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Data-driven Metamodels for Failure Analysis of Power Electronic Modules

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Abstract

This work presents a thorough analysis of machine learning (ML)-based metamodels to assess the reliability of power electronic modules (PEMs). Accurate lifetime prediction pipelines often require frequent updates of the mechanical state of PEMs using finite element simulations (FESs), which are computationally expensive. This compromise between complexity and precision is the motivation behind this study, which aims to harness models that are otherwise not exploitable due to the long computational time of FESs. We deem that ML models are suited for this task thanks to their fast inference speed and high predictive power. The quality of the models is thoroughly studied throughout this paper by analysing often-overlooked statistical properties that have proven to be crucial to analyse and very informative on the behaviour of the model. We applied the approach as a part of a remaining useful life (RUL) estimation pipeline for failure caused by bond-wire degradation in PEMs, but the framework is application-agnostic and can easily be adapted to different systems and degradation forms. The aim of this paper is to present a rigorous yet accessible metamodel implementation framework to appropriately exploit the strengths of ML models when applied to failure analysis.

1. Introduction

Estimating the RUL of PEMs can be approached through various methodologies. Data-driven models [1] learn hidden patterns from historical failure data to predict the lifetime of a module. In contrast, physics-based models rely on established physical laws to simulate degradation mechanisms and assess reliability [2]. Hybrid models [3] combine elements of both approaches, aiming to improve prediction accuracy while addressing limitations such as data scarcity, high computational cost, and limited interpretability associated with purely data-driven or physics-based methods. In this context, knowledge of mechanical quantities such as the strain or the stress intensity factor is crucial to accurately predict the PEM's failure. Over the course of the module's lifetime, these quantities need to be updated to avoid the divergence of the predictions due to state changes of the module. FESs are commonly used to retrieve detailed mechanical information about PEM, where a health indicator is firstly measured to estimate the degradation level of the module. The degradation is

modelled by modifying the geometry of the PEM in the FES according to the estimated degradation level. Loading is then applied to this modified geometry to obtain the updated mechanical quantities.

Repeated FESs can be slow and costly, hence the idea of using metamodels. We illustrate the benefits of this approach by showcasing its superior computational edge and its competitive accuracy in a framework applied to the problem of bond-wire degradations caused by internal heating in an IGBT power module. In our approach, the collector-emitter voltage V_{ce} is used as a health indicator to estimate the crack length l_c in the bond wire.

2. Simulation

To simulate the behaviour of a PEM under loading, a geometric model is utilised as shown in Fig. 1. This geometry is reduced compared to the real structure of an IGBT PEM, allowing us to refine the meshing around the contact area between the wire and the metallization as it contains the mechanical

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information needed to study failure caused by damage in the wire-bonds.

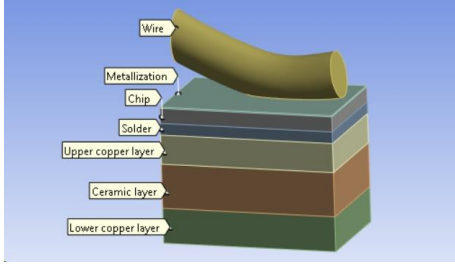


Fig. 1. Simplified geometry of a PEM used for FESs

Updating this information requires measurements of V_{ce} and thus l_c . The geometry in Fig. 1 is then adapted to account for this change in l_c , according to Fig. 2. The contact is assumed to stay elliptic, therefore, we utilise a thin 3D truncated cone to link the wire to the metallization: the lower base is connected to the metallization, and its area is adapted according to l_c . The upper base, which is linked to the wire, is invariant with an area equal to that of the initial contact.

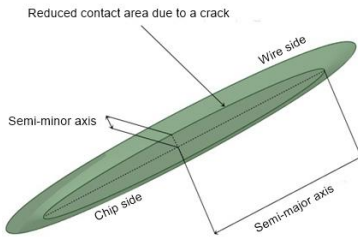


Fig. 2. 3D truncated cone used to adapt the geometry to the crack length

Material assignments of the PEM are given in Table 1. Non-linear behaviour is modelled in both aluminum and copper according to [4] and [5] respectively.

Table 1
Material assignments for the power module's finite elements model

Component	Material
Wire	Aluminum (Al)
Metallization	Aluminum (Al)
Chip	Silicon (Si)
Solder	Silver (Ag)
Ceramic layer	Ceramic (Al_2O_3)
Upper/Lower copper layer	Copper (Cu)

A reference temperature of $T_{ref} = 55^\circ C$ is used as the ambient temperature with a zero heat flux on the boundaries of the module, except for the lower face of the lower copper layer, which has a heat transfer coefficient of $h = 4000 w/m^2$ to model the cooler's effect. A zero potential is imposed on the wire's face that links the geometry to the rest of the circuit. A current I is injected into the upper copper layer, and its value is adjusted to obtain an average chip temperature equal to the cycle's maximum temperature in the loading profile. Typically, its value is roughly equal to αI_{ref} , where I_{ref} is the current value used in reference active cycling tests, and α is the surface reduction value due to simplifying the architecture into a single wire.

A strong electro-thermal coupling is used to generate the temperature profile, which is used afterwards in a weak thermo-mechanical coupling to generate mechanical values, where a fixed support is imposed on the lower face of the lower copper layer.

3. Data generation

In order to create a data-driven metamodel to mimic simulations as in Section 2, synthetic data must be acquired. The procedure begins by generating a database with its inputs being the loading ΔT , the module's state l_c and the geometric coordinates x and y of the mesh nodes, where the mechanical quantities are measured. The output consists of the mechanical quantities of interest, which is chosen as the total equivalent strain ϵ for the sake of illustration. A total of 1000 simulations was carried out, each lasting around 3 minutes, where input parameters were chosen using a random uniform sampling to ensure an even distribution of inputs. The contact radius ranges from $R_h = 0.03mm$ to $R_h = 0.365mm$ corresponding to the initial contact with a crack length $l_c = 0mm$, and the maximal temperature ranges from $\Delta T = T_{ref}$ to $\Delta T = 191^\circ C$. The thickness of the wire is chosen by setting its diameter to $380\mu m$. Finally, x and y are determined automatically from the meshing. Data is then normalized for the sake of the metamodel's stability.

Estimating the output ϵ from the aforementioned inputs is a regression task on tabular data. The data is split into a training dataset used to fit the metamodels, consisting of 70% of the total simulations, and the remaining 30% is the testing dataset used for validation. This split offers a balanced trade-off between having enough data to effectively train the metamodels while retaining a sufficient portion to assess the models' generalization performances on

unseen data. The dataset’s size (1000 simulations) provides a reasonable compromise between training a sufficiently robust model and keeping the computational cost manageable. While this study is based solely on numerical simulations, the RUL estimation results using ML metamodels demonstrate accurate predictions, as highlighted in Section 5. Experimental validation would be a valuable direction for future research.

4. Results and statistical analysis

4.1. Regression

To evaluate the accuracy of each metamodel, statistical metrics are measured such as the mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2). Computational metrics consisting of the fitting and inference times were also tracked to highlight computational gains. Alongside the parameters used for inference, metamodels often need predetermined parameters, called hyperparameters, that control how the model learns, and they are not estimated directly from the data. The choice of hyperparameters is important, therefore we used a technique called cross-validation to make an informed guess on the optimal hyperparameter value to use. Five metamodel families were studied as is presented below.

Linear models (LMs) look for a linear relationship between the inputs and the outputs. They can easily be generalized to more complex models such as the polynomial models.

Regularisation (REG) is a technique used when the dataset is too noisy, and the model learns the noise instead of learning the trend in the data.

Tree-based models (TB) make a decision on the output’s value by sequentially observing the ranges in which input values are in. This approach is highly interpretable as it mimics the human’s decision making process.

Non-parametric (NP) models make predictions based on similarities between the observed data in training and the test case, contrary to other models where the predictor takes a predetermined form.

Neural networks (NN) are complex models often used when the phenomenon observed is highly non-linear. Different variations of neural networks exist, and are used based on the nature of the data.

Results showing statistical and computational metrics are given in Table 2.

Table 2
Evaluation of each family of the tested metamodels^a

Model	MSE (10^{-3})	MAE (10^{-3})	R^2	Training (s)	Inference (ms)
LM	<u>1.851</u>	<u>2.329</u>	<u>0.6</u>	0.031	0.000
REG	<u>1.851</u>	<u>2.329</u>	<u>0.6</u>	1.891	0.000
TB	0.175	0.463	0.962	673.375	<u>0.211</u>
NP	0.475	0.769	0.897	0.422	0.010
NN	0.438	0.829	0.905	<u>991.062</u>	0.022

^aBest metrics in bold, worst metrics underlined

Among all evaluated models, tree-based methods, particularly bagging ensembles, demonstrate the highest prediction accuracy, with non-parametric models (K-Nearest neighbours) offering a good middle ground between accuracy and speed. Illustrations of predictions using the bagging metamodel are given in Fig. 3 and Fig. 4 showcasing the predicted strain (left) compared to the simulated strain (middle) at each meshing node (represented as black dots) of the elliptic contact, along with the absolute error (right) of the model.

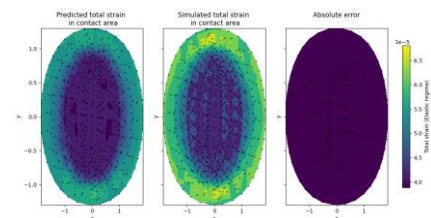


Fig. 3. Predictions in an elastic regime

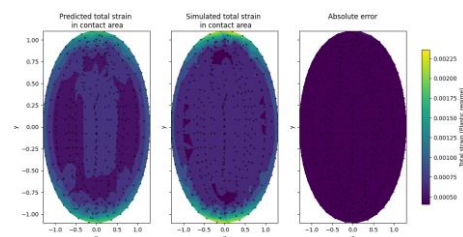


Fig. 4. Predictions in a plastic regime

4.2. Residuals

Residuals, defined as the difference between predicted and actual values, provide insights into potential model bias; an example of the residual plot is given in Fig. 5. Analysing the residuals gives an idea about potential biases in the prediction, which not only assess the quality of the model, but also suggests further improvements.

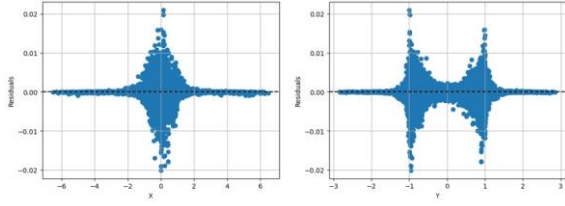


Fig. 5. Residual plot showing prediction error with respect to normalized geometric features

The example above shows that the model presents the highest uncertainty when evaluating the strain in the contact extremities (as the data is normalized, $x = 0$ is the middle-most x value, and $y = \pm 1$ is an extremal y value) where the strain is at its peak, as is the case in Fig. 4 for example. This suggests improving the quality of the data around these values by refining the mesh in the extremities or using a data enhancing technique, for example.

4.3. Consistency

Consistency studies the behaviour of the model when the dataset size increases. A consistent model improves the bigger the dataset gets and it can be verified by plotting a prediction metric with respect to the size of the used data as in Fig.6. In this graph, the data size corresponds to the total number of meshing nodes used to train the metamodel (≈ 450 per simulation, corresponding to ≈ 450000 data set size when using all 1000 simulations). Consistency is important to assess the model's convergence.

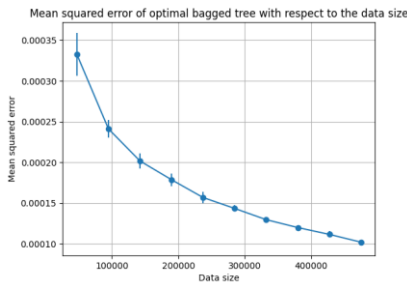


Fig. 6. Decreasing prediction error indicating consistency

5. Application to RUL estimation

To validate our approach, data-driven metamodels were applied within an RUL estimation framework that shows accurate predictions when evaluated across multiple test cases of varying difficulties. An example is illustrated in Fig. 7, and the framework is described in [6] which uses a Markov chain-based approach to simulate degradation. We

refer the reader to the aforementioned work for further details on the methodology alongside the results and the evaluation criteria used.

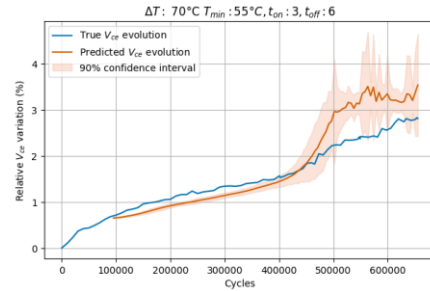


Fig. 7. RUL estimation using data-driven metamodels

6. Conclusion

This research showcases how data-driven metamodels can be used to enable RUL estimation pipelines to harness FESs while cutting down drastically on computational time ($\approx 10^6$ times faster). An emphasis is made on rigorously analysing these models to ensure a high quality of the predictions. Data-driven metamodels can benefit from different ML techniques, which can be used to optimize FESs selection or mesh generation, for example. The code used for this framework is available at <https://github.com/MehdiGhrabli/ML4FE>.

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