Prognostics of Power Electronic Modules Using Machine Learning

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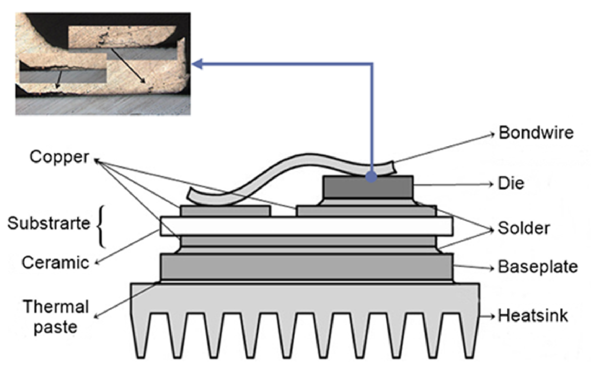
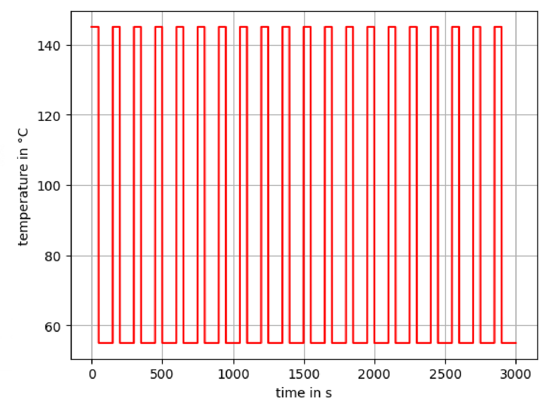
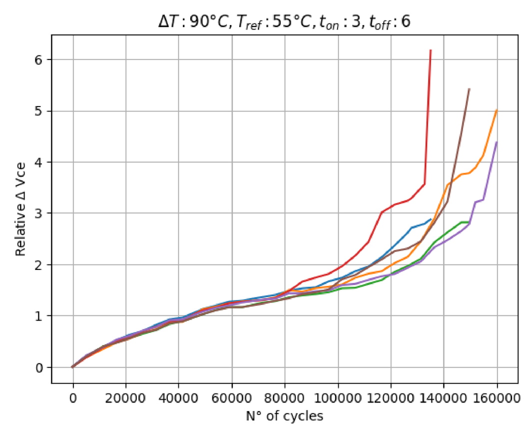
Systèmes et Applications des Technologies de l'Information et de l'Énergie - UMR 8029

1. Power Electronics Prognostics in Context

- Power electronic modules fail gradually due to constraints caused by temperature variation.
- Bondwire degradation induced by self heating is a prevalent cause of failure.
- Experimental assessment consists of cyclical injections of a current I to the module, causing a temperature swing of ΔT for a duration t_{on} and relaxing it for a duration t_{off}.
- Health state is monitored by measuring the voltage V_{ce}. A relative increase ΔV_{ce} beyond a threshold ($\approx 5\%$) indicates failure.

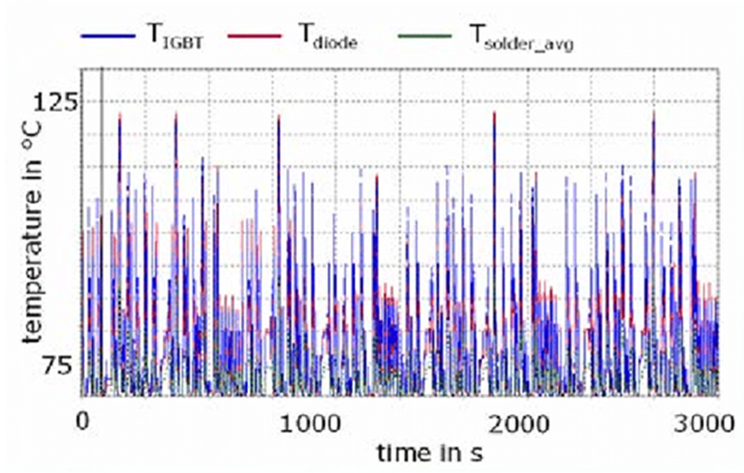


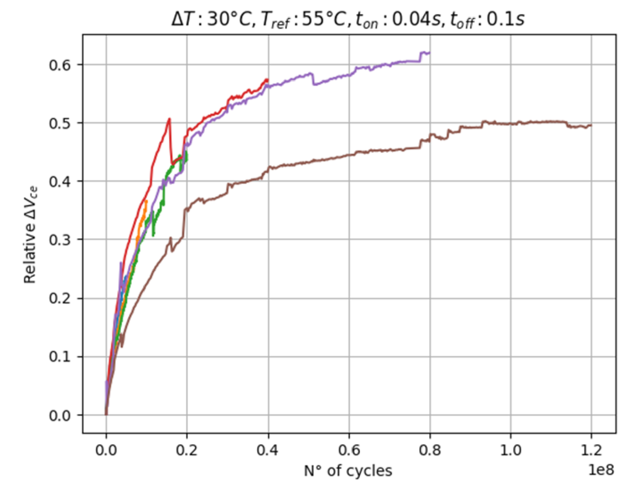




2. Key Challenges in Power Electronics

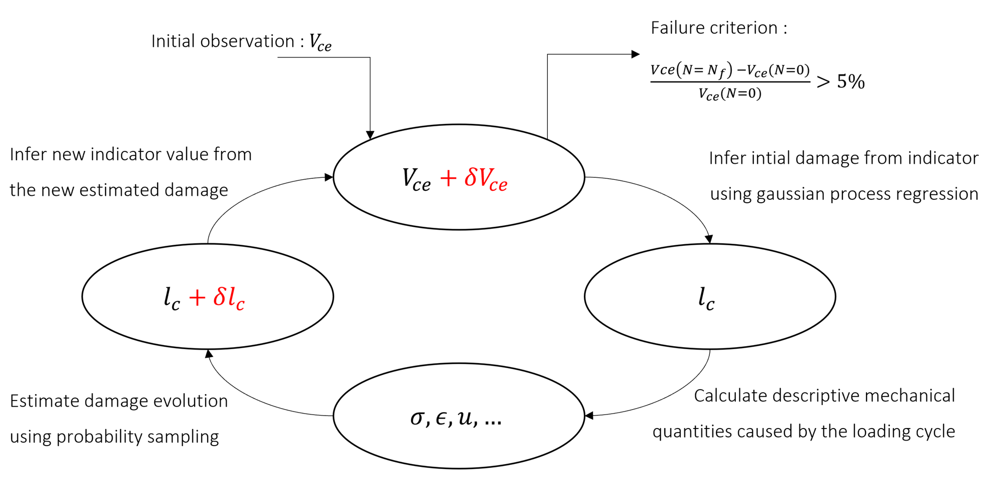
- Real-life loading profiles are complex, with variability in magnitude ΔT and durations t_{on} and t_{off}.
- Failure under realistic conditions is slow, which limits experiments (slow evolution of V_{ce} for $\Delta T = 30°C$).
- Conventional approaches are limited by sparse data, restrictive assumptions, and computational inefficiency.



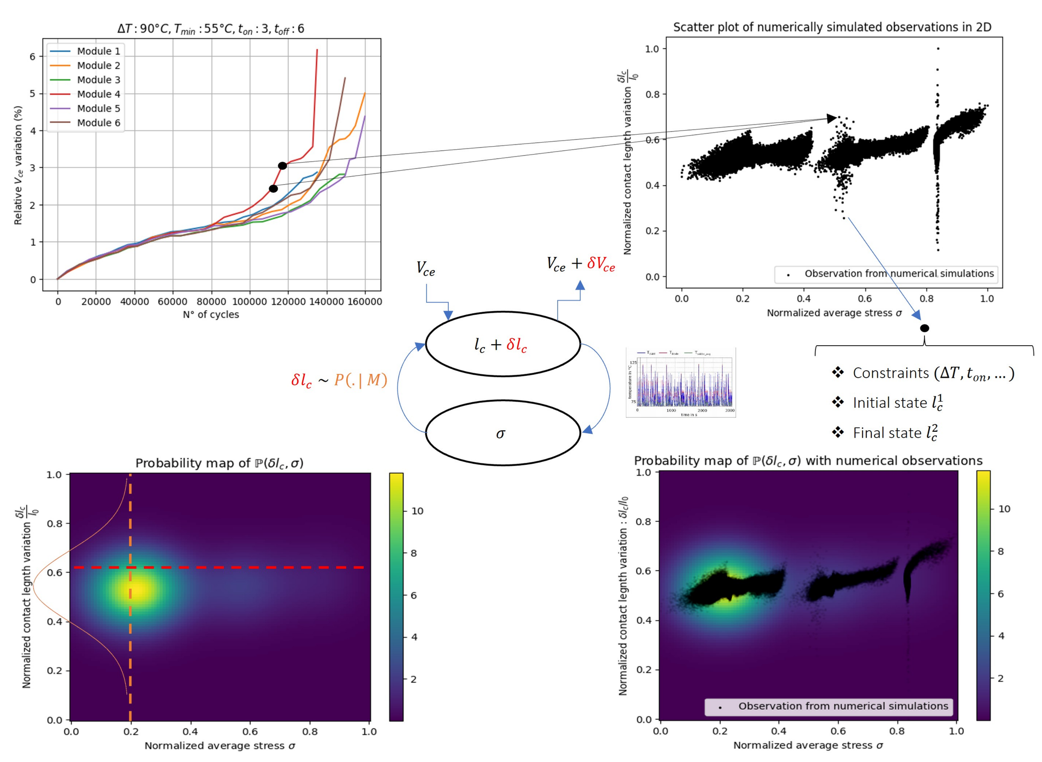


3. Modeling Degradation

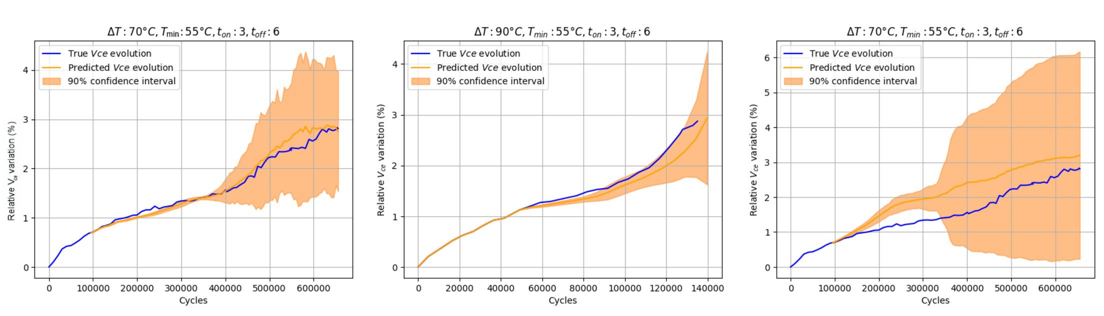
- Recurrent approach which infers damage increments caused by each loading cycle, thus accounting for variability.



- Damage is inferred using a probability density function $\mathbb{P}(\delta l_c|M)$ giving the probability that a degradation δl_c occurs under a given observation M defined by the module's state (current degradation) and a set of mechanical quantities describing the effect of the loading cycle.

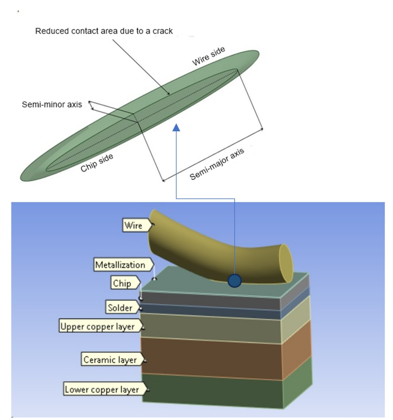


- This approach handles in-distribution predictions (left), interpolation (middle) and extrapolation (right).



4. Surrogates for Simulations

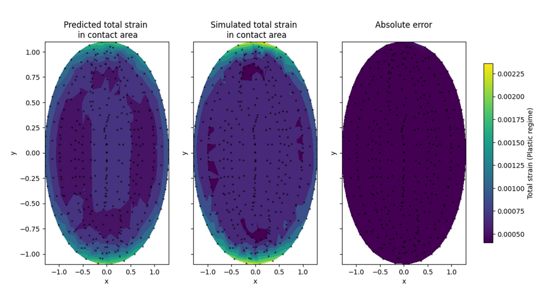
- Frequent numerical simulations are required, drastically increasing computational time. Data-driven metamodels are used as a faster alternative.



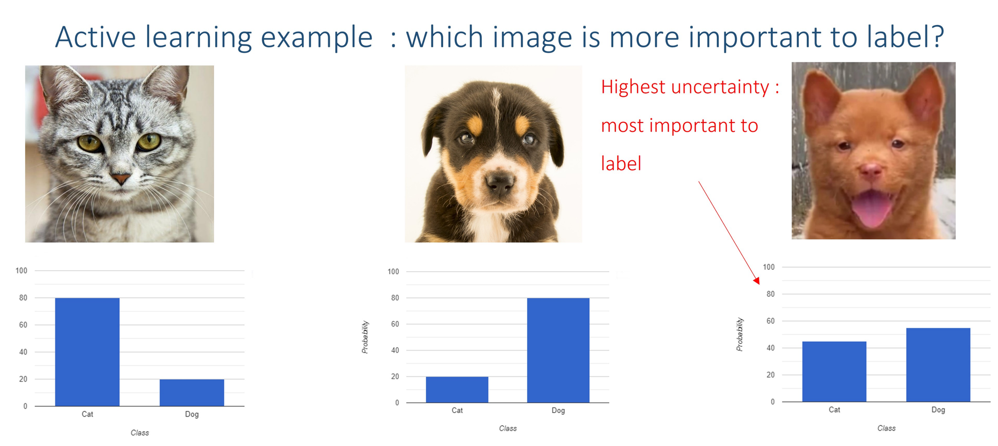
Input				Output
Temperature ΔT	Contact radius R_h	Mech node coordinate x	Mech node coordinate y	Equivalent total strain ε

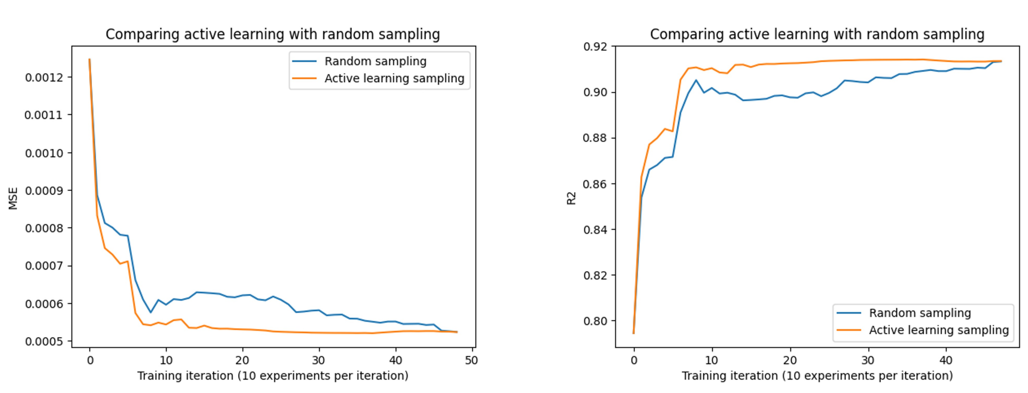
- Tree-based models are strong candidates due to their decision-based regression, while K-NN models offer competitive performance both statistically and computationally.

Models/Metrics	MSE (10^{-3})	MAE (10^{-2})	R²	Fitting time (s)	Inference time (ms)
Linear	1,851	2,329	0,6	**0,031**	**0**
Regularization (linear)	1,851	2,329	0,6	1,891	**0**
Tree-based	**0,175**	**0,463**	**0,962**	673,375	0,211
Non-parametric	0,475	0,769	0,897	0,422	0,010
Neural network	0,438	0,829	0,905	991,062	0,022



- Active learning is utilized to optimize the choice of simulations. Uncertainty is taken as the variance of an ensemble of predictors.

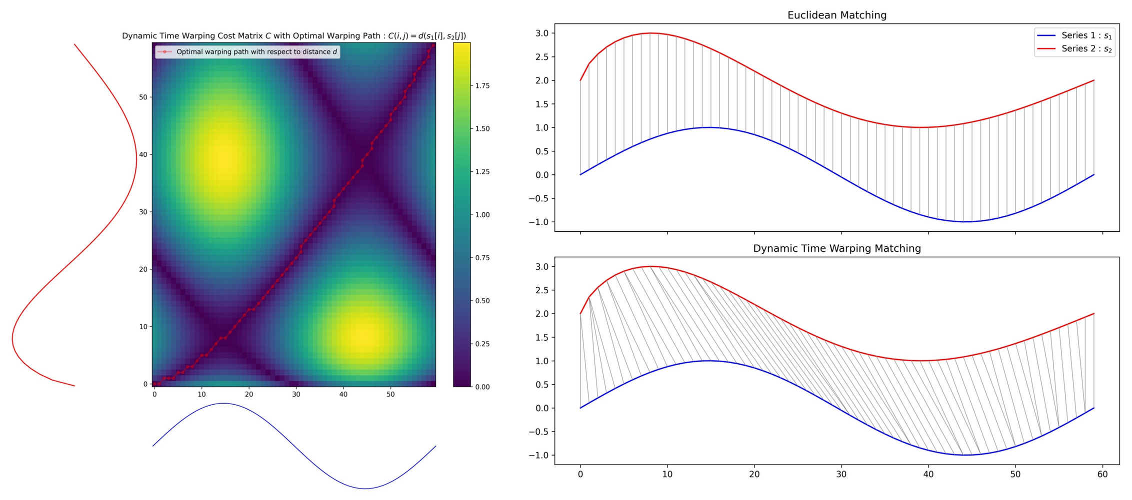




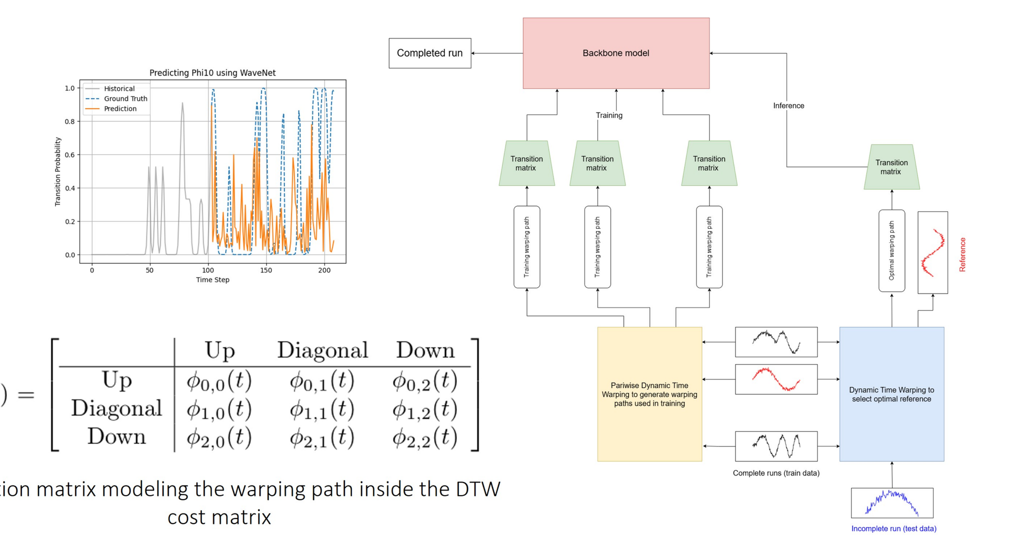
Active learning using 50 test simulations, 50 initial training simulations and a pool size of 500 simulations

5. Forecasts with Incomplete Runs

- BED-Time: a time series forecasting model which accounts for warping : a realization f_{θ_1} parametrized by θ_1 is a non-linear transformation in time g_{θ_1} (warping) of a reference h : $f_{\theta_1}(t) = h(g_{\theta_1}(t))$.



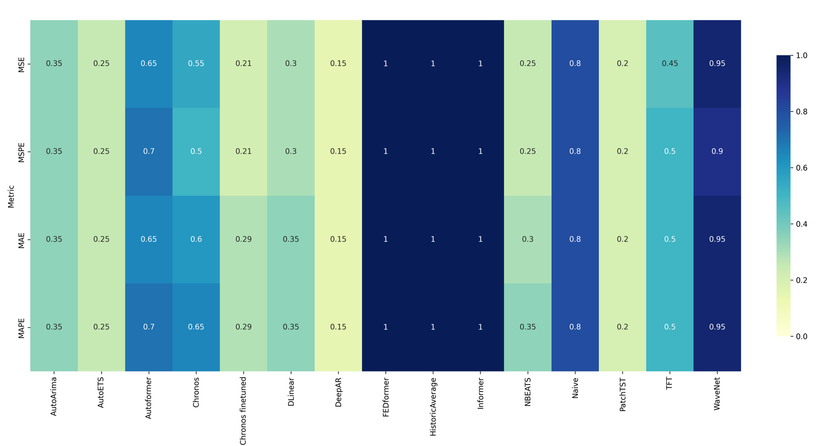
- A time series matching algorithm (Dynamic Time Warping) is used to find optimal matching. The optimal warping path is modeled using a time-inhomogeneous Markov chain (transition matrix $M(t)$).



$$
M(t) = \begin{array}{c|ccc} & \text{Up} & \text{Diagonal} & \text{Down} \\ \hline \text{Up} & \phi_{0,0}(t) & \phi_{0,1}(t) & \phi_{0,2}(t) \\ \text{Diagonal} & \phi_{1,0}(t) & \phi_{1,1}(t) & \phi_{1,2}(t) \\ \text{Down} & \phi_{2,0}(t) & \phi_{2,1}(t) & \phi_{2,2}(t) \end{array}
$$

Transition matrix modeling the warping path inside the DTW cost matrix

- BED-Time improves significantly on SOTA Transformer-based models, shown by the gains-ratio matrix which indicates how many times BED-time improves on the baseline.



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