Kent-PSO optimized ELM fault diagnosis model in analog circuits

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Abstract. Fault information in analog circuits is complex and diverse, so as to improve the accuracy of fault diagnosis, a Kent mapping and Particle Swarm Optimization (PSO) combined optimization Extreme Learning Machine (ELM) model is proposed. Firstly, the original data set of the circuit is normalized to obtain the fault data set. Secondly, Kent mapping is used to initialize the position of particles in the particle swarm, which makes the initial particle swarm more evenly distributed in the search space and enhances the global optimization ability. Third, aiming at the problem of the input weight and hidden layer bias generated randomly by the ELM are easy to lead to poor generalization ability, the Kent-PSO algorithm is used to optimize the input weight and hidden layer bias of ELM to obtain better and more stable ELM network parameters and improve the fault diagnosis ability. The diagnosis example of Sallen-Key bandpass filter shows that the proposed method has better fault diagnosis performance than PSO-ELM model.

1. Introduction

The complexity of analog circuits is increasing, and the corresponding requirements for analog circuit fault diagnosis are also increasing. The continuity, tolerance and sensitivity of analog circuits will lead to low fault recognition rate of analog circuits. Therefore, the research on fault diagnosis of analog circuits has important theoretical and practical significance.

Classical analog circuit fault diagnosis methods such as paper [1-3], have the problem of low diagnostic accuracy. The essence of modern analog circuit fault diagnosis method is pattern recognition and classification. Extreme Learning Machine [4], as a classification and recognition method, can solve complex nonlinear and uncertain modeling problems. Paper [5] proposes a fault diagnosis method based on PCA dimension reduction and ELM classification. The simulation results show that the method is feasible. The initial input weight and hidden layer bias of ELM are randomly generated, resulting in poor generalization ability. In order to solve this problem, Paper [6-9] used adaptive wolf pack algorithm, bat algorithm, improved krill herd algorithm and improvement artificial bee colony algorithm to optimize the input weight and hidden layer bias of ELM respectively. The results show that the use of bionic algorithm to optimize ELM can improve the diagnostic accuracy of ELM.

In this paper, Kent mapping and PSO [10] are used to optimize the input layer weight and hidden layer bias of ELM, and a diagnostic example is given to prove the effectiveness of the model.
2. Kent-PSO algorithm

2.1. PSO

Particle swarm optimization (PSO) algorithm is derived from the study of bird predation behavior. Its main idea is to iteratively solve the particles representing the solution of the problem and seek the optimal solution of the problem.

In the search space, each particle has two attributes: position $x_i$ and velocity $v_i$. The position represents the candidate solution of the problem. The flight process of the particle is the search process. The fitness function $F$ is used as the standard to evaluate the advantages and disadvantages of each particle. After each iteration, the individual particle and the particle swarm are evaluated to find the optimal solution $P_i$ of the individual particle position and the optimal position $P_g$ of the particle swarm in the optimization process. According to this, the direction and size of the particle velocity are adjusted to obtain a new position, so as to continuously approach the expected value.

The particle velocity and position update formula in the algorithm are as follows:

$$
\begin{align*}
    v_i(k+1) &= \omega v_i(k) + c_1 r_1 (P_i(k) - x_i(k)) + \\
    & \quad + c_2 r_2 (P_g(k) - x_i(k)) \\
    x_i(k+1) &= x_i(k) + v_i(k+1)
\end{align*}
$$

(1)

In the formula: $k$ is the current number of iterations, $\omega$ is inertia weight, $c_1$ and $c_2$ are learning factors, $r_1$ and $r_2$ are random numbers uniformly distributed from 0 to 1, $P_i(k)$ is the $i$-th particle and the optimal position in the $k$-th iteration. $P_g(k)$ is the optimal position after the $k$-th iteration of particle swarm. Formula (1) is the core content of PSO algorithm, which shows the iterative optimization path of PSO.

2.2. Kent-PSO algorithm

PSO shares global information by iterative individual optimal solution and global optimal solution, and the search speed is fast, but the characteristics of random initialization of particle swarm position will lead to low global optimization ability. In view of this, this paper uses the method of Kent mapping to initialize the particle swarm position, so that the initial particle swarm position is uniformly distributed in the search space as far as possible, so as to improve the efficiency of particle search and global optimization ability. The Figure 1 is the probability distribution after Kent mapping iteration.

![Fig 1. Probability distribution of Kent mapping](image)

The Kent mapping is applied to the initialization of particle position in the particle swarm to optimize the PSO algorithm. The specific operation is as follows:
In the formula: \( q_{i,j} \) and \( x_i \) dimensions are the same, \( x_{\text{min}} \) is the minimum boundary of particle position, \( x_{\text{max}} \) is the maximum boundary of particle position, \( q_{i,j} \) is calculated by Kent mapping Equation (2), and its value is evenly distributed between 0 and 1.

3. Kent-PSO optimized ELM model

3.1. ELM

Extreme Learning Machine (ELM) is a kind of neural network with unique form and excellent performance. Its structure is simple, the time required for the overall calculation is short, the accuracy is high, and the stability is good. ELM is widely used in analog circuit fault diagnosis. The network structure is shown in Figure 2.

For a N-dimensional sample set, the output of single hidden layer neural network (SLFN) can be expressed as follows:

\[
y_j = \sum_{i=1}^{L} \beta_i g_i(w_i x + b_i) = \sum_{i=1}^{L} \beta_i h_i(x)
\]

where \( L \) is the number of hidden layer nodes, \( y_j \) is the output of the output layer node \( j \), \( w_i \) is the connection weight vector between the input layer and the hidden layer, \( g(x) \) is the incentive function of the hidden layer, \( \beta_i \) is the connection weight between the hidden layer and the output layer, \( b_i \) is the bias of the \( i \) hidden layer node, \( h(x) \) is the activation function.

The parameters \( w_i, \beta_i \) and \( b_i \) in ELM network conform to the following:

\[
\sum_{i=1}^{L} \beta_i g(w_i x + b_i) = t_j, j = 1, 2, \cdots, n
\]

The output matrix of hidden layer is \( H \), \( H \) is ELM nonlinear mapping, then there are the following:

\[
H \beta = T
\]

Where

\[
H = \begin{bmatrix}
g(w_{i1}x_1 + b_1) & \cdots & g(w_{iL}x_1 + b_L) \\
\vdots & \ddots & \vdots \\
g(w_{i1}x_N + b_1) & \cdots & g(w_{iL}x_N + b_L)
\end{bmatrix}, \beta = \begin{bmatrix}
\beta_1^T \\
\vdots \\
\beta_L^T
\end{bmatrix}, T = \begin{bmatrix}
T_1^T \\
\vdots \\
T_n^T
\end{bmatrix}
\]
Given \( w_i \) and \( b_i \), the unique solution \( H^+ \) is solved according to Moore-Penrose generalized inverse theorem, and then according to the formula

\[
\beta = H^+ T
\]

(8)

The connection weights between the hidden layer and the output layer of ELM network are calculated to obtain the ELM model.

3.2. Ken-PSO optimization ELM

ELM randomly produces initial input weights and hidden layer bias, which is difficult to ensure that the trained model has good generalization ability and high prediction accuracy. In view of this deficiency, this paper applies the Kent-PSO algorithm to the optimization of weight and hidden layer bias of ELM. The model optimization process is shown in Figure 3.

![Kent-PSO optimizes ELM process](image)

Fig 3. Kent-PSO optimizes ELM process

4. Application examples of circuit diagnosis

Sallen-key bandpass filter is shown in Figure 4, which is composed of five resistors, two capacitors and one operational amplifier. The tolerance of resistor and capacitor is 5% and 10% respectively. C1, C2, R2 and R3 are selected as the research objects for analog circuit fault analysis. When the parameter value of an element in the circuit is higher or lower than its tolerance range, the circuit is considered to be faulty. In the experiment, considering that the larger the fault value is, the easier it is to detect, only the fault value of the resistance is out of the tolerance range, which is within 20% of the normal value, and the fault value of the capacitor is out of the tolerance range, which is within 40% of the normal value. Sallen-Key bandpass filter fault mode can be expressed as \( R_2^\uparrow, R_2^\downarrow, R_3^\uparrow, R_3^\downarrow, C_1^\uparrow, C_1^\downarrow, C_2^\uparrow, C_2^\downarrow \) and NF (Normal), with a total of nine fault types.

OrCAD/PSpice 17.4 software was used for AC scanning of Sallen-Key bandpass filter. The voltage was 1V, and the scanning frequency was 1.0KHz – 1MHz. The nine fault modes of the circuit were analyzed by 300 Monte Carlo simulations. The voltage data were collected at the output end of the circuit, and a total of 2700 (300 \times 9) input vectors were obtained.

![Sallen-Key bandpass filter](image)

Fig 4. Sallen-Key bandpass filter
4.1. Fault feature selection

When the fault value is shown in Table 1, the circuit output waveform under each fault mode is shown in Figure 5, and the dotted line in the figure is the output waveform under non-fault conditions. It can be seen from the diagram that the output signal fluctuates greatly when the circuit fails between 10KHz and 100KHz, and in this range, the output waveform of each fault mode is roughly above or below the normal mode.

![Fig 5. Comparison of circuit output waveforms](image)

According to the above analysis, the circuit output voltage values at 1KHz, 5KHz, 10KHz, 25KHz, 40KHz, 50KHz, 60KHz, 75KHz, 100KHz, 500KHz, and 1MHz and the mean values of the above 11 voltage values are selected to the 12-dimensional input vector. The data are normalized to obtain the fault data set.

Table 1. Fault types and values of Sallen-Key bandpass filter circuit

| Fault code | Fault mode | Normal value | Fault value |
|------------|------------|--------------|-------------|
| F0         | NF         | —            | —           |
| F1         | R↑ 3kΩ     | 4.5kΩ        |
| F2         | R↓ 3kΩ     | 1.5kΩ        |
| F3         | R↑ 2kΩ     | 3kΩ          |
| F4         | R↓ 2kΩ     | 1kΩ          |
| F5         | C↑ 5nF     | 7.5nF        |
| F6         | C↓ 5nF     | 2.5nF        |
| F7         | C↑ 5nF     | 7.5nF        |
| F8         | C↓ 5nF     | 2.5nF        |

4.2. Fault diagnosis and analysis

The results of ELM model (150 hidden layer nodes) are shown in Table 2, and the diagnostic accuracy is 0.9037.

PSO-ELM and Kent-PSO-ELM are used to diagnose analog circuit fault data. The network hidden layer nodes are 150. The hidden layer transfer function is sigmoid function, the particle swarm size is 50, the number of iterations is 50, the mutation probability is 0.05, the inertia weight is 0.7, and the learning factor is 1.5. The simulation results are shown in Table 3 and Figure 6. The PSO-ELM model optimized by Kent algorithm has stronger global optimization ability, and the diagnostic error rate decreases faster in the iterative process. The final classification accuracy reaches 94.36 %, and the classification performance is better.
Table 3. Comparison of fault diagnosis performance of Sallen-Key bandpass filter

| Model          | ELM   | PSO-ELM | Kent-PSO-ELM |
|----------------|-------|---------|--------------|
| Initial precision | 90.37% | 90.83%  | 88.54%       |
| Final accuracy  | 90.37% | 92.95%  | 94.36%       |

Fig 6. Fault diagnosis results of Sallen-Key bandpass filter

5. Conclusion
This paper combines the advantages of Kent algorithm and PSO, and proposes Kent-PSO optimized ELM model for analog circuit fault diagnosis. The experimental results show that the accuracy of this method is significantly improved compared with the traditional ELM model, and the accuracy is improved compared with PSO-ELM model. The fault diagnosis method of analog circuit in this paper can be extended to other types of analog circuits, and the fault classification can be carried out by combining the characteristics of the output signal of the circuit.

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