A Self-Organizing Map-Based Monitoring System for Insulated Gate Bipolar Transistors Operating in Fully Electric Vehicle

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ABSTRACT

Insulated Gate Bipolar Transistors (IGBTs) are one of the most used power semiconductor devices for energy conversion applications, due to their high performance. In this work we have developed a monitoring system for IGBTs installed in Fully Electric Vehicles (FEVs), which are operating under very variable working conditions. The monitoring system is based on a Self-Organizing Map (SOM), trained considering data collected from healthy IGBTs. An indicator of the IGBT degradation is defined as the distance between the measured SOM input vector, i.e., the signal measured on the monitored IGBT, and its SOM Best Matching Unit (BMU) representative of an healthy IGBT in similar working conditions. Then, a method based on the definition of a utility function for the identification of the threshold value to be used for the classification of the IGBT degradation state is proposed. The approach is verified with respect to experimental data collected from an inverter connected to an electric motor, and is shown able to identify the IGBTs degradation state regardless of the actual operating condition.

1. INTRODUCTION

Power semiconductor devices, such as Insulated Gate Bipolar Transistors (IGBTs), are currently used in a wide range of energy conversion applications due to their high performance. However, recent studies have shown that IGBT malfunctioning are responsible of several industrial failures: 38% of unscheduled maintenance actions in variable speed AC drives (Shaoyong, Bryant, Mawby, P., Dawei, Li, and Tavner, 2011) and 35% of power electronic systems faults are caused by IGBTs (Fuchs, 2003; Hudgins, 2013).

Condition-Based Monitoring (CBM) techniques have been developed over the last decade for IGBT monitoring (Lu & Sharma, 2009; Oh, Han, McCluskey, Han, and Youn, 2015). In Chokhawala and Kiraly (1995), IGBT degradation due to open- and short-circuit faults is considered, whereas in Ji, Pickert, Cao, and Zahawi (2013) and Smet, Forest, Huselstein, Rashed, and Richardeau (2013), the authors focus on IGBT degradation caused by wire bond faults. Although the proposed methods are efficient for monitoring IGBT degradation when it is caused by a single degradation mechanism, they are not apt for an overall monitoring of the component which is typically characterized by multiple and competing degradation mechanisms.

The purpose of this work is to develop a method for the identification of the degradation state of IGBTs operating in Fully Electrical Vehicle (FEV) powertrains. The final objective is to develop an automatic system able to inform the FEV driver of the IGBT degradation state and, eventually, of the necessity of performing maintenance. The proposed monitoring system is expected to increase the safety of the FEV and to reduce the overall maintenance costs.

The main difficulties to be addressed in order to effectively monitor FEV IGBTs are:

i. several signals usually employed to monitor IGBT degradation, such as the current at the collector or the transconductance (Patil, Das, Goebel, & Pecht, 2008) are not measurable during FEV operation, due to the intrusiveness of the measurement device;

ii. laboratories tests performed within the European FP7 project HEMIS (Electrical powertrain Health Monitoring for Increased Safety of FEVs) at CEIT laboratories (Centro de Estudios e Investigaciones Técnicas – San Sebastian, Spain) have shown a great variability in the degradation behavior of different IGBTs, even if they are degrading in the same controlled test conditions. This is due to the fact that IGBTs are subject to different, possibly interacting and competing degradation mechanisms, such as bond wire lift-off, solder joint fatigue, and bond wire heel cracking (Busca, Teodorescu, Blaabjerg, Munk-Nielsen, Helle, Abeyasekera, & Rodriguez, 2011).

iii. FEV IGBTs are operating under continuously varying conditions. In particular, FEV speed and motor load variations cause modifications of the power, temperature and currents experienced by the IGBTS. This complicates the diagnostic task since the variations of the signals due to the degradation process are small if compared to those caused by the variations of the operational conditions.

In order to overtake the difficulty in i), we consider the possibility of monitoring the IGBTs by using only signals which can be measured on FEV IGBTs, such as the Case temperature, T, the collector-emitter voltage, V_{CE}, and the phase current, I_p. In order to measure the V_{CE} when the inverter is connected to an electric motor, we have used the new IR25750 chip developed by International Rectifier (IR).

The approach developed in this work for dealing with the inhomogeneous situation described in ii) and iii) is based on the use of Self-Organizing Maps (SOMs), which allow representing and clustering multidimensional data into a two-dimensional space (Kohonen, 2005; Gonçalves, Schneider, Henriques, Lubaszewski, Bosa, & Engel, 2010). A SOM is trained using signal measurements collected from healthy IGBTs and a degradation indicator is defined by considering the distance between the measured signal values and the corresponding SOM best matching unit (BMU). Finally, a method for setting the thresholds to be applied to the degradation indicator in order to classify the component degradation state is proposed. It is based on the identification of an optimal trade-off between degradation state misclassifications resulting in false and missed alarms, through the definition of a proper utility function which quantified the consequences of false and missed alarms in terms of safety and costs.

The proposed approach has been verified considering experimental data collected at the Centro de Estudios e Investigaciones Técnicas (CEIT, San Sebastian, Spain) from an inverter providing the required three phases AC current to an electric power train. The remaining part of the paper is structured as follows: Section 2 identifies the problem statement and the aim of the methodology; Section 3 illustrates the data pre-processing and the method; Section 4 presents the experimental dataset and describes the data collection process; Section 5 discusses the application of the developed monitoring system; finally, Section 6 recalls the concluding remarks and results.

2. PROBLEM STATEMENT

The purpose of this work is to develop a method for the online identification of the degradation state of IGBTs working under continuously varying operating conditions, such as those characteristics of powertrains used in FEVs. The output of the monitoring system is expected to be one of the following three degradation classes: healthy (no need of maintenance), partially degraded (the component can still work, but a warning should be provided), and very degraded (maintenance is necessary in order to avoid the component failure). The information available for the development of the monitoring system is made by the measurements of S signals performed on C different IGBTs, characterized by different levels of degradation. The S signal values measured from the c-th IGBT, $c = 1,2,\ldots,C$, at the generic time τ, will be indicated by the vector $\vec{x}^{c}(\tau)$ formed by the signal values $\left[x_1^c(\tau) \quad \ldots \quad x_S^c(\tau)\right]$.

The IGBTs considered in this work have undertaken an accelerated degradation process characterized by a series of prolonged on-cycles, which cause thermomechanical stresses and accelerate their degradation. For each one of the C IGBTs, we know the number of accelerated aging cycles performed at the time in which the signals have been measured. Notice that, given the stochasticity of the degradation process, this information is not directly related to the real degradation state of the component.

3. METHOD

In this Section the proposed approach is described; the SOM basic concepts are recalled in Section 3.1, the degradation indicator construction is described in Section 3.2, Section 3.3 presents the data preprocessing procedure, and the developed strategy for setting the method parameters is discussed in Section 3.4.

3.1. Self Organizing Maps

A SOM is a neural network concept, used to classify and cluster S-dimensional vectors in a visually simple 2-dimensional lattice. It is formed by an array of L neurons, or map units, each one represented by a characteristic S-

dimensional vector $\vec{w}^{\ell} = \lfloor w_1^{\ell} \quad \dots \quad w_S^{\ell} \rfloor$, $\ell = 1 \dots L$, known as weight vector. Each neuron is connected to the other neurons of the map by a relationship based on a neighborhood function (Kohonen, 2005).

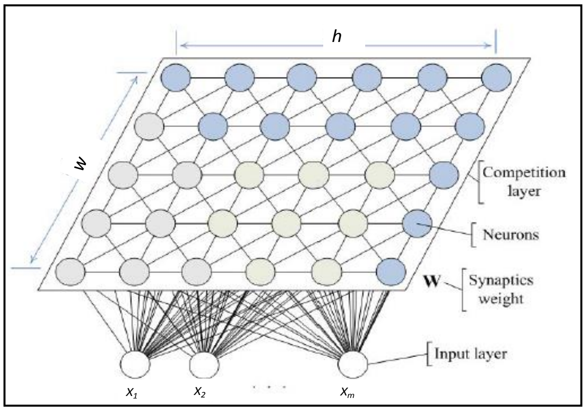

Figure 1. Basic Architecture of a SOM (Goncalves et al, 2010)

Figure 1 shows a representation of a SOM where each neuron is connected to its adjacent neurons and to the input vector. Before the training process, the neurons are properly initialized according to the procedure suggested in (Kohonen, 2005): the weight vectors are selected as a regular array of values between the two largest eigenvectors of the training data. Then, during the training process, the generic *r*-th training step is based on:

1. a sample vector, $\vec{y}^{Training}$, is randomly selected from the training dataset and its distance to the weight vectors of all the SOM neurons is computed;
2. the nearest neuron is identified. It will be referred to as Best Matching Unit (BMU);
3. the weight vector of the BMU and its neighbor vectors are updated in order to obtain weights more similar to that of the chosen random sample vector $\vec{y}^{Training}$. Weight vector updating between training step *r* and *r*+1 is performed by applying:

$$\vec{w}_{\ell}(r+1) = \vec{w}_{\ell}(r) + \alpha(r) h(n_{BMU}, n_{\ell}, r)(\vec{y}^{Training} - \vec{w}_{\ell}(r)) \qquad (1)$$

where $h(n_{BMU}, n_{\ell}, r)$ is the neighborhood function between the best matching neuron n_{BMU} and the ℓ-th neighboring neuron, n_{ℓ}, and $\alpha(r)$ is the learning rate, which decreases at each training step.

Once the training phase is terminated, the SOM structure is caught by the unified distance matrix, U_{dist}, whose generic element $U_{dist}^{\ell_1,\ell_2}$ is defined as the Euclidean distance between the *S*·dimensional weight vectors $\vec{w}^{\ell_1}$ and $\vec{w}^{\ell_2}$, of the corresponding to neurons ℓ_1 and ℓ_2:

$$U_{dist}^{\ell_1,\ell_2} = \sqrt{(w_1^{\ell_1} - w_1^{\ell_2})^2 + (w_2^{\ell_1} - w_2^{\ell_2})^2 + \dots + (w_S^{\ell_1} - w\ell)^2} \qquad (2)$$

The values of the unified distance provide a representation of how similar are the neighboring neurons of a SOM (Figure 2).

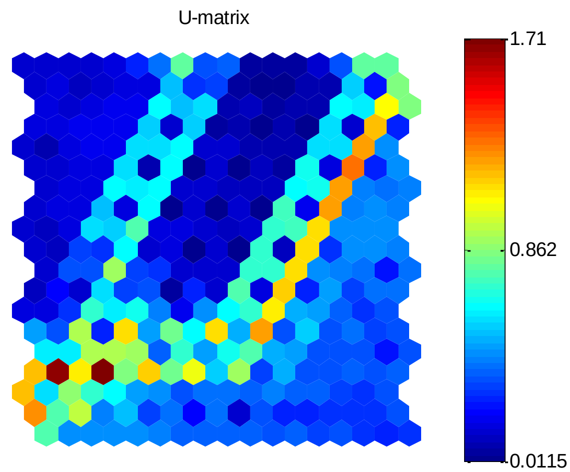

Figure 2. Representation of the Unified Distance Matrix (U-Matrix) of a randomly generated SOM

Notice that clusters formed by neurons characterized by small inter-neuron distances can be easily identified from the observation of the U matrix. In this work, a SOM is trained using data collected from healthy IGBTs. The obtained SOM provides a two-dimensional representation of the training data which minimizes the influence of outliers and noisy data, and catches the characteristic behavior of a healthy component.

3.2. Degradation indicator

In order to identify the degradation state of a monitored IGBT which will be identified by the letter c^{test}, we provide in input to the trained SOM the measured signal values, $\vec{y}^{c,Test}$, and we compute the Euclidean distance between the input vector and the corresponding SOM BMU, $MQE(\vec{y}^{c,Test})$:

$$MQE(\vec{y}^{c,Test}) = \sqrt{(y_1^{c,Test} - w_1^{BMU})^2 + \dots + (y_S^{c,Test} - w_S^{BMU})^2} \quad (3)$$

This distance, which is referred to as Minimum Quantization Error (MQE), indicates how much the vector is different from the behavior represented by the data used for training the SOM (Qiu, & Lee, 2004; Huang, Xi, Li, Richard Liu, Qiu, & Lee, 2007), and can be interpreted as an indicator of the component degradation. Greater the MQE, more the component is behaving differently from an healthy one and, therefore, more the component is degraded.

In this work, the indicator of the component degradation, $QE(\vec{y}^{c,Test})$, is defined as the minimum quantization error,

$MQE(\vec{y}^{c,Test})$, divided by the average quantization error, $MQE_{healthy}$, of a validation set made by healthy data:

$$QE(\vec{y}^{c,Test}) = \frac{MQE(\vec{y}^{c,Test})}{MQE_{healthy}} \tag{4}$$

with:

$$MQE_{healthy} = \sqrt{\frac{1}{N_{healthy}} \sum_{c^{Test}=1}^{N_{healthy}} \left| MQE(\vec{y}^{c,Test}) \right|^2} \tag{5}$$

This normalization allows obtaining a baseline reference value: healthy component will be characterized by a degradation indicator close to 1.

3.3. Data Pre-Processing

The construction of the SOM is preceded by a phase of data preprocessing based on the following two steps:

1. the selection of data in a predefined range of values. In practice, in order to deal with the great variability of the signals in a FEV motor, the model is trained and tested by considering patterns $\vec{x}^c(\tau) = [T^c(\tau) \quad I^c(\tau) \quad Vce^c(\tau)]$ characterized by all signal values within properly selected ranges, i.e., whose phase current, I_p, is in the range [$I_{LowerLimit}; I_{UpperLimit}$], and whose collector-emitter voltage is in the range $[Vce_{LowerLimit}; Vce_{UpperLimit}]$. The ratio of this procedure is to eliminate outlier patterns that are caused by IGBT operational conditions different from those experienced in the training phase and, thus, characterized by high *QE* without corresponding to degraded IGBTs.

2) the computation of the moving average of the signals. This step is performed in order to reduce the impact of the measurement noise on the signal values. The lengths, L_o, of the moving average window will be selected through the optimization procedure described in Section 3.4.

3.4. Degradation state identification

The robustness of the method is improved by considering as indicator of the IGBT degradation the median $QE^{median}(\vec{y}^{c,Test})$ of a number L_o of consecutive $QE(\vec{y}^{c,Test})$ values obtained from the SOM. The median has been chosen since it is more stable than the mean value in case of outliers.

The classification of the IGBT degradation state is then based on the definition of two thresholds $Th_{1\text{-}2}$ and $Th_{2\text{-}3}$ according to the following rules:

- if $QE^{median}(\vec{y}^{c,Test}) < Th_{1\text{-}2}$, then the IGBT is healthy (class 1)
- if $Th_{1\text{-}2} \leq QE^{median}(\vec{y}^{c,Test}) \leq Th_{2\text{-}3}$, then the IGBT is partially degraded (class 2)
- $QE^{median}(\vec{y}^{c,Test}) > Th_{2\text{-}3}$, then the IGBT is very degraded (class 3)

3.5. Setting of the method parameters

The proposed method is based on the following four parameters: i) the length, L_i, of the moving-average window used in the pre-processing phase, ii) the number, L_o, of QE consecutive values which are considered for calculating the median of the degradation indicator, iii) and iv) the threshold values, $Th_{1\text{-}2}$ and $Th_{2\text{-}3}$, used for the classification of the degradation state.

The setting of these parameters is performed considering a set of data (hereafter indicated by “optimization set”), taken from IGBTs not considered for the SOM training and for which the degradation state is known. The objective of the parameter setting is the minimization of the misclassification rates, i.e., the fraction of patterns assigned to an incorrect classification state. To this purpose, the numbers of patterns , $n_{i,j}$, of the optimization set whose correct class is *i* and are misclassified in class *j* are found for any combination of *i* and *j* with $i \neq j$. Then, the fraction of misclassifications, $\alpha_{i,j} = \frac{n_{i,j}}{N_i}$, with N_i indicating the total number of patterns in the optimization set of class *i* is identified and the overall performance of a given parameters quadruplet (L_i, L_o, $Th_{1\text{-}2}$, $Th_{2\text{-}3}$) is defined by the utility function:

$$P = \frac{\sum_{i=1}^{3} \sum_{j=1, j\neq i}^{3} \alpha_{i,j} \cdot IF_{i,j}}{\sum_{j=1, j\neq i}^{3} IF_{i,j}} \tag{6}$$

where $IF_{i,j}$ is a coefficient quantifying the consequences of the misclassification of a pattern whose true class is *i* and is assigned to class *j* in terms of safety and availability of the component. In this work, we assume that the most undesirable event, which can lead to the failure of the component, is that an IGBT whose true state is very degraded (class 3) is classified as healthy (class 1) or partially degraded (class 2). Thus, the highest impact factor is assigned to the coefficients $IF_{3,1}$ and $IF_{3,2}$ (Table 2). Since a preventive maintenance action is suggested only if the degradation state reaches ‘very degraded’ (class 3), the misclassifications with the less remarkable consequences are those between classes 1 and 2. For this reason, the lowest impact factors are assigned to $IF_{1,2}$ and $IF_{2,1}$. An intermediate impact factor value is assigned to the misclassifications which causes an unnecessary preventive maintenance action, i.e. when patterns of classes 1 and 2 are assigned to class 3.

Table 1. Impact factors for the calculation of parameter P

$\alpha_{i,j}$	$IF_{i,j}$
$\alpha_{1,2}$	1
$\alpha_{1,3}$	2
$\alpha_{2,1}$	1
$\alpha_{2,3}$	2
$\alpha_{3,1}$	5
$\alpha_{3,2}$	5

The optimal values of the parameters L_i, L_o, $Th_{1\text{-}2}$, $Th_{2\text{-}3}$ are identified by following a trail-and-error procedure, where different values of the four parameters are tested and the corresponding value of the utility function P is computed. The quadruplet with the associated lowest value of P is selected. Notice that, although the specific values of the coefficients $IF_{i,j}$ depend on the characteristics of the monitored component and the opinion of the expert, the proposed method for the parameter setting is general.

4. CASE STUDY

The method described in Section 3 has been verified with respect to data collected in experimental tests performed on degraded FEV IGBTs at Centro de Estudios e Investigaciones Técnicas (CEIT).

Since the average mean time to failure of an IGBT is around several thousand hours, IGBTs have been degraded by applying an accelerated aging process based on thermal fatigue cycles inducing mechanical deformations on the solder joints, that, in turn, cause an accumulation of microcracking and damage (Thébaud, Woirgard, Zardini, Azzopardi, Briat, & Vinassa, 2000). The IGBTs were connected to a generator, producing a direct current of 5A, and were kept closed (i.e. turned on) as long as the junction temperature reached 270°C. Once this temperature was reached, they were opened (i.e. turned off) until the temperature reached 258°C, and a new degradation cycle begun.

Figure 3 shows the behavior of the collector current (I_c), the collector-emitter voltage (V_{ce}) and the junction temperature (T) during the degradation cycles. Notice that these laboratory data are not used in this work for the development of the monitoring system, since they do not refer to IGBTs working in FEV inverters.

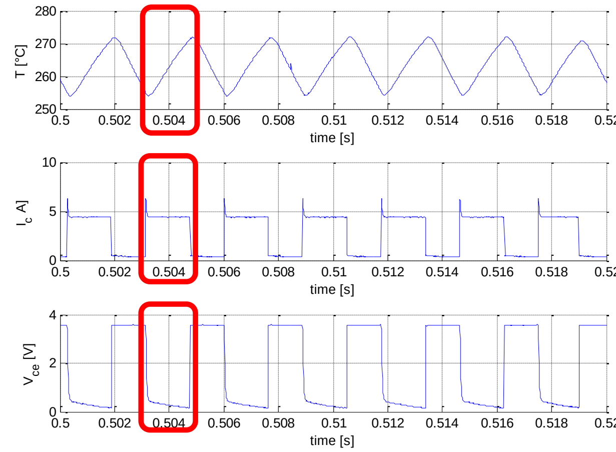

Figure 3. Time evolution of the collector current I_c, the collector-emitter voltage V_{ce} and the junction temperature T during the degradation cycles. The squares indicate a single degradation cycle.

In order to obtain the data necessaries for the development of the monitoring system and its verification, 6 IGBTs have been degraded for a different number of cycles:

- 2 IGBTs were aged for 900 cycles (they will be referred to as IGBT A and B);
- 2 IGBTs were ages for 1800 cycles (they will be referred to as IGBT C and D);
- 2 IGBTs were aged for 2700 cycles (they will be referred to as IGBT E and F).

Then, each degraded IGBTs has been mounted on an inverter connected to a power train and the typical conditions of the IGBT operation in FEVs have been reproduced. In practice, each experiment has been carried out with the powertrain subject to a constant load of 1kW, a 9Nm torque and operating at an average speed of 400rpm. Each experiment lasted on average 3 seconds, producing between 200000 and 380000 measurements. Stator phase current, collector-emitter voltage and the inverter case temperature have been measured at a frequency of 80kHz using low cost sensors which can be easily installed in FEV inverters. With respect to the collector-emitter voltage sensor, notice that it records 0.2V when the IGBT is off.

Figure 4 shows an example of the three signal measurements collected during the test of an IGBT aged for 900 cycles. Due to the high switching frequency of the IGBT in a FEV inverter, only few measurements are collected for each on cycle of the IGBT. Thus, the obtained data are very different from those typically used in literature (Patil et al., 2008) which refers to IGBT in laboratory tests and are similar to those of Figure 3.

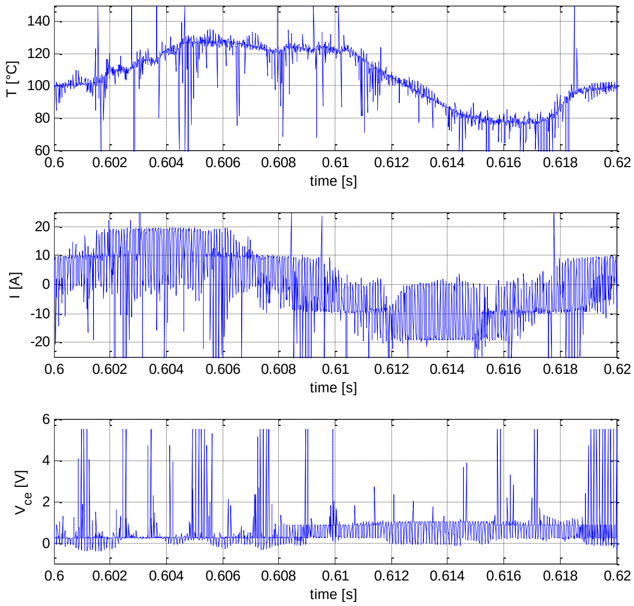

Figure 4. Time evolution of T, I_p and V_{ce} during a 0.02s otor test.

5. RESULTS

5.1. Data Preprocessing

The data acquired during the motor tests are characterized by a great variability of the measured signals. Since the methodology developed in this paper aims at assessing the IGBT level of degradation relying on the quantification of the deviation of the monitored component from its corresponding normal healthy state, it is necessary to limit the analysis on a proper operation region. In practice, the monitoring system is trained and tested only considering patterns whose phase current, I_p, and collector-emitter voltage, V_{ce}, are in the range reported in Table 2.

Table 2. Ranges used for data selection

Variable	Lower Limit	Upper Limit
I_p [A]	-7.05	-6.95
V_{CE} [V]	1.1	1.7

The data corresponding to the two IGBTs A and B aged for 900 cycles, which have suffered the lowest number of degradation cycles, will be considered as a reference for the healthy behavior and used for developing the SOM. Although these data represent a quasi-healthy condition of the IGBT, they are preferred to data referring to new IGBTs, since data collected in experimental tests show that there is a period of IGBT running characterized by a modification of the IGBT behavior.

The data from these two IGBTs are divided into a train set, for the training of the SOM, a validation set, used to calculate the normalization constant $MQE_{healthy}$ in Eq. (5), an optimization set, which will be used to optimize the quadruplet of the model parameters according to the procedure in Section 3.4, and, finally, a test set which will be used to verify the performance of the method. The data relative to the other four IGBTs (namely C, D, E and F) aged by 1800 and 2700 thermal cycles will be divided into an optimization set for the model parameters optimization and a test set. For ease of comprehension, Figure 5 shows how the available dataset has been divided.

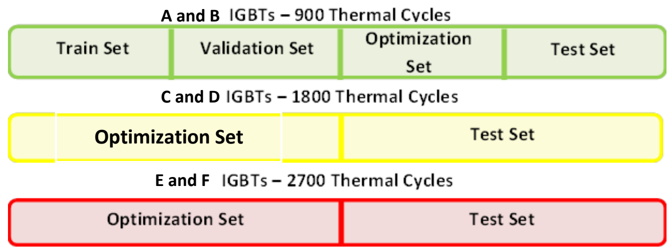

Figure 5. Schematic representation of the available dataset and its division into train, validation and test sets

5.2. The SOM Diagnostic Model

Figure 6 shows the Unified distance matrix of the obtained SOM, and Figure 7 the distribution of the values for the weight vectors associated to each neuron. In particular, it is possible to notice that the right upper corner of the map contains neurons characterized by high T, high I_p and high V_{ce}, whereas the left lower corner neurons are characterized by low T, low I_p and low V_{ce}.

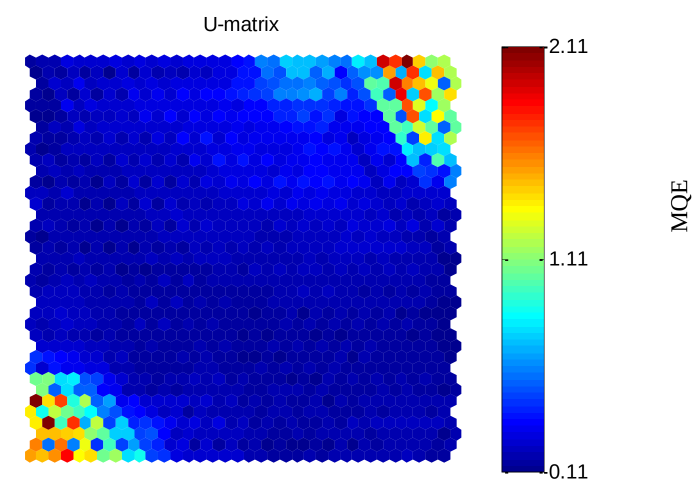

Figure 6. Representation of the unified distances of the SOM map trained with quasi-healthy data

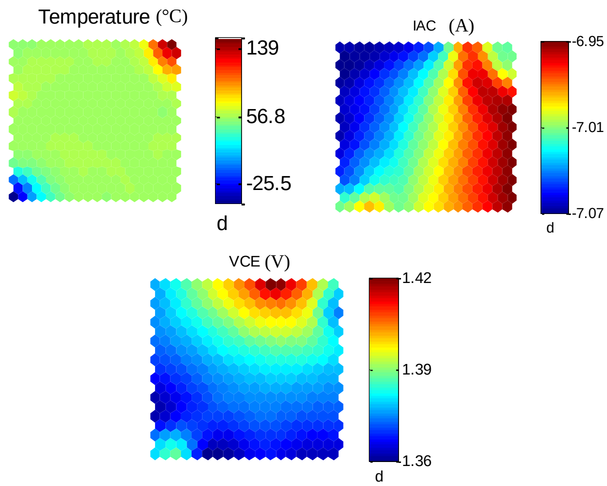

Figure 7. Temperature (top left), Current (top, right) and Voltage (bottom) weights associated to the SOM neurons

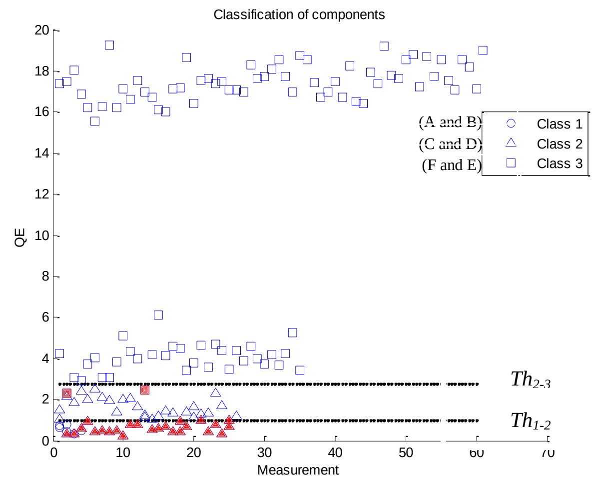

Figure 8. Results of the classification of components, misclassifications are represented by filled in symbols

Once the SOM has been trained, the average MQE of the validation test has been computed in order to allow defining the degradation indicator QE according to Eq. (4).

5.3. Model Parameters Setting

The model parameters L_i, L_o and the two thresholds Th_{1-2} and Th_{2-3}, have been set according to the procedure illustrated in Section 3.4. The first column of Table 3 reports the considered range of variation of the parameters, whereas the identified optimum setting of the parameters, which leads to the best classification results is listed in the second column. Notice that values of L_i and L_o greater than 30 and 60, respectively, are not considered since they would require too long time for the collection of the necessary measurements.

Table 3. Ranges and optimum values for the model parameter setting

Parameter	Range	Optimum
Th_{1-2}	[0;1.4]	1
Th_{2-3}	[1;3]	2.75
L_i	[0;30]	30
L_o	[0;60]	60

5.4. Results

The SOM-based methodology has been applied to test patterns extracted from the 6 IGBTs (A-F) and not used during the SOM training and parameters identification phases.

Figure 8 shows the obtained results. The round markers represent healthy IGBTs (900 degradation cycles), the triangular markers represent partially degraded IGBTs (1800 degradation cycles), whereas the squared markers represent severely degraded IGBTs (2700 degradation cycles). Misclassifications provided by the SOM are represented by colored markers.
Notice that:

1- there are only two cases of missed alarms, i.e. patterns of class 3 (severely degraded) that have been erroneously assigned to class 2 (partially degraded). These patterns correspond to IGBT E, i.e. one of the two IGBTs which have undergone 2700 degradation cycles. It is also interesting to observe that the other patterns obtained from the same IGBT have QE values close to the threshold Th_{2-3}. This may indicate that IGBT E is less degraded than IGBT F, even if they have been aged by the same number of degradation cycles.

2- 97% of the patterns corresponding to partially degraded IGBT C are assigned to class 1. Also in this case, we can interpret the results assuming that IGBT C has been more resistant to the degradation cycles than IGBT D.

3- There are no misclassifications of patterns whose true class is 1 and no cases of false alarms in class 3.

6. CONCLUSION

The objective of this work has been the development of an online method for the classification of the degradation state of IGBTs operating under variable operating conditions. The application of this method is specifically designed for IGBTs used on FEVs, which are characterized by continuously varying temperature and current conditions. The developed method is based on the construction of a SOM, which is trained using only data corresponding to healthy IGBTs. Then, relying on the use of the SOM quantization error as degradation indicator, a condition-based-maintenance strategy has been proposed. The quantization error identified by the SOM is compared to two thresholds, Th_{1-2} and Th_{2-3}, which are the limit values to identify the components as either healthy, partially degraded and severely degraded and thus needing maintenance. A general procedure for the optimum setting of these thresholds and of other parameters has been proposed. The procedure is based on the definition of an utility function which takes into account the consequences in terms of costs and unavailability of the component.

The method has been applied to data representative of IGBTs characterized by different levels of degradation. The data have been collected performing laboratory test at CEIT on IGBTs degraded by means of thermal cycles. The obtained results have confirmed the ability of the proposed method to classify different IGBTs as new, partially degraded or needing maintenance, regardless of the inverter operating conditions. The errors performed by the method are satisfactory from the points of view of reliability and availability: in fact, only the 2% the IGBTs which are very degraded are identified as partially degraded (missed alarms), and no false alarms are provided.

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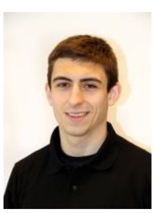

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