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METHODS

# Segmental Degradation RUL Prediction of IGBT Based on Combinatorial Prediction Algorithms

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**ABSTRACT** Aiming at the segmentation nonlinear degradation characteristics of IGBT, the traditional single remaining useful lifetime (RUL) method has low accuracy. This paper proposes a method combining gray prediction and particle filter algorithm. The gray prediction model is used for slow degradation trends prediction in the early stage. When the health precusor parameters reach the fault warning line, the improved particle filter algorithm is used for this stage's prediction with the characteristics of fast nonlinear degradation. The comparison analysis result shows that the combinatorial prediction algorithms used in this paper can be better for tracking the degradation trends of IGBT, and the prediction accuracy is higher than either of the two single prediction methods.

**INDEX TERMS** IGBT, power cycling, accelerated aging, gray prediction, particle filter, RUL prediction.

## I. INTRODUCTION

At present, the insulated gate bipolar transistor (IGBT) has been widely used in AC motor, inverter, switching power supply, aerospace and many other fields. The maintainability of IGBT has put forward higher requirements. Therefore, it is of great significance to study the health status and life prediction of IGBT for the reliable operation and safe production of electrical devices [1], [2], [3], [4].

Fault prediction principles can be divided into three categories:

1) Fault prediction technology based on physical models;

2) Prediction techniques based on statistical probability reliability;

3) Data-driven fault prediction techniques.

Among them, the current models used to predict the lifetime of IGBT are mainly analytical and physical. Based on IGBT life prediction analytical models, such as Norris-Landzberg model, simple Coffin-Manson model, Lesit model and Bayerer model, the lifetime of an object can be reflected by fitting aging data, which is intuitive but cannot explain the intrinsic relationship of variables. IGBT life prediction physical models, such as strain principle, energy principle and cracking mechanism, comprehensively reflect the influence mechanism of life by obtaining the failure mechanism and deformation mechanism of object module, but it is difficult to model. Bai Liangjun et al. established the aging model of IGBT module by using three groups of accelerated aging data, and predicted the remaining useful life (RUL) of IGBT module [5]. Wang He et al. simulated the electric-thermal coupling effect of IGBT module based on MATLAB/Simulink, and obtained the corresponding relationship between junction temperature change and lifetime degradation [6]. The above methods need to obtain a large amount of prior data, material and structure information of IGBT, and the accuracy of the model depends on the parameter estimation and calculation of a large number of experiments. Therefore, it is difficult to accurately establish the lifetime prediction model of IGBT. Data-driven methods have been widely used in recent years because they do not require in-depth knowledge of the internal structure of objects. For IGBT lifetime prediction, only the accelerated degradation data can be obtained to realize modeling and prediction. Typical prediction methods include gray prediction, particle filter prediction and so on.

In terms of gray prediction application, Wei Deshen et al. used gray GM(1,1) model to predict the lifetime of low-voltage circuit breaker based on a small amount of infor-

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mation [7]. Yin Wenkuo et al. derived the corrosion life of the transmission line tower coating based on the historical data of the corrosion area of the coating by using the gray prediction model [8]. Sun Jianmei et al. used the improved gray prediction model to predict the medium and long-term load of power system [9]. Zhu Xianhui et al. used gray prediction model to analyze motor reliability and verified it with measured data [10].

In terms of the application of particle filter prediction, Zhang Malan et al. established the engine performance degradation model with the idea of particle filter, and predicted the RUL of the engine by estimating the time-varying parameters of the model [11]. Jiao Ziquan et al. used particle filtering to predict the RUL of lithium batteries [12]. F. Z. Cheng et al. used particle filtering to accurately predict the remaining life of wind turbine driveline gearboxes [13]. Zhu Jiongjiong et al. first conducted IGBT aging failure experiment under continuous stress impact, and the data obtained were used to verify the fault prediction method based on particle filtering [14].

However, traditional single data-driven algorithm such as gray prediction or particle filter method cannot track and predict the piecewise nonlinear degradation trends of IGBT well, so it is difficult to accurately obtain the RUL of IGBT. The gray model is suitable for predicting the short and medium term data with small sample law and the calculation is simple. While particle filter is suitable for predicting large sample data with nonlinear or unstable degradation law and the calculations are relatively complicated.

In this paper, according to the degradation characteristics of IGBT, the degradation stages of IGBT are mainly divided into two stages. The first stage is the slow degradation stage, which takes a long time and has no obvious degradation effect. The second stage is the rapid degradation stage, which has a short time and significant degradation effect, and directly leads to failure. Considering the characteristics of sample data, computational complexity and accuracy, the combinatorial prediction algorithms are proposed in this paper. The segmental degradation RUL prediction method is proposed which combined gray model with particle filter in order to be more accurately tracking the IGBT's nonlinear and instability degradation trend. What's more, a new double Gaussian function model is proposed to characterize the state equations of the particle filter, and it turns out that this model is more accurate compared with the traditional exponential models.

## II. THE GRAY VERHULST PREDICTION MODEL

The basic principle of the grey model is to use the original data to form the original sequence (0) and generate the sequence (1) by the accumulation generation method, which can weaken the randomness of the original data and make it show a more obvious characteristic law. The gray differential equation can generate future accumulative values, and then obtain the predicted value of the target state.

Considering that the characteristic quantity of IGBT defect development can reflect the degree of IGBT damage degradation development, the gray verhulst model is adopted in this paper to predict the future health status of IGBT devices according to the characteristic quantity of IGBT defect development. In the process of IGBT operation, the characteristic quantity of IGBT defect development is extracted as "partial" known information, and the gray verhulst model of health precusor parameters is established to predict the eigenvalue at a certain time in the future. The specific implementation process of the method is as follows [15], [16].

Set $x^{(0)}$ to be the original data sequence, then

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots x^{(0)}(n)) \tag{1}$$

$x^{(1)}$ is the (1-AGO) sequence of 1-time accumulation generation of $x^{(0)}$, and then

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots x^{(1)}(n)) \tag{2}$$

$z^{(1)}$ is the mean sequence of $x^{(1)}$, then

$$z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \cdots z^{(1)}(n)) \tag{3}$$

$$x^{(0)} + az^{(1)} = b(z^{(1)})^2 \tag{4}$$

(4) is called gray verhulst model, a and b are parameters.

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b(x^{(1)})^2 \tag{5}$$

(5) is the whitening equation of the gray Verhulst model, where t is time.

*Theorem 1:* Let the grey Verhulst model be as described above, if

$$u = [a, b]^T \tag{6}$$

is the parameter column, and

$$B = \begin{bmatrix} -z^{(1)}(2) & (z^{(1)}(2))^2 \\ -z^{(1)}(3) & (z^{(1)}(3))^2 \\ \vdots & \vdots \\ -z^{(1)}(n) & (z^{(1)}(n))^2 \end{bmatrix}$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{7}$$

Then the least squares estimation of the parameter column u is satisfied

$$\hat{u} = [\hat{a}, \hat{b}]^T = (B^T B)^{-1} B^T Y \tag{8}$$

*Theorem 2:* Let the gray model be as described above, then the solution of the whitening equation is

$$x^{(1)}(t) = \frac{\hat{a}x^{(0)}(1)}{\hat{b}x^{(0)}(1) + [\hat{a} - \hat{b}x^{(0)}(1)]e^{\hat{a}t}} \tag{9}$$

The corresponding time series of the gray verhulst model is

$$\hat{x}^{(1)}(k+1) = \frac{\hat{a}x^{(0)}(1)}{\hat{b}x^{(0)}(1) + [\hat{a} - \hat{b}x^{(0)}(1)]e^{\hat{a}k}} \tag{10}$$

The cumulative reduction is

$$\hat{\boldsymbol{x}}^{(0)}(\boldsymbol{k}+1) = \hat{\boldsymbol{x}}^{(1)}(\boldsymbol{k}+1) - \hat{\boldsymbol{x}}^{(1)}(\boldsymbol{k}) \tag{11}$$

The calculated residual is:

$$\varepsilon = (\varepsilon\ (1), \varepsilon\ (2), \cdots \varepsilon(n)) =^{(0)} - x^{(0)} \tag{12}$$

The average relative error of the model is:

$$\Delta = \frac{1}{n}\sum\nolimits_{k=1}^{n} \Delta_k \tag{13}$$

$$\Delta_k = \frac{\varepsilon(k)}{x^{(0)}(k)} \times 100\% \tag{14}$$

## III. THE PARTICLE FILTER PREDICTION MODEL

Partical Filter (PF) has been proved to have good applicability in nonlinear and non-Gaussian problems, so it has been widely used in the field of PHM, state tracking, life prediction and other fields. It mainly contains five important processes:

1) State transition and observation equation

$$x_i = f(x_{t-1}, v_t) \tag{15}$$

$$z_t = h(x_t, \omega_t) \tag{16}$$

$t$ is the time step, $x_t$ is the system state, $z_t$ is the observed value of $x_t$, $v_t$ and $\omega_t$ are process noise and observation noise, respectively.

2) The generation of particles

Particles are generated from the sample distribution and, in many cases, $p(x_t|x_{t-1})$ can be obtained from the sample distribution function.

3) Weight update

When new observations are obtained, the weights are updated as follows:

$$\omega_t^i = w_{t-1}^i p(z_t|x_t^i) \tag{17}$$

4) Resampling

If the weight of many particles is too small, the particles are almost useless. This requires resampling to get more valid particles. Particle degradation can be described by the number of effective samples:

$$ESS_t = (\sum\nolimits_{i=1}^{n} (\omega_t^i)^2)^{-1} \tag{18}$$

$n$ is the number of particles, when $\omega_i = 1/n, i = 1, 2, \cdots n$, $\mathrm{ESS_t}$ reaches the maximum value n. If $\mathrm{ESS_t}$ is too small, resampling is required. The PF algorithm needs to start with a threshold $\mathrm{T_{ESS}}$($\mathrm{TESS} = \mathrm{n/2}$), that is, resampling is required if $\mathrm{ESS_t} < \mathrm{T_{ESS}}$.

5) Prediction

The posterior distribution of $x_t$ can be calculated as follows:

$$p(x_t|z_{0:t}) \approx \sum\nolimits_{i=1}^{n} \omega_t^i \delta(x_t - x_t^i) \tag{19}$$

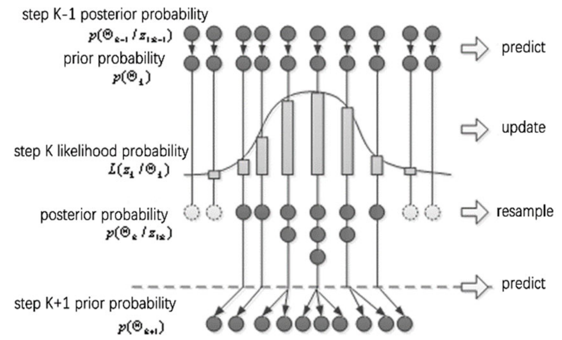



**FIGURE 1.** Illustration of the PF process.

If n is large enough, Equation (19) can approximate the actual value.

The process of particle filtering is based on Bayesian theory for parameter estimation, as described in Fig.1. In the first step, k = 1,.. n samples are taken from the initial distribution and then performed in three steps, In the first step, the posterior distribution of the model parameters in the form of samples in the current k-1 step is used to calculate the prior value of the current k step. The damage state at the current moment is transformed from the damage model samples in the previous step based on the model parameters. The sample of the current step corresponds to that shown in Fig.1, and the next step will be updated. See Fig.1 for the likelihood estimation $L(z_k|\Theta_k)$ of the measured data. Assuming $\omega_k$ a normal distribution, the likelihood estimate of the measured value can be expressed as follows:

$$L(z_k|x_k^i, b_k^i, \sigma_k^i) = \frac{1}{\sqrt{2\pi\sigma_k^i}} \exp\left[-\frac{1}{2}\left(\frac{z_k - x_k^i(b_k^i)}{\sigma_k^i}\right)^2\right], \quad i = 1, 2, \cdots n \tag{20}$$

The PDF value of the ith sample $z_k$ of the unknown parameter $\Theta = x, b, \sigma$ corresponds to the weight of the ith sample, which can be represented by the length of the histogram (as shown in Fig.2). During the resampling stage, the samples with high weights are copied or the samples with low weights are eliminated. The CDF model is constructed through the likelihood function of the equation, as shown in Fig.3. Random values are generated from the U(0,1) distribution as CDF values. Finally, the parameter samples containing CDF values are selected. Repeat the process n times to obtain n samples. The resampling result becomes the posterior probability distribution as shown in Fig.1, which is the posterior distribution of the current step and the prior distribution of the (k + 1) step.

By estimating the parameter values, the future damage state and RUL can reach the failure threshold by evolving the damage state, as shown in Fig.3, the two dashed lines represent the prediction boundary of health indicators, that is, the area in the middle of the dashed line is the prediction interval of health indicators. The PDF shape represents the

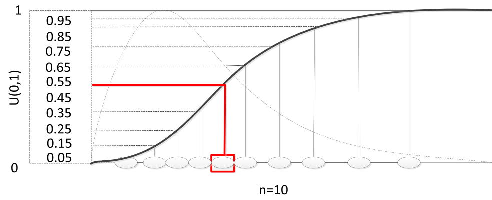



**FIGURE 2.** Illustration of resampling method.

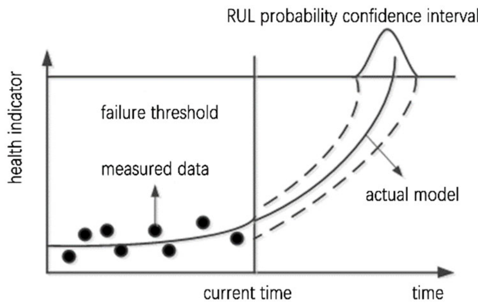



**FIGURE 3.** Illustration of RUL prediction.

distribution of the time when the health indicator reaches the failure threshold. It should be noted that only the damage state is transformed in the prediction step, and the model parameters are not updated. Health indicator is added to the measurement error and the updated standard deviation [17].

## IV. IGBT COMBINATORIAL MODEL AND RUL PREDICTION

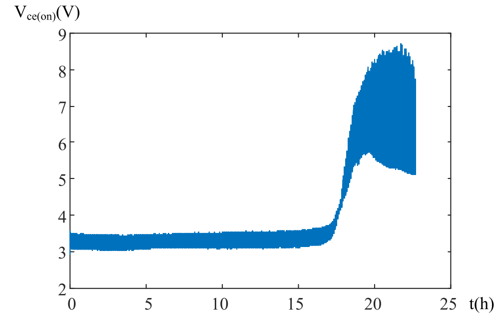
The prediction algorithm proposed in this paper was validated using IGBT power cycle aging data from the University of Maryland CALCE laboratory, using IGBT1 as an example. Fig.4(a) shows the $V_{ce(on)}$ (emitter-collector on-state voltage drop) change process of IGBT1 during the aging test. Before the first sampling point, the IGBT is in the aging stage but has not completely failed, so it is valid data. After the first sampling point, the IGBT has completely failed, so these data is failure data and not used for research applications.

### A. DATA PREPROCESSING AND DEGRADATION ANALYSIS

In this paper, only the rising stage of $V_{ce(on)}$ before failure (i.e. the IGBT aging process) is modelled and predicted, as shown in Fig.4.

As the acquired signal contains a lot of noise, we use a moving average algorithm to filter the acquired signal. The results of extensive tests show that the filtering effect is best when m = 20, as shown in Fig.5. in this paper, the filtered IGBT aging data is used as the data base for algorithm verification.

$V_{ce(on)}$ is used as the health precursor parameter for the IGBT. Fig.6 shows the full life cycle degradation curve of IGBT1. In the initial stage, the IGBT degrades slowly and $V_{ce(on)}$ rises slowly. As the device is repeatedly subjected to stress shocks, damage accumulates. When the specified warning line (which can be set according to different criteria)



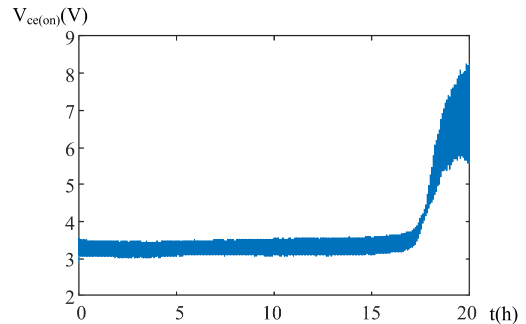




**FIGURE 4.** a) $V_{ce(on)}$ degradation curve. b) $V_{ce(on)}$ degradation curve before failure.

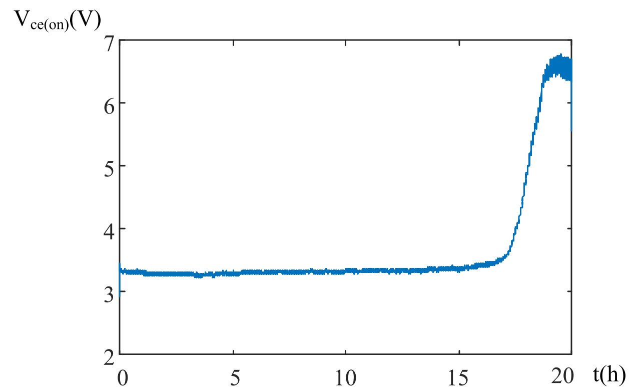



**FIGURE 5.** $V_{ce(on)}$ degradation curve after filtering.

is reached, the value of $V_{ce(on)}$ rises faster compared to the slow degradation stage and can reach its maximum value within a short period of time as the IGBT device starts into the fast degradation stage, at which point the IGBT device fails completely. Therefore, a fault warning is required for the IGBT during the fast degradation stage until the device fails completely.

According to the slow degradation stage where the device degradation pattern is not obvious, this paper uses the gray verhulst model to calculate the AGO for fault prediction and then restore the actual value by calculating the IAGO. For non-linear filtering problems, its random quantities must satisfy the requirements of gaussian distribution, otherwise the obtained filtering effect is invalid. Therefore, this paper uses the particle filter algorithm to model the non-linear

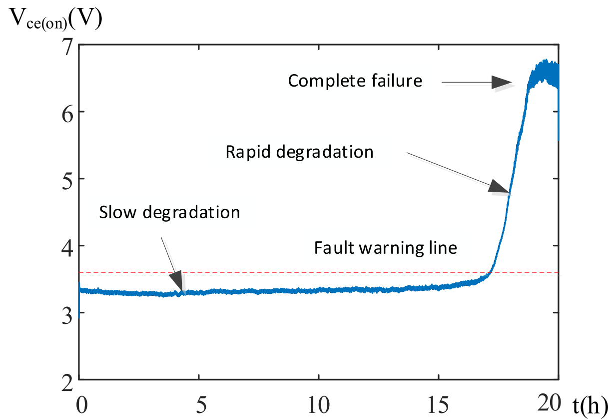



**FIGURE 6.** IGBT whole life cycle degradation stages.

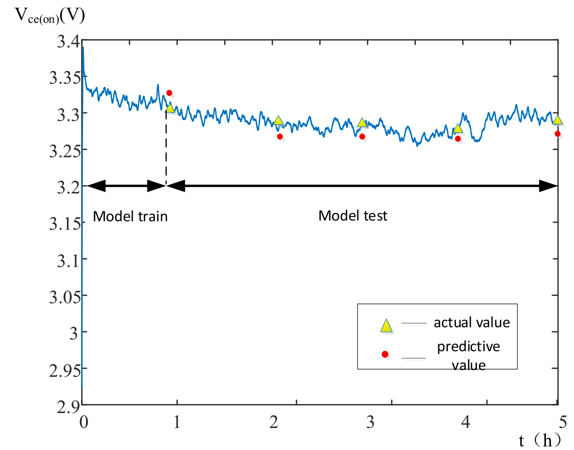



**FIGURE 7.** The prediction and actual values by verhulst model (1 h).

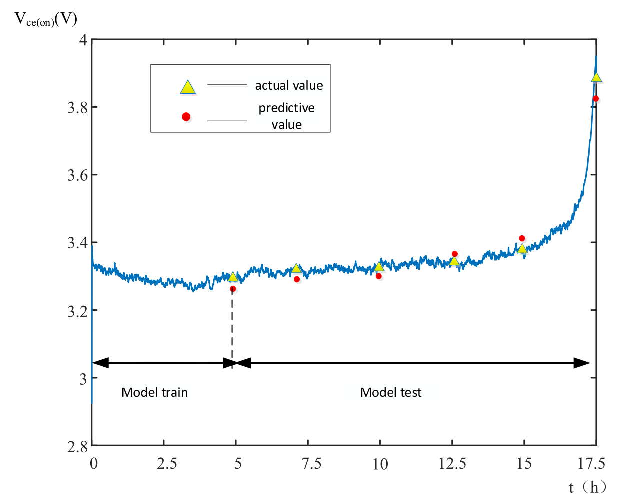



**FIGURE 8.** The prediction and actual values by verhulst model (5 h).

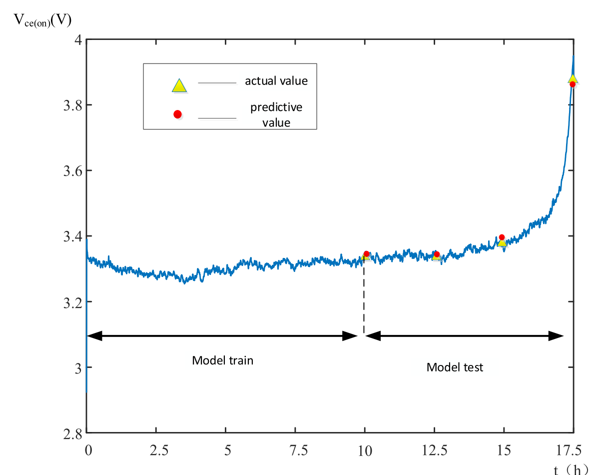



**FIGURE 9.** The prediction and actual values by verhulst model (10 h).

characteristics of the variable parameters, which is more suitable for achieving the prediction effect in the accelerated degradation stages.

Fig.6 shows the whole life cycle data of IGBT, with 40000 sampling points, one sampling point every two seconds. So the lifetime of this IGBT is about 20 hours. The first 17.5 hours are the slow degradation stage before fault warning point, and the last 2.5 hours are the fast degradation failure stage after fault warning point. In this paper, the gray verhulst model is used for fault prediction in the slow degradation stage and particle filter is used for RUL prediction in the fast degradation stage.

### B. THE GRAY VERHULST MODELING AND COMPARATIVE ANALYSIS

During the slow degradation stage of the IGBT (before the fault warning), the $V_{ce(on)}$ data is sampled at approximately points. As can be seen from Fig.6, during this degradation stage, the device degrades slowly and the $V_{ce(on)}$ data varies less, so it is not necessary to use sample particals with high frequency. In this paper, the aging data of the 1st, 5th and 10th hour is used as training data and a certain sequence is sampled from the training data as the initial sequence for the gray verhulst model. Then the predictions are made at intervals of 1 hour (1st to 5h), 2.5 hours (5th to 10h), 2.5 hours (10th to 17.5h), and compared with the actual values. As shown in Fig.7, Fig.8 and Fig.9, the blue curves are the full sampled values of the actual aging data, the red dots indicate the predicted $V_{ce(on)}$ data, and the green triangular symbols indicate the actual $V_{ce(on)}$ data used for comparison.

Fig.7 shows the predictions at 1 hour intervals during the 1st to 5th hour and compares them with the actual values. The maximum error is not higher than 0.02. Fig.8 shows the predictions at 2.5 hourly intervals during the period 5 to 10h and compares them with the actual values. As can be seen, the maximum error is still not higher than 0.02. In Fig.9, which shows the predicted situation from 10 to 17.5 h, the errors are much smaller compared with the previous values. It can be seen that during the slow degradation stage of the device, the proposed method in this paper can predict $V_{ce(on)}$ more accurately throughout the full life cycle of the device, which helps to quickly assess the aging degree and effectively

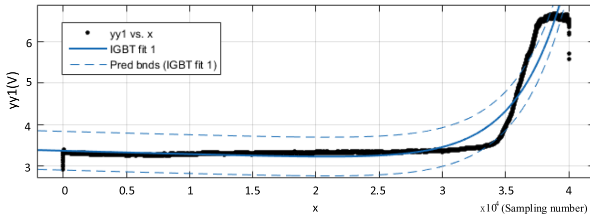



**FIGURE 10.** Double exponential function curve fitting.

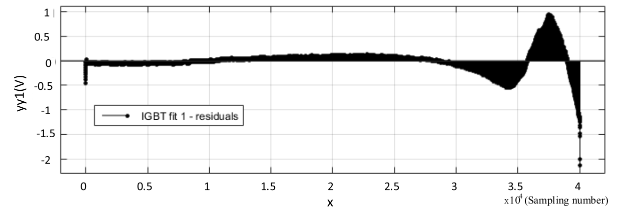



**FIGURE 11.** Double exponential function fitting error.

**TABLE 1.** Comparison of the average error of the GM models.

| | 1 hour | 5 hours | 10 hours |
|---|---|---|---|
| GM(1,1) | 18.5% | 14.3% | 12.7% |
| GM(2,1) | 17.6% | 13.8% | 11.4% |
| Gray Verhulst | 8.1% | 5.1% | 3.2% |

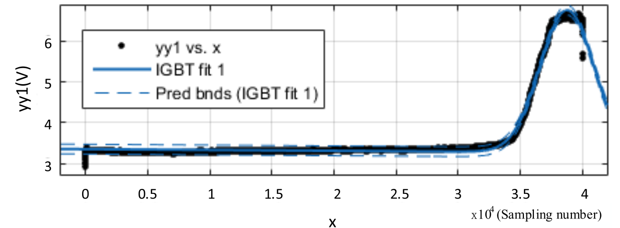



**FIGURE 12.** Double gaussian function curve fitting.

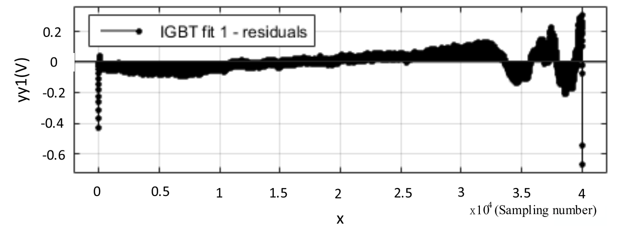



**FIGURE 13.** Double gaussian function fitting error.

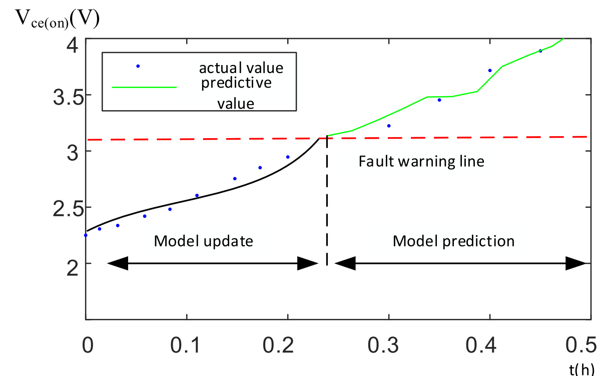



**FIGURE 14.** The prediction and actual values by PF model (0.5 h).

guide the maintenance and replacement of the device. The comparison of the results in Fig.7, Fig.8 and Fig.9 shows that as the aging time longer, the predicted values of the proposed prediction model are more closer to the actual values with less errors.

In this paper, the gray GM(1,1) and GM(2,1) models are used as the comparison algorithm and the same data is used for the error comparison analysis, and the results are shown in Table 1. As can be seen from Table 1, the prediction algorithm proposed in this paper and the two algorithms compared in terms of model error both gradually decrease as the samples of aging data increase. However, the errors of the two compared algorithms are still bigger than 10% after using 10 hours of sampling data, while the prediction error of the gray verhulst model used in this paper is less than 10% at the 1st, 5th and 10th hour, and the prediction error is significantly smaller than the other two compared algorithms. When 10 hours of sampling data are used, the prediction error is only 3.2%, so it has a higher accuracy.

### *C. IMPROVED PARTICLE FILTER MODELING AND COMPARATIVE ANALYSIS*

For the second stage of accelerated degradation, the particle filtering algorithm is used according to its degradation curve to establish its equation of state first, the traditional double exponential function model is:

$$f(x) = ae^{b*x} + ce^{d*x} \tag{21}$$

Within 95% confidence limits, the parameters of the model can be obtained as $a = 3.212$, $b = -0.02851$, $c = 0.02349$, $d = 3.054$. The Root Mean Square Error (RMSE) is 0.2369 and its fitted curve is shown as follows:

And for modelling its curve fitting using a double Gaussian function model, the general model for the double Gaussian function is shown as follows:

By comparing their root mean square error we can find:

$$\text{RMS E}_{\text{Gauss}} = 0.06096 < \text{RMSE}_{\text{Exponential}} = 0.2369 \tag{22}$$

Compared with the traditional double exponential function fitting model, it can be found that the double Gaussian function has better characterisation properties in fitting the IGBT degradation curve. Therefore, in this paper, the double Gaussian function is used as the equation of state for particle filtering to represent the general trend of IGBT state degradation, and thus, the remaining life prediction of IGBTs can be achieved [18].

With the experimental data used in this paper, the whole life cycle of the IGBT is 20 hours, and the duration of the rapid degradation stage is about 2.5 hours. Therefore, the

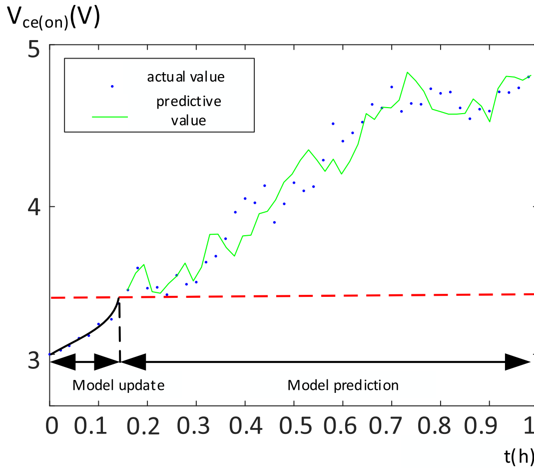



**FIGURE 15.** The prediction and actual values by PF model (1 h).

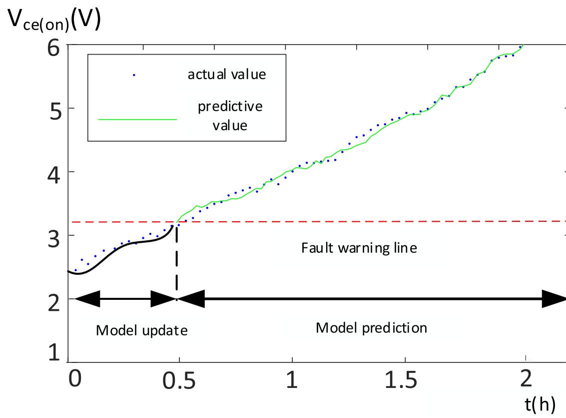



**FIGURE 16.** The predicted and actual values by PF model (2 h).

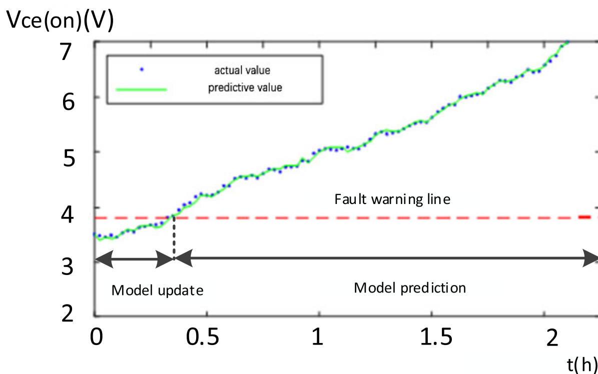



**FIGURE 17.** The predicted and actual values by PF model (2.5 h).

$V_{ce(on)}$ of IGBT at 0.5, 1, 2, and 2.5 h was predicted in this paper. The comparisons between the predicted and the actual values for each time stage are shown in Fig.14, Fig.15, Fig.16 and Fig.17. It can be seen that the PF algorithm is able to complete the prediction of $V_{ce(on)}$ more accurately in IGBT accelerated degradation stage. Among them, the largest error occurs at the 0.5 h stage prediction. As shown in Fig.14, the maximum error in $V_{ce(on)}$ could be 0.2, while the prediction with the smallest error occurs within the 2.5 h stage. In order to compare different PF algorithms' performance, the same number of the particles were used in the tests. It can be seen from Fig.17 that as the aging time increases, the algorithm uses more training samples and the prediction model obtains a smaller error in the predicted value of $V_{ce(on)}$.

**TABLE 2.** Comparison of the prediction models.

| | $PF_G'$ | $PF_E'$ | $PF_G$ | $PF_E$ |
|---|---|---|---|---|
| RMSE(h) | 1.58 | 1.71 | **0.08** | 0.19 |
| Accuracy (%) | 92.1% | 91.4% | **96.8%** | 92.4% |

The following formula is used to calculate the accuracy of the prediction algorithm proposed in this paper:

$$p=\left|\frac{E_r}{RUL_R}\right|\times 100\%=\left|\frac{RUL_R-RUL_p}{RUL_R}\right|\times 100\% \tag{23}$$

$p$ is defined as the accuracy of the prediction algorithm, $E_r$ is defined as the error between the actual remaining life and the predicted remaining life, $RUL_R$ denotes the actual remaining life of the IGBT, and $RUL_p$ denotes the predicted remaining life of the IGBT.

The RMSE (Root Mean Square Error) can be used to evaluate the effectiveness and merit of an algorithm and is calculated as follows.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(-Y_i)^2 \tag{24}$$

$$MSE = \frac{1}{T_f}\sum_{i=1}^{T_f}(RUL_{p_i}-RUL_{R_i})^2 = \frac{1}{T_f}\sum_{i=1}^{T_f}(E_{r_i})^2 \tag{25}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(-Y_i)^2} = \sqrt{\frac{1}{T_f}\sum_{i=1}^{T_f}(E_{r_i})^2} \tag{26}$$

where $T_f$ denotes the time unit during the IGBT accelerated ageing experiment.

For the prediction models used in the accelerated degradation stage of the IGBT, the particle filter with the double Gaussian function model is denoted by $PF_G$, the particle filter with the conventional double exponential function model is denoted by $PF_E$. For the prediction models used in the overall lifecycle, the particle filter with the double gaussian function and the double exponential function model are denoted by $PF_G'$ and $PF_E'$, respectively. The RMSEs are compared in Table 2. In comparison, the RMSEs of $PF_G$ and $PF_E$ decreased significantly than $PF_G'$ and $PF_E'$, and the accuracy rates increased. It means that the proposed prediction algorithms achieved higher prediction accuracy for IGBT compared with traditional single models. Compared with $PF_E$, the RMSE of $PF_G$ is smaller. The results show that the prediction model with a double gaussian function as the state equation is significantly better than the prediction model with a double exponential function as the state equation.

## V. CONCLUSION

In this paper, an IGBT RUL prediction method based on gray verhulst model combined with particle filter algorithm is proposed. With this combinatorial prediction algorithms, the nonlinear and unstable degradation trends of IGBT can be tracked and predicted better. The following main conclusions can be drawn through the test data verification:

1) The prediction accuracy of the method proposed in this paper is higher than that of the single gray prediction method or particle filter algorithm;

2) For the particle filter algorithm, the improved double gaussian function model has higher prediction accuracy than the traditional double exponential function model as the state equations;

3) With the increasing of the training and learning samples' number, the accuracy of IGBT prediction model is gradually improved, and the combinatorial algorithm of particle filter and gray prediction with the double gaussian function as the state equation has the highest prediction accuracy.

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