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Artificial Intelligence-Based Approach for Damage Estimation of Power IGBTs from Real Mission Profiles

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Abstract

The work in this paper is based on an assumption that the fatigue accumulated by a component is not determined by the stress amplitude alone, but also requires information about the sequence in which the loading occurs.

This paper will use clustering methods and artificial neural networks to investigate and identify these events.

1 Introduction and Concept

An increasing number of power electronic converters are pushed into operation due to higher integration of renewables and the modernization of the electrical grid.

This increases the impact of converter reliability on system reliability.

In this paper, the converter loading is seen as a sequence of internally coupled events rather than an uncoupled time series.

The sequences are thought to be the basic building blocks of fatigue and lifetime estimation and can have a variety of different shapes. Still, the Miner's rule is assumed to be valid, but with these sequences or events in place of cycles.

$$\sum_{i=1,\ldots}^{k} \frac{N_i}{NEF_i} = C, \quad (1)$$

N_i being the number occurred event 'i', NEF_i being the number of events to failure and, C, the total accumulated damage.

Regular power cycling also fits within this new paradigm, as each cycle can be considered an event. How a specific mission profile should be divided into events is not clear, however. This work will seek to use Artificial Intelligence-based methods to divide and classify a mission profile into events,

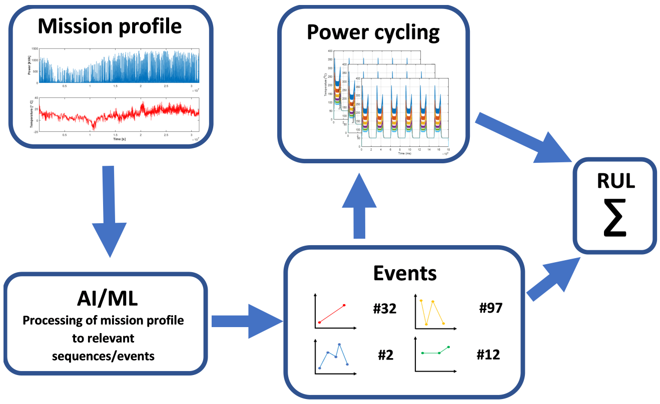

Fig. 1: Flowchart of the 'Block' approach, from real mission profile to RUL.

the basic approach of this can be seen in Fig. 1[1]–[4].

2 Method

An advantage of AI is the ability to infer the connection from cause to effect without total knowledge of the mechanistic relationship. This is well suited for mission profile analysis and lifetime estimation as the exact damage for a single cycle or event cannot be directly calculated, and only estimated at best. Additionally, great amounts of data are available for historical mission profiles. The flowchart of the method is shown in Fig. 2.

Mission Profile: This is the power and temperature

input.
Clustering: Here the blocks will be identified.
Possible sequences: This is the collection of all candidates for relevant events.
Artificial Intelligence: An AI is trained to recognize the dangerous events in the MP, and flag them. This is done iteratively, to lessen the computational load.
FEM simulations: FEM is used to evaluate the stress associated with a given sequence, thus giving an indication of the importance of the sequence.
Collection of relevant events: The end goal is to have a collection of all the relevant events in the MP.

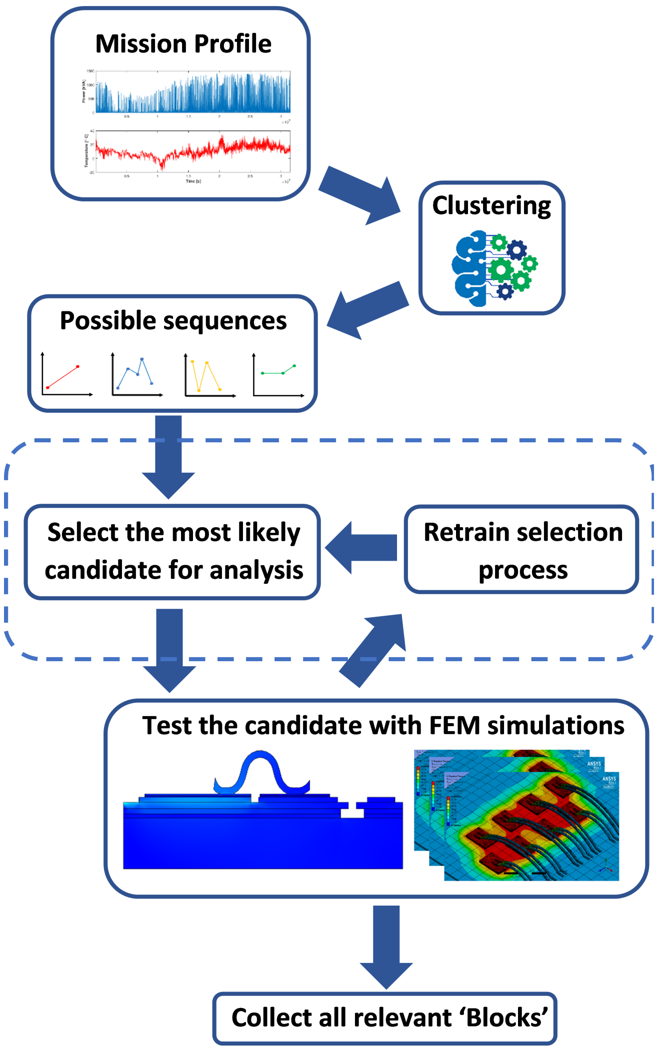

Fig. 2: Flowchart - Detection of relevant events, using AI.

3 Segmentation

A yearly mission profile can be divided into smaller sequences in many different ways. Given that sequences can conceptually consist of everything from two data points to all of the data points in a mission profile, the direct evaluation of all of these different sequences is not recommended. The number of sequences can be calculated using:

$$S = \left(\sum_{i=1}^{N} i \right) - N - 1 = \frac{N\,(N+1)}{2} - N - 1. \quad (2)$$

Where S is the total number of possible sequences, and N is number of observations in the mission profile.

To gain an overview of the mission profile used for this study, a histogram analysis was conducted. This is seen in Fig. 3.

The ambient temperature and power level were divided into a 52x140 grid(1$^\circ C$ and 10 VA bins).

	1	2	3	$\cdots$	52
1	1	2	3	$\cdots$	52
2	53	54	55	$\cdots$	104
3	105	106	107	$\cdots$	156
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
140	7228	7229	7230	$\cdots$	7280

A starting point for analysis is the simplest sequence consisting of only two time points. Sorting the data points in the previously mentioned bins and looking at the potential number of combinations gives 53$\cdot 10^6$ unique 2 length sequence combinations. However the number of unique combinations present in the mission profile is only 29.8$\cdot 10^3$.

4 Cluster Analysis

First of all, the mission profile power and temperature data for a sequence is structured as:

$$(S_1, T_1) \rightarrow (S_2, T_2) \qquad as \qquad [S_1, T_1, S_2, T_2] \quad (3)$$

Please note that

$$[S_1, T_1, S_2, T_2] \quad \neq \quad [S_2, T_2, S_1, T_1] \qquad (4)$$

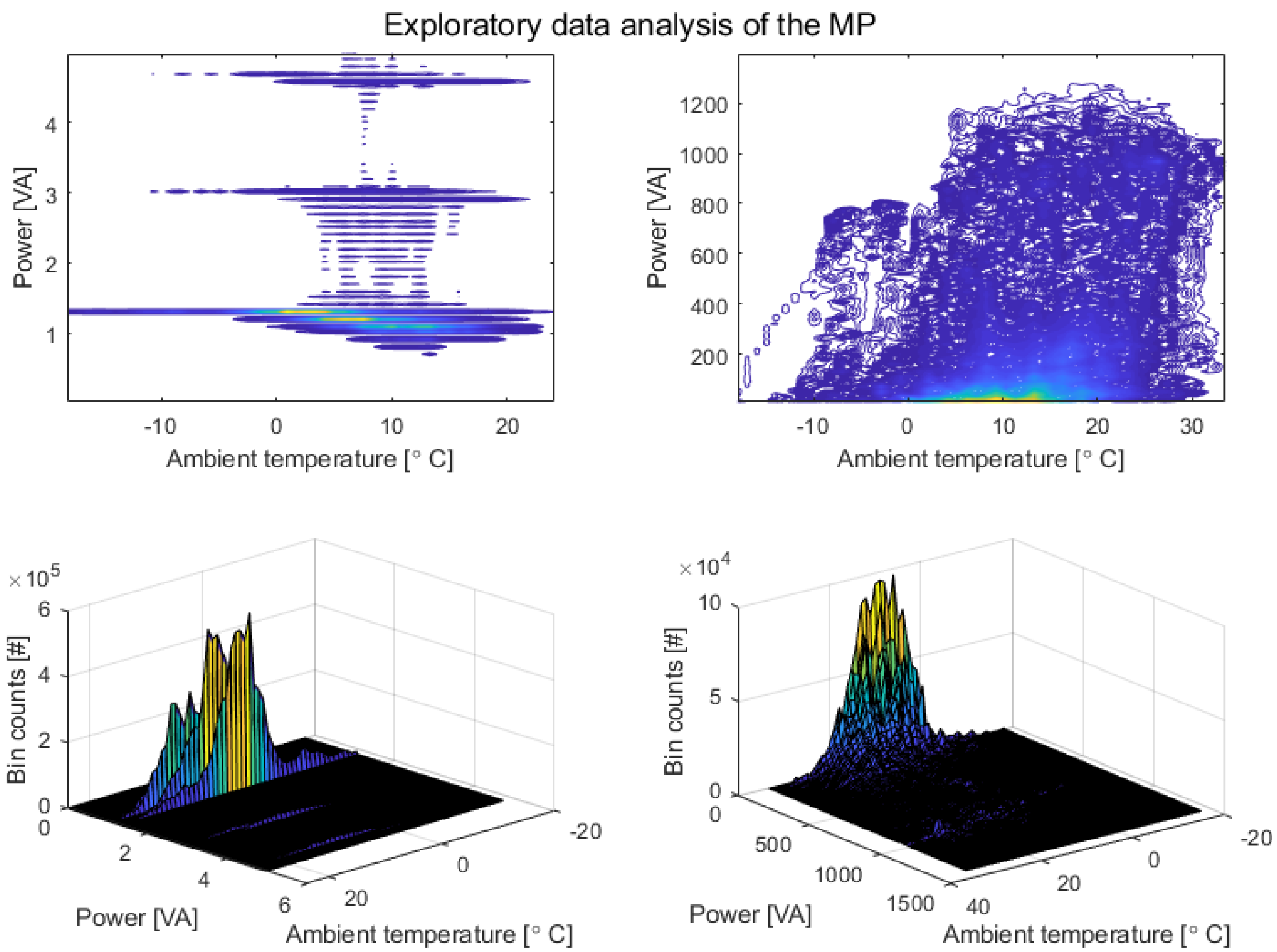

Fig. 3: Various MP histograms. Notice that the power-axis is split due to the large amount of observations in the region below 5VA.

4.1 K-means

The first clustering approach used is the K-means method. The steps of this method are:

1. Observations are assigned to a cluster, based on the minimum distance principle:

$$\arg\min dist(c_i, x_i)^2, \tag{5}$$

where x_i are the observations, and c_i are centroids. The distance function is defined in Eq. 7.

2. The cluster centroids are updated, based on the observations that were assigned to them ($x_i \in C_i$),

$$c_i = \frac{1}{|C_i|} \sum_{x_i \in C_i} x_i. \tag{6}$$

Convergence is achieved when the centroids are stationary from one iteration to the next. The distance metric used was the Manhattan distance:

$$dist(c_i, x_i) = \sum_{j=1}^{n} |c_{ij} - x_{ij}|, \tag{7}$$

Where c is centroids, x are observations and n is the length of the sequence vector from Eq. 3. Different numbers of centroids were tested to find an optimum between accuracy and complexity. The result of this is seen in Fig. 4.

4 centroids were chosen as the trade-off between complexity and accuracy. The identified clusters were as follows:

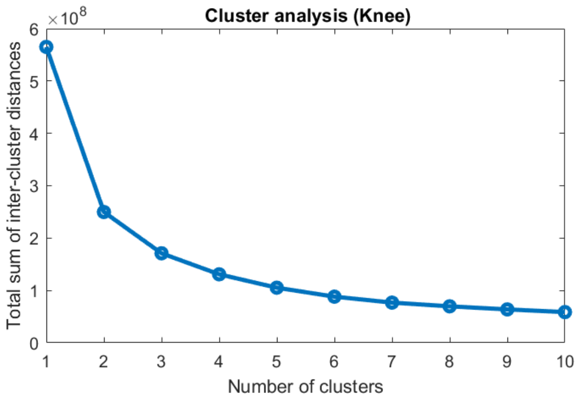

Fig. 4: Evaluation of the total inter-cluster distances during a sweep of number of clusters, to determine the optimal number of clusters for the data sample.

$$\#1 = \begin{bmatrix} 393.8\ VA \\ 12.8°C \\ 393.8\ VA \\ 12.8°C \end{bmatrix}, \quad \#2 = \begin{bmatrix} 1.2\ VA \\ 9.7°C \\ 1.2\ VA \\ 9.7°C \end{bmatrix},$$

$$\#3 = \begin{bmatrix} 763.1\ VA \\ 14.0°C \\ 763.1\ VA \\ 14.0°C \end{bmatrix}, \quad \#4 = \begin{bmatrix} 108.3\ VA \\ 12.0°C \\ 108.3\ VA \\ 12.0°C \end{bmatrix}$$

It is obvious that these sequences are stationary and thus don't help analyse fatigue from waveforms where the dynamic parts are generally considered the main cause of fatigue.

4.2 DBSCAN

DBSCAN was then used for clustering[5], [6]. As DBSCAN analysis becomes very time-consuming with a large amount of data points, an approach was used where the data for a year was split into 52 parts representing the weeks.

The initial results of the BDSCAN is shown in Table 1.

Item	Value
Observations	606.455
Stationary seq.	334.607
Clusters	19.266
Outliers	142.122
Max occurrences	3.916
Epsilon (ϵ)	0.1
Min. points	1

Tab. 1: Summary results from DBSCAN clustering of the MP, with respect to reducing problem size.

While not a complete solution it should be noted that the DBSCAN shows more promise than the K-means approach.

5 FEM Simulations

The ideal method for sequence significance determination would be a full experimental life test for each sequence. As this is a costly and very time-consuming method an alternative was chosen. The significance of a sequence is estimated using multi-physics finite element simulation where the maximum domain temperature and Von Mises stress are used to represent the relative loading and thus significance of a sequence. The following equation is used to express relative significance:

$$\bar{s} = \left[\frac{\max\{T^1_{max}, T^2_{max}\}}{T_{max}}, \frac{\max\{\tau^1_{v,max}, \tau^2_{v,max}\}}{\tau_{v,max}} \right]. \tag{8}$$

Where $\bar{s}$ is relative significance, T_{max} is the maximum temperature in the domain, where the superscript labels it either as the start (1) or the end of an event (2), and the lack of superscript denotes the total maximum. tau_{max} is the maximum Von Mises stress and it is labelled using superscripts in the same manner as the temperature.

6 Event Identification

Finally implementing the approach described in 2, using the artificial neural network to predict the significance of a sequence in the mission profile yielded the significance prediction seen in Fig. 5.

The results of the ANN prediction are shown in Fig. 5.

7 Discussion and Conclusion

The work of this manuscript was purposed to investigate new ways to identify dangerous events in a mission profile. Here an artificial neural network is used to predict the significance of a given sequence.

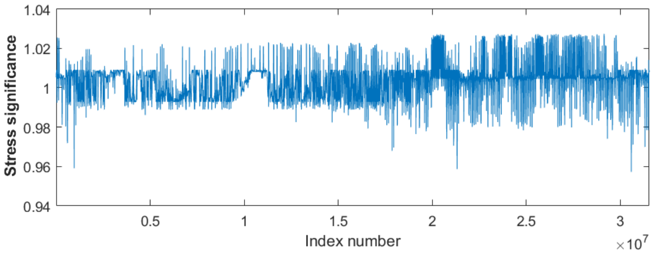

Fig. 5: ANN prediction results on the significance of all possible 2-seq. from the full MP.

The overall approach used the steps detailed in section 2.

The work focused on the analysis of yearly mission profiles, detailing the power and ambient temperature for an application.

The mission profile structure was investigated for clues for how to divide it into sequences and clusters of sequences for analysis.

Histograms, K-means and DBSCAN were used for this investigation. DBSCAN proved to be the most promising of the methods, while it's implementation is incomplete in this work, is the recommended method, of the three, for future work.

Finite element modelling was used to evaluate the significance of a sequence using the Von Mises stress and maximum temperature. While not ideal, it is a much faster and cheaper method than experimental power cycling tests for each sequence.

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