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IGBT Neural Network Prediction Method of Radar Transmitter based on Levenberg-Marquard Optimization

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Abstract

Health parameters prediction of radar transmitter needs to complete the electronic components failure characteristics analysis and fault symptom parameters prediction. The article looks the Insulated Gate Bipolar Transistor (IGBT) as the research object, combines the accelerated life experimental data of NASA-ARC, and determines the turn-off voltage spike peak value of collector-emitter as the basis of failure prediction, carries out IGBT health prediction method research based on process neural network. In view of the slow convergence speed and easily trapped in local minimum of back-propagation learning algorithm in the traditional process neural network, develop a kind of learning algorithm based on orthogonal basis function of Levenberg-Marquardt(LM) optimization. The experimental results show that the process neural network algorithm based on LM optimization can better predict the performance degradation trend of IGBT; it has high accuracy and achieves the short-term prediction of IGBT health state.

Keywords: *IGBT; Process neural network; Levenberg-Marquardt*

1. Introduction

Radar transmitter works under the bad environment with high temperature, high pressure and high speed all year round; its performance will fade away during use. Accurate analysis and grasp the performance degradation rule of the radar transmitter and predict its future state of health have very important significance for ensuring the safety of the whole radar system.

IGBT as the power switches tube used by the radar transmitter change device [1] has reliable failure omen characteristic. Therefore, use IGBT as the replacement parts of radar transmitter health state prediction is a practical and effective method. The present method using the previous performance parameters of IGBT and adopting regression analysis theory to fit performance degradation curve has large error, exists inadaptability in the practical application. Artificial neural network can approximate any continuous function and its derivative with arbitrary precision, and is used for problem solving without prior special modeling and is very convenient for solving complex and practical problems. Due to input synchronization instantaneous limit, the traditional artificial neural network is difficult to reflect the time cumulative effect existing really in the process of IGBT performance degradation, and practice shows the time cumulative effect is just the main reason of IGBT performance producing a sharp degradation or even appearing failure. From the above, actually, the traditional artificial neural network is difficult to accurately handle the time-varying information of performance parameters IGBT [2-3].

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Process neural network is the expansion on the traditional artificial neural network in time domain, can better deal with time-varying input and output information and has great application value for solving many practical problems connected with the time-varying process [4]. Therefore, in this paper, the process neural network is used for IGBT parameter prediction and weak generalization ability is the bottleneck problem restricting process neural network to go to application. To solve this problem, this article aims to improve the generalization ability of process neural network from learning algorithm and sample set structure. In view of the Back Propagation (BP) learning algorithm existing slow convergence speed and easy to limited to local minimum points [5], face the process neural network to develop Levenberg-Marquardt (LM) learning algorithm based on orthogonal basis function, and successfully use the method to performance parameters prediction of radar transmitter IGBT, relative satisfactory results have been achieved.

2. IGBT Failure Mechanism

In the practical application, the IGBT and diode silicon chip are mostly encapsulated in the standard module by the special structure and constitute converter circuit with independent functions. The failure is a complex process related to its dynamic characteristics, involving many factors, such as heat, electricity and machinery. Relevant institutions at home and abroad have studied the failure mechanism of IGBT[6]; according to the failure reasons, the power module failure methods can be roughly divided into the failure related to chip and packaging. Several typical failures include:

2.1. Failure Related to Chip

As the core of power module, semiconductor chip failure is the final cause of module fault. It mainly includes [7-8]:

Latchs-up effect and trigger parasitic transistor. Too much voltage change in the process of turn-off may trigger thyristor in the internal parasitic of IGBT or bipolar transistor in the parasitic MOSFET to produce patch-up effect, which would lead to power devices short circuit. Although the problem has been improved greatly through semiconductor optimization design, and monitoring and restricting the rise rate of maximum voltage in the reverse bias safe operating area is still very important for avoiding patch-up effect.

Electrical overstress (EOS) is often associated with overvoltage and over current. The heating effect under the high voltage condition and secondary breakdown in some power devices require attention. Therefore, fully consider the cooling requirements in power device applications to ensure power devices running in safety work area. On the other hand, too fast voltage rising will produce a lot of displacement current, may cause short circuit for IGBT triggering by mistake.

Other typical failure includes electrostatic discharge (ESD), charge effect (ion contamination and hot carrier injection), *etc*.

2.2. Failure Related to Packaging

The multilayer structure of IGBT power modules and the mismatch of thermal expansion coefficient between different materials cause the fatigue and aging of welding material at the long-term thermal cycle impact, and eventually cause device failure due to chip fracture or temperature increase [9].

3. Experiment Analysis of IGBT Accelerated Degradation

This paper uses the data from NASA PCoE research center, we would combine the data collected by NASA accelerated aging experiment, use improved artificial neural network to estimate the health status of IGBT in a more profound way to describe its degradation failure characteristics.

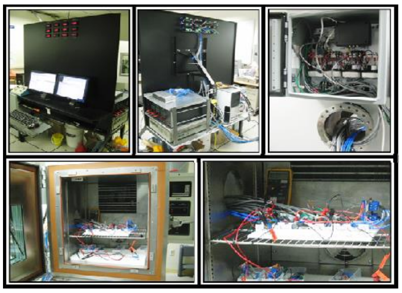


Figure 1. IGBT Accelerated Degradation Experiment Equipment of NASA

The data set of NASA is provided by the standard format *. Mat file of Matlab, the data of IGBT is divided into four folders, respectively is:

(1) SMU for new devices: this file contains 40 groups of electrical properties data under the original condition and 20 groups of MOSFETS IRG520Npbf and 20 groups of IGBTS IRG4BC30K. The characteristic parameters collected are the threshold value voltage, breakdown voltage and leakage voltage and so on.

(2) Accelerated thermal aging experiment under DC portal voltage: The file contains a set of accelerated thermal aging experimental data under the DC portal voltage, the experiment needs 4 hours continuously and there are about 300000 data points collected, latch-up phenomenon experiment terminates until a failure mode appears.

(3) Accelerated thermal aging experiment under square wave gate voltage: the file contains a set of accelerated thermal aging experiment data under square wave gate voltage; in addition to low speed measurement, it also includes the high resolution data with transient characteristic of switchgear, this is expressed "transient measurement" in NASA's international test conference papers [10].

(4) Accelerated thermal aging experiment data under square wave gate voltage and SMU: Among it, the “aging data” contains 4 groups of data collected by sending to university of Havana in Italy. The folder “SMU parameter characterization” contains the parameters characterization data obtained by a SMU, these parameters are threshold value voltage, current shut-off, leakage current, *etc*. Need to pay more attention is that, it has experienced several problems in the process of equipment aging losing a lot of transient measurements in the end; additionally, collector current measurement is not accurate, there are 600 ma drift; Finally, the steady state measurement value is not very precise.

The above analysis is the related data of IGBT collected by NASA. For the normal condition, that IGBT is used as radar transmitter switch, the signal loaded is PWM signal, square wave gate voltage can simulate the signal better, and here we only use the third folder, that is the collected data under the condition of “accelerated thermal aging experiment under square wave gate voltage”, experiment acquisition environment is shown in table 1.

Table 1. Experiment Environment of IGBT Accelerated Aging

Exp. Condition	Numerical Value
Exp. Temperature	330℃
PWM Signal duty cycle	40%
Grid voltage	10V
Protection Temperature	345℃
Switching frequency	10KHz
Maximum cycle times	32918000000

4. Degradation Feature Selection and Data Preprocessing of IGBT

Like most of the electronic components, life cycle time span of IGBT is large and its early failure characteristic is not obvious, data acquisition under actual operation environment is also more difficult. Although there is a correlation analysis of the physical mechanism of IGBT failure, and in the level of condition monitoring of engineering application to achieve its health characterization and state prediction based on health status parameters is still a lack of related theory and technology research.

The failure model of IGBT is mostly appeared with latch-up phenomenon (Latch-Up), that is, most failure is characterized as over-voltage breakdown and has been in a conducting state, making the gate control signal be invalid, specific see the above-mentioned.

In the performance accelerated degradation experiment of IGBT, IGBT's turn-off characteristic reflects a certain change tendency. It is mainly that the falling of transient voltage spike of collector and emitter shows a strong time negative correlation when IGBT is turned off. Its mechanism is the parasitic transistor of IGBT hindered the increasing of anode current, produced a transient voltage from collector to emitter stacking with supply voltage and formed a transient and higher than supply voltage spike [11, 12].

We analyze the spike voltage and give certain trend analysis. Through this research result for a new round of digging, it can be found that looking spike voltage as fault warning parameters and predicting the spike voltage peak value in the life cycle can effectively realize IGBT failure prediction. The spike peak value curve of original turn-off voltage is shown in Figure 2.

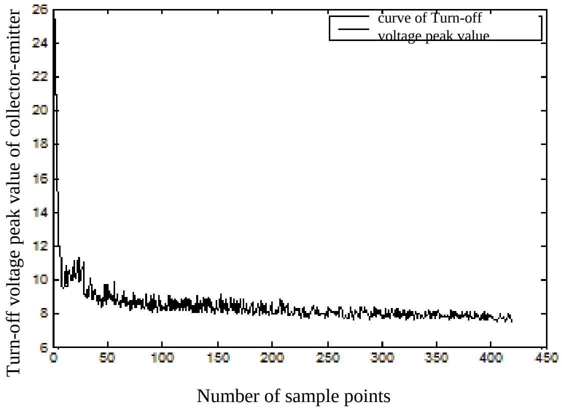
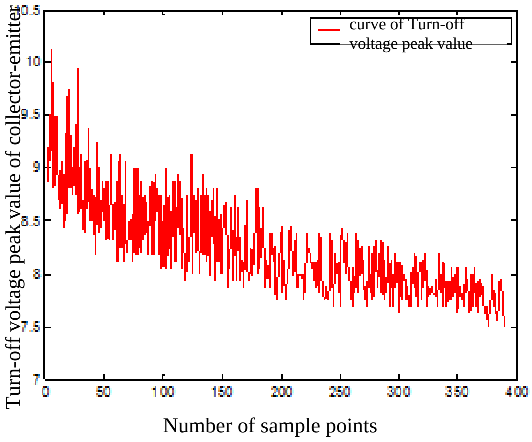
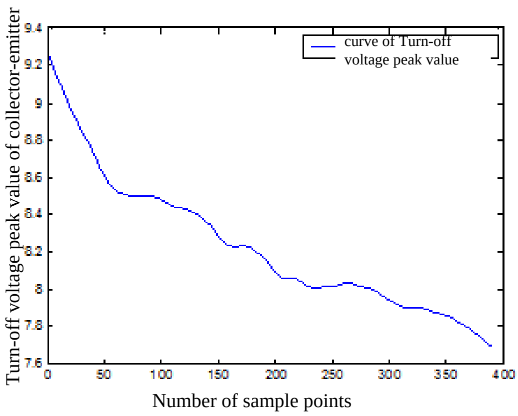


Figure 2. The Original Turn-off Spike Voltage Change Curve of Collector-emitter

Short-term prediction and functional approximation problems are equivalent. A lot of analysis on time series method at home and abroad can be found that, artificial neural network with strong functional fitting ability can be used as a prediction of the fault symptom parameters. The parameters sample points in Figure2 has larger beats and cannot meet the requirement of the neural network input; make the secondary exponential smoothing and abnegate the front of coarse errors, the parameters curve after preprocessing is shown in Figure 3.



(a)Abnegate the Front of Coarse Errors



(b)Smooth the Sample Points

Figure 3. The Turn- off Spike Voltage Change Curve of Collector- Emitter after Preprocessing

In the below, we will introduce the basic principle of process neural network and propose LM learning algorithm based on orthogonal basis functions, and then forecast the health parameters of IGBT and analysis and evaluation of the predicted results.

5. IGBT Health Prediction of Process Neural Network based on LM Optimization

5.1. The Topology Structure of Process Neural Network

The network is composed of a number of process neuron and the traditional artificial neuron according to certain topological structure is the process neural network [15, 16]. Process neuron is composed of weighting, aggregation and inspiration. Compare with the traditional neurons, the input, weights and output of process neuron can be the function related to time. The aggregation operation of process neuron not only contains multiple input of space, but the accumulation of time process.

The input and output relationship of process neuron is the following:

$$Y = f((W(t) \oplus X(t)) \otimes K(\square) - \theta) \tag{1}$$

In which, $X(t)$=[$x_1(t)$, $x_2(t)$,…, $x_n(t)$], $W(t)$=[$w_1(t)$, $w_2(t)$,…, $w_n(t)$]。"θ" is the input threshold value of process neuron. "$\oplus$" is some space aggregation operation，"$\otimes$" is some time(process) aggregation operation. For example:

$$W(t) \oplus X(t) = \sum_{i=1}^{n} w_i(t) x_i(\mathrm{t}) \tag{2}$$

$$A(t) \otimes K(\mathrm{t}) = \int_0^T A(t) K(t) dt \tag{3}$$

In which, $K(\sqcup)$ is an integrable function at [0,T]. Assume that $K(\sqcup)$ is one variable functional, define:

$$A(t) \otimes K(\mathrm{t}) = K(A(t)) \tag{4}$$

Take $K(\sqcup)$=1，so：

$$y = f(\int_0^T \sum_{i=1}^{n} w_i(t) x_i(\mathrm{t}) dt - \theta) \tag{5}$$

Generally, assume that $W(t)$ and $K(\sqcup)$ are both continuous. The process neuron described by the formula, its internal operation is composed of weighted multiplier, accumulated total, integral and excitation function is called the chivalrous process neurons.

The topology structure containing a process neuron process of single hidden layer, multiple input and single output process neural network is shown in Figure 4. According to actual use situation, promote the system to multiple input and output situation. Each unit of the hidden layer is composed of process neuron, m units in total. The threshold and excitation function of each unit can be the same or different. Process neural network with the same excitation function is known as the regular process neural network; process neural network with the same excitation function is called hybrid process neural network. Output layer is a time-invariant and traditional neuron.

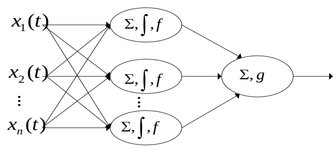


Figure 4. Topology Structure of Process Neural Network

The process neural network showing in Figure4 has n input nodes $x_i(t)$,(i=1,2…,n) totally and m hidden layers; $w_{ij}(t)$ is the connection weight function of input layer node I to hidden layer j; f is the excitation function of process neuron; v_j is the connection weight of hidden layer note j to output node, g is the activation function of output neuron; y is the output system. The input/output relationship of the process neural network can be represented as:

$$y = g(\sum_{j=1}^{m} v_j f(\int_0^T \sum_{i=1}^{n} w_{ij}(t) x_i(\mathrm{t}) dt - \theta_j^{(1)}) - \theta) \tag{6}$$

In which, [0,T] is the input process interval; $\theta_j^{(1)}$ is the excitation value of hidden node j ;θ is the excitation value of output neuron.

5.2. Orthogonal basis Expansion of Process Neural Network Model

Due to the input function of the process neural network is determined by specific problems, the form of weight function is with arbitrary, both can be a function of time. The process neuron contains two types of operations, time aggregation and space aggregation; and process neural network can be composed of different types of neurons, each type of neuron has its own algorithm, *i.e*, (deal with their own input information according to their own algorithm). The learning method based on Basis Functions Expansion (BFE) proposed by literature [5] greatly reduces the computational complexity and simplifies the learning process of process neural network. Introduce a set of appropriate orthogonal basis functions into the input space, expand the input function under the given precision to the limited series of the group of orthogonal basis, and represent network weight function to be the expansion form of the same group of basis functions simultaneously, use the orthogonality of basis function to simplify the complexity of process neuron to time aggregation operation. In this way, eliminate the parameters related to time to simplify the operation.

Assume the input space of process neural network is $(C[0,T])n$, $b_1(t), b_2(t), \ldots, b_n(t)$ is a set of standard orthogonal basis function of $(C[0,T])n$, so under certain precision, $x_i(t)$ $(i = 1,2,\ldots,n)$can be represented to be the series form of basis function expansion:

$$x_i(t) = \sum_{i=1}^{l} a_{il} b_l(t) \tag{7}$$

The corresponding connection weight function $w_{ij}(t)$ uses $b_1(t)$, $b_2(t)$, …, $b_n(t)$ basis function expansion form is:

$$w_{ij}(t) = \sum_{i=1}^{l} w_{ij}^{(l)} b_l(\mathrm{t}) \tag{8}$$

Combine the above two equations into (6) and the network output relationship can be represented to:

$$\begin{aligned} y &= g\left(\sum_{j=1}^{n} v_j f\left(\sum_{i=1}^{n} \int_0^T \left(\sum_{i=1}^{L} w_{ij}^{(l)} b_l(t)\right)\left(\sum_{s=1}^{L} a_{is} b_s(t)\right) \mathrm{dt} - \theta_j^{(l)}\right) - \theta\right) \\ &= g\left(\sum_{j=1}^{l} v_j f\left(\sum_{i=1}^{n} \sum_{l=1}^{L} \sum_{s=1}^{L} a_{is} w_{ij}^{(l)} \int_0^T b_l(t) b_s(t) \mathrm{dt} - \theta_j^{(l)}\right) - \theta\right) \end{aligned} \tag{9}$$

Due to $b_1(t), b_2(t), \ldots, b_n(t)$is a set of standard orthogonal basis at [$0,T$], meet:

$$\int_0^T b_l(t) b_s(t) \,\mathrm{dt} = \begin{cases} 1, & l = s \\ 0, & l \neq s \end{cases} \tag{10}$$

So (9) can be simplified to:

$$y = g\left(\sum_{j=1}^{n} v_j f\left(\sum_{i=1}^{n} \sum_{l=1}^{L} a_{il} w_{ij}^{(l)} - \theta_j^{(l)}\right) - \theta\right) \tag{11}$$

After the above operation, the parameters related to time in the process neural network are eliminated and the rest of parameters can be used the traditional artificial network learning algorithm to optimize. In literature [5], it uses the error Back Propagation (BP) learning algorithm based on gradient descent, good results are obtained. The two methods of are called BFE-BP algorithm comprehensively. A large number of applications show that adopting the method not only simplifies the process of the neural network operations, and increase the stability and convergence in the process of network training.

Learning process based on BFE-BP describes as follows:

Step1 Initialize the network topology result, expand input function and weight function based selected orthogonal basis function;

Step2 Update the weight according to BP algorithm (initial weight is randomly generated);

Step3 Evaluate the performance of process neural network;

Step4 If meet the requirement, end; otherwise, return to step 2.

In order to improve the efficiency of state prediction, it proposes a kind of cascade feed-forward process neural network, which can use single input and single output system as example for description and can be extended to the multi input and multi output.

The input and output relationship of network is:

$$y = g(\sum_{j=1}^{n} v_i f(\int_0^T \sum_{i=1}^{n} w_i(t) x_i(\mathrm{t}) dt - \theta_i) + \int_0^T u(\mathrm{t}) x(\mathrm{t}) - \theta) \tag{12}$$

In which, [0,T] is the input process space; θ_i is the excitation value of hidden layer node i; θ is the excitation value of output neuron.

5.3. LM Learning Algorithm Optimization Process based on the Orthogonal Basis Expansion

The adaptability and information processing ability of process neuron for different practical problems mainly depends on the form of time and space aggregation operators. Through the learning of training concentrated samples, process neuron can generate process memory on the time-varying signal characteristics inputted. Process patterns feature extraction and memory and the mapping relationship on input and output of time-varying system reflect on the connection weight function of process neuron. Therefore, appropriate optimization process of the learning process of neural network can improve the precision of the prediction.

It uses a kind of cascade feed-forward process neural network in order to improve the efficiency of state prediction, which can use single input and single output system as example for description and can be extended to the multi input and multi output. The input and output relationship of network is as follows:

$$y = g(\sum_{j=1}^{n} v_i f(\int_0^T \sum_{i=1}^{n} w_i(t) x_i(\mathrm{t}) dt - \theta_i) + \int_0^T u(\mathrm{t}) x(\mathrm{t}) - \theta) \tag{13}$$

In which, [0,*T*] is the input process space; θ_i is the incentive value of hidden layer node i; θ is the incentive value of output neuron。Expand the network model using standard orthogonal basis function, select standard orthogonal basis $e_1(t)$, $e_1(t)$,…e_k (t), can simplify equation (13) as follows:

$$y = \sum_{i=1}^{n} v_i f(\sum_{k=1}^{K} w_{ik} a_{kl} - \theta_i) + \sum_{k=1}^{K} u_k a_{kl} - \theta \tag{14}$$

In which, $a_{kl}(k=1,2,\ldots K)$ is the basis function expansion coefficient of input function of the l sample; $w_{ik}(k=1,2,\ldots K)$ is the basis function expansion coefficient of connection weight function $w_i(t)$, $u_k(k=1,2,\ldots K)$ is the basis function expansion coefficient of connection weight function $u(t)$, and here, select incentive function $g(t)=1$。

After orthogonal transformation, parameters related to the time in process neural network are eliminated; the rest of parameters can be used a traditional artificial neural network learning algorithm to optimize training.

Assume there are S sets of training samples$\{x_s(t),d_s\}$, s=1,2,…,S，d_s is the expected output of the s sample. Let y_s to be the prediction output of prediction model, the error function of prediction model can be defined as:

$$E=\sum_{s=1}^{S}(d_s-(\sum_{i=1}^{n}v_i f(\sum_{k=1}^{K}w_{ik}a_{ks}-\theta_i)+\sum_{k=1}^{K}u_k a_{ks}-\theta))^2 \qquad (15)$$

Assume R^T = [e_1, e_2,…,e_S]，where $e_s = d_s - y_s$，R^T is the transposed matrix of R；Let 令 $W^T = [w_1, w_2,\ldots, w_L] = W^T = [\omega_{11}, \omega_{12},\ldots, \omega_{1K},\ldots\omega_{nK}, \theta_1,\ldots, \theta_n, v_1,\ldots, v_n, u_1,\ldots, u_K, \theta]$, where $L = n(K+2) + K + 1$，W^T is the transposed matrix of W， and W is the awaiting adjustment parameters based on process neural network model。

Through LM algorithm [17, 18], the iterative adjustment formula of weight coefficient and threshold value coefficient W is:

$$W(m+1)=W(m)-[J^T(W(m))\cdot W(W(m))+u(l)\cdot I]^{-1}\cdot J^T(W(m))\cdot R(W(m)) \qquad (16)$$

In which, m is the iterative times；$\boldsymbol{I}$ is the unit matrix；u is the learning efficiency; when leaning begins, take a small value of u, if E cannot be reduced in some iteration，and let $u = \lambda\cdot u$ (λ>1)，and then repeat this iteration till E value is reduced; if it produces less E value in one iteration, let $u = u/\lambda$（λ>1）in next iteration to guarantee each iteration of LM algorithm can reduce E value every time. The advantage of **L**M algorithm makes it easy to overcome slow convergence speed and easily trapped in local minimum of RBF learning algorithm; $\boldsymbol{J}(\boldsymbol{W})_{\mathrm{SxL}}$is the Jacobi matrix on $\boldsymbol{W}$, its expression form is:

$$\boldsymbol{J}(\boldsymbol{W})=\begin{bmatrix} \frac{\partial e_1}{\partial\omega_{11}}, & \ldots, & \frac{\partial e_1}{\partial\omega_{iK}}, & \ldots, & \frac{\partial e_1}{\partial\omega_{nK}}, & \frac{\partial e_1}{\partial\theta_1}, & \ldots, & \frac{\partial e_1}{\partial\theta_n}, & \frac{\partial e_1}{\partial v_1}, & \ldots, & \frac{\partial e_1}{\partial v_n}, & \frac{\partial e_1}{\partial u_1}, & \ldots, & \frac{\partial e_1}{\partial u_K}, & \frac{\partial e_1}{\partial\theta} \\ \frac{\partial e_2}{\partial\omega_{11}}, & \ldots, & \frac{\partial e_2}{\partial\omega_{iK}}, & \ldots, & \frac{\partial e_2}{\partial\omega_{nK}}, & \frac{\partial e_2}{\partial\theta_1}, & \ldots, & \frac{\partial e_2}{\partial\theta_n}, & \frac{\partial e_2}{\partial v_1}, & \ldots, & \frac{\partial e_2}{\partial v_n}, & \frac{\partial e_2}{\partial u_1}, & \ldots, & \frac{\partial e_2}{\partial u_K}, & \frac{\partial e_2}{\partial\theta} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial e_S}{\partial\omega_{11}}, & \ldots, & \frac{\partial e_S}{\partial\omega_{iK}}, & \ldots, & \frac{\partial e_S}{\partial\omega_{nK}}, & \frac{\partial e_S}{\partial\theta_1}, & \ldots, & \frac{\partial e_S}{\partial\theta_n}, & \frac{\partial e_S}{\partial v_1}, & \ldots, & \frac{\partial e_S}{\partial v_n}, & \frac{\partial e_S}{\partial u_1}, & \ldots, & \frac{\partial e_S}{\partial u_K}, & \frac{\partial e_S}{\partial\theta} \end{bmatrix} \qquad (17)$$

Make $P_s=\sum_{k=1}^{K}w_{ik}a_{ks}-\theta_i$，the element in Jacobi matrix can be got from the following equation:

$$\begin{cases} \frac{\partial e_s}{\partial\omega_{ik}}=-v_i f'(P_s)a_{ks} \\ \frac{\partial e_s}{\partial\theta_i}=v_i f'(P_s) \\ \frac{\partial e_s}{\partial v_i}=-f(P_s) \\ \frac{\partial e_s}{\partial u_k}=-a_{kl} \\ \frac{\partial e_s}{\partial\theta}=1 \end{cases} \qquad (18)$$

The above formula can calculate $\boldsymbol{J}(\boldsymbol{W})$ value of Jacobi matrix in each iteration, and then use LM algorithm to train time series prediction model based on process neural network according to (16).

In conclusion, the learning process of LM learning algorithm of process neural network time series prediction model based on orthogonal basis function expansion is as follows:

(1) Determine the structure parameters of prediction model; Initialize model parameters, expand input function and weight function based on the selected orthogonal

basis function;

(2) Set model learning goal ε, the largest number of iterations M, learning efficiency u and λ;

(3) Construct the vector set $\boldsymbol{W}$ of awaiting adjustment parameters of prediction model;

(4) Calculate Jacobi Matrix $\boldsymbol{J}(\boldsymbol{W})$ according to (17-18);

(5) Calculate the error function E in (15) according to (16)，if $E(s+1) > E(s)$，let $u=\lambda \cdot u$ and repeat (5)；if $E(s+1) < E(s)$，let $u = \lambda / u$，$s = s + 1$，turn to (6)；

(6) If $E < \varepsilon$ or $s > M$, and turn to (7), otherwise, turn to (4);

(7) Output learning results, end.

6. IGBT Health State Parameter Prediction

This section will use process neural network algorithm based on LM optimization to the process of IGBT health state prediction; experimental data adopts the IGBT accelerated aging experiment data of radar transmitter switch preprocessed in section 3. Existing sample curve is shown in Figure 3, a total of 389 sample points. Through the order that the step is 1 to extract 6 sample points as a group, look the first five sample points as input of cascade feedforward to process neural networks, the 6th point as output, 384 groups of samples are achieved; choose the first 300 group as the training sample, the rest of 84 groups of sample as the validation sample.

(1) Initialize the neural network model:

The contents of the initialized neural network model includes: set the neuron number of input layer, output layer and hidden layer. When the training sample is determined, the neuron number s of network input layer and output layer is also determined. Network training parameter refers to the learning rate and the maximum error of network.

Table 2. Process Neural Network Model Parameters

Input node	Output node	Hidden node	Learning efficiency u	inertia amount λ	Error precision	Limited number
5	1	10	0.5	1.5	0.001	1000

(2) The known sample points training process

After complete the training sample preparation and initialize the neural network model, begin to test network model, adjust the input network coefficient, compare mean square deviation and repeat training, training results under the optimum model parameters are achieved. Among them, the training process of process neural network is shown in the Figure below.

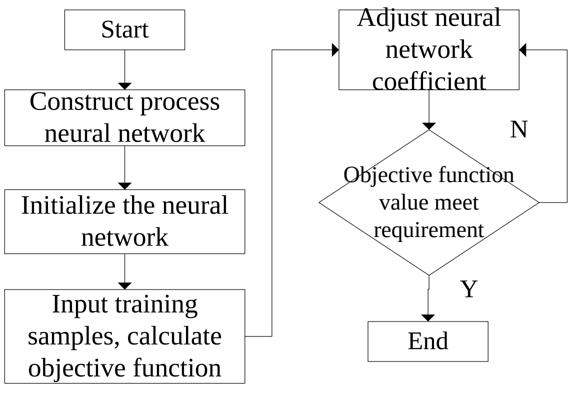


Figure 5. The Training Process of Process Neural

(3) Results prediction and error analysis

Experiment 1: The prediction of traditional process neural network algorithm

Under the experimental conditions, the weight coefficient and threshold value coefficients of neural network both initialize random numbers of range (0, 1), select group training method, the maximum iteration number is 1000 times and the momentum factor is 0.835, the neural network can achieve the convergence precision of MSE = 0.0001 through 230 iterations.

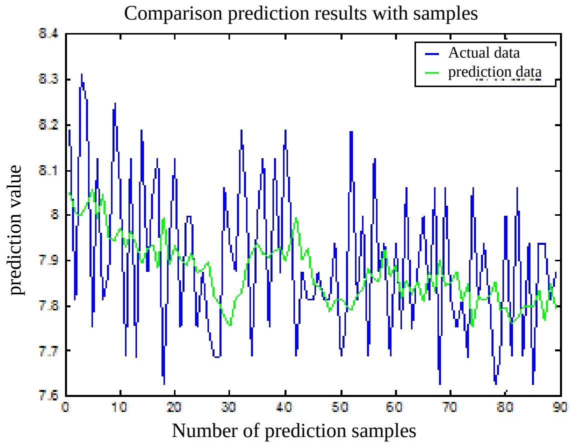


Figure 6. The Actual Data and Prediction Data

Calculate prediction RMS error, RMSE=0.026 from the prediction result of Figure6. The prediction precision is good and there are gaps compared with fitting precision, especially the prediction of sample points behind appears a larger error.

Experiment 2: Process neural network prediction based on LM algorithm

Under the experimental conditions, the weight coefficient and threshold value coefficients of neural network both initialize random numbers of range (0, 1), select group training method, the maximum iteration number is 1000 times, the momentum factor is 0.835, the neural network can achieve the convergence precision of MSE = 0.0001 through 230 iterations, learning rate is improved obviously. The fitting results of training samples are shown in Figure 7 and nonlinear fitting precision is good.

Topological structure of cascade feedforward process neural network locates 5-10-1, expand its input function and connection weight function using Legendre orthogonal basis function and the basis function is selected as 6. Define the maximum training times max_epoch = 1000, neural network initial value deviation of the algorithm mse=0.2, learning efficiency u=0.5, increasing factor of weight function/threshold value is lameda = 1.5.

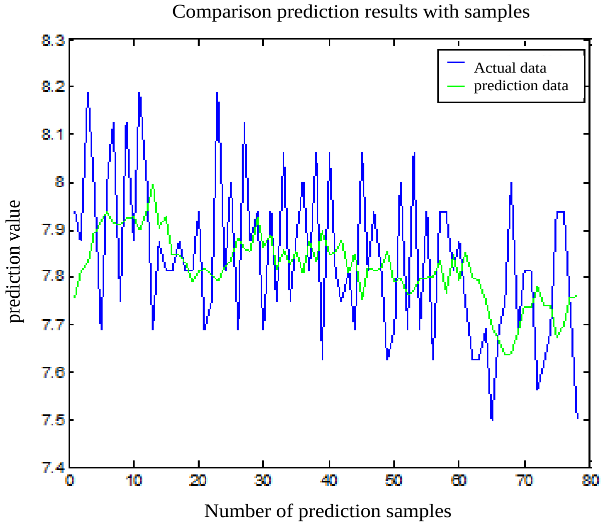


Figure 7. The Actual Data and Prediction Data

As shown in Figure 7, use process neural network into the learning prediction to get the curve, RMSE = 0.014. The prediction precision is superior to the traditional process neural network.

Table 3. Contrast Table of Prediction Results

Prediction method	Time consumption/s	RMSE
Standard process neural network	5.547	0.026
Process neural network based on LM optimization	3.562	0.014

Compare the improved method results proposed with the traditional process neural network algorithm, it can be seen that, the process neural network LM algorithm optimized has higher prediction precision; meanwhile, the consumption of time is more less using this algorithm to optimize process neural network. It proves that the process neural network algorithm optimized by LM is a kind of high efficiency and high prediction precision algorithm.

7. Conclusion

The article is at the basis of radar transmitter power switch IGBT research, combines the accelerated life test data of NASA, determine the collector-emitter turn-off voltage spike peak value as the basis of failure prediction, and carry out IGBT health state prediction method research based on process neural network. In view of the back propagation learning algorithm of traditional process neural network has slow convergence speed and easily trapped in local minimum, developed a kind of learning algorithm LM optimized based on orthogonal basis functions expansion. The experimental results show that the process neural network algorithm based on LM optimization can better predict the performance trend of IGBT degradation with high accuracy and implements the short-term prediction of IGBT health state. The article on the accurate prediction of IGBT health will help realize condition based maintenance and improve the system reliability of the radar transmitter, and has important research and application value.

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