Fault Diagnosis in Analog Circuits Using Wavelet Neural Network

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***Abstract* – In analog circuits, fault diagnosis is a very complex task due to lack of the simple fault models and the presence of component tolerances and circuit non-linearity. The proposed method of fault diagnosis of analog circuits based on Wavelet Neural Network (WNN) is presented in this paper. Wavelet Neural Networks are a new class of networks that combine the classic Neural Networks (NNs) and wavelet transform inherits the advantages of the neural network and wavelet transformation. In this work Wavelet Neural Network is constructed and the network weights are updated according to the relevant formula. The constructed wavelet neural network is detected with training set, and then optimal wavelet function with minimum mean squared error is chosen for classification of faults. Experimental results show that WNN has a good predictive ability, so it can quickly and accurately classify the different types of faults.**

Keywords – Wavelet Neural Network; fault diagnosis; Monte Carlo analysis.

I. INTRODUCTION

Fault diagnosis and testing of electronic circuits and systems is a crucial and complex task in microelectronics and in the semiconductor industry and has appealed to many researchers in the past two decades. The techniques for digital circuit diagnosis and testing have been mature and cost effective, while the testing of analogue and mixed-signal systems is more complicated and less well understood.

Analog circuit for fault diagnosis has been the hot topic of research in the field of circuit theory, and currently, it is still a very challenging problem. Its main difficulties involve three aspects: the first is the input and output in a continuous analog circuit; the second is analog circuits involving nonlinear problem; and the third is the discrete component parameters of analog circuit.

The existing fault diagnosis methods need to know the type of fault in advance, then the fault is located, which becomes a barrier in analog circuit test. But Neural Network solved the problem effectively, with no fault model and knowing less behavioral characteristic of the circuit. Fault localization is realized by limited training of fault samples. The fault diagnosis based on time-frequency domain analysis and Neural Network provides a completely novel problem solving scheme for analog circuit testing. The integration between wavelet properties and Artificial Neural Network (ANN) is a very active research field. Wavelet has the advantage of time-frequency localization property and the Neural Network has the advantage of self-adaptive, robustness, strong inference ability. Wavelet Neural Network (WNN) provides the combined advantage of wavelet and neural network. WNN shortens the learning time of neural network and provides high degree of accuracy. WNNs were first proposed by Zhang and Benveniste [1] as an alternative to the classical feed-forward ANN for approximating arbitrary nonlinear functions. However, the origin of wavelet networks can be traced back to the work by Daugman [2] in which Gabor wavelets were used for image classification. In the hidden layer of the ANN, sigmoidal and Gaussian activation functions were used as hidden layer neurons. These functions are replaced with wavelet functions in WNN. The WNN with self-learning, self-adaptability, resolution characteristic and superior tolerance characteristic, provides a new approach for fault diagnosis.

In our work, WNN is used for fault diagnosis. The output response of the analog circuits is obtained in the form of data set for both fault free and faulty case using Monte Carlo analysis. The normalized data set is given to WNN for training and testing and the faults are classified using minimum mean square error. The simulation part for fault diagnosis uses MATLAB.

The rest of the paper is organized in the following form. In Section II, the fundamentals of wavenets are presented. Section III presents the implementation procedures for the diagnosis of faults in the analog circuits. Training process of the network is revealed in Section IV .Simulation results are presented in Section V and finally conclusions are revealed in Section VI.

II. WAVENET

Wavelet transform is a powerful tool for representing non-linearity, since it has time and frequency localization property. On the other hand Neural Network (NN) has self-adaptive, fault tolerance, robustness, and strong implication capability and also has the ability to approximate any deterministic non-linear process, with little knowledge and no assumptions regarding the nature of the process. The Fig.1 shows the structure of a general Wavelet Neural Network (WNN).

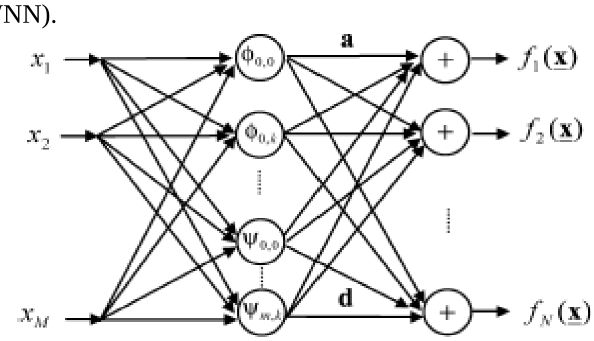

Fig. 1. Wavelet Neural Network structure

A WNN usually has the form of a three layer network. The lower layer represents the input layer, the middle layer is the hidden layer and the upper layer is the output layer. In the input layer the variables are introduced to the WNN. The hidden layer consists of the hidden units (HUs). The HUs are often referred as wavelons, similar to neurons in the classical sigmoid NNs. In the hidden layer the input variables are transformed to dilated and translated version of the other wavelet. Finally, in the output layer the approximation of the target values is estimated. In Wavelet Analysis (WA) one dimensional function f (x) can be approximated in terms of a set of inputs (i.e. x values) and outputs (i.e. f (x) values). The Discrete Wavelet Transformation (DWT) can represent f (x) in terms of shifted versions of a low-pass scaling function, φ(x), and shifted and dilated versions of wavelet function, ψ(x). Wavelet function and scaling functions are defined as follows,

$$\Psi_{m,k}(x) = 2^{m/2}\psi(2^{m/2}x-k) \tag{1}$$

and

$$\varphi_{m,k}(x) = 2^{m/2}\varphi(2^{m/2}x-k) \tag{2}$$

The above two functions form an orthonormal basis on which to carry out such input–output data fitting. The variables m and k scale and dilate the mother function W(x) to generate a family of wavelets. What makes a wavelet basis especially appealing is the fact that, once the mother function has been specified, every unknown function f(x) can be represented using the derived wavelet family,

$$f(x) = \sum_{k=-\infty}^{\infty} a_{0,k}\varphi_{0,k}(x) + \sum_{m=0}^{\infty}\sum_{k=-\infty}^{\infty} d_{m,k}\Psi_{m,k}(x) \tag{3}$$

where the coefficients are defined as follows

$$a_{0,k} = \int_{-\infty}^{\infty} f(x)\,\varphi_{0,k}^{*}(x)\,dx \tag{4}$$

$$d_{m,k} = \int_{-\infty}^{\infty} f(x)\Psi_{m,k}^{*}(x)\,dx \tag{5}$$

Equation (3) is the starting point for developing a wave-net model for multivariable systems (i.e. those involving other than just a single input and a single output).

III. IMPLEMENTATION PROCEDURE FOR FAULT DIAGNOSIS

The proposed method involves four stages: The first stage is about data set construction for the chosen analog circuit. The data set collected gives the information about the output waveform characteristics of the analog circuits in the form of samples. In the second stage the collected data is normalized. The third stage involves the design of WNN. Finally, the last stage is for testing and training the designed WNN. The Fig. 2 shows the process flow of proposed method in the form of block diagram. The ordinary Back Propagation (BP) algorithm is used in WNN. The method is used to update connection weights between the layers, making the prediction output closer to the desired output. The basic idea of BP is to find the percentage of contribution of each weight to the error. The error e for pattern k is simply the difference between the target output y(k) and the network output yˆ(k) obtained during testing of WNN.

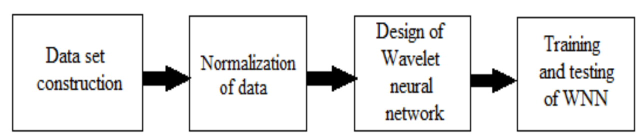

Fig. 2. Process flow for fault diagnosis

For the input signal sequence $x = (x_1, x_2, \ldots \ldots, x_n)$, the output of the hidden layer is calculated as

$$h(j) = h_j\left[\frac{\sum_{i=1}^{m} w_{ij}x_i - b_j}{a_j}\right], \text{ j=1,2,……,m} \tag{5}$$

Where, $h(j)$ is output value for the node j in the hidden layer; h_j is the mother wavelet function; ωij is weight connecting the input layer and hidden layer, b_j is the shift factor, and a_j is the stretch factor for h_j.

Currently, the choice of mother wavelet functions has not yet formed a standard theory; commonly used wavelet functions are Morlet, Haar, Daubechies (dbN), Symlet (symN), Meryer, Coiflet, Biorthogonal wavelets, and so on.

The output of the output layer is calculated as

$$y(k) = \sum_{i=1}^{m} w_{ik} h(i) \text{ , k=1,2,......,l} \quad (6)$$

where $h(i)$ is the output value for node i in the hidden layer; ω_{ik} is weight connecting the hidden layer and output layer; l and m are the number of nodes for output layer and the hidden layer, respectively.

For WNN, the weightupdating algorithm is similar to BP network; the gradient method is used to update mother wavelet function parameters and connection weights between the layers, making the prediction output closer and closer to the desired output. The weights of WNN and the parameters of wavelet function are updated as follows.

1) Calculating the prediction error of WNN

$$e = \sum_{k=1}^{m} yn(k) - y(k) \quad (7)$$

Where, $y(k)$ is the predicted output value, $yn(k)$ is the expected output value for the network.

2) Updating the weights of WNN and the parameters of wavelet function according to the prediction error e.

$$w_{n,k}^{(i+1)} = w_{n,k}^{(i)} + \Delta w_{n,k}^{(i+1)} \quad (8)$$

$$a_{k}^{(i+1)} = a_{k}^{(i)} + \Delta a_{k}^{(i+1)} \quad (9)$$

$$b_{k}^{(i+1)} = b_{k}^{(i)} + \Delta b_{k}^{(i+1)} \quad (10)$$

Where $\Delta w_{n,k}^{(i+1)}$, $\Delta a_{k}^{(i+1)}$, $\Delta b_{k}^{(i+1)}$ are calculated by the network prediction error

$$\Delta w_{n,k}^{(i+1)} = -\eta \frac{\partial e}{\partial w_{n,k}^{(i)}} \quad (11)$$

$$\Delta a_{k}^{(i+1)} = -\eta \frac{\partial e}{\partial a_{k}^{(i)}} \quad (12)$$

$$\Delta b_{k}^{(i+1)} = -\eta \frac{\partial e}{\partial b_{k}^{(i)}} \quad (13)$$

where η is the learning rate.

IV. TRAINING PROCESS

The process of training WNN involves the following steps:

1) Data preprocessing: first, the original data is quantified and normalized, and then the data is divided into training set and testing set for network training and testing, respectively.

2) Initializing WNN: connection weights ω_{ij} and ω_{jk}, translation factor b_k, and scale factor a_k are randomly initialized, and the learning rate η is set.

3) Training network: input the training set into WNN, compute network predicted output values, and calculate the error e between output and the expected value.

4) Updating the weights: update mother wavelet function parameters and networks weights according to the prediction error e, making the predictive value of the network as close to actual values.

5) If the results satisfy the given conditions, use the testing set to test the network, otherwise, return to Step 3.

V. SIMULATION RESULTS

In the implementation of proposed model two benchmark circuits are used. One is Sallen Key Band pass filter and the other is Tow Thomas Low pass filter. The Fig. 3 shows Sallen Key Band pass filter. The resistors and capacitors are assumed to have tolerances of 10%. According to the sensitivity analysis, the frequency response of output voltage waveform is obviously affected by the variation of components values. Assume that if a component value is 10% higher than their nominal values, circuit fault occurs. Therefore, nine fault models are obtained, including no fault state. To generate training data for different fault classes, the component considered as faulty have their value out of tolerance range and other components values are within their tolerances.

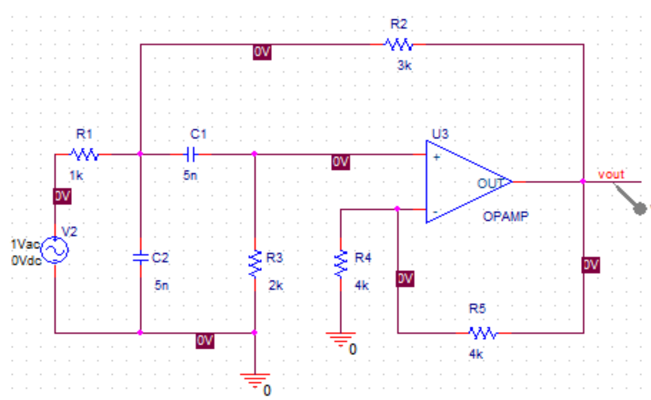

Fig. 3. Sallen Key Band pass filter

TABLE I shows the fault class, fault type, nominal value and faulty value range for components of Sallen Key Band pass filter.

TABLE I FAULT TABLE FOR SALLEN KEY BAND PASS FILTER

Fault Class	**Fault Type**	**Nominal Value**	**Faulty Value Range**
F0	No fault	-	-
F1	R1↑	5.18 KΩ	5.698 KΩ - 9.842 KΩ
F2	R1↓	5.18 KΩ	0.518 KΩ - 4.662 KΩ
F3	R3↑	2 KΩ	2.2 KΩ - 3.8 KΩ
F4	R3↓	2 KΩ	0.8 KΩ - 1.2 KΩ
F5	C1↑	5 nF	5.5 nF - 9.5 nF
F6	C1↓	5 nF	0.5 nF - 4.5 nF
F7	C2↑	7 nF	7.7 nF - 13.3 nF
F8	C2↓	7 nF	0.7 nF - 6.3 nF

Monte Carlo analysis is conducted for every fault pattern of the circuit using PSPICE. Fault features are extracted in the way described in [7]. The Fig. 4 shows the output waveform for no fault case and Fig. 5 shows the output waveform for R1 increasing fault introduced in Sallen key Band pass filter.

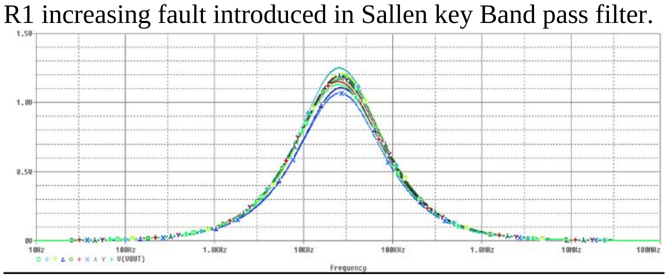

Fig. 4. Monte Carlo analysis output for Sallen key Band pass filter (fault free)

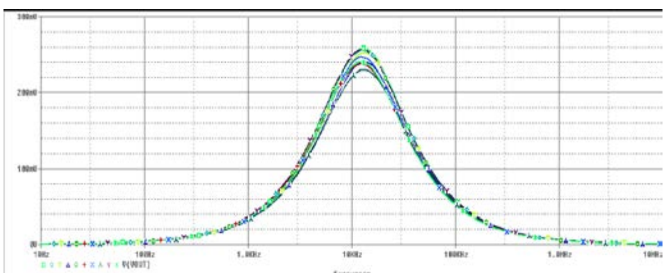

Fig. 5. Monte Carlo analysis output for Sallen Key Band pass filter (R1 increasing fault)

The x-axis gives the frequency value and the y-axis gives the value of voltage. The output waveform obtained by Monte Carlo analysis is stored in the form of samples in excel sheet, which forms the data set. They are used for constructing training patterns and test patterns. The MATLAB is used for designing, training and testing of wavelet neural network. The weights of edges connecting nodes and the number of hidden nodes are chosen randomly and then updated during training process. The accuracy is calculated based on true positive and true negative value. The same process is done for Tow Thomas Low pass filter with increased number of resistors and capacitors compared to Sallen Key Band pass filter. The number of data sets is also increased in this case. The Fig. 6 shows the PSpice simulated circuit for Tow Thomas Low pass filter and TABLE III shows the WNN performance for both the benchmark circuits.

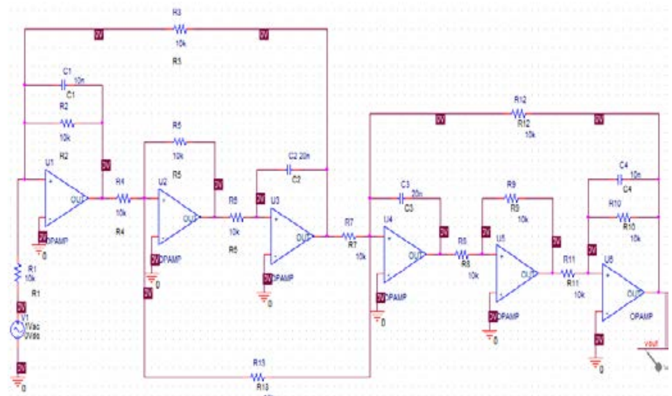

Fig. 6. Tow Thomas Low pass filter

TABLE II shows the fault class, fault type, nominal value and faulty value range for components of Tow Thomas Low pass filter.

TABLE II FAULT TABLE FOR TOW THOMAS LOW PASS FILTER

Fault Class	**Fault Type**	**Nominal Value**	**Faulty Value Range**
F0	No fault	-	-
F1	R1↑	10 KΩ	11 KΩ - 19 KΩ
F2	R1↓	10 KΩ	1 KΩ - 9 KΩ
F3	R2↑	10 KΩ	11 KΩ - 19 KΩ
F4	R2↓	10 KΩ	1 KΩ - 9 KΩ
F5	R3↑	10 KΩ	11 KΩ - 19 KΩ
F6	R3↓	10 KΩ	1 KΩ - 9 KΩ
F7	R4↑	10 KΩ	11 KΩ - 19 KΩ
F8	R4↓	10 KΩ	1 KΩ - 9 KΩ
F9	R5↑	8 KΩ	8.8 KΩ - 15.2 KΩ
F10	R5↓	8 KΩ	0.8 KΩ - 7.2 KΩ
F11	R6↑	8 KΩ	8.8 KΩ - 15.2 KΩ
F12	R6↓	8 KΩ	0.8 KΩ - 7.2 KΩ
F13	C1↑	10 nF	11 nF - 19 nF
F14	C1↓	10 nF	1 nF - 9 nF
F15	C2↑	8 nF	8.8 nF - 15.2 nF
F16	C2↓	8 nF	0.8 nF - 7.2 nF

TABLE III WNN PERFORMANCE FOR THE TWO BENCHMARK CIRCUITS

Parameters	**Sallen key Band pass filter**	**Tow Thomas Low pass filter**
Training Time	32 seconds	33 seconds
Testing Time	0.6 second	1.7 seconds
Mean	2.27e+03	198.7
Accuracy	97.1429	97.1429

VI. Conclusion

In this paper, the Wavelet Neural Network (WNN) method is used for fault diagnosis in the analog circuits. The fault diagnosis in two benchmark circuits: Sallen Key Band pass filter and the Two Thomson Low pass filter are effectively classified and identified using WNN. These circuits are simulated based on Monte Carlo analysis to collect data set. The data sets are normalized and given as input for WNN. The training time, testing time, accuracy and the fault corresponding to the input data set for WNN are obtained through MATLAB simulation. Both the catastrophic and parametric faults of nonlinear circuits can be diagnosed by using this method. The single faults in the circuit are effectively identified using WNN. From the simulation results it can be seen that the WNN technique is fast and robust for fault diagnosis. The combined advantage of wavelet and neural network is used, because of which the processing time is reduced and accuracy is increased.

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