# Neural network data fusion algorithm for electromechanical fault diagnosis based on Multisim

**Lijun Wang, Yuee Zhou**

Nanjing University of Science and Technology Zijin College, Nanjing, China

**Keywords:** Multisim circuit, Electronic circuit, Fault diagnosis, Neural network, Data fusion, Research on Algorithms

**Abstract:** In order to improve the efficiency of circuit pressure testing, a circuit pressure functional equivalent compression testing method based on parallel neural network algorithm is proposed. Firstly, aiming at the execution stage of circuit pressure test, the nonlinear time-varying circuit is modeled as a set of ordinary differential equations, and the circuit network is converted into ordinary differential equations by using the improved MNA to construct an optimization model for circuit pressure functional equivalent compression test, which is based on minimizing flux as an optimization target. Secondly, neural network algorithm is introduced to optimize the minimization flux model for circuit pressure functional equivalent compression test. A parallel neural network circuit pressure test method with multi-thread parallel execution is designed for large circuit pressure test. Finally, the simulation experiment verifies the effectiveness of the proposed algorithm in circuit pressure testing accuracy and efficiency.

## 1. Introduction

With the development of system on chip (SoC) integrated circuits, the number and diversity of mixed signal circuits on the molds have also increased significantly, such as high-speed IOs, sensors, power supply, clock and other different circuit forms. The manufacturing test procedures are generally divided into wafer/sequencing test, encapsulation test (using function and structural test), including stress test/aging test and system test. These steps need to be performed on each component, thus resulting in a lot of testing workload of the components to be tested.

In order to shorten the product's research and development cycle, the test time of each component should be shortened as much as possible. Although short test time can be achieved by adding test equipment, this is not a preferred choice, because of the resulting dramatic increase in capital costs. On the contrary, adopting time compression mode for each test step is a cost-effective way to control testing. Since the test steps themselves cannot be eliminated, reducing the time for each step is the best method. Therefore, reducing the production and test costs has always been the research focus of simulation test.

## 2. Circuit pressure test problems based on electric flux

The nonlinear time-varying circuit is modeled as a set of ordinary differential equations, and modified node algorithm (MNA) is used to transform the electric network into ordinary differential equation. Let $f$ represent the sectionally continuous time-varying nonlinear function of control circuit dynamics, $t \in [0,\infty)$. Let $S \subseteq R^n$ represent the continuous state space of the circuit, $x(t)$ represent the circuit condition at time $t$. The initial state of the circuit is $x(0)$. Let $U \subseteq R^m$ represent the input interval of the circuit, $x$ represent the state variable and $u$ the input variable of the circuit. The test $u(t)$ is a continuous input signal. N-dimensional ordinary differential equation is adopted to describe nonlinear analog circuit:

$$\dot{x} = f(x,u,t) \tag{1}$$

  DOI: 10.25236/mmmce.2020.016

A solution for a circuit at time interval $[t_1;t_2]$ is the path of the circuit from the state $x(t_1)$ to the state of the given input test $u(t)$. For a given state $x(t_1)$ and input $u(t_1)$, the differential constraint in formula (1) determines the running path of the circuit in the interval $t \in [t_1,t_2]$. Then, the solving problem of the circuit running track of the initial state $x(t_i)$ at time $t = t_i$ can be expressed as an initial value problem (IVP) :

$$x(T) = x(t_i) + \int_{t_i}^{T} f\left(x(t),u(t)\right)dt \tag{2}$$

Let $T$ represent the length of the test sequence $u(t)$, $x(T)$ represent the boundary value that denotes the final state of the test process, there may be multiple boundary values $x_1, x_2 \cdots, x_f$ in the solution of the test sequence. Then, the problem can be decomposed into $n-1$ single boundary test compression problems, and each boundary value $x_i$ can be expressed as:

$$x_{i+1}(t_{i+1}) = x_i(t_i) + \int_{t_i}^{t_i+1} f\left(x_i(t),u_i(t)\right)dt \tag{3}$$

Where $x_i$ and $x_{i+1}$ are the initial value and boundary value of the test compression problem. For simplicity, this paper only focuses on the case of one initial value $x_0(0)$ and a single boundary value $x_f(T)$, because multiple boundary values can be divided into multiple unilateral value problems. The dynamics of the analog circuit are smooth and continuous, meeting the local Lipschitz property, which ensures the existence and uniqueness.

Definition 1: (functional equivalence test) we define two test input signals as functionally equivalent ones, if and only if their initial and boundary values are the same for the same nonlinear system. That is, input signal $u$ and $\tilde{u}$ are equivalent under the following circumstance:

$$\int_0^T f(x,t,u)dt = \int_0^{\tilde{T}} f(x,t,\tilde{u})dt \tag{4}$$

Where $T$ and $\tilde{T}$ denote the length of the input signal $u$ and $\tilde{u}$, respectively, which means that, if its initial value $x_0$ is equal, the boundary value of initial test signal $u$ and $\tilde{u}$ is equal. For the test compression process, the functionally equivalent test length after compression should be less than the original test length. Therefore, $\tilde{T} \le T$.

The purpose of the compression test problem is to find all possible functionally equivalent input stimulus, which need to reach the boundary value $x_f$ from the initial value $x_0$ in as short a time as possible. We propose the following optimized objective function:

$$\min \int_{x_0}^{x_f} t(x)dx \tag{5}$$

Where $t(x)$ is the time dimension of each state in the solution. $x$ denotes the state, which is a vector in $R^n$. Formula (5) is an integral describing the electric flux of the circuit along the solution path $x(t)$. Flux is a physical entity that captures both voltage and time. The magnetic flux is measured and quantized by weber and expressed as voltage times time in seconds $(Wb = V \times s)$. We can measure flux by integrating voltage $dv$ or time $dt$. Since we want to minimize the time while remaining the boundary voltage unchanged, we use lebesgue integral in formula (5) to define the test compression objective function.

Because the initial value $x_0$ and boundary value $x_f$ are fixed, the minimization of integral result can be directly realized by minimizing $T$. Although reducing flux function does not necessarily reduce time, the test of the minimum flux function is consistent with that of the minimum time, which means that minimizing the flux function is necessary but not sufficient to minimize the test time. When the flux function converges to the minimum value, we also prove that the test time converges to the optimal value. Since the time required by reaching the boundary value in the output is the same as the input test time, the minimization formula (5) also compresses the input test signal.

## 3. Neural network model based on BP algorithm

### 3.1 Algorithm description

The three-layer BP neural network model adopted in this paper is composed of input layer, hidden layer and output layer. Figure 1 shows a typical three-layer BP neural network model.

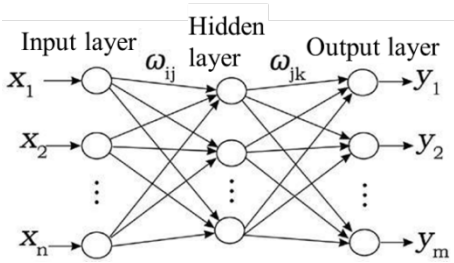


Fig.1. A simple BP neural network model

The feedforward significance of the network is that the input of each layer nodes only come from the output of the previous layer nodes. For the input signal, it is transmitted to the hidden layer node first, and then the output information of the hidden layer nodes is transmitted to the output nodes after the activation function, and finally the output results are obtained.

(1) For the input layer nodes $i(i=1,2,...,n)$, their output $O_i$ is equal to the input $X_i$, and the variable value is transmitted to the second layer.

(2) For the hidden layer nodes $j(j=1,2,...,p)$, their input $I_j$ and output $O_j$ are:

$$I_j = \sum_{i=1}^{n} \omega_{ji} O_i + \theta_j \tag{6}$$

$$O_j = f(I_j) = 1/[1+\exp(-I_j)] \tag{7}$$

Where $\omega_{ji}$ is the weight between hidden layer node $j$ and input layer node $i$, $\theta_j$ is the bias of hidden layer node $j$, and $f$ is a Sigmoid function with the following expression:

$$f(x) = 1/[1+\exp(-x)] \tag{8}$$

(3) For output layer nodes $k(k=1,2,...,m)$, their input $I_k$ and output $y_k$ are:

$$I_k = \sum_{j=1}^{p} \omega_{kj} O_j + \theta_k \tag{9}$$

$$y_k = f(I_k) = 1/[1+\exp(-I_k)] \tag{10}$$

Where $\omega_{kj}$ is the connection weight between input layer node $k$ and hidden layer node $j$, and $\theta_k$ is the bias of output layer node $k$.

For a given training sample $(x_{p1,}x_{p2},...,x_{pn})$, $p$ is the number of samples $(p=1,2,...,P)$, and the mean square error between network output and training target can be expressed as:

$$E=\frac{1}{p}\sum_{p=1}^{p}E_P \tag{11}$$

$$E_P=\frac{1}{2}\sum_{l=1}^{l}(t_{pl-}y_{pl})^2 \tag{12}$$

Where $p$ is the number of samples, $t_{pl}$ is the target output result of the lth output unit of the pth sample, and $y_{pl}$ is the network operation result of the lth output unit of the pth sample. The process of BP network training includes the forward calculation within the network and the back propagation of error, and it aims to minimize the output error of the network through adjusting the connection weight within the network. The connection weight between input layer and hidden layer and between hidden layer and output layer in the multi-layer feedforward network is adjusted by BP algorithm.

### 3.2 Diagnosis steps of neural network information fusion fault

Neural network knowledge representation is an implicit representation of knowledge, and knowledge shows the topology structure and connection weight of the network. Meanwhile, it adopts the expert system of neural network technology, because neural network is a unified network system of information storage and processing. Therefore, among expert systems adopting neural network technology, knowledge storage and reasoning in the problem solving process are carried out in the neural network module of the system, and they are the unity of knowledge base and inference machine. First of all, the feature data is extracted from the existing equipment characteristic signal, after data preprocessing (normalized processing), it is used as the input of neural network. The data extracted from known fault results is used as the neural network output to build BP neural network, and the training sample set formed by the existing characteristic data and known fault data is used to carry out learning and network self-learning of the BP neural network, so as to make the corresponding relation between the weights, threshold values and known fault results of BP neural network achieve the expected results output. When the BP neural network training is completed, BP neural network which has successfully completed training can be used for fault diagnosis. The process of fault diagnosis is as follows:

(1) Input the fault sample to each node of the input layer, and it is also the output of neurons in this layer.

(2) Obtain the output of hidden layer neurons by formula (2-2) and take it as the input of the output layer.

(3) Obtain the output of neurons in the output layer from formula (2-5).

(4) Determine the final output result of neurons in the output layer by the threshold function.

The fault diagnosis of diesel engine firstly extracts data from the fault signals to be diagnosed for preprocessing, and then the fault data to be diagnosed is input into the neural network which has finished training successfully. The fault diagnosis steps of using neural network information fusion are shown in figure 2:

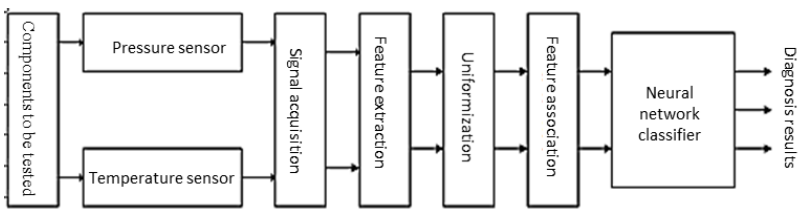


Fig.2. Steps of information fusion for fault diagnosis

## 4. Conclusion

In this paper, a circuit pressure functional equivalent compression test method based on parallel neural network algorithm is proposed, and minimizing the flux as the optimization goal to establish circuit pressure functional equivalent compression test model. Meanwhile, the neural network algorithm is introduced to optimize minimization flux model of circuit pressure functional equivalent compression test, and a parallel execution algorithm is specially designed to promote the computational efficiency of the algorithm. Therefore, it can be used for multi-threaded parallel optimization test of large-scale circuits as well as effectively reduce the product's r&d cycle.

## References

[1] Gan X S, Gao W M, Zhe D, et al. Research on WNN soft fault diagnosis for analog circuit based on adaptive UKF algorithm[J]. Applied Soft Computing, 2017, 50(C):252-259.

[2] Chen H X. Research on multi-sensor data fusion technology based on BP neural network[C]// Advanced Information Technology, Electronic & Automation Control Conference. 2016.

[3] Si L, Wang Z, Liu X, et al. Multi-Sensor Data Fusion Identification for Shearer Cutting Conditions Based on Parallel Quasi-Newton Neural Networks and the Dempster-Shafer Theory[J]. Sensors, 2015, 15(11):28772-28795.

[4] Tadeusiewicz M, Kuczyński A, Hałgas S. Catastrophic Fault Diagnosis of a Certain Class of Nonlinear Analog Circuits[J]. Circuits Systems & Signal Processing, 2015, 34(2):353-375.

[5] Zhang J, Wu Y, Liu Q, et al. Research on High-Precision, Low Cost Piezoresistive MEMS-Array Pressure Transmitters Based on Genetic Wavelet Neural Networks for Meteorological Measurements[J]. Micromachines, 2015, 6(5):554-573.

[6] Zhang B C, Xu R, Yin X J, et al. Research on fault diagnosis for rail vehicle compartment of LED lighting system of analog circuit based on WP-EE and BP neural network[C]// Control & Decision Conference. 2016.