Data-driven Prognostics based on Evolving Fuzzy Degradation Models for Power Semiconductor Devices

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Abstract

The increasing application of power converter systems based on semiconductor devices such as Insulated-Gate Bipolar Transistors (IGBTs) has motivated the investigation of strategies for their prognostics and health management. However, physics-based degradation modelling for semiconductors is usually complex and depends on uncertain parameters, which motivates the use of data-driven approaches. This paper addresses the problem of data-driven prognostics of IGBTs based on evolving fuzzy models learned from degradation data streams. The model depends on two classes of degradation features: one group of features that are very sensitive to the degradation stages is used as a premise variable of the fuzzy model, and another group that provides good trendability and monotonicity is used for the auto-regressive consequent of the fuzzy model for degradation prediction. This strategy allows obtaining interpretable degradation models, which are improved when more degradation data is obtained from the Unit Under Test (UUT) in real time. Furthermore, the fuzzy-based Remaining Useful Life (RUL) prediction is equipped with an uncertainty quantification mechanism to better aid decision-makers. The proposed approach is then used for the RUL prediction considering an accelerated aging IGBT dataset from the NASA Ames Research Center.

Acronyms

RUL	Remaining Useful Life
EOL	End of Life
PHM	Prognostics and Health Management
CM	Condition-based Monitoring
TS	Takagi-Sugeno
UUT	Unit Under Test
RLS	Recursive Least Squares
SFWRLS	Sliding-windowed Fuzzily Weighted Recursive Least Squares
MAPE	Mean Absolute Percentage Error
RA	Relative Accuracy
IGBT	Insulated-Gate Bipolar Transistor
C-trig	Cummulative trignometric function
$V_{\mathrm{CE_{on}}}$	On-state Collector-Emitter Voltage

1. Introduction

The IGBT has long established itself as a competent successor to prior power semiconductors such as the power bipolar junction transistor (BJT), Darlington transistor, and metal oxide semiconductor field-effect transistor (MOSFET). It functions by combining the desirable properties of a high input impedance and high switching speeds of the MOSFET with the low saturation voltage of the BJT, enabling a voltage-controlled transistor that is capable of containing large collector-emitter currents with a virtually zero-gate current drive. The product is a transistor variant that offers medium to high power application abilities, low ON-resistance, and fast switching compared to its predecessors.

As any component in a system, IGBTs are prone to failure under certain operating conditions, primarily from electrical and thermal stress caused by conditions such as high temperature and cycling effects (Lu & Sharma, 2009). However, the critical nature of power semiconductors in the chain of operation of most systems may cause a total shutdown emanating from an otherwise inexpensive source. From an industrial survey by (Yang et al., 2011), the majority of respondents indeed assert that power electronic devices are one of the most fragile components in most industries and the need for increased research interest in reliability monitoring and improvement. This monitoring is essential, especially in critical systems such as aviation, where the neglecting cost may be more than just monetary. In lieu of this, there is a need for reliable and robust diagnostic and prognostics techniques that seek to avert to a low degree any spontaneous call for maintenance that introduces unplanned expenditures and manages faults or deterioration during inception before they escalate to disruptive levels. Using a model-based method, a failure precursor's features or both, a fault source can be detected, isolated, and the RUL of an IGBT predicted for maintenance responses such as planned replacements undertaken at an optimal time before its End of Life (EOL).

Some common failure modes in IGBTs are the gate diode degradation, body diode degradation, the bond wire and solder layer fatigues (Nguyen & Kwak, 2020). For appropriate health management algorithms, it is desirable to study a component's observable parameters that conspicuously show deviation from their normal behaviour reflecting an associated anomaly, i.e., a failure mode when in operation. For instance, during failure modes such as the bond wire and solder layer fatigues, there is an associated increase in measured On-state Collector-Emitter Voltage ($V_{\mathrm{CE}_{\mathrm{on}}}$), which results from an increased bond wire resistance for bond wire fatigues and thermal resistance associated with the latter due to the lack of effective heat dissipation between adjacent layers. The transistor turn off time have also been identified as a parameter of interest for latch-up faults in (Brown et al., 2010). These parameter-failure mode pairing are acquired through a procedure termed FMMEA (Failure Modes, Mechanisms and Effects Analysis) under accelerated aging procedures. The criteria of choosing a specific prognostics parameter depends on its sensitivity to the failure mode and also the ease of attaining accurate measurements from sensors. For example, the junction temperature as a precursor is indicative of most thermal failure modes, but the difficulty in sensor integration during predesigns as well as inaccurate measurements limits its applicability. Therefore, works such as (Eleffendi & Johnson, 2016) considers the junction temperature as a failure precursor, but obtained through a lookup table considering measured $V_{\mathrm{CE}_{\mathrm{on}}}$. With appropriately measured precursors from IGBTs, different prognostics procedures have been studied in literature.

In (Saha, Celaya, Wysocki, & Goebel, 2009), a model-based prognostics procedure using a particle filter is used based on a fitted model on the collector-emitter leakage current obtained from an accelerated aging procedure. However, in (Haque, Choi, & Baek, 2018) an auxillary particle filter proved to have a better variance and robustness of RUL predictions compared to particle filters using the $V_{\mathrm{CE}_{\mathrm{on}}}$ as a failure precursor, a predominant choice in most papers. Data-based algorithms have also been extensively studied, both statistically and in the area of artificial intelligence. Statistically, for a data-based prognostics of IGBTs, (Ismail, Saidi, Sayadi, & Benbouzid, 2019) employed the Gaussian process regression, whilst later in (Ismail, Saidi, Sayadi, & Benbouzid, 2020) the authors used a modified maximum likelihood method to predict the RUL. The results show that the Gaussian process regression has better prognostics metrics than the modified maximum likelihood method. With the $V_{\mathrm{CE}_{\mathrm{on}}}$ as a chosen precursor in (Ahsan, Stoyanov, & Bailey, 2016), Neural Network (NN) and Adaptive Neuro Fuzzy Inference System (ANFIS) models are used to predict the RUL, the NN showed better performance compared to the ANFIS. In (Alghassi, Perinpanayagam, & Samie, 2016), the authors proposed a time delay neural network algorithm in tandem with a probabilistic function with $V_{\mathrm{CE}_{\mathrm{on}}}$ as the precursor parameter, which proved to be more efficient than a stand alone NN model. Comprehensive reviews exists in literature on the broad subject, encompassing the type of failures (Nguyen & Kwak, 2020; Hanif, Yu, DeVoto, & Khan, 2019), precursor parameter attainment (Zhang, Liu, Li, & Li, 2020) and prognostics methods (Degrenne, Kawahara, & Mollov, 2019; Kabir, Bailey, Lu, & Stoyanov, 2012) employed on power semiconductors in general.

Although adaptive prognostics methods are able to modify their parameters according to the data stream behavior to reduce the modeling error, their structure are fixed and there is no clear relationship between their evolving degradation stage and their parameters (Angelov, 2012). Otherwise, evolving systems are known by their ability of modifying both parameters and structure to provide explainable representations for data-streams. While their parameters are adapted to minimize the modeling error, the structure becomes more complex to represent novel dynamics which can be related to the achievement of novel degradation stages in prognostics problems. Recently, evolving fuzzy degradation models are proposed for aiding data-stream-driven Prognostics and Health Management (PHM) systems (Camargos, Bessa, D'Angelo, Cosme, & Palhares, 2020; Camargos et al., 2021; Ahwiadi & Wang, 2022). In particular, those models are used to capture the degradation dynamics and predict the equipment RUL. In this regard, evolving prognostic approaches have been successfully applied to ball bearings (Camargos et al., 2020) and lithium-ion batteries providing (Camargos et al., 2021; Ahwiadi & Wang, 2022) competitive results with some interpretability features. This motivates the application of those methods for the challenging IGBT prognostic problem.

Properties such as monotonicity and trendability of a chosen extracted feature or dimensionally reduced subspace of selected features is a strong prerequisite for attaining a good RUL prediction, employed in prognostics algorithms. However, the downside of this procedure is that the granularity of the degradation data is diminished or lost when smoothing tools are applied to attenuate these properties. This result in algorithms that sacrifice interpretability for improved RUL predictions. Even though it is agreed that the primary end goal of prognostics algorithms is to improve the RUL prediction, there must be a motivation to consider characteristics of the degradation trend, which may be used for secondary purposes or aid in a better RUL prediction. This especially comes in handy when considering degradation data as used in this paper, a stage-based degradation process, where classification of the stages may prove to be important for better estimating the RUL.

The approach in this paper considers a data-based evolving fuzzy model that uses two classes of input features: an interpretable feature as a premise variable and a RUL prediction-friendly counterpart in the autoregressive consequent of the fuzzy model. In particular, the degradation representation is based on the Evolving Ellipsoidal Fuzzy Information Granules (EEFIG), whose has already been applied for clustering (Cordovil, Coutinho, Bessa, D'Angelo, & Palhares, 2020), fault diagnosis (Cordovil et al., 2020), and leaning-based control (Cordovil, Coutinho, Bessa, Peixoto, & Palhares, 2022) approaches. The merit of this methodology over others is that it provides a platform with a dual function mode: (1) Providing a good RUL prediction in conjunction with (2) classifying the different stages of degradation, as shown in Figure 1, enabling interpretability.

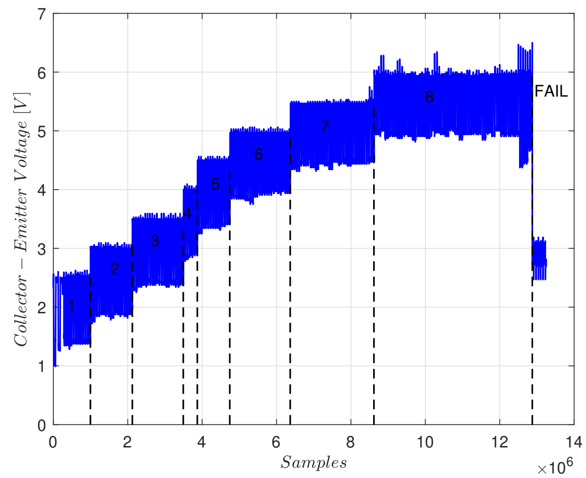

Figure 1. Measured collector-emitter voltage from aging test of IGBT1 showing stages of degradation.

2. IGBT Aging and Degradation

As stated in the prequel, for prognostics, it is imperative to acquire parameters that explicitly represent the failures, such that a study of their behaviour can inherently constitute a knowledge of the failure mechanism. To measure all useful related precursor parameters, the IGBTs are subject to aggressive thermal or electrical cycles of stress in an experimental environment until a failure happens. In this work, a run-to-failure experiment on 4 IGBTs undertaken by (Sonnenfeld, Goebel, & Celaya, 2008) is considered. The experiment involves subjecting power transistor devices to DC square wave signals at the gate, placing the devices under thermal stress. This aging process is undertaken until a latch-up or thermal runway (EOL) when signals are switched steadily between $0V$ and $4V$, with temperature controlled between $329°C$ and $330°C$ outside the rated temperature of the test transistors. The transient data collected when the devices switch are the (i) Collector-emitter turn on Voltage; (ii) Gate Voltage; and (iii) Collector current.

3. Data-driven Prognostics based on evolving fuzzy degradation model

3.1. Degradation features extraction and selection

From the literature, the $V_{\mathrm{CE_{on}}}$ is the predominantly chosen precursor, which has proven its efficacy as well as practicability compared to other parameters, with various pre-evaluated metrics supporting its selection. Therefore, the $V_{\mathrm{CE_{on}}}$ is selected as the parameter of interest in this paper. With $V_{\mathrm{CE_{on}}}$ as the selected Condition-based Monitoring (CM) data, features are extracted serving as a pseudo-representation of the degradation behaviour. The raw data, shown in Figure 2, are almost always noisy, an undesirable characteristic for a RUL prediction. These features, either frequency or temporal based, must exhibit desirable characteristics that ensures accurate RUL extrapolations with less uncertainty (Gouriveau, Medjaher, & Zerhouni, 2016). Two types of characteristics of input data into the proposed algorithm are considered. First, a feature that satisfies the traditional desirable properties of monotonicity, trendability and prognosticability for an accurate and less uncertain RUL prediction is considered and a feature that represents the shape of degradation showing the different stages. Unlike the first case, the accuracy of the RUL is not deemed a factor. Thus, for the autoregressive consequent feature, a feature construction from (Javed, Gouriveau, Zerhouni, & Nectoux, 2015) is considered. The authors employ the standard deviation (SD) of Cummulative trignometric function (C-trig) on the data set. This was proven to possess overall better prognostics characteristics backed with more accurate RUL compared to generic features when tested on a case study. Two C-trigs, as proposed in (Javed et al., 2015), are considered and the best selected based on the suitability metric (1), as proposed in (Celaya, Saxena, Saha, & Goebel, 2011).

$$\text{Suitability} = \begin{bmatrix} \text{Monotonicity} \\ \text{Trandability} \\ \text{Prognosticability} \end{bmatrix}^\top \begin{bmatrix} 1 \\ 0.976 \\ 1 \end{bmatrix} \qquad (1)$$

For the premise variable of the fuzzy model, features of the mean and the root mean square is considered for selection presented in Table 2. Smoothing is done with the moving average and the window length selected equal to the number of samples in each testsets performed on individual IGBTs. Considering a data-stream $X = [x_1, x_2, \ldots, x_n] \in \mathbb{R}^n$ the selected features are presented in Table 1.

Table 1. Trigonometric features for the premise variable.

Feature	Formula
SD of asinh(X)	$\sigma\left(\log\left[x_i + (x_i^2+1)^{\frac{1}{2}}\right]\right)$
SD of atan(X)	$\sigma\left(\frac{i}{2}\log\left(\frac{i+x_i}{i-x_i}\right)\right)$

Table 2. Features for the autoregressive consequent variable.

Feature	Formula
Energy	$\sum_{i=1}^{n} E(x_i)$
Root Mean Square (RMS)	$\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$

The cumulative function as from (Javed et al., 2015), is done by considering a simultaneous point-wise running total and scaling of a time series:

$$\mathrm{CF}_i(X) = \frac{\sum_{i=1}^{n} X(i)}{|\sum_{i=1}^{n} X(i)|^{\frac{1}{2}}} \tag{2}$$

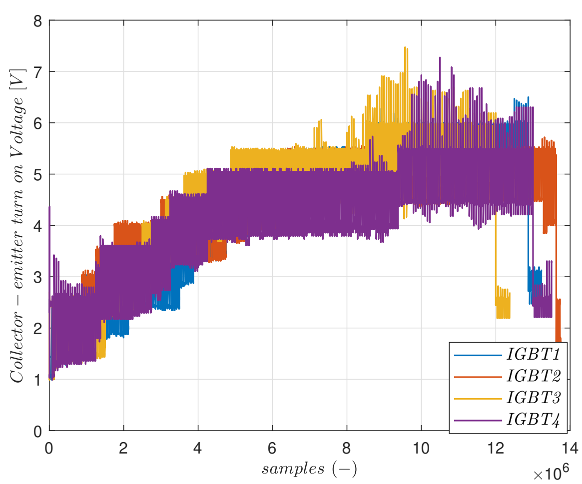

Figure 2. Measured collector-emitter voltage from aging test of 4 IGBTs.

Feature selection. For the auto-regressive consequent feature of the fuzzy model, the *cummulative SD of* $(atan)$ is selected, with a suitability score of 2.972 compared to 2.957 of $(asinh)$. For the premise variable, the RMS feature was selected based on the best results from the two features (i.e Table 2) as inputs.

3.2. Evolving Ellipsoidal Fuzzy Information Granules

In (Cordovil et al., 2020), the Evolving Ellipsoidal Fuzzy Information Granules (EEFIG) model and its evolving granular learning algorithm are introduced. The learning algorithm is an online data processing that employs evolving fuzzy information granules based on the parametric principle of justifiable granularity (Pedrycz & Wang, 2016). In this paper, we propose employing the EEFIG algorithm to model the degradation of the IGBTs.

An EEFIG is a collection of N granules $\mathbb{G}_k = \{\mathcal{G}_k^1, \ldots, \mathcal{G}_k^N\}$, where each granule is a fuzzy set $\mathcal{G}_k^i = (\mathbb{R}^{n_z}, g_k^i)$, where $g_k^i : \mathbb{R}^{n_z} \to [0,1]$ is the membership function of the EEFIG $\mathcal{G}_k^i$. The membership function ω_k^i is parameterized by the granular prototype $\mathcal{P}_k^i$ of the i-th granule at the time instant k, which is also a numerical evidence basis for the granulation process. The granule prototype is defined as follows:

$$\mathcal{P}_k^i = \left(\underline{\mu}_k^i, \mu_k^i, \overline{\mu}_k^i, \Sigma_k^i\right), \tag{3}$$

where $\underline{\mu}_k^i$, μ_k^i and $\overline{\mu}_k^i$ are the lower, mean and upper bound vectors of the i-th EEFIG at time k and Σ_k^i is the inverse of its covariance matrix. Given the granule prototype $\boldsymbol{\mathcal{P}}_k^i$, the membership function of an EEFIG is parameterized as

$$\omega_k^i(z_k) = \exp\left\{-\left[(z_k - \mu_k^i)^\top \left(\Delta_k^i\right)^{-1}(z_k - \mu_k^i)\right]^{1/2}\right\}, \tag{4}$$

where, for $p \in \mathbb{N}_{\leq n_z}$,

$$\Delta_k^i = \mathrm{diag}\left\{\left(\frac{\overline{\mu}_{k,1}^i - \underline{\mu}_{k,1}^i}{2}\right)^2, \ldots, \left(\frac{\overline{\mu}_{k,p}^i - \underline{\mu}_{k,p}^i}{2}\right)^2\right\},$$

being $\overline{\mu}_k^i$, and $\underline{\mu}_k^i$ the semi-axes of the i-th EEFIG prototype such that $\underline{\mu}_k^i < \mu_k^i < \overline{\mu}_k^i$ (Wang, Shi, Wang, & Zhang, 2014). The normalized membership functions g_k^i at the k-th time instant for i-th granule is

$$g_k^i(z_k) = \frac{\omega_k^i(z_k)}{\sum_{i=1}^{N}\omega_k^i(z_k)}. \tag{5}$$

Moreover, the distance of a given data sample $z_k \in \mathbb{R}^{n_z}$ to the i-th EEFIG is given by the square of Mahalanobis distance:

$$d(z_k, \mu_k^i) = (z_k - \mu_k^i)^\top \Sigma_k^i (z_k - \mu_k^i). \tag{6}$$

The granulation process is the updating of the EEFIG model-based on the data stream. The updates are performed aiming at improve the so-called granular performance index with re-

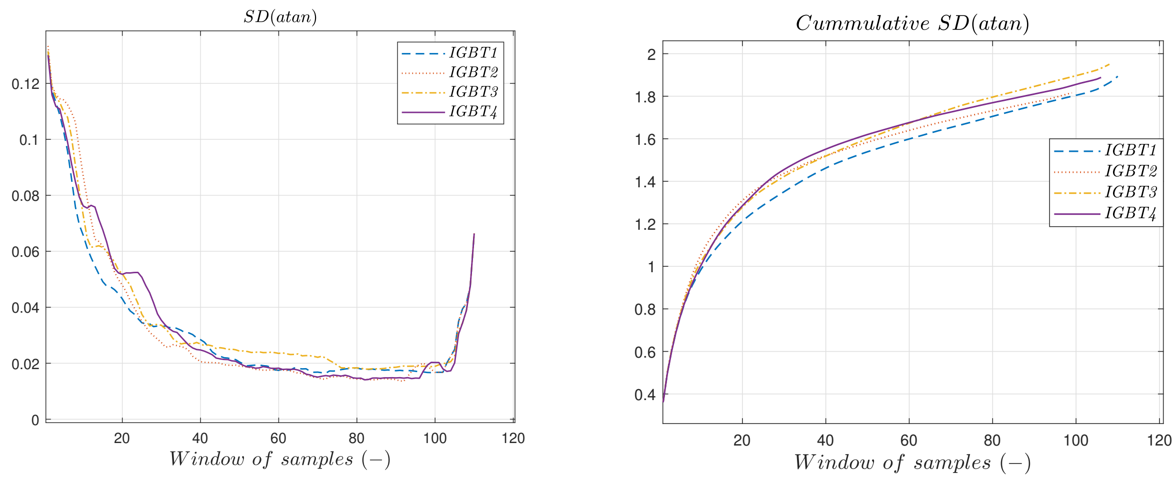

Figure 3. Selected auto-regressive consequent feature of the 4 IGBTs. (Left.) SD(atan) (Right.) C-SD(atan).

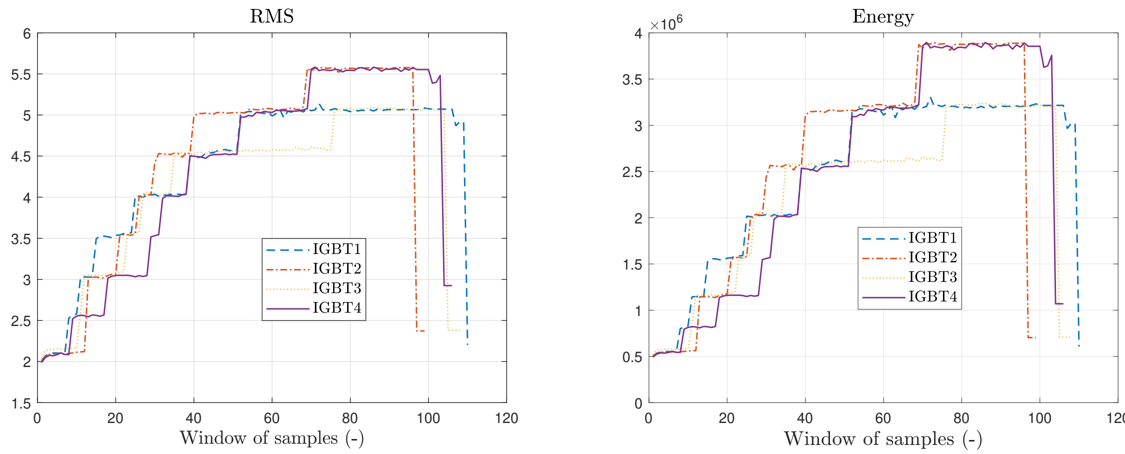

Figure 4. Considered premise features of the 4 IGBTs.

spect to a data sample. The performance index of the i-th granule with respect the sample z_k, denoted $\bar{\mathcal{Q}}_k^i$, is defined as

$$\bar{\mathcal{Q}}_k^i(z_k) = d(z_k, \mu_k^i)|\mathcal{G}_k^i| \tag{7}$$

where $|\cdot|$ is the fuzzy cardinality operator of the i-th EEFIG, whose update is performed as follows

$$|\mathcal{G}_k^i| = |\mathcal{G}_{k-1}^i| + g_k^i(z_k) - \frac{\partial g_k^i(z_k)}{\partial \mathcal{P}_k^i}, \tag{8}$$

where the term $\frac{\partial g_k^i(z_k)}{\partial \mathcal{P}_k^i}$ is computed as described in (Cordovil et al., 2022). The total EEFIG performance index is the sum of the data sample contribution index of each granule:

$$\mathcal{Q}_k^i = \frac{1}{k}\sum_{j=1}^{k} \bar{\mathcal{Q}}_j^i(z_j). \tag{9}$$

To decide whether a granule must be updated or not, the concept of data sample admissibility is used. A data sample z_k is said to be admitted by a given granule prototype $\mathcal{P}_k^i$ if it is used to update the granule prototype parameters. In this sense, two criteria are used to evaluate the data sample admissibility:

$$d(z_k, \mu_k^i) < \nu, \tag{10}$$

$$\mathcal{Q}_k^i > \mathcal{Q}_{k-1}^i, \tag{11}$$

where $\nu = \left(\chi^2\right)^{-1}(\gamma, n)$ is a threshold parameterized by the inverse of chi-squared statistic with $n + m$ degrees of freedom, leading EEFIG prototype to cover around $100\gamma\%$ of the stream sample. A data sample z_k which does not meet the first condition (10) for some granule is denominated an anomaly. In parallel, as the data samples are available and evaluated, a structure named tracker whose objective is to follow the data stream dynamics to indicate change points, is established.

The tracker is parameterized by a mean vector μ_k^{tr} and an inverse covariance matrix Σ_k^{tr}, which are recursively updated (Moshtaghi, Leckie, & Bezdek, 2016). A new granule is created if the following conditions hold:

1. The tracker is c-separated from all the existing granule prototypes. The c-separation condition is expressed as follows

$$\|\mu_k^{\mathrm{tr}} - \mu_k^i\| \geq c\sqrt{n_z \max(\bar{\xi}(\Sigma_k^{\mathrm{tr}}), \bar{\xi}(\Sigma_k^i))}, \tag{12}$$

   for all $\mathcal{G}_k^i \in \mathbb{G}_k$, where $\bar{\xi}\left(\Sigma_k^{\mathrm{tr}}\right)$ is the largest eigenvalue of Σ_k and, $c \in [0, \infty)$ specifies the separation level. Here, c is assumed as 2.

2. The number of consecutive anomalies is $n_a > \zeta$ where ζ is a hyper-parameter defined by the user to control the minimum amount of anomalies which may enable the rule creation.

3.3. EEFIG-based degradation modelling and RUL estimation

Based on the EEFIG model described in the previous section, the following Takagi-Sugeno fuzzy model is proposed for the degradation modeling

$$\begin{aligned} &\textbf{Rule } i : \text{IF } z_k \text{ is } \mathcal{G}_k^i \\ &\qquad \text{THEN } y_k^i = {\boldsymbol{\theta}_k^i}^\top \left[y_{k-1}, y_{k-2}, \dots, y_{k-L}\right]^\top, \end{aligned} \tag{13}$$

for $i \in \mathbb{N}_{\leq C_k}$, where $y_k \in \mathbb{R}$ is the health index, $z_k \in \mathbb{R}^{n_z}$ is the vector of premise variables, $\boldsymbol{\theta}_k^i \in \mathbb{R}^L$ are the coefficients of the i-th fuzzy rule at instant k, $L \in \mathbb{N}$ is the number of regressors in the autoregressive consequent, and $C_k \in \mathbb{N}$ is the number of rules at instant k. Using the center-of-gravity defuzzification for (13), the health index y_k is

$$y_k = \sum_{i=1}^{C_k} g_k^i\left(z_k\right) {\boldsymbol{\theta}_k^i}^\top \left[y_k \; y_{k-1} \; \dots \; y_{k-L+1}\right]^\top \tag{14}$$

$$\boldsymbol{\Theta}_k h_k\left(\mathbf{y}_k\right), \tag{15}$$

where

$$\boldsymbol{\Theta}_k = \left[{\boldsymbol{\theta}_k^1}^\top \; \dots \; {\boldsymbol{\theta}_k^{C_k}}^\top\right],$$

$$\mathbf{y}_j = \begin{bmatrix} y_j \\ \vdots \\ y_{j-L+1} \end{bmatrix}, \; h_k\left(\mathbf{y}_l\right) = \begin{bmatrix} g_k^1\left(z_k\right) \mathbf{y}_j \\ \vdots \\ g_k^{C_k}\left(z_k\right) \mathbf{y}_j \end{bmatrix}.$$

As described in (Cordovil et al., 2020; Cordovil et al., 2022), the consequent parameters $\boldsymbol{\Theta}_k$ are estimated based on Recursive Least Squares (RLS) methods. In particular, here we use the Sliding-windowed Fuzzily Weighted Recursive Least Squares (SFWRLS) where the weights are the membership degrees and the data window contains the last φ samples:

$$H_k = \left[h_k\left(\mathbf{y}_{k-1}\right) \; \dots \; h_k\left(\mathbf{y}_{k-\varphi}\right)\right] \tag{16}$$

$$X_k = \left[y_k \; \dots \; y_{k-\varphi+1}\right] \tag{17}$$

Therefore, the recursive equation for the SFWRLS estimator are provided as follows

$$\Upsilon_k = P_k H_k \left(\eta I_\varphi + H_k^\top P_k H_k\right)^{-1} \tag{18}$$

$$P_{k+1} = \eta^{-1}\left(P_k - \Upsilon_k H_k^\top P_k\right) \tag{19}$$

$$\boldsymbol{\Theta}_{k+1} = \boldsymbol{\Theta}_k + \left(X_k - \boldsymbol{\Theta}_k H_k\right)^\top \Upsilon_k^\top \tag{20}$$

where $P_k \in \mathbb{R}^{LC_k \times LC_k}$ is an estimate of the inverted regularised data autocorrelation matrix, $\Upsilon_k \in \mathbb{R}^{n_x}$ is the SFWRLS gain vector, and $\eta \in (0, 1]$ is the forgetting factor.

Given the estimate of the parameters of (13), the one-step ahead prediction of the degradation at instant k is computed as follows

$$\hat{y}_{k+1|k} = \sum_{i=1}^{C_k} g_k^i\left(z_k\right) {\boldsymbol{\theta}_k^i}^\top \left[y_k \; y_{k-1} \; \dots \; y_{k-L+1}\right]^\top \tag{21}$$

For any $N \in \mathbb{N}$, define

$$\hat{\mathbf{y}}_{k+N|k} = \begin{cases} \left[y_k, y_{k-1}, \dots, y_u\right]^\top, & \text{if } N = 1, \\ \left[\hat{y}_w, \dots, \hat{y}_{k+1}, y_k, \dots, y_u\right]^\top, & \text{if } 1 < N < L, \\ \left[\hat{y}_w, \dots, \hat{y}_u\right]^\top, & \text{if } N \geq L, \end{cases} \tag{22}$$

where $u = k + N - L$ and $w = k + N - 1$. The N-step ahead health index prediction $\hat{y}_{k+N|k}$ is computed as follows:

$$\hat{y}_{k+N|k} = \mathbf{A}_k \hat{\mathbf{y}}_{k+N|k}, \tag{23}$$

where $\mathbf{A}_k = \sum_{i=1}^{C_k} \omega_k^i\left(z_k\right) {\boldsymbol{\theta}_k^i}^\top$.

Based on the long term prediction described in (23), the RUL can be estimated by predicting the future health state of the system given the current and past system's condition, which are provided by $\hat{\mathbf{y}}_{k+N|k}$ and z_k. Indeed, the RUL can be defined as the amount of time until the system's health index reaches a predefined threshold, that is:

$$\hat{\mathrm{RUL}}_k = \inf\{N \in \mathbb{Z}_{\geq 0} : \hat{y}_{k+N|k} \leq \eta\}, \tag{24}$$

where $\hat{\mathrm{RUL}}_k \in \mathbb{Z}_{\geq 0}$ denotes the RUL estimate computed at instant k given the observations of degradation state until k, and η is the end of life threshold, which must be defined based on historic data.

3.4. Uncertainty quantification

Consider a state transition function given by a Takagi-Sugeno (TS) model, with rules as in (13). The degradation propagation (23) can be rewritten as

$$\hat{y}_{k+N|k} = \mathbf{A}_k \mathbf{y}_{k+N|k} + \epsilon_{k+N}, \quad \forall N > 0. \tag{25}$$

To account for prediction uncertainties, white Gaussian noise is added to (25) from

$$\epsilon_k \sim \mathcal{N}\left(0, \sigma_\epsilon^2\right), \tag{26}$$

where σ_ϵ^2 is considered constant. The noise variance can be estimated through Monte Carlo simulations using the consequent parameters' covariance matrix estimated via RLS until time instant k (Camargos et al., 2020) or by recursively tracking the covariance of estimation errors through the online learning operation, i.e., for time instances $n \in \mathbb{N}_{\leq k}$ (Camargos et al., 2021). In the univariate case, the mean error is recursively tracked as

$$\Delta_{\epsilon,k} = \epsilon_k - \hat{\mu}_{\epsilon,k-1}, \tag{27}$$

$$\hat{\mu}_{\epsilon,k} = \hat{\mu}_{\epsilon,k-1} + \frac{1}{k}\,\Delta_{\epsilon,k}. \tag{28}$$

The initial mean error is $\hat{\mu}_{\epsilon,0} = 0$. Given the estimated mean error, the sum of squares is obtained recursively from

$$s_{\epsilon,k} = s_{\epsilon,k-1} + (\epsilon_k - \hat{\mu}_{\epsilon,k-1})^2, \tag{29}$$

being $s_{\epsilon,0} = 0$. The variance σ_ϵ^2 in (26), used for long-term prediction, is then approximated by the error covariance matrix at time instant n:

$$\sigma_\epsilon^2 = \frac{s_{\epsilon,k}}{k-1}. \tag{30}$$

3.5. Uncertainty propagation

After obtaining the initial uncertainty in one step estimates, its long term propagation considers the input vector (22) to be a vector composed of estimated random variables. Note that if $N = 1$, the previous degradation states are known and, naturally, are non-random variables. Accordingly, the output $\hat{x}_{k+N}$ of the state transition relation (25) is also a random variable. Computing variances in a multi-step prediction framework is needed for uncertainty propagation. The first step gives

$$\begin{aligned}\mathrm{Var}\left(\hat{y}_{k+1|k}\right) &= \mathbf{A}_k \mathrm{Cov}(\mathbf{y}_{k+1|k})\mathbf{A}_k^\top + \sigma_\epsilon^2 \\ &= \mathbf{A}_k \mathbf{\Lambda}_1^L \mathbf{A}_k^\top + \sigma_\epsilon^2 \\ &= \sigma_\epsilon^2 \\ &= \lambda_1^2,\end{aligned} \tag{31}$$

in which $\mathbf{\Lambda}_N^L \triangleq \mathrm{Cov}(\mathbf{y}_{k+N|k})$, and $\lambda_N^2 \triangleq \mathrm{Var}(\hat{y}_{k+N|k})$. Note that $\mathbf{\Lambda}_1^L = 0$, since previous degradation states are known at $N = 1$. Then, the **N-step variance** is computed recursively as

$$\mathrm{Var}(\hat{y}_{k+N|k}) = \mathbf{A}_k \mathbf{\Lambda}_N^L \mathbf{A}_k^\top + \sigma_\epsilon^2. \tag{32}$$

The covariance matrix of the random vector $\mathbf{y}_{k+1|k}$ is

$$\mathbf{\Lambda}_N^L = \begin{bmatrix} \lambda_{N-1}^2 & \cdots & \lambda_{N-L}\lambda_{N-1}\hat{\rho}_{L,1} \\ \vdots & \ddots & \vdots \\ \lambda_{N-1}\lambda_{N-L}\hat{\rho}_{1,L} & \cdots & \lambda_{N-L}^2 \end{bmatrix}. \tag{33}$$

Moreover, $\lambda_i^2 = 0$ when $i < 0$, meaning that x_{k+N} is known. The convariance matrix (33) is weighted by Pearson correlation coefficients, $\hat{\rho}$, estimated through historic data.

Considering the degradation to be a random variable with Gaussian distribution, whose expected value is propagated by successive iterations of (25), then RUL lower and upper bounds at an $(\alpha)(100)\%$ significance level are given as

$$\widehat{\mathrm{RUL}}_k^{\mathrm{lb}} = \inf\{N \in \mathbb{Z}_{\geq 0} : \hat{y}_{k+N|k} + z_{1-\frac{\alpha}{2}}\,\lambda_N \leq \eta\}, \tag{34a}$$

$$\widehat{\mathrm{RUL}}_k^{\mathrm{ub}} = \inf\{N \in \mathbb{Z}_{\geq 0} : \hat{y}_{k+N|k} + z_{\frac{\alpha}{2}}\,\lambda_N \leq \eta\}. \tag{34b}$$

4. Experimental Setup

To evaluate the proposed data-driven prognostics based on evolving fuzzy degradation model, we use the accelerated aging IGBT dataset from the NASA Ames Research Center[1]. This dataset contains sensor data from four devices. In particular, there are aging time series for the collector-emitter voltage ($V_{\mathrm{CE_{on}}}$), gate-emitter voltage, collector current, thermal and electrical resistance, and the times in which the switch is on and off. The health index y_k is selected to be

$$y_k = SD\left(\arctan\left(V_{\mathrm{CE_{on}}}\right)\right), \tag{35}$$

and the premise variables vector is

$$z_k = \left[\bar{E}_k \ \bar{E}_{k-1} \ \bar{E}_{k-\tau+1}\right]^\top \tag{36}$$

where $\bar{E}_k$ is the energy of $V_{\mathrm{CE_{on}}}$ described in Table 2.

The proposed evolving fuzzy prognostics require the tuning of some hyper-parameters, namely: L, the number of lags in the autoregressive model for the health index y_k (cf. (13)); τ, the number of lags of E_k used in the premise vector z_k; η, the forgetting factor of SFWRLS (cf. (18), (19) and (20)); φ, the size of the data windows used in SFWRLS (cf. (16) and (17)); and ζ, the number of necessary consecutive anomalies to enable the granule creation.

For choosing the hyper-parameters of the proposed algorithm, we designate a test dataset regarding one of the four devices

[1]The dataset is available for download in `ti.arc.nasa.gov/project/prognostics-data-repository`

and perform a grid search to solve the following problem

$$\ell(D) = \arg\max_{l} \sum_{k=1}^{\text{EOL}_D} k\text{RA}_k(D, l) \quad \text{s.t.} \quad l \in \mathcal{L} \quad (37)$$

where $l = (L, \tau, \eta, \varphi, \zeta)$ is the vector of hyper-parameters, $\mathcal{L} = [2, 5] \times [2, 5] \times [0.96, 1] \times [2, 6] \times [2, 6]$ is the search space, EOL_D is the end of life of the D-th device, and $\ell(D)$ are the optimal parameters within the the search space $\mathcal{L}$, and the Relative Accuracy (RA) is

$$\text{RA}_k = 1 - \frac{\left|\text{RUL}_k - \hat{\text{RUL}}_k\right|}{\text{RUL}_k}, \quad (38)$$

5. Experimental Results

In this section, the results for the RUL prediction for IGBTs based on evolving fuzzy models are presented and discussed. For evaluating the results, the Mean Absolute Percentage Error (MAPE) is used as figure of merit:

$$\text{MAPE}_k = \frac{100}{\text{EOL} - k + 1} \sum_{i=k+1}^{\text{EOL}} \left| \frac{\text{RUL}_i - \hat{\text{RUL}}_i}{\text{RUL}_i} \right|, \quad (39)$$

where EOL is the end of number of the UUT; r_k and $\hat{\text{EOL}}_k$ are the current and estimated RUL at k, respectively.

Table 3 provides the MAPE results computed from $k = 20$. Notice that the EEFIG-based prognostics was able to guarantee MAPE results below of 50% for the IGBT devices 1, 2 and 4. However, the third IGBT presents more challenging data which results in higher MAPE for any parameter set.

Table 3. MAPE_{20} results

UUT dataset \ Parameter tuning dataset	1	2	3	4
1	20.3560	31.5868	59.6492	48.3150
2	23.0306	15.1883	34.4047	15.2904
3	67.4113	76.0535	70.8395	74.9962
4	40.7839	31.4586	37.6570	28.2187

Figures 5-7 depict the RUL prediction results in α-λ plots with accuracy cones of $\pm 30\%$. In particular, Figure 5 presents the results for the second IGBT using the parameters obtained by solving (37) for the dataset extracted from the fourth IGBT. Figure 6 presents the results for the first IGBT using the parameters obtained by solving (37) for the dataset extracted from the second IGBT. And, Figure 7 presents the results for the second IGBT using the parameters obtained by solving (37) for the dataset extracted from the third IGBT.

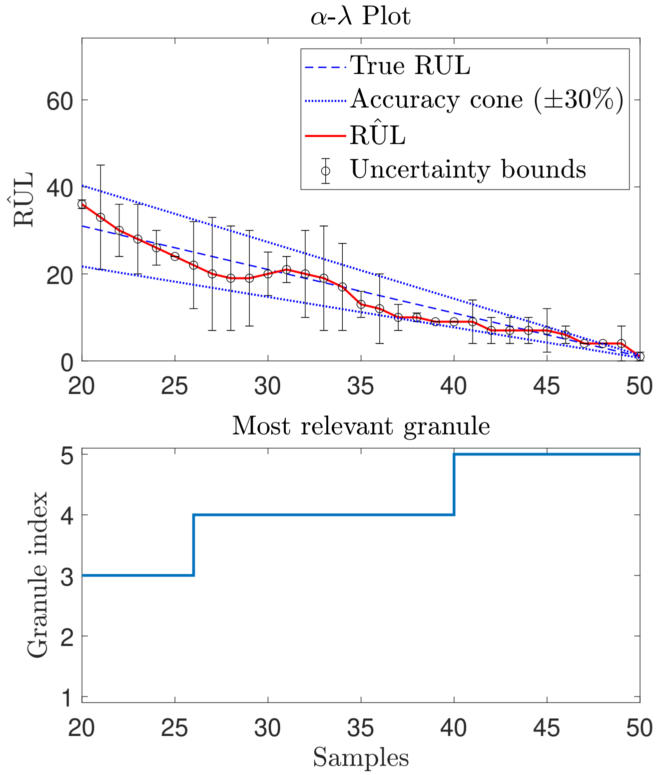

Figure 5. RUL prediction for the 2nd IGBT with parameters obtained for the test dataset with data from the 4th IGBT.

In Figures 5 and 6, notice that the RUL predictions remain inside of the accuracy cone in most of the time, and the true RUL tends to be within the predicted RUL bounds. However, the results become considerably worse for the Figure 7, as already indicated in Table 3.

One of the key advantages of applying evolving fuzzy methods is the interpretability. In this regard, the bottom plots of Figures 5, 6, and 7 indicate the granule with maximum membership degree at each sample. It is possible that news granules are being created and becoming more relevant since they are capturing novel degradation stages. Indeed, the transitions between the most relevant granules could be used as an failure or degradation stage indicator.

6. Conclusions

This paper presented a novel data-driven prognostics approach based on the evolving granular fuzzy models denominated EEFIG for IGBTs. The EEFIG is able to learn degradation processes from data-stream adapting the parameters of the degradation process representation and modifying its structure by means of granule creation for representing novel stages of the degradation process. The results indicate that the application of EEFIG for data-driven prognostics of IGBTs is promising, mainly due to its interpretability features.

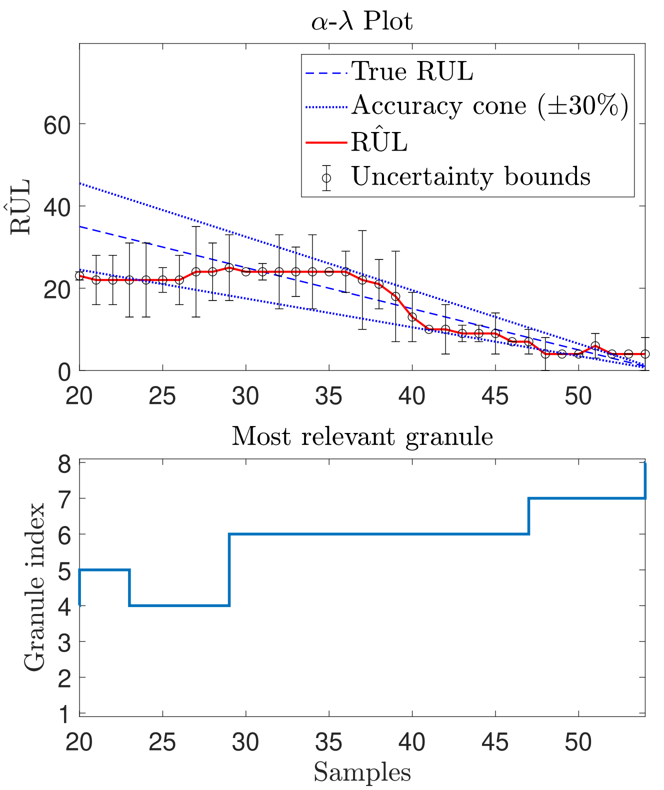

Figure 6. RUL prediction for the 1st IGBT with parameters obtained for the test dataset with data from the 2nd IGBT.

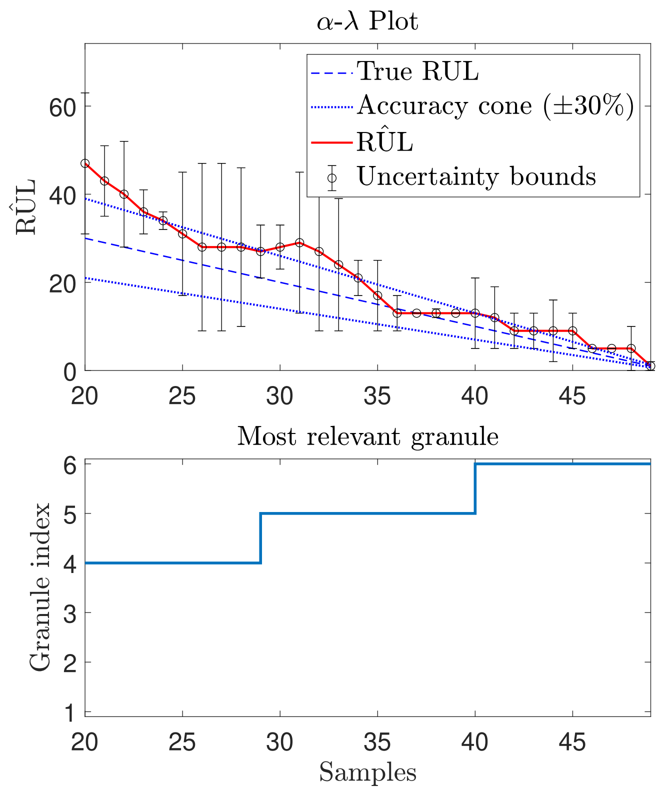

Figure 7. RUL prediction for the 2nd IGBT with parameters obtained for the test dataset with data from the 3rd IGBT.

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REFERENCES

Ahsan, M., Stoyanov, S., & Bailey, C. (2016). Data driven prognostics for predicting remaining useful life of IGBT. In *39th International Spring Seminar on Electronics Technology (ISSE)* (p. 273-278). doi: 10.1109/ISSE.2016.7563204

Ahwiadi, M., & Wang, W. (2022). An adaptive evolving fuzzy technique for prognosis of dynamic systems. *IEEE Transactions on Fuzzy Systems*, *30*(3), 841-849. doi: 10.1109/TFUZZ.2021.3049916

Alghassi, A., Perinpanayagam, S., & Samie, M. (2016). Stochastic RUL Calculation Enhanced With TDNN-Based IGBT Failure Modeling. *IEEE Transactions on Reliability*, *65*(2), 558-573. doi: 10.1109/TR.2015.2499960

Angelov, P. (2012). *Autonomous learning systems: from data streams to knowledge in real-time*. John Wiley & Sons.

Brown, D., Abbas, M., Ginart, A., Ali, I., Kalgren, P., & Vachtsevanos, G. (2010, 01). Turn-off time as a precursor for gate bipolar transistor latch-up faults in electric motor drives. *Annual Conference of the PHM Society (PHM)*.

Camargos, M., Bessa, I., D'Angelo, M. F. S. V., Cosme, L. B., & Palhares, R. M. (2020, November). Data-driven prognostics of rolling element bearings using a novel error based evolving takagi–sugeno fuzzy model. *Applied Soft Computing*, *96*, 106628. doi: 10.1016/j.asoc.2020.106628

Camargos, M., Bessa, I., Junior, L. A. Q. C., Coutinho, P., Leite, D. F., & Palhares, R. M. (2021). Evolving fuzzy system applied to battery charge capacity prediction for fault prognostics. In *Atlantis studies in uncertainty modelling*. Atlantis Press. doi: 10.2991/asum.k.210827.010

Celaya, J., Saxena, A., Saha, S., & Goebel, K. (2011, 01). Prognostics of power MOSFETs under thermal stress accelerated aging using data-driven and model-based methodologies. *Annual Conference of the PHM Society*

(PHM), *2*.

Cordovil, L. A. Q., Coutinho, P. H. S., Bessa, I., D'Angelo, M. F. S. V., & Palhares, R. M. (2020). Uncertain data modeling based on evolving ellipsoidal fuzzy information granules. *IEEE Transactions on Fuzzy Systems*, *28*(10), 2427-2436. doi: 10.1109/TFUZZ.2019.2937052

Cordovil, L. A. Q., Coutinho, P. H. S., Bessa, I., Peixoto, M. L. C., & Palhares, R. M. (2022, January). Learning event-triggered control based on evolving data-driven fuzzy granular models. *International Journal of Robust and Nonlinear Control*, *32*(5), 2805–2827.

Degrenne, N., Kawahara, C., & Mollov, S. (2019, 09). Prognostics framework for power semiconductor igbt modules through monitoring of the on-state voltage. *Annual Conference of the PHM Society*, *11*. doi: 10.36001/phmconf.2019.v11i1.829

Eleffendi, M. A., & Johnson, C. M. (2016). Application of kalman filter to estimate junction temperature in igbt power modules. *IEEE Transactions on Power Electronics*, *31*(2), 1576-1587. doi: 10.1109/TPEL.2015.2418711

Gouriveau, R., Medjaher, K., & Zerhouni, N. (2016). *From prognostics and health systems management to predictive maintenance 1: Monitoring and prognostics*. doi: 10.1002/9781119371052

Hanif, A., Yu, Y., DeVoto, D., & Khan, F. (2019). A comprehensive review toward the state-of-the-art in failure and lifetime predictions of power electronic devices. *IEEE Transactions on Power Electronics*, *34*(5), 4729-4746. doi: 10.1109/TPEL.2018.2860587

Haque, M. S., Choi, S., & Baek, J. (2018). Auxiliary Particle Filtering-Based Estimation of Remaining Useful Life of IGBT. *IEEE Transactions on Industrial Electronics*, *65*(3), 2693-2703. doi: 10.1109/TIE.2017.2740856

Ismail, A., Saidi, L., Sayadi, M., & Benbouzid, M. (2019). Gaussian Process Regression Remaining Useful Lifetime Prediction of Thermally Aged Power IGBT. In *45th Conference of the IEEE Industrial Electronics Society (IECON)* (Vol. 1, p. 6004-6009). doi: 10.1109/IECON.2019.8926710

Ismail, A., Saidi, L., Sayadi, M., & Benbouzid, M. (2020). Remaining useful life estimation for thermally aged power insulated gate bipolar transistors based on a modified maximum likelihood estimator. *International Transactions on Electrical Energy Systems*, *30*(6), 1-18.

Javed, K., Gouriveau, R., Zerhouni, N., & Nectoux, P. (2015). Enabling health monitoring approach based on vibration data for accurate prognostics. *IEEE Transactions on Industrial Electronics*, *62*(1), 647-656. doi: 10.1109/TIE.2014.2327917

Kabir, A., Bailey, C., Lu, H., & Stoyanov, S. (2012, 05). A review of data-driven prognostics in power electronics. In (Vol. 6273136, p. 189-192). doi: 10.1109/ISSE.2012.6273136

Lu, B., & Sharma, S. K. (2009). A literature review of igbt fault diagnostic and protection methods for power inverters. *IEEE Transactions on Industry Applications*, *45*, 1770-1777.

Moshtaghi, M., Leckie, C., & Bezdek, J. C. (2016, June). Online clustering of multivariate time-series. In *Proceedings of the SIAM international conference on data mining.* doi: 10.1137/1.9781611974348.41

Nguyen, H., & Kwak, S. (2020, 12). Enhance reliability of semiconductor devices in power converters. *Electronics*, *9*, 2068. doi: 10.3390/electronics9122068

Pedrycz, W., & Wang, X. (2016). Designing fuzzy sets with the use of the parametric principle of justifiable granularity. *IEEE Transactions on Fuzzy Systems*, *24*(2), 489–496.

Saha, B., Celaya, J. R., Wysocki, P. F., & Goebel, K. F. (2009). Towards prognostics for electronics components. In *2009 ieee aerospace conference* (p. 1-7). doi: 10.1109/AERO.2009.4839676

Sonnenfeld, G., Goebel, K., & Celaya, J. R. (2008). An agile accelerated aging, characterization and scenario simulation system for gate controlled power transistors. In *2008 ieee autotestcon* (p. 208-215). doi: 10.1109/AUTEST.2008.4662613

Wang, G., Shi, P., Wang, B., & Zhang, J. (2014). Fuzzy n-ellipsoid numbers and representations of uncertain multichannel digital information. *IEEE Transactions on Fuzzy Systems*, *22*(5), 1113–1126.

Yang, S., Bryant, A., Mawby, P., Xiang, D., Ran, L., & Tavner, P. (2011). An industry-based survey of reliability in power electronic converters. *IEEE Transactions on Industry Applications*, *47*(3), 1441-1451. doi: 10.1109/TIA.2011.2124436

Zhang, Y., Liu, Y., Li, C., & Li, J. (2020, November). Analysis of fault precursor parameters under accelerated aging tests for IGBT modules. In *17th china international forum on solid state lighting & international forum on wide bandgap semiconductors china.* doi: 10.1109/sslchinaifws51786.2020.9308699