Fault prediction method of analog circuits based on MLSTM

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Abstract. According to statistics, most of the electronic equipment fault cases are related to the analog circuit, which may lead to the failure of the whole system due to the drift or performance degradation of the parameters of an electronic component in the analog circuit. However, because of the continuity of the parameters of each component, the lack of test nodes and the nonlinearity problems, the analog circuit becomes more difficult to prognose. The fluctuation and inconspicuousness of the degradation trend in analog circuits lead to the difficulty in extracting characteristic parameters and low accuracy of fault prediction. Therefore, a fault prediction method for analog circuits based on Multi-scale and Long-Short Term Memory (MLSTM) is proposed in this paper. Multi-scale feature learning method can divide the original data into different scales to improve the learning accuracy of small sample data. LSTM can well identify the temporal sequence of the widely separated events in the noise input stream. In this paper, the multi-scale feature learning method is combined with LSTM to improve the accuracy of fault prediction. Finally, the DC-DC switching power supply is taken as a case for verification, and the proposed method is compared with other algorithms to verify its accuracy and applicability.

1. Introduction

With the increasing maturity of PHM technology of mechanical products, fault prediction of various functions, scales and categories of electronic products contained in complex mechanical systems have gradually entered people's vision[1]. In the whole large-scale system or complex equipment, electronic system has gradually become the part with the highest failure rate. As the core basis and basic component unit of electronic system, analog circuit is the key to determine the reliability level of the whole system or the whole machine[2]. However, as electronic components become more and more precise and smaller in scale, and the internal structure of electronic products becomes more and more complicated, it is more and more difficult to monitor the corresponding characteristic parameters in the degradation state, and the relationship between failure state and degradation of components is no longer one-to-one. In addition, there are some hidden defects in the circuit and the circuit. There is no degradation characteristic, or the degradation characteristic cannot be detected[3]. What is shown is random failure or sudden failure, which adds many difficulties to the realization of fault prediction. Therefore, the research on fault prediction methods of analog circuits is a hot topic at present.

Current fault prediction techniques for analog circuits can be divided into two categories according to prediction principles: data-driven fault prediction methods and fault physical model-based fault prediction methods[4]. The prediction technology based on the fault physical model is a method based on the principle of Failure Physics to form the functional relationship between the operation mechanism of the tested object and the Physics of Failure (PoF), and to estimate the remaining service life and complete the evaluation of reliability. The fault prediction method based on the fault physical
model can reflect the physical nature of the failure of the tested object, but it requires high accuracy of the mathematical model. It is often difficult for large electronic systems or highly integrated analog circuits to establish physical models that meet the requirements, which has caused varying degrees of influence on the engineering application and practical effect of the method, making the prediction difficulty increase greatly with the increase of the complexity of the object.

Based on data-driven fault prediction method based on the system or equipment related parameters under normal working conditions remain relatively stable and meet certain degradation law assumption, characteristic parameters will increase as time presents a certain regularity of change trend, for the monitoring and analysis of characteristic parameters, and can get the system or the state of equipment in the future[5]. The core of this method is the fault prediction algorithm. The commonly used basic prediction algorithms include: Auto-regressive moving-average (ARMA), Bayesian Estimation (BE), Neural Networks (NN), Genetic Algorithms (GA), Particle Filter (PF), Support Vector Machine (SVM), Relevance Vector Machine (RVM), etc. Fault prediction method based on data driven does not need the complicated operating condition of electric and electronic system, the material characteristics, mechanical structure and the failure mechanism of deep understanding, only need to signal analysis of measurement data, and machine learning method is applied to modeling and forecasting, so there is no need to set up a large amount of complex physical or mathematical model. The disadvantage of this method is that the prediction accuracy depends on the parameters of the technology, such as the learning rate of neural network and the number of hidden layers. The penalty factor and width factor of SVM need to be set[6]. The width factor of the RVM needs to be set. When the parameters set are unreasonable, the prediction accuracy is not high.

In this paper, neural networks are used to predict the fault of analog circuits. Compared to other intelligent algorithms, neural network has great advantages. Neural network can not only be used in pattern recognition and fault diagnosis, but also in the field of fault prediction[7]. Many scholars devoted to the study of neural network fault prediction algorithm[8][9], zhi-gang tian by using generalized Weibull - FR function fitting values to generate training artificial neural network (ANN) input, using actual measured values build ANN validation set, reducing the noise of the has nothing to do with the equipment degradation factor influence, improve the performance of the ANN model[10]. However, the existing neural network-based prediction algorithms still have some shortcomings, such as the model's accuracy is too dependent on the initial value, the over-fitting phenomenon will appear in the training process, the required training sample data is large, and has the disadvantage of local convergence. Recurrent Neural Network(RNN) is a kind of recursive Neural Network for time series data, long-term dependence problems of RNN, namely in the treatment of the long span of time series nonlinear data, produces the gradient disappeared phenomenon, which makes the RNN in long time series forecasting the effect not well[11]. In order to solve the problem of very long interval and delay in time series, LSTM is proposed.

LSTM can overcome basic deep learning problems without any unsupervised training, and can also conduct deep learning without local sequence predictability[12]. The LSTM solved many deep learning can't solve the problem, including: identification of noise in the input stream is widely separated time sequence of events, in the long time interval data storage and high precision in a reliable way, arithmetic, extract event in continuous input stream passing through the time distance between information and noise in the input sequence time extension mode identification, precise timing interval generated by stable and smooth, and not smooth periodic trajectory. Multi-scale feature learning can divide the original data into different scales, improve the availability of small sample data and improve the learning accuracy of small sample data[13]. This paper combines multi-scale feature learning with LSTM[14], optimizes the LSTM algorithm, predicts the fault of analog circuit, and compares the prediction accuracy with other algorithms to verify the effectiveness of this method.

This paper is arranged in the following order: Section II introduces some basic theories including RNN, LSTM algorithm and multi-scale feature learning method. In the section III, fault prediction method based on multi-scale and long short-term memory network is mentioned. The Buck DC-DC
switching power supply is taken as an example to predict the fault in the section IV. It is verified that the method can obtain higher prediction accuracy in a long time and has practical application value. Finally, summary and future work prospects are provided in Section V.

2. Basic theory

2.1. Recurrent neural network
The unique ability of recurrent neural network (RNN) to process time series data is related to its special structure. The basic structure of RNN is shown in figure 1. In figure 1, the basic structure of RNN is shown on the left and its expanded form is shown on the right. X represents the input layer, s represents the hidden layer, and o represents the output layer. U is the weight matrix from the input layer to the hidden layer. W is the weight matrix from the hidden layer to the hidden layer, and V is the weight matrix from the hidden layer to the output layer. In the general neural network model, the information is transferred from the input layer to the hidden layer, and then from the hidden layer to the output layer. In RNN model, the state value of the hidden layer is also transferred to the hidden layer at the next moment. At time t, hidden layer s

\[ s_t = f(Ux_t + Ws_{t-1}) \]

where g and f are activation functions.

2.2. Long short-term memory network
Long Short-Term Memory Network (LSTM) is a kind of time RNN. Due to the problem of gradient disappearance, the RNN is difficult to process long sequence data. By improving the hidden layer structure, the LSTM structure solves the gradient disappearance problem in the RNN, making it possible to process long interval and high delay time series data. Its basic structure is shown in figure 2.

In the LSTM structure, there is an extra channel Ct for the information transfer between the hidden layers, which is called Cell State and denoted as C(t). Forget gate is also added between the original transfer channel and the input channel of input layer x, which is used to select with a certain probability whether to forget the hidden cell state of the previous layer in the hidden layer, usually controlled by the activation function sigmoid. After the forget gate, forget gate is combined with the
activation function tanh to form the input gate, which processes the input of the current sequence position and multiplicates the results of the two to update the cell state. The cell state is obtained by multiplying the output $\sigma$ of forget gate with the cell state $C_{t-1}$ at the previous time, and then adding the output of the input gate. The output $o_t$ at the current time is composed of two parts, namely the hidden layer $S_{t-1}$ at the previous time and the cell state $C_t$ at the current time, and the product of the two together constitutes the output $o_t$ at the current time.

![Figure 2. The basic structure of LSTM.](image)

2.3. Multi-scale feature learning

Multi-scale feature learning method is a data processing algorithm, which can divide the original data into different scales and obtain more abundant and complementary information. It can improve the availability of small sample data to a certain extent and improve the learning accuracy of small sample data, which is often used in the diagnosis of mechanical signals.

The basic principle of multi-scale learning is shown in equation (3).

$$y_{j}^{(s)} = \frac{1}{s} \sum_{i=\lfloor j/s \rfloor + 1}^{\lfloor j/s \rfloor + s} x_{i} \cdots \cdots 1 \leq j \leq \frac{N}{s}$$

where $x = \{x_1, x_2, \cdots, x_n\}$ is the original data, $i$ is the time mark, the total length is $N$; $S$ is coarse grained, usually a natural number; $Y$ is the data after multi-scale classification. The multi-scale feature learning method for an original signal is shown in figure 3.

In multi-scale feature learning method, coarse-grained operations naturally smooth. This operation can be thought of as a low-pass filtering process, moving the average value through a non-overlapping window to filter out high-frequency perturbations and random noises to some extent. It provides a more efficient way to characterize the original signal at a scale of one, where multiple coarse-grained signals contain different complementary fault information. In fault prediction, by adding time labels to signals of different coarse granularity, complementary information of different coarse granularity in the same time series can be obtained. Then, through the multi-input layer structure of neural network, better fault prediction results can be obtained.

3. Fault prediction method based on multi-scale and long short-term memory network

In this paper, an analog circuit fault prediction method based on MLSTM is proposed by combining multi-scale feature learning with long and short-term Memory network. The basic structure of MLSTM is shown in figure 4.
The specific steps are:

Step 1: Feature extraction. According to the functions of different analog circuits, the corresponding feature parameters are extracted, and the extracted feature vectors are divided into training set and test set.

Step 2: Multi-scale feature learning. The training set data is divided into multiple dimensions by multi-scale feature parameter learning method, and the multi-dimensional complementary data is obtained.

Step 3: Train LSTM model. Input the obtained multidimensional data into the multidimensional input layer of LSTM to train the LSTM network.

Step 4: Fault prediction. After the complete LSTM model is established, the test set are input into the model, the predicted values of future moments are obtained and compare it with the real data to verify the accuracy of the prediction model.

Figure 3. The example of multi-scale feature learning with coarse granularity of 2 and 3.
4. Case study
In this paper, a Buck-type DC-DC switching power supply\textsuperscript{[15]} is selected as the experimental object to verify the proposed fault prediction method. By analyzing the circuit schematic diagram and querying the selected component model, the simulation circuit model of the Buck type DC-DC switching power supply is drawn in Pspice, which is shown in figure 5. R1 is the equivalent resistance equivalent series resistance (ESR) of the aluminum electrolytic capacitor C1.

![Figure 5. Simulation circuit of Buck DC-DC switching power supply.](image)

![Figure 6. The ripple voltage of the sampling interval.](image)

4.1. Feature extraction
Aluminum electrolytic capacitor in 50 KHZ, 25℃, work conditions, the initial equivalent resistance ESR (0) = 0.045 Ω. The rated life of this type of aluminum electrolytic capacitor is generally around 2000h under the working conditions of 50KHz and 25℃. Therefore, the variation rule of ESR of this type of aluminum electrolytic capacitor over time can be calculated by using equation (4)\textsuperscript{[16]} as shown in figure 6.

\[
\frac{1}{ESR(t)} = \frac{1}{ESR(0)} \left(1 - kt \cdot \exp\left(-\frac{4700}{T + 273}\right)\right)
\]

where ESR(t) is the ESR value at time t, ESR(0) is the ESR value at the initial time, T is the temperature at which the capacitor operates, K is a constant, which is related to the design and materials of capacitors.

In Pspice, the resistance value of R1, the equivalent resistance of C1 in the simulation circuit diagram, was set according to the variation law to simulate the degradation process of the actual aluminum electrolytic capacitor. The simulation was carried out at the ambient temperature of 25℃. Set the simulation time to 6ms, the sampling interval to 5ms-6ms, and the sampling interval to 1us. When the ESR is 0.045Ω, the sampling interval ripple voltage is shown in figure 6.

Ripple voltage is an important parameter to measure circuit performance. When the aluminum electrolytic capacitor is degraded, the value of the output ripple voltage will increase. Therefore, the peak-to-peak value of the ripple voltage is selected to measure the magnitude of the ripple voltage, which is used as a characteristic parameter. The degradation process of aluminum electrolytic capacitors is relatively slow. Therefore, according to the change rule of aluminum electrolytic capacitor ESR, simulation is performed every 40h, and the peak-to-peak value of the ripple voltage in the sampling interval is extracted by time domain analysis.

4.2. MLSTM vs. Other Optimization Algorithms
The peak-to-peak value of the ripple voltage at the time of 0–30Δt in the table is selected as the training sample, and the value of the future time is predicted by using MLSTM, LSTM, SVM, and grey model. The comparison results are shown in figure 7 and figure 8. Among them, the grey model
The prediction algorithm takes 34.5s, the SVM algorithm takes 75.03s, and the MLSTM algorithm takes 25.485s.

It can be seen from figure 7 and figure 8 that MLSTM method is more accurate than LSTM method, especially with smaller error in long-term prediction. In the comparison of grey model prediction algorithm and SVM prediction algorithm, MLSTM fault prediction algorithm has certain advantages in accuracy and operation time, which proves the value of this method in analog circuit fault prediction.

Figure 7. The prediction results of MLSTM, LSTM, grey model prediction method and SVM method.

Figure 8. Prediction error comparison of MLSTM, LSTM, grey model prediction method and SVM method.

4.3. The performance of MLSTM method in fault prediction under noisy signal
In order to test the fault prediction performance of MLSTM method for noisy signals due to various noises when the electronic equipment is working, this paper adds ±0.2 random disturbance to each value of the training set, and then makes fault prediction. The prediction results are shown in figure 9.

As can be seen from figure 9, with the addition of noise disturbance, the fault prediction accuracy of MLSTM can still reach 6.37%, still with high accuracy, which proves that this method has certain anti-interference ability and is suitable for fault prediction of analog circuit.

Figure 9. The fault prediction results of MLSTM and LSTM under noise signal.

5. Conclusion
In this paper, the principle, algorithm and structure of circular neural network RNN and LSTM are studied, and the multi-scale feature learning method is introduced into the LSTM method, and an
analog circuit fault prediction method based on MLSTM is proposed. Based on the degradation data of Buck type dc-dc switching power supply, the fault prediction method is analyzed, and compared with grey model prediction algorithm and support vector machine prediction algorithm. Finally, the prediction performance of MLSTM under noise signal is studied. The results show that MLSTM method has certain advantages in prediction accuracy, running time and anti-interference, and has certain practical value in fault prediction of analog circuit.

Several directions for future research are proposed. Firstly, some public datasets should be tested in the future to validate and extend the proposed algorithm. Secondly, the MLSTM method based fault prediction method is only applied in the fault prediction of DC-DC switching power supply. In the future, it can be applied to other electronic products to verify the applicability of the proposed method.

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