Forecast-based predictive analytics and operational control for utility-scale photovoltaic power plants

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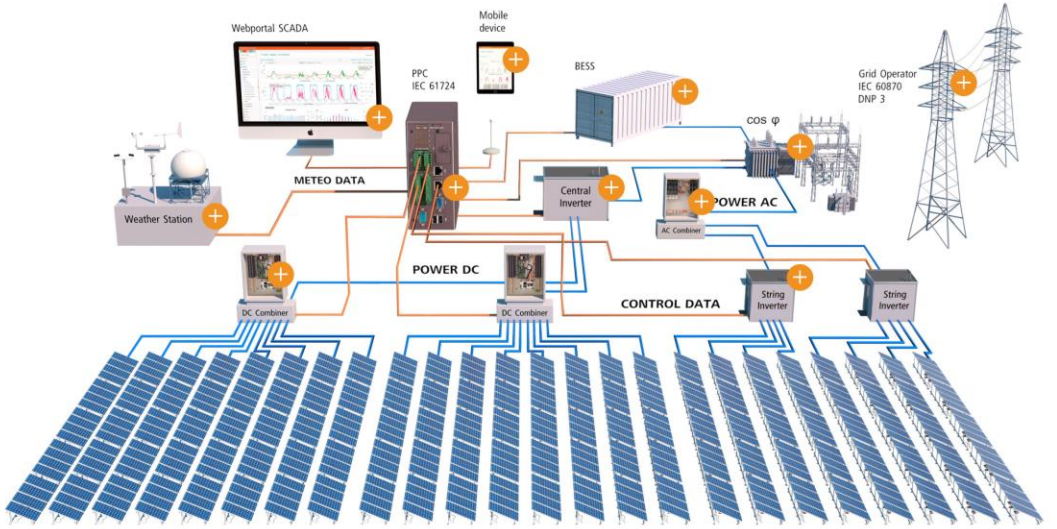
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Introduction

- Key enabling factor for PV uptake is to:
  - Improve lifetime performance
  - Enhance system operations
- Data-driven analytics:
  - Digital twin models for performance monitoring
  - Predictive analytics for the diagnosis and prognosis of common PV faults



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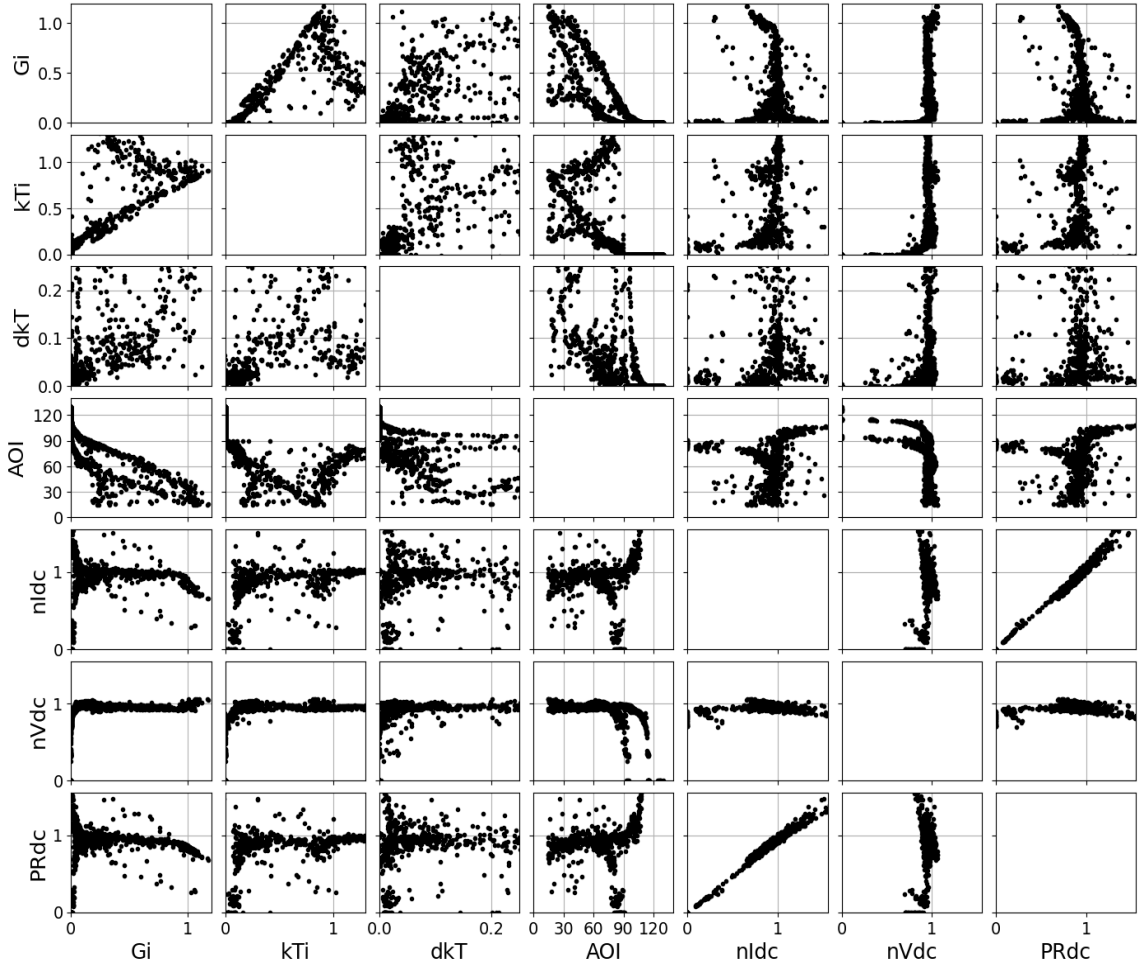
Methodology

- Sequence of steps to implement the forecast-based framework

Experimental setup and naming convention of data streams

- Test PV systems
- Unified naming and normalization [*I*, *V*, *P*, *G*]

Data acquisition and normalization
- High-resolution PV and weather data
- Normalize to rated values



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Methodology

- Approach followed to implement the forecast-based framework

Exp. setup and naming convention of data streams

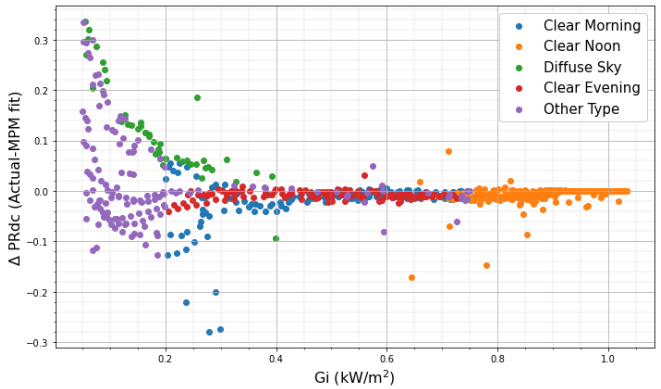
- Unified naming and normalization [*I*, *V*, *P*, *G*]

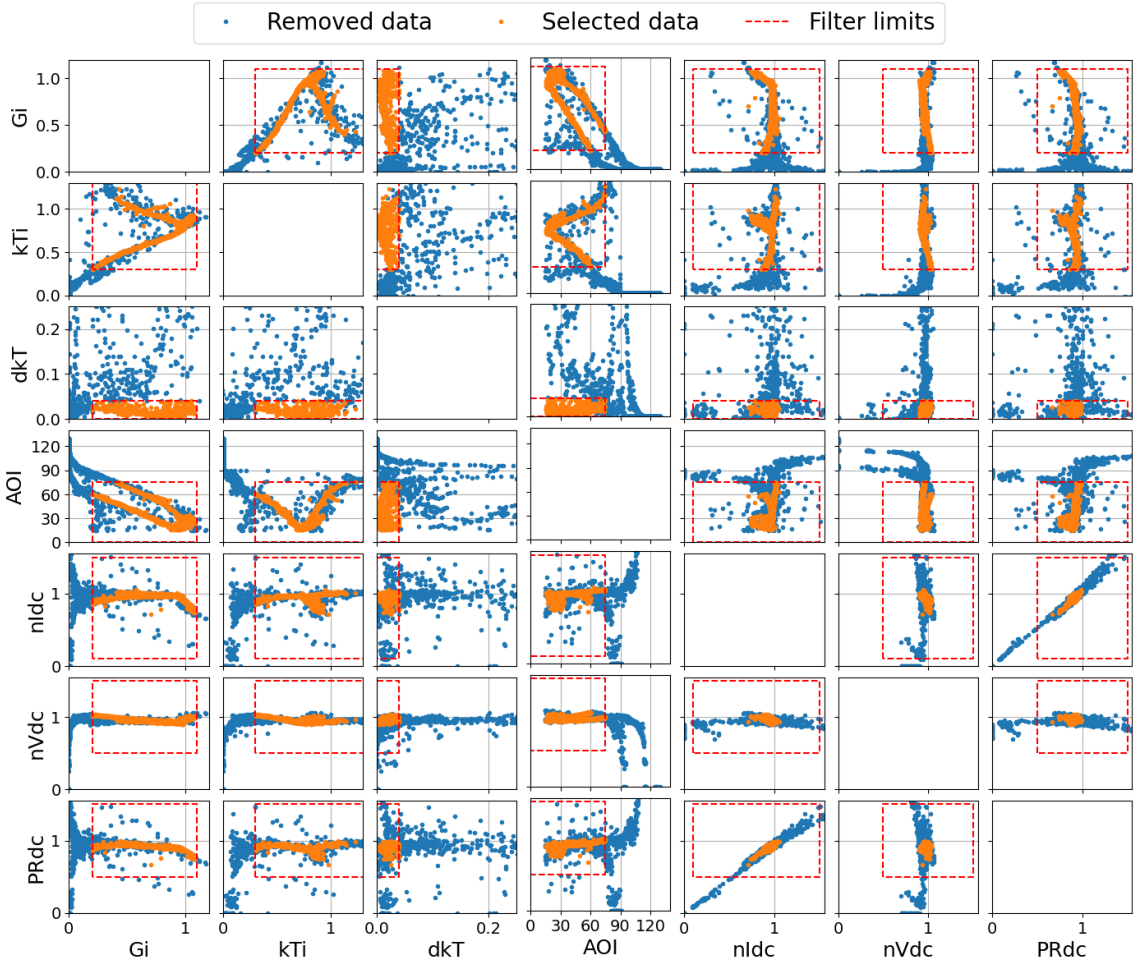
Data acquisition and normalization
- High-resolution data
- Normalize to rated values

Data enrichment and filtering

- Data sanity and filtering for stable *G*, T_{amb}, AOI, and k_T conditions

Example of filters
- 0.2<Gi<1.1
- 0<Tmod<70
- 0.1<performance Ratio (PR)<1.0
- 0.3<clearness index (kT)





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Methodology

- Approach followed to implement the forecast-based framework

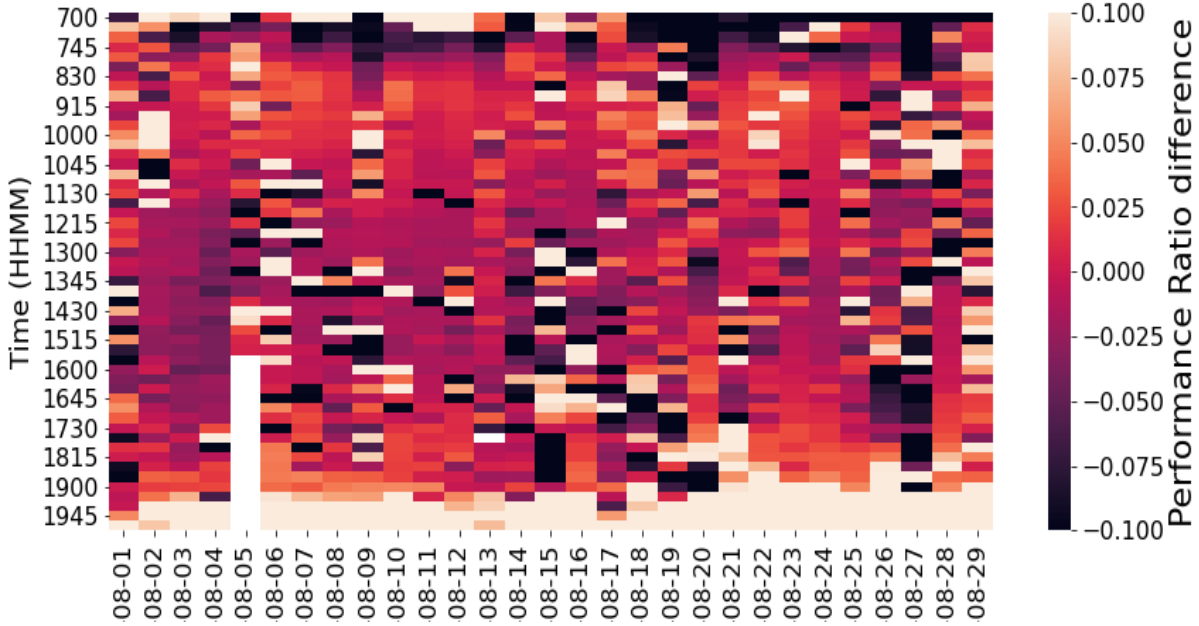
Digital Twin (predictive model) – Fault detection controls

- Digital Twin models
- Fault detection controls

Digital Twin models
- XGBoost (machine learning)
- Mechanistic Performance Model (MPM) for predicting PR
- Statistics/decision rules (secondary controls) for faults

$$MPM_{Param} = C_1 + C_2*(T_{MOD}-25) + C_3*Log_{10}(G_I) + C_4*G_I + C_5*WS$$

e.g., PR, nVdc, nIdc — Tolerance — Temperature — Voc and Rshunt — R_{SERIES} — Wind



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Methodology

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Digital Twin (predictive model) – Fault detection

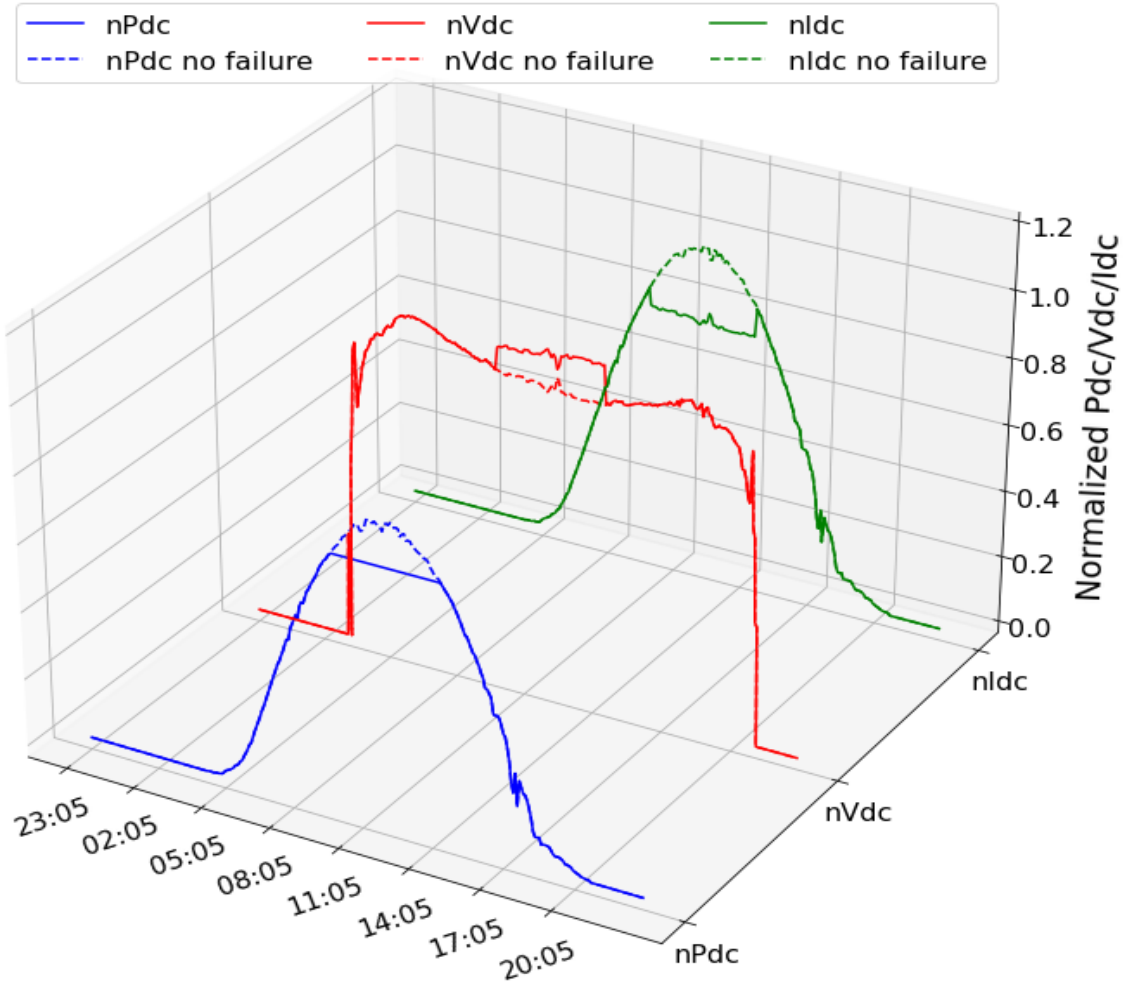
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- Fault detection controls

Digital Twin models
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Health-state – Fault diagnosis (AI and fault patterns)

- Emulated faults
- Creation of fault signatures
- Labeled conditions
- Trend loss detection

Example of signatures
- Clipping/curtailment
- Inverter faults
- PID

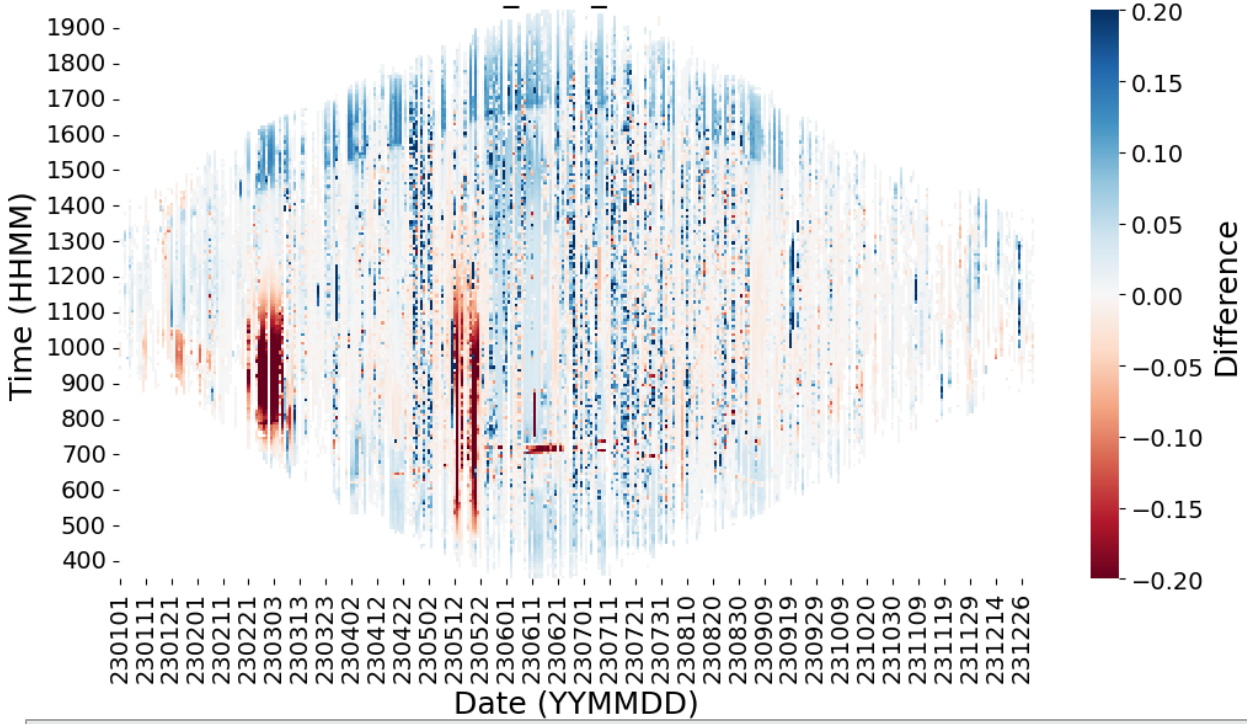


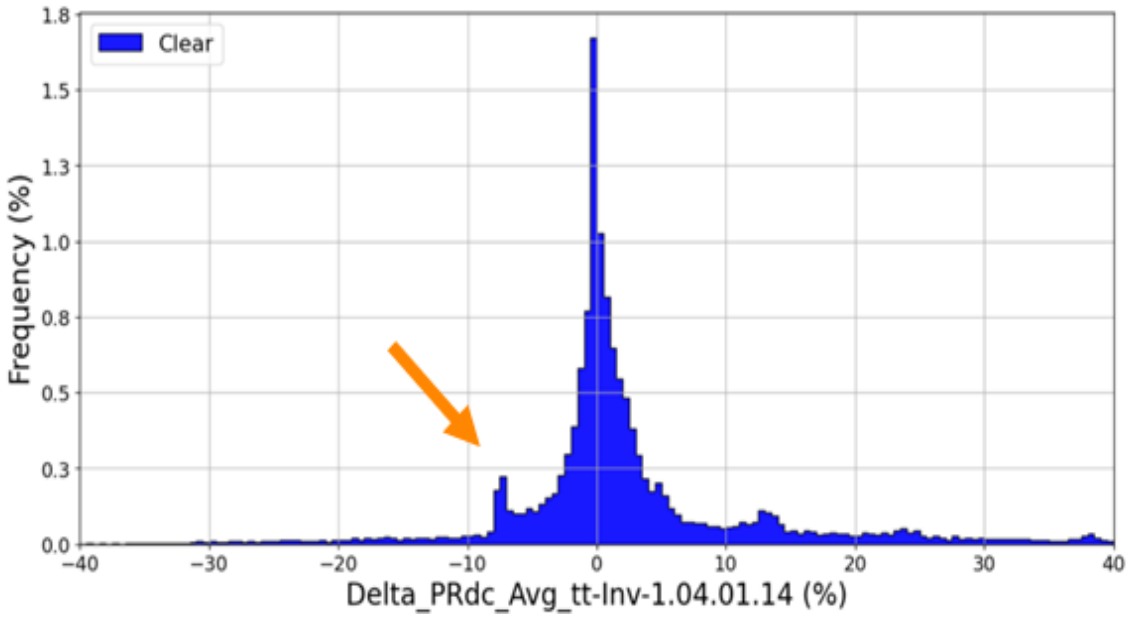
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Results – Digital twin

- Digital twin (MPM) application on data from utility-scale PV plant:
  - 1 month training with filtered data (*G*, *T, solar angle* and *PR*)





PR heatmaps: deviations < 0.2% for normal conditions

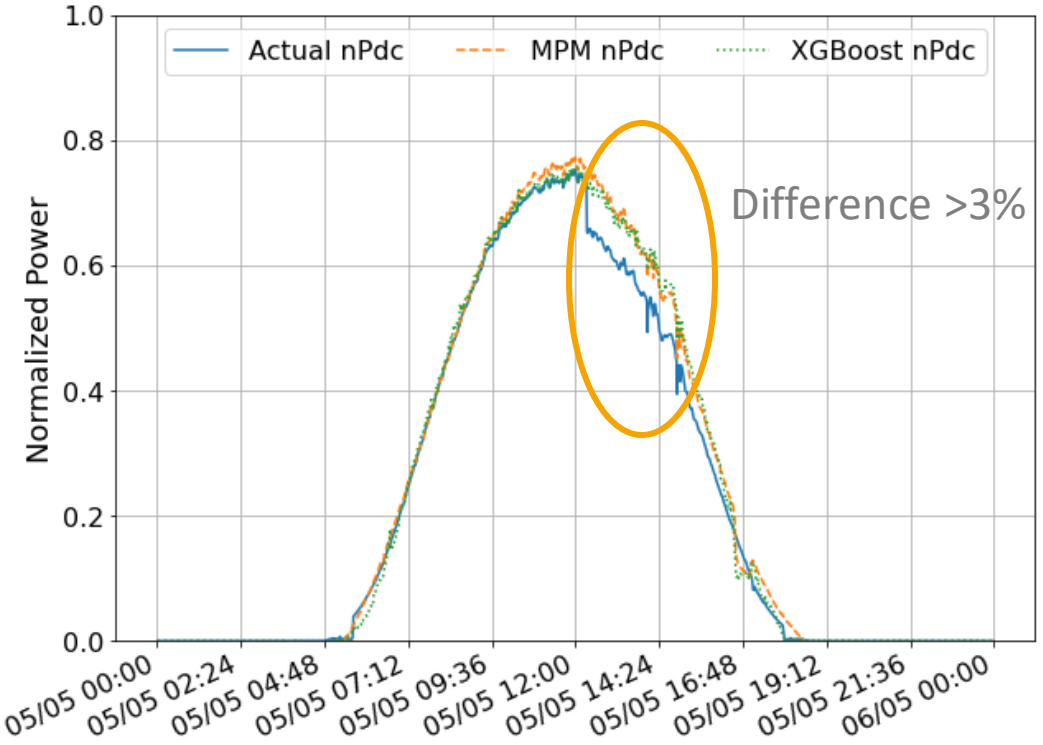
- *Faults exhibited as outliers in frequency distribution plots*

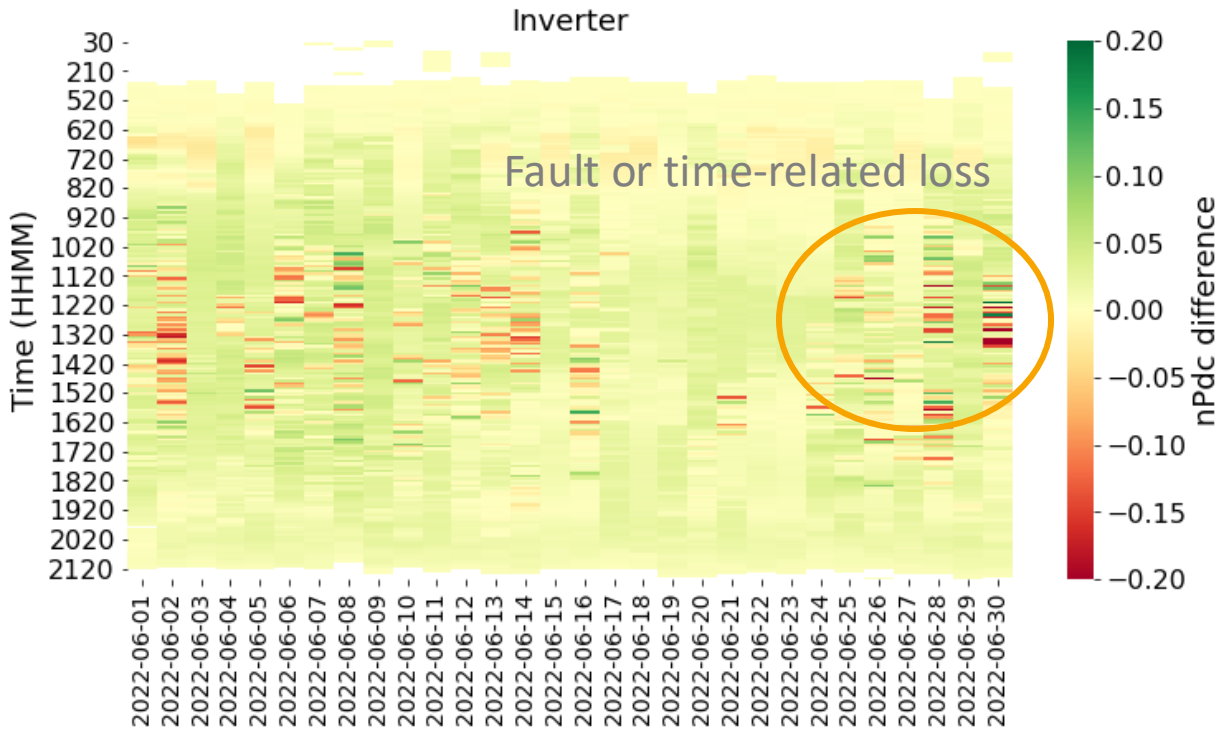
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Results – Failure detection

- Digital twin operation in-line to data streams of utility-scale PV plant:
  - Daily loss deviations >3% categorized with control heatmaps (fault or time-related loss)





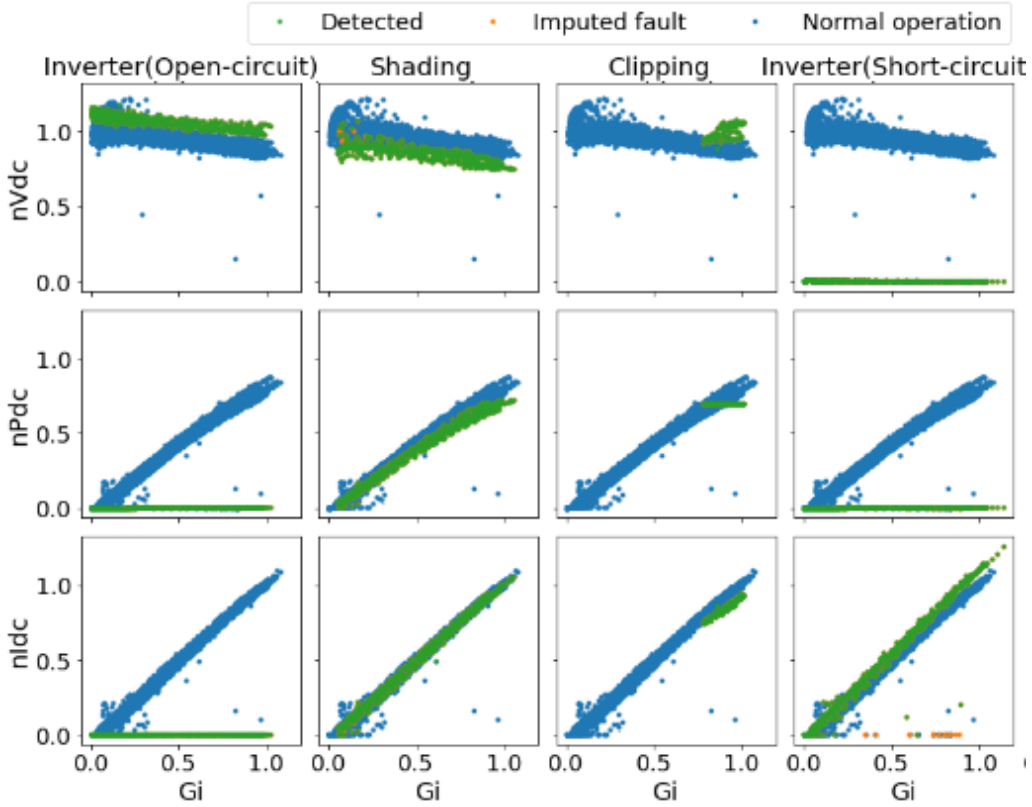
Digital Twin is capable to detect fault conditions (>3%) and categorize their persistency

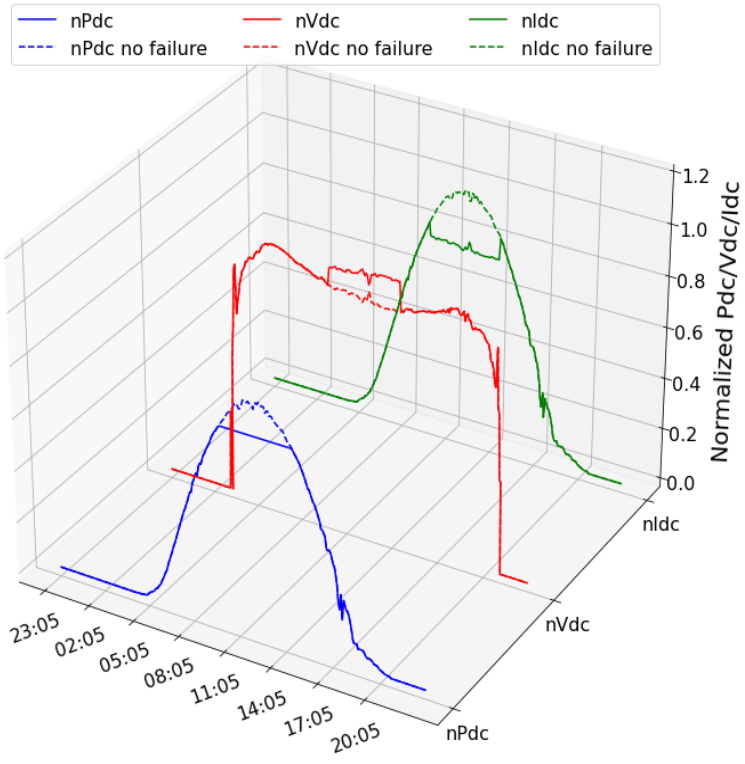
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Results – Failure classification

- Failure diagnosis using XGBoost classifiers for P, V and I faults at utility-scale plants





Classification accuracy >90% (>3% *P*, *V* and *I* faults)

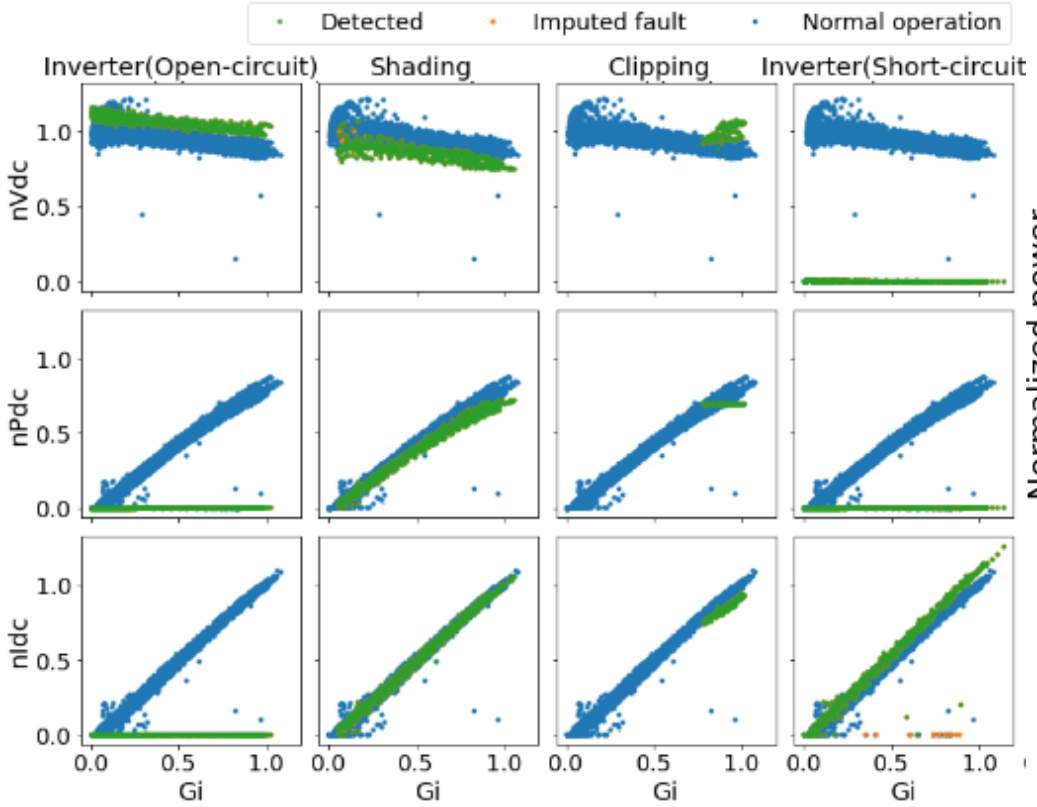
- *Clipping/curtailment, open/short-circuit faults*

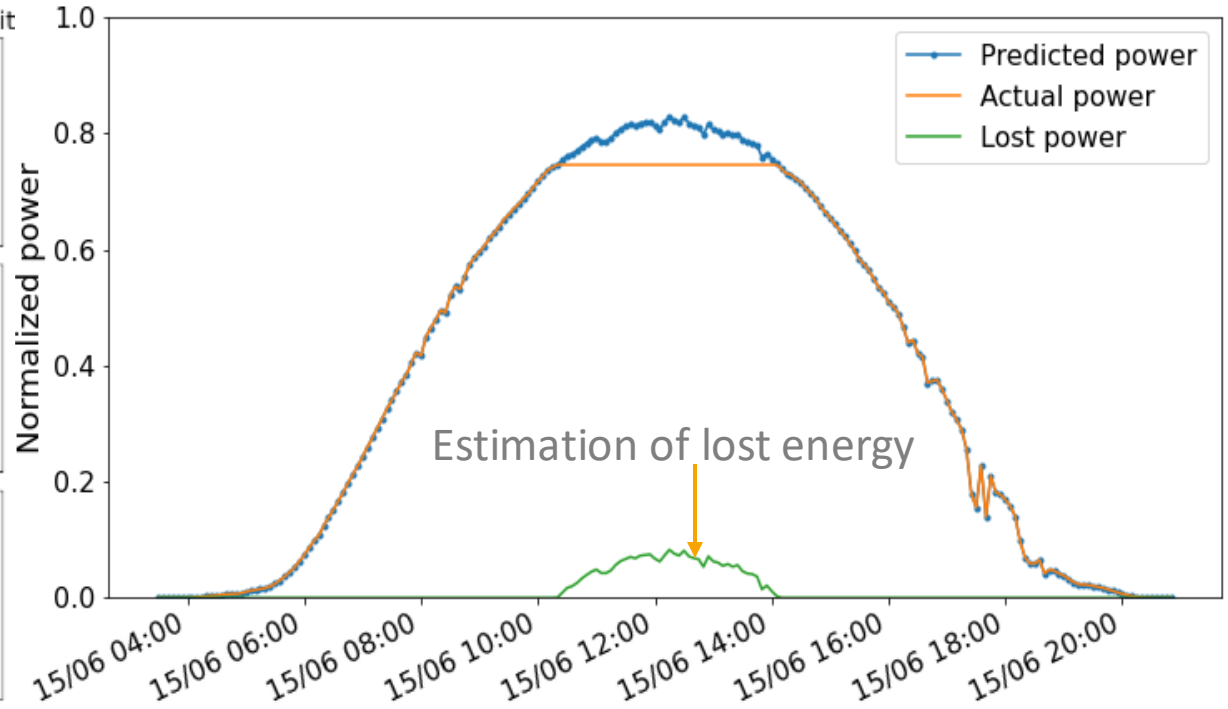
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Results – Failure classification & energy loss estimation

- Failure diagnosis using XGBoost classifiers for P, V and I faults at utility-scale plants





Classification accuracy >90% (>3% *P*, *V* and *I* faults)

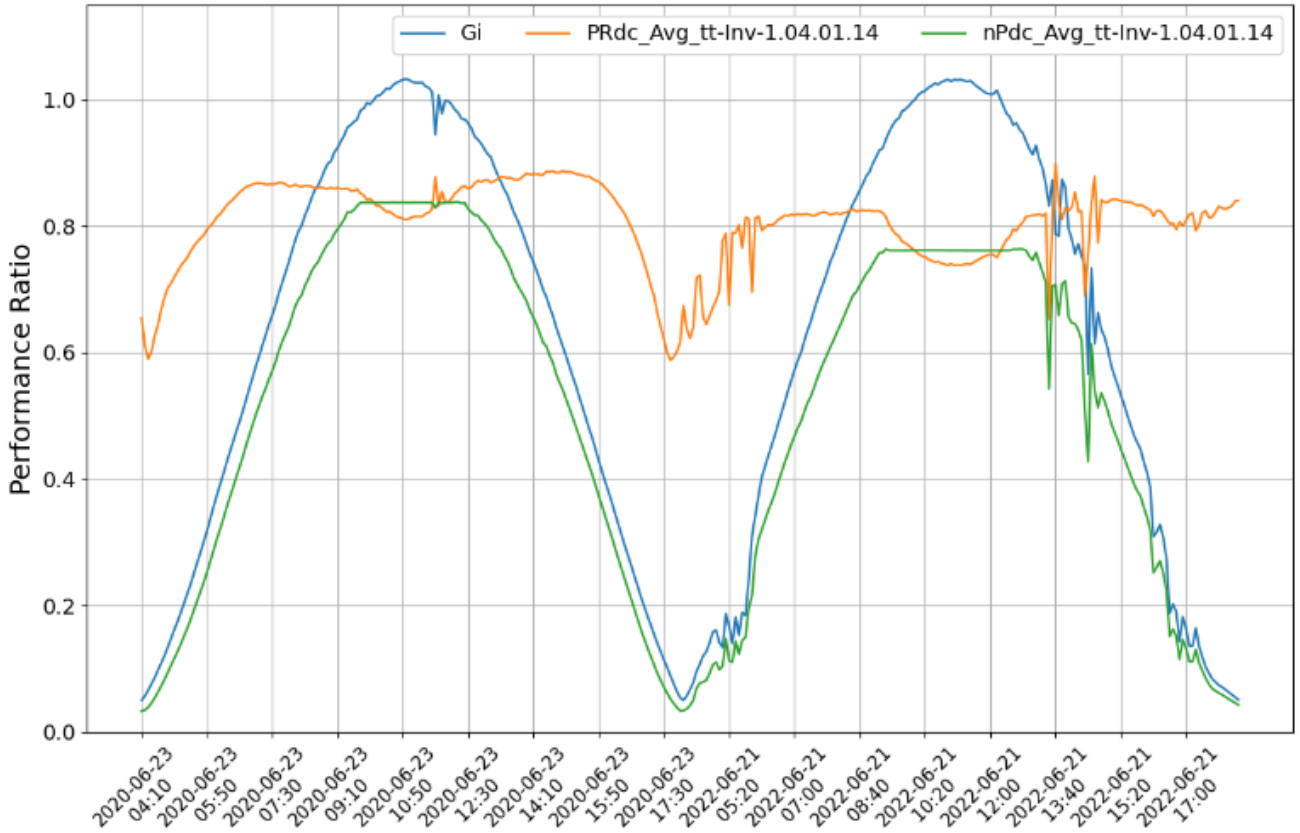
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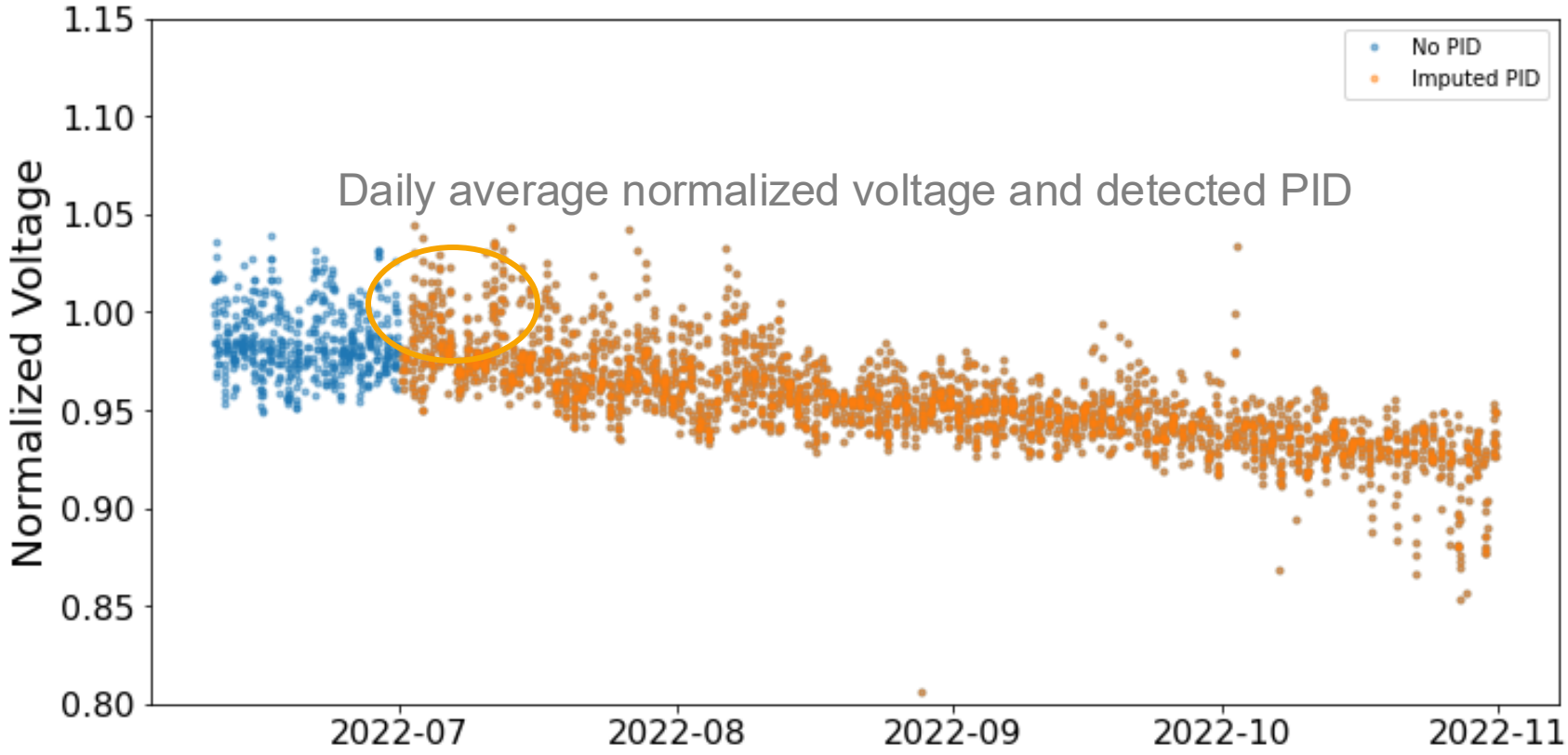
Results – Failure diagnosis (examples)

- Failure detection of inverter clipping conditions (visible as midday plateaus in the performance ratio curves) over a two-days period



Results – Failure prediction

- Failure detection/prediction of PID conditions (10%/year drop of voltage)

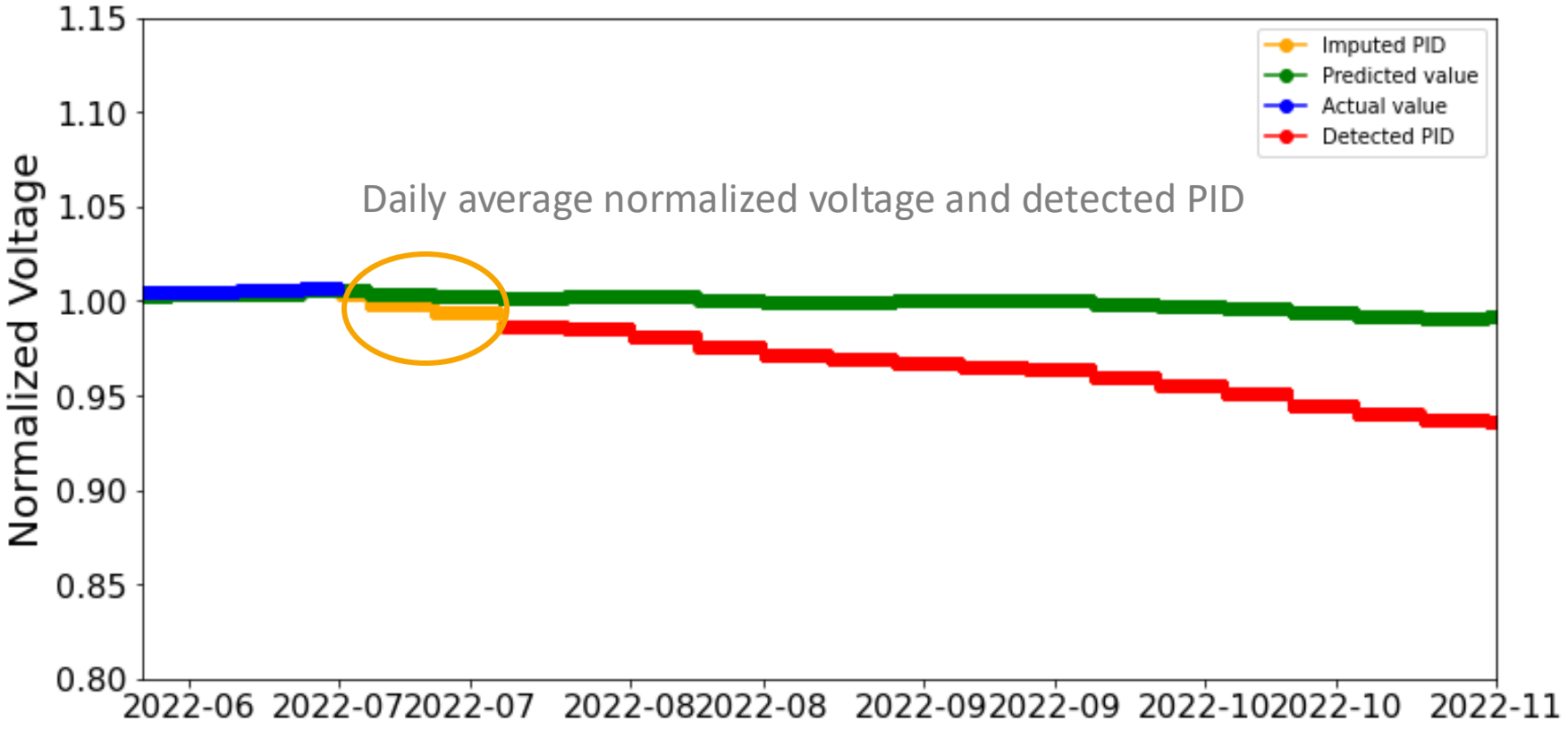


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Results – Failure prediction

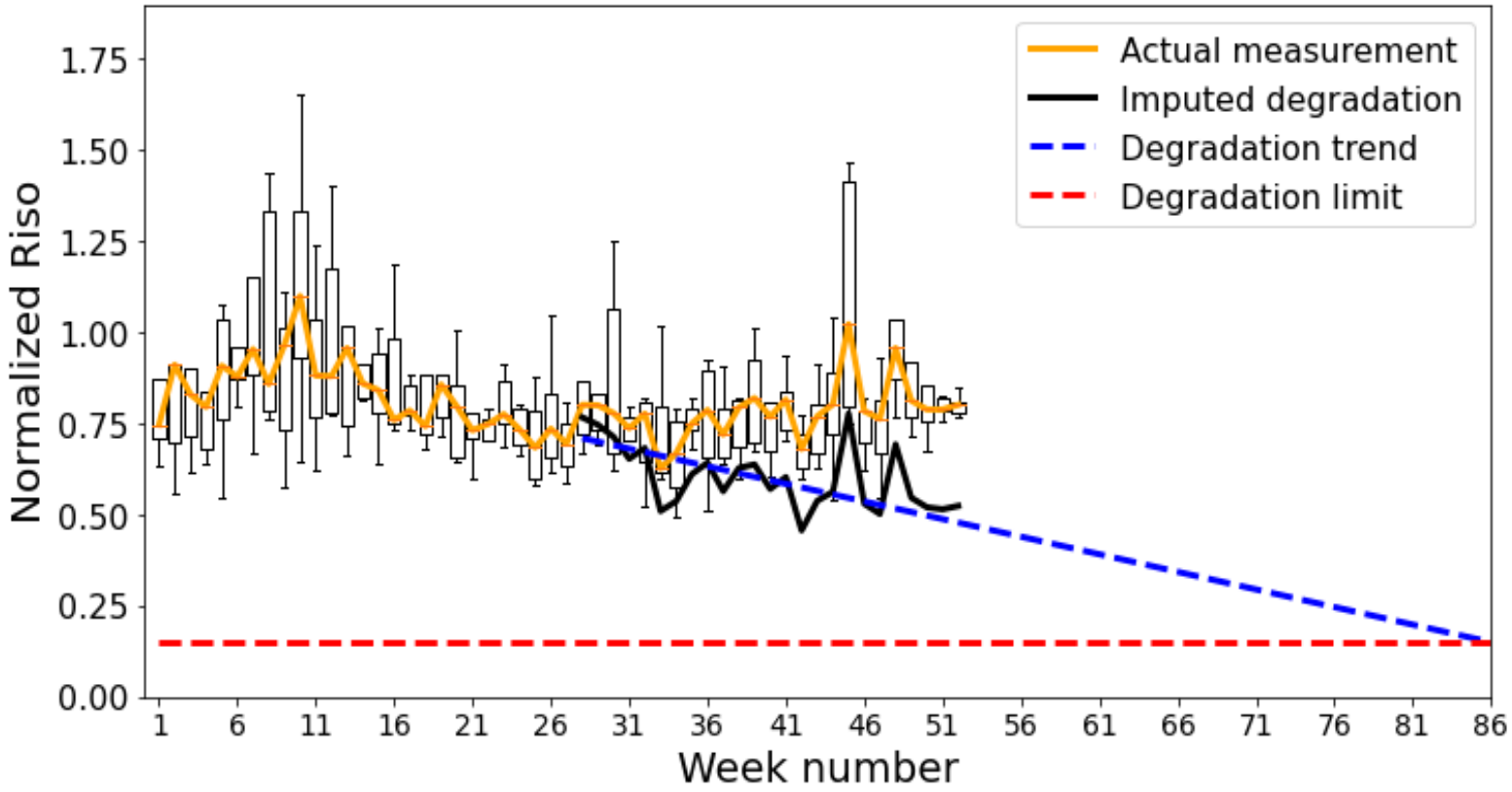
- Failure detection/prediction of PID conditions (10%/year drop of voltage)



Detection (~week) of PID conditions by analyzing the average weekly voltage slope

Results – Failure prediction

- Failure detection/prediction of insulation resistance (Riso) degradation



Timely capturing of trend loss and prediction of Riso < 100 kΩ

Conclusions

- Digital twin model based on MPM was developed and combined with secondary controls (heatmaps) for fault diagnosis
- Faults were classified by comparing the exhibited patterns to fault signatures of common faults
- The model was capable to predict emulated trend-based (e.g., PID) and Riso faults
- Future work involves the application to different locations, verification against actual maintenance logs and enhanced modelling of more inverter faults

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Thank You

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