IGBT lifetime prediction based on EMD-LSTM

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Abstract. Aiming at the problem of fatigue failure caused by the cyclic impact of thermal stress and electrical stress during IGBT operation, a long short-term memory (LSTM) network life prediction method based on EMD (Empirical Mode Decomposition) decomposition is proposed. This experiment uses the accelerated aging data set provided by the NASA PCoE laboratory, analyse and select the collector-emitter transient spike voltage as the failure characteristic parameter, and use the EMD algorithm to decompose the original time series into multiple relatively stable and with different characteristic scales the eigenmode function and trend term reduce the complexity of the time series. Through the LSTM network prediction model, the decomposed eigenmode function components and trend items are respectively predicted, and then the prediction results are superimposed to obtain the result. The results show that the prediction accuracy of the EMD-LSTM model is higher, and it can better realize the life prediction of IGBT, and it also has certain reference value for the life prediction of other power electronic devices.

1. Introduction

Insulated gate bipolar transistor (IGBT) is a composite device that combines power field effect (MOSFET) and bipolar power transistor (BJT) structure. It has the advantages of low driving power, fast switching speed, and ability to withstand higher voltages. At present, IGBT as a basic electronic device has been widely used in power electronics, especially in fields such as switching power supplies and inverters [1]. Unexpected or sudden failures of IGBTs may occur during use, resulting in excessive equipment downtime, resulting in high maintenance costs and large revenue losses. The gradual degradation of IGBT performance reduces the working efficiency of electronic equipment, and the failure of the device will also cause the failure of the entire electronic system [2]. Therefore, the prediction of the remaining service life of the IGBT is of great significance for the safe and reliable operation of the equipment.

The life prediction methods of IGBT can be divided into two categories: 1) Methods based on physical models. Deng [3] used COMOL to model IGBT with multi-physics coupling and conduct power cycle simulation and substitute the change law of stress and strain during power cycle into a suitable prediction model to predict the life of IGBT. When the simulated failure model of the actual failure mechanism is accurate, the physical model-based method can provide effective predictions. However, in actual working conditions, it is difficult to build the accurate physical model of the device is established, so this method is greatly restricted. 2) Based on a data-driven approach. The characteristic information of the health status is extracted from the historical data of product performance. These
historical data can usually describe the aging development process of the device, and by establishing a reasonable mathematical model for in-depth analysis of the historical data of its characteristic parameters, the healthy development of the device can be effectively predicted [4, 5]. Li [6] used NASA’s accelerated aging data of IGBTs, analysed and selected the collector-emitter transient spike voltage as the failure characteristic parameter, and used BP neural network to construct the life prediction model of the IGBT, but its extreme value is small. And the training time is long and the prediction effect is average. Chen Bing et al. [7] proposed a prediction model based on DBN, which analysed and predicted the failure characteristic parameters of IGBT. Although it overcomes the shortcomings of local optimization and long training time in the training process, its prediction accuracy is not high. Therefore, this paper proposes a long short-term memory (LSTM) network model based on the decomposition of the EMD (Empirical Mode Decomposition) algorithm to apply to the life prediction of IGBT. LSTM can effectively capture long-term time-varying information, and has achieved excellent results in handwriting recognition, natural language concise translation and time series data prediction. This paper constructs an LSTM network prediction model and constructs an ARIMA prediction model and an ELMAN neural network prediction model as a comparative analysis, aiming to verify the superiority of the EMD-LSTM network in predicting the life of IGBTs.

2. IGBT failure modes and mechanisms

The reliability of IGBT is defined as the ability to complete its design function under certain conditions, that is, the ability to not fail. The standard for measuring reliability is the probability of failure. Reliability is directly related to the probability of failure. According to the causes of its failure, IGBT failure is divided into thermal breakdown and electrical breakdown, which are caused by many factors, and at different stages of the IGBT’s entire life cycle, the main factors and probability of failure are also different.

Research shows that there are three failure modes of IGBT: 1) Defect failure. Defect failures are caused by the defects or damages of the IGBT itself. The defects of various processes in the manufacturing process, including the structural design of the device itself, the equipment process, the accuracy of quality control, the quality of raw materials, etc., are often impossible to produce. Avoided, the quality inspection before leaving the factory cannot be guaranteed to be completely eliminated. 2) Random failure. The occurrence of random failures is not caused by the IGBT itself, but by some external random factors (pulse error, drive failure, overcurrent, overvoltage, etc.). The occurrence of failure is random and accidental. If it exceeds the safe working area of the IGBT, it may cause failure. 3) Fatigue failure. IGBTs are subjected to the cyclical impact of electrical and thermal stresses during operation. After long-term accumulation, they will cause chip and package fatigue, resulting in failure. The life cycle of IGBTs is directly related to fatigue failure. In view of the above three failure modes, there are three phases corresponding to them: the initial stage, the middle stage and the later stage. The probability distribution diagrams of the three types of failures are shown in Figure 1.

![IGBT Failure rate curve](image1)

![IGBT turn-off peak voltage curve](image2)
The initial defect failure can be detected by the defect detection before the finished product leaves the factory, effectively avoiding the initial defect failure after the product is put into use. Random failures in the mid-term can be effectively avoided in the mid-term after its use by improving the design level and the level of operation and use. In the later period of fatigue failure, fatigue damage gradually accumulates as the use time of IGBT increases. This process is unavoidable and irreversible. Therefore, fatigue failure is the key to the life cycle of IGBT. In the process of fatigue failure, some of its internal characteristic parameters will change and have a certain trend of change, which plays a vital role in the life prediction research of IGBT.

3. IGBT thermal stress accelerated aging test analysis

3.1. Accelerated aging test equipment and aging data

In order to explore the aging failure process of IGBT and provide a basis for its life prediction and health diagnosis, NASA has developed an accelerated aging experiment system. The accelerated aging test of IGBT is a project of NASA to study the degradation characteristics of electronic components. Because the consumption of electronic components in power equipment is increasing, and the number of electronic failures is also increasing, it is necessary to conduct systematic research. Fault diagnosis, prediction of remaining service life and health management play an important role in avoiding catastrophic failures and reducing maintenance costs. Normally, the service life of IGBT is the same as most power devices, and the cycle is relatively long, and researchers cannot collect the characteristic parameter data of the complete aging process. Therefore, the accelerated aging data of IGBT can be collected through the thermal stress accelerated aging experimental device [8]. This paper analyzes and selects the aging characteristic parameters through the accelerated aging data set provided by the NASA Prediction Center and uses the LSTM network prediction algorithm to predict the data.

3.2. Selection of failure characteristic parameters

In the early use process, the external aging characteristic parameters of the IGBT basically did not change, but as the use period increases, the aging characteristic parameters of the IGBT will change according to a certain trend. The service life of the device can be predicted by observing the changes of these parameters. The application scenarios of IGBT are often used as switching devices. Frequent turn-on and turn-off of IGBT will produce switching loss, so it can be considered that it has caused the aging failure of IGBT [9]. Observe through aging data analysis shows that the transient spike voltage value of collector-emitter (V_{CE-p}) has an obvious downward trend, so it can be selected as the failure characteristic parameter and the life expectancy can be carried out. The change process of the V_{CE-p} with the sampling period in the accelerated aging data set published by NASA Forecast Center is shown in Figure 2. Through observation, the V_{CE-p} changes with the degradation of the IGBT decrease gradually.

4. IGBT lifetime prediction based on EMD-LSTM network

4.1. LSTM network

![Figure 3 LSTM neural network structure](image-url)
LSTM is a variant of Recurrent Neural Network (RNN), proposed by Sepp Hochreiter and Jürgen Schmidhuber in 1997. RNN may experience gradient disappearance and gradient explosion when processing distant sequences, which makes it lose its ability to perceive distant moments. The unique structure of LSTM can effectively solve the above-mentioned problems in the RNN training process. As shown in Figure 3, the LSTM cell unit is composed of a gating unit and a memory unit, and the gating unit includes input gates, output gates and forgetting gates [10].

The expression of the forget gate structure is as follows:

\[ f_t = \text{sigmoid}(W_f[h_{t-1}, x_t] + b_f) \] (1)

Where: \( f_t \) is the output of the forget gate, \( x_t \) is the input sequence, \( W_f \) is the weight matrix, \( h_{t-1} \) is the final output of the cell unit at the previous moment, and \([h_{t-1}, x_t]\) represents the connection of two vectors into a long vector, \( b_f \) is the offset term, the probability of 0 to 1 is output after passing the sigmoid function. Similarly, the input gate and output gate can be expressed by the following formula:

\[ i_t = \text{sigmoid}(W_i[h_{t-1}, x_t] + b_i) \] (2)

\[ g_t = \tanh(W_a[h_{t-1}, x_t] + b_a) \] (3)

\[ c_t = i_t \odot g_t + f_t \odot c_{t-1} \] (4)

\[ o_t = \text{sigmoid}(W_o[h_{t-1}, x_t] + b_o) \] (5)

\[ h_t = o_t \odot \tanh(c_t) \] (6)

In the above formula: it is the output of the input gate, \( g_t \) may be added to the cell state as a candidate value of the current layer, \( c_t \) is the current memory cell state, and the whole process is to update the memory cell state at the previous moment. That is, the process of discarding useless information and adding new information. \( o_t \) is the output of the output gate, and \( h_t \) is the final output of the LSTM at the current moment.

4.2. EMD Time sequence decomposition

The prediction of time series requires the establishment of an accurate prediction model for the training data, so as to establish the internal relationship of the time series and provide an accurate basis for the subsequent prediction process. Most time series models in engineering applications have typical nonlinear and non-stationary characteristics. For these time series with high complexity, if the forecast model is directly established, it is difficult to meet the forecast accuracy requirements. This study uses the EMD-LSTM algorithm to reduce the complexity of the time series by EMD decomposition of complex non-stationary time series, thereby Complete the LSTM modeling of the less complex IMF component.

EMD is a new type of signal decomposition method. It has good results in the processing of nonlinear and non-stationary signals [11]. The EMD algorithm decomposes complex signals into multiple IMFs and a trend term. The expression is:

\[ s(t) = \sum_{i=1}^{n} \text{imf}_i(t) + r(t) \] (7)

Among them, \( S_t \) is the original signal; \( \text{imf}_i \) is the i-th IMF component; \( r(t) \) is the trend item.

5. Simulation analysis

It can be seen from Figure 2 that the original time series of \( t \) presents strong nonlinearity and instability, and the complexity of the sequence is relatively high. The EMD decomposition method is used to process the original data sequence to reduce the complexity of the sequence. The result is shown in Figure 4.
For each IMF component and trend item, construct a prediction model. Select the first 334 data as the training set, and the remaining 84 data as the test set. Take root mean square error (RMSE) and mean absolute error (MAE) as indicators to measure EMD-LSTM algorithm’s ability to predict time series.

\[
RMSE = \left( \frac{1}{n} \sum_{i=1}^{n} \left( y_i - \hat{y}_i \right) \right)^{1/2}
\]

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|
\]

Where: \( n \) is the number of predictions, \( y_i \) is the true value, and \( \hat{y}_i \) is the predicted value.

The \( V_{CE-p} \) value is time series data. The sequence is divided into training set and test set. The first 80% of the sequence is used for training and the 20% is used for testing. The solver is set to ‘Adam’, the initial learning rate is 0.005, and 500 rounds of training are performed, the learning rate drop factor is set to 0.2, and the drop period is 250. In order to prevent the gradient from exploding, the gradient threshold is set to 1. The prediction result of the EMD-LSTM network model is shown in Figure 5.
Table 1  Comparison of prediction model evaluation indicators

| Model    | RMSE   | MAE   |
|----------|--------|-------|
| ARIMA    | 0.0653 | 0.0134|
| LSTM     | 0.0376 | 0.0121|
| EMD-LSTM | 0.0197 | 0.0089|

Figure 6 shows the comparison between the prediction results of the ARIMA, LSTM and EMD-LSTM networks with the real data. Through the comparative analysis of the predicted value curve in the figure and the true value curve and the evaluation indicators in the table 1, the EMD-LSTM network prediction is feasible for the life prediction of the IGBT, and it can be well predicted, and it can be used for other power electronics. The lifetime prediction of the device also has certain reference value.

6. Conclusion

Aiming at the problem of IGBT lifetime prediction, this paper proposes a lifetime prediction method based on EMD-LSTM network. Using the IGBT accelerated aging data set provided by NASA Prediction Center and selecting its failure characteristic parameters, the failure characteristic parameters are predicted through the constructed LSTM network prediction model, and the prediction results of the ARIMA model are compared and analysed. The results show that the method used in this paper has higher accuracy and applicability, which is conducive to the evaluation of IGBT operating conditions and equipment maintenance. Therefore, the life prediction method proposed in this paper has a certain reference value for the life prediction of other power electronic devices. In future research work, the optimization algorithm of LSTM can be further improved, and the learning ability of time series prediction can be improved.

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