Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 11, No. 2, 2024

A Complex Analog Circuit Fault Diagnosis Method based on IMODA Improved Deep Belief Network

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Abstract: Aiming at the problems of time-consuming and low diagnosis accuracy during the unsupervised training process of traditional DBN, an analog circuit fault diagnosis method based on Improved Multi-Objective Dragonfly Optimized Deep Belief Network (IMODA-ADBN) is proposed. The method employs an improved MODA algorithm instead of the BP algorithm, which improves the classification accuracy of the network and ameliorates the problem of being prone to falling into local optima. The algorithm is tested on three multi-objective mathematical benchmark problems and compared with three well-known meta-heuristic optimization algorithms such as MODA, MOPSO and NSGA-II, and the results demonstrate the stability of the IMODA-ADBN network model. Finally, IMODA-ADBN is applied to the diagnostic experiments of a two-stage quad op-amp dual second-order low-pass filter, and the results show that the method improves the classification accuracy and diagnostic rate while guaranteeing the convergence speed, and is able to effectively realize the classification and localization of difficult faults.

Keywords: Analog Circuit; MODA; Deep Belief Network; Fault Diagnosis.

1. Introduction

Analog circuits, as an important pillar in military, defense, and aerospace fields [1], have become a research hotspot in the field of circuit testing [2], and the development of efficient and accurate diagnostic strategies has become an urgent need in the field of analog circuit fault diagnosis [3-5]. However, due to the complex fault phenomena of analog circuits, the input-output relationship of analog circuits is often a nonlinear mapping relationship, which makes it difficult to establish an accurate mathematical model of circuit response in practical applications. Since the actual parameter values of the non-faulty components of analog circuits will fluctuate randomly above and below the nominal values, it makes it difficult for the traditional analog circuit fault diagnosis methods such as the fault dictionary method and the parameter identification method [6-7] to play an important role in real production life. With the in-depth study of fault diagnosis technology, signal processing methods such as wavelet transform are widely used in nonlinear system fault feature extraction and diagnosis [8], but the signal processing methods are prone to ignore the essential features in the process of feature extraction, which leads to the low efficiency and accuracy of nonlinear analog circuit fault diagnosis [9].

In order to solve the above problems, data-driven artificial intelligence methods such as Support Vector Machine (SVM) [10] and Extreme Learning Machine (ELM) [11] are widely entered into the research field, providing feasible technical support for analog circuit fault diagnosis. Literature [12] proposed a conventional time-domain feature vector based on the impulse response characteristics of a control system, and according to the Least Squares Support Vector Machine (LSSVM) experiments show that the classification performance of LSSVM can be improved by using the improved vector. Literature [13] utilizes the particle swarm optimization (PSO) algorithm with Mahalanobis distance (MD) to optimize the classifier and select the feature vectors reasonably so as to improve the classification accuracy. However, literature [14] points out that the use of shallow learning models cannot comprehensively and thoroughly reveal the complex intrinsic relationship between fault root causes and signal features.

In recent years, deep learning such as Deep Belief Network (DBN) [15] has been widely applied in the field of fault diagnosis with its powerful learning and feature extraction capabilities [16]. Literature [17] uses DBN network to adaptively extract the features of signals and automatically classify them, which can flexibly and efficiently diagnose the faults of analog circuits, and provide new solution ideas for different diagnostic problems. Literature [18] proposed that Gauss-Bernoulli Deep Confidence Network (GB-DBN) can capture the higher-order semantic features in the original output signals more efficiently and make the diagnosis results more accurate. These literatures provide references for this paper during the research process.

Although DBN shows a wide range of application prospects in several fields, however, since the traditional DBN utilizes the BP algorithm to inversely fine-tune the weights, the BP algorithm suffers from the problem of easily falling into the local minima, so that its performance will be affected by this as well. In order to obtain a DBN model with strong robustness and at the same time able to avoid local minima, the IMODA algorithm is utilized to fine-tune the weights, and finally simulation experiments are carried out using a two-stage quad-op-amp dual second-order complex circuit to verify the superiority of the diagnostic model in this paper. In summary, the main contributions of this paper are summarized as follows.

1) Considering that the BP algorithm used in the supervised learning part of the traditional DBN has problems such as easy to fall into local optimization. Therefore, IMODA algorithm is used to replace the traditional BP algorithm to improve the classification effect of the model. In addition, three multi-objective mathematical benchmark problems are used to verify the stability and convergence of the IMODA algorithm.

2) Based on the Matlab\Simulink platform, a two-stage

four-op-amp dual second-order low-pass filter is constructed, and the simulation experiments about the IMODA-ADBN model are verified to show that the IMODA-DBN model has a high level of accuracy, reliability and generalization performance.

2. DBN Structure

2.1. Section Headings

In 2006 Hinton proposed DBN, which is a probabilistic generative model consisting of a stack of multiple restricted boltzmann machines (RBM). The RBM acts as a two-layer network, consisting of a visible layer and a hidden layer connected bi-directionally, and the neurons in the same layer of the network are independent of each other. The main role of the visible layer is the input of training data, while the hidden layer is used to extract features. The structure of RBM is shown in Fig. 1. Where *w* denotes the connection weight; *b* is the bias coefficient of the hidden layer; *a* is the bias coefficient of the visible layer.

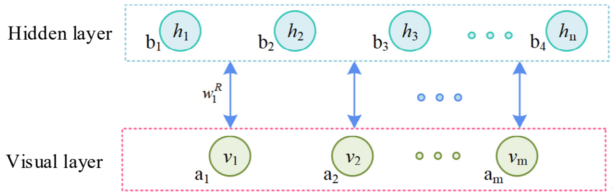

Fig 1. RBM structure diagram

3. Improved IMODA-DBN Learning Algorithm

3.1. Supervised Fine-tuning based on Improved Multi-objective Dragonfly Optimization

There are three main behaviors of insect swarms:

1) Separation, denoting avoidance of static collisions between individuals and neighboring individuals;

2) Alignment, which denotes the matching of velocity between individuals and neighboring individuals;

3) Cohesion, refers to the tendency of individuals to aggregate to the center of the surrounding group.

The main features of Improve Multi-Objective Dragonfly Algorithm (IMODA)2 are as follows: to alleviate the local optimum, elite individuals are added to MODA and opposition-based jumping.

3.1.1. Initialization of Dragonfly Populations

Dragonfly populations are usually initialized randomly. In order to improve the diversity of the initial population and avoid the algorithm from producing premature convergence, unlike the original MODA algorithm with the random initialization, the population initialization in this paper utilizes Logistic mapping instead of the traditional random initialization, and the calculation formula is as follows:

$$X_{i+1}=\eta X_i\left(1-X_i\right),\ 0\le X_0\le 1 \tag{1}$$

where X_i is the logistic value of the ith dragonfly; X_0 is the initial value of the dragonfly population; $\eta=4$, $X_0\in(0,1)$, $X_0\notin\{0.0, 0.25, 0.75, 1.0\}$.

3.1.2. Population Diversity based on Oppositional Jumps

The performance of evolutionary algorithms can be effectively improved based on oppositional jumps. In this paper, the MODA algorithm is optimized based on opposite jumps to prevent falling into the local optimum. The formula based on opposing jumps is:

$$X_{i'}\left(t\right)=\left(Lb_i+Ub_i\right)-X_i\left(t\right) \tag{2}$$

where, Lb_i represents the upper bound of the search space, and Ub_i represents the lower bound of the search space.

4. Simulation Experiments and Research Analysis

The IMODA-DBN fault diagnosis model proposed in this paper is characterized by the following five processes:

(1) Apply pulse signals to both ends of the circuit under test to collect fault data;

(2) Fault coding is performed on the data;

(3) Divide the data set into a training set and a test set;

(4) Retaining the weights during unsupervised learning and accelerating the training process using the adaptive learning rate; fine-tuning the weights using the IMODA optimization algorithm during supervised learning;

(5) Model testing: the real coding of the test set is compared with the predicted coding of the model; if the predicted coding is consistent with the real coding, the classification is correct; if the predicted coding is inconsistent with the real coding, the classification is incorrect.

4.1. Supervised Fine-tuning based on Improved Multi-objective Dragonfly Optimization

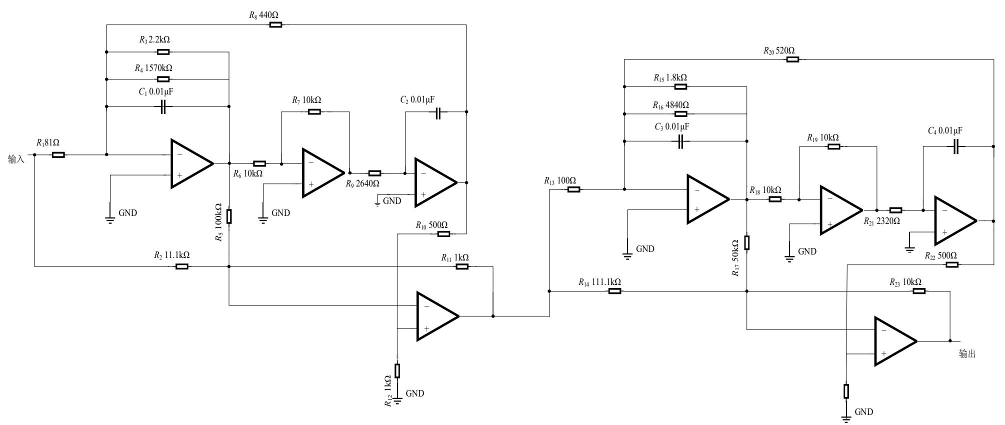

Fig 2. Two-stage quad op-amp dual second-order low-pass filters

Table 1. Failure modes of a two-stage quad op-amp dual second-order low-pass filter circuit

Code	Type	Tolerance/ (%)	Standard value	Fault value
f1	Norm	-	-	-
f2	R_9↑	5	2640Ω	3960Ω
f3	R_9↓	5	2640Ω	1320Ω
f4	C_1↑	5	0.01nF	0.005nF
f5	C_1↓	5	0.01nF	0.015nF

In this paper, a two-stage quad-op-amp dual second-order low-pass filter (Fig. 2) excited by a sinusoidal signal with an amplitude of 5 V and a frequency of 10 kHz is used as the input. To validate the IMODA-DBN model proposed in this paper, the tolerances of the resistors and capacitors in the circuit are both set to 5%, respectively. According to the sensitivity test results, the four components of resistors R_9 and capacitors C_1 are selected as research objects for experimental analysis, as shown in Table 1.

4.2. Comparison Experiment

4.2.1. Performance Validation of IMODA Optimization Algorithm

To increase the diversity of the MODA optimization process and improve the situation of falling into local optimum, we add logistic mapping and oppositional jumps to the traditional MODA optimization algorithm. The two can improve the diversity of the initial population and reduce the probability of "early maturity"; three test functions, ZTD function, Schaffer, and DTLZ function, are chosen to verify the performance of the IMODA algorithm, and compared with three well-known multi-objective optimization algorithms (MODA, MOPSO [19]), and the performance results of different algorithms are summarized in Table 2. summarizes the performance results of different algorithms.

Table 2. Performance comparison of test functions for different algorithms

Function	Index	ZTD1	ZTD2	Schaffer	DTLZ1	DTLZ2
MODA	Mean value	0.00587	0.00426	0.00372	0.00608	0.01098
	Standard deviation	0.00301	0.00271	0.00399	0.00409	0.00901
MOPSO	Mean value	0.00472	0.00672	0.00507	0.05922	0.05140
	Standard deviation	0.00418	0.00395	0.00500	0.03061	0.01525
IMODA	Mean value	0.00553	0.00350	0.00288	0.00572	0.00921
	Standard deviation	0.00292	0.00192	0.00319	0.00308	0.00088

From Table 2, it can be seen that the IMODA Calculation A method, compared with the MODA algorithm and the MOPSO algorithm, the IMODA algorithm achieves the best performance in the 3 test functions in terms of mean, standard deviation, and total of the 2-evaluation metrics.

4.2.2. IMODA-DBN Model Validation

Comparison experiments are conducted between the method of this paper and some commonly used methods for analog circuit fault diagnosis and classification to demonstrate the effectiveness and superiority of the IMODA-DBN model for diagnosing and classifying complex circuit faults. On the shallow side, BP, ELM, are used for classification and diagnosis, and on the deep side, traditional DBN and CDBN are used for validation. The above models are compared with the IMODA-DBN proposed in this paper in 10 independent diagnostic experiments, as shown in Table 3, where the comparison metrics include F1-Measure and average accuracy rate.

Table 3. Performance comparison of different models

Method	F1 Measure	Average accuracy/%
BP	0.796	75.92
ELM	0.802	80.09
DBN	0.913	91.08
CDBN	0.942	92.72
Proposed	0.9602	95.23

From the perspective of average correct rate, the average correct rate of the shallow machine learning methods BP and ELM used as diagnostic models are lower than that of the deep machine learning models. Among the deep machine learning models, DBN as a diagnostic model had the lowest average diagnostic accuracy (91.08%), while the improved models of DBN, CDBN and IMODA-ADBN models, had average diagnostic accuracies of 92.72% and 95.23%, respectively, and the optimal performance was achieved by the IMODA-ADBN diagnostic model.

5. Summary

DBN, as the most typical model in deep learning, has been studied and applied in different fields. DBN is prone to fall into local optimality in the process of backward fine-tuning due to the nature of BP algorithm. To address the above problems, this paper proposes an IMODA-ADBN-based analog circuit fault diagnosis method to cope with the challenges of time-consuming training and backward fine-tuning of DBN in the context of big data. The research innovations are as follows: the MODA algorithm is optimized by adding Logstic chaotic mapping and oppositional jumps to increase the diversity, and the improved IMODA algorithm is compared with the traditional MODA algorithm and MOPSO algorithm, and experimentally verified by using the test function, which shows that the distribution of the Pareto solutions generated by the IMODA algorithm is more uniform. Finally, the IMODA-DBN is verified by simulation experiments using dual second-order four-op-amp low-pass filters. The results of the simulation experiments show that the IMODA-DBN model is able to achieve efficient classification and localization of faults, and can be used as a new solution in areas such as analog circuit fault diagnosis.

Acknowledgments

The authors gratefully acknowledge the financial support from the Excellent Doctoral Program of Gansu Provincial Science and Technology Plan Project (23JRRA809).

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