CNN-based Approach for Estimating Degradation of Power Devices by Gate Waveform Monitoring

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***Abstract*—A Convolutional Neural Network (CNN) is applied to estimate the emitter resistance (R_E), the junction temperature (T_J), the collector current (I_C), and the threshold voltage (V_{TH}) of power devices just by monitoring the gate drive waveforms. R_E, T_J and I_C are essential parameters for power device reliability. By using the detailed circuit simulation results for IGBT, it is shown that the above-mentioned four parameters can be estimated with the success rate more than 93% by the proposed AI-based approach for the first time. The measurement results also show that R_E and I_C are successfully estimated with the success rate >99%. The discussions are made on the success rate change depending on the resolution and the sampling rate of an A/D converter and the convolution filter kernel size.**

Keywords-CNN, Neural Network, AI, IGBT, power device, degradation, reliability, gate driver, IoT

I. INTRODUCTION

A long-term degradation of power devices induces severe reliability issue of power systems and thus estimating the degradation of power devices are vitally important. Among power devices, IGBTs (Insulated Gate Bipolar Transistor) are most widely used for high-voltage, high-current applications and the effects of the device breakdown are significant. For that reason, the IGBTs are mainly discussed in this paper, although the other types of power devices, such as a SiC MOSFET is also successfully handled with the proposed scheme.

The most frequent cause of the long-term degradation of the IGBTs is considered to be the emitter resistance increase due to the crack developing of an emitter contact, the peeling-off of an emitter pad, the partial detachment of an emitter bonding and so on [1,2]. These degradations over time are induced from heat cycles and the high current, that is, R_E, T_J and I_C are essentially important parameters for power device reliability.

The estimation of I_C for an IGBT using the collector-emitter voltage, V_{CE}, gate-emitter voltage, V_{GE}, V_{TH}, and T_J as input has been investigated based on a neural network [3], it is very costly to know these voltages and T_J beforehand using sensors and only I_C can be estimated. The estimation of T_J by measuring the peak voltage of the gate drive voltage has been proposed [4] but the estimation is only for T_J and since it does not use an AI-based approach, the estimation needs very high precision of the peak voltage measurement without noise, which is practically very difficult. In this paper, the first successful application of a deep learning is described to estimate reliability-related parameters only by monitoring gate drive waveforms. As R_E can be estimated in a live power system, it is possible to know when to replace power devices before a system breakdown.

II. TARGET SYSTEM AND CURCUITS

Conventionally, in order to know the values of R_E, T_J, V_{TH}, and I_C, it is customary to put sensors for current, voltage and temperature in the main circuit as shown in Fig.1 (a). Instead, in this paper, only gate driving voltage waveforms are monitored to estimate these parameters as shown in Fig.1(b). This approach reduces the cost for various sensors and related circuits, assembly and wiring. The gate drive waveforms in power electronics circuits include lots of information through the parasitic coupling capacitance, the parasitic inductances, and resistances within the loop of the gate drive and the emitter terminal of the power device.

Since the gate driver circuit is becoming digital and smarter as described in [5], the gate driver chip can integrate an A/D converter easily and in a cost-efficient way. Moreover, it is not difficult to implement CNN-based recognition system on the gate driver chip in the future. There is no need to integrate the performance-hungry machine learning system, but only the recognition logic needs to be integrated. Even if the integration of the CNN on the digital gate driver is not a choice, it is not difficult to send digital data from the A/D converter to a main controller and conduct the recognition process, since it can be slow because only the long-term degradation is of interest here.

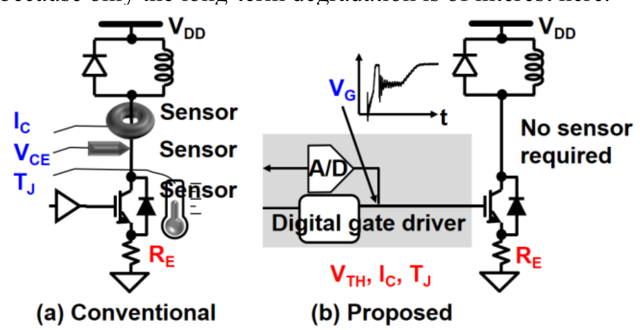


Fig. 1. (a) Conventional and (b) proposed schemes for parameter estimation. Blue parameters are input data and red parameters are calculated and estimated from input data.

III. CONVOLUTIONAL NEURAL NETWORK APPROACH

In this paper, the approach used for estimating the parameters is a widely-used deep learning approach, CNN. Other types of machine recognition algorithms are also tried, namely LDA (Linear Discriminant Analysis) and PCA (Principal Component Analysis) together with KNN (K-Nearest Neighbor classification). Both algorithms failed to correctly estimate parameters. Especially, estimating R_E turned out to be difficult with the low success rate of less than 50%.

The CNN machine learning software is implemented by Python and Keras [6]. The network architecture adopted for a measurement is shown in Fig.2. The input is a voltage waveform of the gate driver output during the turn-on of IGBT. The input vector length is chosen to be 500, which corresponds to 6-ns cycle sampling for the entire turn-on process of 3-μs. The output is the categorized in 5 classes for the simulation in Section IV and 6 classes for the measurement in Section V. The way how the classes are categorized are tabulated in the corresponding Section.

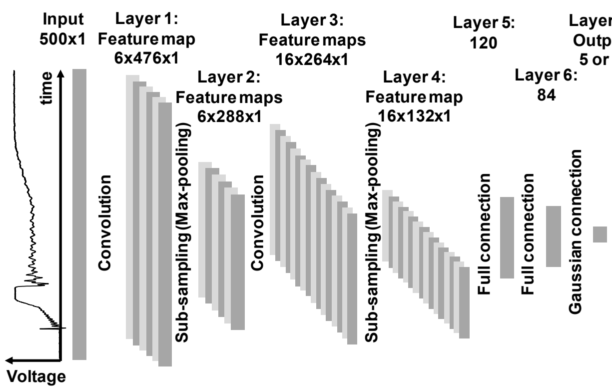


Fig. 2. Employed neural network layer architecture

IV. RESULTS WITH SIMULATION DATA

Double pulse simulation is carried out using the circuit in Fig.3 to generate training data and test data. Table I shows the category of classes for each condition. Varying parameters of the emitter resistance (R_E), the junction temperature (T_J), the collector current (I_C), and the threshold voltage (V_{TH}), 110000 waveforms are generated and used as the machine learning input samples and the recognition test samples. The ratio of the number of the leaning samples, the validation samples and the test samples is chosen to be 0.6:0.2:0.2.

First, the convolution filter size (kernel size) is optimized. It is conducted by changing the filter size from 2x1 to 10x1. The overall best success rates for four parameters are obtained when the kernel size is chosen to be 8. Thus, the following parameter estimation attempt is made with this filter size.

The parameter estimation results are tabulated in Table III. Four neural networks are generated, each of which is a specific CNN for the emitter resistance (R_E), the junction temperature (T_J), the collector current (I_C), and the threshold voltage (V_{TH}), The success rate is 0.98 for R_E. Thus, it is possible to suggest the increase in the emitter resistance before it becomes alarmingly high.

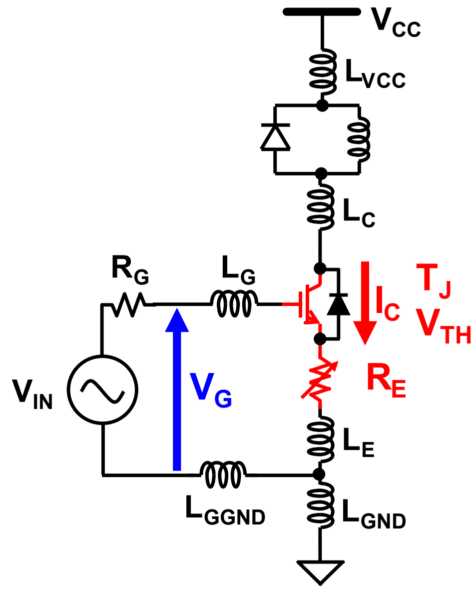


Fig. 3. Circuit diagram used for simulation

Table I. Class number, labels and number of simulations for each class

(a) R_E: Emitter resistance

Class #	0	1	2	3	4	Total
Label: R_E range	0mΩ	2mΩ	4mΩ	6mΩ	8mΩ	10mΩ
# of waveforms	22000	22000	22000	22000	22000	110000

(b) T_J: Junction temperature

Class #	0	1	2	3	4	Total
Label: T_J range	25°C	40°C	55°C	70°C	85°C	100°C
# of waveforms	22000	22000	22000	22000	22000	110000

(c) I_C: Collector current

Class #	0	1	2	3	4	Total
Label: I_C range	15A	20A	25A	30A	35A	40A
# of waveforms	22000	22000	22000	22000	22000	110000

(d) V_{TH} : Threshold voltage

Class #	0	1	2	3	4	Total
Label: V_{TH} range	3V	3.6V	4.2V	4.8V	5.4V	6V
# of waveforms	22000	22000	22000	22000	22000	110000

In the label description, a class does not include the lower limit but includes the upper limit.

Table II. Convolution filter size (kernel size) optimization

Parameter to be estimated		Convolution filter size								
		2	3	4	5	6	7	8	9	10
R_E	Emitter resistance	0.76	0.83	0.96	0.82	0.70	0.91	0.98	0.89	0.75
T_J	Junction temperature	0.96	0.98	0.99	0.99	0.99	0.99	1.00	0.99	0.99
I_C	Collector current	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
V_{TH}	Threshold voltage	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

(Values are success rate.) Best choice

Table III. Achieved success rate for estimating four parameters

(a) R_E: Emitter resistance

Success rate: 0.983

		Correct class					
		0	1	2	3	4	Ratio
Guessed class	0	5430	47	0	0	0	0.991
	1	110	5316	26	0	0	0.975
	2	0	52	5426	32	0	0.984
	3	0	0	70	5444	42	0.980
	4	0	0	0	83	5422	0.985
	Ratio	0.980	0.982	0.983	0.980	0.992	

\# of epochs: 200

(b) T_J: Junction temperature

Success rate: 1.00

		Correct class					
		0	1	2	3	4	Ratio
Guessed class	0	5403	0	0	0	0	1.00
	1	0	5657	0	0	0	1.00
	2	0	0	5491	0	0	1.00
	3	0	0	0	5506	0	1.00
	4	0	0	0	0	5443	1.00
	Ratio	1.00	1.00	1.00	1.00	1.00	

\# of epochs: 200

(c) I_C: Collector Current

Success rate: 1.00

		Correct class					
		0	1	2	3	4	Ratio
Guessed class	0	5577	0	0	0	0	1.00
	1	0	5499	0	0	0	1.00
	2	0	0	5478	0	0	1.00
	3	0	0	0	5453	0	1.00
	4	0	0	0	0	5493	1.00
	Ratio	1.00	1.00	1.00	1.00	1.00	

\# of epochs:200

(d) V_{TH}: Threshold voltage

Success rate: 1.00

		Correct class					
		0	1	2	3	4	Ratio
Guessed class	0	5559	0	0	0	0	1.00
	1	0	5568	0	0	0	1.00
	2	0	0	5382	0	0	1.00
	3	0	0	0	5475	0	1.00
	4	0	0	0	0	5516	1.00
	Ratio	1.00	1.00	1.00	1.00	1.00	

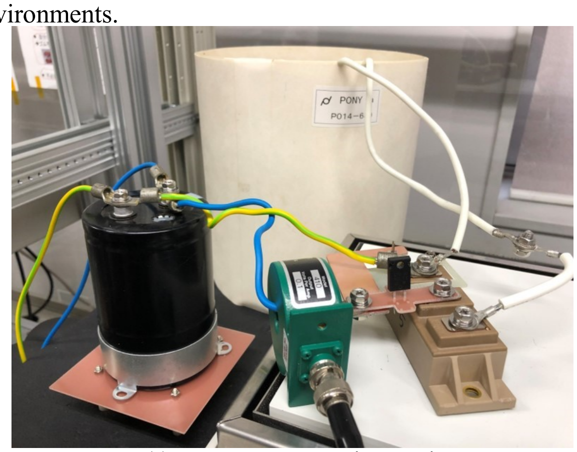
\# of epochs: 200

V. Results with Measurement Data

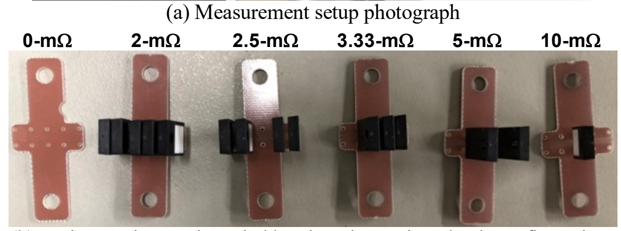
The same estimation scheme is applied for the measurement using IGBT whose model number is 2MBI100TA from Fuji electric. The measurement setup is shown in Fig.4 where the emitter resistance is varied by changing the number of resistors in parallel. The measured waveforms are shown in Fig.5. In the measurement, only the emitter resistance (R_E) and the collector current (I_C) are varied, since it was difficult to change V_{TH} and T_J in the measurement setup this time. It is seen from the measured waveforms that it is difficult to estimate R_E and I_C using human eyes. The machine recognition is needed for estimating the parameters. R_E and I_C are categorized into 6 classes this time as shown in Table IV.

The results of estimation using the CNN approach are tabulated in Table V. The success rate is very high amounting up to 99.5%. The number of epochs in the table shows the number of deep learning optimization loops needed for the entire learning process. Using i7 Intel processor with the clock rate of 2.5-GHz, one epoch needs approximately 1-s, which is sufficiently fast to be practical. In order to know the robustness of the estimation, one class of data (sample waveforms) is excluded from the learning process. The results are shown in Table VI. The excluded class of data when tested is classified to the nearest class for most of the cases. This means that the proposed estimator based on the deep learning understands the ordering of R_E magnitude and thus can be considered as a naturally robust estimator.

After all, it has been shown that the proposed method is effective not only in the simulations but also in the real environments.



(a) Measurement setup photograph



(b) Emitter resistance is varied by changing resistor bank configurations

Fig. 4 Measurement setup: (a) overall view, (b) mechanism to show how to change emitter resistance (R_E)

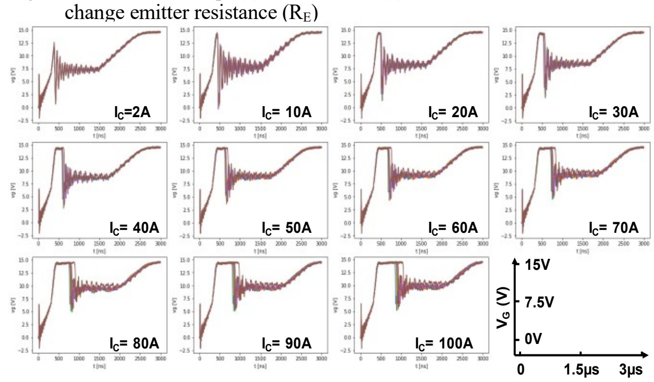


Fig. 5 Measured waveforms. Each figure contains multiple of V_G waveforms corresponding to various R_E conditions.

Table IV. Number of measurements for each class

(a) R_E: Emitter resistance

Class #	0	1	2	3	4	5	Total
Label: R_E=	0mΩ	2mΩ	2.5mΩ	3.33mΩ	5mΩ	10mΩ	
# of waveforms	1100	1100	1100	1100	1100	1100	6600

(b) I_C: Collector current

Class #	0	1	2	3	4	5	Total
Label: I_C range	0A 15A	30A	45A	60A	75A	100A	
# of waveforms	1200	600	1200	600	1200	1800	6600

Table V. Estimation results for measurement data

(a) R_E: Emitter resistance

Success rate: 0.995

		Correct class						
		0	1	2	3	4	5	Ratio
Guessed class	0	275	3	0	0	0	0	0.989
	1	0	265	0	0	0	0	1
	2	0	0	264	0	0	0	1
	3	0	0	0	262	4	0	0.985
	4	0	0	0	1	279	0	0.996
	5	0	0	0	0	0	297	1
	Ratio	1	0.989	1	0.996	0.986	1	

# of epochs: 74

(b) I_C: Collector current

Success rate: 1.000

		Correct class						
		0	1	2	3	4	5	Ratio
Guessed class	0	315	0	0	0	0	0	1
	1	0	144	0	0	0	0	1
	2	0	0	272	0	0	0	1
	3	0	0	0	155	0	0	1
	4	0	0	0	0	298	0	1
	5	0	0	0	0	0	466	1
	Ratio	1	1	1	1	1	1	

# of epochs: 213

Table VI. Estimation results when a class of data are excluded from learning

		Excluded class (n=1100)					
		0mΩ	2mΩ	2.5mΩ	3.33mΩ	5mΩ	10mΩ
Class to which excluded class data is classified	0mΩ		434	0	0	0	0
	2mΩ	1100		701	0	0	0
	2.5mΩ	0	666		190	0	0
	3.33mΩ	0	0	398		815	53
	5mΩ	0	0	1	760		1047
	10mΩ	0	0	0	150	285	

VI. Discussions and Conclutions

The discussions are made on the success rate dependence on the resolution and the sampling rate of the A/D converter. The success rate depends of these parameters as shown in Fig.6. 6-ns sampling and 8-bit resolution are acceptable to obtain the reasonably high success rate for estimation. An A/D converter with 6-ns sampling and 8-bit resolution is easy to implement on a Si chip. Thus, it can be said that this approach is practical and provides promising way to estimate long-term degradation of power devices.

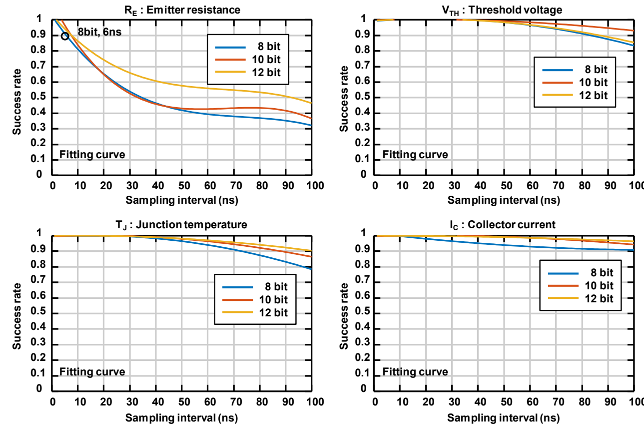


Fig. 6 Success rate depending on sampling rate and resolution of A/D

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