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Machine Learning and Digital Twins for RUL Prediction of DC Semiconductor Circuit Breakers

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Machine Learning and Digital Twins for RUL Prediction of DC Circuit Breakers

Outline



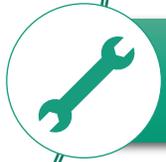
Motivation



Digital Twin Framework



RUL Prediction MOSFET Reference Dataset



Demonstrator Setup



Conclusion and Outlook

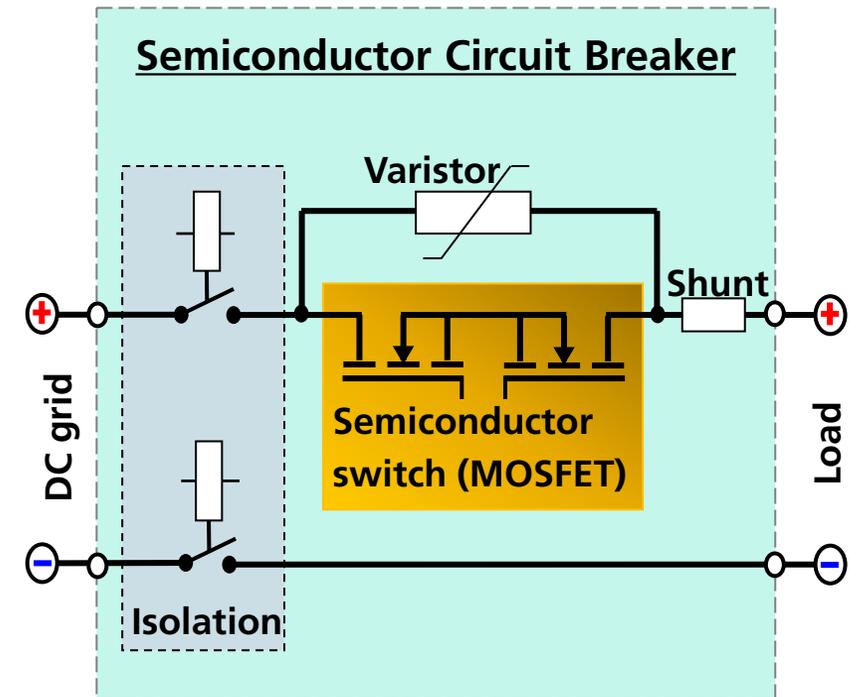


Motivation

Need for RUL Prediction of DC Semiconductor Circuit Breakers

- DC Networks
 - Increasingly utilized for e.g., integrating renewable energy.
- DC Circuit Breakers
 - Requirements: Interrupt DC currents without zero-crossing in short times.
 - Types: Mechanical, Semiconductor (SCCB) and Hybrid.
 - SCCBs interrupt currents in a range of microseconds.
- Challenges
 - High currents / voltages and harsh environmental conditions stress especially the semiconductor modules of the SCCBs.

Electric schematic of a DC semiconductor circuit breaker



Remaining Useful Life (RUL) prediction of SCCBs is essential for reliable operation and efficient usage.



Motivation

Lifetime Assessment of DC SCCBs



- Lifetime assessment in power electronics
 - Long history and high research interest.
 - In contrast to power converters: less research activity for SCCBs but transfer of methods possible.



- Lifetime assessment methods

- Physics-based
- Data-driven
- Hybrid

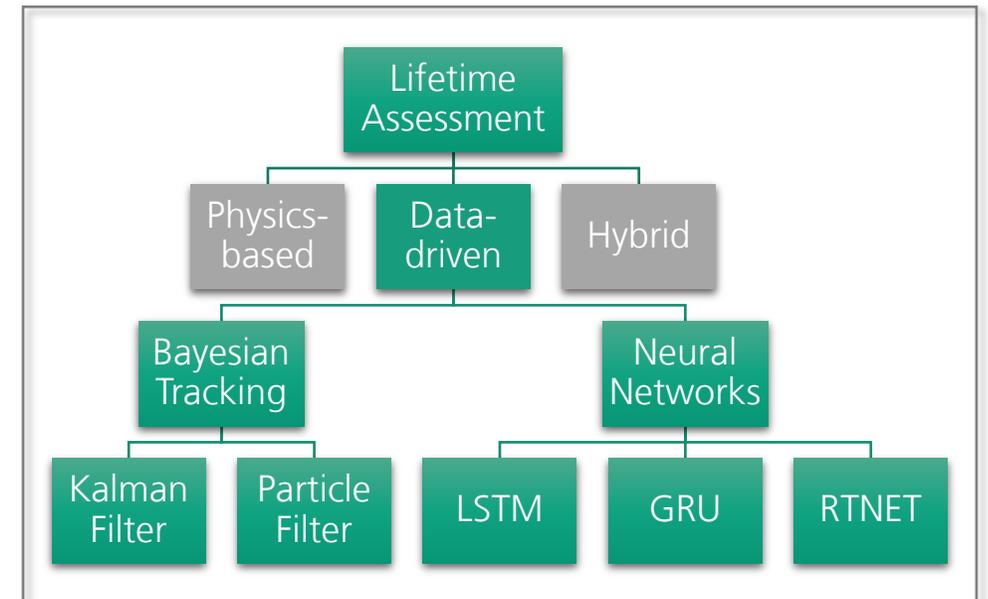


- Focus of this work

- Data-driven RUL prediction of the semiconductor module through forecasting a degradation indicator.



Overview of lifetime assessment methods





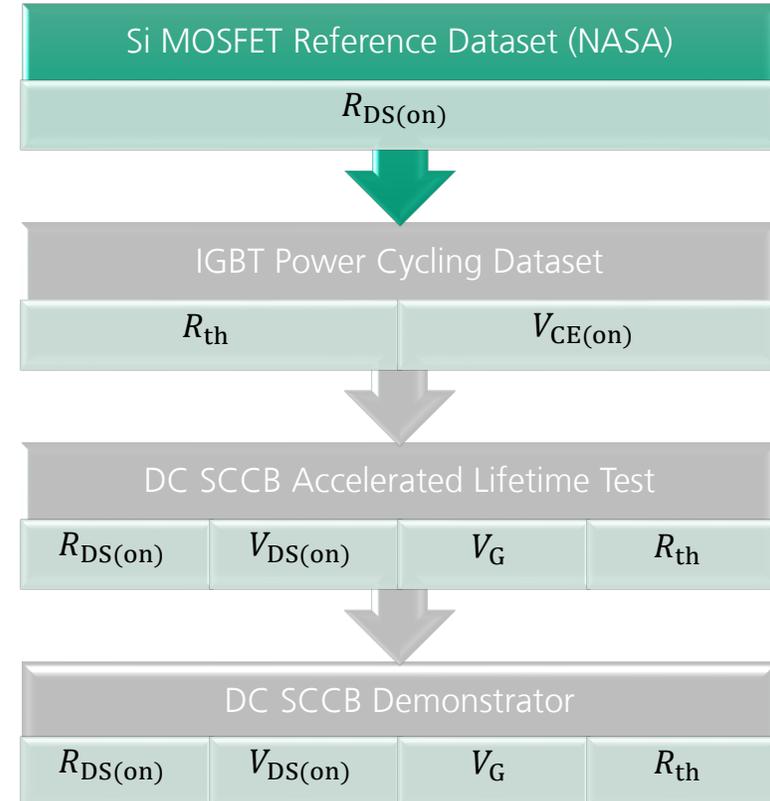
Digital Twin Framework

Approach

- Develop a digital twin framework for
 - Degradation indicator-based RUL prediction according to sensor measurements.
 - Application in lifetime tests, real-world industrial applications, and research on devices.
- Requirements
 - Continuous tracking of multiple degradation indicators.
 - Integration of historical and real-time data.
 - Providing digital services to support predictive maintenance.



Overview of data sources for the training of RUL prediction models





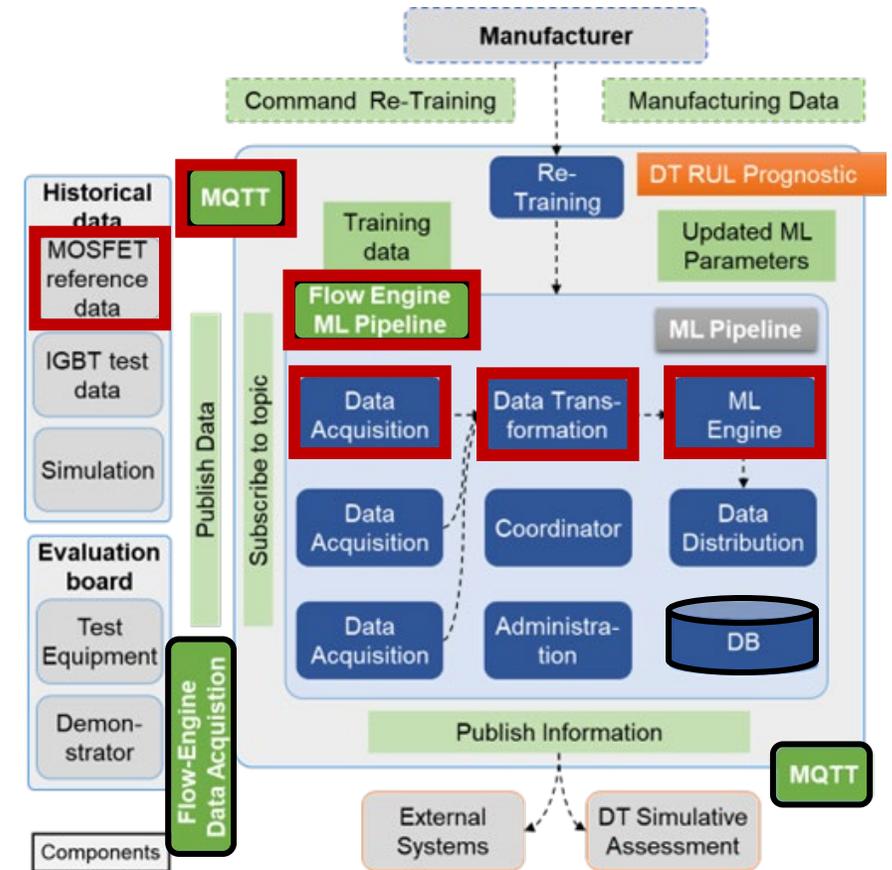
Digital Twin Framework

Architecture and Components

- Architecture
 - Design for seamless integration of different data sources.
 - Distributed edge-cloud architecture to monitor degradation indicators of multiple SCCBs during real-time operation across
- Key components
 - Flow engine
 - MQTT
 - Central database (DB): stores data, models, and model parameters.

 Components base implementation

Digital twin architecture including main components and interfaces for data transformation and ML pipeline





RUL Prediction for a MOSFET Reference Dataset

Dataset and Data Transformation



- MOSFET Reference Dataset
 - NASA's Prognostics Data Repository.
 - Thermal and power cycling of Si MOSFETs.
 - 42 different IRF520Npbf MOSFETs in a TO-220 package.
 - $R_{DS(on)}$ as degradation indicator.



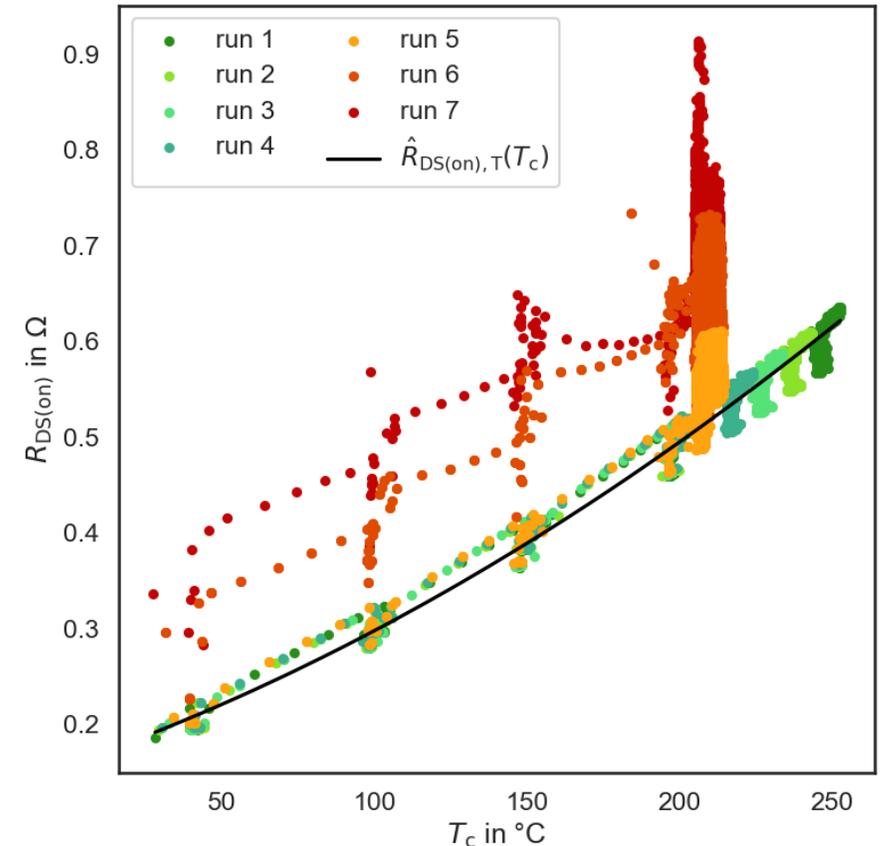
- Data transformation: Normalization of $R_{DS(on)}$
 - Temperature and degradation dependent.
 - Temperature dependency as quadratic relationship:

$$\hat{R}_{DS(on),T} = a \cdot T^2 + b \cdot T + c. \quad (1)$$

- Normalization according case temperature:

$$R_{DS(on),norm,k} = R_{DS(on),k} - \hat{R}_{DS(on),T,k}. \quad (2)$$

$R_{DS(on)}$ vs temperature for run 1-7 of device 9





RUL Prediction for a MOSFET Reference Dataset

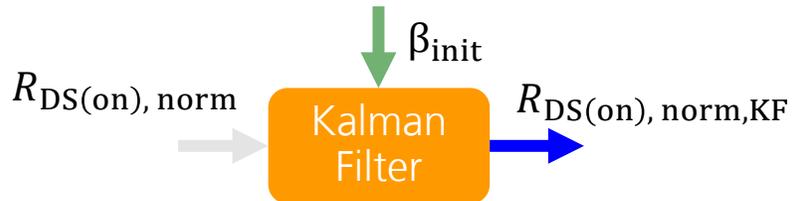
Implementation of RUL Algorithm



- Exponential degradation model + Kalman filter to forecast $R_{DS(on),norm}$.

- $R_{DS(on),norm}(t) = \alpha \cdot e^{\beta \cdot t}$ (3)

- $R_{DS(on),norm,k+1} = \underbrace{(1 + \beta \cdot \Delta t)}_{\text{state matrix } F} \cdot R_{DS(on),norm,k}$ (4)



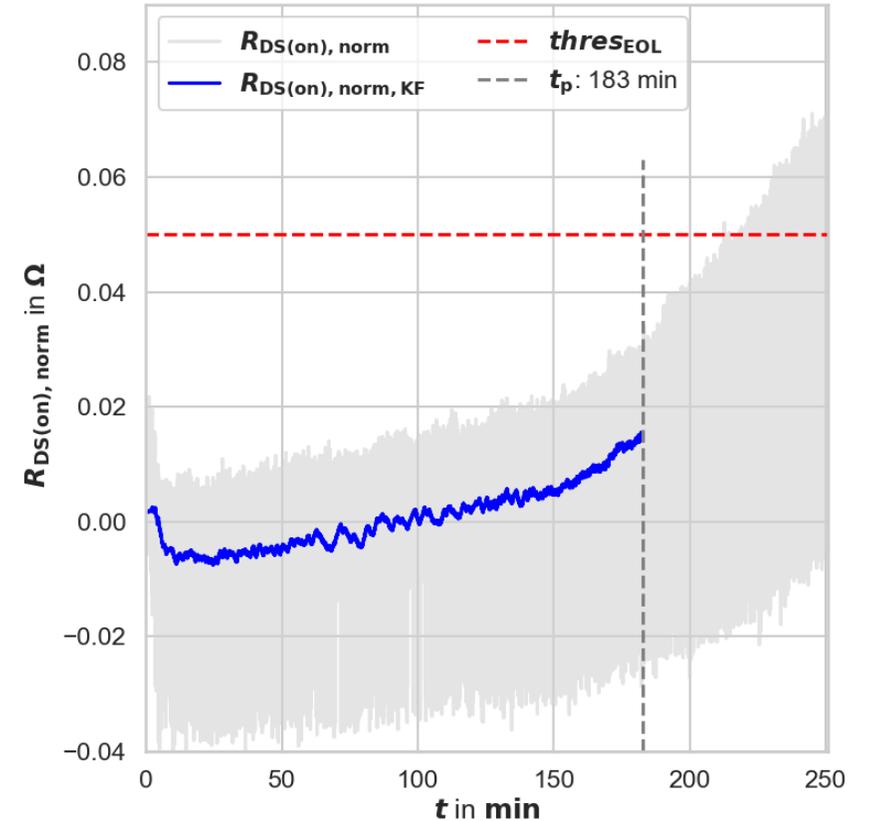
- KF predict step: $x_{pred,k} = F_k x_{KF,k-1} + B_k u_k$ (5)

- KF correct step: $x_{KF,k} = x_{pred,k} + K_k (z_k - H x_{pred,k})$ (6)

- $x_{KF,k} = R_{DS(on),norm,KF,k}$

- $z_k = R_{DS(on),norm,k}$

Kalman filter estimates $R_{DS(on),norm,KF}$ until t_p





RUL Prediction for a MOSFET Reference Dataset

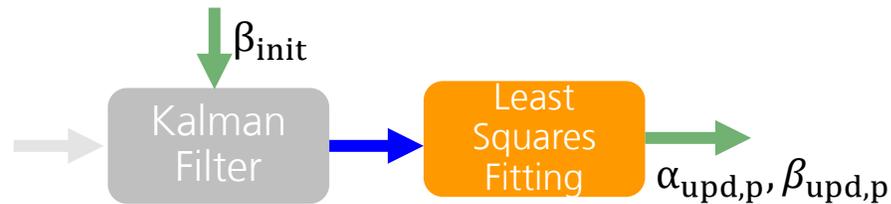
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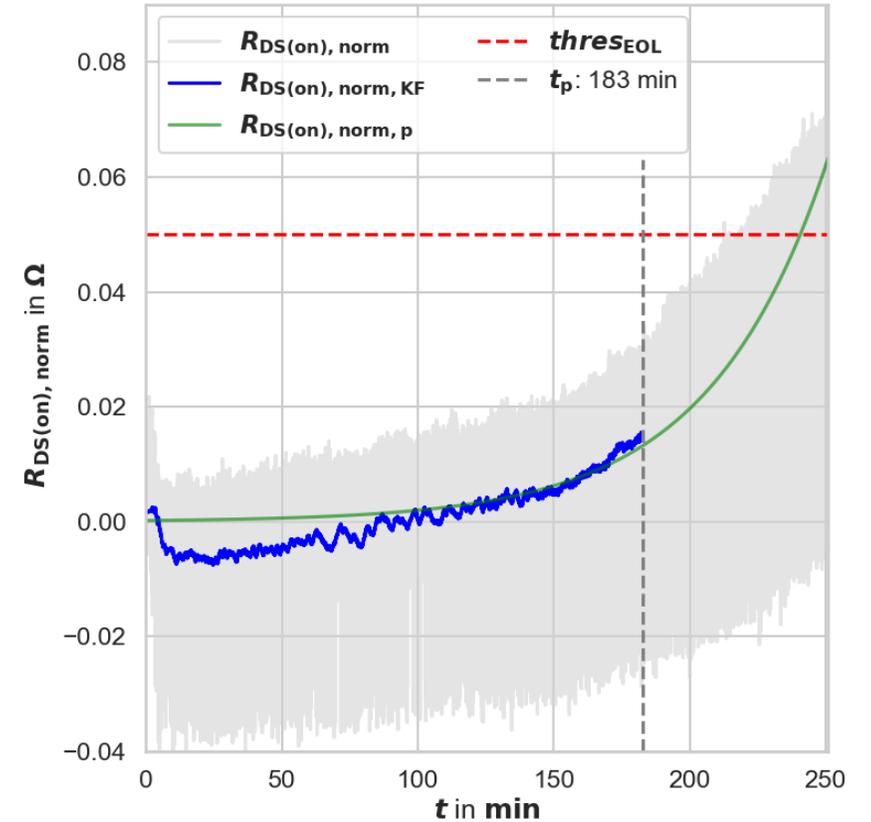
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Forecast $R_{DS(on),norm,p}$ based on Kalman filter estimates





RUL Prediction for a MOSFET Reference Dataset

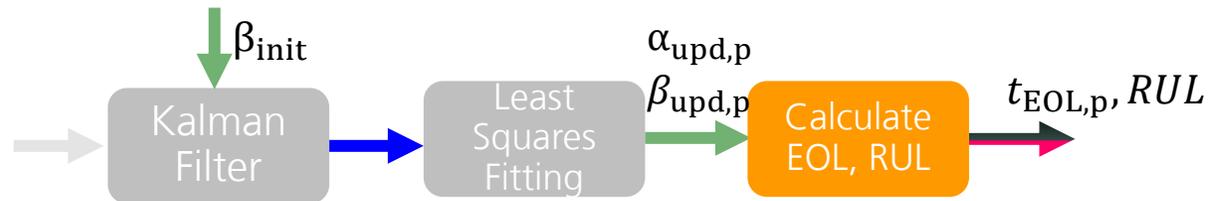
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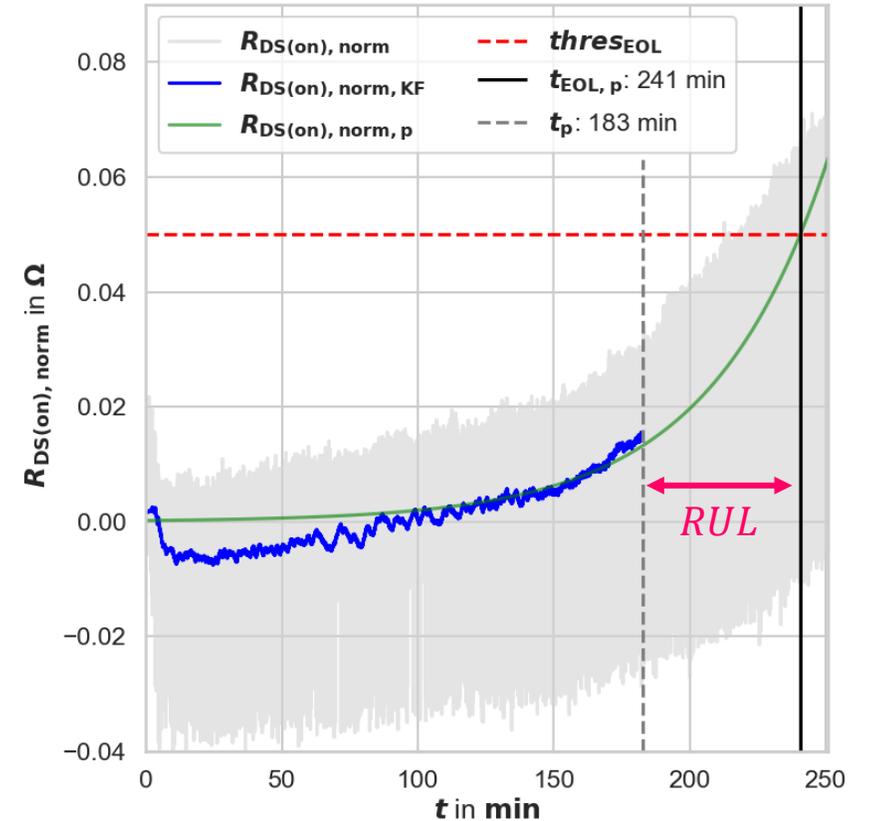
- $R_{DS(on),norm,k+1} = (1 + \beta \cdot \Delta t) \cdot R_{DS(on),norm,k}$ (4)



- $t_{EOL,p} = (\log(thres_{EOL}) - \log(\alpha)) / \beta$ (7)

- $RUL = t_{EOL,p} - t_p$ (8)

Forecast $R_{DS(on),norm,p}$ based on Kalman filter estimates





RUL Prediction for a MOSFET Reference Dataset

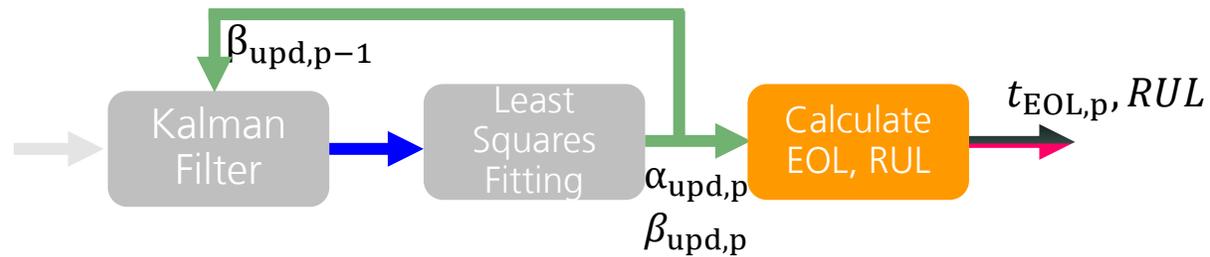
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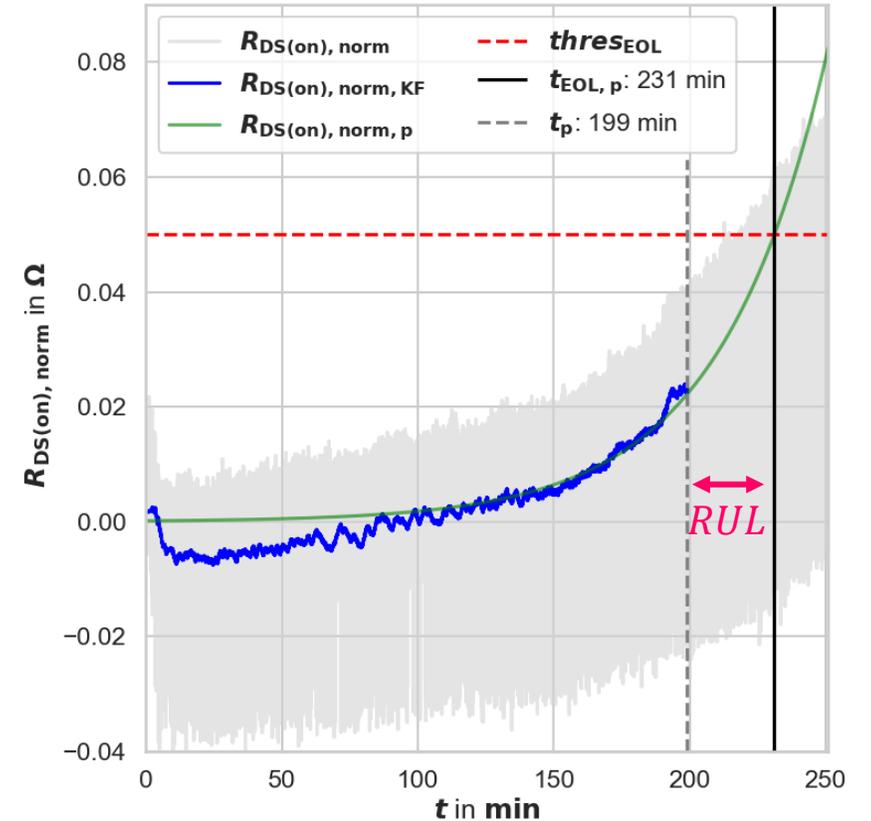
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Forecast $R_{DS(on),norm,p}$ based on Kalman filter estimates



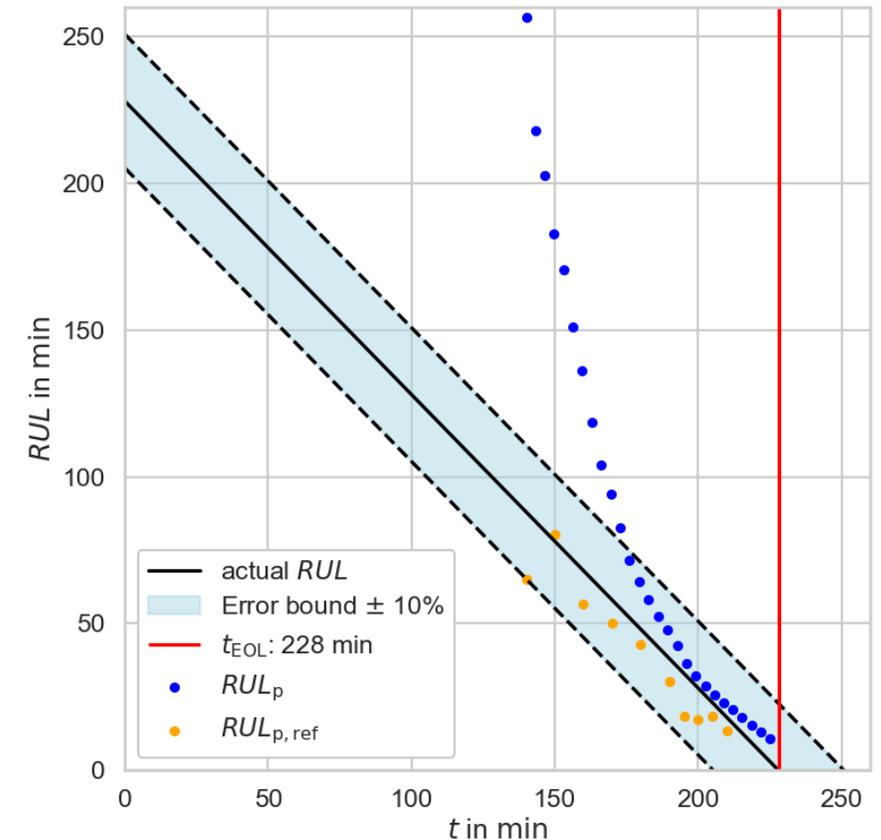


RUL Prediction for a MOSFET Reference Dataset

Results

- Base implementation
 - Best RUL predictions: 199 - 206 minutes, absolute error: 4 min.
 - Afterwards: results slightly diverge.
 - Comparable to reference implementation, thus satisfactory.
- Reference implementation (extended Kalman filter)
 - Signal is filtered with mean filter before.
 - Best RUL prediction: 150 min, absolute error: 2 min.
- Planned developments
 - Improve prediction at pristine state.
 - Generalize algorithms for accelerated lifetime tests and real-world applications.
- Data from accelerated lifetime tests do not capture all operating conditions → future work will incorporate real-world field data.

RUL predictions of base implementation and reference implementation





Demonstrator Setup

Motivation

- Enable testing for real-world conditions of DC grids to gather practical aging behavior data.
- DC networks can vary significantly:
 - Grounding systems: TN-S, AC-sided grounding, IT (floating high ohmic midpoint grounding).
 - Load dynamics: Fast (e.g., welding) vs slow (e.g., PV).
 - Grid characteristics: cable length → variations in inductances and resistances.
 - Faults: Low/high resistive short circuits, ground faults, arc faults.

Parameter ranges of the demonstrator

Parameter	Value Range
Voltage	$\leq 1500 \text{ V}$
Nominal current	$\leq 100 \text{ A}$
Short-circuit current	$\leq 10 \text{ kA}$
Power grid replication	Inductance $\leq 400 \mu\text{H}$ Resistance $\leq 20 \text{ m}\Omega$
Capacitance	108 mF up to 850 V 54 mF up to 1500 V

A testing system is developed that can flexibly replicate the diversity of DC grids and potential faults.



Conclusion and Outlook

- Objective
 - Ensure reliability of DC SCCBs through accurate RUL predictions and digital twin services.
- Achievements
 - Base implementation of an RUL prediction in a digital twin framework realized.
 - Concept and design phase for a real-world demonstrator completed.
- Future work will include RUL prediction for
 - IGBT power cycling data,
 - Testing of SCCBs with integrated SiC MOSFETs,
 - Data for real-world load profiles collected on the demonstrator setup.
- Challenges
 - Generalize models for the different data sets and applications.
 - Develop additional ML algorithms to further enhance prediction accuracy.



Acknowledgement

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**Thank you for
the attention!**

I'm pleased to answer your
questions.
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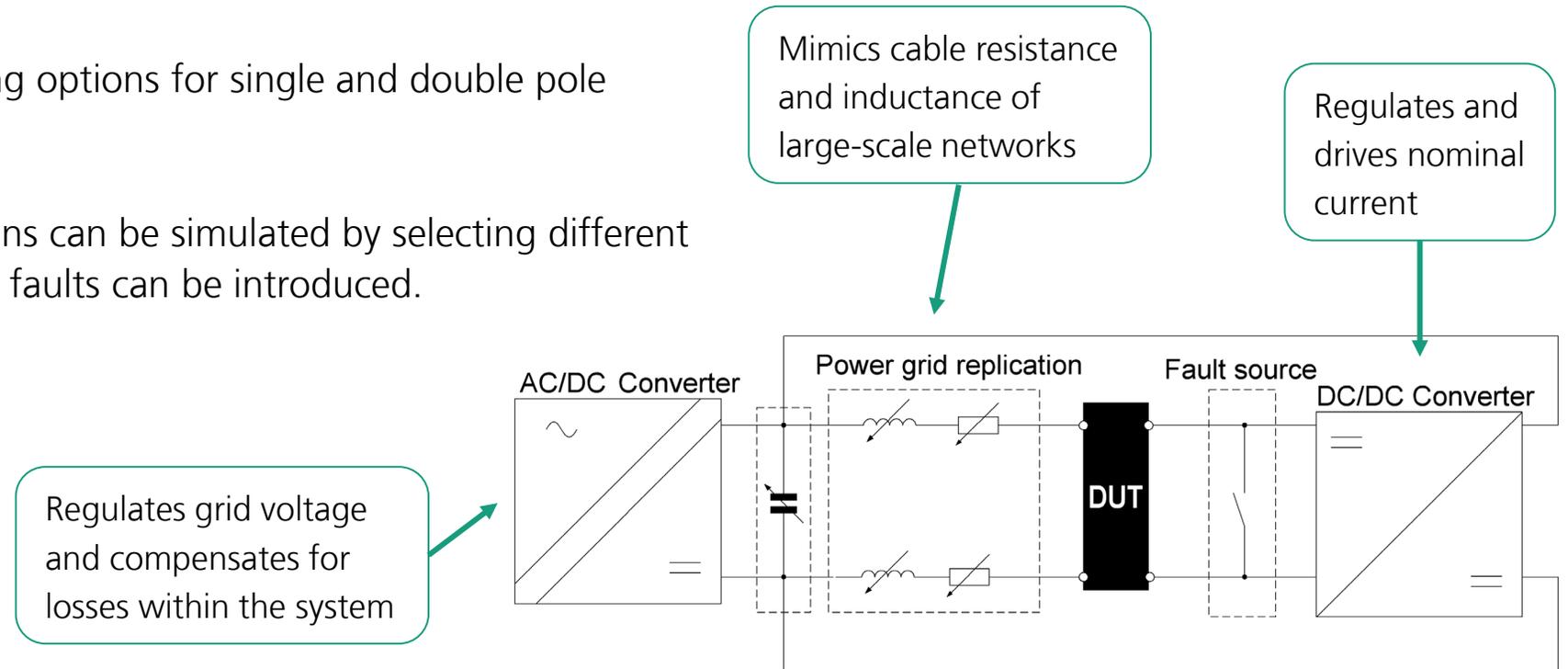


Demonstrator Setup

Hardware Realization



- The demonstrator operates as a single DC line in a sink-source configuration (bidirectional energy flow is possible).
- Integration and testing options for single and double pole circuit breakers.
- Various DC applications can be simulated by selecting different load profiles and grid faults can be introduced.



Electric schematic of the demonstrator setup