Analog Circuit Fault Diagnosis Using Multi-Input Convolution Techniques

Mrs.C.Nirmala[1]., G. Volga shivani[2]

1 Assistant Professor, Department of ECE, Malla Reddy College of Engineering for Women., Maisammaguda., Medchal., TS, India

2, B.Tech ECE (19RG1A04D8),

Malla Reddy College of Engineering for Women., Maisammaguda., Medchal., TS, India

Abstract:

It is not feasible to categorize components in analog circuits because of the poor capability of fault feature extraction. It suggests an attention-based multi-input convolution neural network (MIL-CNN) model. The model's circuit, which consists of a two-stage four-op amplifier and a double-second order low-pass filter, demonstrated superior comprehensive performance in the fault diagnostic experiment, precisely classifying and localizing all faults with remarkable efficiency.

1. Introduction

Research into the most effective methods for diagnosing problems with analog circuits has recently emerged as a priority in the area of circuit testing, due to the growing use of analog circuits in integrated circuits and other applications [1-3]. The adjoint network approach, the network tearing method, and the fault diagnosis theorem were the mainstays of early fault identification for analog circuits [4], but their complicated calculations and restricted applicability made them unsuitable for nonlinear fault diagnosis. The wavelet transform and other signal processing methods have seen extensive use in fault feature extraction and diagnosis of nonlinear systems [5-7]. However, when it comes to nonlinear analog circuit fault diagnosis, signal processing methods have a tendency to overlook important features during feature extraction, which leads to poor efficiency and accuracy [8-10]. Several data-driven AI approaches, including as BP neural networks, support vector machines (SVMs), and Extreme Learning Machines (ELMs), have recently made their way into the study area in an effort to address this issue. Using DBN for feature extraction with the Grey Wolf optimization (GWO) technique to improve SVM for classification was suggested by Su et al. [11]. To increase the accuracy of fault diagnosis, Zhang et al. [12] suggested the DE-ELM model and optimized the model parameters using the differential Evolution (DE) method. Due to its powerful data feature extraction capabilities and outstanding capacity to describe nonlinear fault dynamics, deep science has recently found widespread usage in fault diagnostics [13–15]. From what we can tell from the aforementioned works, the writers are limited to using either the time domain or the frequency domain to diagnose faults. An MIL-CNN, or multi-input convolution neural network model, was therefore built in this study. As an example, the mil-CNN model's complete performance is validated using the fault diagnosis of a two-stage four-op amplifier's double-order low-pass filter.

2. Materials and methods

This study makes use of the MIL-CNN model, the architecture of which is shown in Figure 1. The MIL-CNN multi-input layer is capable of merging the fault data's time domain and frequency domain information graphs. The layers of Net1 are the convolution layer plus ReLU, the layers of Net2 are the BN layer and the pooling layer, in that sequence. In order to extract the feature from the input data, a convolution layer is used. Over fitting may be lessened by using a BN layer. Computing may be reduced by using a pooling layer. Both Net2 and Net1 procedures are identical. Net3 merges the feature data from Net1's time domain with Net2's frequency domain, and then it delivers the output value to the classifier for classification.

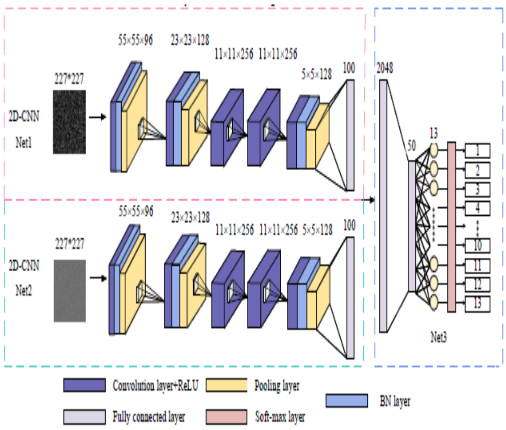
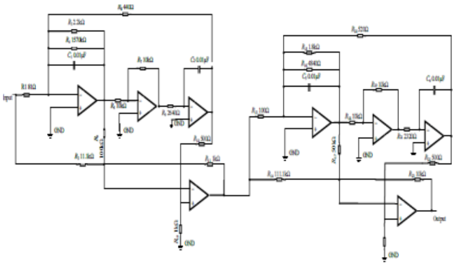


Figure 1: Model with MIL-CNN

The capacitance and resistance of the item, a two-stage four-op amplifier double-order low-pass filter (figure 2), go outside of the typical tolerance range due to external component interference. By simulating scenarios with varying sizes of inputs and outputs, we were able to confirm that the MIL-CNN diagnostic model worked as expected.



The two-stage four-op amplifier double-order low-pass filter is shown in Figure 2.

For each kind of defect, 160000 data points are gathered by building the circuit in the Multiuse environment and adding a pulse signal with a voltage of 10V and a frequency of 1000Hz at both ends of the circuit. Overlapping sampling is used to rectify the issue of inadequate data by augmenting it. First, utilize the labeled data from Net1 to identify the different types of faults; second, feed the frequency domain information graph produced by the image Fourier transform into the second sub network, Net2.

Here are the detailed procedures of the experiment described in this paper:

For the purpose of collecting fault data, 1) pulse signals should be added to both ends of the tested circuit.

2) Arrange defect data into categories and assign codes to each.

Thirdly, obtaining the time domain image set using image processing technology, and then obtaining the frequency domain data set through the image Fourier transform, all with the goal of expanding the data set.

4) Separate the image collection into three parts: training, testing, and verification sets.

5) Create a MIL-CNN model, train it using the training set, and then use the verification set to fine-tune the network model until it's perfect.

6) The model's predicted coding is contrasted with the test set's actual coding.

Areas affected by the drought and their severity levels are shown in Table 1.

Grade	Scope of influence	Station proportion of drought frequency
1	Global Drought	$P_i \geq 50\%$
2	Regional Drought	$50\% > P_i \geq 33\%$
3	Partial Regional Drought	$33\% > P_i \geq 25\%$
4	Local Drought	$25\% > P_i \geq 10\%$
5	No Obvious Drought	$P_i < 10\%$

3. Results and analysis

Using a two-stage four-op amplifier double-second-order low-pass filter, the simulation results showed that the suggested MIL-CNN network was better and effective in fault detection of complicated circuits. For this study, we choose to focus on resistors R3, R4, R6, R7, and R9, as well as capacitors C2 and C4. You can see the possible failure modes in table 2.

Table 2: Disruption mode of a double-order low-pass filter based on a two-stage four-op amplifier

Fault code	Fault type	Tolerance range/%	Nominal value	The fault value
f1	Normal	—	—	—
f2	R_3 increase	5	3kΩ	4.5kΩ
f3	R_3 decrease	5	3kΩ	1.5kΩ
f4	R_4 increase	5	1570kΩ	2355kΩ
f5	R_4 decrease	5	1570kΩ	785kΩ
f6	R_6 increase	5	10kΩ	15kΩ
f7	R_6 decrease	5	10kΩ	5kΩ
f8	R_9 increase	5	2640Ω	3960Ω
f9	R_9 decrease	5	2640Ω	1320Ω
f10	C_2 increase	5	0.01nF	0.005nF
f11	C_2 decrease	5	0.01nF	0.015nF
f12	C_4 increase	5	0.01nF	0.005nF
f13	C_4 decrease	5	0.01nF	0.015nF

The two-stage four-op amplifier double-order low-pass filter's average fault diagnostic accuracy is shown in Table 3.

Method	Average accuracy/%
WTF+PCA+ELM	50.93
WTF+PCA+BP	73.24
WTF+PCA+SVM	85.72
CNN	88.93
MIL-CNN	93.82

One may see that MIL-CNN achieves an average accuracy of 98.52% from table 3. MIL-CNN outperforms conventional CNN, and as complicated circuits preprocess data before classification, shallow learning is unable to do a good job of fault classification. Given the foregoing, it seems that MIL-CNN can function just well without gaining more complete features, time domain and frequency domain information splicing, or complicated data preparation. In complicated circuits, the suggested technique clearly outperforms the alternatives.

4. Conclusions and Discussion

This research proposes a model for defect diagnostics of MIL-CNN analog circuits. Here are the key findings:

The diagnostic experiment findings of the two-stage four-op amplifier's double-second order low-pass filter show that MIL-CNN networks outperform regular CNNs when it comes to problem identification. Both their feature extraction and learning capabilities were substantially enhanced by MIL-CNN. A novel approach to the problem of diagnosing faults in analog circuits and other areas, the MIL-CNN network outperforms shallow learning in this regard.

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