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https://hdl.handle.net/2324/7391175

出版情報：2025-09. Institute of Electrical and Electronics Engineers (IEEE)
バージョン：

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***Abstract*— This study utilised machine learning to analyse the switching waveforms of power semiconductor devices, with a particular focus on wire lift-off and the objective of detecting power cycling failures. Power semiconductor device losses generate heat during the operation of power electronics systems, resulting in power cycling failures. The gate voltage waveform (V_{gs}), the drain-source voltage waveform (V_{ds}), the source current waveform (I_s), and the combination of V_{gs} and I_s were employed as detection signals, and the accuracy of the analysis was compared using each waveform. Additionally, different types of M-shunts, with and without a coupling area, were utilised for current measurements to examine the effect of deliberate field coupling on the accuracy. The results demonstrate that the analysis employing the V_{gs} waveform and the combined V_{gs} and I_s waveforms yield high accuracy for both the turn-off and turn-on conditions, with and without coupling. The use of shunts with coupling structures enables the chosen approach to distinguish between no cut and a single cut. By incorporating coupling structures, the theoretical approach gains practical applicability, as it allows for the detection of slight degradation effects in addition to discrete wire cuts.**

Keywords*— *SiC-MOSFET, Power Cycling Degradation, Wire Lift-Off, Convolutional Neural Network

I. Introduction

Power semiconductor devices such as IGBTs and power MOSFETs are widely used in power electronics systems such as converters and inverters. Main causes of the system failure are power semiconductor devices, capacitors, and gate drivers. Thus, reducing the failure rate of power semiconductor devices is a critical issue [1]. In particular, degradation and failure behaviour of power semiconductor devices have been studied for power electronics systems demanding high reliability, such as renewable energy, power grids, electric vehicles, railroads, and industrial equipment.

This study focuses on package-induced power cycling degradation, which is the main cause of wear-out failure during long-term operation. Typically, package lifetime is evaluated through power cycling tests, which apply a cyclic stress and used for relative evaluations. However, usual system operating conditions generate various stresses, and so power cycling test results cannot assess lifetime under system operations. Therefore, real-time monitoring is desirable for failure detection and lifetime estimation in the actual system.

Several monitoring methods such as switching waveform changes [2], [3], gate plateau voltage [4], [5], electrical resistance, and temperature [6], have been demonstrate. However, these methods require expensive measurement systems with high noise immunity and the ability to detect subtle changes with high precision. As a solution, a degradation detection method combining gate voltage measurement and machine learning has been proposed [7], [8], [9], because no unique measurement circuit is required. High-accurate detection of wire lift-off in silicon IGBT modules was demonstrated by a Convolutional Neural Network (CNN).

This paper reports the detection results for silicon carbide (SiC) MOSFETs, which switch faster than the silicon IGBTs used in previous studies. Types of detection signals other than gate voltage are discussed focusing on their accuracy and validity.

This research was supported by the Japan Society for the Promotion of Science (JSPS) under the Bilateral Joint Research Project JPJSBP120243506.

II. CREATION OF DATASET FOR ANALYSIS

A. Setup

This experiment investigates bond wire lift-off, a form of power cycling degradation. When lift-off occurs, the parasitic inductance introduced by the chip's source bonds changes slightly, affecting the switching waveform. By analysing these waveform variations, wire lift-off can be detected.

To generate training and test data for machine learning, switching waveforms were collected using a double-pulse test, with wire lift-off simulated by manually cutting the bond wires. The experimental setup is shown in Fig. 1, and the PCB test bench is depicted in Fig. 2. Voltage and current waveforms were measured using an oscilloscope (MSO64, TEKTRONIX) with a 12.5 GS/s sampling rate, ensuring sufficient time resolution and high reproducibility.

A low-inductance M-shunt was used for current measurement [10]. The self-inductance of the M-shunt, including its connector, was determined to be approximately 1 nH, minimising the increase in parasitic inductance in the main circuit loop caused by shunt insertion [11]. In general, SiC-MOSFETs exhibit much higher switching speeds than silicon-based power semiconductors, requiring precise high-frequency measurement techniques. To capture high-frequency harmonics and detect small inductance variations due to wire lift-off inside the SiC-MOSFET, an M-shunt with optimised frequency response was employed.

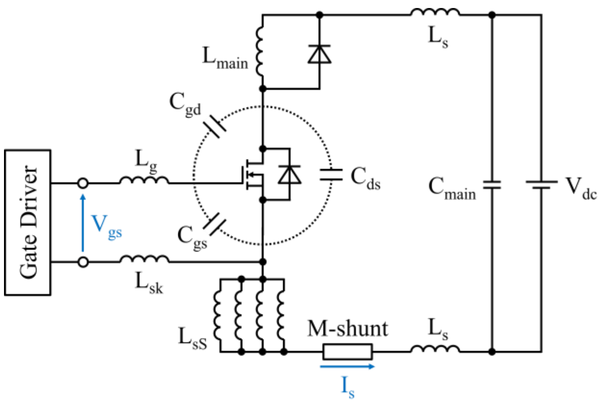


Fig. 1. Double pulse test circuit

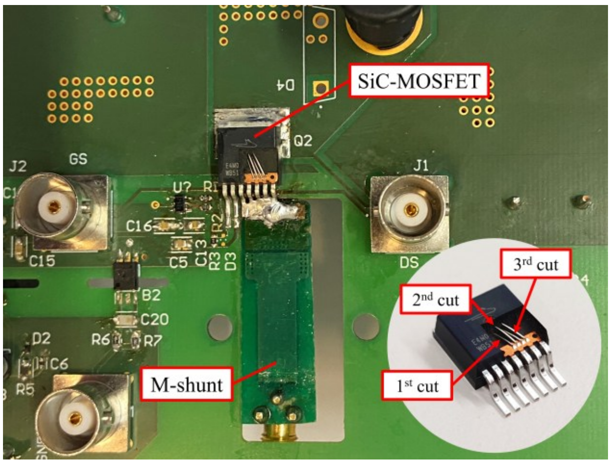


Fig. 2. PCB board with DUT for double pulse test.

B. Coupling-Enhanced M-Shunt for Improved Detection

Two types of M-shunts were utilised in this experiment: one with a standard design and one incorporating deliberate field coupling. The concept of coupling in shunt resistors was initially proposed in [10], thereby demonstrating its ability to correct skin effect-induced capacitive behaviour. As shown in Fig. 3 and Fig. 4, by implementing a coupling mechanism, di/dt can be restored to its original undamped value, enhancing sensitivity to high-frequency components. Overcompensation can amplify the highest di/dt transients relative to lower-frequency components.

While this approach does not increase the absolute amplitude of switching transients without additional post-processing, it enhances the visibility of even minimal di/dt variations. This property is particularly useful for detecting minor inductance changes caused by bond wire degradation.

The standard M-shunt, [11] is well-suited for analysing fast switching transients in the SiC double-pulse test due to its low insertion inductance and high bandwidth. However, the coupling structure described in [10] and [12] introduces modifications to the transfer characteristics, as shown in Fig. 6. These coupling elements significantly increase the high frequency signals of the shunts by (over-) compensating for errors induced by skin effects [12].

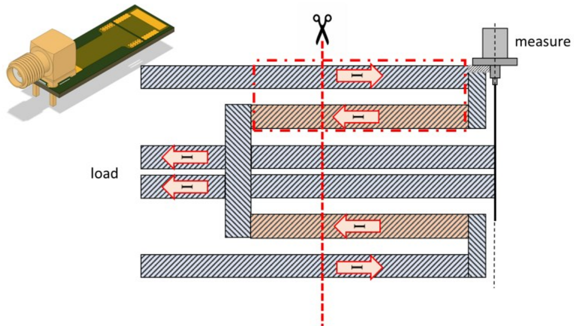


Fig. 3. Structure of the M-Shunt with the cross-section location indicated, as shown in Fig. 4

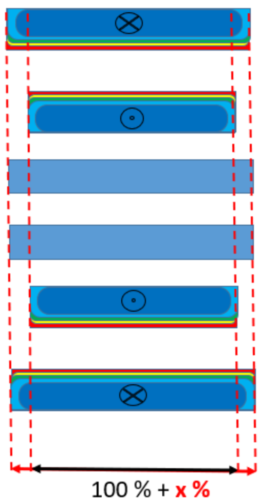


Fig. 4. Cross-section of the M-Shunt with highlighted overhanging coupling areas. The percentage of coupling width results in different transfer functions and measurement outputs, as illustrated in Fig. 5 and Fig. 6

In this specific application, the absolute current value is not critical; rather, the focus is on relative waveform changes. The use of an overcompensated M-shunt is beneficial in this context, despite its inherently lower 3 dB bandwidth. By amplifying small changes in inductance and transient steepness, it enables a more accurate assessment of degradation effects.

As DUTs, discrete SiC-MOSFETs (E4M0060075J2, Wolfspeed, 750 V/60 mΩ, TO-263-7 XL package [13]) were used in this first experiment. The gate drive voltage of the SiC-MOSFET was set to V_g = -3/+15 V, and the test voltage was V_{dc} = 500 V. Test current was adjusted by the pulse width of the first pulse and set to I_s = 80 A, which was 80 % of the rated maximum pulse current.

Fig. 2 shows the wire-cut positions and cutting sequence of the discrete SiC-MOSFET. Four wires connect to the source pad in the SiC-MOSFET chip, and waveforms were measured under four conditions: without cutting any wires (no damage) and by cutting one, two, and three wires (small, medium, and large damage). Wires were cut one by one from the left to the right. For each condition, 1000 waveform measurements were taken to create the data set. In creating the data set, the turn-on and turn-off portions of the acquired characteristic switching waveforms were extracted, and integrated to create the data set. The data length of the dataset was 3000 plots.

III. Analysis by CNN

After the dataset was created, a deep learning algorithm, CNN, was used to estimate the delamination state of the bonding wires. In this estimation, the data were classified into four levels: no damage, small, medium, and large, each represented by a value from 0 to 3. These values correspond to the number of bonding wires cut. As the data set, the gate voltage waveform V_{gs}, drain-source voltage waveform V_{ds}, and source current waveform I_s obtained during the double-pulse test of the power device were used. Two types of CNN models were constructed: a 1-input model (Keras, Sequential) with one type of waveform input and a 2-input model (Keras, Functional API), which has two types of waveforms as input.

The architectural structure of each model is shown in Fig. 7. Although the number of inputs differs between the two models, the basic design combines multiple convolutional layers and pooling layers. Finally, classification is performed through all coupling layers. The number of epochs during training was set to 37 (= 2+5+10+20), and training was conducted using training data. After training, classification accuracy was evaluated using test data, and the model's performance was analysed. Accuracy was used as an indicator for performance evaluation. In this experiment, the effect of the type of input waveforms and their number on the classification accuracy was verified.

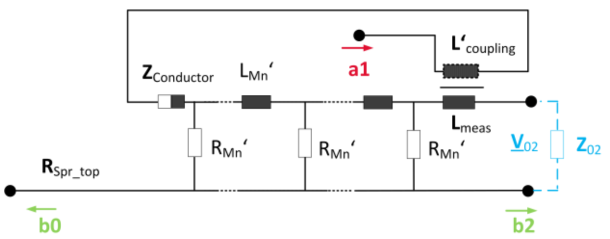


Fig. 5. Modelling of the coupling effect used in ideal M-shunts [12] or ideal coaxial shunts [14]. Field is coupled into the measuring tap by the current distribution.

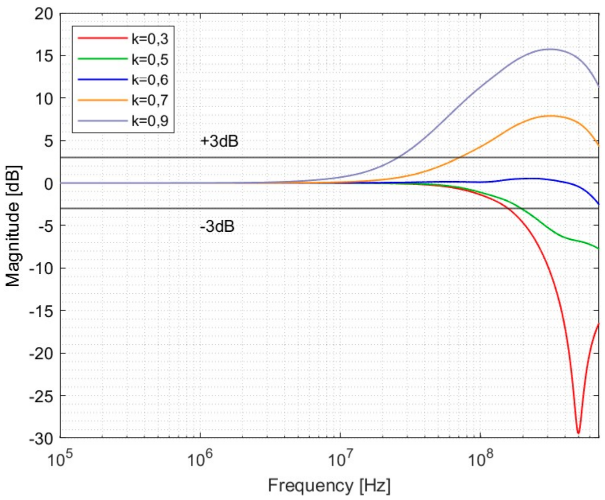
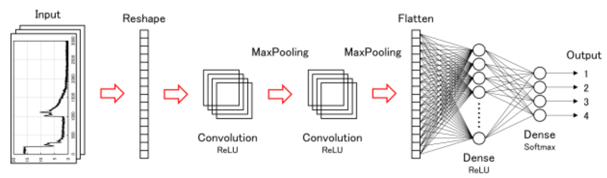


Fig. 6. Influence of the coupling factor k in Fig. 5 on the transfer characterisitc of the sensor.

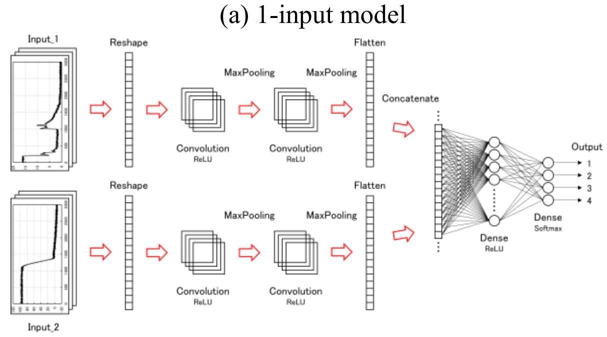
IV. Experimental Results and Discussion

A. Results of CNN Analysis

Table 1 presents the percentage of correct classifications when CNN analysed each waveform. When using the V_{gs} waveform, the classification accuracy reached 100 % for both turn-off and turn-on conditions, demonstrating exceptionally high reliability. Fig. 8 and Fig. 9 illustrate the measured waveforms obtained using M-shunts with and without coupling under each switching condition. The V_{gs} waveform varies significantly depending on the number of wire cuts. Due to the extremely high switching speed of SiC-MOSFETs, parasitic inductance causes waveform ringing, which superimposes high-frequency harmonics onto the gate voltage. These harmonics, being highly sensitive to even minor changes in parasitic inductance caused by wire cuts, contribute to the high classification accuracy of V_{gs} based analysis. Additionally, combining V_{gs} and I_s waveforms further improved classification performance. It should be noted that the present experimental setup with digital gate driver permits the measurement of gate voltage. However, the focus on

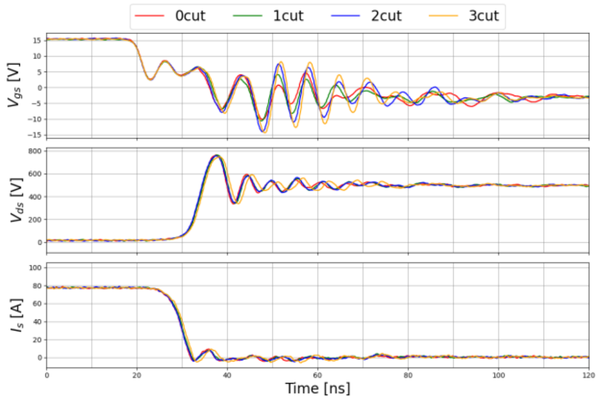


(a) 1-input model

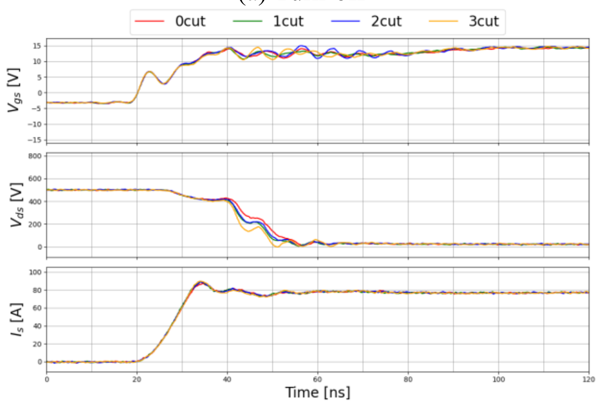


(b) 2-input model

Fig. 7. CNN architecture layer

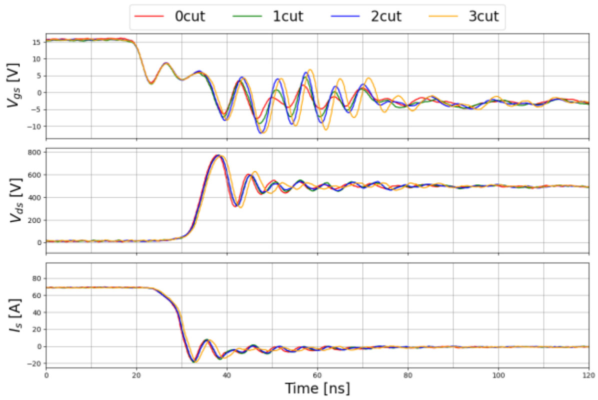


(a) Turn-off

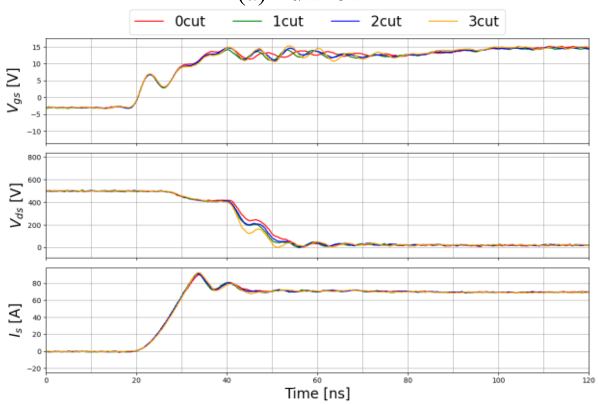


(b) Turn-on

Fig. 8. Switching waveform of SiC-MOSFET (Without Coupling)



(a) Turn-off



(b) Turn-on

Fig. 9. Switching waveform of SiC-MOSFET (With Coupling)

current should be given greater consideration if optimal results are to be achieved.

In contrast, classification accuracy depended on the switching state for V_{ds} and I_s waveforms. A high accuracy was achieved for V_{ds} only at turn-on, whereas I_s yielded high accuracy only at turn-off. Fig. 9(b) highlights the V_{ds} waveform at turn-on, where noticeable waveform changes due to wire cutting contributed to high classification accuracy. However, the waveforms showed no significant changes at either turn-on or turn-off, making the reason for the high classification rate at turn-off unclear. Notably, these trends remained consistent regardless of the presence or absence of M-shunt coupling in the first place. This consistency suggests that the coupling effect of the M-shunt has limited influence on waveform features relevant to classification, indicating robustness in waveform-based degradation detection under varying sensor configurations.

B. Effect of M-Shunt Coupling on Classification Accuracy

The influence of the M-shunt coupling on classification accuracy is analysed as follows. The results suggest that coupling has minimal impact on classification accuracy under most conditions. However, in cases where classification accuracy was relatively low, the use of coupled M-shunts resulted in a slight improvement compared to uncoupled ones. This improvement is attributed to coupling-induced gain flattening in the high-frequency range (see Fig. 6), enabling more accurate detection of small inductance variations caused by wire degradation. Nevertheless, the enhancement was limited, with classification accuracy improving by only approximately 5-9 %, suggesting that coupling alone is insufficient to achieve substantial improvement.

Table 1. CNN accuracy with discrete SiC-MOSFET and comparison of with and without M-Shunt coupling

Type of Waveforms	Accuracy [%]			
	Without Coupling		With Coupling (20 %)	
	Turn-off	Turn-on	Turn-off	Turn-on
V_{gs}	*100*	*100*	*100*	*100*
V_{ds}	32.4	*99.9*	43.9	*99.5*
I_s	*100*	41.9	*100*	46.9
$V_{gs} + I_s$	*100*	*100*	*100*	*100*

M-shunts are designed to minimise parasitic inductance while maintaining high bandwidth, ensuring accurate capture of high-speed transients. The theoretical benefit of coupling lies in its ability to compensate for high-frequency attenuation due to parasitic effects, thereby improving sensitivity to small variations in parasitic inductance. However, the findings indicate that overcompensation through coupling, while reducing the theoretical bandwidth, slightly enhances classification accuracy. Since the dominant frequency components necessary for classification are well captured even by uncoupled M-shunts, coupling provides the most benefit when the measurement system lacks sufficient bandwidth to capture these critical high-frequency components.

C. Implications for SiC-MOSFET Waveform Classification

SiC-MOSFETs inherently produce waveforms rich in high-frequency harmonics due to their fast-switching speeds. The slight improvement in classification accuracy when using coupled M-shunts suggests that certain transient components, such as high-frequency ringing or sharp voltage spikes, were captured more effectively. However, the primary mechanism of degradation detection relies not only on these high-frequency harmonics but also on significant overall changes in the switching waveform. As a result, the additional benefits of coupling are inherently limited. This observation aligns with the theoretical expectation that, while coupling enhances harmonic measurement, it does not fundamentally alter the dominant frequency components influencing classification accuracy.

The results indicate that for SiC-MOSFET waveform classification, changes in the waveform due to wire cuts are generally pronounced, ensuring effective detection even without coupling. The marginal improvement from compensating coupling suggests that a relatively narrow frequency bandwidth and a lower sampling rate are still sufficient for accurate classification in this case. The future studies on SiC modules will explore how overcompensation leads to further improvement of the results of the analyses.

V. Influence of The Coupling Area on The Accuracy of The Detection for SiC-MOSFETs with Fast Transients

In the previous section, it was demonstrated that detecting bond-wire lift-off during turn-on measurement at source current I_s and V_{ds} at turn-off measurements is the most challenging task, particularly when the objective is limited to distinguishing between a 0-cut and a 1-cut scenario. To further investigate this phenomenon, the experiment described in this section employs five M-shunts, each featuring a different coupling area while maintaining an identical resistive layer. In the previous experiment, a discrete SiC-MOSFET was used; however, in the present study, a comparable device was not available. Since the objective of the experiment was to investigate the relationship between the 0-cut/1-cut distinction and the presence or absence of coupling in the M-shunt, the specific type of device was not considered critical. Therefore, a SiC-MOSFET module (BSM080D12P2C008, Rohm, 1200 V / 80 A, C-type housing [15]) available on hand was employed. The test circuit used was the same double-pulse test configuration shown in Fig. 1, with a test voltage of V_{dc} = 500 V and a switching current of I_s = 80 A. A photograph of the experimental setup is shown in Fig. 10.

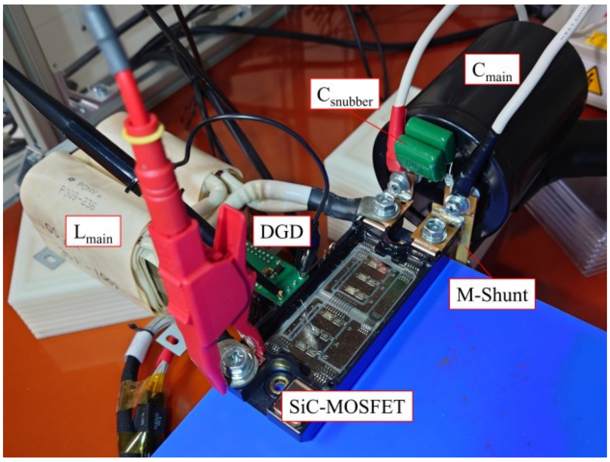


Fig. 10. Experimental setup used in the additional measurement.

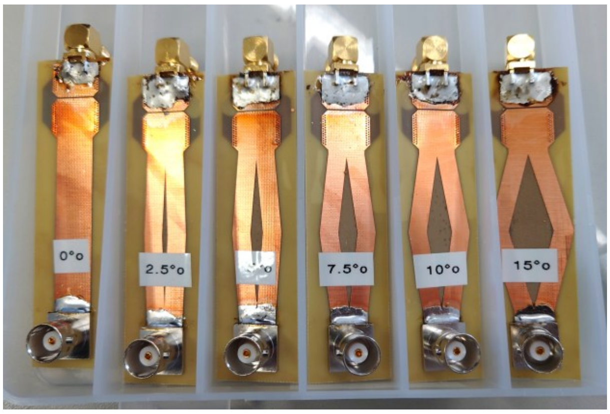


Fig. 11. M-shunt with different couplings used in the experiment

Fig. 11 shows the M-shunts with different couplings used in the experiment. Aside from the varying coupling areas, all shunts are otherwise identical. Table 2 presents the detection probability for correctly identifying the number of cuts using CNN (0 or 1) as a function of the coupling area, expressed in percentage. It was hypothesised that an increase in the coupling area would result in an enhancement of the system's capacity to differentiate between the two cases. This hypothesis was confirmed through experimentation, with a clear distinction observed between the 0 % and 10 % coupling steps. The findings further suggest that excessive overcompensation can lead to amplified noise, consequently impeding the AI's performance due to overlearning. While the combination of V_{ds} and I_s in the AI results in perfect detection probability, this is not entirely true for single values at I_s.

Table 2. Detection Probability of Correct Cut Identification (0 or 1) as a Function of Coupling Area

	Coupling Area [%]	CNN Accuracy [%]		
		V_{gs}	V_{ds}	I_s
Turn-off	0	100	*47.2*	100
	10	100	*99.0*	100
	20	100	*100*	100
	30	100	*99.5*	100
	40	100	*99.5*	100
Turn-on	0	74.3	100	*88.0*
	10	63.7	100	*99.5*
	20	47.2	100	*51.2*
	30	98.0	100	*47.2*
	40	99.8	100	*97.5*

Epochs = 20

VI. Other Consideration

This study focused on building a machine learning model for wire lift-off, while addressing other degradation modes remains a subject for future research. Wire lift-off was chosen because it is a representative and experimentally reproducible degradation mode, and the study prioritized the establishment of methods to improve detection accuracy. The insights gained, along with the data processing techniques and feature design guidelines developed through this work, can be applied to other degradation modes. Future efforts include collecting data and developing models for various failure modes such as solder joint cracks and chip damage, with the goal of constructing a more general-purpose classification model.

VII. Conclusion

This study has successfully demonstrated the feasibility of detecting minimal changes in inductance caused by bond wire lift-off. A power cycle degradation detection method using the switching waveforms of discrete SiC-MOSFETs was investigated. The percentage of correct responses was compared by the type of the detection signal and the effect of the coupling design in the M-shunt was discussed. It was found that using V_{gs} enabled the detection of wire lift-off with a high percentage of correct responses in both turn-off and turn-on conditions. The implementation of the coupling shunt resulted in a notable enhancement in the sensitivity of di/dt measurements. While practical applications may potentially experience some degree of degradation rather than abrupt detachments, even these gradual and subtle changes can be discerned across a multitude of switching devices, provided that suitable measurement techniques are deployed. The integration of the coupling shunt concept presents a promising way for enhancing the monitoring and detection of bond wire degradation in modern power electronics systems.

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