# Junction Temperature Prediction of IGBT Power Module Based on BP Neural Network

## Junke Wu<sup>†</sup>, Luowei Zhou\*, Xiong Du\* and Pengju Sun\*

**Abstract** – In this paper, the artificial neural network is used to predict the junction temperature of the IGBT power module, by measuring the temperature sensitive electrical parameters (TSEP) of the module. An experiment circuit is built to measure saturation voltage drop and collector current under different temperature. In order to solve the nonlinear problem of TSEP approach as a junction temperature evaluation method, a Back Propagation (BP) neural network prediction model is established by using the Matlab. With the advantages of non-contact, high sensitivity, and without package open, the proposed method is also potentially promising for on-line junction temperature measurement. The Matlab simulation results show that BP neural network gives a more accuracy results, compared with the method of polynomial fitting.

**Key words:** IGBT, Junction temperature prediction, BP neural network, Saturation voltage drop, Collector current

#### 1. Introduction

IGBT is one of the most widely used power modules in power electronic converters, and its reliability has drawn much attention since it is one of the most fragile components in power converters [1-3]. Researches have shown that the thermal behavior of IGBT has a significant effect on the reliability of the power conversion system. The mean temperature and its variations of the chip inside the module are closely related to the reliability and the lifetime of the IGBT module [4-6]. The monitoring of IGBT junction temperature is very useful for improving the reliability, cost effectiveness and performance of the power electronic system. Almost all of the reliability evaluation strategies of IGBT are related to junction temperature. Therefore, the measurement or evaluation of IGBT junction temperature is becoming a key issue in power semiconductor's reliability.

At present, three types of junction temperature evaluation techniques have been proposed by researchers: direct temperature measurement, thermal model-based method and TSEP method of measuring the collector-emitter voltage drop.

Direct temperature measurement with contact or noncontact sensors is widely employed in laboratory. The contact sensors, such as thermocouple and thermal resistor, are simple but have the shortage of long response time, limited space inside the module and electric safety problems. While non-contact sensors, such as infrared temperature measurement techniques and optical fibers [7-8], can provide a good dynamic response, but they require modules with package open. Compared with the direct measurement, the following two types of temperature evaluation methods belong to indirect evaluation technologies.

Based on the second method, the thermal model-based method, some semiconductor manufactures provide simulation software for junction temperature evaluation [9], and there has been a great deal of development in real time calculation of the operating junction temperature for IGBT power module [10-15]. This method is good for temperature prediction; however, its accuracy may be questionable because of the accuracy of power loss calculation and the changing parameters of thermal model with aging process. Due to individual difference among modules, the model based temperature estimation may not be consistent for each device.

The third temperature evaluation method is based on TSEPs such as saturation current, gate-emitter voltage, threshold voltage and collector-emitter voltage correlated with temperature [16-22]. The largest advantage of TSEP measurement is that it can be performed on packaged power modules [16]. Among these TSEPs, the saturation voltage drop under small current is often used to predict the junction temperature [17], but this method is not suitable for online measurement while the IGBT is in operation. Some authors improve this method by providing a sense current of 100mA after turn-off of the large load current. But the interference generated by the switch action increases the difficulty of measurement, which limits its application. While TSEP method with collect-emitter saturation voltage drop under large current gives good results for on-line measurement with certain accuracy, but

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Me	ethods	Specific examples	Advantages	Disadvantages
* thermocouple  * thermal resistor  * infrared techniques  * optical fibers  * cauer thermal network  * foster thermal network  * fem simulation  * collector-emitter voltage  * thermocouple  * thermocouple  * thermal resistor  * infrared techniques  * optical fibers  * cauer thermal network  * foster thermal network  * fem simulation  * collector-emitter voltage  * thereshold voltage	• simple • direct • high accuracy	need surface view     contact may disturb temperature     no contact is expensive		
Indirect		foster thermal network	<ul><li>non-contact</li><li>on-line application</li><li>convenient</li></ul>	*average temperature     *model parameter changes as service life     *individual difference
	TSEP method	_	packaged device     non-contact     on-line application     high application	averages temperature     require high accurate measurement device     need calibration

· high sensitivity

**Table 1.** Comparison on different junction temperature evaluation methods

switching time

its application is limited because of the nonlinear relationship among the saturation voltage drop, the collector current and the junction temperature. Table 1 gives the comparison on different junction temperature evaluation methods.

In order to deal with the nonlinear relationship among the parameters of the TSEP method, an artificial intelligence approach is introduced to estimate the IGBT junction temperature in this paper. As the relations between saturation voltage drop, collector current and the junction temperature are nonlinear and complex. BP neural network. having been used in many fields such as load prediction, fault diagnosis, temperature prediction, may be suitable as a temperature prediction tool, which has the ability of strong nonlinear mapping, the self-learning and selfadaptive [23-24]. But no research on IGBT junction temperature prediction by using artificial neural network has been reported until now. It is desirable that the work of this paper makes some beneficial exploration on semiconductor chip temperature evaluation from another point of view.

## 2. Principles of Junction Temperature Evaluation

Before temperature evaluation, the structure and temperature evaluation principle of the IGBT module should be introduced. Fig. 1 gives the outside view of an opened IGBT module, which is provided by Fuji Electric Device Technology Hong Kong Co. Ltd. And Fig. 2 shows the basic structure of a two units module. In the module, two IGBT chips are in series with each other, and the freewheeling diode (FWD) is parallel with the corresponding IGBT chip. Lots of Al bonded wires are used to connect these chips, as well as the chips and the copper plate. Besides, there are two solders inside the module, one is between the chip and the copper, and the other is between the substrate and the baseplate. As for the substrate, it is usually made up of direct bonded copper (DBC), which plays a role of electrical insulation and heat inducting. The interior space of the module is filled up with silica gel, and the whole module is inside a hard plastic case.

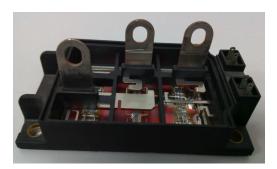


Fig. 1. Outside view for an open package IGBT module.

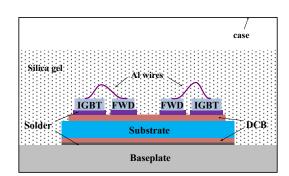
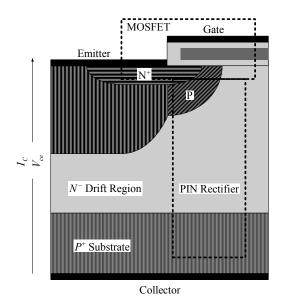


Fig. 2. Structure for a type of IGBT power module.

The mismatch of thermal expansion coefficients [5] among different layers of IGBT power module results in unbalanced thermal-mechanism stress, which leads to the problems such as degeneration and aging of the solders, and lift-off of the bonded Al wires. These problems not only affect the normal operation of the power module, but also the temperature evaluation. Fig. 3 gives the schematic diagram of IGBT as a combination of PNP BJT and MOSFET.

As the saturation voltage drop  $V_{\rm ce}$  and collector current  $I_{\rm C}$  are used to predict the junction temperature of the IGBT chip, the corresponding theoretical relations of them are required to study before prediction. The collector-emitter saturation voltage of the IGBT chip is given by [25]

$$V_{ce} = \left(\frac{2kT}{q}\right) \ln \left\{ \frac{I_{ce}d}{2qW_{R}ZD_{a}n_{i}F(d/L_{a})} \right\} + \frac{(1-\alpha_{PNP})I_{ce}L_{ch}}{\mu_{ns}C_{ox}Z(V_{ge}-V_{Th})}$$
(1)



**Fig. 3.** Schematic diagram of IGBT as a combination of PNP BJT and MOSFET.

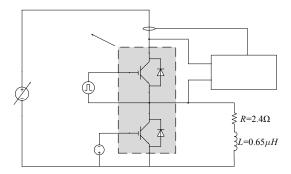
where k is Boltzmann's constant, T is absolute temperature, q is the electronic charge,  $V_{N^-}$  is the voltage drop across the middle N base of a PNP BJT,  $I_{ce}$  is collector-emitter current,  $\alpha_{PNP}$  is the current gain of the PNP transistor,  $\mu_{ns}$  is the average electron mobility in the inversion layer,  $W_R$  is the base width, Z is the cell width perpendicular to the cross section,  $D_a$  is the ambipolar diffusion constant,  $n_i$  is intrinsic carrier concentration,  $L_a$  is the ambipolar diffusion length, d is the thickness of gate oxide,  $C_{ox}$  is the specific capacitence of the oxide, and  $L_{ch}$  is the channel length. In Eq. (1),  $F(d/L_a)$  is given by

$$F(d/L_a) = \frac{d}{L_a} \tanh\left(\frac{d}{L_a}\right) \frac{\exp(-\frac{qV_{N^+}}{2kT})}{\sqrt{1 - (1/4)\tanh^4(d/L_a)}}$$
(2)

From the above Eq. (1), it can be seen that  $V_{\rm ce}$  and  $I_{\rm C}$  are temperature sensitive electrical parameters. As a result, these TSEPs can be used to evaluate the junction temperature, which are difficult to be obtained directly. Here we use BP neural network to reflect the nonlinear mapping relations between these TSEPs and the junction temperature. The next two sections will give an introduction of experimental testing system and the modeling of the BP neural network.

## 3. Experimental Testing System

Before using the BP neural network to predict the temperature, the corresponding experimental circuit for measuring the collector-emitter saturation voltage  $V_{\rm ce}$  and collector current  $I_{\rm C}$  will firstly be given, and the scheme is



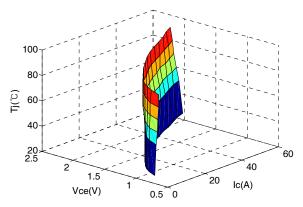
**Fig. 4.** Experiment circuit for measuring  $V_{ce}$  and  $I_C$ .

shown in Fig. 4. In order to obtain different collector currents under various temperatures, the IGBT module under test is put into a thermostat, and the internal temperature of the thermostat can be regulated according to the request. Meanwhile, a power resistor with constant value is used to get a specific load current by adjusting the voltage source supply 62150H-450 produced by Chroma. The power rating, the maxim output voltage and the output current of the voltage source supply are 15kW, 450V and 34A, respectively. Here we use three parallel connected power supplies to provide the desired load current. To prevent self-heating effect of the power module, a single pulse gate voltage which lasts only one microsecond is used to drive the module, so that the heat generated by the chip is little enough to be ignored. Meantime, a dual channels oscilloscope DPO 7104C produced by Tektronix, is used to measure the desired voltage and current. The bandwidth of this oscilloscope is 1GHz, and the sampling rate is 20Gs/s. So it is accurate enough to measure the saturation voltage drop and the collector current of the IGBT module.

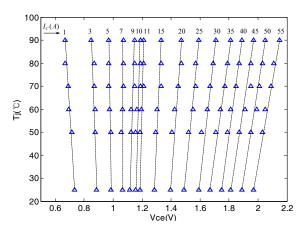
For convenience of laboratory test, a kind of IGBT module with proper collector current should be considered. Here we use the IGBT module 2MBI75S-120 produced by Fuji Electric Co. Ltd., to accomplish the experiment. The rated current and rated voltage are 75A and 1200V, respectively.

We carry out the experiment scheme by increasing the load current and the thermostat's temperature step by step. The IGBT inside the thermostat is the DUT (device under test) IGBT. When we set the thermostat to a certain temperature, the temperature of the IGBT module increases gradually. With the IGBT being heated for a considerable time, its temperature equals the thermostat's inner temperature. Then a single pulse gate voltage is used to drive the IGBT module. Under the condition of ignoring the short time's self-heating effect, it is supposed that the junction temperature of the IGBT equals the inner temperature of the thermostat. Consequently, the junction temperature  $T_j$ , the instantaneous collector current  $I_C$ , and the saturation voltage drop  $V_{ce}$  can be measured.

Some of the experimental data are used for training, and the others are used for testing. Fig. 5 shows the relations of



**Fig.5.** Relations of the measured  $I_C$ ,  $V_{ce}$  and  $T_i$ .



**Fig. 6.** Relations of  $T_j$  and  $V_{ce}$  under different collector current  $I_C$ .

the measured collector current  $I_{\rm C}$ , collector-emitter saturation voltage drop  $V_{\rm ce}$  and the junction temperature  $T_{\rm j}$ . And the planar figure of  $T_{\rm j}$  and  $V_{\rm ce}$  under different collector current  $I_{\rm C}$  is shown in Fig. 6. It must be pointed out that there is a demarcation value of the collector current in Fig. 6 and this value is about 10A. Fig. 6 also reveals that  $V_{\rm ce}$  has positive temperature coefficient when  $I_{\rm C}$  is above the 10A; while it has negative temperature coefficient when  $I_{\rm C}$  is below it. Besides, it presents that no matter below or above this demarcation value, the curve has good linearity.

## 4. Design and Modeling of BP Neural Network

## 4.1 Design of BP NN

BP neural network was proposed by Rumelhart and other specialists. Fig. 7 shows its basic structure, which includes input layer, hidden layer and output layer. Each layer is composed of several neurons, each of which has an excitation function. If the neuron is triggered, the output value of the function will transfer to the next layer. In addition, there is a variable weighted value in the transmission path between the layers. Generally, as Fig. 7

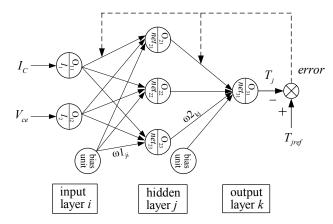


Fig. 7. The structure of BP neural network.

shows, there are bias units in both the input layer and the output layer. Actually, the hidden layer can be more than one layer. The input variables of the network are collector current  $I_{\rm C}$  and saturation voltage  $V_{\rm ce}$ , and the output variable is the prediction results of junction temperature  $T_{\rm i}$ .

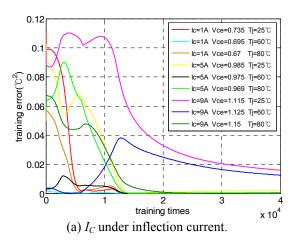
To improve the learning and testing performance of the network, a proper number of neurons in the hidden layer should be selected. Generally, an empirical formula is used to determine the node number

$$n = \sqrt{n_i + n_0} + a \tag{3}$$

where n,  $n_i$ , and  $n_0$  represent the neuron number of the hidden layer, the input layer and the output layer respectively. The parameter a is a constant ranging between 0 to 10. Because the results of Eq. (3) include several numbers, we set the neuron number for three by trial and error method after calculation.

## 4.2 The training process of BP NN

When the parameter design of neural network is completed, the training process will be carried out. The algorithm of BP learning process is composed of two processes, namely the forward propagation of signal and back propagation of the output error. Through the back propagation, the output errors are apportioned to all nodes of each layer, and the weights and bias of the network are updated towards the direction of most rapid increase, so as to minimize the error of the output of the network. The function of input hidden layer tansig will saturate if the inputs go beyond a certain range. At the beginning of training process, descent gradient function becomes very small due to the saturation of the hidden layer function, so the training speed will become very slow. Therefore, it is necessary to normalize the raw data, and the range of input and output value is mapped to [-1, 1], so as to improve the network performance and the training efficiency. A lot of tests are needed when training the model, meanwhile, in



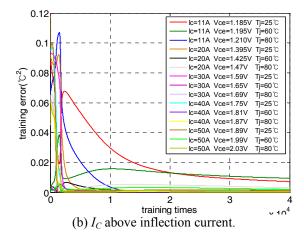


Fig. 8. Convergence performance of BP neural network.

**Table 2**. Training data and results for  $I_{\rm C}$  under inflection current

$I_{\rm C}({ m A})$	1	1	1	5	5	5	9	9	9
$V_{\rm ce}({ m V})$	0.735	0.695	0.670	0.985	0.975	0.969	1.115	1.125	1.150
target value $T_{j}(^{\circ}\mathbb{C})$	25	60	80	25	60	80	25	60	80
training results(°C)	26	60	80	25	60	79	26	59	80
training error(°C)	1	0	0	0	0	-1	1	-1	0

**Table 3**. Training data and results for  $I_{\rm C}$  above inflection current

$I_{\rm C}({\rm A})$	11	11	11	20	20	20	30	30	30	40	40	40	50	50	50
$V_{\rm ce}({ m V})$	1.185	1.195	1.210	1.395	1.425	1.470	1.590	1.650	1.690	1.750	1.810	1.870	1.890	1.990	2.030
target value $T_j(^{\circ}\mathbb{C})$	25	60	80	25	60	80	25	60	80	25	60	80	25	60	80
training results(°C)	25	61	80	25	61	80	25	61	79	25	61	80	25	60	80
training error(°C)	0	1	0	0	1	0	0	1	-1	0	1	0	0	0	0

**Table 4**. Testing data and temperature prediction results of BP NN for I<sub>C</sub> under inflection current

$I_{\rm C}({\rm A})$	3	3	3	7	7	7	10	10	10
$V_{\rm ce}({ m V})$	0.875	0.870	0.849	1.055	1.070	1.070	1.155	1.190	1.190
actual value $T_j(^{\circ}\mathbb{C})$	50	70	90	50	70	90	50	70	90
testing results ( $^{\circ}$ C)	55	69	89	53	73	90	52	76	90
relative error (%)	10.00	-1.43	-1.11	6.00	4.29	0	4.00	8.57	0

order to determine the parameters a and n, the trial and error method is also applied.

The initial values of the weights have an impact on the accuracy of the prediction results. And the learning rate also affects the system's stability. BP neural network's learning algorithm is back-propagation algorithm, which will take place if the output values are not the desired ones. The training error is propagated back and the neuron weights of each layer are kept being changed till the training reaches a minimum of the performance.

To accurately predict the temperature, we classify the measurement data into two categories, one of which is under the inflection point current, and the other is above it. Meanwhile, demarcation value of the collector current is set to 10A. Tables 2 and 3 provide the training data and the corresponding training results. The convergence performances of BP neural network in Fig. 8 show that the convergence rate near the inflection current point is slower

than the rate under or above the point.

## 4.3 The prediction results and its analysis

This section will give the testing results of the designed neural network model. And a comparative analysis of temperature prediction between neural network and polynomial fitting method is also given. From the testing results shown in Tables 4 and Table 5, it is appreciated that the BP neural network has a good approximation, and the prediction errors are under 10% for collector current from 1A to 55A.

In order to estimate the prediction effect of the neural network model, a comparative study given by polynomial fitting scheme is presented. Here the junction temperature is described by polynomial of collector current  $I_{\rm c}$  and saturation voltage drop  $V_{\rm ce}$ , based on the experimental data. From Fig. 6 it can be seen that there is a good linear

**Table 5.** Testing data and temperature prediction results of BP NN for  $I_C$  above inflection current

$I_{\rm C}({\rm A})$	15	15	15	25	25	25	35	35	35	45	45	45	55	55	55
$V_{\rm ce}({ m V})$	1.295	1.330	1.330	1.520	1.570	1.590	1.710	1.770	1.810	1.870	1.950	1.970	2.030	2.090	2.150
actual value $T_{j}(^{\circ}\mathbb{C})$	50	70	90	50	70	90	50	70	90	50	70	90	50	70	90
testing results (°C)	51	72	90	50	74	90	50	71	89	50	69	90	46	71	88
relative error (%)	2.00	2.86	0	0	5.71	0	0	1.43	-1.11	0	-1.43	0	-8.00	1.43	-2.22

**Table 6**. Results of polynomial fitting for  $I_{\rm C}$  below inflection current

actual value $T_{j}(^{\circ}\mathbb{C})$	50	70	90	50	70	90	50	70	90
polynomial fitting $T_{j}(^{\circ}\mathbb{C})$	56	61	79	67	67	67	52	88	88

**Table 7**. Results of polynomial fitting for  $I_C$  above inflection current

actual value $T_j(^{\circ}\mathbb{C})$	50	70	90	50	70	90	50	70	90	50	70	90	50	70	90
polynomial fitting $T_j(^{\circ}\mathbb{C})$	55	79	79	45	77	90	43	77	99	44	79	88	54	72	89

relationship between  $T_{\rm j}$  and  $V_{\rm ce}$  when  $I_{\rm c}$  equals a certain value. So the polynomial fitting equation of junction temperature for current values below the inflection point can be expressed as

$$T_{j} = f(I_{c}, V_{ce})$$

$$= g_{1}(I_{c})V_{ce} + g_{2}(I_{c})$$

$$= (a_{1}I_{c}^{2} + b_{1}I_{c} + c_{1})V_{ce} + (d_{1}I_{c}^{2} + e_{1}I_{c} + f_{1})$$
(4)

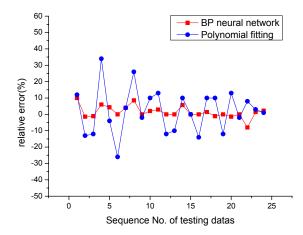
where  $g_I$  and  $g_2$  are coefficients of  $I_C$  dependent function. The parameters  $a_1$ ,  $b_1$ ,  $c_1$ ,  $d_1$ ,  $e_1$  and  $f_1$  in the above equation can be obtained by using the curve fitting toolbox of Matlab/Simulink. And the training data in Table 2 is used to fit the equation. Therefore, we can obtain the fitted coefficients:  $a_1 = 19.12$ ,  $b_1 = 22.7$ ,  $c_1 = -1114$ ,  $d_1 = -31.78$ ,  $e_1 = 134.2$ ,  $f_1 = 704.3$ . By putting the testing data of  $I_C$  and  $V_{ce}$  (as shown in Table 4) into fitting Eq. (4), the corresponding testing results are shown in Table 6.

Similarly, the polynomial fitting equation for current values above the inflection point can also be expressed as

$$\begin{split} T_{j} &= f(I_{c}, V_{ce}) \\ &= h_{1}(I_{c})V_{ce} + h_{2}(I_{c}) \\ &= (a_{2}I_{c}^{2} + b_{2}I_{c} + c_{2})V_{ce} + (d_{2}I_{c}^{2} + e_{2}I_{c} + f_{2}) \end{split} \tag{5}$$

where  $h_1$  and  $h_2$  are coefficients of  $I_C$  dependent function. Based on the training data in Table 3, the coefficients of the equation can be obtained by using the curve fitting tool of Matlab/Simulink:  $a_2 = -0.1413$ ,  $b_2 = -0.532$ ,  $c_2 = 751.9$ ,  $d_2 = 0.521$ ,  $e_2 = -28.41$ ,  $f_2 = -558.9$ . By putting the testing data of  $I_C$  and  $V_{ce}$  (as shown in Table 5) into fitting Eq. (5), the corresponding testing results are shown in Table 7.

Tables 6 and Table 7 reveal that the prediction error of polynomial fitting method is large when the current value is below the inflection point. Fig. 9 gives the relative error for the two types of temperature evaluation methods. It is obvious that the neural network method has better



**Fig. 9.** Comparison of testing error for BP neural network and polynomial fitting.

performance than the polynomial fitting method. The prediction accuracy of the current values above the inflection point is also better than that below the point. The reason may be that the IGBT shows a highly nonlinear characteristic when the collector current value is below the inflection point.

#### 5. Conclusions

The precise acquisition of IGBT's junction temperature is always a challenging issue. The TSEP method by using collect-emitter saturation voltage drop seems to be the most potential one for junction temperature evaluation. However, its accuracy is limited by the complex nonlinear relationship between the electrical parameters and the junction temperature. The novelty of this paper is that it solves this problem from the artificial intelligence point of view. In order to predict the junction temperature of IGBT power module more accurately, a BP artificial neural network model is established. The physics theoretic analysis of the relations among the device's junction

temperature, saturation voltage and collector current is presented. By measuring the device's saturation voltage and collector current under specified temperature, we give a prediction method to evaluate the junction temperature. The testing results show that the BP neural network has the ability to predict the junction temperature, so long as the saturation voltage and collector current are obtained accurately. The predict results of the proposed method are also compared with that of the polynomial fitting method. At last, it must be pointed out that this paper is only a preliminary study for semiconductor temperature prediction by using neural network, and the prediction accuracy can be improved as the quantity of training data increases.

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