



HAL
open science

Discussion on Classification Methods for Lifetime Evaluation of a Lab-Scale SiC MOSFET Power Module

Malorie Hologne-Carpentier, Bruno Allard, Guy Clerc, Hubert Razik

► **To cite this version:**

Malorie Hologne-Carpentier, Bruno Allard, Guy Clerc, Hubert Razik. Discussion on Classification Methods for Lifetime Evaluation of a Lab-Scale SiC MOSFET Power Module. ELECTRIMACS 2022, Serge Pierfederici, Jean-Philippe Martin, May 2022, NANCY (54), France. pp.153-166, 10.1007/978-3-031-24837-5_12 . hal-04562710

HAL Id: hal-04562710

<https://hal.science/hal-04562710>

Submitted on 29 Apr 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Discussion on classification methods for lifetime evaluation of a lab-scale SiC MOSFET power module

Malorie Hologne-Carpentier · Bruno Allard · Guy Clerc · Hubert Razik

Abstract This paper focuses on classification methods for evaluating the lifetime consumption (LC) of power electronics modules. The generalization of power electronics devices introduces new issues concerning the reliability of equipment, especially in the transportation field. To meet these expectations, this paper discusses an approach to evaluate the percentage of lifetime of a lab-scale SiC MOSFET power module, designed for an aircraft application. This module is based on a planar technology, and presents typical failure modes concerning the SiC MOSFET chip itself and its environment. The modules have been aged on a specific instrumented test bench to trigger the expected failure modes. Thanks to this test campaign, a large database of 50 parameters have been obtained in order to find a relevant failure signature. Once the signature was obtained, a comprehensive solution is required to classify the signatures into relevant classes related to the module lifetime consumption. To meet the issue, three types of classification have been tested with learning data set: Support Vector Machine, k-Nearest Neighbors and neural network. The last contribution of this paper is a discussion on the evaluation of the percentage of lifetime consumption of a new test module thanks to the most promising model obtained from the learning data set.

M. Hologne-Carpentier
LabECAM, ECAM Lasalle, Université de Lyon
69321 Lyon, France
E-mail: malorie.carpentier@ecam.fr

B. Allard, G. Clerc, H. Razik
AMPERE, Université de Lyon, INSA Lyon, UCB Lyon
69100, Villeurbanne, France
E-mail: bruno.allard@insa-lyon.fr, guy.clerc@univ-lyon.fr

1 Introduction

In the last decades, the electrification of systems in the field of transportation has been generalized. The motor drives are now mostly electrical and are constituted of electrical motors controlled by power electronics converters. The electric mobility required more and more compact and light systems to be easily embedded for a higher and higher power density. This trend for power density has led the industrials to develop new technologies of semiconductor devices as Silicon Carbide (SiC) components and new designs of planar power module. Such a power density in a confined environment can lead to failure mechanisms mainly due to CTE mismatching [1]. Besides, when the SiC component is a MOSFET, a certain failure mode has been identified as being a weakness of this technology: the Gate Oxide issues [2].

Power electronics technologies will be more and more used in the transportation system drives and will require a particular attention to allow a relevant maintenance strategy and a large availability of the systems. In this challenging context, another way to think the maintenance is to realize an online tracking of pre-determined parameters that constitute a signature of potential failure mechanisms. By the way, health monitoring of power electronics could be achieved online to avoid scheduled maintenance, which creates unavailability of the systems, or avoid failure without warning.

Relevant online-compatible failure signature have to be determined for each new technology. This paper proposes to make this preliminary work for an SiC MOSFET based power module, whose description and failure modes will be briefly given in part 2. In this part, we will see also how to automatically select the relevant parameters to constitute a failure signature. The 3rd part will be dedicated to the issues of classification with a reduced signature or not to evaluate

the lifetime consumption of the power module thanks to learning data set. Finally, a 4th part will show how it is possible to estimate the percentage of lifetime consumption of a new power module thanks to the most promising model of diagnosis obtained in the learning phase.

2 From the module failure study to the signature

2.1. SiC MOSFET based power modules

The DUT is a lab-scale power module created to model the behavior of the final full module, which will be inserted in a compact 45kW inverter for an aircraft application. It is constituted of one SiC MOSFET (C2M0025120D, 63A, 1200V) and one power diode and tested in a chopper configuration. The focus of reliability has been directed on the MOSFET and its environment; so we will let the diode apart in the analysis.

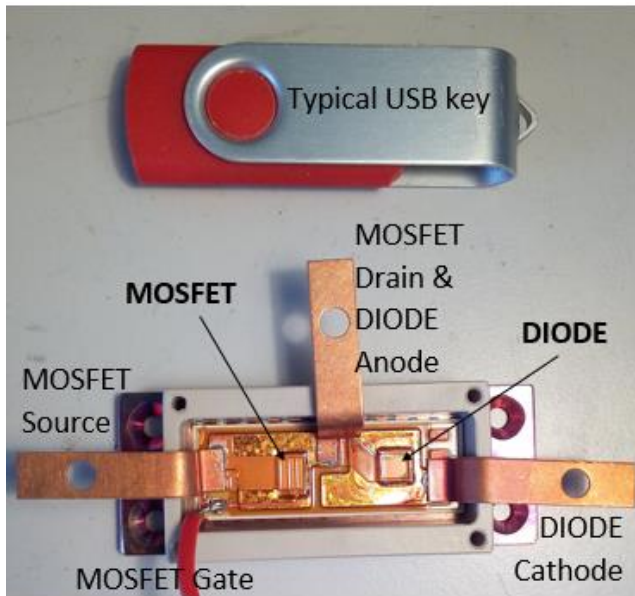


Fig. 1 Lab-scale power module at real dimensions.

Module dimensions being minimized, many failure mechanisms can occur and are briefly described in the following subpart.

2.2. Possible failure mechanisms

The different failure mechanisms expected in similar power module have been reviewed in [3] and the most relevant ones for this technology are the Gate Oxide degradation and the top metallization lift-off.

Ten power modules have been tested and their post-mortem analysis has shown three identified failure causes: Drain-to-Source short-circuit (DSSC), Gate oxide perforation (GOP) and metallization lift-off (MLO). These failure mechanisms are certainly not the only ones that can occur but the lot of ten Test Modules (TM) and the available equipment of post-mortem analysis allow identifying precisely only these three ones.

The level of stress was imposed thanks to a self-heating of the MOSFET according to the following pattern: 1s of self-heating under a constant current until reaching a maximum health junction temperature, 4s of cooling thanks to a forced air cooling. At this level of stress, the lifetime of each module is varying along the test campaign and has been gathered in Tab.1.

Table 1 Test campaign synthesis

| TM | Lifetime (cycles) | DSSC | GOP | ML O | Stress profile T_{jmax}/I_{DC} |
|----|-------------------|------|---------|------|----------------------------------|
| 1 | 6 400 | Yes | No | No | 145°C/ 50A |
| 2 | 75 600 | No | Yes | No | 125°C/48A |
| 3 | 176 000 | Yes | No | Yes | 120°C/46A |
| 4 | 93 700 | No | Yes | Yes | 130°C/48A |
| 5 | 31 400 | Yes | No | Yes | 125°C/46A |
| 6 | 69 000 | Yes | No | No | 115°C/46A |
| 7 | 11 500 | No | Partial | No | 111°C/46A |
| 8 | 20 200 | Yes | No | No | 115°C/46A |
| 9 | 23 000 | No | No | Yes | 115°C/46A |
| 10 | 35 000 | Yes | No | No | 114°C/46A |

Such a variety of results on a small lot of test modules (10) needs a high attention in the signature constitution. The following subpart will detail the main issues of this work.

2.3. How to constitute a relevant failure signature?

As detailed in [4], the constitution of a relevant failure signature meets the following issues:

- What is the best strategy of accelerated ageing tests to trigger the most expected failure modes?
- Among all the measurable parameters, which ones are monotonous and are correlated with at least a failure mechanism?
- Among correlated parameters, how to select the ones carrying the most relevant information (most important drift from an initial value)?
- Are the selected parameters sensitive to one or several failure mechanisms?
- Can we constitute a signature for each mechanism in this study or only a signature representative of at least one of them?

In this study, Active Power Cycling of the module leg was selected as the accelerated lifetime test. A chopper configuration using a DC current to trigger self-heating is readily available as well as a forced cooling phase in passive electrical conditions. The cooling phase was used to realize two characterization tests in order to obtain 50 potential candidates for the signature: Thermal Sensitive Parameters (TSEP) measurement and a Double Pulse test. The parameters obtained during these tests are given in [4]. To select the most relevant parameters to constitute a failure signature, a methodology, given in Fig.2, has been adopted to meet all the issues previously cited.

By using this methodology, the parameters selected for each TM has been different. This result could be expected

knowing that the observed failure mechanisms were different.

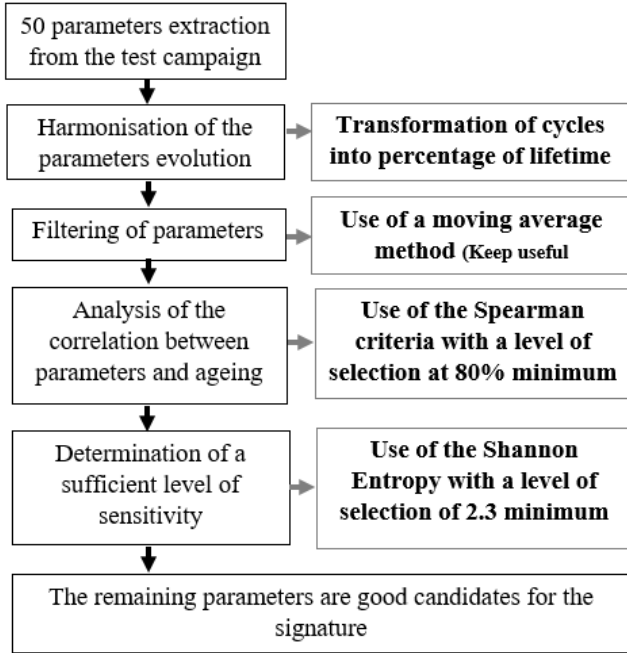


Fig. 2 Methodology to select relevant parameter in order to constitute the failure signature

The issue is now to choose the suitable strategy to build the signature. We can even choose to build several signatures for each failure mechanism or to build a general signature composed of parameters which are, together, discriminative enough to indicate a potential failure mechanism in progress. Since this study has been led on lab-scale TM, no relevant signature has been identified to deal with each failure mode distinctly. For example, TM 1, 6, 8 and 10 show the same failure mode (DSSC) and their most sensitive parameter is the Junction Temperature (TM1, TM6), the On-state resistance (TM8) or the Rise Time to V_{G8TH} (TM10). Therefore, it has been decided to keep all the parameters that present a sufficient Shannon Entropy [5] (2.3 minimum) for at least two TMs. The obtained signature (1) is a 10-dimension signature constituted of parameters more or less sensitive to each failure mechanism but which is a good image of the TM health state along its lifetime.

$$Signature = \begin{pmatrix} Temperature \\ R_{DSON} \\ V_{DSON} \\ IdVg \\ IdP \\ P_{Miller} \\ Mean_{plateau} \\ Rise_{time\ to\ 8V} \\ Coef_{linear} \\ T_{mean_{plateau}} \end{pmatrix} \quad (1)$$

The next part details different solutions to obtain the diagnosis of the TM by classifying the signature for several percentage of consumed lifetime with learning data set.

3 Classification of a 10-dimension signature

Classical approaches for lifetime evaluation are reported in [6]. The classification of signature obtained thanks to a learning phase have been chosen in this study. This choice is justified by the non-maturity of the technology and the lack of relevant model that can be used online. TM 2, TM3, TM5, TM6, TM8 and TM9 have been chosen to construct the learning classes of the supervised classification. In a first approach, we have decided to construct only four classes among the lifetime consumption, knowing that the more numerous the classes, the more difficult it is to discriminate them. Signatures extracted from the six TM signals in a random way following the above limits define the chosen classes:

- Class 1: between 0% and 5% of the lifetime.
- Class 2: between 28% and 33% of the lifetime.
- Class 3: between 58% and 63% of the lifetime.
- Class 4: between 95% and 100% of the lifetime.

For the learning phase, 5 signatures of each period of time (class) have been extracted of each learning TM (6). The extraction is a matrix of dimension 120x10 and is noted S_{10} .

3.1. Reduction of the signature

Several methods of classification are faster if they are used in a 2D or 3D space and use hyperplane to discriminate each class. To test these methods in this study we have to reduce the signature into a 3-dimension one at least. To avoid a too large loss of information, we have to keep the most important parameters by reducing the size of the signature by creating only three variables issued from a linear combination of the ten initial parameters. This reduction method is called Principal Component Analysis (PCA) and allows to represent each signature of the learning database in a 3D-space (Fig. 3). The first step to obtain this 3D signature, is to create a covariance matrix from the 10-column data matrix S_{10} (2):

$$A = S_{10}' \times S_{10} \quad (2)$$

With S_{10}' the transposed of S_{10} data matrix.

The eigenvalues of the obtain matrix A (λ_i , with i from 1 to 10) are extracted and ordered. The three higher values will be named λ_1, λ_2 and λ_3 . The next step is to find out the new vector V , defining the new basis, that verifies (3):

$$A \cdot V = V \times \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix} \quad (3)$$

With $size(V) = (10,3)$.

To obtain the signature in the new basis, we have to project S_{10} thanks to the vector V (4).

$$S_3 = S_{10} \cdot V \quad (4)$$

With $Size(S_3) = (120,3)$.

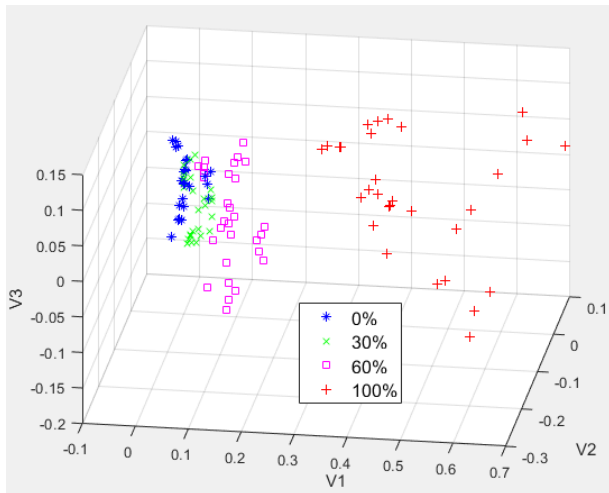


Fig. 3 Representation of the database signatures after a PCA in a 3D-space

Fig.3 indicates that obtaining hyperplanes allowing a discrimination of the four classes is not trivial. To try to meet this issue, two methods have been tested in the next subpart: the Support Vector Machine (SVM) [7] and k-Nearest-Neighbors (kNN) [8] methods.

3.2. Classification with SVM and kNN using S_3 and S_{10}

In a first approach, we have tested the SVM method. SVM method proposes to share the hyperspace in different part separated by borders, which can be lines, plans, spheres, etc, according to the dimension. The algorithm places the borders by clustering all the data of one class together and maximizing the margin between class points and the border. The shape of the border is various and for this study, the most common solutions have been tested thanks to a supervised classification: try to discriminate signature of the learning base in the four known classes. We have realized the learning phase with the two signatures S_3 and S_{10} , and the better border type is not the same: Fine Gaussian (85%) with a reduced signature and Cubic Gaussian (97.5%) with the complete one. Fig. 4 details the performance of classification of each SVM method on S_3 and S_{10} signature respectively.

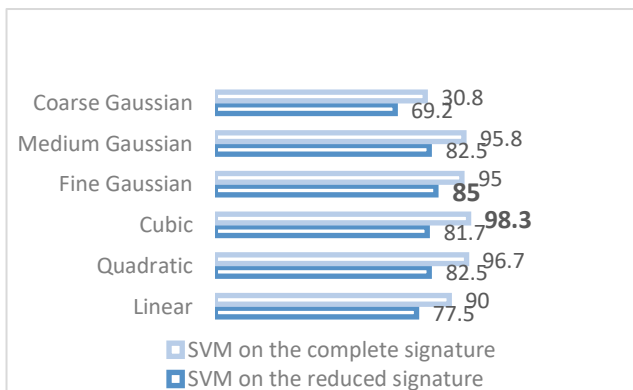


Fig. 4 Comparison of the discrimination level with several SVM border types for 3D and 10D spaces.

A result at 85% on learning data set is not very satisfying and choosing this type of classification is risky, as we want to discriminate in classes unknown signatures from other modules. We can firstly conclude that the SVM with a reduced signature presenting many advantages in terms of simplicity and calculation time will not be efficient to discriminate a new signature in classes. If we want to use SVM, a 10-Dimension signature classification is finally the most promising and will be tested in the next part.

To continue the investigations, we have decided to test the classification with the kNN method. This method lays on an attribution of a point to a class thanks to its proximity to another point belonging to this specific class. It requires also a learning phase. As previously, different types of the kNN method have been tested: global and subspace kNN. The first method realizes a learning phase on all the signatures and the second one makes successive learning phase (30 on the 120 values of S_{10}). As in SVM, the kNN borders can be various and have been examined for the first method and results are gathered in Fig. 5.

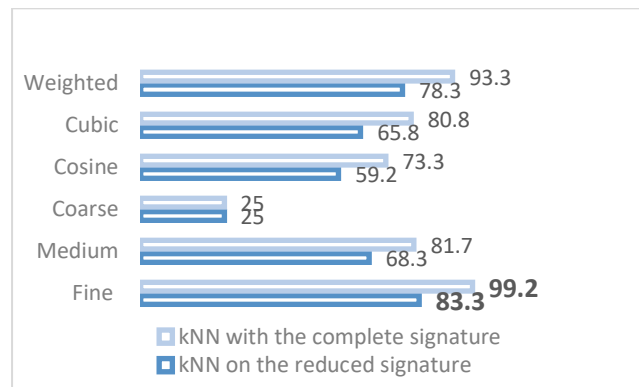


Fig. 5 Comparison of the discrimination level with several kNN border types for 3D and 10D spaces.

The best level of discrimination is obtained for the same type of border for both reduced and complete signature: Fine kNN. The level of discrimination for the reduced signature is not satisfying (83.3%) compared to the one with the complete signature (99.2%). The second method, the subspace kNN, has been tested with reduced (88,3%) and complete signature (96,7%), the level related to the best result obtained previously (99,2%), the next investigations for diagnosis will focus on the classical kNN approach.

3.3. With the neural network

The Neural Network (NN) approach presents a high adaptability to physic model [9] and can be a good candidate for classifying the learning data of module lifetime. The

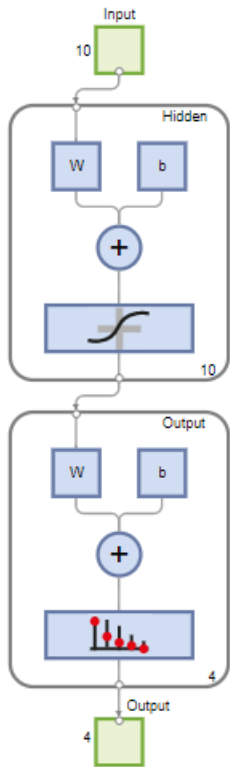


Fig. 6 Neural Network principle

principle, pictured in Fig. 6, shows that the NN works with the complete signature (10-dimension). The 10 features are treated in 10 parallel hidden layers. For each one, a weight (W) and a bias (B) are attributed to each point. Next, an activation function is applied (Boolean, linear or sigmoid). After several tests, the sigmoid function gives better results. After the hidden layer, the data reaches the 4D output layer linked to the four predetermined classes. In this layer, the learning phase helps to choose a weight and a bias to align data from a class to this specific class.

The algorithm proposes to work with the 120 extracted signatures in several steps: learning (84 signatures), validation (18 signatures) and test (18 signatures). By the way the algorithm adjusts the

values of weight and bias and propose a classification of an excellent performance: 100%.

At the end of this part, we can say that three models of classification are promising: the Cubic SVM (98.3%), the Fine kNN (99.2%) and the Neural Network (100%). Before testing these methods with a new module, we have to look at the result of performance with precautions. All the previous models have been obtained after several trainings, the level of performance changes with the initial learning signature chosen to establish the model settings. The given performances are the maximum ones obtained after 30 trainings. The settings have been recorded to test new signature from an unknown module.

4 Discussion on the lifetime evaluation of a new module

In this part, data of TM10 has been considered to test the previous methods. We have extracted some signatures in the same intervals of lifetime than the ones of the learning phase. By the way, the selected models will normally attribute the five first signatures to the class 1, the 5 following ones to the class 2, etc.

4.1. Test of Cubic SVM, Fine kNN and Neural Network approach on data from a new module

Although the models of performance were promising on the learning data set, the test realized with the TM10 signatures extracted at known periods of lifetime corresponding to the specified classes is not very satisfying. Fig. 7 gives the

expected classes knowing the lifetime of extraction (dash line) and the class attribution according to the previous methods. We can see that Fine kNN mismatches nine signatures what gives a performance of 55%. The Cubic SVM mismatches only three signatures what gives a performance of 85%. Finally, the NN mismatches five signatures and thus gives a performance of 75%.

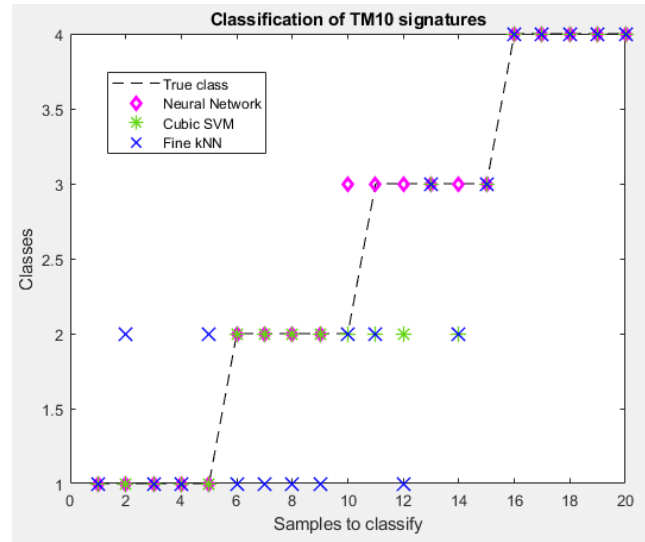


Fig. 7 Classification of 20 signatures from TM10 extracted at known lifetime percentage (0%, 30%, 60% and 100%)

Cubic SVM and Fine kNN attribute a class with a binary approach: the signature is in a class or not. It is difficult to explain the bad result obtained with Fine kNN in particular.

However, NN method gives for each signature a confidence level in the class attribution. This confidence level can open a track to analyze the previous results obtained for TM10 data and more generally, to understand the mismatching of such classifiers.

4.2. How to interpret the classification of the neural network model?

When we look at Fig.7, it appears clearly that the signatures of class 2 are not well discriminated and are attributed to class 3. We can begin the investigation by looking at the confidence level of attribution of each signature to each class. Fig.8 gives the confidence level of class attribution for extracted signatures at predetermined dates from TM10 data. We observe that class 1 and class 4 for the beginning and the end of the lifetime are well discriminated. Class 3, around 60% of lifetime, is discriminated with a very good level after 60% and with a relative confidence level under 60% but the attribution can be acted with the study of neighbor signatures. However, if we look at the signatures around 30% of lifetime, we see that the higher confidence level attributes it to class 3 (and not class 2 as expected). The trend of attribution lets think that the class 2 of TM10 will be earlier in the percentage of lifetime. That is why we have tested signatures between 18% and 27%. As expected, the model discriminates the major part of signatures between 19% and 27% as being in class 2.

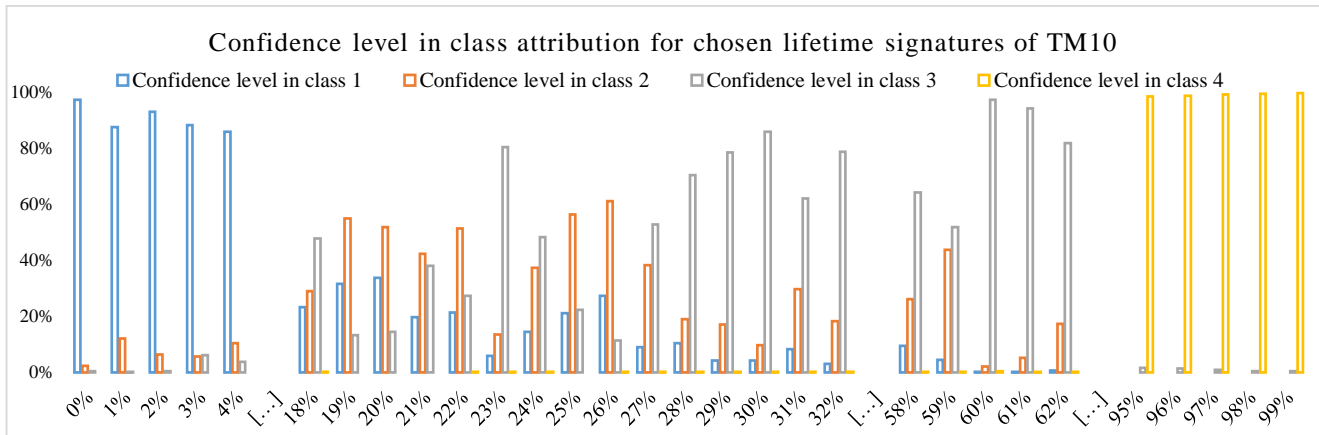


Fig. 8 classification confidence level of 30 signatures from TM10 extracted at known lifetime percentage

The observation shows the non-robustness of the model constructed with only six modules for the learning phase. The evolution of the learning signals around these values of lifetime obviously contain not enough information (not enough drift). To confirm this assumption, we can check the time evolution of the signals for learning and test modules (Fig. 9). The drift of the time signal between 30% and 60% is less important for TM10 than other TMs. It can be a clue to understand the non-robustness of the model on this test module.

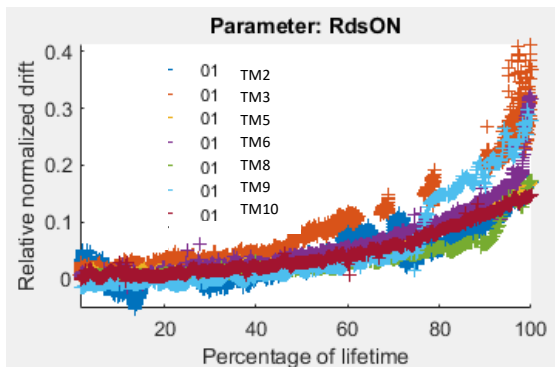


Fig. 9 Evolution of one parameter of the signature according to time

It could be interesting to test also TM1, TM4 and TM7 but the data obtained for these TMs are partial (recording issues or noise during the measurements) and cannot be used to test the NN approach.

5 Conclusion

In this study, we have experimented a lifetime estimation approach for a new technology of planar SiC MOSFET power module. The data have been obtained through an accelerated ageing process applied to only 10 TMs. The observed failure modes are various and required an investigation on the diagnosis method to better discriminate them. Three classification methods have been compared based on the same learning data set: SVM, kNN and Neural Network. Finally, the Neural Network is not the best method to obtain the lifetime consumption estimation but this

approach is interesting. Thanks to the obtained confidence level, the model and the diagnosis strategy could be improved. For example, on this study, the drift being very small under 50%, maybe it could be interesting to construct classes only between 50% and 100% of the lifetime to obtain a robust indicator.

Acknowledgements Authors acknowledge the financial support of the EU H2020 project I²MPECT, grant n°636170.

References

1. C. Durand, M. Klingler, D. Coutellier, and H. Naceur, "Confrontation of failure mechanisms observed during active power cycling tests with finite element analyze performed on a mosfet power module," in *14th International Conference on Thermal, Mechanical and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems (EuroSimE)*, Cardiff, UK, April 2013, pp. 1–4.
2. T. T. Nguyen, A. Ahmed, T. V. Thang, and J. H. Park, "Gate oxide reliability issues of SiC MOSFETs under short-circuit operation," *IEEE Transactions on Power Electronics*, vol. 30, no. 5, pp. 2445–2455, May 2015.
3. S. Yang, D. Xiang, A. Bryant, P. Mawby, L. Ran, and P. Tavner, "Condition monitoring for device reliability in power electronic converters: A review," *IEEE Transactions on Power Electronics*, vol. 25, no. 11, pp. 2734–2752, Nov 2010.
4. M. Hologne, G. Clerc, B. Allard, H. Razik. "Determination of parameters for lifetime evaluation of SiC MOSFETs based power modules". *Evolution of Functional Performance and Expected Lifetime of Electrical Equipments (ELTEE)*, Oct 2018, Grenoble, France. ([hal-01922194](https://hal.archives-ouvertes.fr/hal-01922194))
5. C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, vol. 27, no. 3, pp. 379–423, 1948.
6. S. Zhao, F. Blaabjerg and H. Wang, "An Overview of Artificial Intelligence Applications for Power Electronics," in *IEEE Transactions on Power Electronics*, vol. 36, no. 4, pp. 4633–4658, April 2021, doi: 10.1109/TPEL.2020.3024914.
7. D. Tibaduiza Burgos and H. Ceron-M, "Damage classification based on machine learning applications for an unmanned aerial vehicle," in *The 11th International Workshop on Structural Health Monitoring*, Stanford, CA, USA, September 2017.
8. T. K. Ho, "Nearest neighbors in random subspaces," in *Advances in Pattern Recognition*, A. Amin, D. Dori, P. Pudil, and H. Freeman, Eds. Berlin, Heidelberg: Springer Berlin, Heidelberg, 1998, pp. 640–648.
9. A. Soualhi, "Du diagnostic au pronostic de pannes des entraînements électriques," Ph.D.dissertation, Université Claude Bernard Lyon 1, Lyon, France, 2013