



Signal-based meta-modelling of temperature in short-circuit testing of power semiconductors

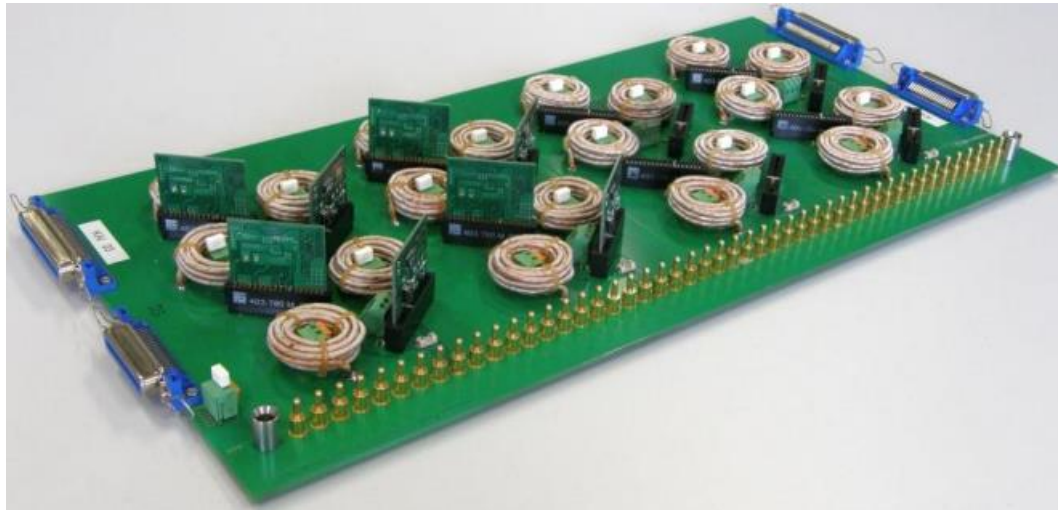
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Introduction

- Repetitive short circuit capability is a requirement of smart power ICs in automotive applications
- Short circuit load conditions result in a high power dissipation, temperature rise and thermal stresses
- Thermo-mechanical fatigue of the chip metallization leads to progressively degrading electrical performance and eventually failure
- Short circuit testing is done to prove meeting required quality standards and to collect data for lifetime modelling



Electro-thermal behavior of power MOSFET transistors

- In a short-circuit test, the MOSFET is operating in the so-called saturation mode, where the current is given by

$$I_d = \frac{1}{2} \mu_n C_{ox} \frac{W}{L} (V_{GS} - V_{th})^2$$

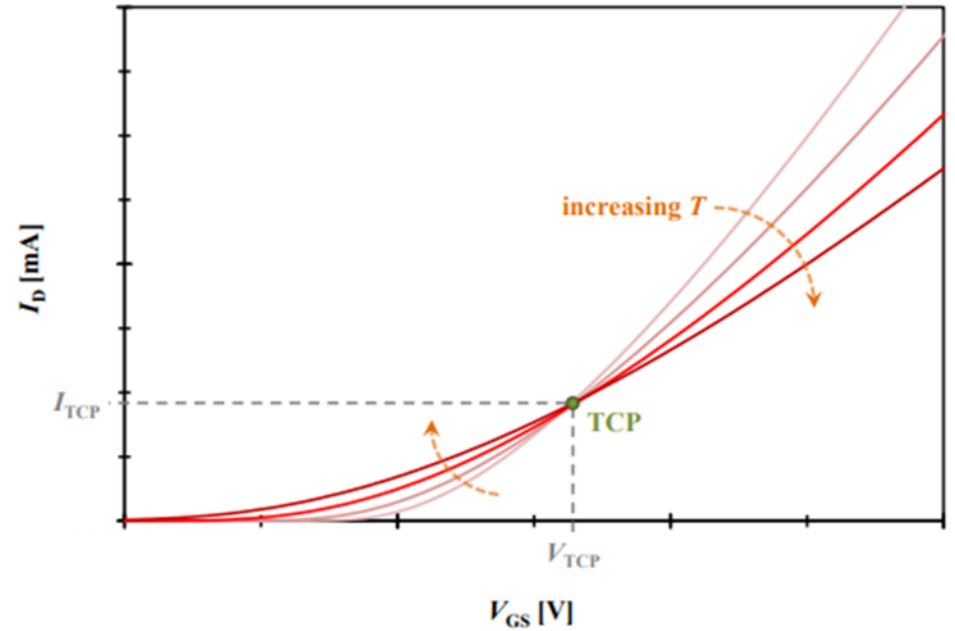
$$\mu_n(T) = \mu_0 \left(\frac{T}{T_0} \right)^{-M}$$

Electron mobility

$$V_{th}(T) = V_{th0} - \varphi(T - T_0)$$

Threshold voltage

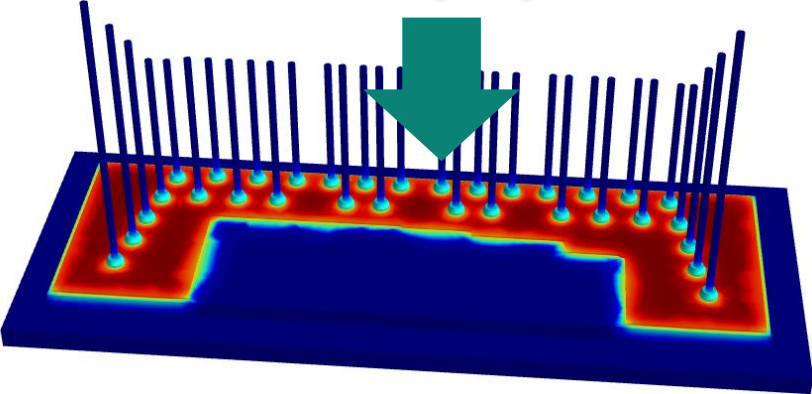
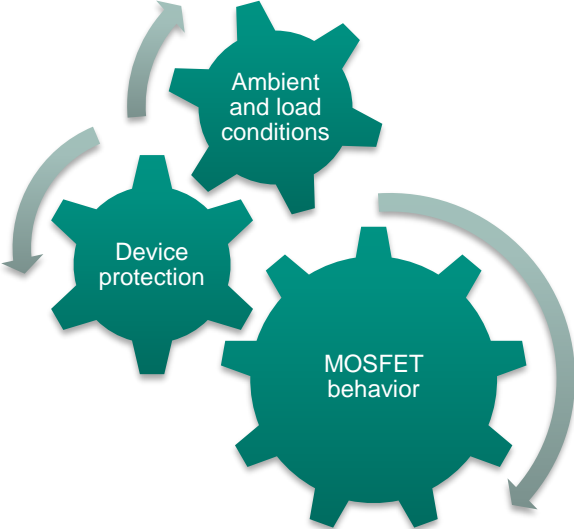
- When the decrease of the threshold voltage with temperature is dominant, an increase in temperature leads to an increase in current density. The increase in current density implies a local increase of power within the cell, which in turn induces a further temperature rise. This positive feedback between the current and the temperature may lead to localization of current and even thermal runaway.



Exemplary MOSFET electrical behavior

Electro-thermal FEM simulation of smart power semiconductors

– Due to the strong interaction between the electric field, temperature and current distribution, coupled electro-thermal simulations are necessary to analyse short-circuit loadings



– The governing equations for the temperature and electric field are

$$\rho c \frac{\partial T}{\partial t} - \nabla \cdot (\lambda \nabla T) = \vec{E} \cdot \vec{j}$$

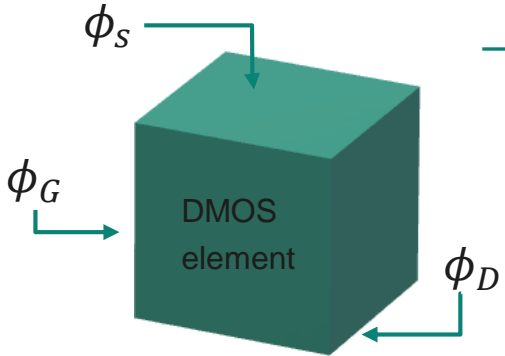
Heat equation with Joule heating

$$\nabla \vec{j} = \nabla \cdot (\gamma \nabla \phi) = 0$$

Current continuity equation

– The electrical conductivity for the DMOS region is derived from the current density characteristic

$$\gamma = \gamma(\phi, T) = \gamma(V_{GS}, V_{DS}, T)$$



– Elements meshing the DMOS introduce a non-local coupling because the electrical conductivity depends on the drain- and source-side potential

$$V_{GS} = \phi_G - \phi_s$$

$$V_{DS} = \phi_D - \phi_s$$

Electro-thermal FEM simulation of smart power semiconductors

Given the solution $T(x, t_n)$, $\phi(x, t_n)$ and boundary condition $V(t_{n+1})$ and $I_d(t_{n+1})$, solve

... with linearized conductivity

- The DMOS conductivity is approximated with an effective conductivity, which is updated at every time step based on the field solution for each element
- Solver: Ansys Mechanical APDL [1]

... with fully nonlinear conductivity

- The DMOS conductivity model is used with the full non-local dependence on the electric field and temperature
- Solver: openCFS [2], COMSOL Multiphysics

Typical solution times depending on the model size are 1 to 6 hours

- It is feasible to simulate a test series of e.g. a dozen devices in a reasonably short time. Once this computational cost has been paid sufficiently often, it is desirable to have meta-models for key properties to avoid repetitive simulations and to enable quick parametric studies

[1] de Filippis et al., ANSYS based 3D electro-thermal simulations for the evaluation of power MOSFETs robustness, Microelectronics Reliability, Volume 51, Issues 9–11, 2011

[2] Eisner et al. (2017). Finite-Element Analysis of Coupled Electro-Thermal Problems With Strong Scale Separation. IEEE Transactions on Power Electronics, 32(1), 561–570. <https://doi.org/10.1109/tpel.2016.2527690>

Electro-thermal FEM simulation of smart power semiconductors

– Simulation workflow

- Device and test data are collected from a database
- Processed simulation results are collected and stored in the database

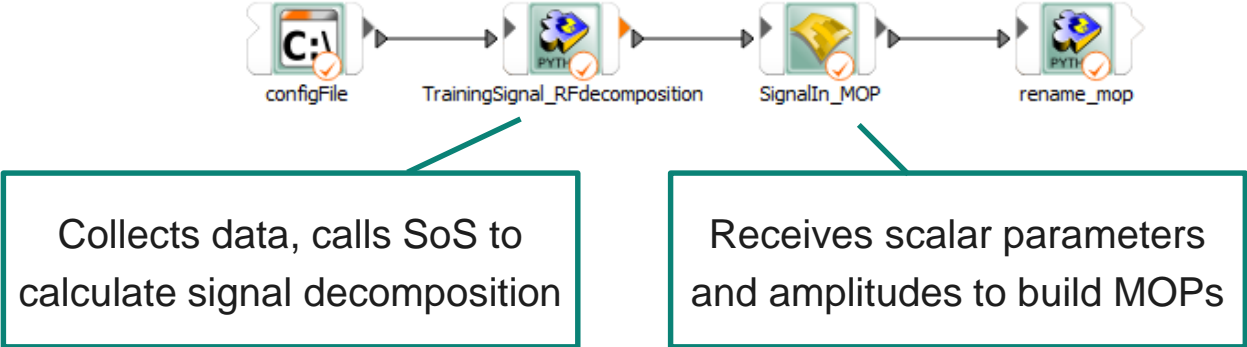


– Meta-modelling challenge

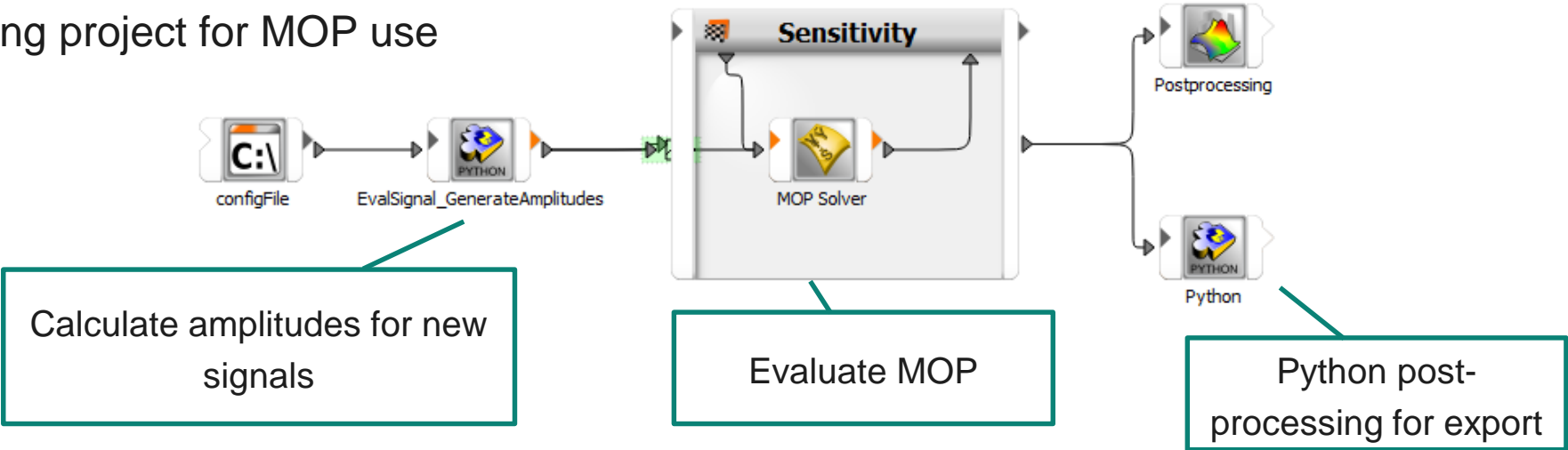
- The load during a short-circuit test cannot be described by a set of scalar parameters
- The meta-modelling workflow must be able to work with input **signals** in addition to scalars

optiSLang workflow

– optiSLang project for MOP creation



– optiSLang project for MOP use



optiSLang workflow

- MOP creation and evaluation are conveniently done via a web application to run the optiSLang projects
- MOP workflow development version; to be linked to internal data environment using Python APIs

Interface for creating the MOP

Signal-In/Signal-Out Analysis

Create MOP

Evaluate MOP

Create MOP

Training Dataset	<input type="text" value=""/>
First training design	<input type="text" value="0"/>
Last training design	<input type="text" value="0"/>
Number of input shapes	<input type="text" value="0"/>
Variability fraction	<input type="text" value="0"/>

Project settings



Interface for evaluating the MOP

Signal-In/Signal-Out Analysis

Create MOP

Evaluate MOP

Evaluate MOP

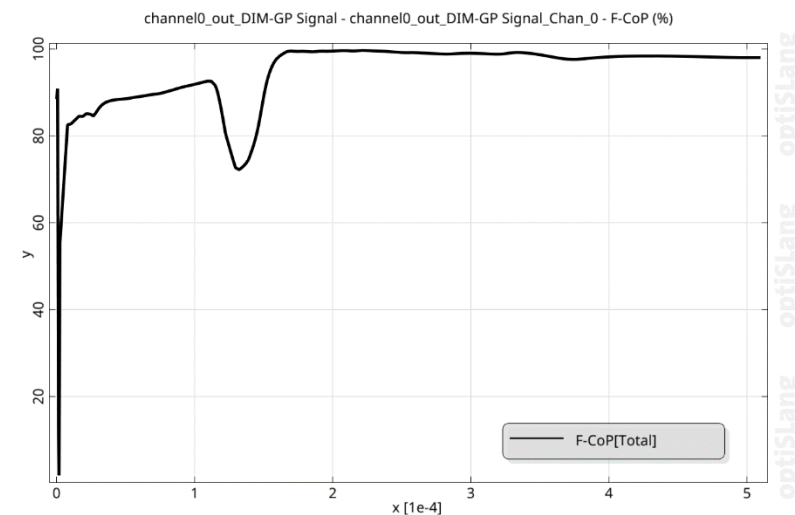
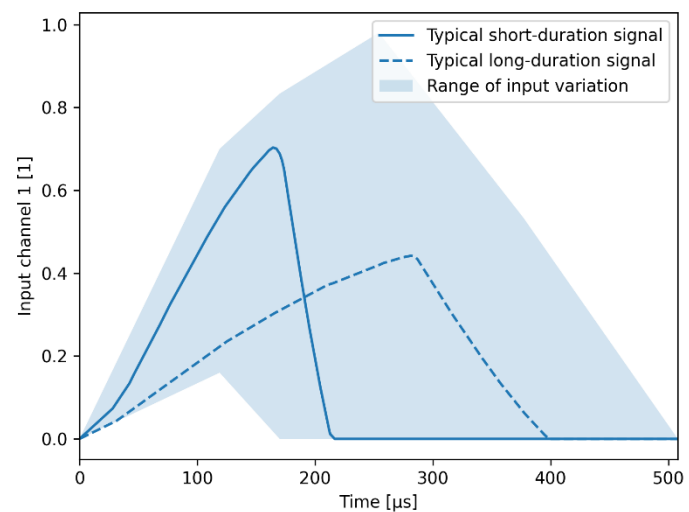
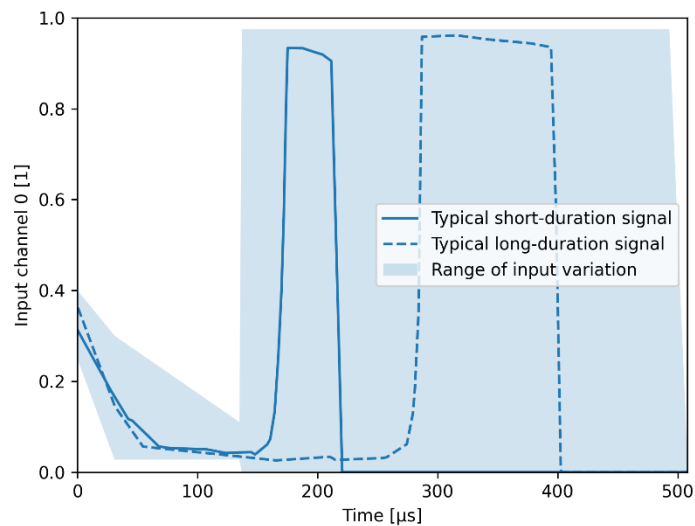
MOP	<input type="text" value=""/>
First training design	-
Last training design	-
Number of in shapes	-
Var fraction	-
Evaluation Dataset	<input type="text" value=""/>
First evaluation design	<input type="text" value="0"/>
Last evaluation design	<input type="text" value="0"/>

Project settings



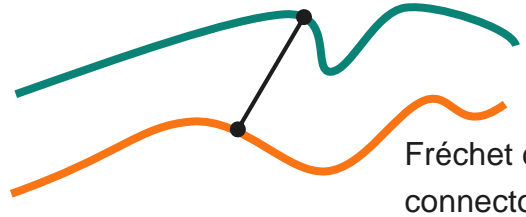
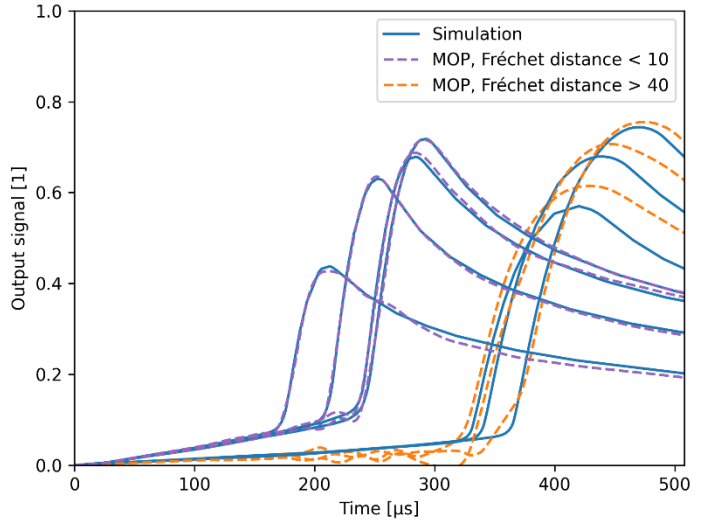
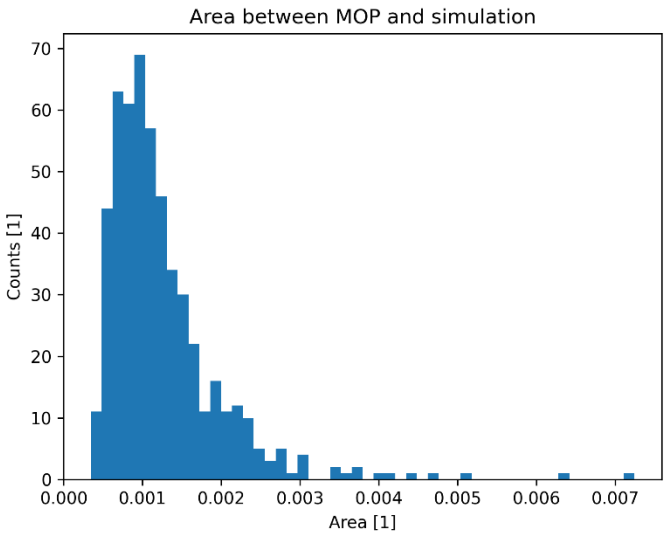
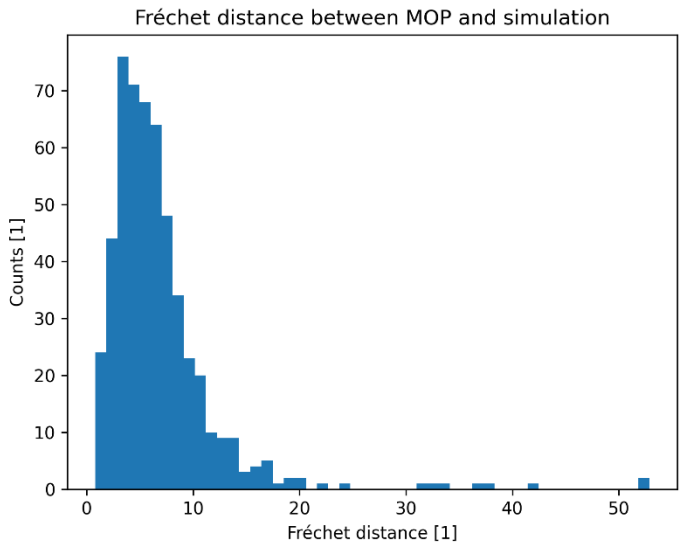
Designs for MOP training

- 350 designs covering various loads as well as 2 operation modes of the chip and 2 physically different variants of the interconnect layer have been used to create the DIM-GP signal MOP
- F-CoP is better than 95% in the most important time range
- Time for training was ~45 minutes on Intel Xeon workstation



Testing the MOP on new data

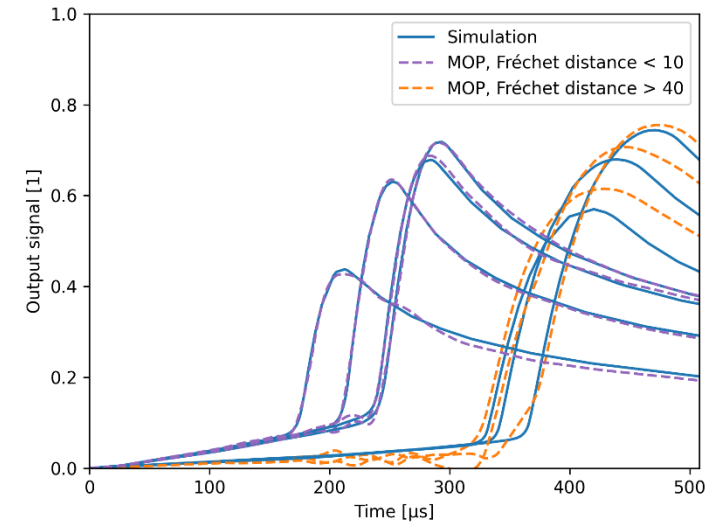
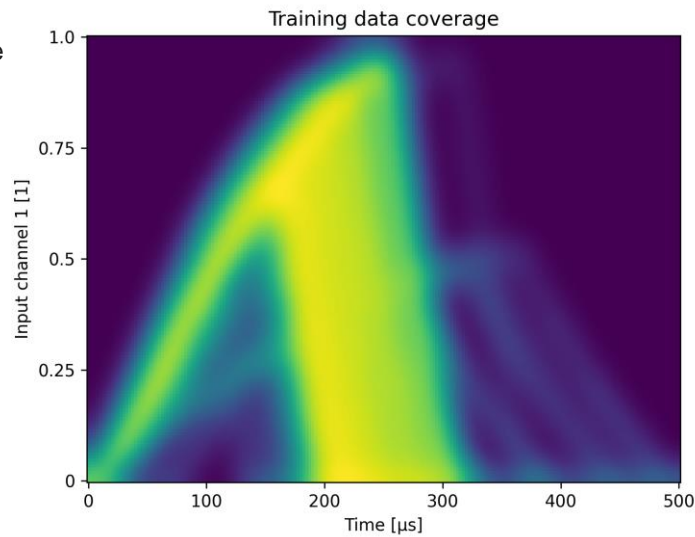
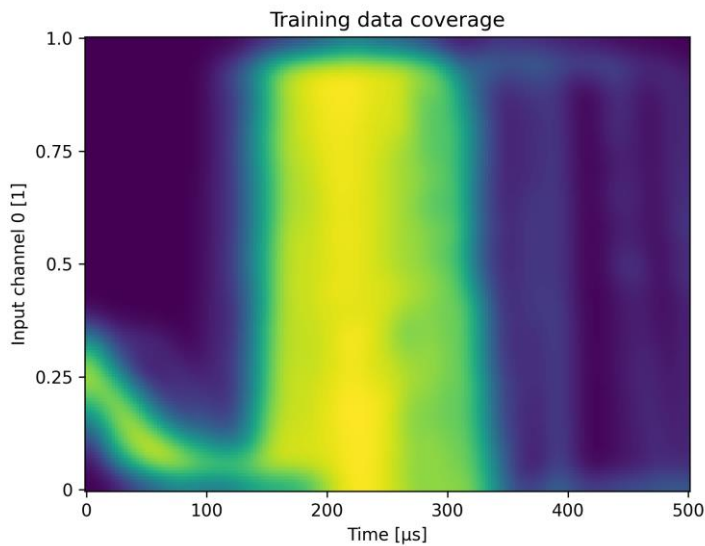
- MOP predictions of 613 designs that were not used for training are in very good agreement with simulated signals
- Errors measures show only a small number of designs that are approximated poorly by the MOP



Fréchet distance: shortest inextensible connector able to traverse both curves

Testing the MOP on new data

- The low quality predictions were obtained for signals in the time range where only a small amount of designs was available for training
- Selection of training data was for demonstration purposes and not optimized for coverage!



Summary

- A workflow to use signals and scalar parameters as input for a metamodel has been developed and applied for the prediction of the electro-thermal behavior of a smart power switch
- Building the MOP using two input channels and two scalar parameters is as fast as performing a single electro-thermal simulation
- Current limitations
 - All input signals must have a common sampling, which requires pre-processing in the case of irregularly sampled data
 - Need for dense sampling to correctly interpolate steep flanks in the signals
 - Output predictions are limited to the sampled time range

