ANALOG CIRCUITS FAULT DIAGNOSIS USING GENETIC ALGORITHM BASED WAVELET NEURAL NETWORK

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Abstract –**In analog circuits, fault diagnosis is a complex task due to lack of simple fault models and the presence of component tolerances and circuit non- linearity. The method of fault diagnosis in analog circuits using Genetic Algorithm (GA) based 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 (WT) which inherits the advantages of the Neural Network and wavelet transformation. In this work Wavelet Neural Network is constructed and the network weights are updated to get the desired value at the output nodes of WNN. The constructed WNN is trained with training set until the objective function is minimized and the faults are classified. Then the parameters of WNN are optimized using Genetic Algorithm (GA). The simulation results obtained for WNN and GA based WNN are compared. A comparison of the proposed work of GA based WNN with WNN reveals that the proposed method performs significantly better in fault diagnosis of analog circuits with improved classification accuracy.**

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

I. INTRODUCTION

Fault diagnosis and testing of electronic circuit is a crucial and complex task in microelectronics and semiconductor industry. Many researchers have indicated that analog circuit fault diagnosis is a significant fundamental for design validation and performance evaluation in the integrated circuit manufacturing fields. The main purpose of testing is to detect malfunctions and locate their cause. The quality of a test system can be evaluated on the basis of its availability, reliability and cost effectiveness. The techniques for digital circuit testing have been mature and cost effective. However the methodologies for fault diagnosis of analog circuits are more complicated as well as challenging task. Testing of integrated circuits represent a key cost factor in the production process and test time. Testing time of analog portion of an IC dominates total test time. An optimal test strategy is needed for reducing the test cost and test time of analog circuits.

The fault diagnosis based on time-frequency domain analysis and Neural Network (NN), provides an absolutely novel problem solving scheme for analog circuit testing. Wavelet Transform has been proved to be an effective tool for many signal processing applications. It is a multi-resolution, time-frequency analysis method which can simultaneously interpret a signal in both time and frequency domain. Neural Network has the advantage of self-adaptive, robustness and strong inference ability. The integration of wavelet properties and Neural Network is a very active and attractive area of research. 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. WNN was first proposed by Zhang and Benveniste [1] as an alternative to the classical feed-forward ANN for approximating arbitrary non-linear 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 WNNs, the wavelets are integrated into the hidden layer of the ANN, where 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, multi resolution characteristic and superior tolerance characteristic, provide a new approach for fault diagnosis. A novel fault diagnosis technique of GA based WNN has been proposed in this paper. Since the weights connecting the layers of WNN affect the classification accuracy, Genetic Algorithm (GA) is used in this work for optimal selection of weights.

The organization of the paper is as follows. Section II provides basic description of analog circuit fault diagnosis Section III discusses the system description. In Section IV, the fundamentals of Wavelet Neural Network are presented.

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Section V presents the implementation procedures for the diagnosis of faults in the analog circuits using GA based WNNand Simulation results are discussed in Section VI .The conclusions are presented in Section VII.

II.ANALOG CIRCUITS FAULT DIAGNOSIS

A system which includes the capacity of detecting, isolating, identifying or classifying faults is called as fault diagnosis system. A major difficulty in analog circuit fault diagnosis is defining the line of distinction between fault-free and faulty circuits, which leads to uncertainty in the control of product yield. Testing of analog circuit is more difficult than testing of digital circuits due to the following reasons:

- Analog circuits do not have detailed accept/reject criteria in terms of clearly defined thresholds.
- Analog components do not have superior fault models like the stuck-at or stuck-open models widely accepted in digital circuit testing.
- Element tolerances and signal noise enhance the complexity of analog testing.
- Analog components parameter values are continuous.

Some of the earliest publications in this area [11] and [12] described basic techniques and their limitations as well as difficulties in analog testing. Analog circuit fault diagnosis methods are classified into Simulation Before Test (SBT) and Simulation After Test (SAT). The SBT methods consists of two major steps. The first step is to construct a fault dictionary by analyzing the circuit being tested for various faults with given measurements points. The second is to compare the measured responses with the simulated results in this dictionary to locate faults. SAT methods try to locate faults directly from measurement data by verifying faulty assumptions which is called as fault verification techniues or by calculating parameter values called parameter identification techniues.

A. FAULT MODELS IN ANALOG CIRCUITS

In analog circuits there exist different failure modes such as open circuit, short circuit, degraded performance and functional failures. Degradation faults depend mainly on variations of certain parameters of the components used in a circuit from its nominal values. This may be due to manufacturing defects, process variations, change in the environment or ambient temperature and/or wear out due to aging. Functional faults, on the other hand, are based on the fact that a circuit may continue to function, but some of its performance specifications may lie outside their acceptable ranges.

However, component value changes are usually significant in these failure models. A faulty value with a value of ten times larger or ten times smaller of its nominal value is a reasonable assumption in generating the fault list. Open faults and short faults are considered as extreme cases. Therefore, if ten times larger or ten times smaller faults can be covered, the open and short faults can also be detected. In IC models, short and open faults may be considered as resistive values according to the technology and process.Fault modes that can occur in analog ICs are classified as

- Abrupt (sudden) faults, i.e., step-like changes.
- Incipient (slowly developing) faults, e.g., drift or bias.

In the study of fault diagnosis the construction of a fault dictionary using fault simulation techniques are widely used for choosing the test strategy. Faults in analog ICs are generally classified in to the following two categories

• **Catastrophic (hard) faults:** Catastrophic faults are all those changes to the circuit that cause the circuit to fail catastrophically. These faults include shorts, opens or large variations of a design parameter. Catastrophic faults are caused by major structural deformations or extreme out of range parameters and lead to failures that manifest themselves in a completely malfunctioning circuit.

• **Parametric (soft) faults:** Parametric faults are those changes that cause performance degradation of the circuit. These faults are due to the process fluctuations. These faults involve parameter deviations from their nominal value that can consequently quit their tolerance band.

The fault models of resistors and capacitors are as shown in Figure 1..Addition of a high resistance in series (e.g., RS $\geq$ 1 MΩ) with the component (e.g., resistor, capacitor or diode) can simulate the open faults. Short faults, on the other hand, are a short between terminals of the component (effectively shorting out the component from the circuit). A small resistor in parallel (e.g., RP $\leq$ 1 Ω) with the component can simulate this type of fault for resistors, capacitors.

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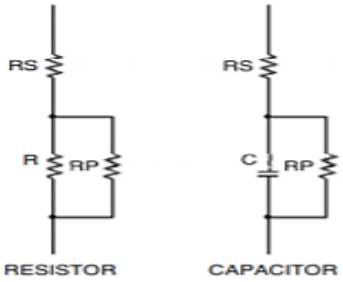


Figure 1. Fault models of resistors and capacitors

III.SYSTEM DESCRIPTION

The block diagram of fault diagnosis of analog circuits using GA based WNN is shown in Figure2.The proposed method involves four stages: The first stage is data set construction for the Circuit Under Test (CUT). In this work, two bench mark circuits Sallen Key Band pass filter and Tow Thomas Low pass filter are used as Circuit Under Tests (CUTs).

Fault dictionaries were created by using PSPICE with Monte Carlo analysis method. A normal data set was collected by varying device parameters within operational limits. Then the faults are injected by varying the component value above and below its tolerance value and it is simulated. The data set collected gives the information about the analog circuits in the form of samples.

Input stimulus is a 1V sine wave input. The input data set for Sallen Key bandpass filter has 30 samples for each fault class. It has nine fault classes so totally the corresponding input data set has 270 samples and each sample has 51 sampling points. The input data set for Tow Thomas lowpass filter has 30 samples for each fault class. It has 13 fault classes so totally the corresponding input data set has 390 samples and each sample has 101 sampling points. In the second stage the collected data is normalized. Data in the fault dictionary were normalized to be in the range between 0 and 1. The third stage involves the training and testing of WNN. 70% samples of the normalized data set are used for training and 30% of the samples are used for testing. The fourth stage is for training and testing the GA based WNN. The results of third and fourth stage are compared. The faults are classified based on the target set for each fault class. WNN is used for fault diagnosis in analog circuits.

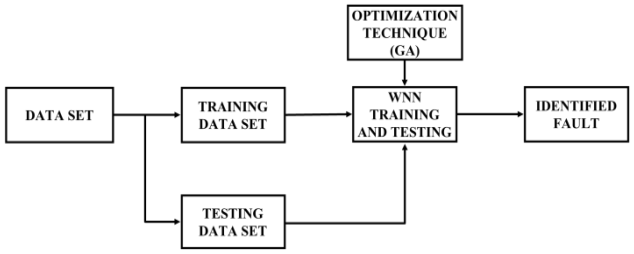


Figure. 2. Block diagram

The main contribution of the paper is summarized as follows.

- The GA based WNN is capable of diagnosing fault in analog circuits efficiently.
- The comparison of our work with fault diagnosis of analog circuits using WNN and GA based WNN indicates the importance of optimizing the weights and biases of WNN with GA, reducing the training time and improving the accuracy.

IV.WAVELET NEURAL NETWORK

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. The structure of a general Wavelet Neural Network (WNN) is shown in Figure 3.

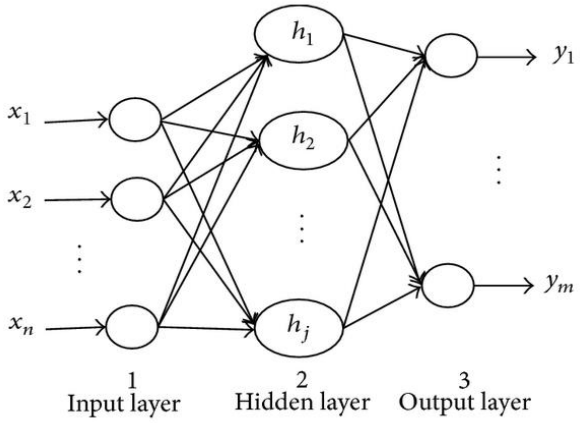


Figure 3.Wavelet Neural Network structure

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 Neural Networks. In the hidden layer the input

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variables are transformed by dilated and translated version of the mother wavelet. Finally, in the output layer the approximation of the target values are 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. y values). The Discrete Wavelet Transformation (DWT) can represent outputs y in terms of shifted and dilated versions of a scaling function φ(x), and shifted and dilated versions of wavelet function ψ(x). Wavelet function is expressed as Eqn. (1) and scaling function is expressed as Eqn. (2).

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

and

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

scaling function, φ(x), and wavelet function ψ(x) form an ortho-normal basis. The variables 'm' and 'k' scale and dilate the mother Wavelet function to generate a family of daughter wavelets. The fact which makes a wavelet basis especially appealing is that, once the mother function has been specified, every unknown function f(x) can be represented using the derived wavelet family as Eqn. (3).

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

Where the coefficients are defined as Eqn. (4) and Eqn. (5)

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

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

The process of training WNN involves the following steps

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

Step 2) Initializing WNN: The 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.

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

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

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

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

$$h(j) = h_j\left[\frac{\sum_{i=1}^{n} w_{ij}x_i - b_j}{a_j}\right], \text{ j=1,2,……,m} \quad (6)$$

Where h(j) is output value for the node j in the hidden layer; h_j is the mother wavelet function, ω_{ij} 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.

The output of the output layer is calculated as shown in (7).

$$y(k) = \sum_{i=1}^{m} w_{ik}h(i) \text{ , k=1,2,.....,l} \quad (7)$$

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 gradient decent method is used to update the connection weights between the layers, making the prediction output closer to the desired output. The weights of WNN are updated as follows.

- Calculating the prediction error of WNN

$$e = \sum_{k=1}^{m} y\hat{}(k) - y(k) \quad (8)$$

Where y (k) is the predicted output value, $y\hat{}$ (k) is the expected output value for the network.

- Updating the weights of WNN according to the prediction error 'e'.

$$w_{n,k}^{(i+1)} = w_{n,k}^{(i)} + \Delta w_{n,k}^{(i+1)} \quad (9)$$

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

$$\Delta w_{n,k}^{(i+1)} = -\eta\frac{\partial e}{\partial w_{n,k}^{(i)}} \quad (10)$$

Where 'η' is the learning rate.

When the training process is done, the WNN is tested and the classification accuracy is calculated. The training time, testing time and accuracy are compared for WNN and GA based WNN.

V. FAULT DIAGNOSIS USING GA BASED WNN

The process flow diagram of GA based WNN is shown in Figure 4. Back Propagation (BP) algorithm is used in WNN. The basic idea of back propagation 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 y(k) obtained during testing of WNN. Then GA is applied for obtaining the optimized weights of WNN.

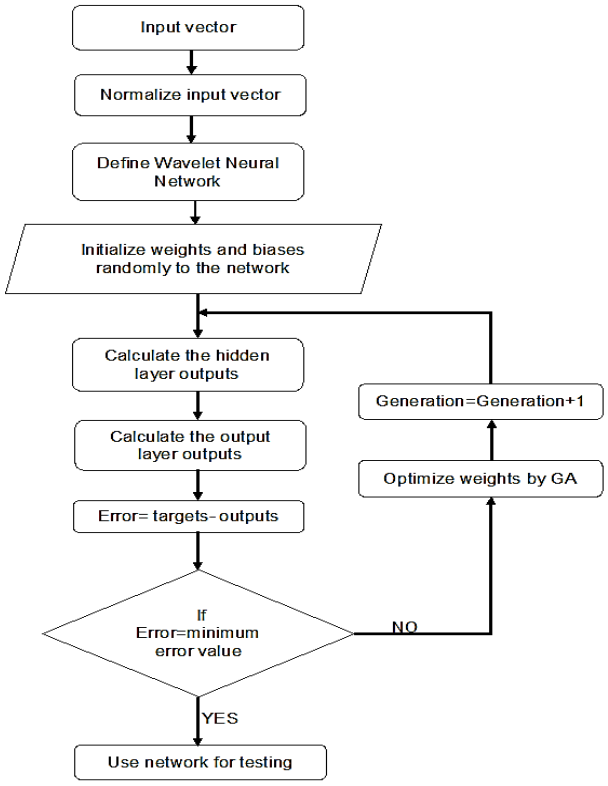


Figure 4. Fault diagnosis using GA based WNN

The network for classification is defined and the weights for the network are initialized randomly. The input vectors are normalized and applied to input layer of WNN. The output is predicted from the output layer of WNN. The mean square error is calculated. If the error is equal to the minimum error assigned, then the network is used for testing. Else, the GA is used for optimizing the weights connecting the layers of network. This process continues until the error reaches minimum error.

Genetic Algorithms (GA) are a family of computational models inspired by Evolution. GA is a global optimization method based on natural selection and genetic principle with the abilities of parallel computation and heuristic search. These algorithms encode a potential solution to a specific problem on simple chromosomes like data structure and apply recombination operators to these structures so as to preserve critical information.

The evolution usually starts from a population of randomly generated individuals.The genetic algorithm involves three types of operators. They are Selection, crossover and mutation.The crossover and mutations are the main operators that randomly impact the fitness value. A fitness function assesses the quality of a solution in the evaluation step. Chromosomes are selected for reproduction by evaluating the fitness value.The Selection operator selects chromosomes in the population for reproduction.

In each generation, the fitness of every individual in the population is evaluated, multiple individuals are selected from the current population (based on their fitness), and modified (recombined and possibly mutated) to form a new population. The fitter the chromosome, the more times it is likely to be selected to reproduce. The Crossover operator randomly chooses a locus and exchanges between two chromosomes to create two offspring. The Mutation operator randomly flips some of the bits in a chromosome. Mutation can occur at each bit position in a string with very small probability.

There are 3 termination conditions.

- There is no improvement in the population for more number of iterations.
- To have already predefined an absolute number of generation for algorithm.
- When the fitness function has reached a predefined value

The fitness function plays a very important role in guiding GA to obtain the best solutions within a large search space. Good fitness functions help GA to explore the search space more effectively and efficiently. Bad fitness functions, on the other hand, can make GA get trapped in a local optimum solution. The fitness function used in this work is Mean Square Error (MSE) given in Eqn. (11)

$$MSE = 1/m\left(\sum_{k=1}^{m}(y\hat{}(k) - y(k))^2, k = 1,2,3....m \right) \quad (11)$$

Where m is the number of output nodes in WNN, yˆ (k) is the target output and y (k) is the network output.

In this work GA is used for optimizing weights connecting the layers of WNN. The initial set of Population is produced by a random number generator. Each solution in the population is a string comprising of 'n' elements, where 'n' is the number of trainable connection weights. The population used in this work is connecting weights between input layer and hidden layer, and connecting weights between hidden layer and output layer.

The number of parameters to be determined by GA corresponds to the number of genes in the chromosome. The numbers of genes in the chromosome are identical to the total weight plus the number of bias of the layers of network. The chromosome pattern containing weights and biases of a single layer of WNN is shown in Figure 5.

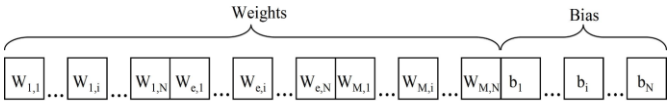


Figure 5. Chromosome pattern

Where 'W' is the weights connecting the layers of network, 'b' is the biases of neurons in the i^{th} layer of network, 'N' is the number of neurons in the i^{th} layer if network and 'M' is the number of inputs to the i^{th} layer of network.

VI. SIMULATION RESULTS

The simulation part in this work uses two software. PSpice for Monte Carlo analysis and MATLAB R2012a for normalization of data, training and testing of WNN and GA based WNN. The following parameters are used in all simulations. The resistors and capacitors are assumed to have tolerances of 5% and 10% correspondingly. 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 higher than or lower than their tolerance range, then the component is considered as faulty.

Example 1. Sallen Key Band Pass filter. The Filter circuit is shown in Figure 6. There are nine possible fault classes examined, including no fault state. By using the method proposed in Section II, CUT is simulated.

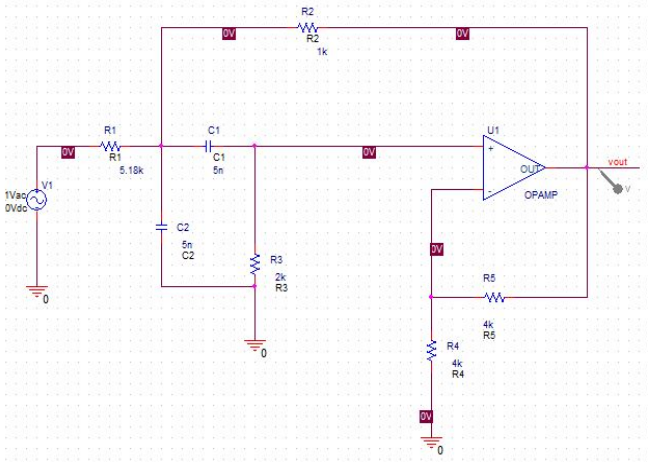


Figure 6. Sallen Key Band pass filter

TABLE I shows the fault class, fault type, nominal value and faulty value for components of Sallen Key Band pass filter. Here the components with value 10% to 90% higher than their nominal value are considered as increasing fault and 10% to 90% lower than their nominal value are considered as decreasing fault.

TABLE I FAULT TABLE FOR SALLEN KEY BAND PASS FILTER

Fault Class	Fault Type	Nominal Value	Faulty Value
F0	No fault	-	-
F1	R2↑	1 KΩ	1.1 KΩ – 1.9 KΩ
F2	R2↓	1 KΩ	0.1 KΩ – 0.9 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↑	5 nF	7.7 nF - 13.3 nF
F8	C2↓	5 nF	0.7 nF - 6.3 nF

Monte Carlo simulations are run for each fault case. The number of runs considered for Monte Carlo analysis is 30. The output waveform for no fault case is shown in Figure 7 and Figure 8 shows the output waveform for R2 increasing fault introduced in Sallen key Band pass filter.

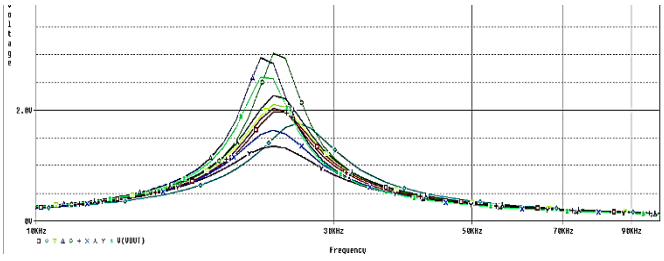


Figure 7. Monte Carlo analysis output for Sallen key Band pass filter (fault free)

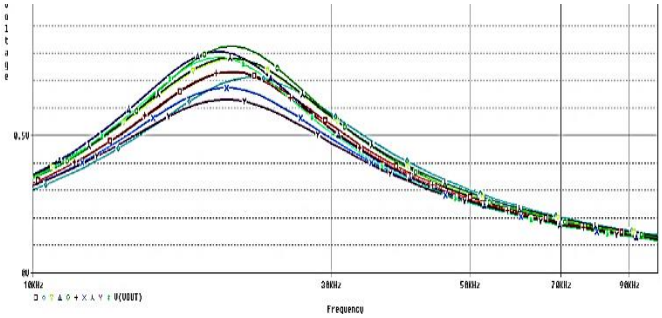


Figure 8. Monte Carlo analysis output for Sallen Key Band pass filter (R2 increasing fault)

The x-axis represents the frequency value and the y-axis represents the output 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 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. True Positive (TP) is the number of correctly classified faults and the True Negative (TN) is the number of misclassified faults. Then GA is applied for optimizing weights of WNN and accuracy is calculated. Accuracy and Specificity are calculated as shown in Eqn. (12) and Eqn. (13).

$$Accuracy = \frac{Number\ of\ faults\ identified\ by\ WNN}{Total\ number\ of\ fault\ class} = \frac{TP}{TP+TN} \quad (12)$$

$$Specificity = \frac{Number\ of\ faults\ misclassified\ by\ WNN}{Total\ number\ of\ fault\ class} = \frac{TN}{TP+TN} \quad (13)$$

Example 2. Tow Thomas Low pass filter circuit is shown in Figure 9. This filter circuit has increased number of resistors and capacitors compared to Sallen Key Band pass filter. The same process is repeated to generate fault dictionary and the size of data set and number of fault class are also increased in this case.

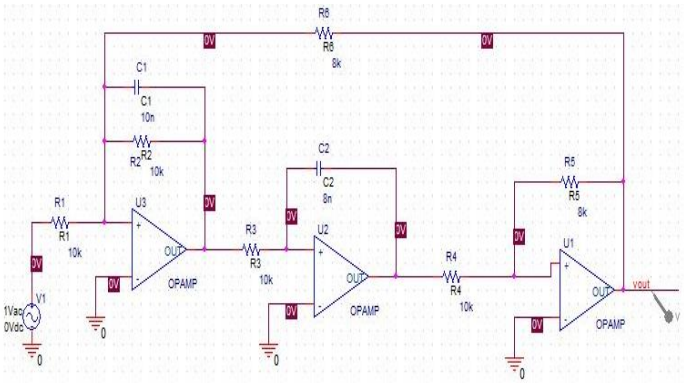


Figure 9. Tow Thomas Low pass filter

TABLE II shows the fault class, fault type, nominal value and faulty value for the 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
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

The performance of WNN and GA based WNN methods for identifying faults for the Sallen key band pass filter and Tow Thomas Low pass filter circuits are analysed.

TABLE III- PERFORMANCE FOR WNN AND GA BASED WNN

PARAMETERS	SALLEN KEY BPF		TOW THOMAS LPF	
	WNN	GA-WNN	WNN	GA-WNN
TRAINING TIME (S)	26.3730	8.6763	30.1349	7.6444
TESTING TIME (S)	0.0130	0.1471	0.0171	0.0166
CLASSIFICATION ACCURACY	80.37%	86.66%	91.28%	98.20%
SPECIFICITY	19.62%	13.33%	8.58%	1.79%

The performance of GA based WNN algorithm is compared with WNN for fault diagnosis. The main function of this algorithm is to repeatedly adjust and train the weights by using back propagation algorithm for making the prediction output closer to the desired output. The measures used for analysing the performance are training time, testing time, accuracy and specificity. The above measures are computed using formulas and the comparison of WNN and GA based

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WNN are shown in TABLE III. The GA based WNN method provides classification accuracy of 86.66% for Sallen key band pass filter and 98.46 % for Tow Thomas Low Pass filter.

VII.CONCLUSIOIN

In this paper, the Wavelet Neural Network (WNN) method is used for fault diagnosis in the analog circuits and Genetic Algorithm (GA) is used for optimized weights connecting the layers of WNN. The fault diagnosis for two benchmark circuits Sallen Key Band pass filter and the Tow Thomson Low pass filter are effectively identified and classified using WNN. These circuits are simulated based on Monte Carlo analysis to collect data set. 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 non-linear circuits can be diagnosed by using this method. The single faults in the circuit are effectively identified using GA based WNN. The Comparison between WNN and GA based WNN shows that GA based WNN technique reduces training time and increases the fault classification accuracy.

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