FAULT DIAGNOSIS OF RADIO FREQUENCY LOW NOISE AMPLIFIER USING GMM-HMM

Han DU[1] ,Yang LI[1] ,Lu SUN[1] ,Zheng GAO[1],Fushun NIAN[2]

[1]*School of Mechanical and Electrical Engineering, Xidian University, Xi'an, China*

[2]*The 41st research institute of China electronics science and technology group, Qingdao,China*

**760038035@qq.com*

Keywords: Hidden Markov Model, Gaussian Mixture Model, Fault diagnosis, Low Noise Amplifier

Abstract

Radio Frequency (RF) analog circuit faults often occur in broadband, high voltage and high temperature environment, so the detection of faults location and prediction of faults occurring time are important research subject. As GMM-HMM (Gaussian Mixture-Hidden Markov Model) algorithm has strong capability for sequential data processing, it is proposed in this paper a fault diagnosis method based on GMM-HMM and has been successfully applied to the fault diagnosis of low noise amplifier circuit based on ATF54143 transistor. Through multiple testing datasets, the experimental results have verified the feasibility of proposed method, the fault model has 100% accuracy for open circuit and short circuit fault diagnosis of the radio frequency circuit.

1 Introduction

Radio frequency circuits works in the high frequency band,switching rate of semiconductor devices is fast, and some semiconductor devices often need to work under high power conditions. Which may increase the probability of different radio frequency circuit faults. It can be seen from Fig.1 that semiconductor and soldering failures in device modules account for 34% of the fault rate in the energy conversion system[1].

Circuit fault diagnosis can be divided into digital circuit fault diagnosis and analog circuit fault diagnosis. Radio frequency circuit is a special application of analog circuit operating frequency at high frequency. Due to the high frequency band, the analysis method of traditional analog circuit is no longer applicable[2]. RF circuit propagates through the electromagnetic field due to energy transfer, so it is of little significance to analyze the working state of the circuit by extracting the input excitation and output response. In addition, since the electromagnetic field is very sensitive to changes in the working environment, this also brings great difficulties to the selection of test points for radio frequency circuits. At present, RF circuit fault diagnosis mainly focuses on the physical fault of semiconductor devices[3-4], and due to the difficulty of model constructing, non-linear of circuits, inevitable component errors and interference caused by measurements and noises, the theories of radio frequency circuits fault diagnosis are relatively lagging[5-6]. It is difficult to meet the fault diagnosis requirements of radio frequency circuits using traditional fault diagnosis methods. As GMM-HMM algorithm has strong data processing capabilities for continuous time model, it can improve fault diagnosis efficiency and solve the circuit tolerance and nonlinear problems.

At present, The research area has few achievements about radio frequency circuit fault diagnosis methods. Reasonable extraction and processing of the fault characteristic information in the circuit can solve the problem of radio frequency circuit fault diagnosis simply and quickly.

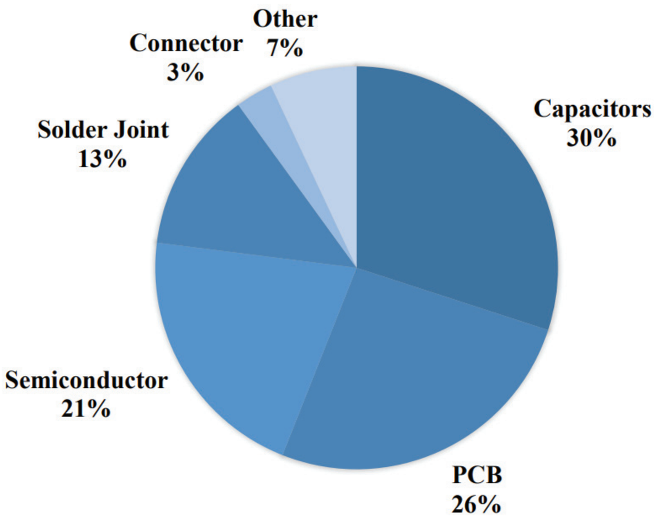

Fig. 1 Proportion of Various Circuit Faults

2 Methodology

2.1 Hidden Markov Model(HMM)

HMM is developed on the basis of Markov chain. Markov chain is a kind of random variable sequence with discrete time parameters and finite or enumerable state space set[7]. Unlike Markov chain, HMM state is hidden, and the hidden transition state and observable sequence satisfy a certain probability distribution. Therefore, HMM is a double random process. Markov chain with hidden transition states is modeled through the relationship between the observable sequence and the hidden state. An HMM model is shown in the figure below, Markov state is hidden, and the observable variables are represented by O[8].

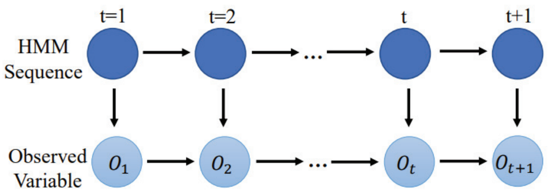

Fig. 2 Structure of HMM Model

Hidden Markov model can be expressed as: $\lambda=(N,M,\pi,A,B)$, N is the number of states in the Markov chain, and M is the number of possible observations corresponding to each state. π is the initial probability distribution. A is the observation value transition matrix, and B is the observation value probability matrix.

2.2 Gaussian Mixture Model(GMM)

The Gaussian mixture model refers to a probability distribution model with the following form[9]

$$P(y\mid\theta)=\sum_{k=1}^{K}\alpha_k\phi(y\mid\theta_k) \tag{1}$$

Where α_k is the coefficient, $\alpha_k \ge 0$, $\sum\alpha_k=1$, $\phi(y\mid\theta_k)$ is Gaussian distribution density, $\theta_k=(\mu_k,\sigma_k)$.

$$\phi(y\mid\theta_k)=\frac{1}{\sqrt{2\pi\sigma_k}}\exp\left(-\frac{(y-\mu_k)^2}{2\sigma_k^2}\right) \tag{2}$$

2.3 Gaussian Mixture Hidden Markov Model(GMM-HMM)

GMM is developed on the basis of the single Gaussian probability distribution density function. GMM can be used to simulate training sample data and has good applicability to some continuous probability distribution problems[9], so it can be used with HMM to overcome the shortcomings of HMM in solving continuity problems.

For the j state in the HMM model, the probability density function of the observation vector O can be written as[10]:

$$b_j(O)=\sum_{l=1}^{M}\bar{c}_{jl}N\left(O,\bar{\mu}_{jl},\bar{U}_{jl}\right),1\le j\le N \tag{3}$$

Where M is the number of Gaussian elements in the j state, and $\bar{c}_{jl}$ represents the weight of the l Gaussian element in the j state; N represents the standard normal distribution, $\bar{\mu}_{jl}$ represents the mean vector of the l Gaussian element in the j state; $\bar{U}_{jl}$ is the covariance matrix of the l Gaussian element in the j state.

The re-estimation formula of the probability density function is as follows, $\gamma_t(j,l)$ represents the output probability of the l Gaussian element of state j at time t:

$$\bar{c}_{jl}=\frac{\sum_{t=1}^{T}\gamma_t(j,l)}{\sum_{t=1}^{T}\sum_{m=1}^{M}\gamma_t(j,m)} \tag{4}$$

$$\bar{\mu}_{jl}=\frac{\sum_{t=1}^{T}\gamma_t(j,l)o_t}{\sum_{t=1}^{T}\gamma_t(j,l)} \tag{5}$$

$$\bar{U}_{jl}=\frac{\sum_{t=1}^{T}\gamma_t(j,l)\left(o_t-\bar{\mu}_{jl}\right)\left(o_t-\bar{\mu}_{jl}\right)'}{\sum_{t=1}^{T}\gamma_t(j,l)} \tag{6}$$

$$\gamma_t(j,l)=\left[\frac{\alpha_t(j)\beta_t(j)}{\sum_{i=1}^{N}\alpha_t(i)\beta_t(i)}\right]\left[\frac{c_{jl}N\left(o_t,\mu_{jl},U_{jl}\right)}{\sum_{m=1}^{M}c_{jm}N\left(o_t,\mu_{jm},U_{jm}\right)}\right] \tag{7}$$

2.4 *Gaussian Mixture Hidden Markov Training Model*

Through the GMM algorithm to fit the probability density function of the observation vector in each state, the probability matrix B of the observation vector can be obtained. Then combined with Baum-Welch algorithm for model training. The complete GMM-HMM training steps are as follows:

1) First input the number of states of the model, the initial probability distribution π, the initial state transition matrix

A, the iteration error ε, the maximum number of iteration steps L and the observation vector sequence O;

2) Initially estimate the Gaussian mixture density parameters by the K-means algorithm to obtain the initial model λ_0 of GMM-HMM;

Calculate the parameters of GMM-HMM according to the re-estimation formula, and obtain the re-estimation model $\overline{\lambda}_i$ of the i-th iteration.

3) Calculate the output probability $P(O|\overline{\lambda}_i)$ of the observation sample sequence under the re-estimation model by the Viterbi algorithm, and calculate the growth error of the re-estimation model output probability. If the error condition ε is not met, then return to the third step. Satisfy the error condition and converge, and use the re-estimated model $\overline{\lambda}$ as the final result model.

Bring the trained fault model into the test set for training, analyze the recognition accuracy, and analyze the experimental results.

3 Experiment

The fault diagnosis of the radio frequency circuit can be divided into two steps. The first step is the extraction and preprocessing of circuit fault parameters. The second step

is the establishment of parameter model and fault diagnosis.

3.1 Fault parameter extraction

1) Inject the open circuit and short circuit fault types into the capacitance, inductance, and resistance used in the circuit to obtain the fault characteristic parameters of the circuit, and record each fault type and the corresponding fault characteristic parameter data.

2) Because the degraded performance of electronic circuits is related to working time and ambient temperature. By changing the environmental temperature of the electronic circuit to accelerate its aging process, the extraction of characteristic parameters of the electronic circuit fault is completed. The advantage of this method is that it can better reflect the normal degradation process of electronic circuits and is more in line with the physical characteristics of electronic circuits.

We combined the two extraction method and proposed the ambient temperature used as the independent variable, the components in the circuit are injected with faults (open circuit, short circuit), and the S21 parameter of the low noise amplifier circuit is used as the dependent variable to extract the fault characteristic parameters.

3.2 Fault Model Training and Identification

According to the environment temperature as the independent variable, the components in the circuit are injected with faults (open circuit, short circuit), and the S21 parameter of the low-noise amplifier circuit is used as the fault characteristic parameter of the dependent variable to train the corresponding GMM-HMM fault models.

Through the GMM algorithm to fit the probability density function of the observation vector in each state, the probability matrix B of the observation vector can be obtained. Then combined with Baum-Welch algorithm for model training. The complete GMM-HMM training steps are shown in the Fig.3.

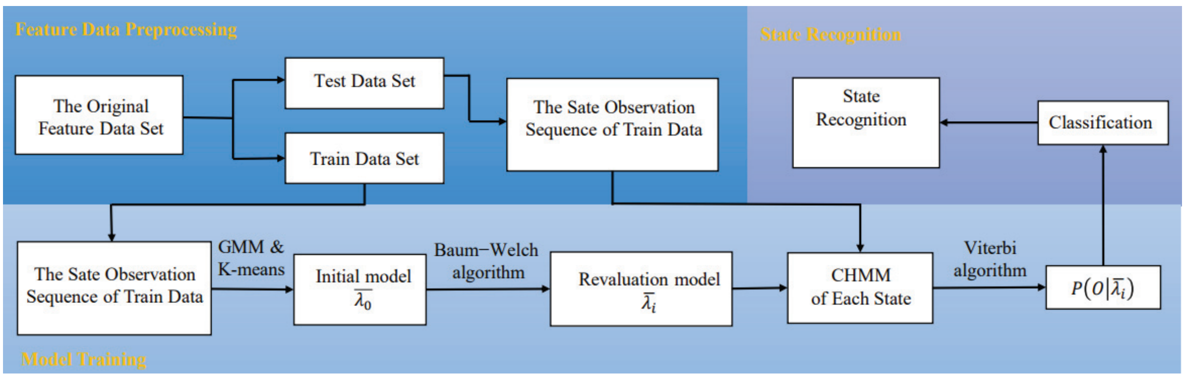

Fig. 3 Flow Chart of Fault Model Training

4 Simulation experiment and analysis

4.1 Simulation circuit

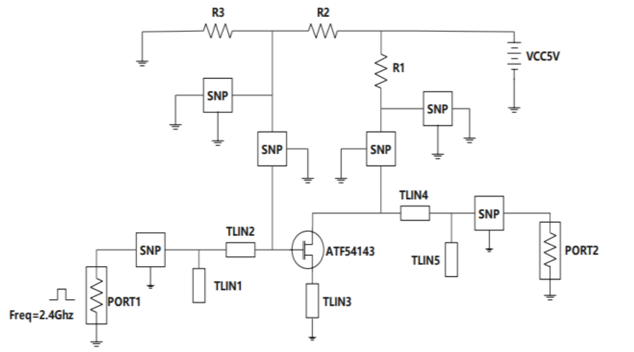

Fig. 4 ATF54143 Low Noise Amplifier Simulation Circuit

Low noise amplifier circuit is selected as the verification circuit, and results of the experiment will verify the effectiveness of the diagnostic method. As shown in Fig.4, considering the accuracy of components, this article considers that the resistance value deviation is ±5% as a reasonable range, and when the resistance value deviation exceeds this range, the circuit working state deviates from the normal working state.

4.2 Diagnostic steps

Combined with the diagnosis model proposed in this article, it is applied to the fault diagnosis of analog circuits. The diagnosis steps are as follows:

1) Inject faults into the circuit, such as opening and shorting R1, R2 and R3 respectively.

2) Change the ambient temperature, increase the simulated temperature from 25°C to 261°C, conduct a test every 2°C, and record S21 in each fault state.

Open or short R1, and set the deviation of other components to ±5%. The temperature was increased from 25°C to 261°C, and a test was performed every 2°C. The recorded part was extracted from S21 as shown in Table 1.

4.3 Analysis of diagnosis results

It is performed preliminary processing on the data to remove duplicate data and extracted fault data by injecting faults.After training data is removed, 30 sets of data are identified, five sets of 30 sets of data are one fault, and there are 6 sets of faults in total. They are R1 open circuit (R1O), R1 short circuit (R1S), R2 open circuit (R2O), R2 short circuit (R2S), R3 open circuit (R3O), R3 short circuit (R3S). The diagnosis results are shown in Table 2.

Table 1 Part of the Fault Data

T(℃)	**R1O** (S21)			**R1S** (S21)		
25	15.082	15.123	15.054	-11.909	-11.991	-11.850
27	15.069	15.110	15.041	-11.913	-11.995	-11.854
29	15.056	15.096	15.027	-11.917	-11.999	-11.859
31	15.042	15.083	15.014	-11.921	-12.002	-11.863
33	15.028	15.069	15.000	-11.925	-12.006	-11.867
35	15.014	15.056	14.986	-11.930	-12.010	-11.872
37	15.001	15.042	14.972	-11.934	-12.014	-11.877
39	14.986	15.028	14.958	-11.938	-12.018	-11.881
41	14.972	15.014	14.943	-11.943	-12.022	-11.886
43	14.958	14.999	14.929	-11.947	-12.026	-11.891
45	14.943	14.971	14.919	-11.952	-12.030	-11.895
…	…	…	…	…	…	…

Table 2 Fault Diagnosis Results

Fault type	Identification Sample/Test Sample
R1O	5/5
R1S	5/5
R2O	5/5
R2S	5/5
R3O	5/5
R3S	5/5

From the experimental results, five test samples of six fault categories can all be identified, fault identification accuracy rate is 100%, and the current fault data injection is mainly based on open circuit and short circuit. It can be seen from Table 1 that the difference between the two types of fault data is obvious, and the fault model trained in this way is also more distinguishable. Therefore, GMM-HMM fault diagnosis model is suitable for the extreme fault diagnosis of the low noise amplifier.

5 Conclusion

We proposed the method of fault diagnosis based on GMM-HMM algorithm for LNA circuit. ATF54143 transistor is used as the model to establish a low-noise amplifier circuit, and the method to extract the fault parameters is proposed. It is injected open circuit and short circuit fault types into active devices such as capacitors, inductance, and resistors used in the circuit to obtain the fault characteristic parameters. Component level fault diagnosis of the low-noise amplifier circuit is studied. The experimental results verify the feasibility of this method for radio frequency circuit fault diagnosis, and the accuracy of the fault model for short-circuit and open-circuit fault diagnosis is 100%.

It can be seen from the above research that the training sample data or the test sample data is small in size and the sample data is concentrated, and the recognition rate of the test samples is high. For the further research, We will adjust the critical state of more faults, select as many training and test samples as possible, and train and verify GMM-HMM. We can also extend to other radio frequency devices or radio frequency circuit life prediction and other fields.

6 Acknowledgements

This research would like to thank the support by the following three funds: China National Major Scientific Research Instrument Projects under Grant No.61727804, National Key R&D Program of China under the Grant 2017YFF0106705 and Automatic Detection Technology and Instrument in Guangxi Key Laboratory Open Fund under Grant No. YQ1520.

References

[1] Choi, U M., Blaabjerg, F., Lee, K B.:'Study and Handling Methods of Power IGBT Module Failures in Power Electronic Converter Systems', IEEE Transactions on Power Electronics, 2014, 30, (5), pp 2517-2533

[2] Binu,D., Kariyappa, B S. RideNN.:'A New Rider Optimization Algorithm-Based Neural Network for Fault Diagnosis in Analog Circuits', Instrumentation and Measurement, IEEE Transactions on, 2019, 68, (1), pp 2-26

[3] Lai W., Chen M., Ran L., et al:'Study on lifetime prediction considering fatigue accumulative effect for die - attach solder layer in an IGBT module', IEEJ Transactions on Electrical and Electronic Engineering, 2018, 13, (8), pp 613 – 621

[4] Xia Y, Xu Y, Gou B.: 'A Data-Driven Method for IGBT Open-Circuit Fault Diagnosis Based on Hybrid Ensemble Learning and Sliding-Window Classification', IEEE Transactions on Industrial Informatics, 2020, 16, (8), pp 5223-5233

[5] Zhibo L.: 'The Health Assessment of RF Circuit Based on Performance Degradation Data'. Master's Thesis, University of Electronic Science and Technology of China, 2015

[6] Zhigang L.: 'Research of Fault Prediction Method for RF Amplifier Module'. Master's Thesis, University of Electronic Science and Technology of China, 2018

[7] Hailin F, Lijun B.: 'Stochastic processes: Calculation and application'. (Xidian University Press, 2012, 1st edn.)

[8] Zhiwen Z, Xiaofeng W.: 'Incipient Fault Diagnosis of Analog Circuits Based on HMM-SVM'. Computer Measurement & Control, 2017,11, (25), pp 13-17

[9] Liangpei H， Hua H， Yonghua L.: ' A Fault Diagnosis Approach for Rolling Bearing Based on Wavelet Packet Decomposition and GMM-HMM', International Journal of Acoustics and Vibration, 2019, 24, (2), pp 199-209

[10] Ying-Rong Z, Wen-Bo S, Chang-Feng W U, et al.: 'Based on Improvement of HMM Analog Circuit Fault Prognostics Model', Fire Control & Command Control, 2018, 2, (43), pp 91-97