



# IGBT Performance Degradation Feature Construction and Real-Time Prediction Based on Machine Learning

Xin Wang<sup>1,2</sup>, Zhenwei Zhou<sup>1</sup>(✉), Shilie He<sup>1</sup>, Hanguang Jia<sup>1</sup>, and Yun Huang<sup>1</sup>

<sup>1</sup> The Science and Technology on Reliability Physics and Application of Electronic Component Laboratory, China Electronic Product Reliability and Environmental Testing Institute, Guangzhou 510610, China

zhouzw\_ceprei@163.com

<sup>2</sup> School of Automation and Engineering, South China University of Technology, Guangzhou 510641, China

**Abstract.** Insulated gate bipolar transistor (IGBT) has developed rapidly in recent years, and its performance is excellent in high voltage, high current and high frequency applications, which makes it been regarded as an ideal power module. However, due to the long-term operation in harsh conditions, the degradation of IGBT occurs from time to time, which will cause irreversible damage to electronic equipment and even affect the normal operation of the whole system. Therefore, it is necessary to establish a reliable IGBT anomaly detection system and apply the performance degradation prediction technology to the prediction of IGBT in the whole life cycle. In this paper, based on the data-driven method of degradation characteristic parameters, combined with grey correlation degree, Mahalanobis distance, Kalman filter, support vector regression and other methods, the performance degradation prediction of IGBT is completed and the above methods are verified and analyzed based on NASA public data.

**Keywords:** IGBT · performance degradation prediction · Feature dimension reduction

## 1 Introduction

Insulated gate bipolar transistor (IGBT) has developed rapidly in recent years, which has the advantages of bipolar transistor (BJT), such as high current density, low saturation voltage and strong current handling ability, and metal oxide semiconductor field effect transistor (MOSFET), such as simple driving circuit, high switching speed and low switching loss [1]. IGBT can show the incomparable performance of other semiconductor devices in the application scenarios of high voltage, high frequency and high current. As a national strategic emerging industry, IGBT is widely used in rail transit, smart grid, aerospace, electric vehicles and new energy equipment [2].

However, if the IGBT is operated under high voltage and high current conditions for a long time, overheating and overvoltage may occur, which will speed up the failure process of the IGBT. According to a survey conducted by German Wind Energy on converters, the results showed that converter failures caused by IGBTs and welding accounted for 34% of the total failures [3]. As the core device of electronic equipment, the failure of IGBT will cause the electronic equipment failed to work normally, thus causing the failure of the entire system and bringing huge economic loss. Therefore, it is necessary to establish a reliable IGBT anomaly detection system to perform reasonable performance degradation prediction and remaining life (RUL) estimation for IGBTs in the whole life cycle.

The data-driven method based on degradation characteristic parameters is the most widely used IGBT performance degradation prediction method with relatively excellent prediction effect. Its idea is to construct characteristic parameters that can characterize IGBT performance degradation by relying on historical degradation data collected by sensors, through preprocessing, feature extraction, feature selection, feature dimensionality reduction, etc., and then use machine learning, deep learning and other methods to establish a degradation prediction model to predict IGBT performance degradation in the whole life cycle.

The parameter information that the sensor can monitor usually includes collector-emitter voltage, collector-emitter current, gate current, gate voltage, etc. These parameters that can characterize IGBT performance degradation after feature extraction, dimension reduction and other operations are usually called fault precursor parameters. Ge et al. used the peak-to-peak value of transient collector-emitter voltage as the characteristic parameter of performance degradation, and based on DeepAR time series prediction model, drew the prediction curve of IGBT performance degradation, achieving the remaining life prediction of IGBT [4]. In reference [5], the peak data of IGBT collector-emitter voltage is extracted and input into the Stacking fusion model for the real-time prediction of IGBT performance degradation. In addition, all references [6–12] chose the collector-emitter voltage as the precursor parameter of the prediction model.

The related research on using collector-emitter voltage as a fault precursor parameter has been very comprehensive, but other parameters collected by sensors also have the potential as precursor parameters. In this paper, gate current and collector-emitter current are selected as precursor parameters, and the performance degradation characteristics are extracted by using the theory based on Kalman filter, grey correlation degree and Mahalanobis distance. Based on the basic principles of support vector regression (SVR) and time series prediction, the real-time prediction of IGBT performance degradation is completed, and the highest training score reaches 0.919, which proves the feasibility and accuracy of this method. In addition, the feature extraction method for extracting the peak-to-peak or tip value of the data set can still be further optimized. This paper extracts the time domain features of 13 channels of the data set for selection and fusion, which can reflect the degradation process of precursor parameters more comprehensively and objectively.

## 2 Introduction of the IGBT Degradation Prediction Model

The specific process of IGBT performance degradation prediction in this paper is shown in Fig. 1, and the key part of the algorithm is the construction of degradation characteristics and the establishment of prediction model. This section will introduce the algorithm principle involved in the prediction model in detail.

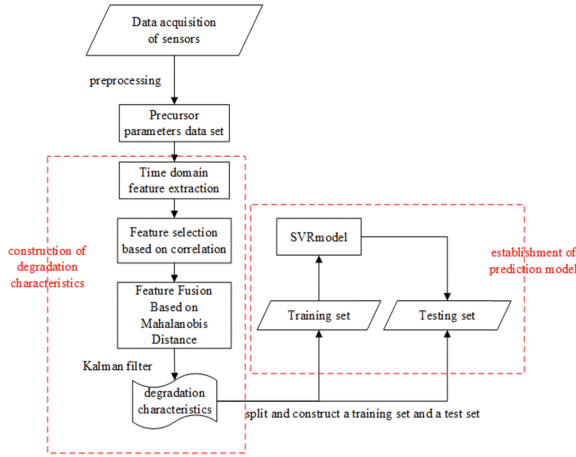


Fig. 1. Flow chart of performance prediction algorithm

### 2.1 Construction of Degradation Characteristics Based on Grey Correlation Degree and Mahalanobis Distance

Time domain features of 13 channels will be obtained after selection, but not all features contain degradation information of IGBT. In this paper, the gray correlation degree is used to analyze the periodic correlation of the obtained time domain features, and then the time domain features with high periodic correlation and obvious degradation information are selected.

Deng’s correlation degree is widely used at present. It is a method to measure the correlation of two series ( $X_0$  and  $X_i$ ) curves from the perspective of similarity. The calculation formula is as follows:

$$\gamma(X_0, X_i) = \frac{1}{n} \sum_{k=1}^n x_i(x_0(k), x_i(k)) \tag{1}$$

$$\xi_i(x_0(k), x_i(k)) = \frac{\min\min|x_0(k) - x_i(k)| + \zeta \max\max|x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \zeta \max\max|x_0(k) - x_i(k)|} \tag{2}$$

where  $\zeta$  represents the resolution coefficient, which is generally within the range of (0, 1).

To obtain one-dimensional performance degradation features, Mahalanobis distance is chosen in this paper. The larger Mahalanobis distance is, the greater the deviation between sample sets is, which is consistent with the degradation process of IGBT. There are sample set  $X$  and sample set  $Y_{m \times n}$ , where  $X$  is a row vector composed of  $n$  sample points, and the Mahalanobis distance between  $X$  and  $Y_{m \times n}$  is calculated as shown in formula (3).

$$MD = \sqrt{|(X - \bar{Y}) \sum^{-1} (X - \bar{Y})^T|} \tag{3}$$

### 2.2 Establishment of Prediction Model Based on SVR Model and Basic Theory of Time Series Prediction

Support Vector Regression (SVR) is a supervised learning algorithm for predicting discrete values. The model function of SVR is the same as that of linear function, but loss calculation principles, objective function and optimal algorithms of them are different.

SVR constructs a “gap zone” on both sides of the linear function, and all the sample points covered by the “gap zone” aren’t included in the loss. Compared with the strict fitting rules of linear regression, SVR is more tolerant, and  $\xi_i$  and  $\xi_i^*$  are relaxation variables that SVR needs to introduce.

$$\begin{cases} \xi_i = y_i - (f(x_i) + \varepsilon) & y_i > f(x_i) + \varepsilon \\ \xi_i = 0 & \text{others} \end{cases} \tag{4}$$

$$\begin{cases} \xi_i = (f(x_i) - \varepsilon) - y_i & y_i > f(x_i) + \varepsilon \\ \xi_i = 0 & \text{others} \end{cases} \tag{5}$$

Equations (4) and (5) are expressions of relaxation variables. The mathematical description of SVR problem is as follows:

$$\min_{w, b, \xi, \xi^*} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\xi_i + \xi_i^*) \quad \xi_i \geq 0; \xi_i^* \geq 0; i = 1, 2, \dots, m \tag{6}$$

$$w = \sum_{i=1}^m (\alpha_i^* - \alpha_i) x_i \tag{7}$$

$$f(x) = \sum_{i=1}^m (\alpha_i^* - \alpha_i) x_i^T x + b \tag{8}$$

$$b = \frac{1}{|S_u| + |S_d|} \left[ \sum_{s \in S_u} (y_s + \varepsilon - wx_s) + \sum_{s \in S_d} (y_s - \varepsilon - wx_s) \right] \tag{9}$$

If the result obtained by the above formula is not good, you can try to map the sample to a higher space, that is, the feature space, for SVR learning.

Time series can be considered as the numerical series formed on each time node. Single-step prediction is the basis of time series prediction model [13], which can complete the real-time prediction of IGBT performance degradation by outputting the results

of the next time node according to the past data. It should be noted that the prediction of time series is not about the regression of time, but about the study of its own changing law. Blindly using prediction algorithm to fit time series data is likely to get over-fitting results with high time correlation.

### 3 Experimental Results and Discussion

#### 3.1 Data Preprocessing

This section takes the extraction of trailing current ( $I_{CE}$ ) as an example to illustrate the acquisition of precursor parameter data set. After the IGBT is turned off, the process of collector current decline can be divided into two stages: sharp drop and slow drop, and the collector current in the slow drop stage is called trailing current. The extraction of gate leakage current ( $I_G$ ) is similar, and finally the precursory parameter data set of 700 cycles can be obtained.

To better characterize the degradation process of IGBT in the whole life cycle, the collected precursor parameter data sets were extracted in time domain, and the time domain characteristics of 13 channels, such as maximum, minimum, variance and skewness, were obtained.

#### 3.2 Feature Selection Based on Correlation Analysis

In this section, taking the time domain characteristics of ICE as an example, Deng's correlation degree is used to measure the correlation between the two sequences.

According to formulas 1 and 2, the correlation degree between each feature is calculated. Considering the performance of features comprehensively, the time domain features with less degradation information and higher correlation degree are eliminated. The finally selected time domain features are shown in the following table (Table 1):

**Table 1.** Selected time domain characteristics and periodic correlation degree

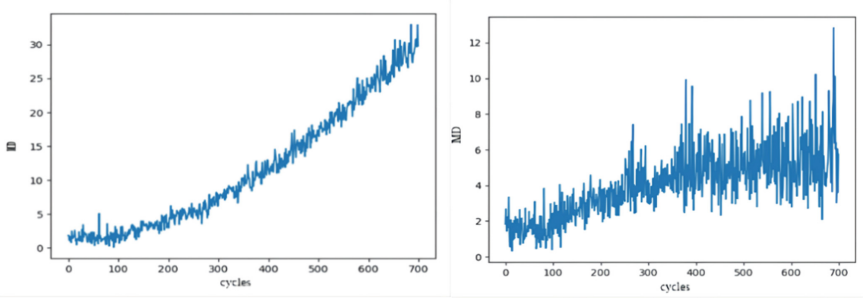
	Feature1	Feature2	Feature3
$I_{CE}$	Minimum /0.79	Skewness/0.75	Square root amplitude/0.75
$I_G$	Root mean square/0.67	Kurtosis/0.94	Crest factor/0.97

#### 3.3 Dimension Reduction with Mahalanobis Distance and Kalman Filter

To reduce the dimension of the feature matrix obtained in Sect. 3.2, using the data of the first 100 cycles as the healthy sample set  $Z_{100 \times 3}$  and the characteristic matrix  $Y_{700 \times 3}$  as the input of formula (3), two healthy deviation degree  $MD_{700 \times 1}$  matrices are obtained.

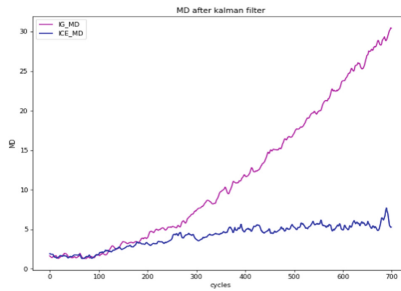
The obtained degradation characteristics of IGBT performance (i.e. healthy deviation MD) are shown in Figs. 2. It can be observed that with the increase of cycle period, MD

gradually increases, and the performance of  $I_G$  is particularly obvious, indicating that IGBT gradually degrades until it fails. There is obvious noise in the features extracted from the trailing current in Fig. 2(b), so the Kalman filter is trained to reduce the noise of the noisy deviation. The results are shown in Fig. 3.



(a) Health deviation of  $I_G$ .(b)Health deviation of  $I_{CE}$ .

**Fig. 2.** Mahalanobis distance deviation matrix timing diagram



**Fig. 3.** MD timing diagram processed by Kalman filter

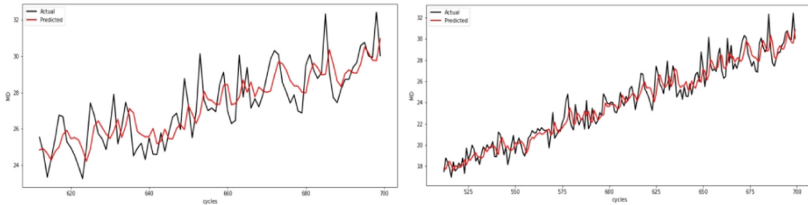
### 3.4 Prediction of IGBT Performance Degradation Based on SVR

As the degradation of  $I_G\_MD$  in Fig. 2 is obvious, this section uses this as the training data of the prediction model to predict the performance degradation of IGBT. The prediction of MD time series depends on historical data. The MD input matrix is defined as  $(X_{t1}, X_{t2}, X_{t3}, \dots, X_{t700})$  and it is necessary to artificially add a historical window to MD at each T moment. After a lot of experiments, 10 cycles are used as historical window here.

MD matrix is then split into training set and test set. The history windows added in the previous section are taken as the characteristics (x), and the MD at the current time t is taken as the label (y). In this experiment, two groups of MD samples were predicted, and the predicted lengths were 200 cycles and 100 cycles respectively.

Figure 4(a) shows the MD prediction curve with a predicted length of 100 cycles, in which the abscissa is the cycle period, the ordinate is MD, the red curve is the prediction

curve, and the black curve is the actual deviation curve. The training score of the model is 0.645 (the total score is 1). The lateral deviation of the predicted curve can be clearly observed. At the end of degradation of IGBT, each deviation peak may be the time node of device failure. The lateral deviation will lead to the forward or backward movement of the predicted failure time, and the backward movement of the predicted failure time will cause the staff to stop the failed device in time.



(a) MD prediction curve of 100 cycles (b) MD prediction curve of 200 cycles

**Fig. 4.** Prediction of  $I_G\_MD$

Figure 4(b) shows the MD prediction curve with a prediction length of 200 cycles, and the training score of the model is 0.919. Compared with the prediction curve in Fig. 4(a), the prediction curve in Fig. 4(b) is obviously closer to the actual situation. It is worth mentioning that the prediction curve in Fig. 4(b) can accurately cover the MD peak in the actual situation, but in terms of longitudinal value, the prediction curve is always lower than the deviation value of the actual time  $T$ .

## 4 Conclusion

- (1) In this paper, gate leakage current and collector-emitter tail current are used as precursor parameters to conduct prediction research. For degradation feature construction, the grey correlation analysis, Mahalanobis distance and Kalman filter method are integrated. For IGBT performance degradation prediction, SVR model is used in combination with the basic theory of time series.
- (2) After feature selection and feature dimensionality reduction, the degradation characteristics of IGBT, that is, healthy deviation, gradually increase with the increase of cycle period, which proves the existence of degradation. The degradation characteristics extracted from gate leakage current also show time-sensitive characteristics.
- (3) Based on the basic theory of SVR and time series prediction, a prediction model of IGBT performance degradation is constructed. Through the prediction experiment of gate leakage current degradation characteristics, the training score is as high as 0.919, and the peak of the prediction curve basically covers the actual data curve, which proves the accuracy and feasibility of the model.

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