Research on Life Prediction of IGBT Devices Based on Elman Neural Network Model

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ABSTRACT: IGBT, as a new generation of composite full-controlled voltage-driven power semiconductor devices, has been widely used in the field of modern power electronics. The study of IGBT device life prediction has important guiding significance for the stable operation and reliability management of power system. In this paper, the Coffin-Manson-Arrhenius extended exponential model based on thermal load is analyzed, and the model parameters are trained and modified by the Elman neural network in order to improve the prediction accuracy of life prediction model. The Coffin-Manson-Arrhenius extension exponential model and the new improved model are simulated and validated by experiments. The results are compared with the actual life of IGBT. It is concluded that the Coffin-Manson-Arrhenius extension exponential model based on Elman neural network has higher accuracy in life prediction than the Coffin-Manson-Arrhenius extension exponential model.

1. Introduction

IGBT (Insulated Gate Bipolar Transistor) has many characteristics, such as large capacity, low loss and high frequency. Therefore, it is widely used in the field of modern power electronics.

The life prediction of high-power IGBT is of great significance in maintaining the normal and stable operation of IGBT and reliability management. Life prediction is to estimate the number of cycles that IGBT devices can work normally under given external conditions, including voltage, current, temperature, etc. At present, domestic and overseas scholars have done a lot of research work on the life prediction of IGBT. In reference [1], two kinds of IGBT life prediction models, analytical life model and physical life model are introduced. In reference [2,3], the simple coffin Manson model is used for life prediction. Although the life can be estimated to some extent, there is a large error because the effect of junction temperature fluctuation is not considered. In reference [4-6], lesit model is used to predict the life of IGBT. This model comprehensively considers the impact of junction temperature fluctuation and average junction temperature on the life of IGBT, but it still does not consider the impact of other factors such as working frequency on the life. In reference [7], Norris landzbery model is used to consider the influence of power frequency on life and improve the prediction accuracy. In reference [8], a new model named Bayer model is proposed, which takes into account the factors such as heating up time and load current. So it has a high prediction accuracy, but also increase the amount of calculation, leading to higher prediction difficulty.

Although there are many researches on IGBT life prediction, the prediction accuracy of the IGBT life prediction model still needs to be improved. Based on the usual coffin Manson Arrhenius life prediction model, this paper proposes to optimize the parameters of life prediction model by Elman neural network algorithm, so as to further improve the accuracy of life prediction. Finally, the
corresponding thermal load damage accumulation model is established, and the prediction accuracy of
the new life prediction model is verified by the experimental method, and the results are compared
with the original model.

2. Improvement of life prediction model

2.1 Coffin-Manson-Arrhenius extensive index model
For the life prediction model of IGBT, some scholars have proposed the coffin Manson Arrhenius
extensive index model [9], and its formula is shown in (1):

\[ N_f = A_3 \cdot \Delta T_j \cdot e^{\left(\frac{E_a}{k_B(T_m+273)}\right)^{\beta_3}} \]  

(1)

Where: \(N_f\) is the total number of cycles of the module, i.e. lifetime. \(\Delta T_j\) and \(T_{jm}\) are the junction
temperature fluctuation and average junction temperature of IGBT chip, respectively. \(A_3, \alpha_3\) and \(\beta_3\) are
all life-related parameters. The value of \(\beta_3\) is between 0-1. \(E_a\) is material related activation energy
\((9.89 \times 10^{-20} J)\), \(k_B\) is Boltzmann constant \((1.38 \times 10^{-23} J \cdot K^{-1})\).

2.2 Extended index model of CMA based on Elman neural network
Although the coffin Manson Arrhenius extended index model comprehensively considers the effect
of junction temperature fluctuation and average junction temperature on the life of IGBT, and the
extended index is proposed to modify the life prediction model of IGBT, increasing the prediction
accuracy of model, but under the long-term continuous working conditions, the accuracy of life
prediction is still unable to meet the working requirements. Considering that the coffin Manson
Arrhenius extensional index model contains 5 constants, in addition to the material related activation
energy \(E_a\) and Boltzmann constant \(k_B\), there are three constants \(A_3, \alpha_3\) and \(\beta_3\).

According to the actual failure mechanism of IGBT, the main reason of IGBT failure is the
repeated expansion and contraction of materials in the process of thermal cycle, which finally leads to
fatigue, deformation and even fracture of materials [10]. Therefore, compared with the average
junction temperature of the chip, the junction temperature fluctuation has a more important impact on
the life of IGBT. Training and modifying the parameter \(\alpha_3\) which reflects the correlation between
junction temperature fluctuation and life of IGBT can improve the prediction accuracy of IGBT life
prediction model.

Compared with the traditional BP neural network, Elman neural network adds a hidden layer as a
one-step delay operator to make the model have memory function, so that the system has the ability to
adapt to the time-varying characteristics of the parameters in the model, and finally enhances the
global stability of the network. Therefore, the above three constants can be modified during working
period by Elman neural network to improve the prediction accuracy [11].

Structure of Elman neural network is shown in Figure 1, which consists of four parts: input layer,
feedback layer, hidden layer and output layer. The feedback layer and hidden layer have the same
number of neurons. The input layer transfers the data sequence, the feedback layer remembers the data
of the previous time sequence of the hidden layer and feeds it back to the input layer, and finally the
output layer get the result by the means of linear weighting.
At $k$ time, Elman neural network has the following formula:

$$
\begin{align*}
    y(k) &= g(w_1 \cdot x(k)) \\
    x(k) &= f(w_2 \cdot z(k) + w_3 \cdot u(k-1)) \\
    z(k) &= x(k-1)
\end{align*}
$$

(2)

Where $y(k)$ is the input vector, $x(k)$ is the output vector of the hidden layer, and $z(k)$ is the vector fed back to the input by the feedback layer.

Finally, the sum of squares of errors is used as the learning index function, and the formula is

$$
E(w) = \sum_{k=1}^{n} [y_k(w) - \tilde{y}_k(w)]^2
$$

(3)

Where $y_k(w)$ is the actual output and $\tilde{y}_k(w)$ is the target output.

The training process is shown in Figure 2. Firstly, the data of junction temperature fluctuation and average junction temperature in IGBT are obtained, and three constant data are obtained as sample set by fitting. Then, the sample set is divided into two groups: training sample and test sample. Elman neural network algorithm is used to analyze and train the samples, and the corresponding change curve is obtained and put into the life prediction model. Finally, the accuracy of the model is verified by the test data.

3. Life prediction model based on thermal load

3.1 Parameter prediction based on Elman neural network

According to the content above, the paper establishes the life prediction model with heat load as input based on the Coffin-Manson-Arrhenius extensive index model and the Coffin-Manson-Arrhenius extensive index model based on Elman neural network respectively, and conducts simulation research on the prediction accuracy of the proposed model.
It can be seen from Figure 3 that during the working process of IGBT, the fatigue degree of the device first increases linearly and slowly, then gradually changes to non-linear growth. At this time, the reliability of the device decreases dramatically. The change curve of parameter $\alpha_3$ in the fatigue cumulative extensive index model can be obtained by Fig. 3, as shown in Fig. 4.

The first ten groups of data in the $\alpha_3$ curve are taken as input, and the eleventh data as output. Finally, 500 groups of data sample groups are obtained. The first 450 groups were used for training model, and the last 50 groups were used for accuracy test.

After initializing Elman neural network, according to the number of input and output, it is determined that the number of neurons in the input layer is 10 and the number of neurons in the output layer is 1. Set the maximum number of iterations for training as 20000, the maximum allowable error as 0.0001, and stop the training process when the error is equal to or less than 0.0001. The prediction results of the final parameter $\alpha_3$ are shown in Figure 5.

It can be concluded from Figure 5 that the parameter prediction model based on the elman neural network has a good prediction accuracy with a maximum error of 2.6722%. So it can be used to achieve a more accurate life prediction of IGBT.
3.2 Simulation model

The simulation process is shown in Figure 6. For the junction temperature estimation of IGBT chip, the junction temperature estimation method based on curve fitting is used. The junction temperature obtained is taken as input into the life prediction model of IGBT chip. Finally, the prediction results are obtained.

![Fig.6 Life prediction model based on thermal load](image)

In order to predict the life of IGBT, it is necessary to input the data of junction temperature fluctuation $\Delta T_j$ and average junction temperature $T_{jm}$. The temperature measurement method commonly used is the thermal parameter measurement method, which estimates the junction temperature through a specific thermal parameter under a certain state of IGBT. However, due to noise interference and other problems, the measurement results will have some errors [12-14]. Therefore, the temperature measurement of IGBT chip is carried out by the temperature measurement method of Cauer electric heating coupling model [15].

For the IGBT module, considering the initial value selection of curve fitting, the Cauer model is used to characterize the heat flow path of the IGBT module. The Cauer heat transfer model of IGBT module is shown in Figure 7.

![Fig.7 Cauer model of IGBT](image)

Where, $R$ is the thermal resistance of the material, $C$ is the heat capacity of the material, and the number represents the material. The twice to sixth layers of material are omitted in the figure, which are represented by dotted lines. The heat source of the model is represented by current source, and the value is the power loss of IGBT, which can be represented by formula (4).

$$P = U_{ce} \cdot I_c$$  \hspace{1cm} (4)

The thermal capacity resistance of each material of IGBT are determined by curve fitting method. The voltage $U_{ce}$ and current $I_c$ of IGBT in operation are taken as input to obtain the instantaneous voltage of heat source, which is the instantaneous junction temperature of IGBT chip. The initial value of curve fitting can be obtained from the formula (5) of thermal capacity resistance of each material.

$$\begin{align*}
    R_i &= \frac{d}{\lambda_i S} \\
    C_i &= \rho V c_{pi}
\end{align*}$$  \hspace{1cm} (5)

Where $D$ is the height of the material, $S$ is the area, $\lambda_i$ is the thermal conductivity, $\rho$ is the density, $V$ is the volume, and $c_{pi}$ is the specific heat capacity.
4. Example analysis

4.1 Life prediction simulation

Based on the content above, the simulation model as shown in Figure 3 is built. Firstly, the power loss produced in the normal operation of IGBT is taken as the input, which is the power of the heat source of the Cauer model. Then, the junction temperature of IGBT chip during operation is obtained through the simulation of the electric heat coupling model, and the data of average junction temperature $T_{jm}$ and junction temperature fluctuation $\Delta T_j$ are obtained through the junction temperature curve of IGBT chip. The data are input into the original coffin Manson Arrhenius extensive index model and the modified coffin Manson Arrhenius extensive index model based on Elman neural network respectively. The prediction results are compared and analyzed.

![Fig.8 Simulation model](image)

In the simulation model, IGBT is connected with diode in reverse parallel, voltage source and load resistance in series. The operation state of IGBT is changed by changing the output voltage of voltage source and the duty cycle of driving signal. Monitor the collector-emitter voltage $U_{ce}$ and collector current $I_c$ of IGBT, and get the waveform as shown in Figure 9. It can be seen from Figure 9 that in the low-frequency working environment, the power loss of IGBT mainly comes from the conduction voltage drop in the opening stage. With the increase of operating frequency, switching loss becomes the main part of IGBT power loss.

Take the power loss of IGBT as the value of heat source, input it into the Cauer heat transfer model of IGBT, monitor the voltage of heat source, which can be equivalent to the junction temperature of IGBT chip. The trend of IGBT junction temperature in the simulation is shown in Figure 10.

![Fig.9 Waveform of voltage, current and power loss of IGBT](image)
It can be analysed from Figure 10 that on the whole, IGBT chip enters into a stable state after a short heating process, and the junction temperature of IGBT chip tends to be stable without any change. In a single cycle, the IGBT chip first heats up and then cools down. The temperature fluctuation is an important factor affecting the reliability of IGBT.

The junction temperature fluctuation $\Delta T_j$ and average junction temperature $T_{jm}$ in IGBT thermal cycle are obtained from Figure 10, and the parameters are substituted into the life prediction model for life prediction.

4.2 Life prediction experiment

Based on the simulation circuit shown in Figure 8, a related experimental platform is built to verify the life prediction accuracy of the new model. The experimental principle is shown in Figure 11. The chip junction temperature of IGBT in the working circuit is extracted by infrared thermometer. Finally, the junction temperature of IGBT chip is shown in Figure 12. After a period of long duration and stable average junction temperature, junction temperature will experience a sudden rise before failure of IGBT. Finally, high temperature leads to chip damage and failure.

4.3 Life prediction results

The life prediction results of the modified coffin Manson Arrhenius extensive index model based on Elman neural network are shown in Figure 13. It can be seen from the figure that the life of IGBT will decrease dramatically with the increase of average junction temperature and junction temperature fluctuation. When the junction temperature fluctuation is more than 60 °C, IGBT chip will be damaged.
almost immediately.

Compared with the coffin Manson Arrhenius extensive index model, the accuracy comparison is shown in Figure 14. The vertical coordinate in the figure shows the difference between the error of the improved model and the error of the improved model. The formula is as follows:

$$\Delta \varepsilon = \varepsilon_1 - \varepsilon_2$$ (6)

Among them, $\varepsilon_1$ is the relative error of the origin model, and $\varepsilon_2$ is the relative error of the improved model. It can be seen from the figure that when the input is small, the error between the coffin Manson Arrhenius model and the coffin Manson Arrhenius model based on Elman neural network is not large. With the increase of input, especially the increase of junction temperature fluctuation, the prediction result of the latter is obviously closer to the actual life and has higher inherent prediction accuracy.

![Fig. 13 Life prediction results](image1)

![Fig. 14 Comparison of errors in life prediction](image2)

5. Conclusion

Based on the coffin Manson Arrhenius extended index model, this paper proposes the coffin Manson Arrhenius extended index model based on Elman neural network. By training the constants in the model, the model is more consistent with the actual fatigue accumulation process, and the purpose of improving the life prediction accuracy is achieved. Through simulation and experiment, the life prediction accuracy of the model is studied, and the feasibility of the model is verified.

Meanwhile, this paper only trains one of the three constants of the coffin Manson Arrhenius extensive index model, and does not verify the feasibility of the method of training all three constants.

References

[1] Fang Xin, Zhou Luowei, Yao Dan, et al. An Overview of IGBT Life Prediction Models[J]. Journal of Power Supply, 2014, 12(3):14-21.
[2] Ciappa M. Selected failure mechanisms of modern power modules[J]. Microelectronics Reliability, 2002, 42(4-5):653-667.
[3] Musallam M, Johnson C M, Yin C, et al. Real-time life expectancy estimation in power modules[C]// Electronics System-Integration Technology Conference, 2008. ESTC 2008. 2nd. IEEE, 2008.
[4] Ciappa M, Castellazzi A. Reliability of High-Power IGBT Modules for Traction Applications[C]// IEEE International Reliability Physics Symposium. IEEE Computer Society, 2007.
[5] Chen Ming, Hu An, Liu Binli. Failure Mechanism and Lifetime Prediction Modeling of IGBT Power Electronic Devices[J]. JOURNAL OF XI'AN JIAOTONG UNIVERSITY, 2011, 45(10):65-71.

[6] Bryant A T, Mawby P A, Palmer P R, et al. Exploration of Power Device Reliability using Compact Device Models and Fast Electro-Thermal Simulation[C]// Industry Applications Conference. IEEE, 2006.

[7] I.F. Kovačević, Drofenik U, Kolar J W. New physical model for lifetime estimation of power modules[C]// Power Electronics Conference (IPEC), 2010 International. IEEE, 2010.

[8] Bayerer R, Herrmann T, Licht T, et al. Model for Power Cycling lifetime of IGBT Modules - various factors influencing lifetime[C]// Integrated Power Systems (CIPS), 2008 5th International Conference on. VDE, 2008.

[9] I.F. Kovačević, Drofenik U, Kolar J W. New physical model for lifetime estimation of power modules[C]// Power Electronics Conference (IPEC), 2010 International. IEEE, 2010.

[10] Morozumi A, Yamada K, Miyasaka T, et al. Reliability of power cycling for IGBT power semiconductor modules[J]. IEEE Transactions on Industry Applications, 2003, 39(3):665-671.

[11] Wang J, Wang J, Zeng M, et al. Prediction of Internet Traffic Based on Elman Neural Network[C]// Control & Decision Conference. 2009.

[12] Chen Ming, Wang Bo, Tang Yong. The Experimental Research on Transient Thermal Impedance of IGBT[J]. Power Electronics, 2010(9).

[13] Avenas Y, Dupont L, Khatir Z. Temperature Measurement of Power Semiconductor Devices by Thermo-Sensitive Electrical Parameters—A Review[J]. IEEE Transactions on Power Electronics, 2012, 27(6):3081-3092.

[14] Gachovska T K, Tian B, Hudgins J L, et al. A Real-Time Thermal Model for Monitoring of Power Semiconductor Devices[C]// Energy Conversion Congress and Exposition (ECCE), 2013 IEEE. IEEE, 2013.

[15] Yin J, Wyk J D V, Odendaal W G, et al. Comparison of transient thermal parameters for different die connecting approaches[C]// Industry Applications Conference, 2003. 38th IAS Annual Meeting. Conference Record of the. IEEE, 2003.