



Application of artificial neural network for switching loss modeling in power IGBTs*

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Abstract: The modeling of switching loss in semiconductor power devices is important in practice for the prediction and evaluation of thermal safety and system reliability. Both simulation-based behavioral models and data processing-based empirical models are difficult and have limited applications. Although the artificial neural network (ANN) algorithm has often been used for modeling, it has never been used for modeling insulated gate bipolar transistor (IGBT) transient loss. In this paper, we attempt to use the ANN method for this purpose, using a customized switching loss test bench. We compare its performance with two conventional curve-fitting models and verify the results by experiment. Our model is generally superior in calculation speed, accuracy, and data requirement, and is also able to be extended to loss modeling for all kinds of semiconductor power devices.

Key words: Insulated gate bipolar transistor (IGBT), Switching loss, Modeling, Artificial neural network (ANN)

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1 Introduction

Loss in power electronic devices depends on the type of device and the operating conditions. These factors directly determine the selected rating and system requirements such as cooling and overheating protection. It is crucial to predict the loss (the heat generated) in specified applications during the early design stages to guarantee an optimized balance between cost and reliability. Loss in a voltage controlled switching power device like an insulated gate bipolar transistor (IGBT) comes from two main sources: conduction and switching. Simple and steady relations between current and temperature are found in the case of conduction loss, which can be estimated fairly accurately according to the operation modes and datasheets. However, transient losses, including

those arising from turn-on and turn-off, are more difficult to estimate, as many more influential factors need consideration. Hence, models far more complicated than the simple curves used in the case of conductive loss, are needed for switching loss evaluations.

Many attempts have been made in recent decades to obtain comprehensive models for IGBTs. Mainstream technologies can be classified as:

1. Micro behavioral models with exact equivalent circuits, derived from the intrinsic physics and parameters, which provide the operation details such as real-time voltage and current waveforms under different conditions, by simulation. With good performance and high modeling cost, switching losses are obtainable from these models (Hefner, 1994; Hefner and Diebolt, 1994; Kraus *et al.*, 1998; Sheng *et al.*, 1999; Bryant *et al.*, 2008; Michel *et al.*, 2009).

2. Macro behavioral models based on the combination and modification of existing component models, which take IGBTs as the combination of existing well modeled components such as metallic oxide semiconductor field effect transistors (MOSFETs)

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and bipolar junction transistors (BJTs). The results can be close to reality, but sometimes not, especially in precise switching characterization simulations (Sheng *et al.*, 2000; Hu *et al.*, 2008).

3. Non-behavioral methods based on datasheets that extract loss-related key data from device manuals. These can be simple and fairly precise, but give only rough results in most cases (Rosu *et al.*, 2008; Bazzi *et al.*, 2009).

4. Empirical models based on measurement, having nothing to do with the physics mechanisms, include only mathematical mapping between influential factors and losses. These are non-behavioral and only for loss estimation (Blaabjerg *et al.*, 1996; Xu *et al.*, 2002; Cavalcanti *et al.*, 2003; Poulsen and Sørensen, 2004).

Both the behavioral and non-behavioral models are useful for loss prediction once the result is sufficiently accurate, but they differ in their user-friendliness and in their usefulness for specific applications. A high-end-device user can be short of support in a project with tough restrictions such as designing converters in satellites or slim sealed underwater pump drivers, suffering tight constraints on space or weight, or with narrow margins of design redundancy. In these cases, better loss models with more detail and better accuracy may be desirable, in contrast to the simplicity of datasheets. Generally, the establishment of behavioral models is complex in principle and in practice, even for professional semiconductor scientists, while the empirically calculated loss models are basically derived from loss measurement and data processing, which are more accessible to engineers using a common device. To obtain the loss, the behavioral models also require simulation tools while the empirical models need only regular computing programs. Additionally, the empirical non-behavioral modeling, in this paper referred to as ‘math modeling’, does not need a complete software reset but only another batch of measurement and recalculation to adapt to shift as much as from IGBT to MOSFET. Problems for math modeling include either lack of accuracy or the heavy duty in loss measurement and data calculation. Improvement of math modeling is possible only with the backup of appropriate switching loss measurement. A well-developed 1200 V/200 A test bench for discrete IGBTs, using a conventional

dual pulse test mode, records turn-on and turn-off waveforms and loss data in groups automatically (Shen *et al.*, 2006b). In this paper, we have attempted to apply the neural network method to IGBTs switching loss modeling to make progress in math modeling performance.

2 Math modeling

The purpose of the math models for IGBT switching loss is to obtain the function-like relationship between the influential independent variables such as voltage and current, and the dependent variables, the losses.

2.1 Conventional math models

Typical conventional math modeling methods, i.e., function or curve fittings, include: power functions, interpolations, and polynomial functions. For example, if only voltage, current, and temperature are considered, loss models typically look like

$$E_{\text{on}} = aI_c^b \left(\frac{U_{\text{DC}}}{U_{\text{ref}}} \right)^c \left(\frac{T_j}{T_{\text{ref}}} \right)^d,$$

or

$$E_{\text{on}} = a(b + cI_c + dI_c^2)(e + fU_{\text{DC}} + gU_{\text{DC}}^2)(h + iT_j + jT_j^2),$$

in which E_{on} , I_c , U_{DC} , and T_j are the turn-on energy loss, switching current, voltage, and temperature respectively, while U_{ref} and T_{ref} are the reference voltage and temperature respectively. The function types and structures in the modeling are fixed in advance and only the unknown parameters, such as the coefficients a, b, \dots, i, j mentioned above, need to be determined using the data from experiments. In fact, the Fourier transform indicates that with a unified form of polynomials, all the conventional math models can be expressed in longer or shorter polynomial expressions of the decisive factors.

It is apparent that the preset form of the model function plays the main role in determining the performance of the modeling. The expressions are not related to the inherent mechanisms of loss and are random in selection. Therefore, whether the model builders set the reference values or orders of a specific input to obtain a remarkable or negligible effect over

the output, in either a positive or negative direction, will also be random. The higher the order of the model equations, the larger the number of coefficients to be determined and the larger the size of the backing data package, the more accurate the models will be, and vice versa. Thus, there is a conflict between the accuracy of the model and heavy data acquisition and processing. The massive calculation required for good loss prediction could in practice disable the modeling. Consequently, compromises are always made to mitigate the stress of calculation, resulting in rough math models for device loss (Blaabjerg *et al.*, 1996; Xu *et al.*, 2002; Cavalcanti *et al.*, 2003).

2.2 Modeling with artificial neural network technology

In some cases, conventional models suffer from the non-mechanism oriented definition. Artificial neural network (ANN) technologies can be put to good use in applications where other models would be difficult or even useless. One of the stronger capabilities of ANN is function mapping, which is often used in situations with very complicated, undisclosed, and nonlinear relationships between multiple inputs and outputs. For ANN modeling, the object is considered as a black box and the measured input and output data are used to modify the model networks to fit the external characteristics of the real system. This is the process of 'training' or 'learning'. In the case of IGBT switching loss modeling, the operating voltage, current, temperature, driving voltages (here the negative gate bias is ignored owing to its minor effect on switching loss), and driving impedance are taken as inputs for the ANN models, and the turn-on/turn-off losses are taken as outputs, all of which can be measured and recorded automatically by the test bench. Well configured ANN models are expected to require less data and calculation to achieve better accuracy than conventional models.

Although an ANN is considered to be a black box, the basic structure needs to be defined. Neurons from creatures are referenced in the configuration of elementary cells (Fig. 1). The feed forward network is the most common and demonstrative type in ANN technologies. ANN models are special cases in math models, with complicated configurations and function expressions. The aim of the modeling process, or

'training', is to obtain the numerous parameters for each neuron such as the input weights and the biases. More hidden layers, or more neurons in hidden layers, will improve performance. An appropriate tradeoff must be made between complexity and precision for any modeling. According to experience, multiple hidden layers can be largely substituted by having enough neurons in a single hidden layer, and a three-layer feed forward network will be sufficient for modeling of systems with such a scale. Therefore, the fundamentals of newly adopted ANN models for IGBT switching loss can be sorted out but several issues are still awaiting optimization.

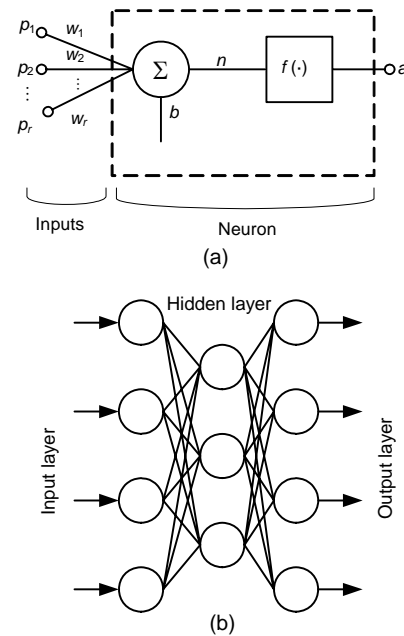


Fig. 1 Structures for an artificial neural network (ANN) (a) Model for a single neuron cell; (b) A typical three-layer feed forward ANN

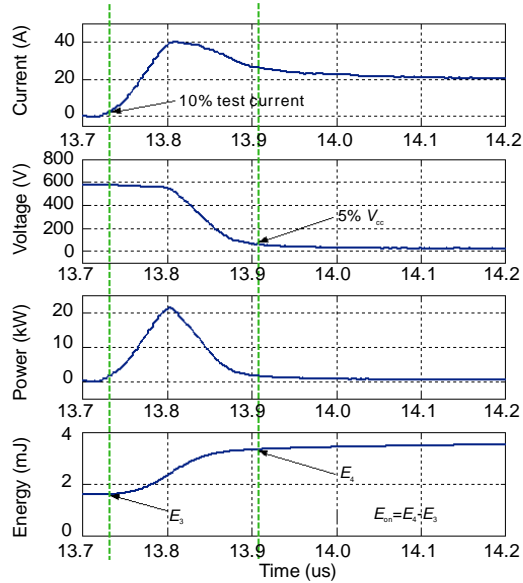
3 Modeling description

The math modeling of switching loss is based on experimental data for developing the function expressions. Collector current (i_c), DC link voltage (V_{DC}), junction temperature (T_j), drive voltage (V_g), and gate resistance (R_g) are included in the equations as follows:

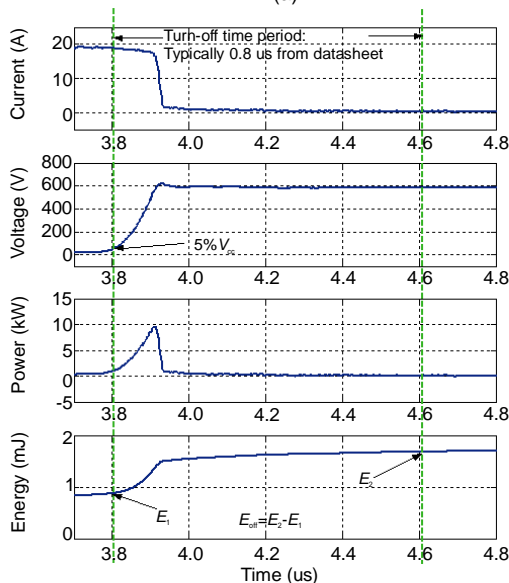
$$\begin{cases} E_{on} = f(i_c, V_{DC}, T_j, V_g, R_g), \\ E_{off} = f(i_c, V_{DC}, T_j, V_g, R_g). \end{cases} \quad (1)$$

3.1 Data acquisition

A 1200 V/200 A switching behavior test bench for IGBTs was used for our research, obtaining data automatically in batches for modeling. Typical measurement results are shown in Fig. 2 along with the interval definitions in the routine transient process, which can be easily adjusted by software. The product of voltage and current across the transistor can then be integrated over time during the defined interval to



(a)



(b)

Fig. 2 Measured switching waveforms

(a) Turn-on detail and interval definition; (b) Turn-off detail and interval definition

obtain the switching loss. Other factors affecting the losses are also considered and deactivated. A turn-on loss model is essentially freewheeling diode related and the same type of diode used in practice should be tested in pair with IGBT. The parasitic parameters of the circuit layout are analyzed and minimized in the system and should be consistent for each device under test (Shen *et al.*, 2006a).

A discrete non-punch-through (NPT) IGBT rated at 1200 V/40 A was selected as the switching loss measuring and modeling candidate. For better description of the loss characteristics, parameters of the switching loss measurements are recommended to be distributed evenly over the complete operating range. An example is shown in Table 1. The total number of measured points is thus 2160 ($N=5 \times 4 \times 6 \times 6 \times 3=2160$) and the sample sets for loss modeling can be selected from among them.

Table 1 Test conditions for modeling candidate IGBT

Switching parameter	Test points
Collector current, I (A)	5, 10, 20, 30, 40
DC link voltage, V_{cc} (V)	200, 400, 600, 800
Junction temperature, T_j ($^{\circ}\text{C}$)	25, 50, 75, 100, 125, 150
Gate resistance, R_g (Ω)	5.1, 10, 20, 30, 39, 51
Gate drive voltage, V_g (V)	15, 17, 19

3.2 Neural network model building

With their strong ability in measuring switching loss, models can be made and verified using the abundance of samples. Data processing and model building were carried out by Matlab, but numerous other software tools are also available.

3.2.1 Sample selection and model error definition

To obtain enough accuracy, all 2160 test points were used to build the initial model (actually, the sample scale can be very flexible, as shown later). First of all, the selected data are normalized into the region of $[-1, 1]$ to avoid supersaturation. The total composite relative error is used to evaluate the accuracy of the model (later referred to as the 'model error') as

$$\text{Err} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{E_{ci} - E_{mi}}{E_{ci}} \right)^2} \times 100\%, \quad (2)$$

where E_m is the measured loss value, E_c is the value calculated using the model, and n is the sample number used.

3.2.2 Definition of key parameters in the neural network model

Generally, three key factors are very important to the performance of feed forward neural network modeling: the number of hidden neurons, the expected error, and the training algorithm. They are determined by a lot of trial and error, making use of existing theory and experience.

1. Number of neurons in the hidden layer

In this specified modeling, 1 loss (on or off) is decided by 5 factors (voltage, current, etc.), making 5 input neurons and 1 output neuron in the three-layer neural network, with the neuron number N of the hidden layer to be determined. An excessive number of neurons lead to excessive calculation with no further accuracy gain while an insufficient number of neurons result in longer training time, larger model errors, or even convergence problems. A moderate number of hidden neurons are desirable. There are empirical equations that can be used to find the suitable number of hidden neurons by using input or output numbers, but no theoretical proof is available. In practice the number of hidden neurons can be obtained by a trial-and-error method, starting from an initial number obtained by the above equation, and then observing the performance after increasing or decreasing the number. Or in networks with minor scales (such as this case), a single digit number of neurons can be selected and increased until a change is seen. Such a process is shown in Table 2 in which a cost-error product valley is found at an N of 20.

2. Values of expected errors

Mean square absolute errors between real sample data and output data after each training are adopted as the training effect index in the feed forward ANN modeling module in Matlab. Here the threshold is referred to as the 'expected error'. Clearly, the smaller the error, the better will be the model's accuracy, which is related mainly to increasing the number of hidden neurons and training times. However, too rough an expected error would even stop the training before convergence is reached. So a compromise here is also necessary. Several examples are shown in Table 3. The threshold selection could be

different case by case, according to the change in the model error gradient in response to training. An expected error of $2E-5$ was used in the proposed model training, where a sharp increase in training times would have been found if a lower value had been adopted.

Table 2 The influence of the number of hidden-layer neurons on training times and the model error

Number of hidden neurons	Epochs*	Err (%)
15	238	2.64
18	269	2.33
20	44	2.43
22	160	3.19
25	167	2.73

* Training times. Cost-error product valley was found at 20 hidden neurons

Table 3 The influence of the value of the expected error on training times and the model error

Expected error	Epochs*	Err (%)
1.6×10^{-5}	312	2.89
2×10^{-5}	44	2.43
3×10^{-5}	32	3.20
4×10^{-5}	26	3.38

* Training times. The expected error of 2×10^{-5} was used in the proposed model training

3. Training algorithms

Different training algorithms can perform quite differently in ANN modeling. Frequently used training algorithms were tested in the same network (Table 4).

Table 4 The influence of the training algorithm

Training algorithm	Expected error	Epochs*	Err (%)
LM	2×10^{-5}	44	2.43
Basic gradient descent	0.017	1793	>100
Adaptive learning rate	0.002	3000	43.37
Modification of the LM training algorithm	0.035	640	2.11

LM: Levenberg-Marquardt. * Training times. The boldface indicates that LM is the best training algorithm

The Levenberg-Marquardt (LM) algorithm involved much less training time but gave acceptable accuracy while some other algorithms even failed in this case. We have found this result in most of our practical experience of IGBT switching loss modeling; thus, only LM was used as the training algorithm for this study.

4 Model implementation and results

The feed forward neural network models of turn-on and turn-off losses were built although only the turn-on loss model is shown as an example. The model was constructed with three layers, i.e., an input layer with 5 nodes, an output layer with 1, and a hidden layer with 20. The transfer function between the input and hidden layers is tan-sigmoid (a saturated tangent type function in Matlab with an ‘S’ shaped curve) and between the hidden and output layers is purely linear. The learning function is trainlm, a term in Matlab for the LM algorithm.

The expected error vs. training times of the neural network modeling is shown in Fig. 3a. After 44 epochs (training times) a target expected error of 2E-5 is reached. Fig. 3b shows the perfect regression curve ($A=T$) and the best linear fit curve for training, where A represents the actual output values of neural networks, T the target output values, and R the related coefficient between the target output and the network’s output. The two curves almost overlap, implying the excellent performance of the model.

The mathematical description of the model is given as

$$E_{on} = \text{purelin}[W_{out} \cdot \text{tansig}(W_{in} \cdot P + b_{in}) + b_{out}] \tag{3}$$

$$= W_{out} \cdot \text{tansig}(W_{in} \cdot P + b_{in}) + b_{out},$$

$$W_{in} = \begin{bmatrix} -1.5290 & 0.4825 & -1.4696 & 0.7868 & 0.9111 \\ -0.6281 & -0.4797 & -0.1531 & -0.2195 & 0.1743 \\ -0.1471 & -0.0916 & -2.0617 & 0.0133 & 0.0600 \\ 0.6104 & 1.1710 & -0.2022 & -0.6137 & -0.7307 \\ 0.2153 & 1.7142 & -0.0015 & -1.8321 & -0.3113 \\ -0.3760 & -0.3441 & -0.0458 & 0.7450 & 0.0335 \\ -0.7947 & -0.8280 & -0.0091 & -0.3054 & 2.5534 \\ 0.2019 & -1.0847 & -0.0780 & 0.1816 & 0.0036 \\ 0.3312 & 0.4369 & 0.0932 & 0.0698 & -0.0596 \\ -2.9756 & 2.3019 & 0.5727 & -1.0057 & 0.4769 \\ 0.1794 & 0.1777 & -0.1592 & 0.0841 & -0.1061 \\ 0.0117 & 0.0469 & -2.2659 & 0.0374 & 0.0850 \\ -0.2700 & -0.5339 & 0.0943 & 0.0172 & 0.0277 \\ 5.4380 & 3.2061 & 2.2475 & 2.8524 & 2.2388 \\ -0.4899 & 0.4646 & -0.5204 & -0.4750 & 0.2097 \\ -0.0235 & 0.0202 & -0.2599 & 0.1466 & -0.1577 \\ -0.6868 & 1.4685 & -0.7768 & 1.9483 & 0.1101 \\ -1.8643 & -0.1022 & -0.7622 & 0.7946 & -0.4503 \\ -0.4258 & 0.6302 & 0.1165 & 0.0519 & -0.0656 \\ -1.4117 & 0.5420 & 0.1787 & -1.2104 & -0.1213 \end{bmatrix}, \quad b_{in} = \begin{bmatrix} 2.3564 \\ 2.1386 \\ 0.1005 \\ -1.2584 \\ 0.6721 \\ 2.2842 \\ 2.4737 \\ 0.1076 \\ -0.6219 \\ 0.9608 \\ -0.3541 \\ 0.3860 \\ -0.1312 \\ 3.4203 \\ 1.8653 \\ -0.7001 \\ -1.5470 \\ -2.8338 \\ -1.6588 \\ -3.1294 \end{bmatrix}, \quad W_{out} = \begin{bmatrix} 0.0006 \\ -2.2311 \\ 0.0481 \\ 0.0158 \\ 0.0070 \\ 0.6072 \\ 0.0101 \\ 0.0704 \\ 1.0795 \\ -0.0040 \\ -0.9256 \\ -0.0431 \\ -0.2921 \\ -0.0009 \\ 0.0743 \\ 0.4725 \\ -0.0031 \\ -0.0114 \\ -0.6773 \\ 0.0289 \end{bmatrix}^T$$

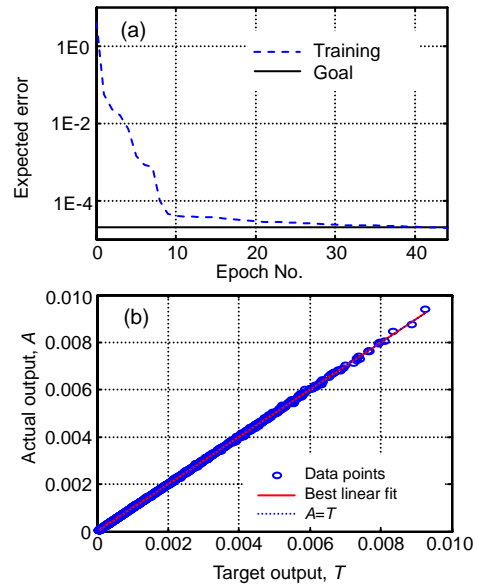


Fig. 3 Artificial neural network model training

(a) Expected error versus training times (performance is 1.98211E-005, and the goal is 2E-005); (b) Training performance analysis (best linear fit: $A=RT+(3.08E-007)$, $R=1$)

where W_{in} is the input weight matrix, b_{in} represents the input bias vector, W_{out} represents the output layer weight matrix, and b_{out} is the output layer bias vector. P is the input vector (including $I, U, T, R_g,$ and U_g). The $W_{in}, b_{in},$ and W_{out} used in this implementation are given below, and $b_{out}=0.7284$.

The relative errors of the turn-on loss model are shown in Fig. 4. Most of the relative errors of the data points are controlled to lie within $\pm 10\%$, and most of those beyond $\pm 10\%$ are located in the low-voltage low-current range, which is of little practical significance. The total composite relative error of this model is 3.6%.

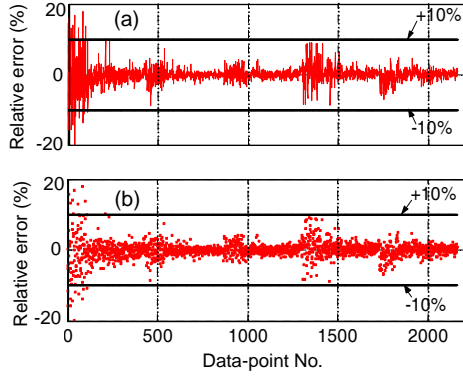


Fig. 4 The relative error in (a) curve and (b) dots of the ANN turn-on loss model ($N=2160$)

In contrast tests for the same IGBT, operating points other than those used by the model training were also measured and compared with predictions from the model. In a case with 16 measured data not embodied by the training dataset and evenly located in the switching voltage and current space, the largest relative error of this model on each individual point was only 5.67%.

5 Model comparison

In contrast to the ANN models, two conventional math models for IGBT switching loss were also tested: a power function method (referred to here as Model-1) and a polynomial-power function combination (Model-2).

The power function model is expressed as

$$E_{sw,x} = aI_d^b \left[\frac{U_{DC}}{U_{base}} \right]^c \left[\frac{T_j}{T_{base}} \right]^d \left[\frac{R_g}{R_{gbase}} \right]^e \left[\frac{U_g}{U_{gbase}} \right]^f, \quad (4)$$

where $U_{base}=600$ V, $T_{base}=10$ °C, $R_{gbase}=30$ Ω , $U_{gbase}=17$ V and a, b, c, d, e, f are the coefficients to be identified (Blaabjerg *et al.*, 1996).

Model-2 is based on both polynomial and power functions (Cavalcanti *et al.*, 2003), as follows:

$$\left\{ \begin{array}{l} E_{sw} = f(I)f(V)f(T)f(R_g)f(V_g), \\ f(I) = (a + bI^c)I^d, \\ f(V) = (V / V_{base})^e, \\ f(T) = fT^3 + gT^2 + hT + i, \\ f(R_g) = \begin{cases} jR_g^3 + kR_g^2 + lR_g + m, & E_{sw} = E_{on}, \\ (j + kR_g^l)R_g^m, & E_{sw} = E_{off}, \end{cases} \\ f(V_g) = nV_g^4 + oV_g^3 + pV_g^2 + qV_g + r, \end{array} \right. \quad (5)$$

where a, b, \dots, q, r are the coefficients to be identified.

The switching loss model based on neural network is referred to as Model-3.

The relative errors of the three models when trained by different numbers of measured sample data points, are listed in Table 5.

A totally different type of IGBT rated in 600 V/30 A was also tested and modeled as an additional verification. The measurement and modeling results are shown in Table 6.

The proposed Model-3 had the highest accuracy over a wide range of sample scales. It improves faster in response to increasing amounts of training data while the other two methods change little or even deteriorate. Taking the modeling cost into consideration, Model-1 certainly uses the least resources with

Table 5 Comparison of model accuracy for a 1200 V/40 A IGBT for different numbers of test-points

Model	ERR _{off} (%)					ERR _{on} (%)				
	2160	1296	648	486	243	2160	1296	648	486	243
Model-1	12.1	13.3	12.4	12.3	12.6	14.5	15.0	15.3	16.0	18.1
Model-2	9.1	9.3	9.2	9.4	16.1	12.6	13.4	14.2	15.5	24.4
Model-3	5.7	7.8	8.9	10.4	11.6	3.6	7.8	7.4	8.6	6.6

Model-1: power function method; Model-2: polynomial-power function combination; Model-3: switching loss model based on neural network

Table 6 Comparison of model accuracy for a 600 V/30 A IGBT for different numbers of test-points

Model	ERR _{off} (%)					ERR _{on} (%)				
	2592	1296	648	486	243	2592	1296	648	486	243
Model-1	19.51	19.74	16.12	16.26	16.24	25.71	27.84	24.22	24.80	24.04
Model-2	8.98	9.07	9.40	9.81	17.45	11.10	11.03	12.13	12.49	20.16
Model-3	2.89	5.93	15.40	11.47	18.60	4.08	6.76	13.05	18.20	15.03

Model-1: power function method; Model-2: polynomial-power function combination; Model-3: switching loss model based on neural network

only 6 coefficients waiting for fitting. Model-2 has 18 coefficients and can be slow, taking more than 10 min for our system (CPU AMD Sempron 2200+, RAM 768 MB) to finish, while Model-1 takes only several seconds. Model-3 is moderate. The model training calculation can be quite fast: despite having many more coefficients under estimation than in Model-2, it takes only 1 or 2 min to complete, which is much quicker than Model-2. This is because of the intrinsic advantages of the fast learning gradient in ANN.

6 Discussion

The proposed ANN modeling method displays superiorities over the conventional empirical models including higher accuracy in the case of similar average modeling cost (data number and calculation consumption). However, it has disadvantages in certain aspects. First of all, the lack of a theoretical basis may necessitate a lot of trial-and-error work and a reliance on experience. Therefore, we cannot claim that our model is an optimized ANN and we can expect that better ANN structures and algorithms will be developed. ANN models usually perform quite well but when the number of training datasets is smaller than the number of coefficients under identification (here it is 141), the network may have more than one result in varied training, which leads to longer training time and reduced accuracy. In the extreme, if the number of sample datasets is very small, such as only 20 points, the ANN models will be disabled by the huge errors while the compared models will seem better but will also show deterioration and unacceptable errors. The performance of ANN models decays faster once the sample scale declines beyond a threshold. However, these extreme cases are of little significance in practice because no one would like to use such inadequate sample data.

7 Conclusions

For the first time, we have introduced artificial neural network technology into semiconductor power device switching loss modeling. The construction of ANN switching loss models for power IGBTs is described in comparison with two kinds of curve-fitting models. Our results suggest that the neural network method obtains higher accuracy than the conventional math models, as long as the training data are sufficient. It is feasible for ANN models to calculate and predict the switching losses of power switching devices by proper model building, and the new method can achieve short training time and good calculation efficiency. Measured data from a power device test bench and corresponding calculated modeling results validate our conclusions. In future research, device loss measurement from a practical power converter is expected to confirm and improve the proposed modeling method.

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