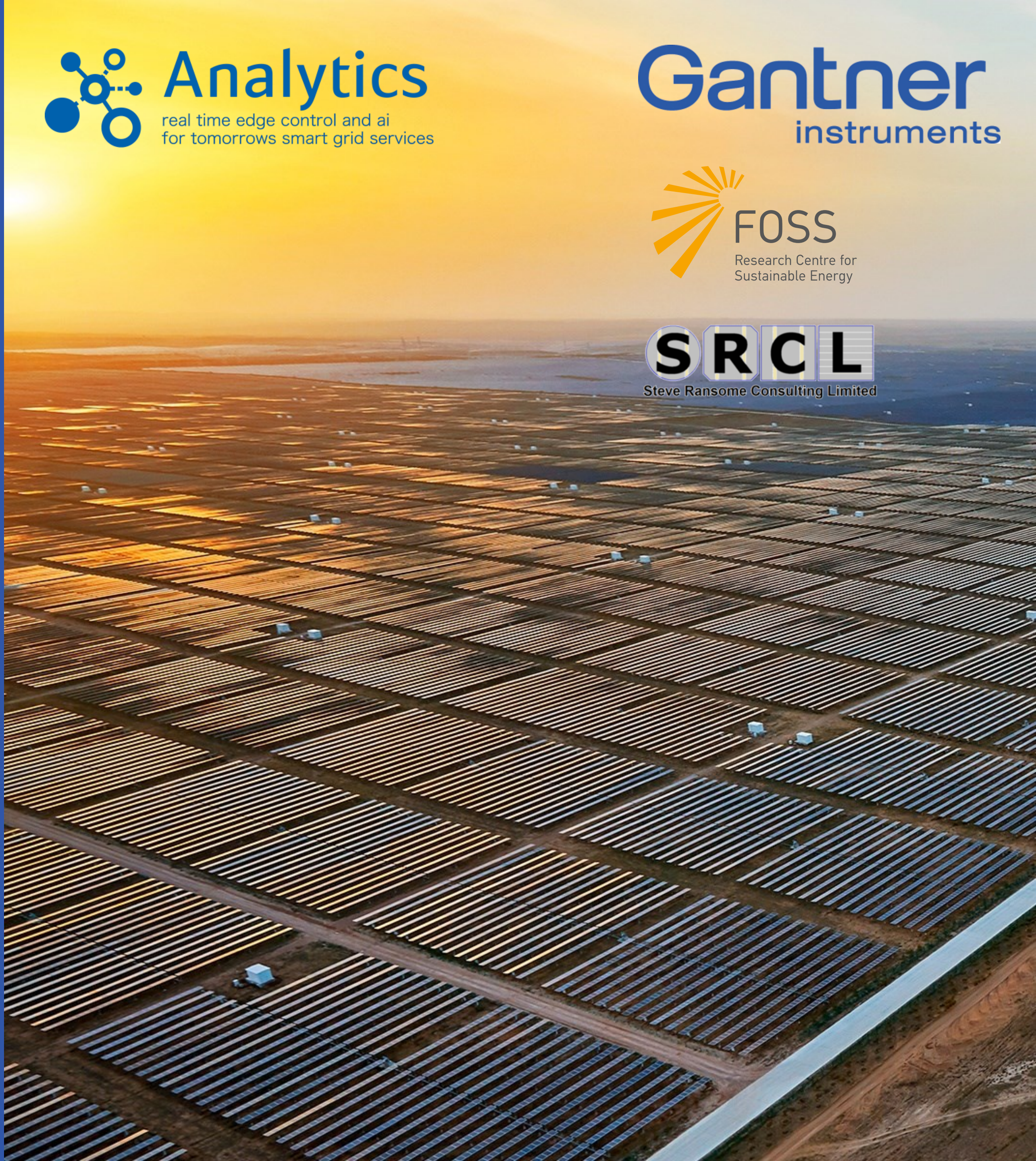
Advanced system monitoring and artificial intelligent data-driven analytics to serve GW-scale photovoltaic power plant and energy storage requirements

PVPMC Workshop
Aug 24th, Salt Lake City, UT

Jürgen Sutterlüti et. al.
j.sutterlueti@gantner-instruments.com



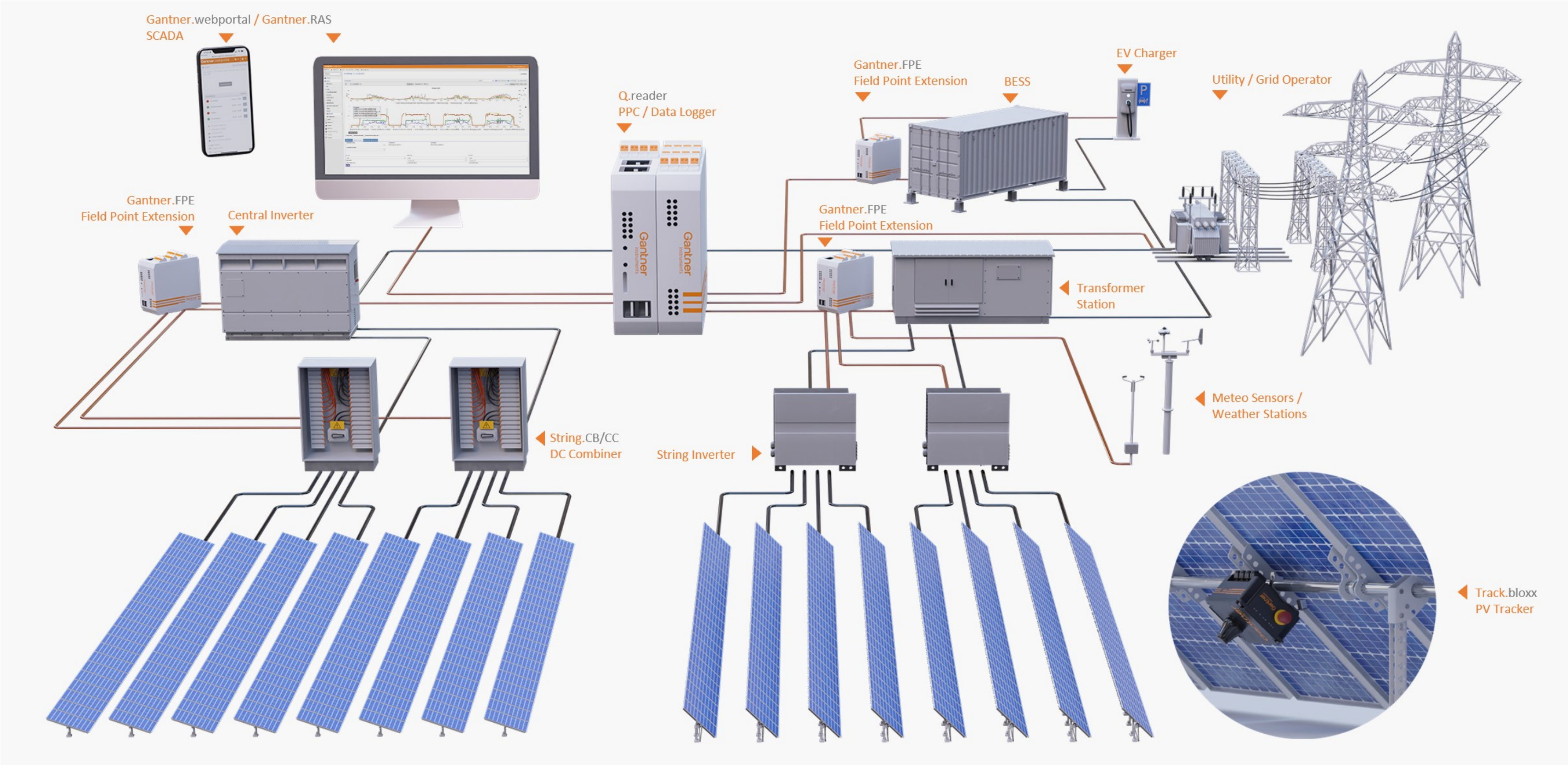
Introduction

- Future PV uptake → reduction of the Levelized Cost of Electricity (LCoE)
- Reduced LCoE achieved by increasing lifetime performance & reducing O&M costs

$$\downarrow \boxed{\begin{array}{c}\text{LCoE}\\(\$/\text{MWh})\end{array}} = \frac{\text{CapEx} + \boxed{\text{O\&M}}\downarrow}{\boxed{\begin{array}{c}\text{Energy}\\\text{yield}\end{array}}\uparrow}$$

Agenda

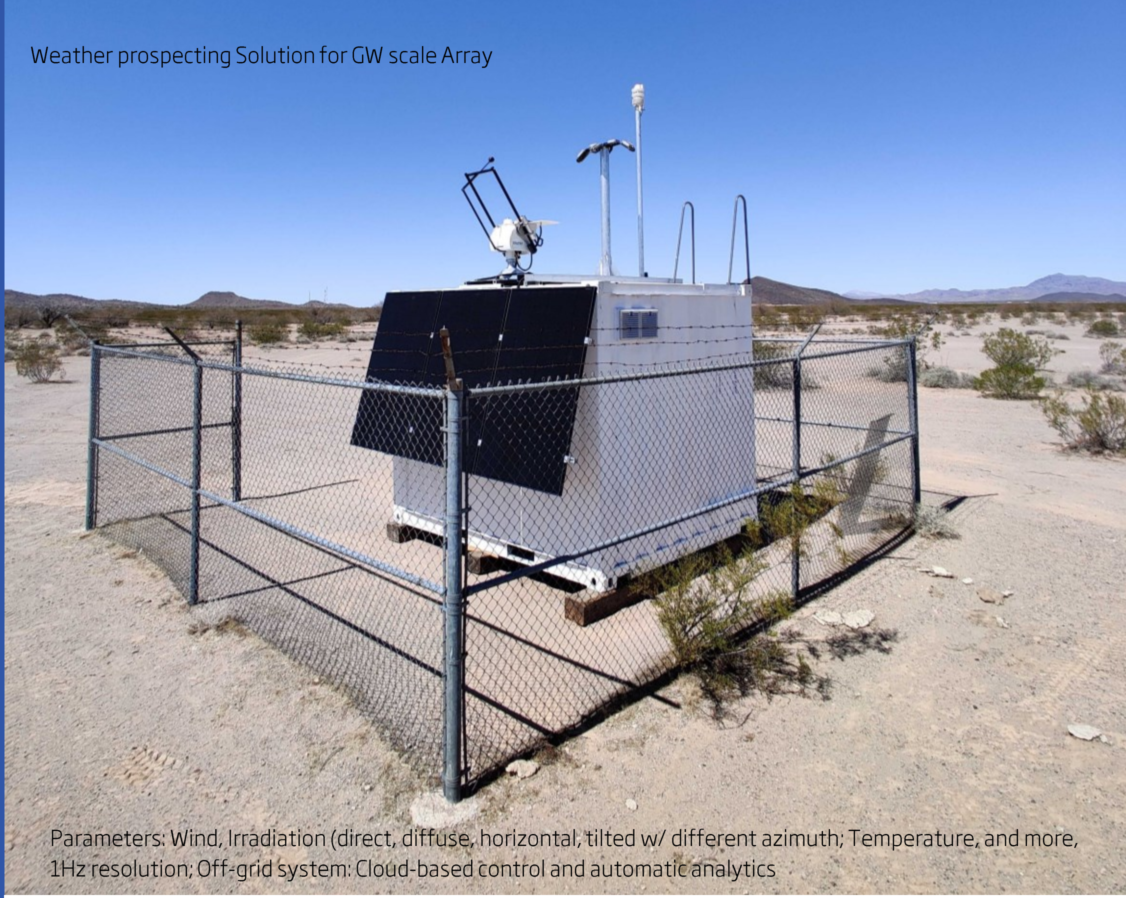
- Weather prospecting
- PV Module analytics
- PV Power Plant analytics, ML
- Smart Grid integration
- Lessons learned

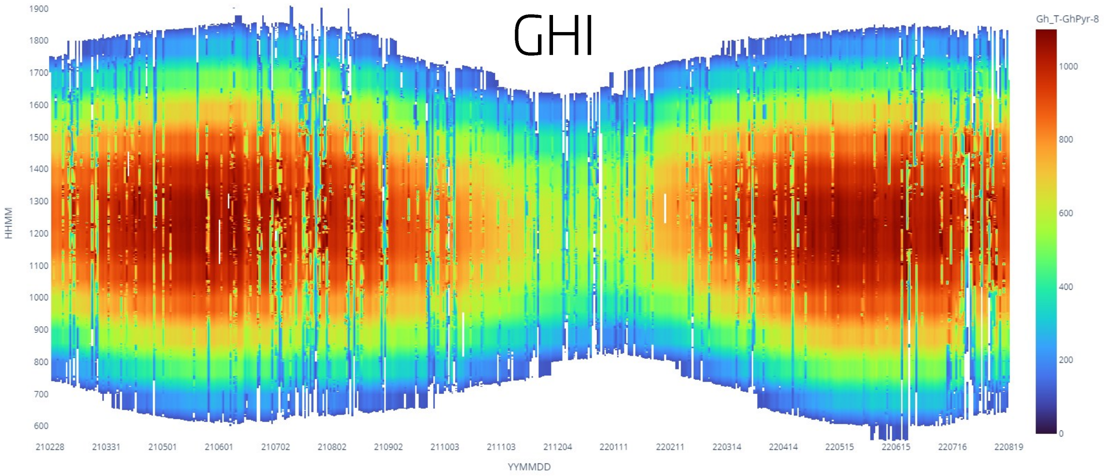


With Gantner's turn-key monitoring and control, Europe's largest PV park (600MW) is under way.

Weather prospecting

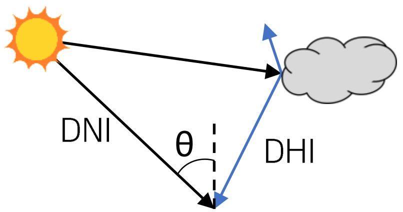
Reliable Information for Optimum Energy Output



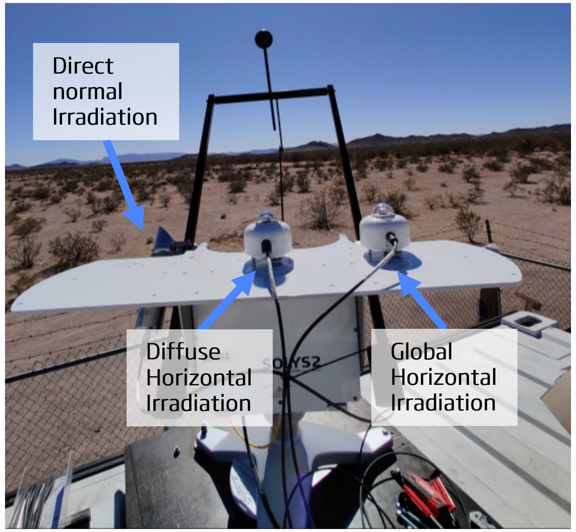


Horizontal Irradiation, 1m resolution, Feb. 2021 to Aug. 2022, Filter: >100W/m2

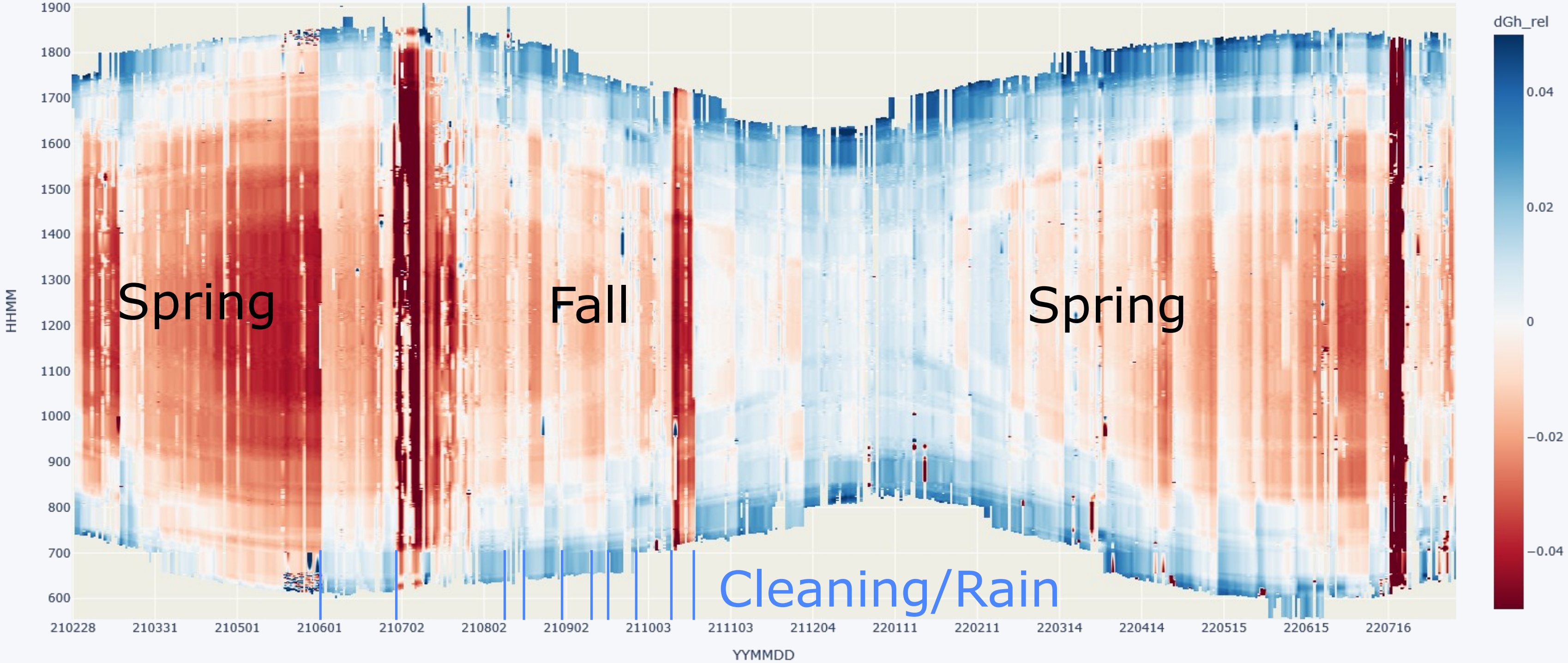
Why measure the weather before you start to construct?



GHI=DNI×cos(θ)+DHI



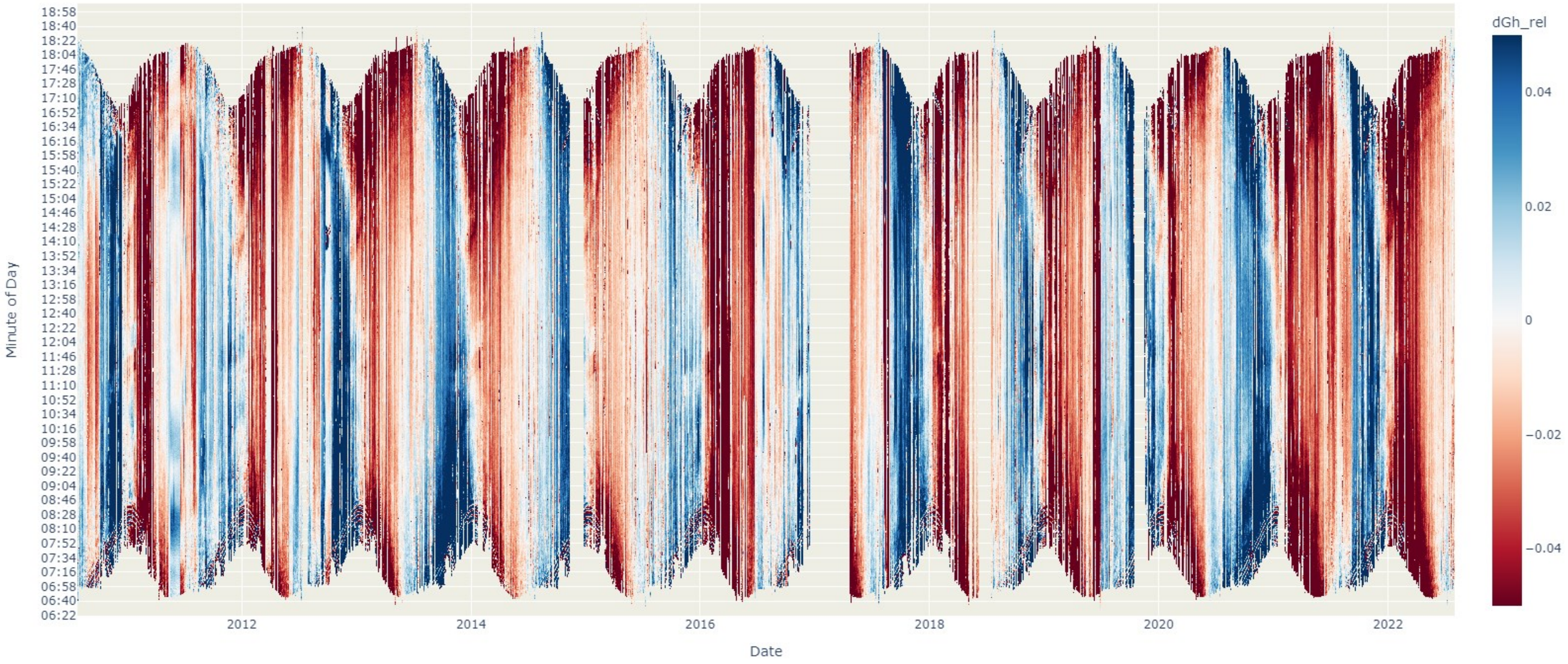
Validation example of horizontal irradiation (GHI) in Arizona, USA:



- Comparing Ratio of GHI_calc vs. GHI measured: up to ± 4% difference
- Clear correlation with cleaning dates → Consider for O&M and real-time PR validation and periodical reporting
- **Seasonal trend remaining → Which parameter to trust?**

Location: Arizona; 18 month, 1m resolution, filtered for Gi>100W/m²;

High seasonal variation of GHI, Location: Tempe, Arizona
Calculated vs. Measured horizontal irradiation



(Possible) reasons:

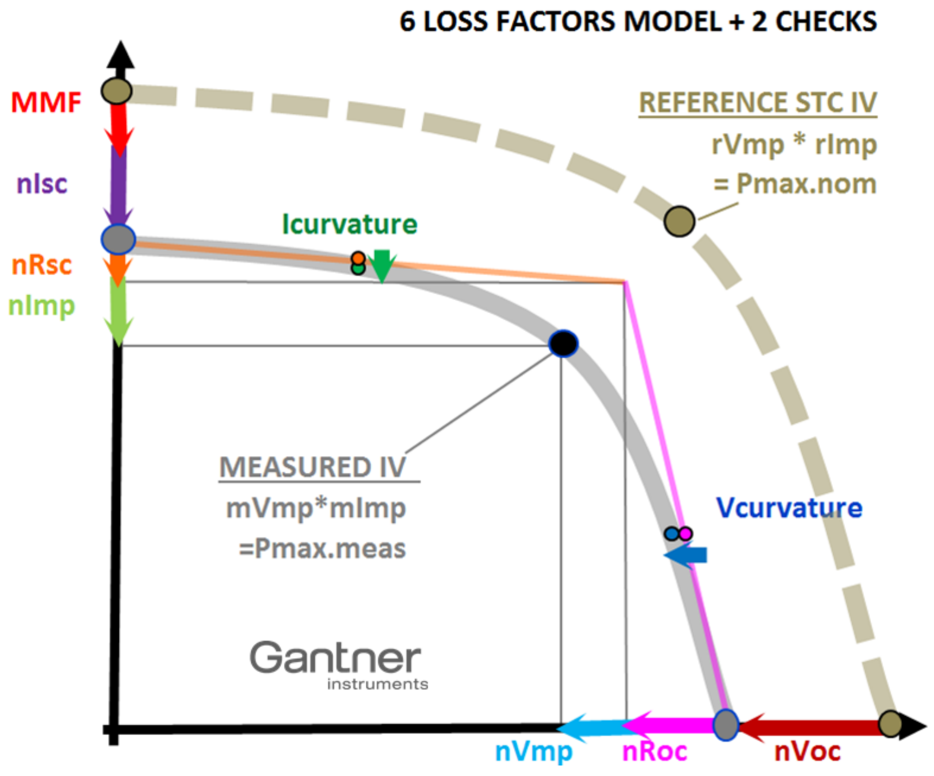
- ~~Cleaning, dust~~
- ~~Wrong measurement~~
- ~~Sensor Calibration~~
- Asymmetric behavior (over the day)
- Isotropic Assumption for diffuse good enough?

Clear seasonal trend: Calculated values are lower in Spring and higher in Autumn

What would be your explanation?

Gantner Instruments Research Site, OTF4; Location: Arizona; 12 years of data, 1m resolution; filtered for Gi>100W/m²;
Site with regular cleaning (weekly) and sensor calibration, 2017: sensor tracker outage,

IVscans – The DNA of PV modules



Loss Factors Model (LFM)
The LFM determines a module's performance from its I-V curve as the product of six physically significant and independent normalized "loss factors" and spectral and temperature corrections. All normalized LFM parameters multiplied together show PRdc.

Turnkey Outdoor Test Facility Solution, 8,16, 32 Channels

Outdoor Test Facility Solution 30 Channels, Gantner Instruments Research site, Arizona

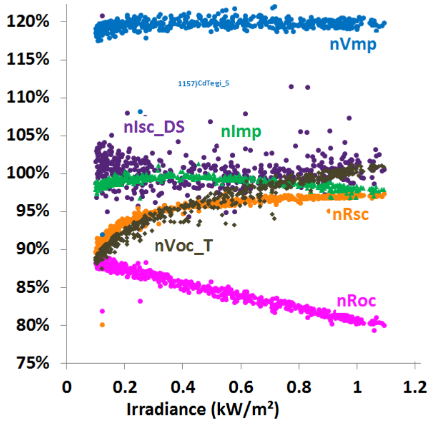
Robust extraction of key values with the Loss Factors Model (LFM)

The **Loss Factors Model (LFM)** provides a powerful analysis of indoor or outdoor IV curves.

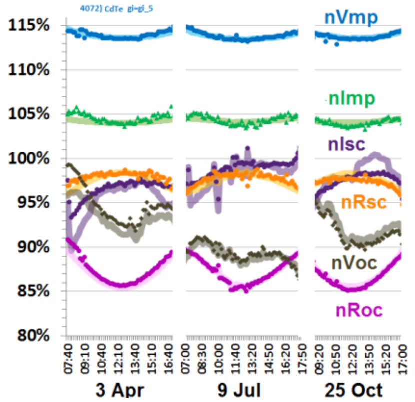
$$PR_{DC} = nI_{SC} * nR_{SC} * nI_{MP} * nV_{MP} * nR_{OC} * nV_{OC}$$

LFM parameters are:
technology agnostic, area independent, normalized, meaningful, e.g., "% power loss due to R_{SERIES}"

Characterize a module vs. G_I, Tmod, etc.



Predict performance vs. time and weather



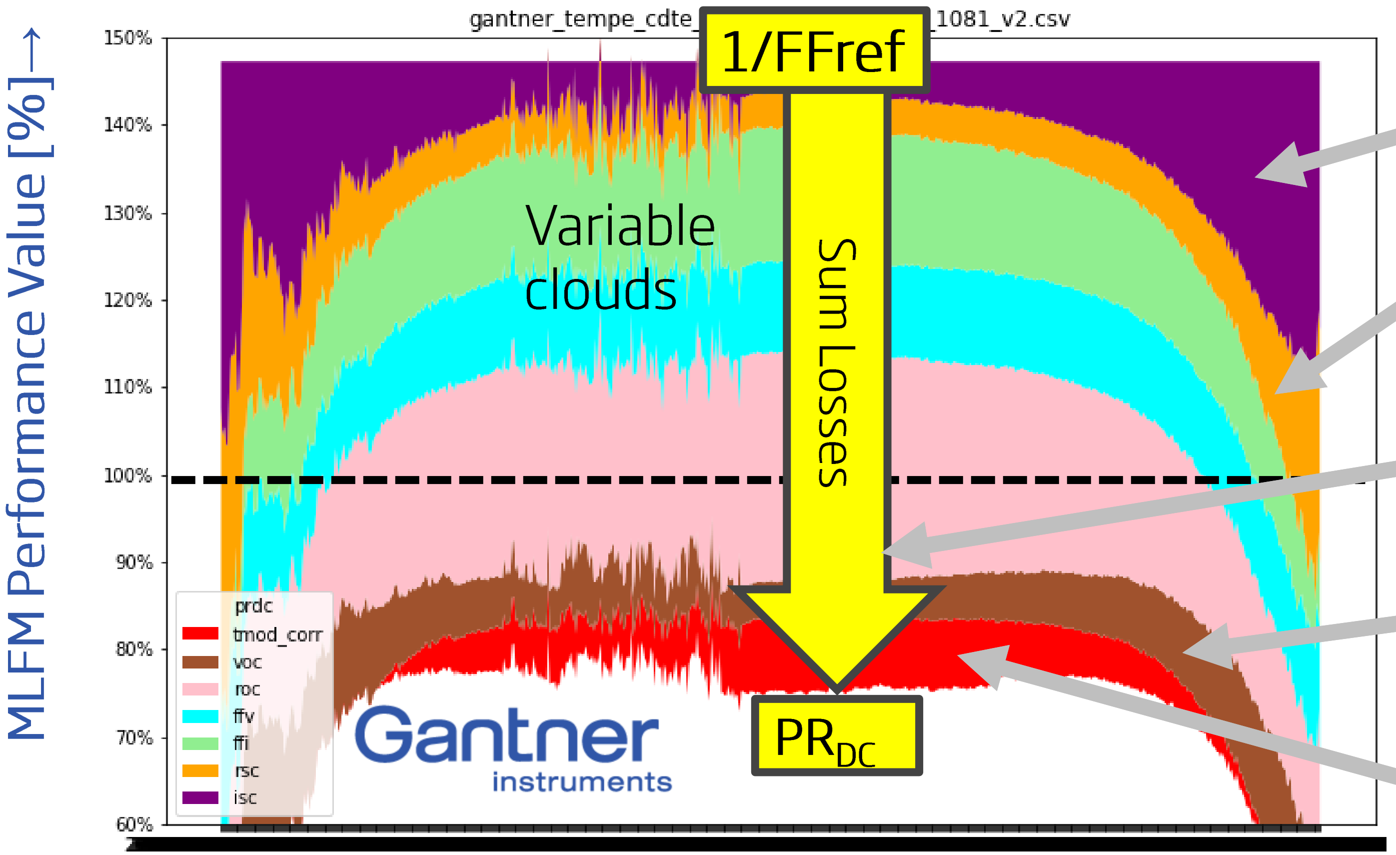
LFM can easily find any discrepancies, degradation, poor measurements, etc.

Validation: Stein et al. 28th PVSEC Paris 2013

Stacked losses vs. time: 1 day

CdTe: Clear day in March, Tempe AZ

PRdc = 1/FFref – stacked_loss[(isc + rsc + ffi) + (ffv + roc + voc_Tcorr + t_mod)]



When are losses greatest?

(1) Isc loss (AOI/reflectivity, spectrum)→ morning, evening

(2) ~Rshunt loss (low irradiance) → morning, evening

(3) ~Rseries loss (high I^2.Rseries) → noon

(4) Voc_tcorr (temp_corrected) (Voc~log(Gi) → low irradiance

(5) Temperature loss → noon - afternoon (high temperature)

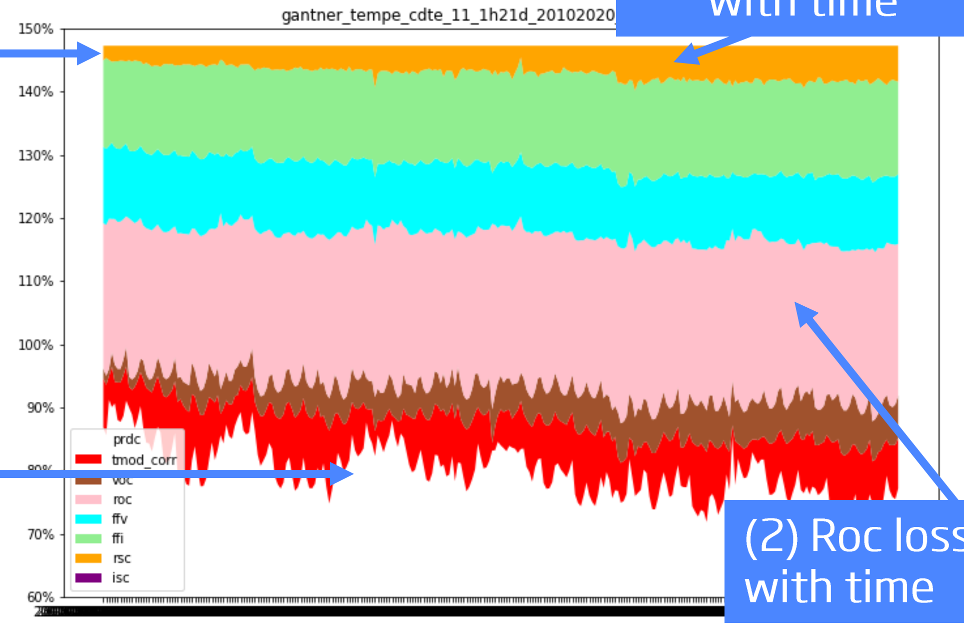
Identify causes and rates of any long-term degradation

Stacked loss graphs, 2010-2017+

$$PRdc \propto 1/FF\_ref - stacked\_loss[(isc + rsc + ffi) + (ffv + roc + voc\_Tcorr + t\_mod)]$$

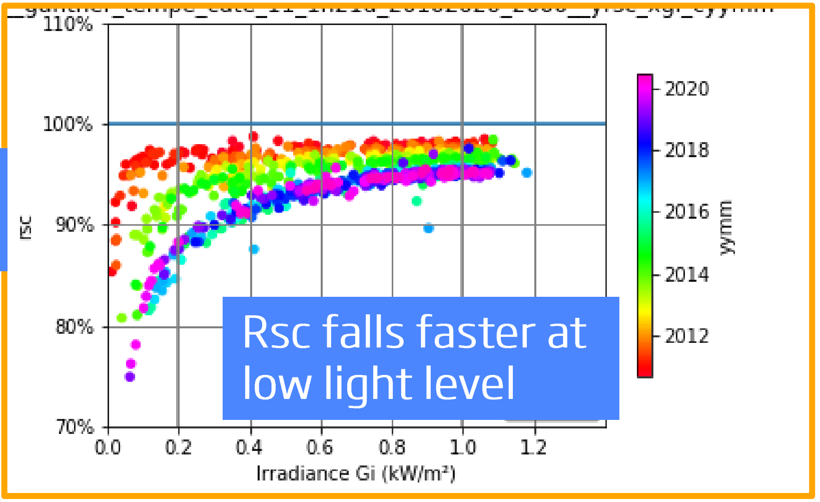
1/FF -
↓Rsc
↓ FFi
↓ FFv
↓ Roc
↓ Voc
↓ Tmod
= PRdc

↓ Losses

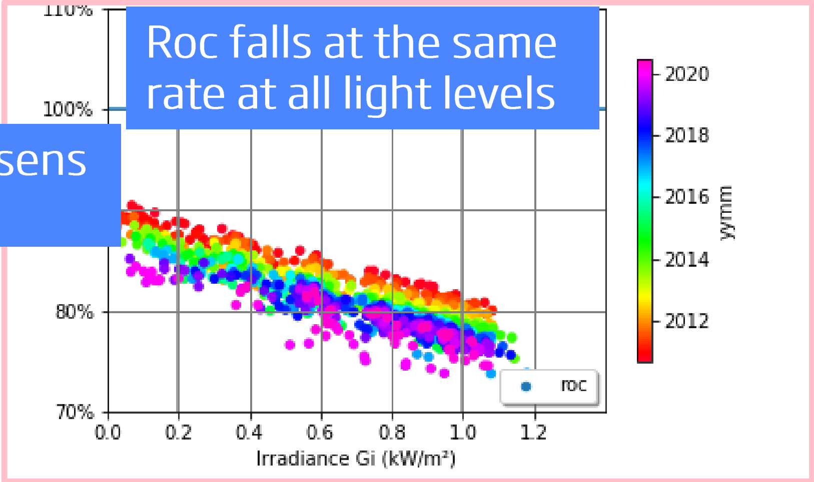


(1) Rsc loss worsens with time

(2) Roc loss worsens with time



Rsc falls faster at low light level



Roc falls at the same rate at all light levels

6 Parameter version, Method: self-referenced Isc for clarity; Temp correction subtracted from Voc for simplicity; unstable device
Source: S. Ransome, J. Sutterlueti: Modelling of PV modules and systems, PVCost, 2021

Mechanistic Performance Modelling for Large PV Arrays

Mechanistic Performance Model (MPM) for PV Arrays

Gantner instruments

MPM assigns a meaningful normalized coefficient to expected performance behavior to fit observed measurements with understandable loss coefficients

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

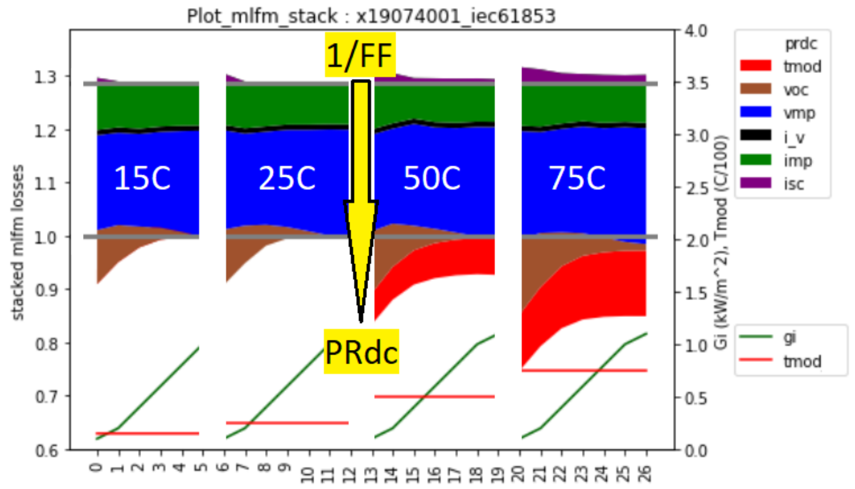
e.g., PR, nVdc, nIdc — Tolerance — Temperature — Voc and Rshunt — R_{SERIES} — Wind

MPM Advanced

5 Coeff. for typical sites

MPM is best

- To fit measured PR vs. Irradiance and Tmodule
- To look for discrepancies or poor-fit coefficients
- Predict performance



MPM Coefficients are meaningful, orthogonal, robust & normalised; Inputs: G_I, T_{MOD}, WS, $P_{NOMINAL}$
Graph shows losses per component from 61853 matrices of only Isc, Imp, Vmp and Voc. IV curves weren't provided

Mechanistic Performance Model (MPM) for PV Arrays

Gantner instruments

MPM assigns a meaningful normalized coefficient to expected performance behavior to fit observed measurements with understandable loss coefficients

$$MPM_{Param} = C_1 + C_2 * (T_{MOD} - 25) + C_3 * Log_{10}(G_I) + C_4 * G_I + C_5 * WS + C_7 f_{Asym} + fClip(C_8, C_6)$$

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

MPM Advanced

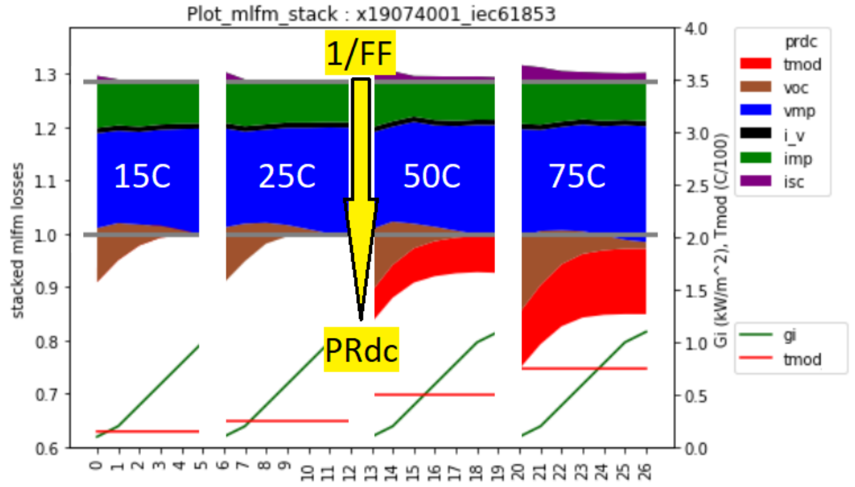
5 Coeff. for typical sites

MPM Professional

covers also clipping, asymmetric behavior

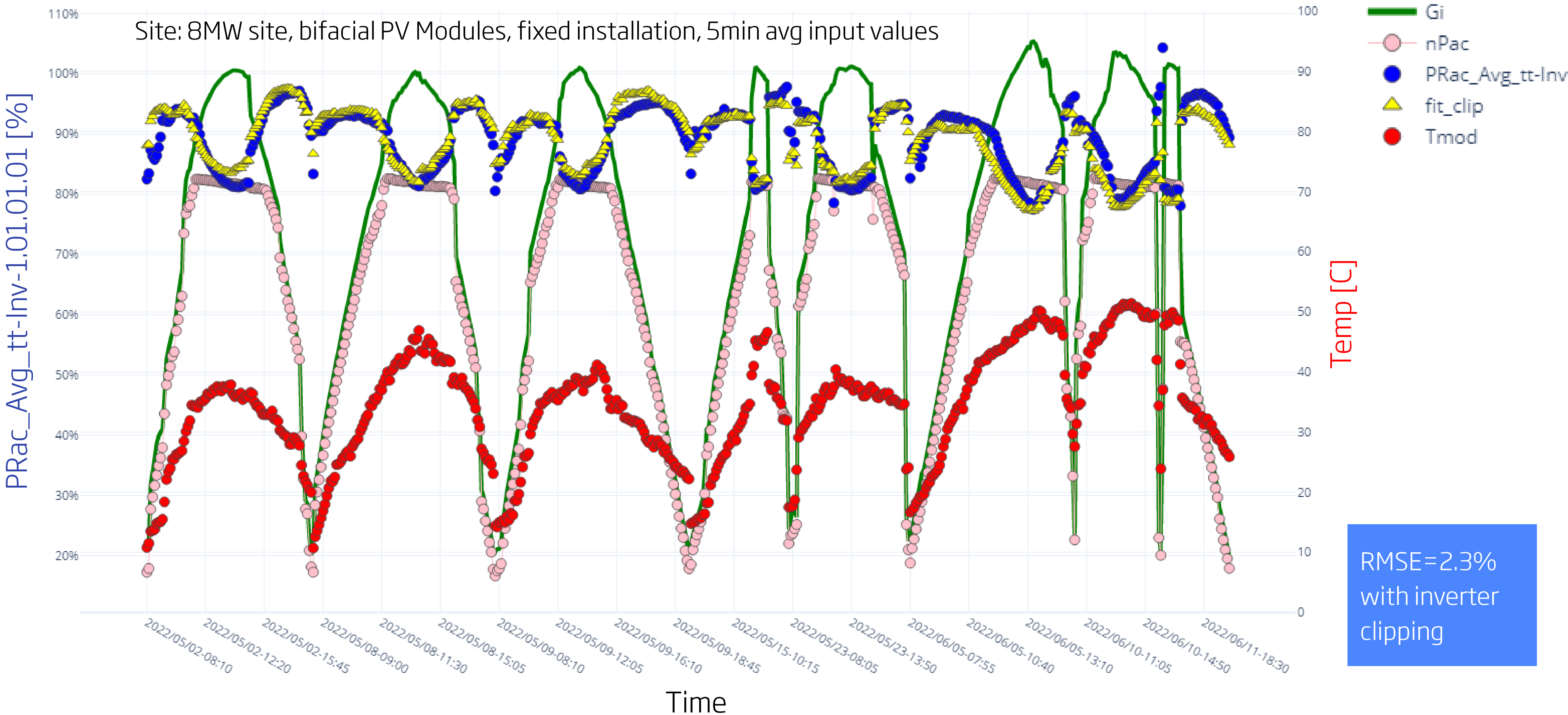
MPM is best

- To fit measured PR vs. Irradiance and Tmodule
- To look for discrepancies or poor-fit coefficients
- Predict performance



MPM Coefficients are meaningful, orthogonal, robust & normalised; Inputs: G_I, T_{MOD}, WS, $P_{NOMINAL}$
Graph shows losses per component from 61853 matrices of only Isc, Imp, Vmp and Voc. IV curves weren't provided

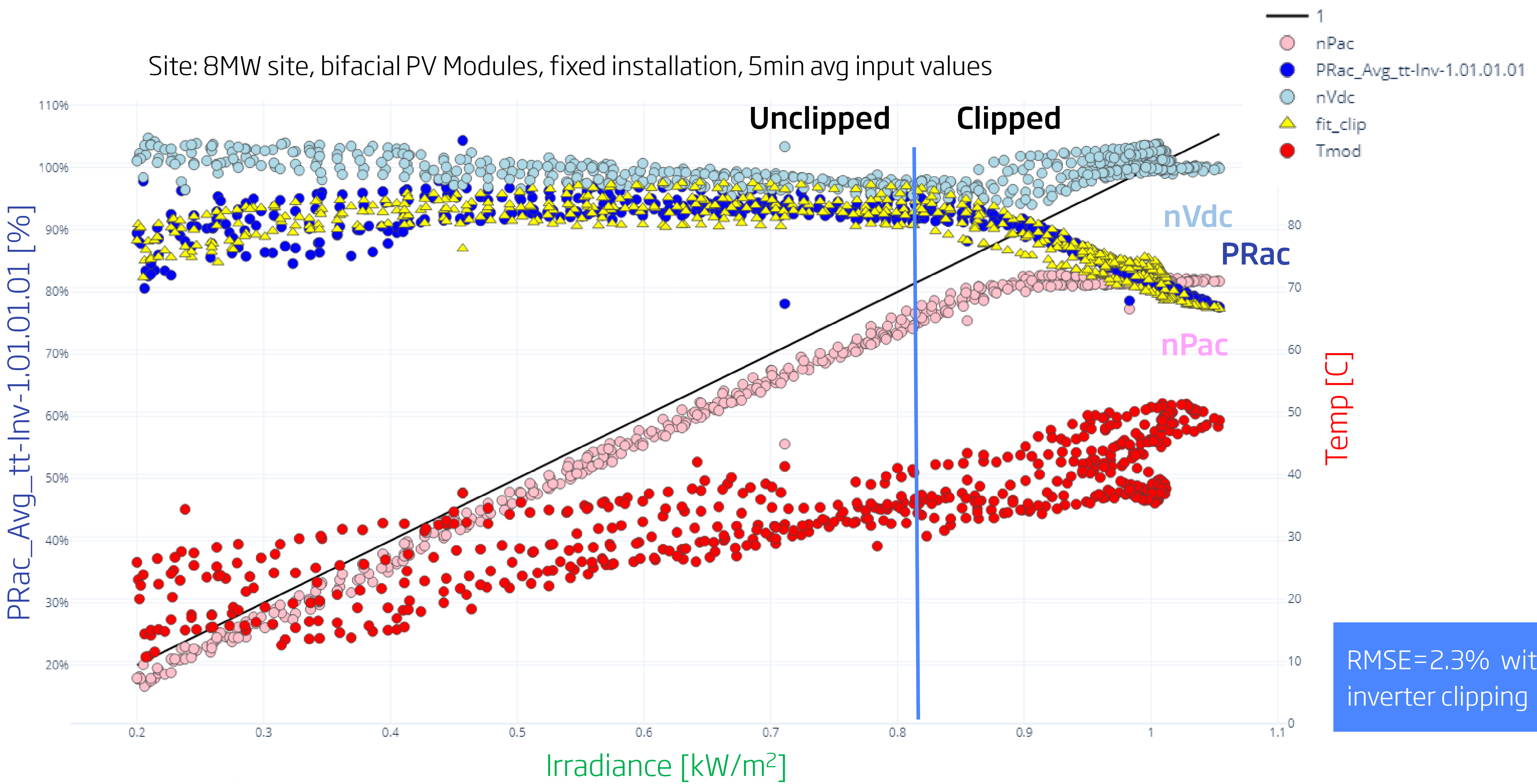
MPM Professional– PRac.meas, PRac.fitclip vs. time



RMSE=2.3%
with inverter
clipping

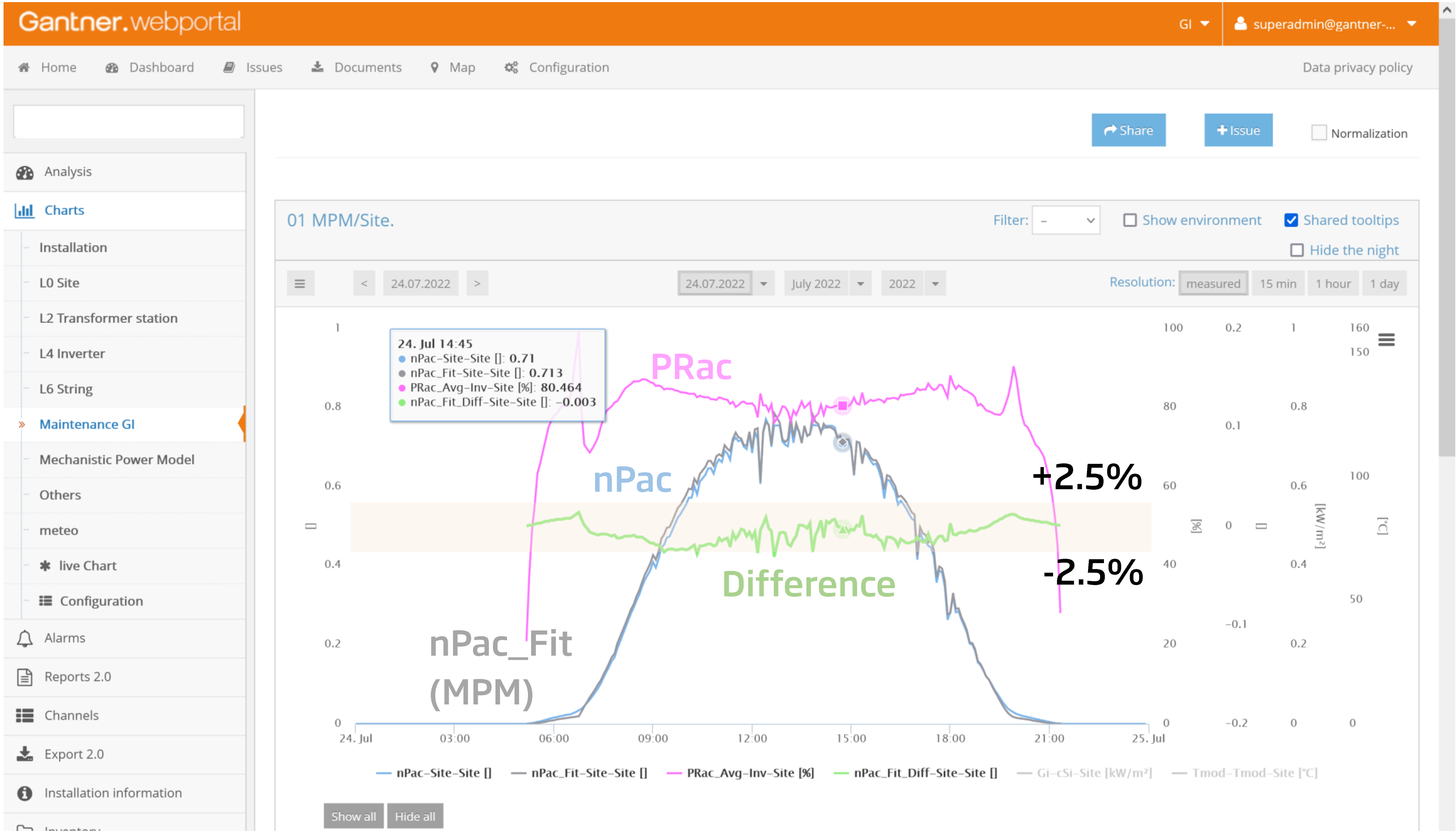
MPM Professional– nPac , PRac.meas, PRac.fit vs. Irradiance

Gantner instruments



RMSE=2.3% with inverter clipping

MPM part of Gantner's Monitoring and control platform

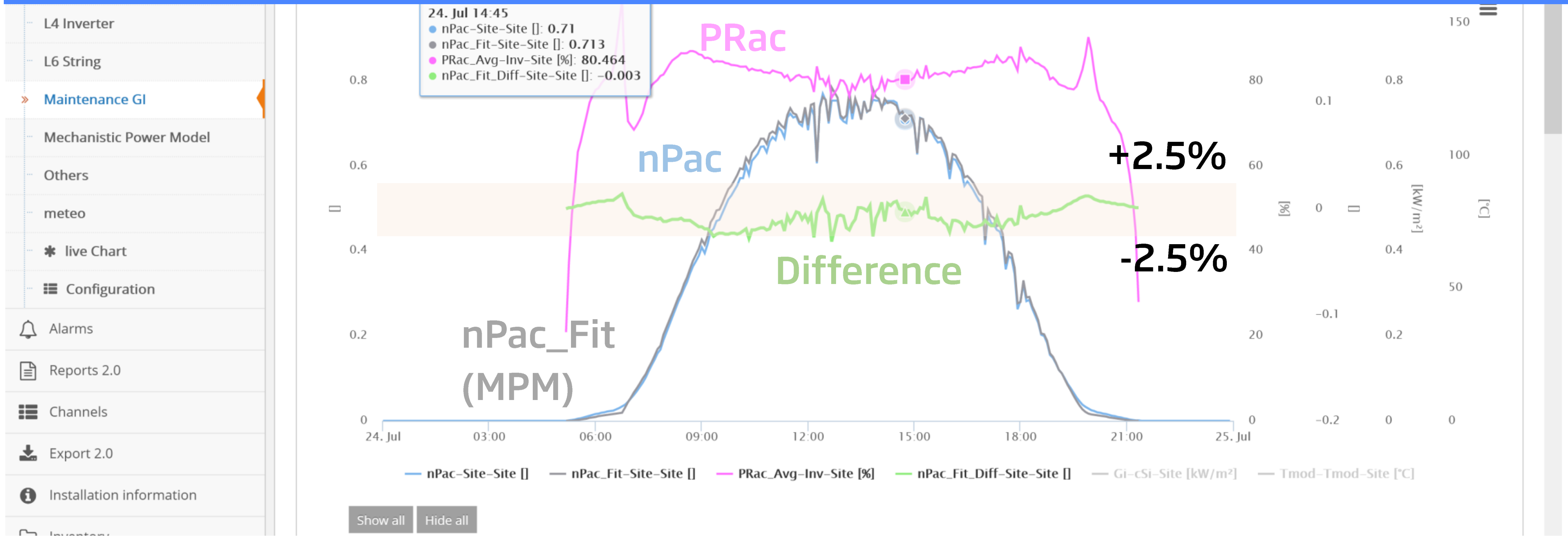


MPM part of Gantner's Monitoring and control platform

Gantner instruments

MPM for PV Plants

- Best accuracy for short-term forecasts for grid integration
- Identifies component quality issues or unexpected power loss w/o extensive pre-calculation
- Works for each component and level (String, CB, MPPT, Inverter, SubStation, Site), Accuracy up to ± 2.5%
- Deviation can be converted directly into losses (kWh or $)



Mechanistic model (MPM) for PV Arrays
Works for all components

MW-scale PV Power Plants (PRac of inverter or site level)

Site ID	Country	Pac_nom	MPM Coeffs	Quality	Temp	LowLi	HighLi	WindSp	Ramp	Aft.	Peak		PR_STC
		[MW]	Fit to Parameter	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	RMSE	C1+C4
JbBc	GBR	4.1	PRac_Avg_tt-Inv-1.A.1	97.2%	-0.17%	22.78%	-10.56%	-0.09%	0.00%	0.08%		1.65%	87%
MeAs	GER	3.9	PRac_Avg_tt-Inv-Site	129.4%	-0.21%	50.21%	-44.47%	0.13%	0.00%			1.15%	85%
TfWl	NED	96	PRac_Avg_tt-Inv-1.08.01.01	63.8%	-0.40%	-49.50%	30.66%	0.23%	0.00%	-0.16%		3.66%	94%
TtTe	GBR	3.6	PRac_Avg_tt-Inv-Site	139.5%	0.24%	39.35%	-59.13%	-0.02%	0.00%	11.42%		3.83%	80%
FeTv	DNK	28.1	PRac_Avg_tt-Inv-Site	123.6%	-0.40%	51.58%	-25.43%	-0.50%	-55.61%	1.63%	82%	4.17%	98%
FeSo	DNK	8.1	PRac_Avg_tt-Inv-1.01.01.01	111.20%	-0.40%	34.36%	-11.23%	-0.49%	-55.18%	0.80%	82%	2.3%	100%

8MW site, bifacial modules, inverter clipping: MPM for Prac and nVdc, nIdc

Site ID	Country	Pac_nom	MPM Coeffs	Quality	Temp	LowLi	HighLi	WindSp	Ramp	Aft.	Peak		PR_STC
		[MW]	Fit to Parameter	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	RMSE	C1+C4
FeSo	DNK	8.1	PRac_Avg_tt-Inv-Site	113.83%	-0.40%	36.03%	-13.55%	-0.48%	-50.93%	0.40%	82%	2.0%	100%
FeSo	DNK	8.1	PRac_Avg_tt-Inv-1.01.01.01	111.20%	-0.40%	34.36%	-11.23%	-0.49%	-55.18%	0.80%	82%	2.3%	100%
FeSo	DNK	8.1	nVdc-Inv-1.01.01.01	102.87%	-0.40%	4.13%	-1.99%	-0.09%	40.98%	0.14%	82%	1.0%	101%
FeSo	DNK	8.1	nIdc-Inv-1.01.01.01	106.14%	0.01%	27.58%	-6.18%	-0.36%	-99.06%	0.81%	82%	2.7%	100%

- RMSE range 1.15% to 4.17%,
- Results impacted by site design, quality & data aggreg.
- RMSE < 2.7%
- nVdc fit very robust

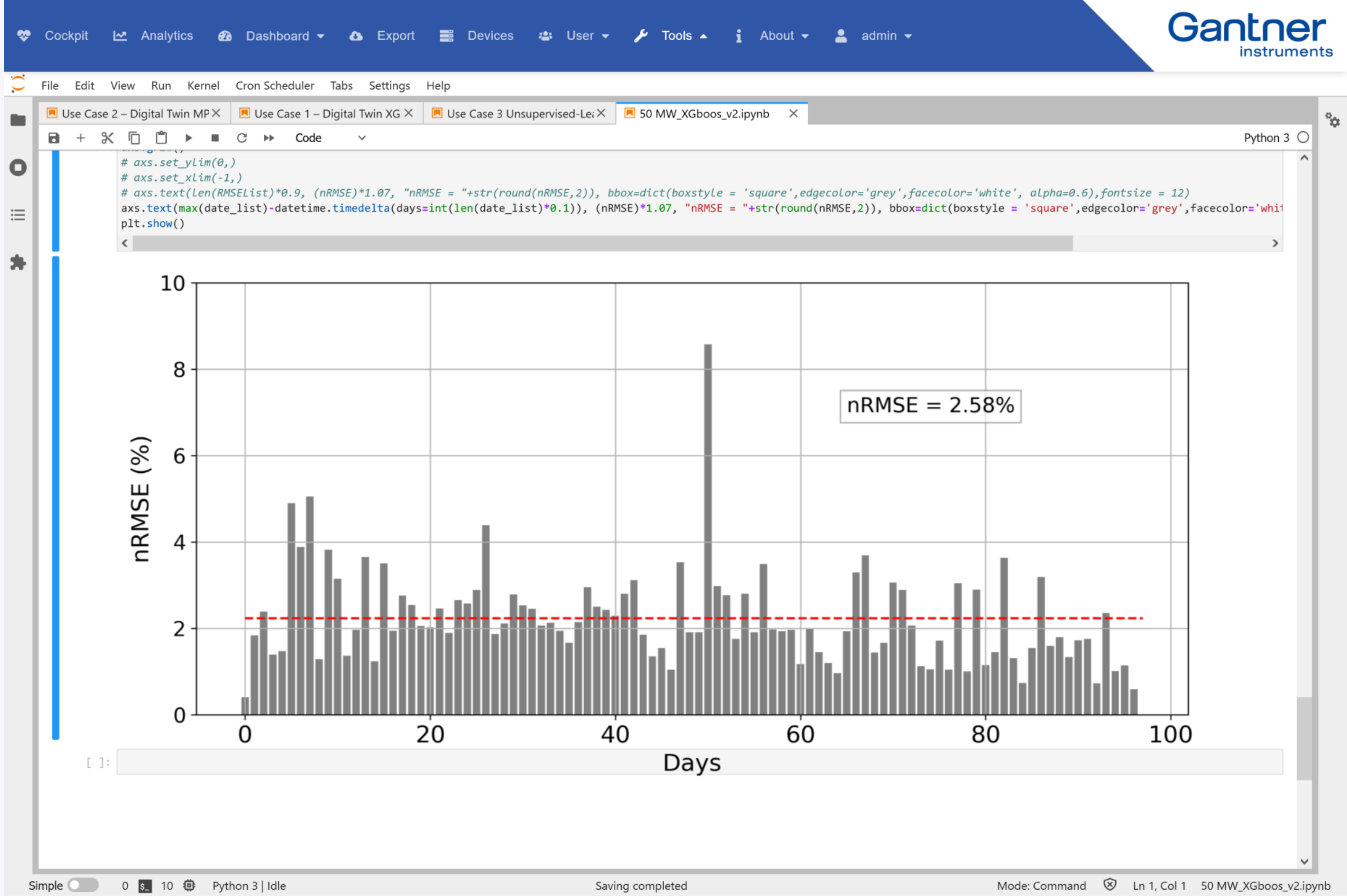
Key for reproducible results: Reliable Sensors, Sanity check, Steady conditions (kTx)

Machine Learning for Large PV Arrays

Prediction of performance

- Asset: PV Power Plant, 50MW; 15m inverter data

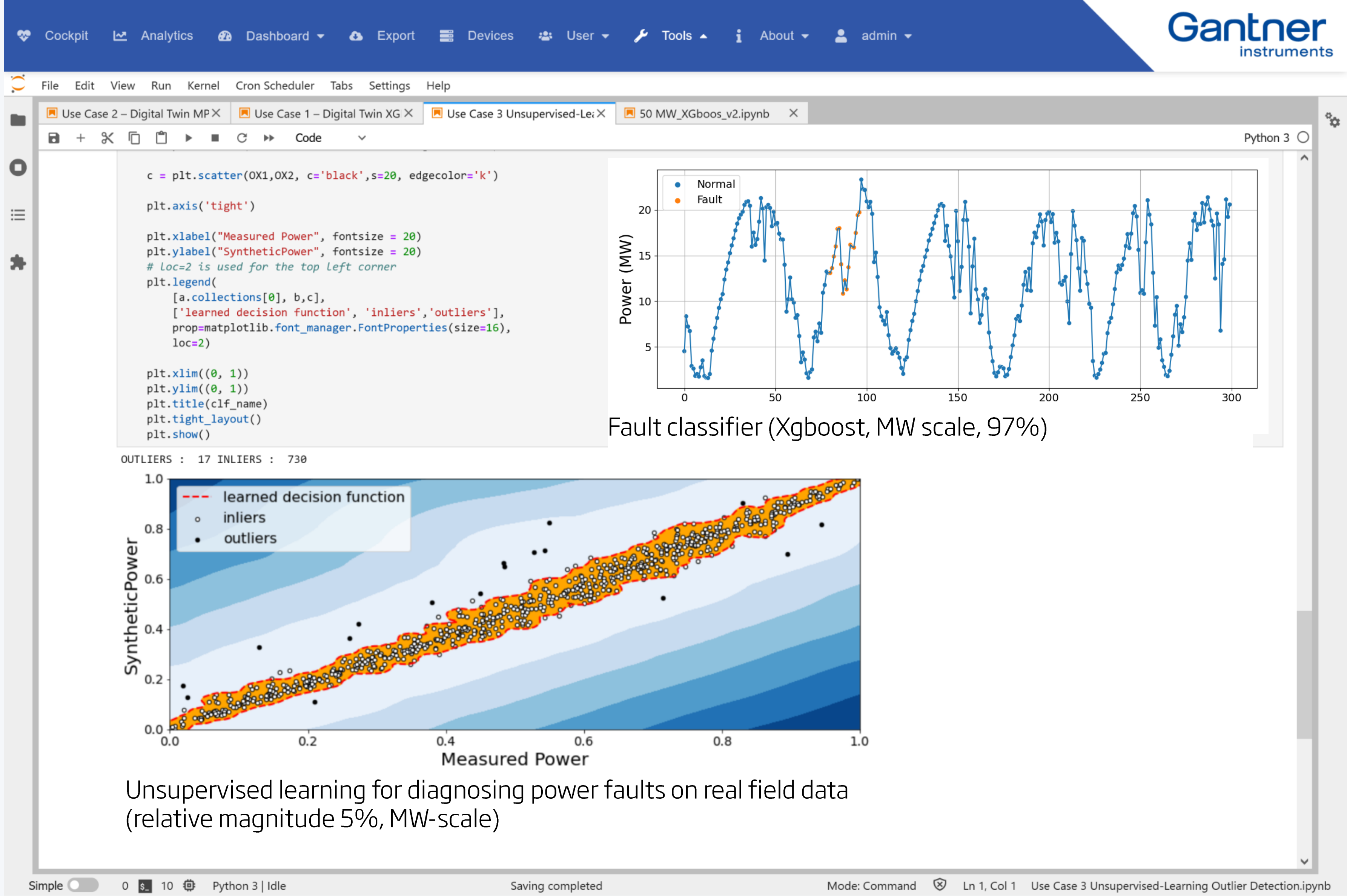
- Residuals of **Measured** vs. **Predicted**
- Algorithm:
  - Extreme Gradient Boosting (XGboost) with training
  - Mechanistic model
- Low error of 2.58%
  - Successive samples
  - Error reduced to 1.92% for random samples



Predictive performance of digital twin with errors < 3 % on MW-scale

Unsupervised-Learning

- Faults detection (outlier classification) for MW-scale & Microgrid
- Methods qualified:
  - Angle-based Outlier Detector (ABOD)
  - One-Class Support Vector Machine
  - Support vector data description (DeepSVDD)
  - Histogram-base Outlier Detection (HBOS)
  - Isolation Forest
  - k-nearest neighbors' algorithm (KNN)
  - Extreme Gradient Boosting (XGboost)



Fault classifier (Xgboost, MW scale, 97%)

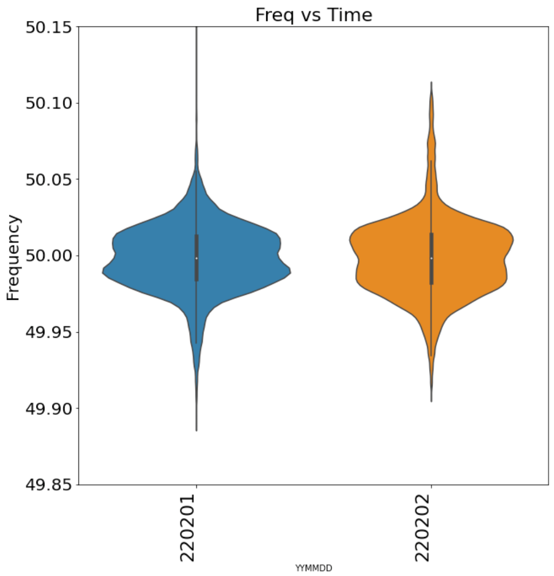
Unsupervised learning for diagnosing power faults on real field data (relative magnitude 5%, MW-scale)

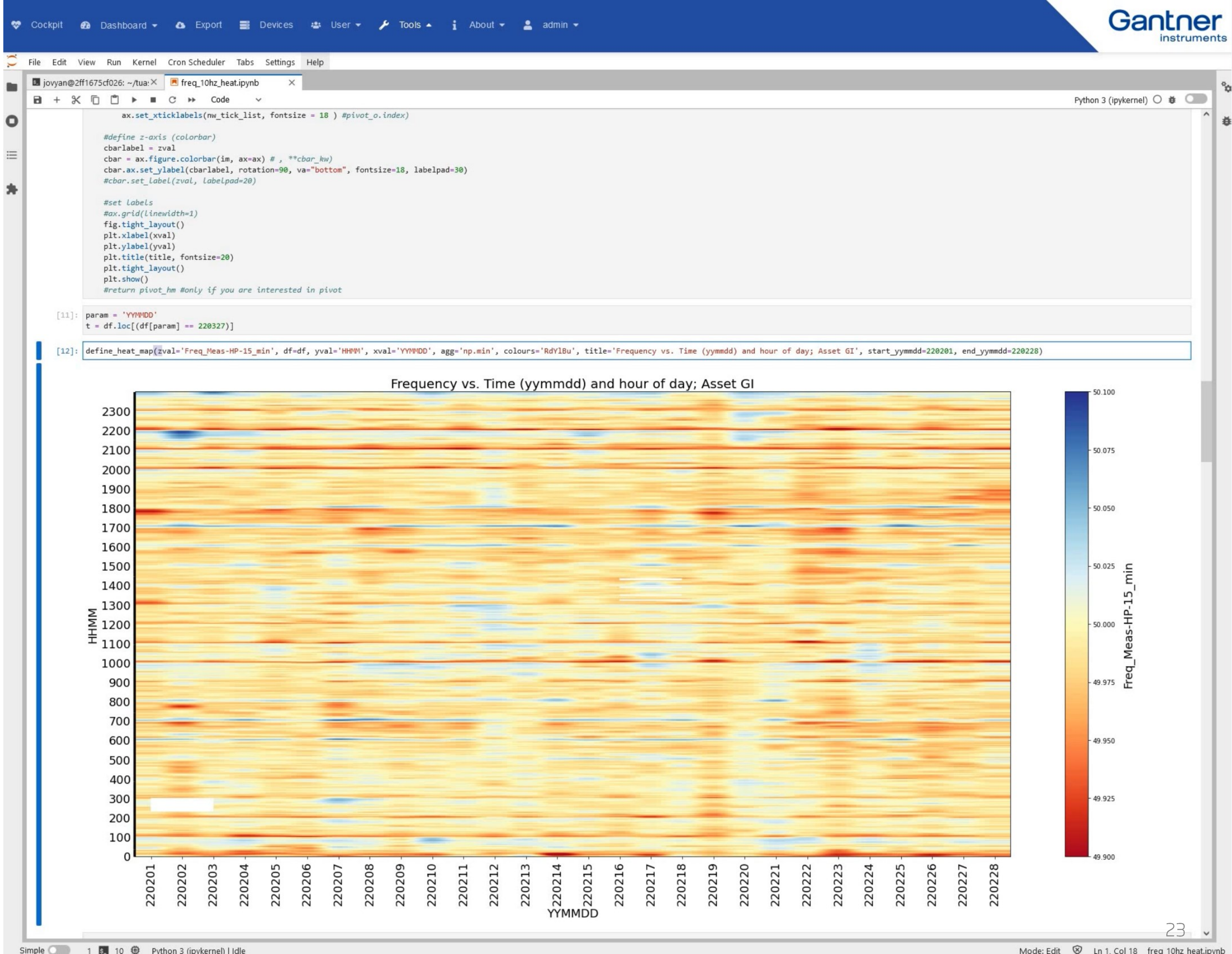
Works for different granularity and asset types; results available in Backend and API

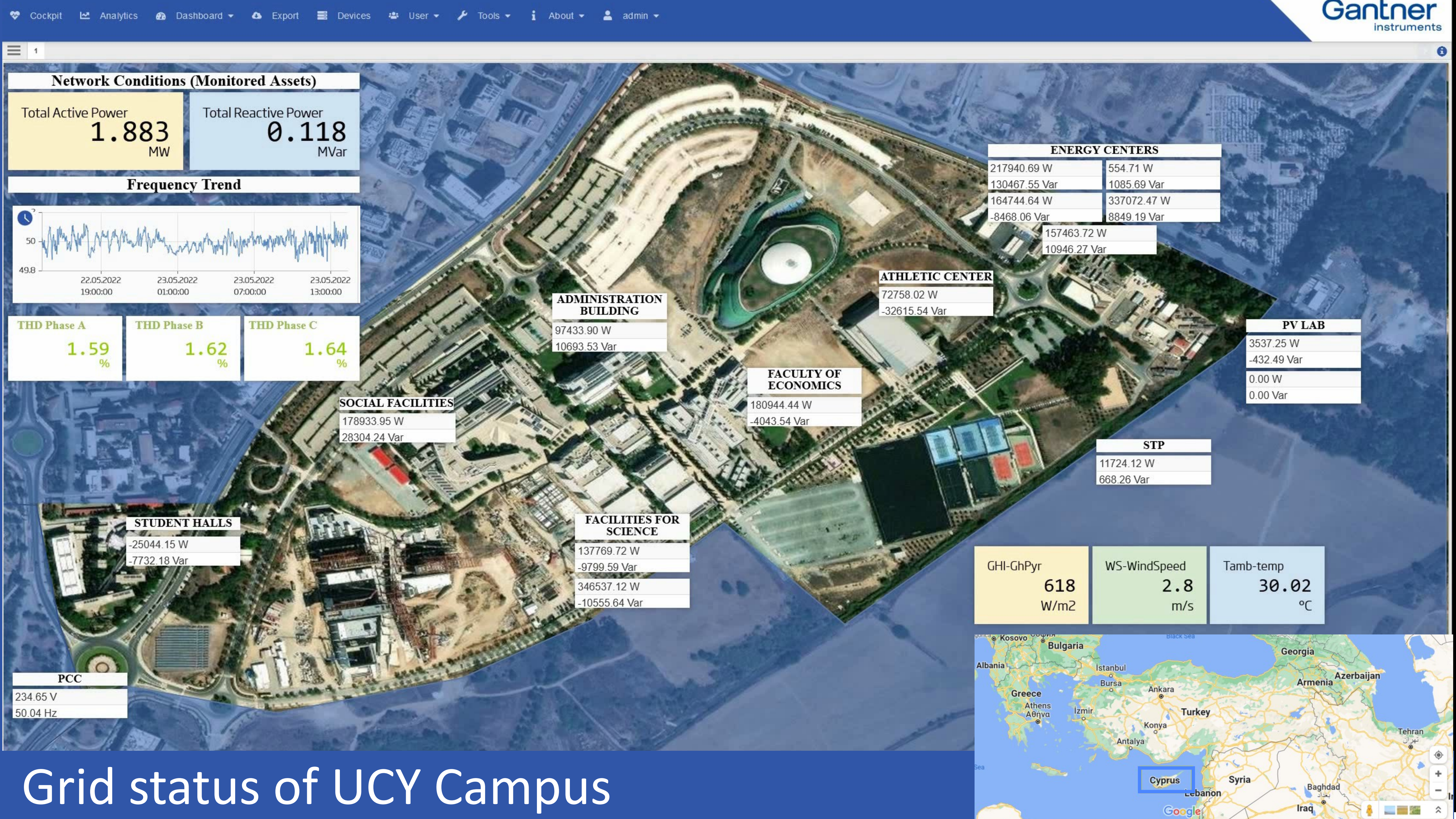
Gantner instruments

Microgrid
Real-time Interaction

A stable Frequency keeps the lights on…







Grid status of UCY Campus

Microgrid setup at University Campus in Cyprus

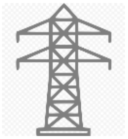
Gantner instruments

PV

BESS

EV Charging

Grid / Load



Digitalization and interoperability open communication standards

PROFINET

EtherCAT

Modbus

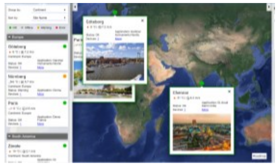
OPC UA

Real-time data stream

Centralized supervision and control

WAN

GI.cloud UI

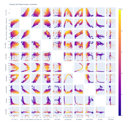


Visualize
Operate
Analyze
Setup

jupyter

python

Analytics
Digital Twin
ML



Distributed, scalable, clustered, API

GI.data

kafka

Event Sourcing
Persistent log
Real-time Enrichment

Indexing
Aggregation
Fast data access

Read/write data streams
Real-time control

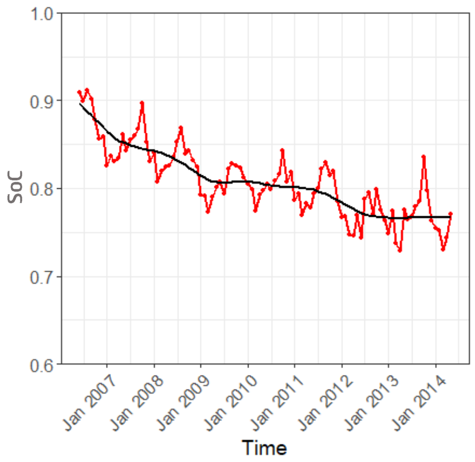
... bidirectional data flow

Real-time energy grid control with advanced data processing and qualified models for digital twins

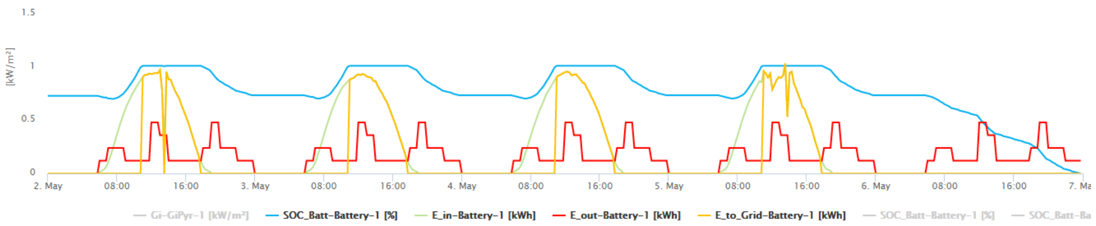
Data acquisition system (DAQ)
Real-world data or Test-bench

Data quality routines (DQRs)
- Identify missing/erroneous data
- Correction of data

Degradation rate



Health-state detector



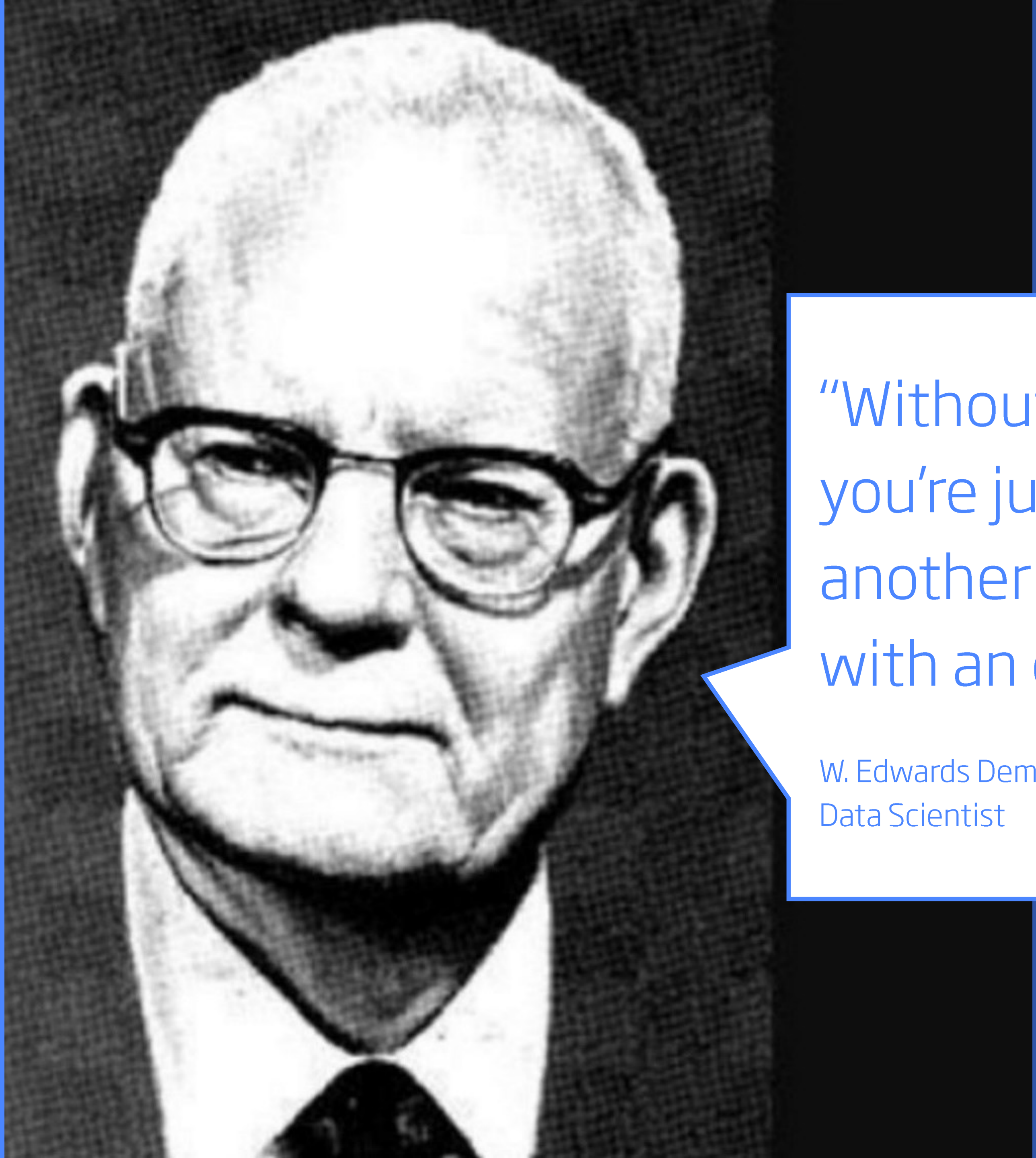
System model prediction
Predict characteristics of the system, residuals

Failure diagnosis routines

Lessons learned - which we also had to work hard for …

Gantner instruments

- Real-world performance data cannot be accelerated
  - Invest in sensors you trust
  - Start early and be consistent in the O&M
- Measure - not only model
  - Precise and reliable monitoring is critical for effective data analytics
  - Make sure you understand the dependencies (e.g., dGh_rel); it will pay off
- Structured and scalable data processing
  - Is essential to get fast and repeatable modeling results
  - Make use of metadata and automation
- Modelling for the industrial usage
  - Run models against each other
  - Robust results with a combination of MPM (normalized, physical) and ML (classification, detection, etc.)



Gantner instruments

"Without data you're just another person with an opinion."

W. Edwards Deming,
Data Scientist

Know the weather

Know the technology

Know your O&M strategy

Know your PV output

→ **Generate continuous profit**

Thank you very much!

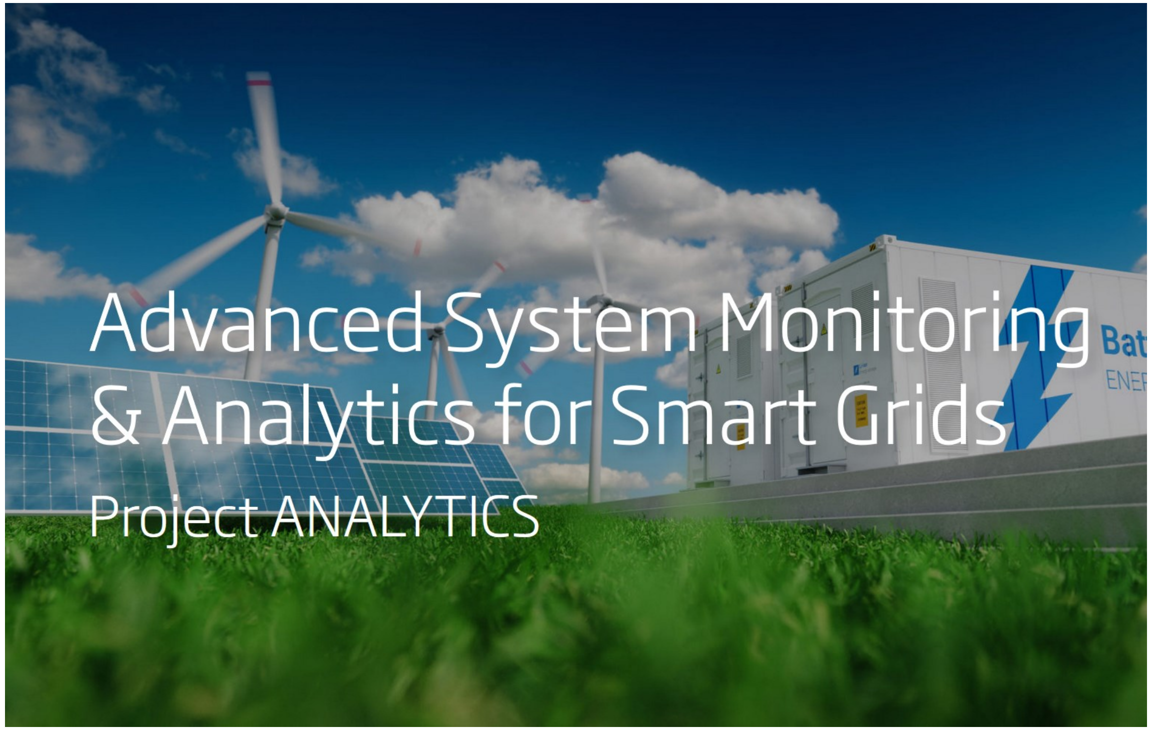
j.sutterlueti@gantner-instruments.com

Appendix

The Analytics project

Analytics
real time edge control and ai
for tomorrows smart grid services

Gantner instruments



More info at:

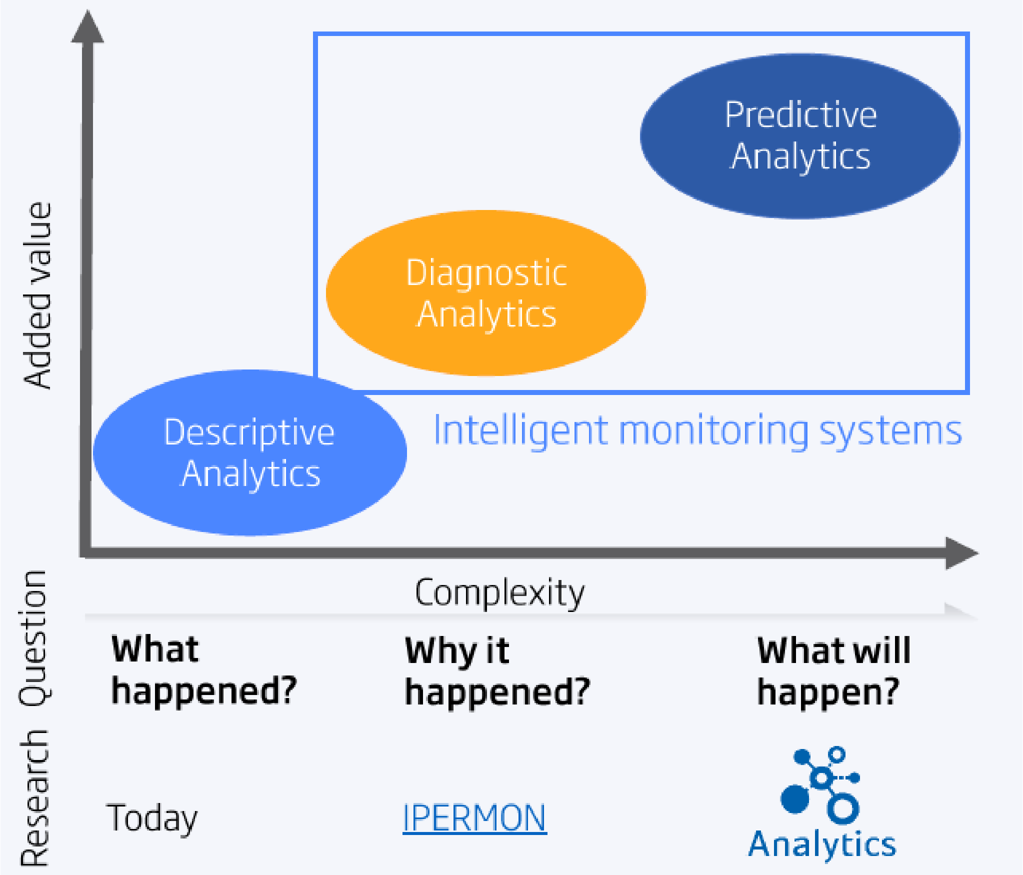
https://www.gantner-instruments.com/research/advanced-system-monitoring-analytics-smart-grid/

powered by

FFG Promoting Innovation.

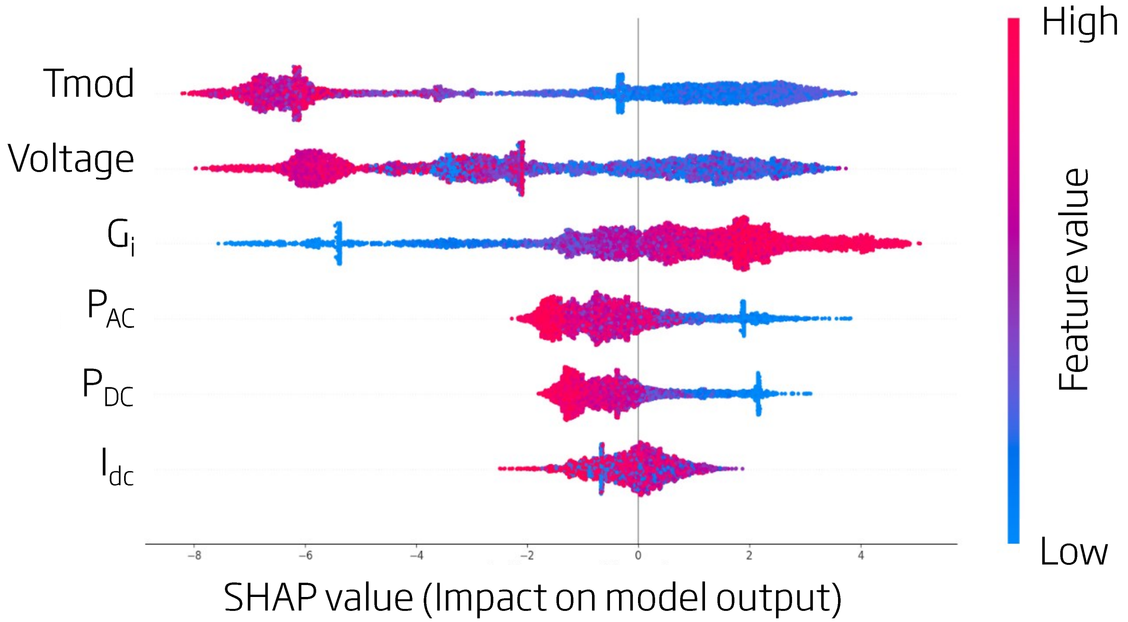
SOLAR-ERA.NET

University of Cyprus
PV Technology

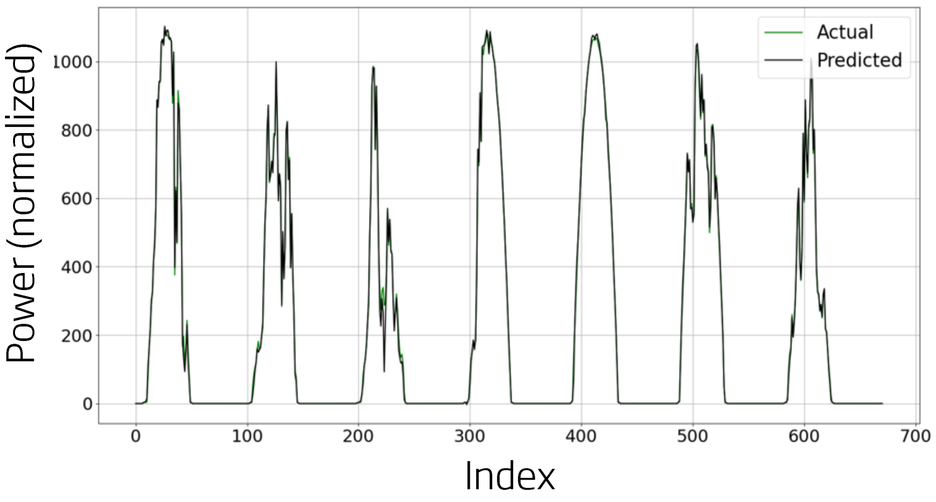


Digital Twin modelling and replica
PV power plants (W to MW scale)

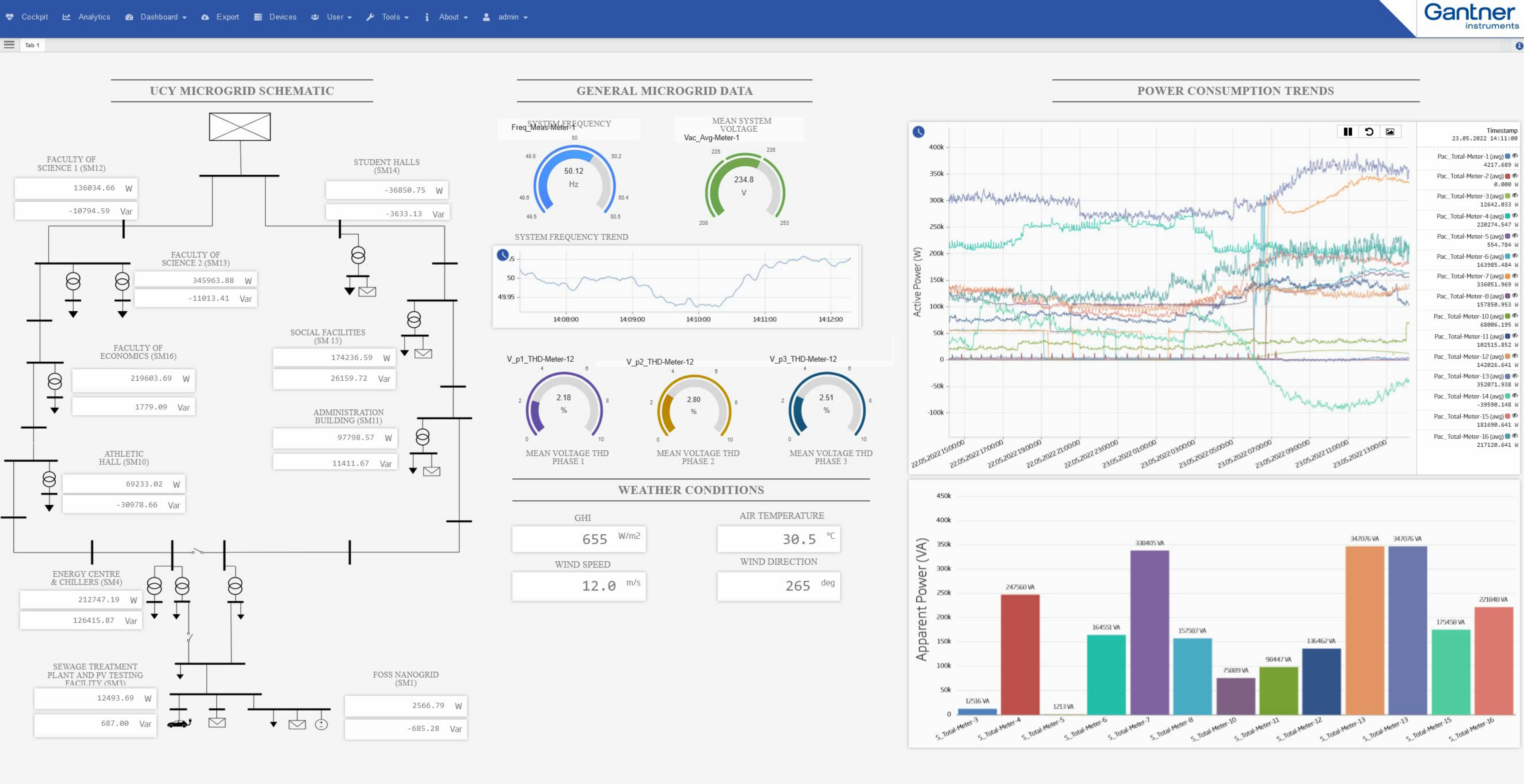
Optimal feature detection for machine learning model using SHAP



Actual and predicted PV power using Xgboost (W to MW scale)



SHapley Additive exPlanations (SHAP)): Improving individual predictions using game theoretic optima.
eXtreme Gradient Boosting (XGBoost): more precise determination of target variables



Smart Grid SCADA Dashboard of UCY campus

Data processing

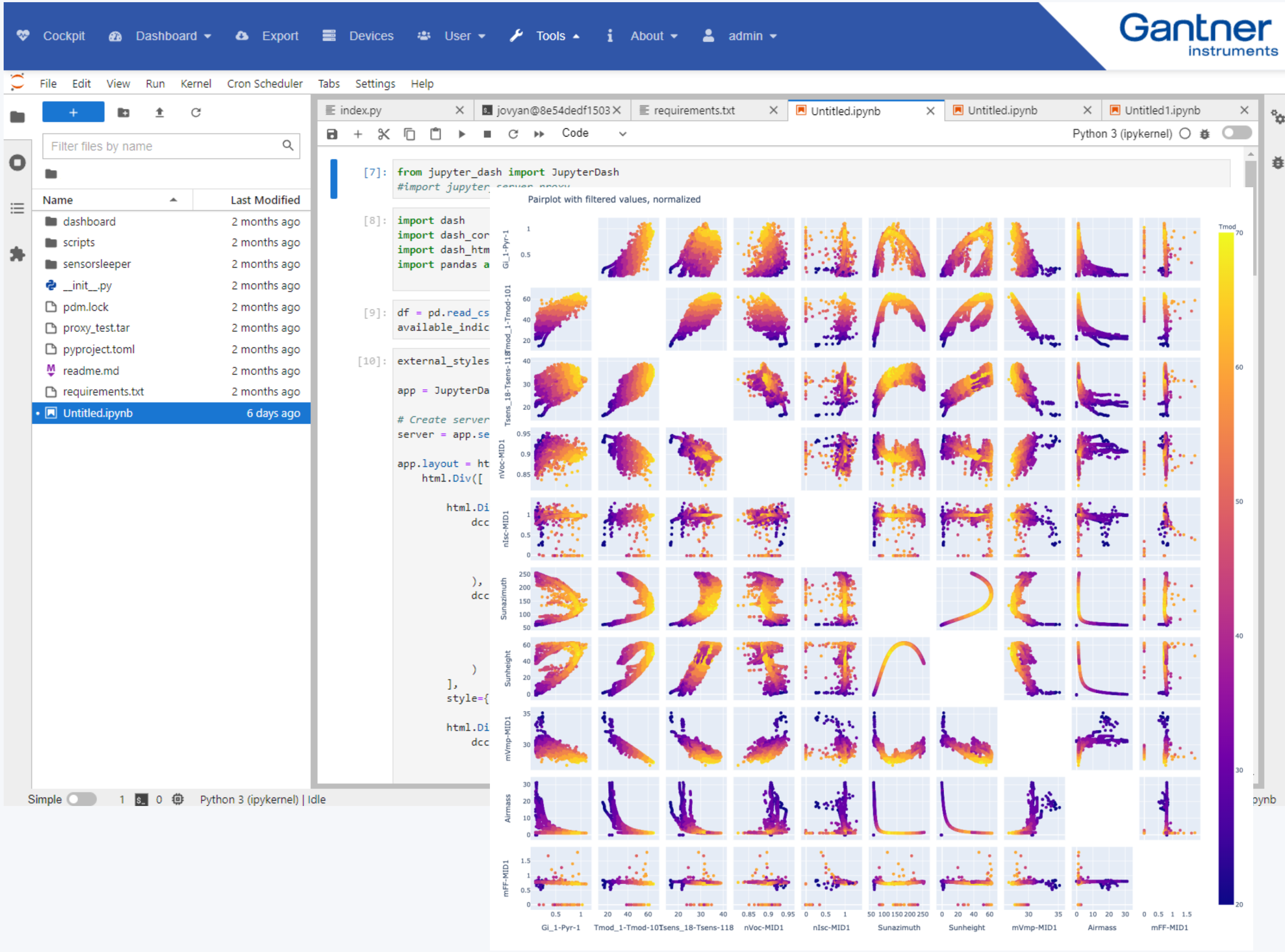
with

python™ & jupyter

integrated into GI.cloud.

Features:

- Open platform and API
- Read/Write access
- Machine Learning
- Real-time processing
- Dashboard integration



Mechanistic modelling: How does it work?
Characterising PV with an empirical/mechanistic model

– DC Performance Ratio $PR_{DC} = Eff_{DC.MEAS}/Eff_{STC}$ or MPR

Optimise fit coefficients C_N to minimise rms error using e.g. Python, Excel

Measurements

WEATHER:
Irradiance G_I
T_{MODULE}
WindSpeed

ELECTRICAL:
$PR_{DC.MEAS}$

EMPIRICAL or MECHANISTIC MODEL:

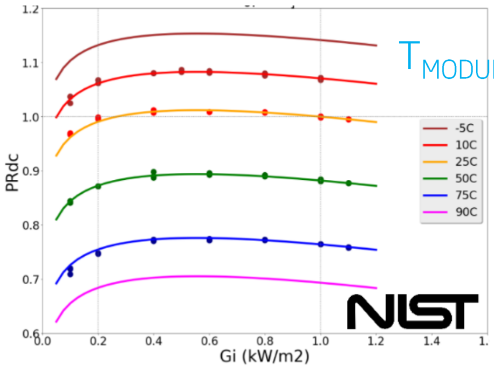
$$PR_{DC.PREDICT} = \Sigma_N C_N * func_N(G_I, T_{MOD}...)$$

PREDICTED PERFORMANCE:
$PR_{DC.PREDICT}$

3-7 Fit Coefficients C_N functions

Weather

PR_{DC}→



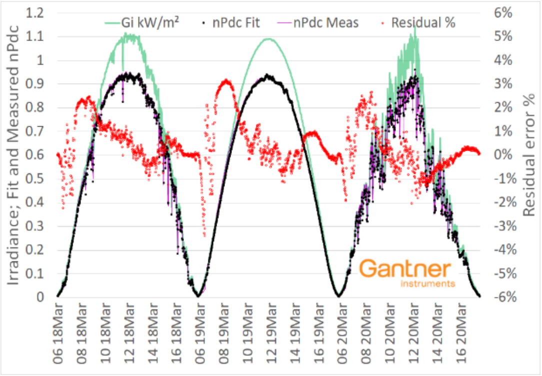
T_{MODULE}

Irradiance→

Indoor
IEC-61853-1
matrix
(NIST/CFV)

Outdoor
data and fit
vs. time

nP_{DC}→



Time→

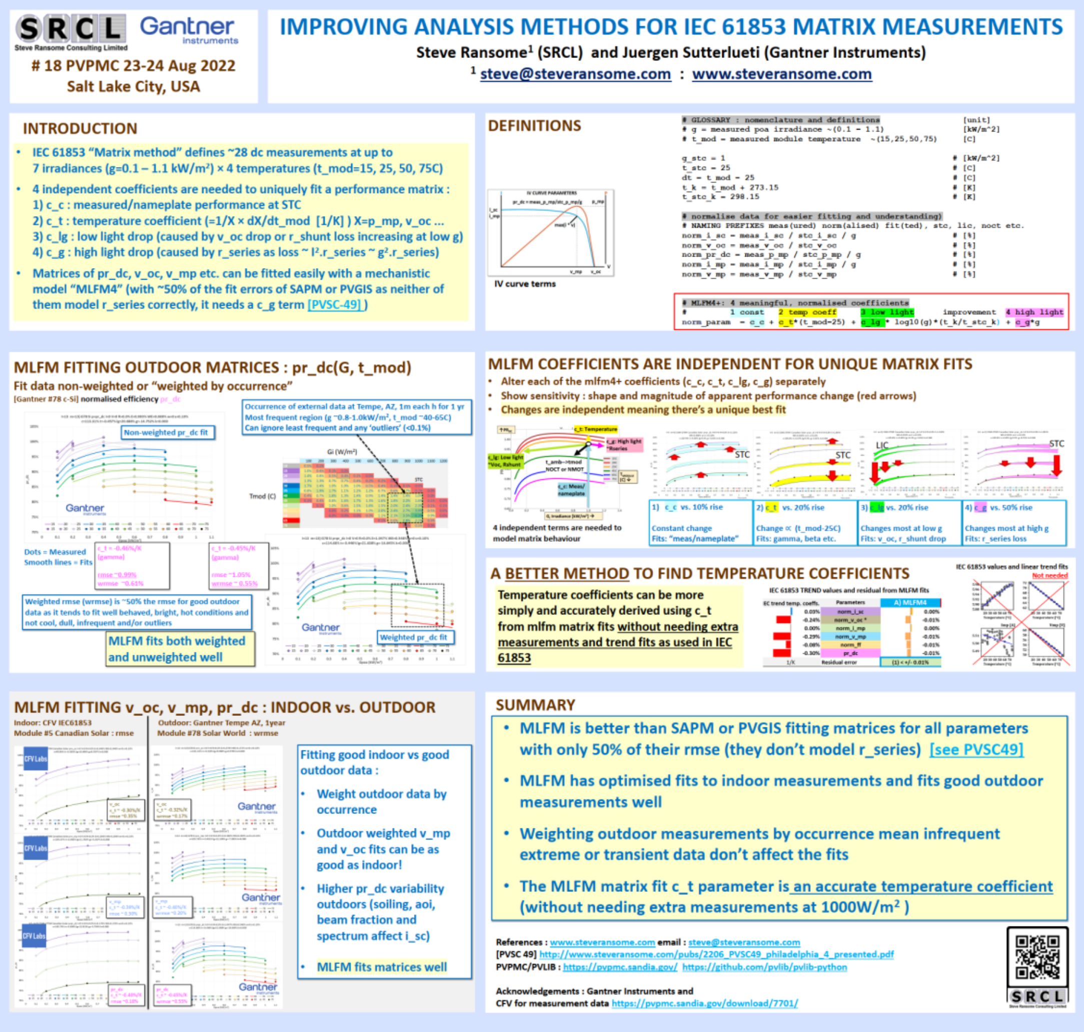
Latest Information and long-term data (>12 years):

This conference:

- Poster #18: IMPROVING ANALYSIS METHODS FOR IEC 61853 MATRIX MEASUREMENTS
  - Benchmarking of mLFM vs. SAPM or PVGIS fitting matrices for all parameters
  - Relevance or indoor/outdoor matrix fitting
  - Sensitivity to noise
  - A better and simpler method for temperature coefficients without extra measurements (as used in IEC 61853)

Further information:

- Quantifying Long Term PV Performance and Degradation under Real Outdoor and IEC 61853 Test Conditions, PVSEC 35, 2019
- Benchmarking PV performance models with high-quality IEC 61853 Matrix measurements (Bilinear interpolation, SAPM, PVGIS, MLFM, and 1-diode), PVSC 49, 2022



References

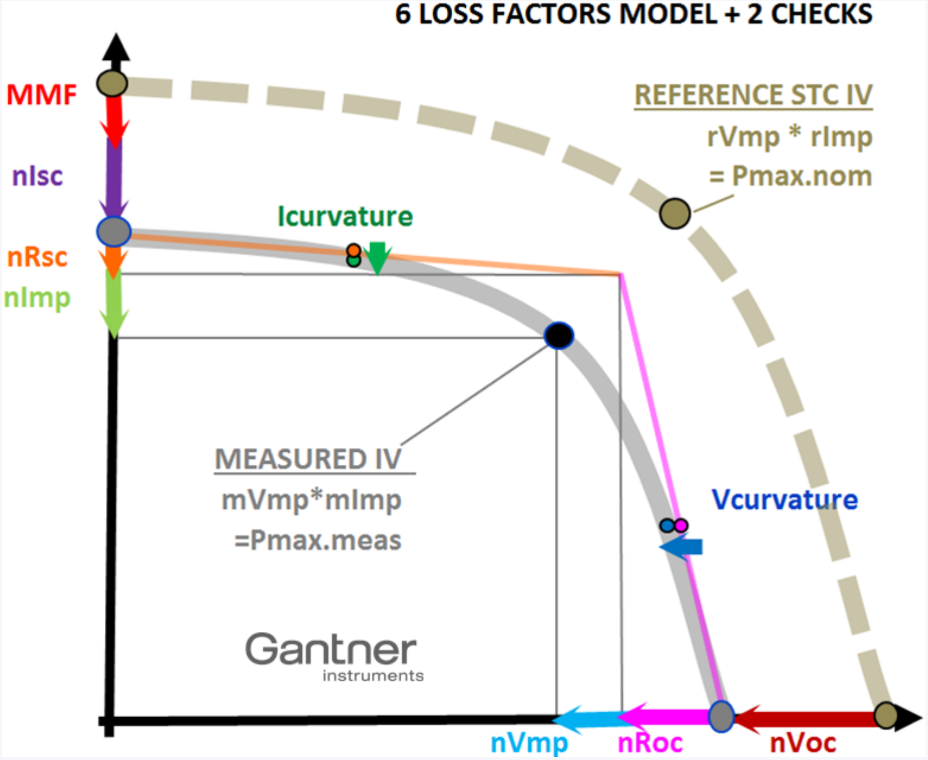
- Ransome, S. : "Benchmarking PV performance models with high quality IEC 61853 Matrix measurements (Bilinear interpolation, SAPM, PVGIS, MLFM and 1-diode)", PVSC 49,
- PVPMC / PVLIB: https://pvpmc.sandia.gov/, https://github.com/pvlib/pvlib-python
- Ransome, S., Sutterlueti, J., "A Systematic comparison of 12 empirical models used for energy yield prediction VS PV technology," in 33rd European Photovoltaic Solar Energy Conference, 2017.
- Livera, A., Theristis, M., Makrides, G., Sutterlueti, J., Ransome, S., Georghiou, G.E., "Performance analysis of mechanistic and machine learning models for photovoltaic energy yield prediction", in 36th European Photovoltaic Solar Energy Conference, 2019.
- Livera, A., Theristis, M., Koumpli, E., Theocharides, S., Makrides, G., Sutterlueti, J., Stein, J.S., Georghiou, G.E., 2021. Data processing and quality verification for improved photovoltaic performance and reliability analytics. Prog. Photovolt. Res. Appl. 29, 143– 158. https://doi.org/10.1002/pip.3349
- J. Sutterlueti, "Advanced PV performance analysis on modules and power plants using cloud-based processing" in 12th PV Performance Modeling and Monitoring Workshop, May 2019.
- A. Livera, G. Makrides, M. Theristis, G. E. Georghiou, "Recent advances in failure diagnosis techniques based on performance data analysis for grid-connected photovoltaic systems" Renewable Energy. vol. 133, pp. 126-133, Apr 2019.
- A. Livera, M. Theristis, G. Makrides, J. Sutterlueti, S. Ransome and G. E. Georghiou, "Performance analysis of mechanistic and machine learning models for photovoltaic energy yield prediction", in 36th European Photovoltaic Solar Energy Conference, 2019, pp 1-6.
- A. Livera, G. Makrides, J. Sutterlueti and G. E. Georghiou, "Advanced failure detection algorithms and performance outlier decision classification for grid-connected PV systems", in 33rd European Photovoltaic Solar Energy Conference, 2017, pp 2358-2363.
- G. Makrides, A. Phinikarides, J. Sutterlueti, S. Ransome and G. E. Georghiou, "Advanced performance monitoring system for improved reliability and optimized levelized cost of electricity", in 32nd European Photovoltaic Solar Energy Conference, 2016, pp 1973-1977.
- J.Sutterlueti et al.: Using similar mathematical modelling with both single module IV curve measurements and array Inverter data, PVPMC 2018
- S. Ransome and J. Sutterlueti: Optimised fitting of indoor (e.g. IEC 61853 matrix) and outdoor PV measurements for diagnostics and energy yield predictions, PVSEC, Shiga, Japan, 2017
- J. Sutterlueti and S. Ransome: Quantifying and analysing the variability of PV module resistances RSC and ROC to understand and optimise kWh/kWp modelling, PVSEC, Shiga, Japan, 2017
- S. Ransome and J. Sutterlueti: A systematic comparison of 12 empirical models used for energy yield prediction vs PV technology, EUPVSEC, Amsterdam, 2017
- Andreas Livera et al.: Impact of Missing Data on the Estimation of Photovoltaic System Degradation Rate, IEEE, PVSC2017, Washington, 2017
- S. Ransome and J. Sutterlueti: How to Choose the best Empirical Model for Optimum Energy Yield Predictions, IEEE, PVSC2017, Washington, 2017
- more at https://www.researchgate.net/scientific-contributions/Juergen-Sutterlueti-2133552590

IV scan solution

Interested?
Contact us for any data sharing, validation, PV Module testing or IV scan solution at otf@gantner-instruments.com

OTF
Technical Features I

- Data acquisition: proven dynamic electronic load with all necessary current & voltage ranges allows measurement of all available PV Modules; Typical range: 20A, 200V, 500W, Peak: 800W; customized range on demand
- Four wire concept to eliminate cable influence and ohmic losses
- 24bit resolution with high galvanic isolation voltage (1200 VDC permanent)
- Fast & high accuracy digitalization, 1 kHz sample rate per channel, accuracy 0.01 % typical
- Fast response time: (10…100%): 100us
- Dynamic sweep time and scan interval (from seconds to hours)
- Module IV scans are performed in synchronous way – resulting in highest accuracy for PV module comparisons
- On the fly calculation of all key parameters Isc, Rsc, Imp, Vmp, Roc, Voc



Loss Factors Model (LFM)
The LFM determines a module's performance from its I-V curve simply as the product of six physically significant and independent normalized "loss factors" as well as spectral and temperature corrections.
All normalized LFM parameters multiplied together shows PRdc

OTF
Technical Features II

- Data acquisition based on a user specific time interval (e.g. 1min)
- One measurement channel per module – best long term accuracy, highest uptime
- Different tracking methods available per channel (Pmpp/max. power point, Voc/open circuit, Isc/short circuit)
- Reliable software with special self monitoring features and automatic user alerts (e.g. email notification), automatic data check in database
- State of the art data security & protection on hardware and software level
- High performance data base allows allows real time performance prediction and enables optimized O&M concepts for large plants
- Special Mode for Self – Calibration check
- Outdoor spectroradiometer for understanding the spectral influence
- Reliable and proven industry components and calibrated sensors (reference cells, pyranometer)
- Indoor / Outdoor configuration