given that each weight on the network must be altered for each input, global approximation networks like the BP network have a slow learning rate. If a few link weights have an effect on the output for a particular limited region of the input space, the network is said to be a local approximation network. The three most common RBF functions are the Gaussian function, Inversion of s-type functions, and Quasi multi-quadratic function.

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The RBF approach has undergone the following development. The fundamental RBF conducts fault simulation of an analog circuit using a constant amplitude sinusoidal signal source. It also establishes a fault dictionary by extracting characteristic values of the output signal waveform from the frequency domain. A number of optimizations then arise. First off, the multi-output decay Radial basis function (MDRBF) can do uniform approximation with arbitrary precision without training, Single - Output DRBF (SDRBF) neural network can only be used to handle the problem of a Single output variable. This significantly decreases the complexity of model development. [1]. Second, the RBF Neural Network Local Retraining Algorithm modifies and expands the algorithm in the topology of the power network, which may greatly enhance the RBF Neural Network's Relearning Efficiency. Thirdly, RBFNN based on the adaptive K_ means clustering algorithm outperforms RBFNN based on the conventional K_ means clustering algorithm, BPNN, and IEC ratio approach. Additionally, adaptive training and the multi-core MKALSSVR design can decide how many training[2]. The multi-kernel design alters the RBF's width and offers more versatile tuning options. This makes it possible to process analog circuit evaluation online. This approach enables vector sparsity and prevents norm LSSVR overflow. Additionally, MKALSSVR is both inexpensive and accurate in its evaluation[3].

There are currently a number of optimization techniques for diagnosing analog circuit faults. The first is the fuzzy neural network, which mimics the functional manual system and physical systems of the human brain using computers that are already in existence. The wavelet analysis is the second. On the basis of wavelet analysis and investigation into a particular type of feed-forward network, the wavelet neural network was introduced. Its foundation is the RBF network. The fundamental concept is to replace neurons with wavelets. The wavelet function base is the activation function. By using an affine transform, it establishes a link between the wavelet transform and neural networks.[4].

The essential steps in an analog circuit diagnosis based on RBF are to choose the test point, define the fault type for the particular circuit, and ascertain the network topology. Ltspice is used to get training sample material. After training, an RBF network is produced. The test point's input vector serves as the network's input and the associated fault is the output. The element tolerance is allocated uniformly throughout each training scenario at 5%.

3. Methodology

3.1. Radial Basis Function Network

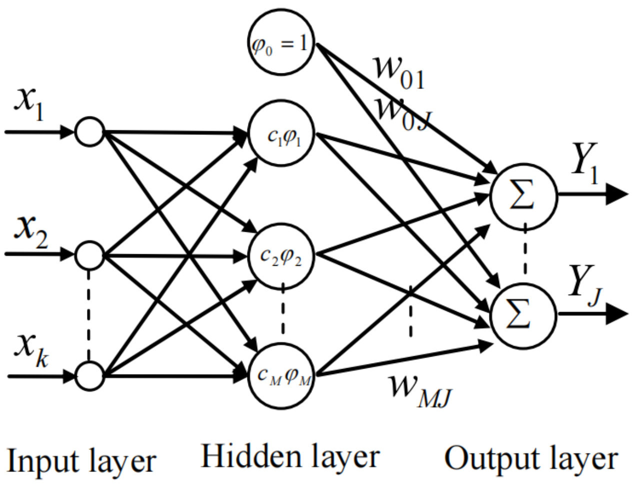

Figure 1. Structure of RBF neural network.

There are three layers in the RBF neural network: an input layer, a hidden layer, and an output layer. The independent variables, defined as $X_k(k = 1,2,...,K)$, inputted into the first layer, and then

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transported to the middle layer. In the hidden layer, a series of calculations operates the independent variables, which are called the Φ functions. A series of linear combinations is used to transfer the computations' results to the output layer. The weights for each individual linear combination are defined as $w_{ij}(i = 1,2,\ldots,I, j = 1,2,\ldots,J)$. The dependent variables, designated as $Y_j(j = 1,2,\ldots,J)$, represent the output of the linear combinations. Following is an explanation of the two formulars used in this process:

Firstly, the Φ functions are defined as

$$\Phi\left(X_{k,}C_i\right) = e^{\left(-\frac{\|X_k - C_i\|^2}{2\sigma_i^2}\right)} \tag{1}$$

Different Φ function has different parameters, defined as C_i, which should be found by machine learning. The Φ functions are also called RBF functions, which is the characteristic of RBF method. RBF function is a set of functions. The RBF function used in this research is the Gaussian function, which plays the role of an activation function in this neural network.

Secondly, the linear combinations are defined as

$$y_j(X) = w_{0j} + \sum_{i=1}^{M} w_{ij}\,\Phi\,(X_k, C_i), j = 1,2,\ldots,J \tag{2}$$

It includes a constant as the reference plane and the linear combination of the results of the Φ calculations by different weights.

The basic training process of RBF neural network is: firstly, input the independent variables, guess the parameters (C_i,w_{ij}); and then, get the predicted values of the dependent variables, compare it with the actual values and calculate E; guess the parameters again to reduce E, until the parameters to the minimum of E are found. E is defined as

$$E = \frac{1}{2}\sum_{i=1}^{M}(y_d - y_i)^2 \tag{3}$$

3.2. Analog circuit fault diagnosis

RBF neural network can learn from the sample set and identify the defect in the circuit in the analog circuit fault diagnosis problem. A studyable example circuit is the one that follows.

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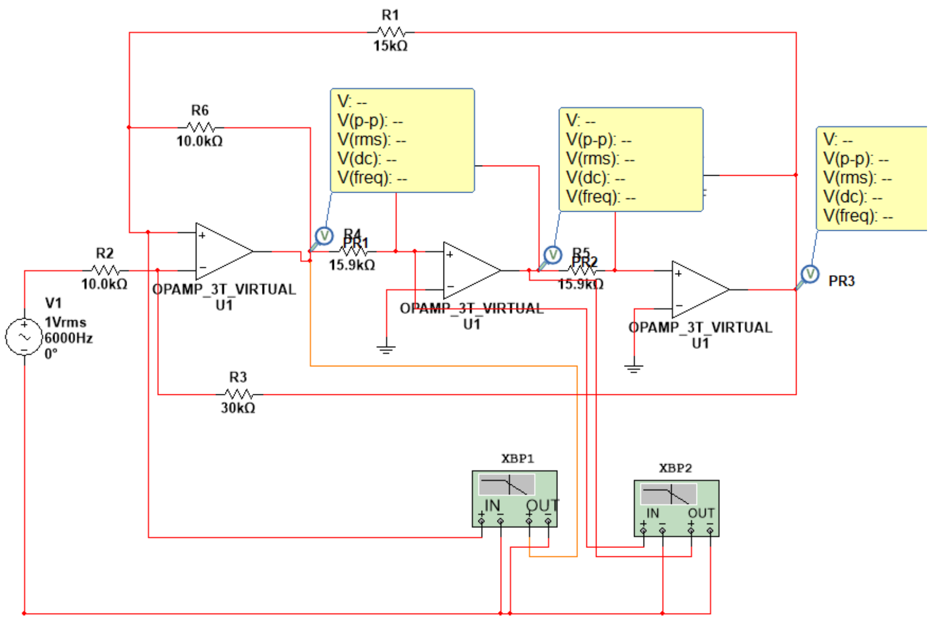

Figure 2. Reference circuit.

The circuit to study consists of N devices, defined as $D_1, D_2, \ldots, D_N$. Only considering the fault of a single device, there are 2N different fault conditions, defined as D_N High and D_N Low. D_N High represents the actual value of the element that is higher than the set value in the circuit illustrated above within certain limits. The limits can be different for different types of devices and in this research, we only focus on the resistors and capacitors. For the resistors, D_N High means the actual value is 110% to 150% greater than the set value. D_N Low means the actual value is 50% to 90% smaller than the set value. From 90% to 110% is the permissible range considered normal. For the capacitors, D_N High means the actual value is 105% to 150% greater than the set value. D_N Low means the actual value is 50% to 95% smaller than the set value. From 95% to 105% is the permissible range considered normal (the principle is shown in Table.1).

Table 1. Principle of defining condition.

Element types	Conditions	Value Range
Resistor	Low	[50%, 90%)
	Normal	[90%, 110%]
	High	(110%, 150%)
Capacitor	Low	[50%, 95%)
	Normal	[95%, 105%]
	High	(105%, 150%)

Among the 2N fault conditions, we can choose n conditions from them to diagnose. In the example above, there are eight deceives and we choose eight different fault conditions to diagnose. Then we should represent the $2n + 1$ conditions(2n fault conditions and one normal condition) by the target vectors Y with n features $Y_1, Y_2, \ldots, Y_n$. That is $Y = Y_1 Y_2 \ldots Y_n$. The normal condition is defined as $Y = 00\ldots0$. We define the 2n fault conditions as $F_1, F_2, \ldots, F_n$, then when $F_i (i = 1, \ldots n)$ happens, the $(2n + 1 - i)$th component of the target vector Y will be 1.

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Table 2. Fault dictionary (n dimensions).

Fault code	Fault type	Target vector Y(2n features)
F_0	Normal	0000…0000
F_1	D_1 High	0000…0001
F_2	D_1 Low	0000…0010
F_3	D_2 High	0000…0100
F_4	D_2 Low	0000…1000
.	.	.
.	.	.
.	.	.
F_{n-1}	D_N High	0100…0000
F_n	D_N Low	1000…0000

In the given example, $2n = 8$, so the faults are defined as follows.

Table 3. Fault dictionary (8 dimensions).

Fault code	Fault type	Target vector Y(8 features)
F_0	Normal	00000000
F_1	R_1 High	00000001
F_2	R_1 Low	00000010
F_3	R_3 High	00000100
F_4	R_3 Low	00001000
F_5	C_1 High	00010000
F_6	C_1 Low	00100000
F_7	C_2 High	01000000
F_8	C_2 Low	10000000

There are seven steps in the process of using RBF to achieve analog circuit diagnosis.

Step 1: An amplitude-frequency analysis should be performed to select the frequency for testing. Compare the parameter amplitudes of normal and faulty devices at different frequencies and choose m frequencies with the largest amplitude difference to be the test frequencies. The number of test frequencies can be determined according to the actual situation. Then set the input power source as $V_{in1} = \sin 2f_1 \times 10^3\ \pi\ t$ v,$V_{in2} = \sin 2f_2 \times 10^3\ \pi\ t$ v,…,$V_{inm} = \sin 2f_m \times 10^3\ \pi\ t$ v. In the example, the amplitude-frequency analysis is as follows, it can be seen from the graph that the amplitude difference is most obvious in the range of 5kHz to 10kHz, so we choose 6kHz, 7kHz, and 9kHz as the test frequencies. That means the input power source should be determined as $V_{in1} = \sin 12 \times 10^3$ $\pi\ t$ v,$V_{in2} = \sin 14 \times 10^3\ \pi\ t$ vand $V_{in3} = \sin 18 \times 10^3\ \pi\ t$ v respectively.

Step 2: Find out the test points. The locations and number of test points can be chosen and adjusted according to the actual circuit. We choose t test points,$T_1, T_2, \ldots, T_t$. In the example, we choose V_1 and V_2 as the test points($t = 2$). Measure V_1(6kHz,7kHz,9kHz) and V_2(6kHz,7kHz,9kHz).

Step 3: Define the independent variable X with mt features $X_1, X_2, \ldots, X_{mt}$, representing T_1 ($f_1, f_2, \ldots, f_m$), T_2 ($f_1, f_2, \ldots, f_m$), …, T_t ($f_1, f_2, \ldots, f_m$). In the example, $X = X_1X_2X_3X_4X_5X_6$, representing V_1(6kHz,7kHz,9kHz) and V_2(6kHz,7kHz,9kHz) respectively.

Step 4: In step 3, we get the independent variable X for the normal case, so the corresponding Y should be $Y = 000000000$. Change the parameter of D_1 to D_1 High, measure $T_1, T_2, \ldots, T_t$ again on the m different frequency. Similarly, we can get more samples for every fault conditions. The recommended number of samples for every condition is 10mt, so there are $10mt \times (2n + 1)$ samples in total in the learning sample set. Input the learning sample set to the RBF neural network. After

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learning, the RBF neural network will find out the parameters, C_i and w_{ij}, for analyzing the circuit. In the example, $mt = 6, n = 4$, so there are $60 \times 9 = 540$ samples in the learning sample set. They are shown as follows.

Table 4. Reference experimental table (8 dimensions).

Fault code	Fault type	Input vector X(6 features)						Target vector Y(8 features)
		V_1(6kHz)	V_1(7kHz)	V_1(9kHz)	V_2(6kHz)	V_2(7kHz)	V_2(9kHz)	
F_0	Normal	…						00000000
F_1	R_1 High							00000001
F_2	R_1 Low							00000010
F_3	R_3 High							00000100
F_4	R_3 Low							00001000
F_5	C_1 High							00010000
F_6	C_1 Low							00100000
F_7	C_2 High							01000000
F_8	C_2 Low							10000000

Step 6: Use a similar method to get the test sample set. The number of samples for every condition can be chosen accordingly. In the example, we choose 20 samples for every condition, so there are $20 \times 9 = 180$ samples in the test sample set.

Step 7: Test the accuracy of the analog circuit diagnosis based on RBF neural network. Record the number of correct diagnosis for every condition and calculate the accuracy rate. It is shown as follows:

Table 5. Reference experimental table (2n dimensions).

Fault code	Fault type	The number of correct diagnosis(s samples)	The type identification accuracy rate %
F_0	Normal	C_1	$C_1/s \times 100\%$
F_1	D_1 High	C_2	$C_2/s \times 100\%$
F_2	D_1 Low	C_3	$C_3/s \times 100\%$
F_3	D_2 High	C_4	$C_4/s \times 100\%$
F_4	D_2 Low	C_5	$C_5/s \times 100\%$
.	.	.	.
.	.	.	.
.	.	.	.
F_{2n-1}	D_N High	C_{2n-1}	$C_{2n-1}/s \times 100\%$
F_{2n}	D_N Low	C_{2n}	$C_{2n}/s \times 100\%$

If the accuracy rate for every condition is higher than 90%, we can say the method of using RBF neural network to achieve analog circuit fault diagnosis is reliable in this research.

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4. Discussion

If you wish to diagnose the simultaneous fault of two components, define it as a new type of fault that requires the same number of samples to input to the RBF network learn in order to get the correct diagnosis output. In this way, $\binom{2}{n}$ more fault types should be defined, and $\binom{2}{n} \times 10\mathrm{mt}$ more samples are required as learning samples.

Similarly, the simultaneous failure of several or even n components can be generalized. You just need to specify the component's range of fault values and add learning samples in the same manner if you wish to diagnose problems in components other than resistors and conductors.

The number of X 's dimensions, such as the frequency and number of test points, can be increased in order to increase accuracy rates. On the other hand, to raise the accuracy rate until it achieves a constant value, you can increase the quantity of learning samples.

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