

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

PVPMC Workshop  
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Jürgen Sutterlüti et. al.  
[j.sutterlueti@gantner-instruments.com](mailto:j.sutterlueti@gantner-instruments.com)



# Introduction

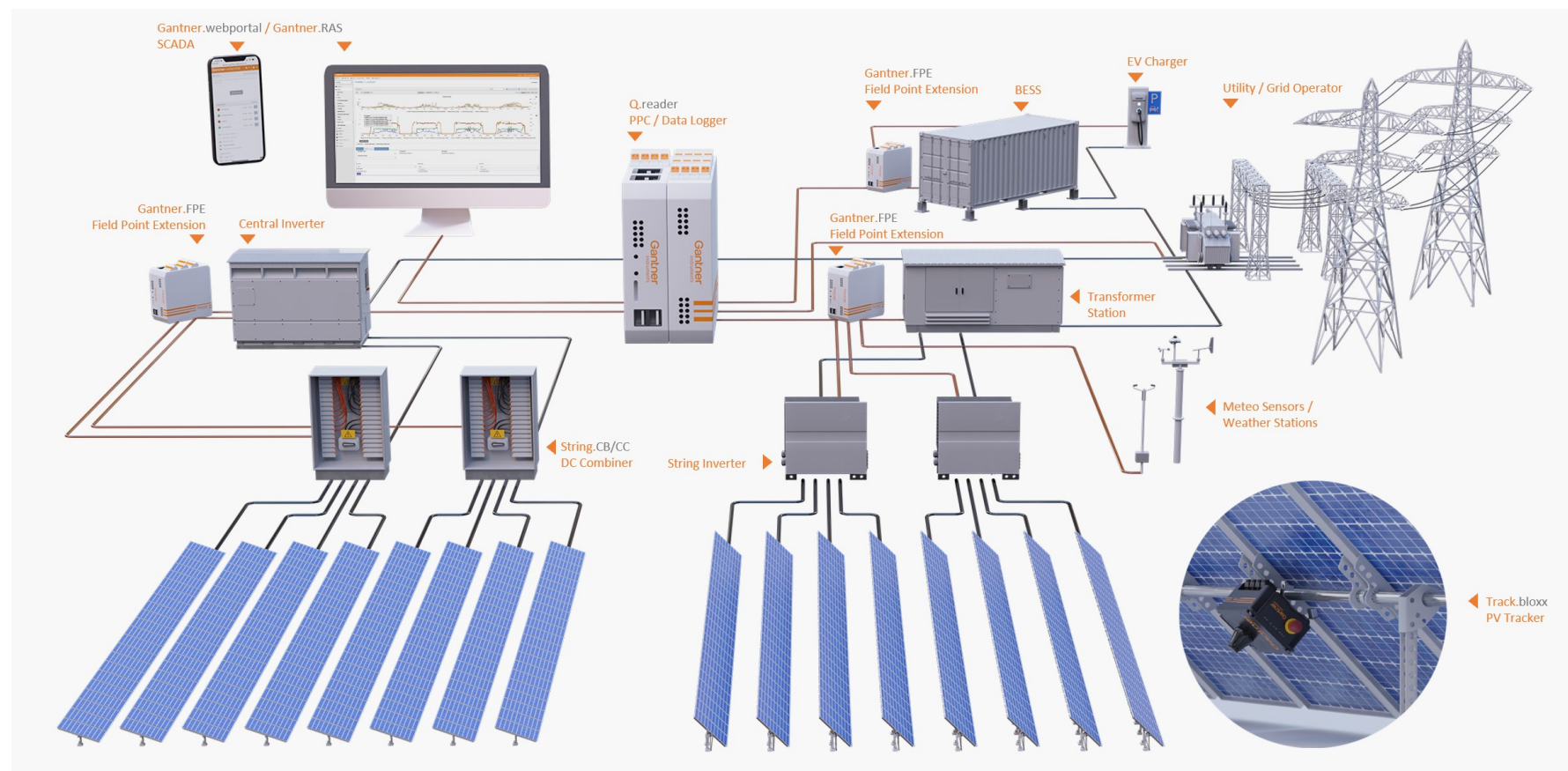
- Future PV uptake → reduction of the Levelized Cost of Electricity (LCoE)
- Reduced LCoE achieved by increasing lifetime performance & reducing O&M costs

$$\text{LCoE } (\$/\text{MWh}) = \frac{\text{CapEx} + \text{O\&M}}{\text{Energy yield}}$$

↓ (LCoE)      ↓ (O&M)      ↑ (Energy yield)

## Agenda

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

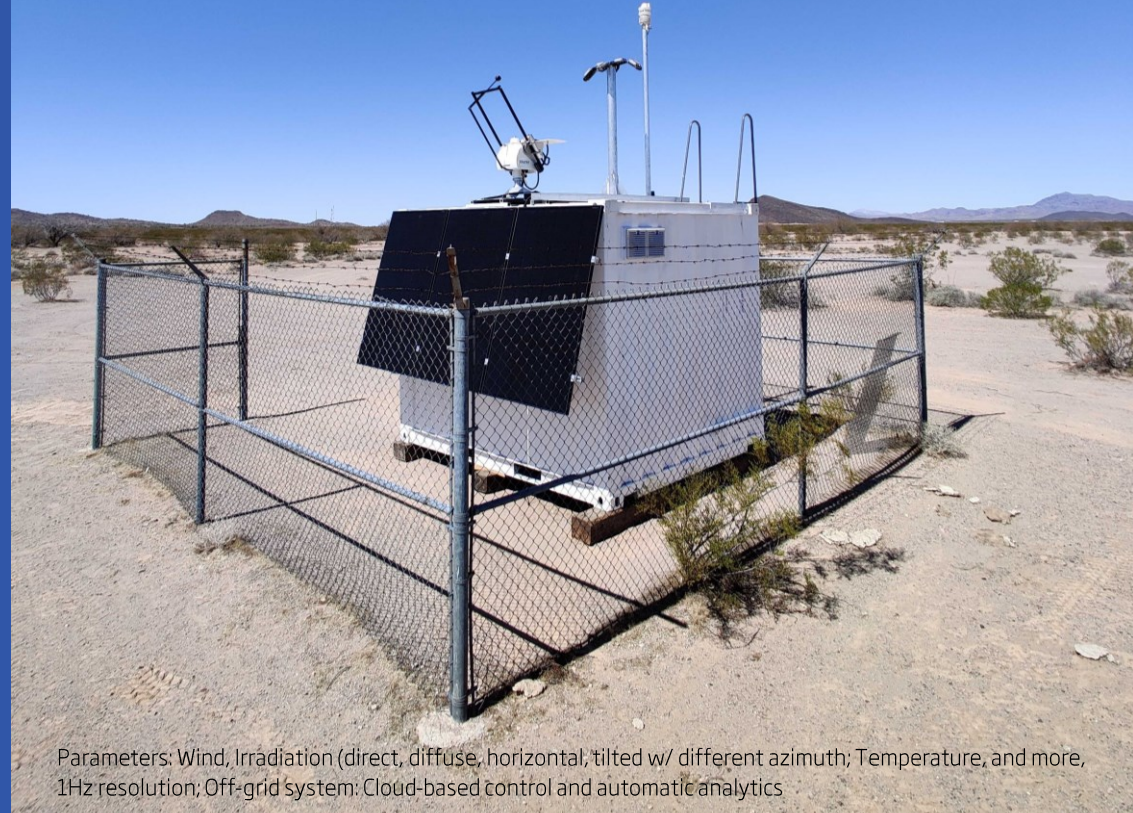


With Gantner's turn-key monitoring and control, Europe's largest PV park (600MW) is under way.

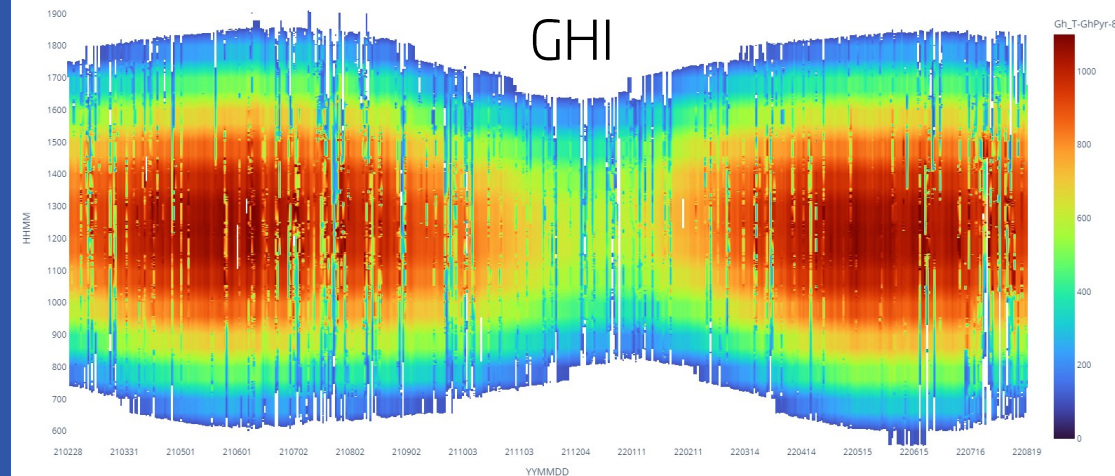
Weather prospecting

# Reliable Information for Optimum Energy Output

Weather prospecting Solution for GW scale Array

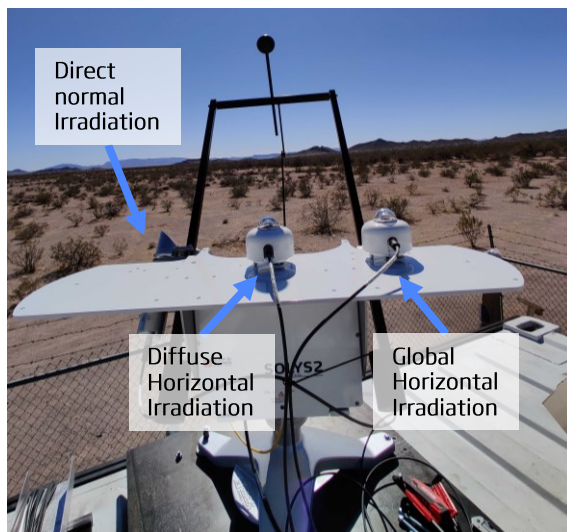
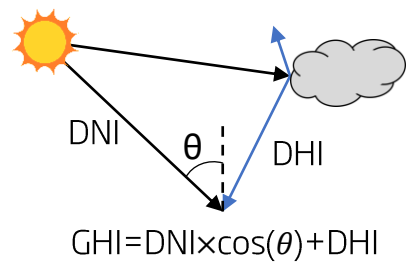


Parameters: Wind, Irradiation (direct, diffuse, horizontal, tilted w/ different azimuth; Temperature, and more, 1Hz resolution; Off-grid system: Cloud-based control and automatic analytics

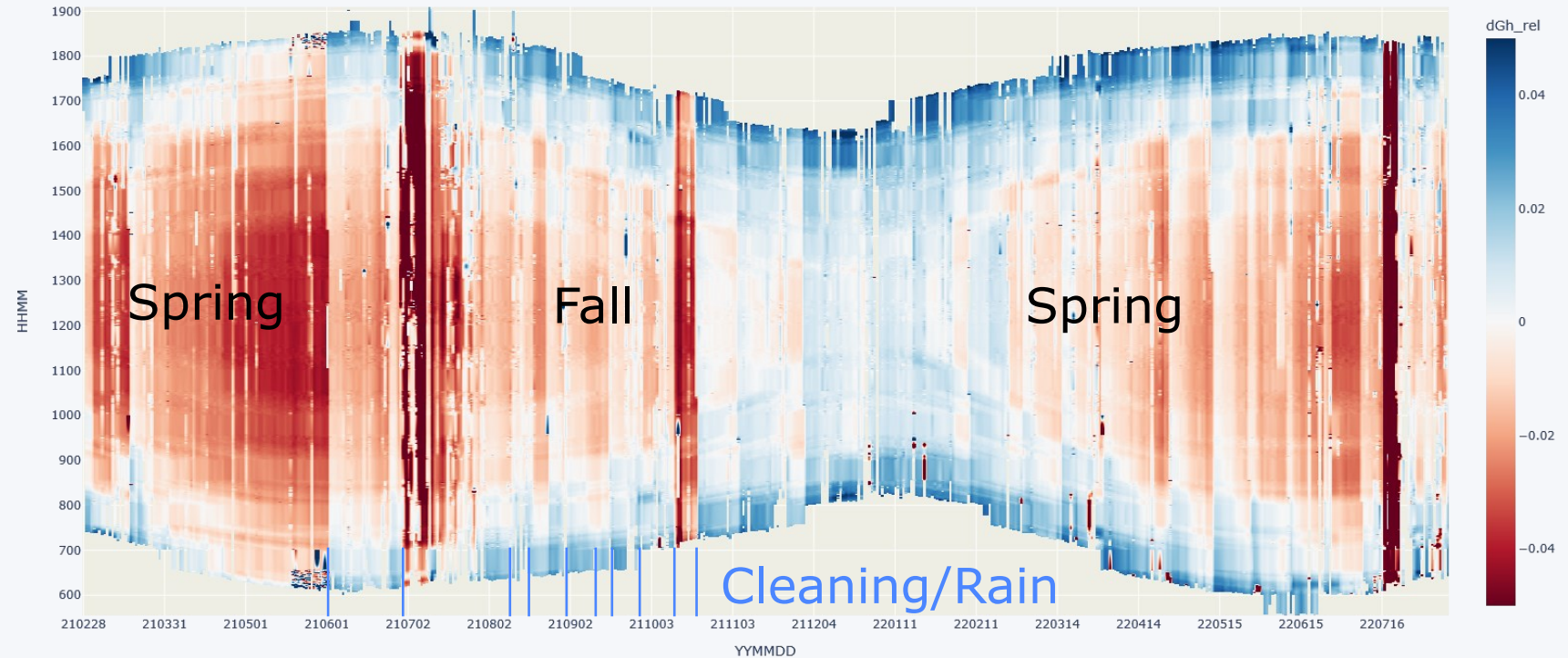


Horizontal Irradiation, 1m resolution, Feb. 2021 to Aug. 2022, Filter: >100W/m2

# Why measure the weather before you start to construct?

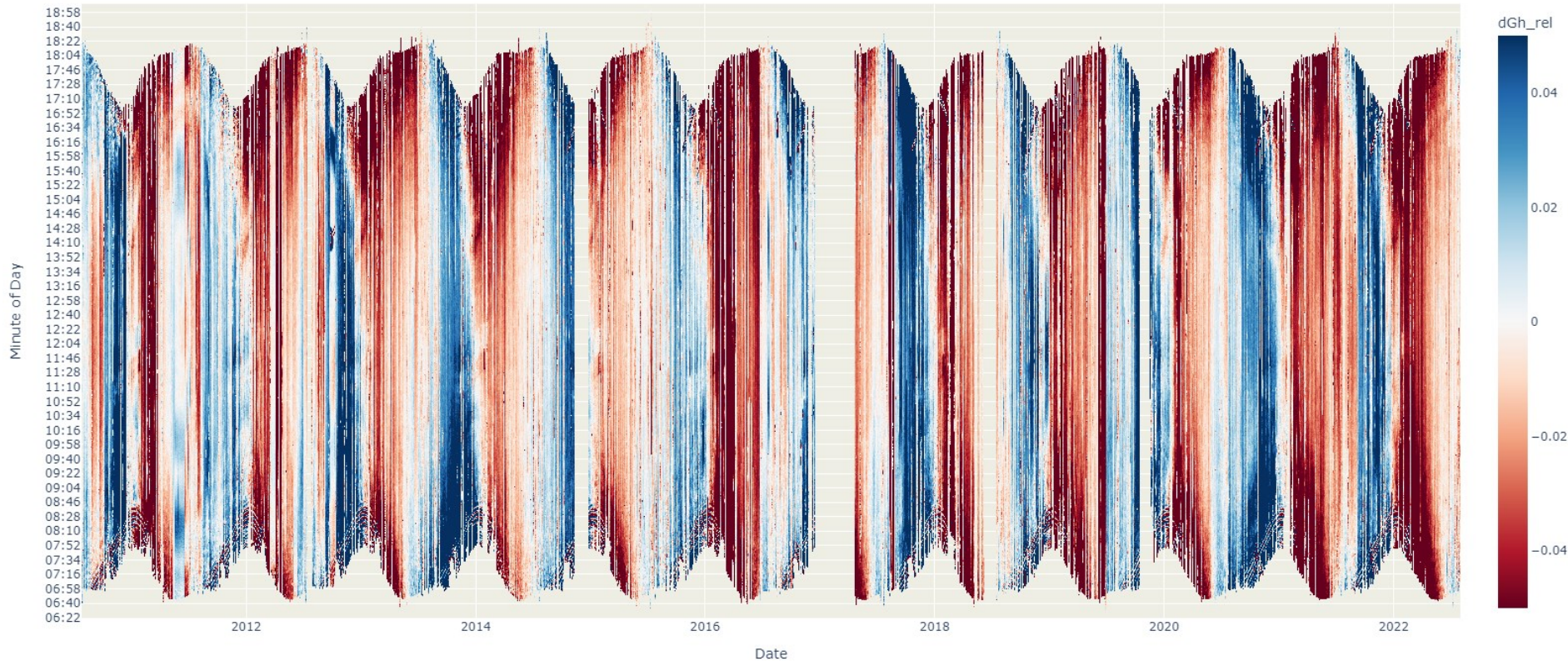


## Validation example of horizontal irradiation (GHI) in Arizona, USA:



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

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



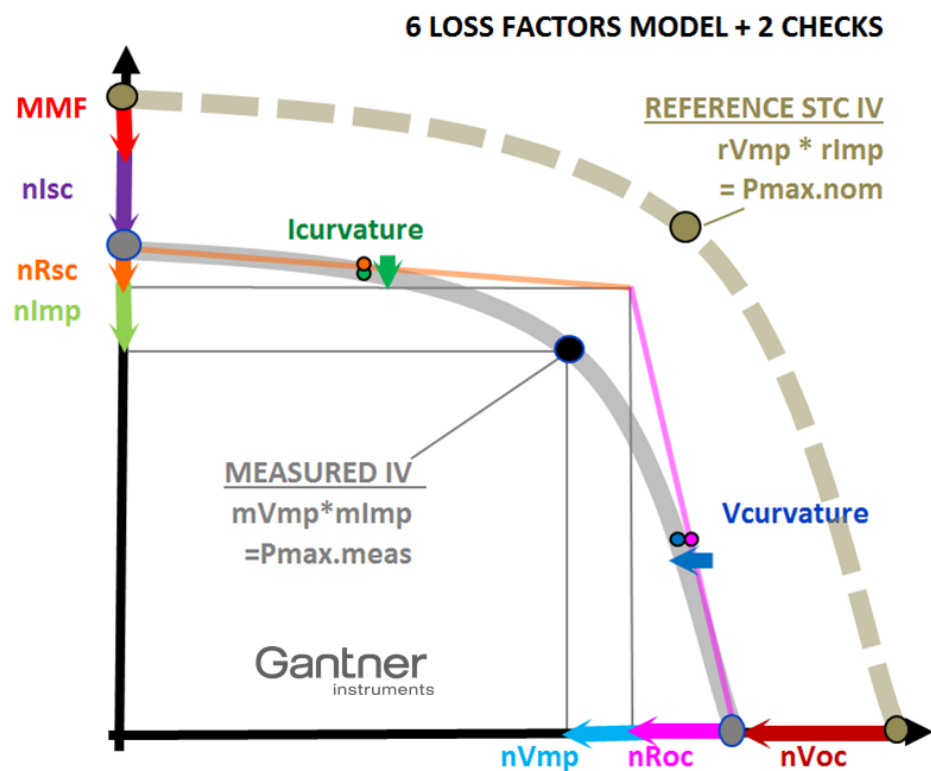
## (Possible) reasons:

- ~~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?**

# 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

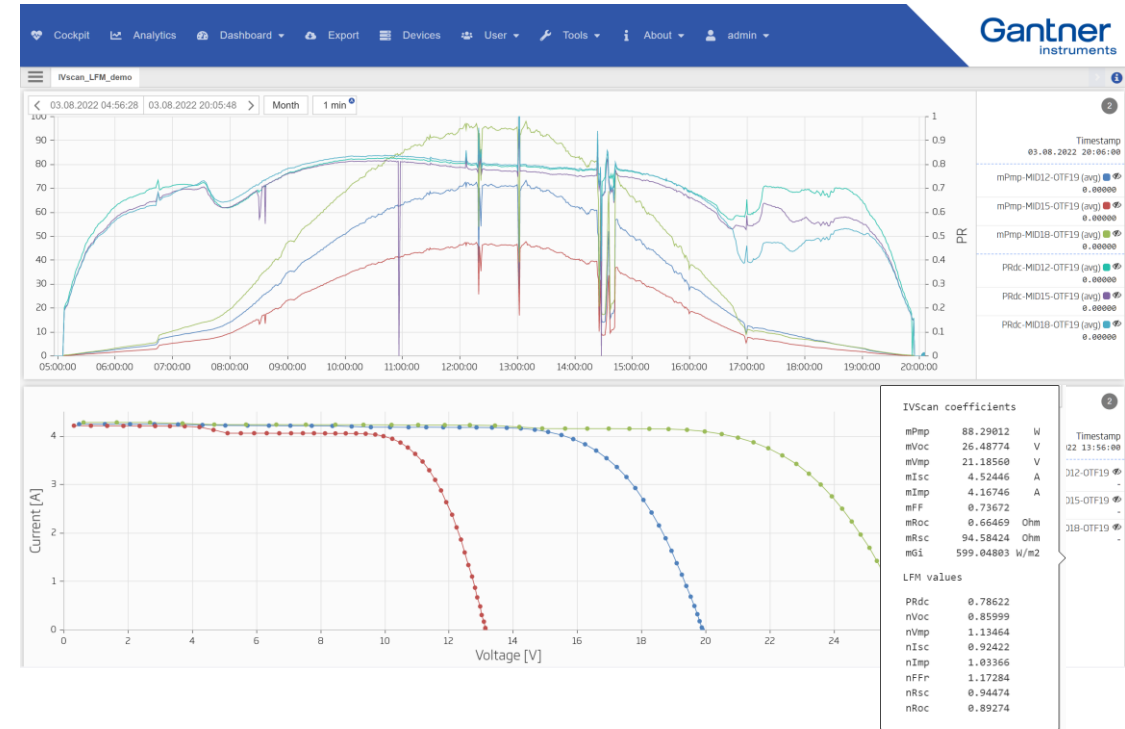
# Robust extraction of key values with the Loss Factors Model (LFM)

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

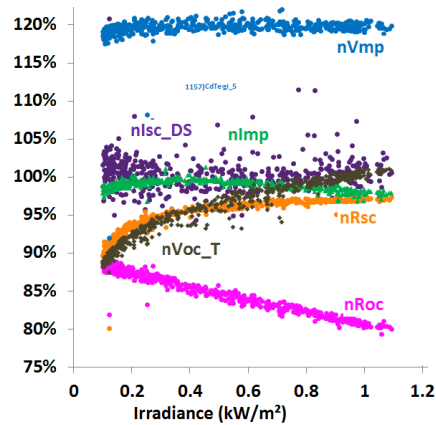
$$PR_{DC} = n_{Isc} * n_{Rsc} * n_{Imp} * n_{Vmp} * n_{Roc} * n_{Voc}$$

## LFM parameters are:

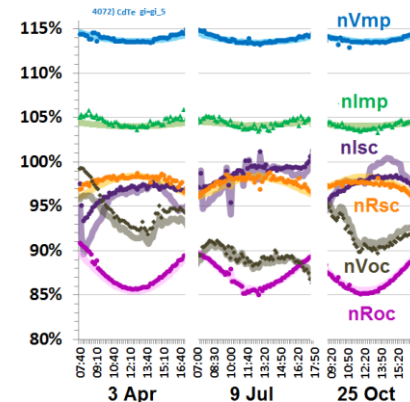
technology agnostic, area independent, normalized, meaningful, e.g., "% power loss due to  $R_{SERIES}$ "



Characterize a module vs.  $G_p$ ,  $T_{mod}$ , etc.



Predict performance vs. time and weather

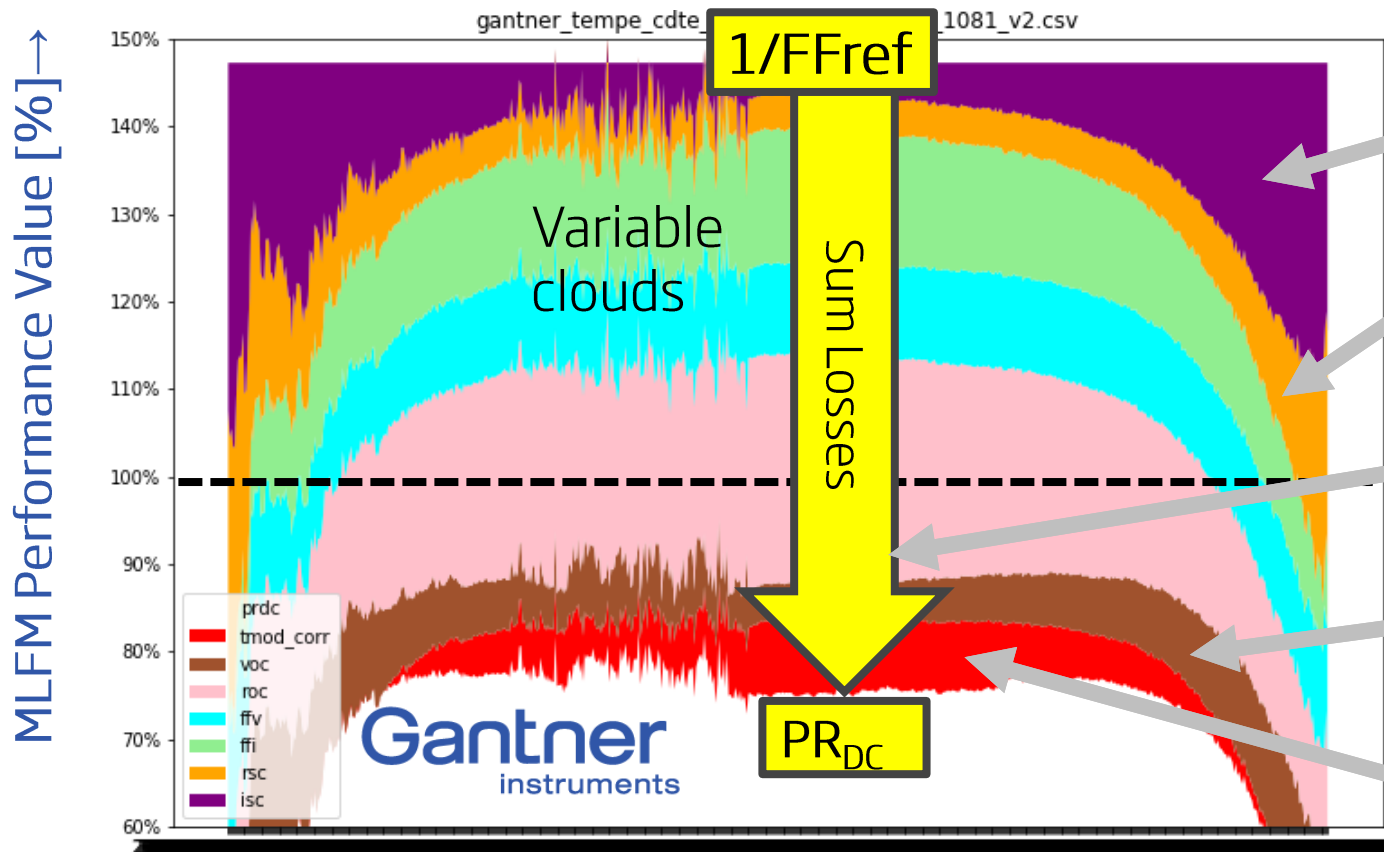


LFM can easily find any discrepancies, degradation, poor measurements, etc.

# Stacked losses vs. time: 1 day

CdTe: Clear day in March, Tempe AZ

$$PR_{DC} = 1/FF_{ref} - \text{stacked\_loss}[(isc + rsc + ffi) + (ffv + roc + voc\_Tcorr + t\_mod)]$$



## When are losses greatest?

- (1) **Isc loss** (AOI/reflectivity, spectrum) → morning, evening
- (2) **~Rshunt loss** (low irradiance) → morning, evening
- (3) **~Rseries loss** (high  $I^2 \cdot R_{series}$ ) → noon
- (4) **Voc\_tcorr** (temp\_corrected) ( $Voc \sim \log(G_i)$ ) → low irradiance
- (5) **Temperature loss** → noon - afternoon (high temperature)

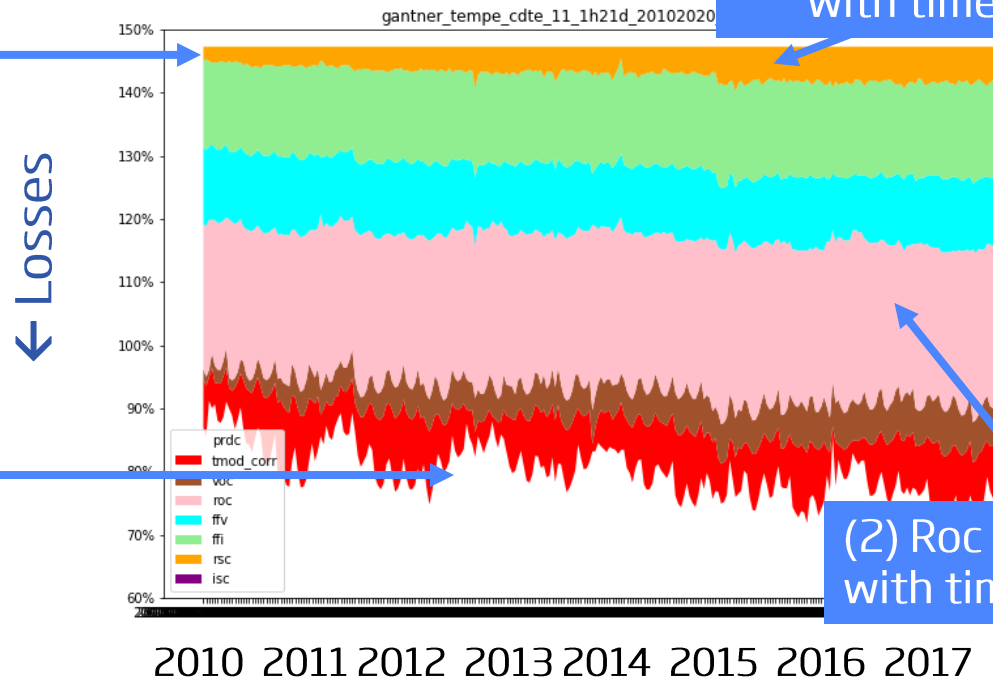


# Identify causes and rates of any long-term degradation

Stacked loss graphs, 2010-2017+

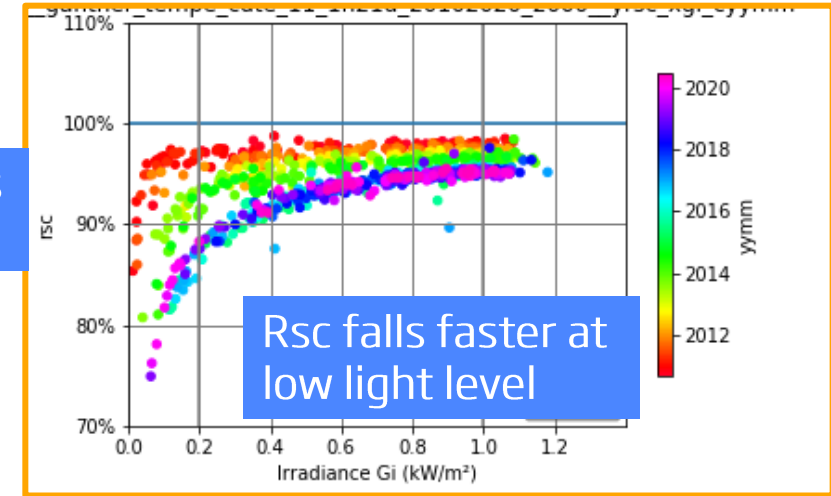
$$PR_{dc} \propto \frac{1}{FF_{ref}} - \text{stacked\_loss}[(isc + rsc + ffi) + (ffv + roc + voc\_Tcorr + t\_mod)]$$

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

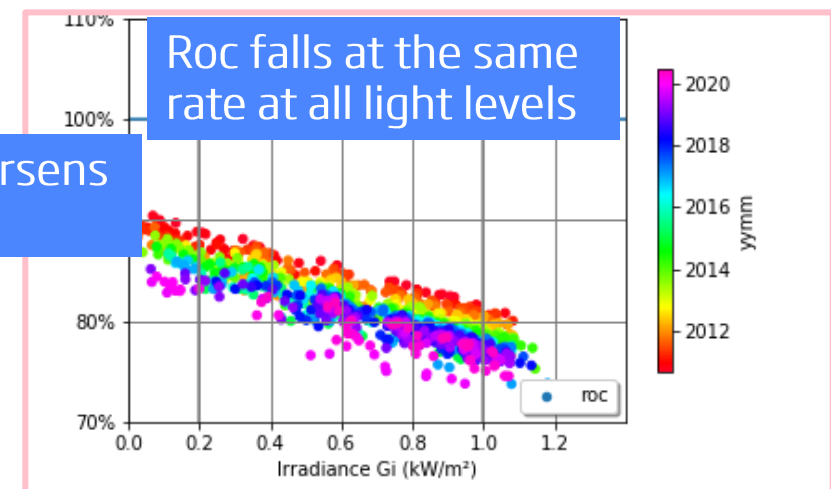


(1) Rsc loss worsens with time

(2) Roc loss worsens with time



Rsc falls faster at low light level



Roc falls at the same rate at all light levels

# Mechanistic Performance Modelling for Large PV Arrays

# Mechanistic Performance Model (MPM) for PV Arrays

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

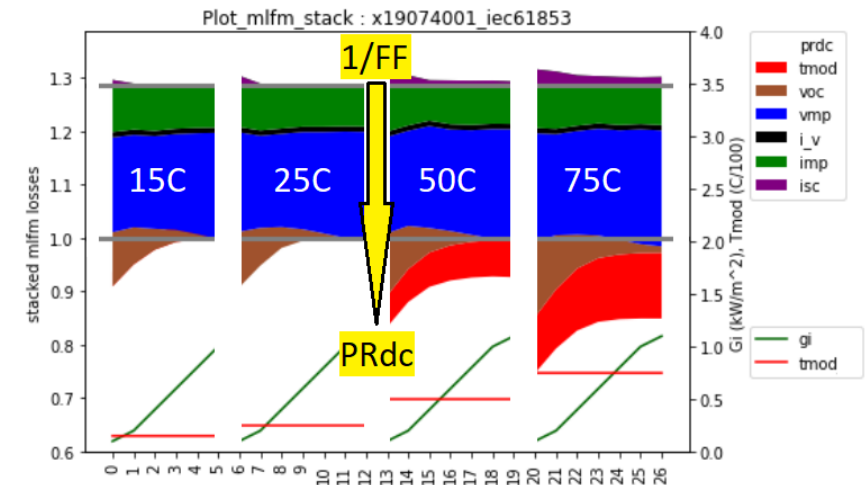
$$\text{MPM}_{\text{Param}} = C_1 + C_2 * (T_{\text{MOD}} - 25) + C_3 * \text{Log}_{10}(G_i) + C_4 * G_i + C_5 * \text{WS}$$

e.g., PR, nVdc, nldc      Tolerance      Temperature      Voc and Rshunt      R<sub>SERIES</sub>      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



# Mechanistic Performance Model (MPM) for PV Arrays

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

$$\text{MPM}_{\text{Param}} = C_1 + C_2 * (T_{\text{MOD}} - 25) + C_3 * \text{Log}_{10}(G_i) + C_4 * G_i + C_5 * WS + C_7 f_{\text{Asym}} + f_{\text{Clip}}(C_8, C_6)$$

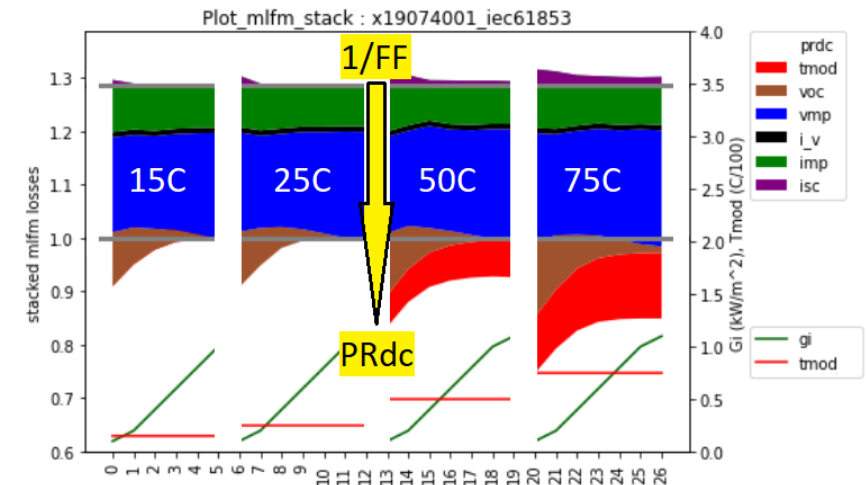
e.g., PR, nVdc, nldc      Tolerance      Temperature      Voc and Rshunt      R<sub>SERIES</sub>      Wind      Asymmetry      ClipMax      ClipRamp

MPM Advanced  
5 Coeff. for typical sites

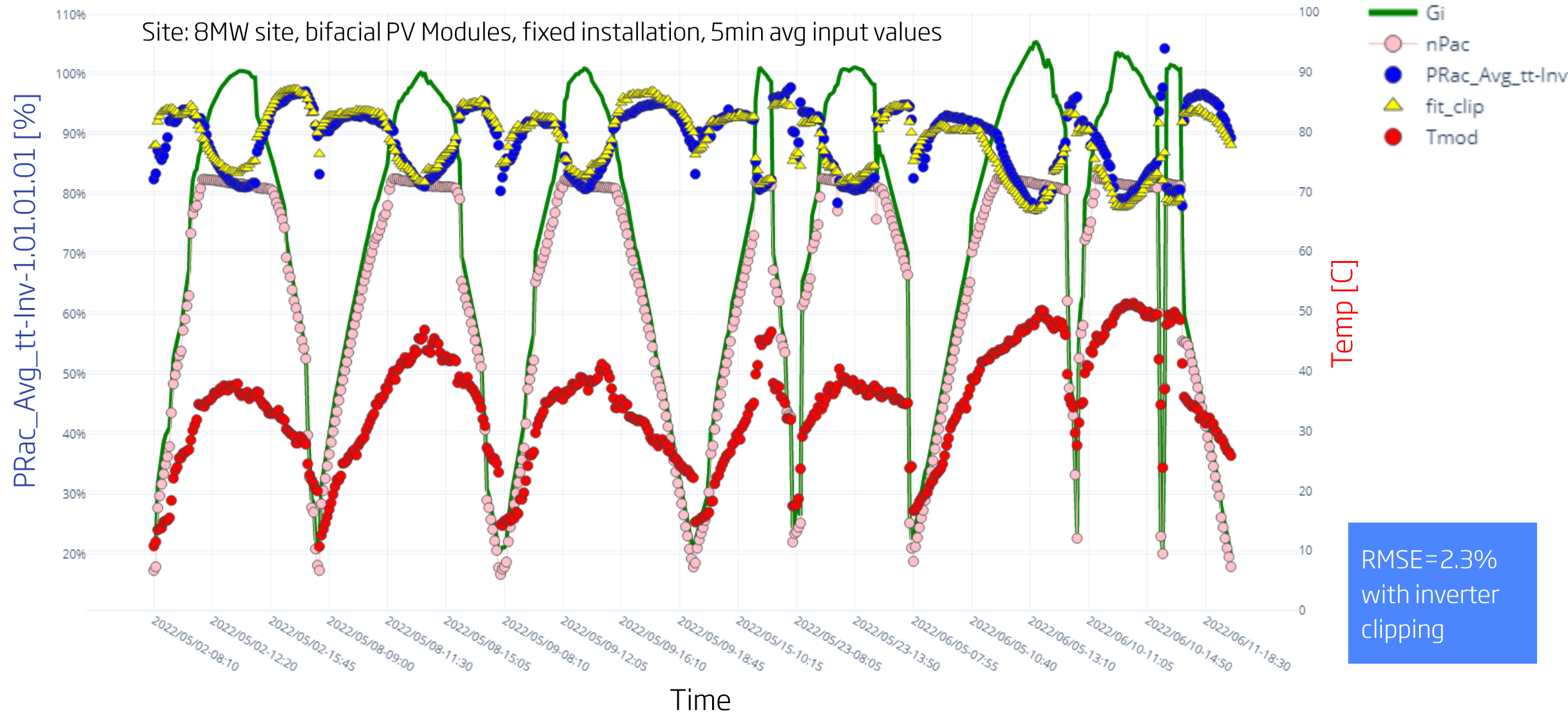
MPM Professional  
covers also clipping, asymmetric behavior

MPM is best

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

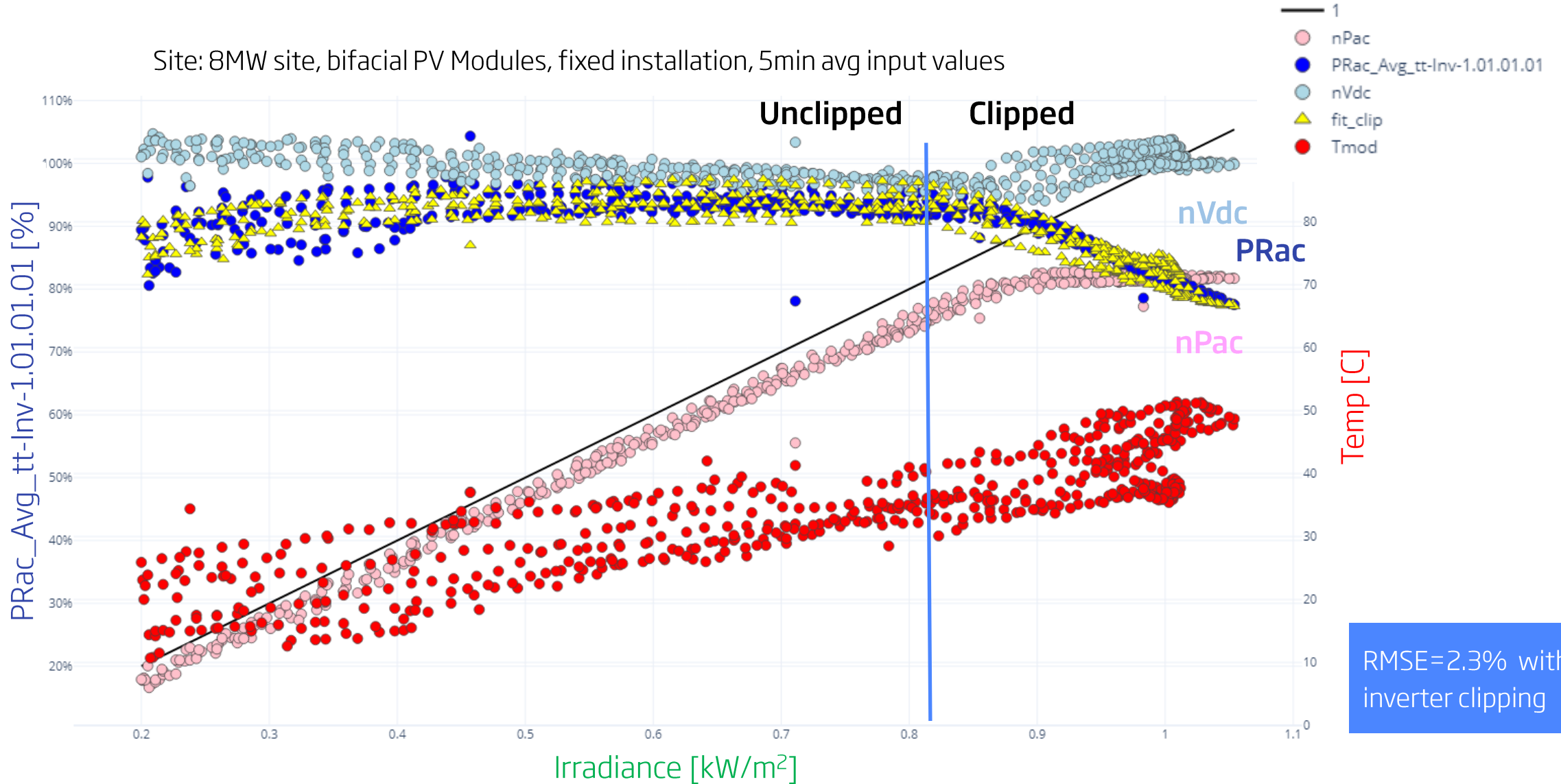


# MPM Professional- PRac.meas, PRac.fitclip vs. time

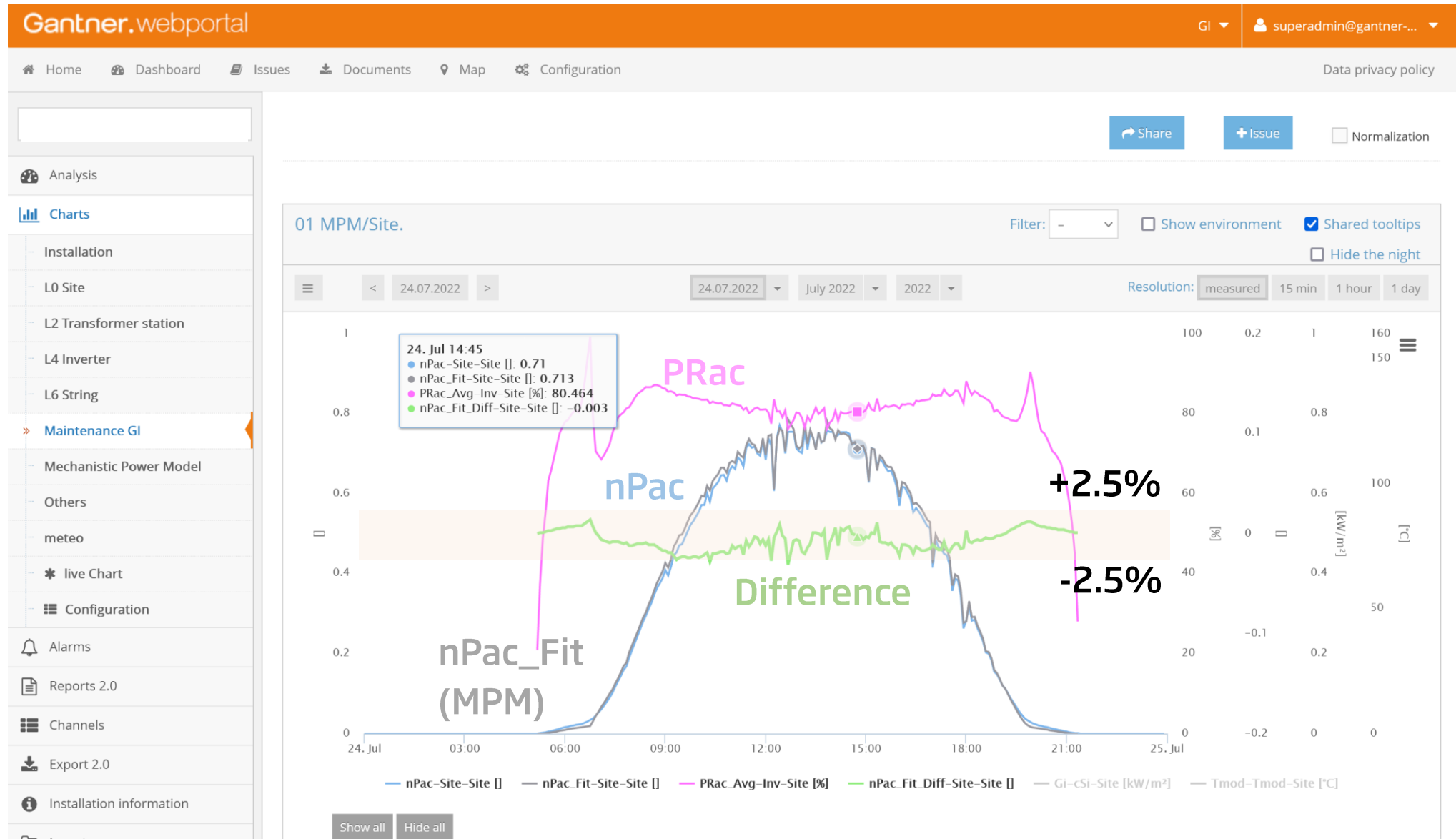


# MPM Professional- nPac, PRac.meas, PRac.fit vs. Irradiance

Site: 8MW site, bifacial PV Modules, fixed installation, 5min avg input values



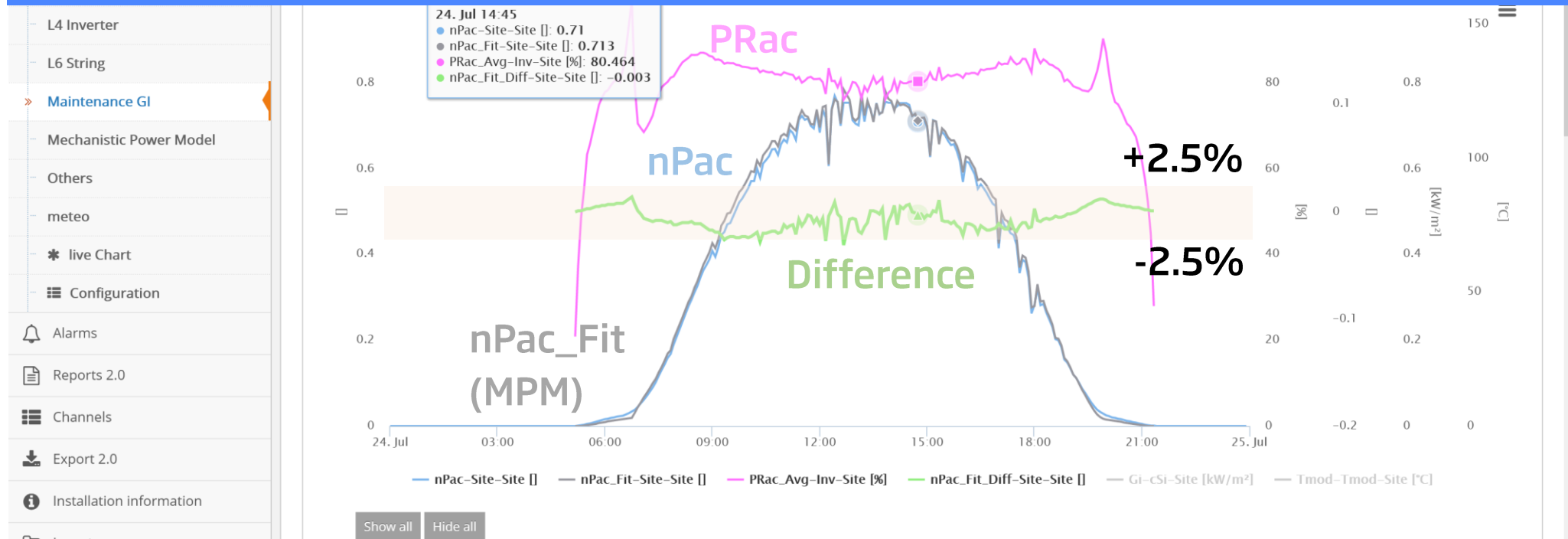
# MPM part of Gantner's Monitoring and control platform



# MPM part of Gantner's Monitoring and control platform

## 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  $\pm 2.5\%$
- 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	RMSI	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%

- RMSE range 1.15% to 4.17%,
- Results impacted by site design, quality & data aggreg.

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	RMSI	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 < 2.7%
- nVdc fit very robust

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

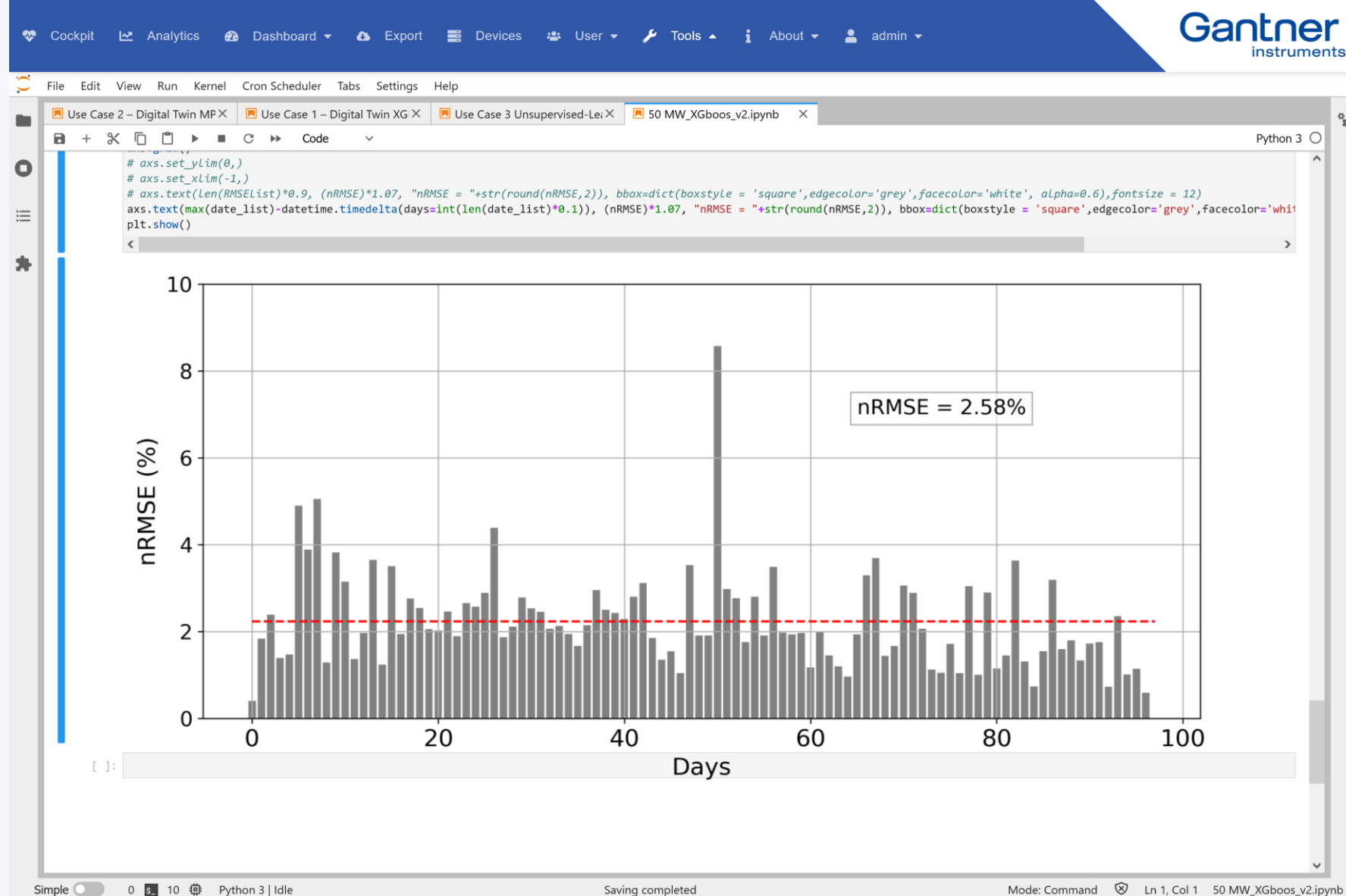
# Machine Learning for Large PV Arrays

# 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)

Use Case 3 Unsupervised-Le: X

```

c = plt.scatter(OX1,OX2, c='black',s=20, edgecolor='k')

plt.axis('tight')

plt.xlabel("Measured Power", fontsize = 20)
plt.ylabel("SyntheticPower", fontsize = 20)
# Loc=2 is used for the top left corner
plt.legend(
    [a.collections[0], b,c],
    ['learned decision function', 'inliers', 'outliers'],
    prop=matplotlib.font_manager.FontProperties(size=16),
    loc=2)

plt.xlim((0, 1))
plt.ylim((0, 1))
plt.title(cif_name)
plt.tight_layout()
plt.show()
    
```

OUTLIERS : 17 INLIERS : 730

Power (MW)

• Normal  
• Fault

Fault classifier (Xgboost, MW scale, 97%)

SyntheticPower

Measured Power

--- learned decision function  
○ inliers  
● outliers

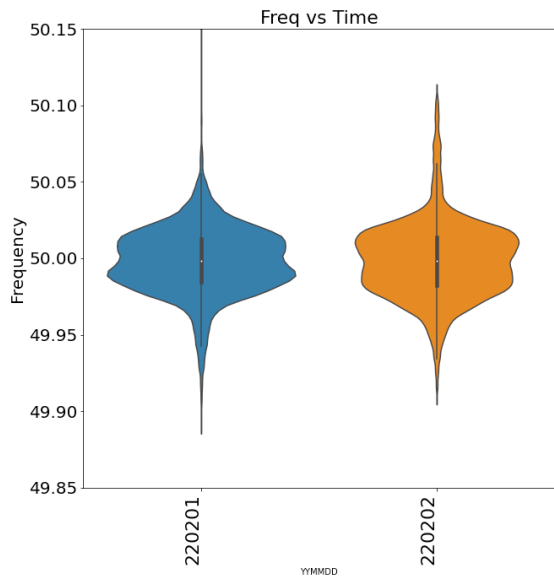
Unsupervised learning for diagnosing power faults on real field data (relative magnitude 5%, MW-scale)

Simple 0 10 Python 3 | Idle Saving completed Mode: Command Ln 1, Col 1 Use Case 3 Unsupervised-Learning Outlier Detection.ipynb

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

# Microgrid Real-time Interaction

# A stable Frequency keeps the lights on...



Python 3 (ipykernel) interface showing code and a heatmap.

```

ax.set_xticklabels(nw_tick_list, fontsize = 18 ) #pivot_o.index

#define z-axis (colorbar)
cbarlabel = zval
cbar = ax.figure.colorbar(im, ax=ax) # , **cbar_kw
cbar.ax.set_ylabel(cbarlabel, rotation=90, va="bottom", fontsize=18, labelpad=30)
#cbar.set_label(zval, labelpad=20)

#set labels
#ax.grid(linewidth=1)
fig.tight_layout()
plt.xlabel(xval)
plt.ylabel(yval)
plt.title(title, fontsize=20)
plt.tight_layout()
plt.show()
#return pivot_hm #only if you are interested in pivot

[11]: param = 'YYMMDD'
      t = df.loc[(df[param] == 220327)]

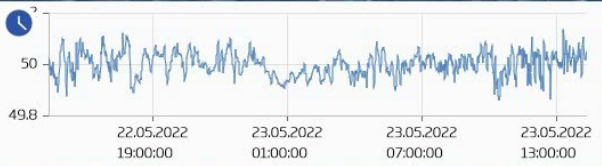
[12]: define_heat_map(zval='Freq_Meas-HP-15_min', df=df, yval='HHMM', xval='YYMMDD', agg='np.min', colours='RdYlBu', title='Frequency vs. Time (yyymmdd) and hour of day; Asset GI', start_yymmdd=220201, end_yymmdd=220228)
    
```

**Network Conditions (Monitored Assets)**

Total Active Power  
**1.883**  
MW

Total Reactive Power  
**0.118**  
MVar

**Frequency Trend**



**THD Phase A**  
**1.59**  
%

**THD Phase B**  
**1.62**  
%

**THD Phase C**  
**1.64**  
%

ENERGY CENTERS	
217940.69 W	554.71 W
130467.55 Var	1085.69 Var
164744.64 W	337072.47 W
-8468.06 Var	8849.19 Var

157463.72 W  
10946.27 Var

**ADMINISTRATION BUILDING**  
97433.90 W  
10693.53 Var

**ATHLETIC CENTER**  
72758.02 W  
-32615.54 Var

**PV LAB**  
3537.25 W  
-432.49 Var  
0.00 W  
0.00 Var

**FACULTY OF ECONOMICS**  
180944.44 W  
-4043.54 Var

**SOCIAL FACILITIES**  
178933.95 W  
28304.24 Var

**STP**  
11724.12 W  
668.26 Var

**STUDENT HALLS**  
-25044.15 W  
-7732.18 Var

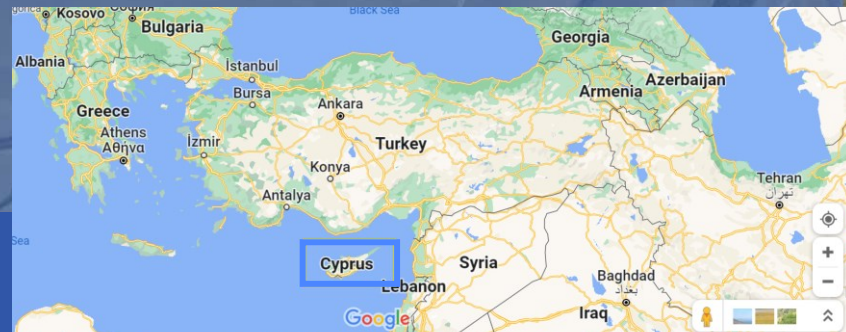
**FACILITIES FOR SCIENCE**  
137769.72 W  
-9799.59 Var  
346537.12 W  
-10555.64 Var

GHI-GhPyr  
**618**  
W/m<sup>2</sup>

WS-WindSpeed  
**2.8**  
m/s

Tamb-temp  
**30.02**  
°C

**PCC**  
234.65 V  
50.04 Hz

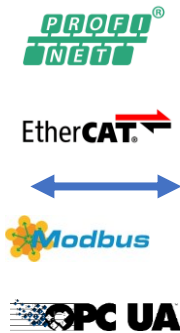


# Grid status of UCY Campus

# Microgrid setup at University Campus in Cyprus



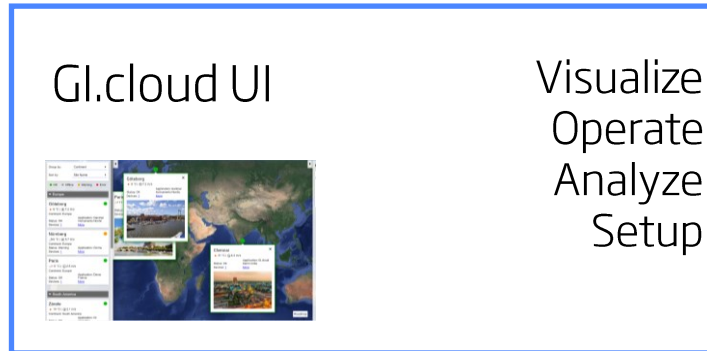
Digitalization and interoperability  
open communication standards



Real-time data stream



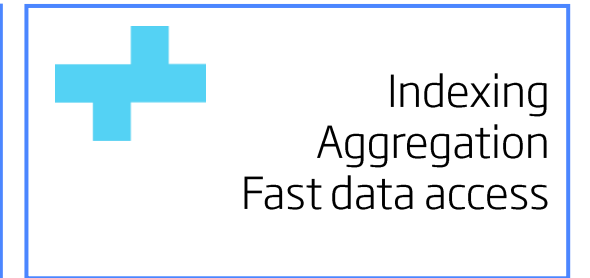
Centralized supervision and control



Distributed, scalable, clustered, API

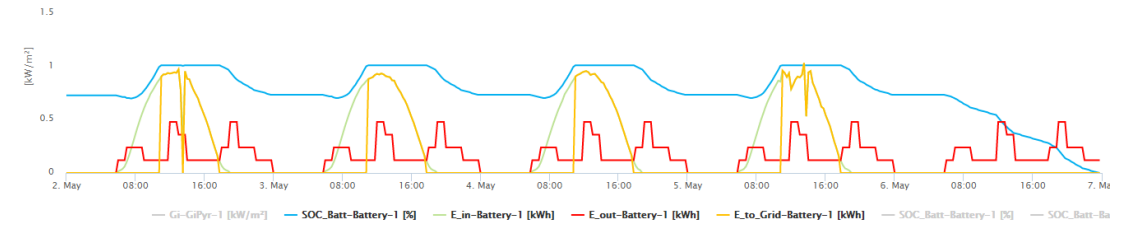
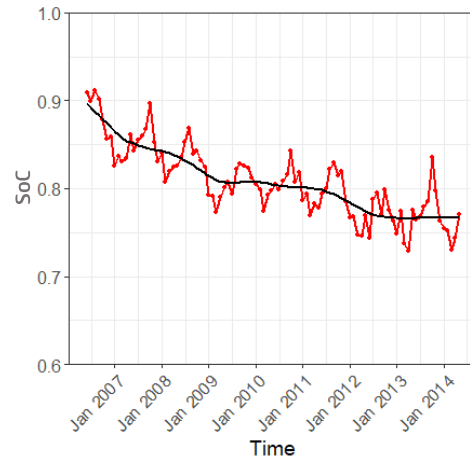
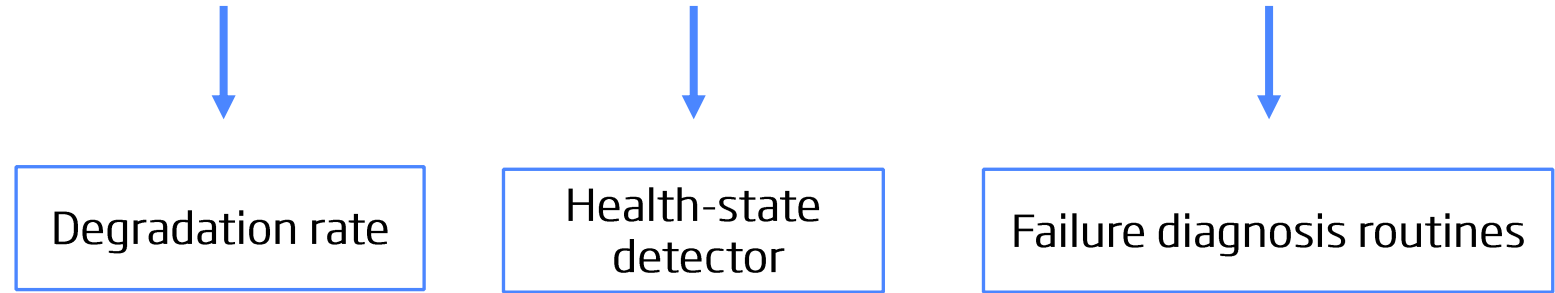
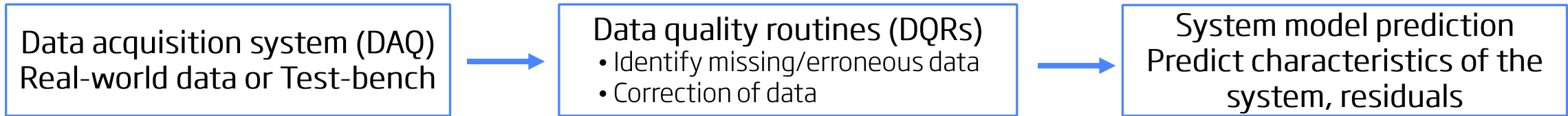


Read/write data streams  
Real-time control






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



# Lessons learned - which we also had to work hard for ...

- 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.)



“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**

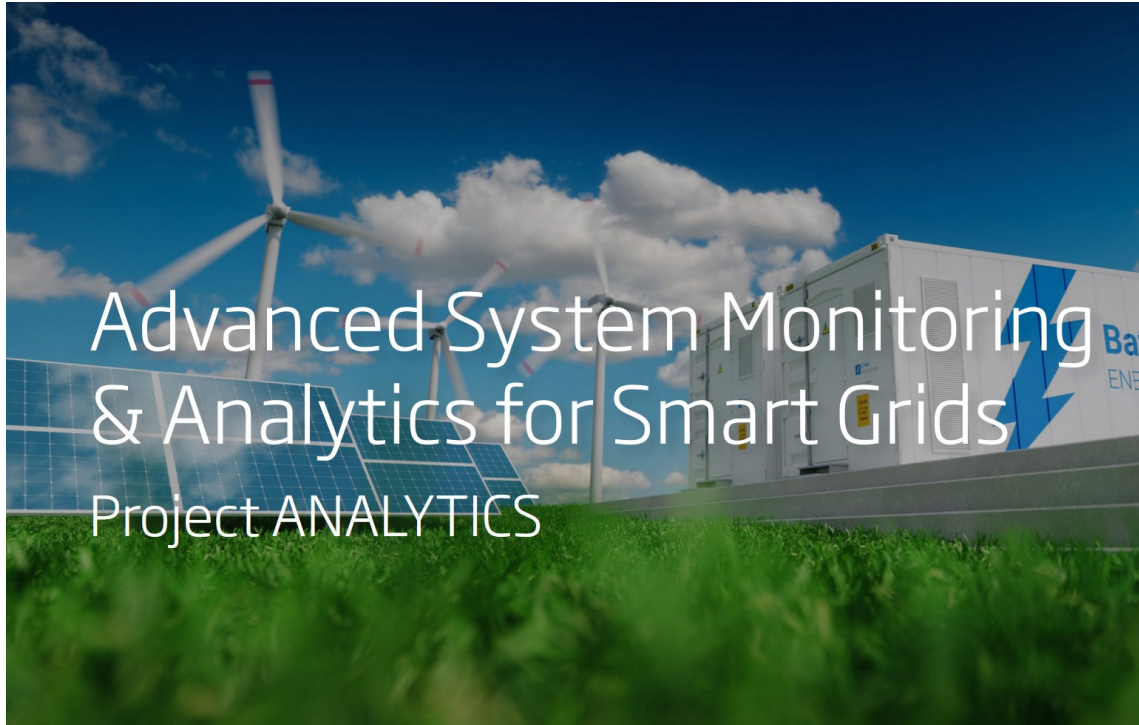
**Thank you very  
much!**

[j.sutterlueti@gantner-instruments.com](mailto:j.sutterlueti@gantner-instruments.com)

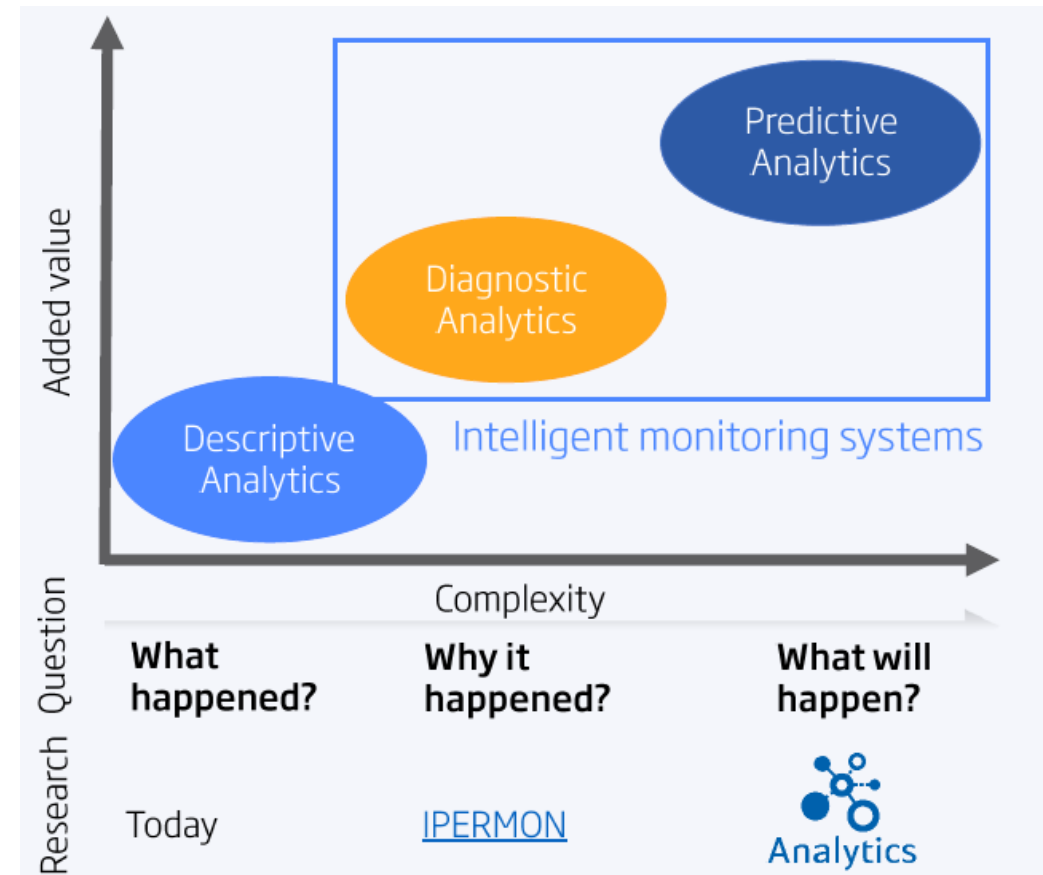


# Appendix

# The Analytics project



powered by

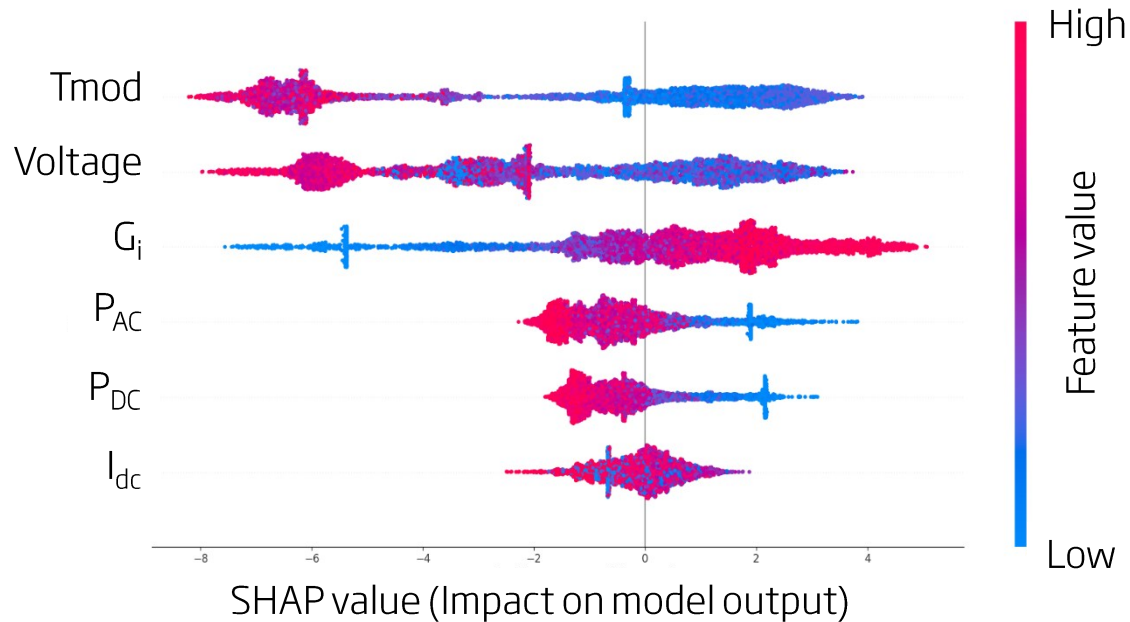


More info at:

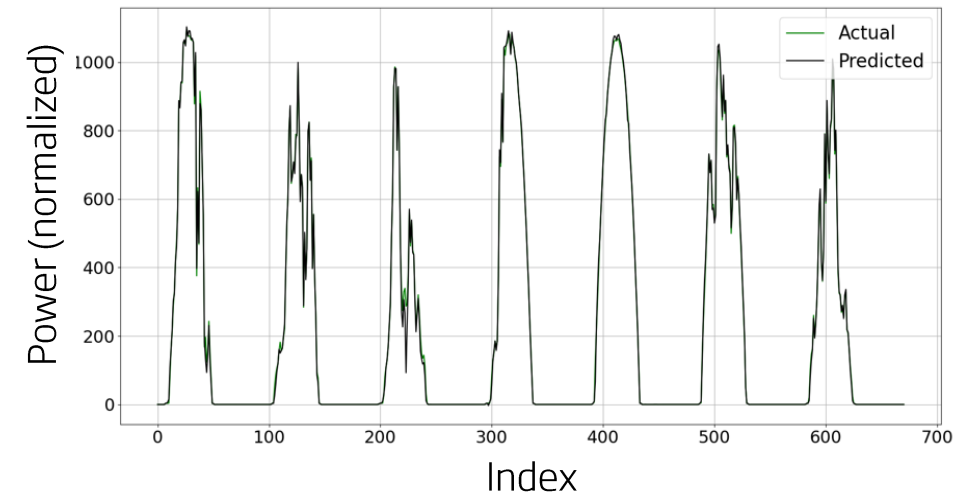
<https://www.gantner-instruments.com/research/advanced-system-monitoring-analytics-smart-grid/>

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

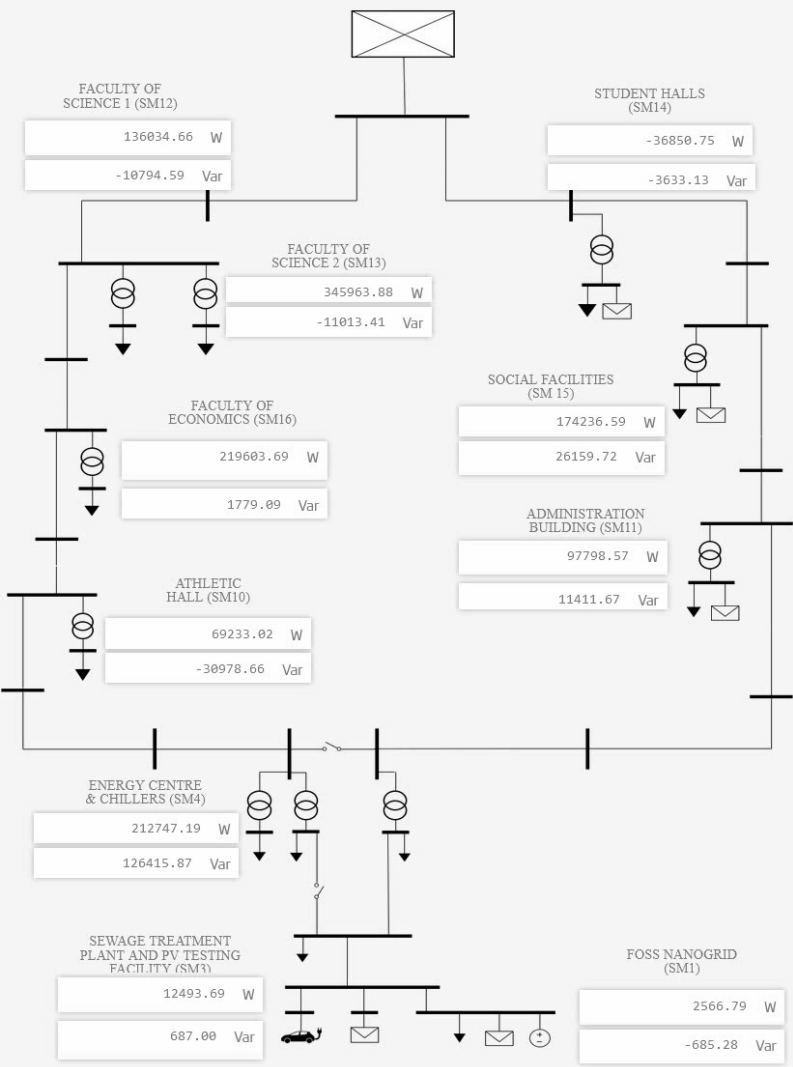
Optimal feature detection for machine learning model using SHAP



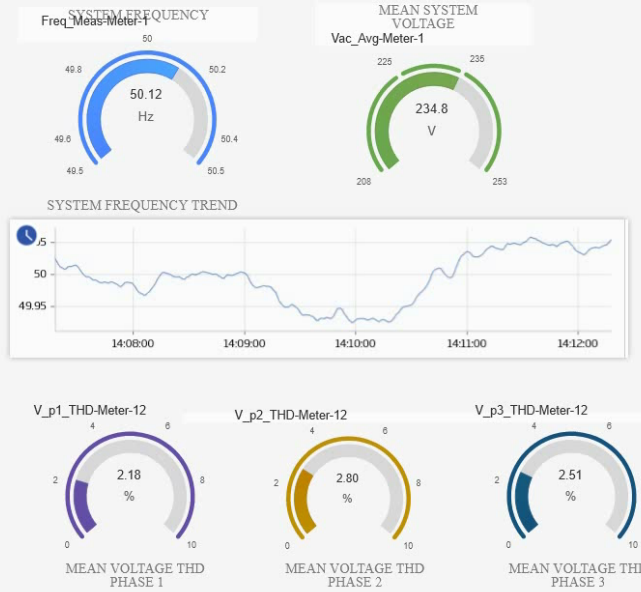
Actual and predicted PV power using Xgboost (W to MW scale)



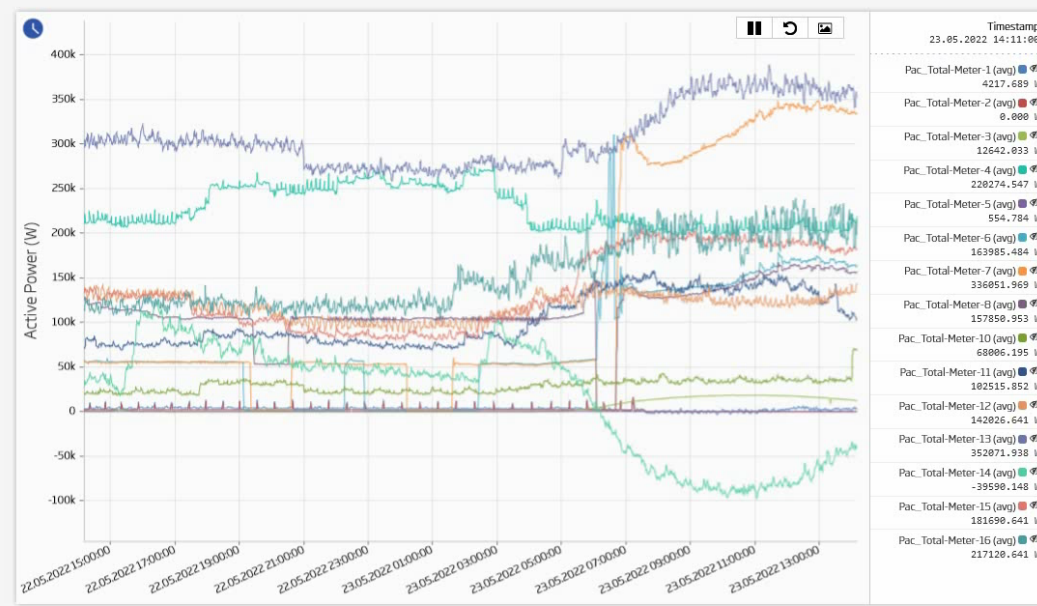
### UCY MICROGRID SCHEMATIC



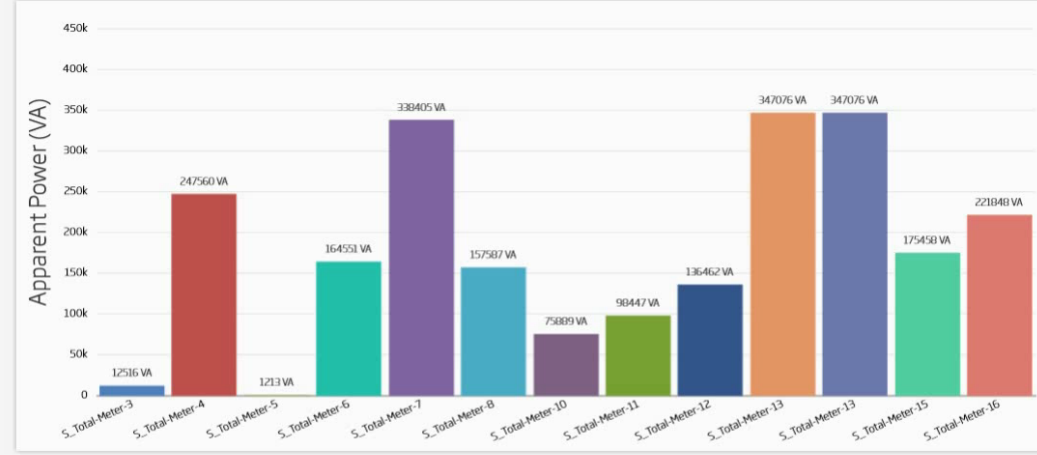
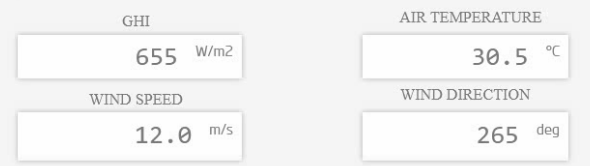
### GENERAL MICROGRID DATA



### POWER CONSUMPTION TRENDS



### WEATHER CONDITIONS



# Data processing

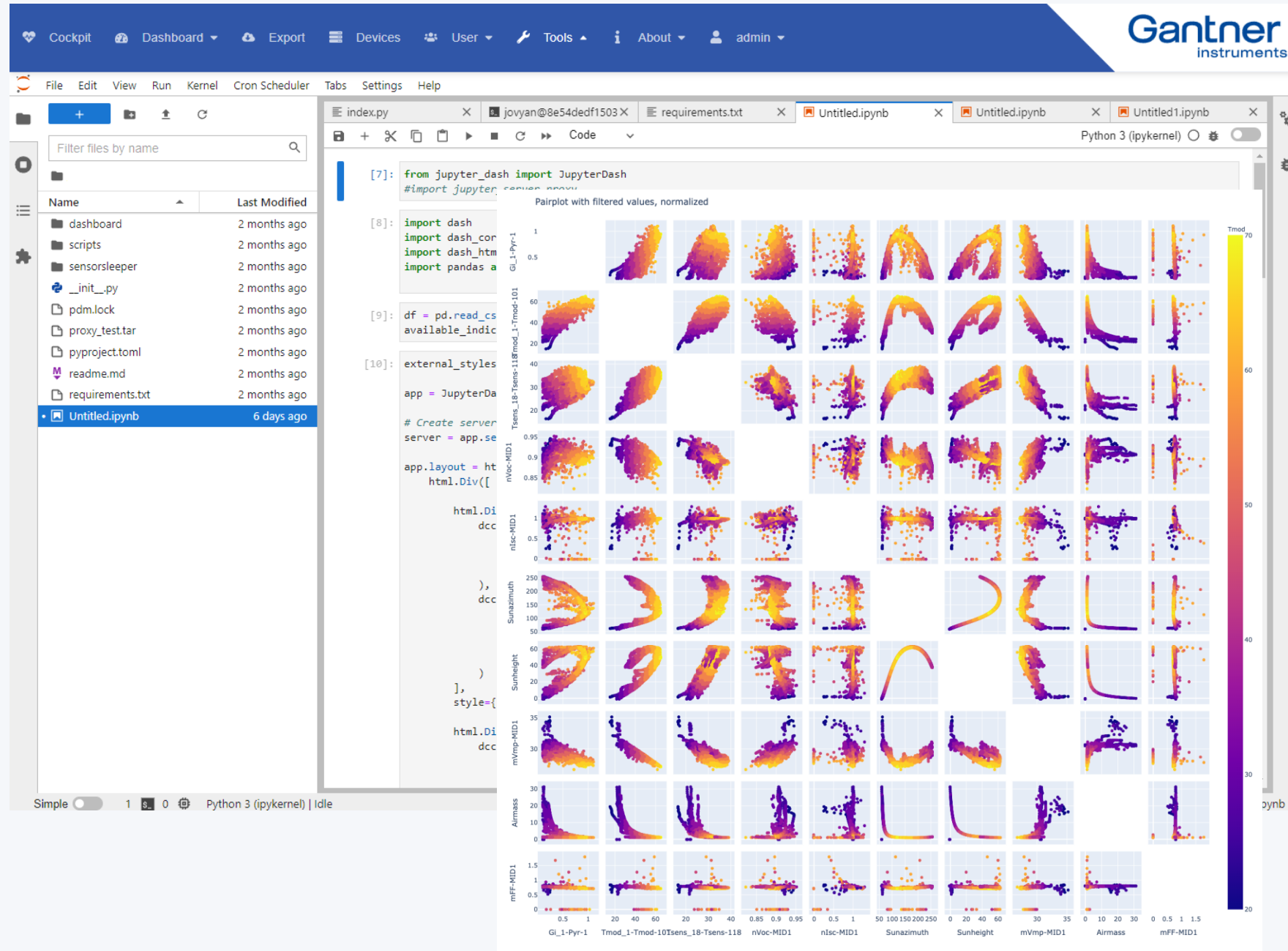
with



integrated into Gl.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  $PR_{DC} = \text{Eff}_{DC,MEAS}/\text{Eff}_{STC}$  or MPR

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

Measurements

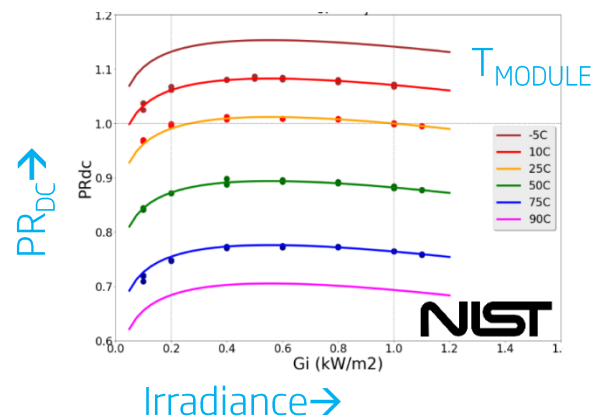
**WEATHER:**  
Irradiance  $G_i$   
 $T_{MODULE}$   
WindSpeed

**ELECTRICAL:**  
 $PR_{DC,MEAS}$

**EMPIRICAL or MECHANISTIC MODEL:**  
 $PR_{DC,PREDICT} = \sum_N C_N * \text{func}_N(G_i, T_{MOD} \dots)$

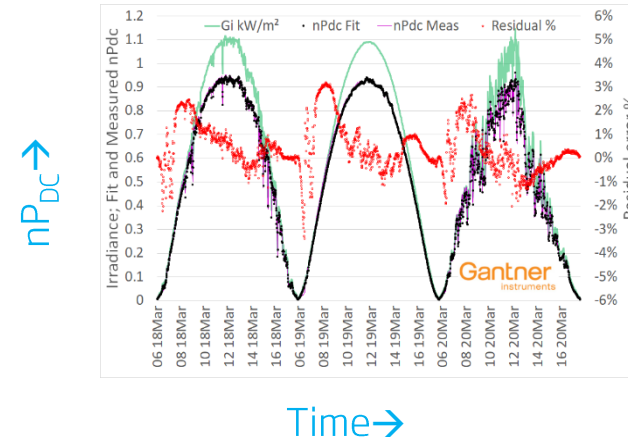
**PREDICTED PERFORMANCE:**  
 $PR_{DC,PREDICT}$

3-7 Fit Coefficients  $C_N$  Weather functions



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

Outdoor data and fit vs. 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

# 18 PVPMC 23-24 Aug 2022  
Salt Lake City, USA

## IMPROVING ANALYSIS METHODS FOR IEC 61853 MATRIX MEASUREMENTS

Steve Ransome<sup>1</sup> (SRCL) and Juergen Sutterliueti (Gantner Instruments)  
<sup>1</sup>steve@steveransome.com : www.steveransome.com

### INTRODUCTION

- IEC 61853 "Matrix method" defines "28 dc measurements at up to 7 irradiances ( $g=0.1 - 1.1 \text{ kW/m}^2$ ) x 4 temperatures ( $t_{\text{mod}}=15, 25, 50, 75\text{C}$ )
- 4 independent coefficients are needed to uniquely fit a performance matrix :
  - 1)  $c_{\text{c}}$ : measured/nameplate performance at STC
  - 2)  $c_{\text{t}}$ : temperature coefficient ( $-1/K \times dX/dt_{\text{mod}}$  [1/K])  $X=p_{\text{mp}}, v_{\text{oc}} \dots$
  - 3)  $c_{\text{lg}}$ : low light drop (caused by  $v_{\text{oc}}$  drop or  $r_{\text{shunt}}$  loss increasing at low  $g$ )
  - 4)  $c_{\text{hg}}$ : high light drop (caused by  $r_{\text{series}}$  as loss  $\sim P_{\text{r\_series}} \sim g^2 \cdot r_{\text{series}}$ )
- Matrices of  $pr_{\text{dc}}, v_{\text{oc}}, v_{\text{mp}}$  etc. can be fitted easily with a mechanistic model "MLFM4" (with ~50% of the fit errors of SAPM or PVGIS as neither of them model  $r_{\text{series}}$  correctly, it needs a  $c_{\text{g}}$  term [PVSC-49])

### DEFINITIONS

```

GLOSSARY - nomenclature and definitions
# g = measured poa irradiance - (0.1 - 1.1) [kW/m^2]
# t_mod = measured module temperature - (15,25,50,75) [C]
g_atc = 1 [kW/m^2]
t_atc = 25 [C]
dC = t_mod - 25 [C]
t_k = t_mod + 273.15 [K]
t_atc_k = 298.15 [K]

# Normalized data for easier fitting and understanding
# NAMING PREFIXES meas (used) norm(alised) fit(ted), etc. lic, root, etc.
norm_v_oc = meas_v_oc / atc_v_oc / g [V]
norm_pr_dc = meas_pr_dc / atc_pr_dc / g [W]
norm_v_mp = meas_v_mp / atc_v_mp / g [V]
norm_p_mp = meas_p_mp / atc_p_mp / g [W]

# MLFM4: 4 meaningfull, normalized coefficients
# 1 const: 2 temp: 200K 3 temp: 200K 4 temp: 200K Improvement: # High: Light
norm_param = @_g + @_c * (t_mod-25) + @_t * log10(g) * (t_k/t_atc_k) + @_g * g
                    
```

IV curve terms

### MLFM FITTING OUTDOOR MATRICES : $pr_{\text{dc}}(G, t_{\text{mod}})$

Fit data non-weighted or "weighted by occurrence"

Occurrence of external data at Tempe, AZ, 1m each h for 1 yr  
Most frequent region ( $g=0.8-1.0 \text{ kW/m}^2, t_{\text{mod}}=40-65\text{C}$ )  
Can ignore least frequent and any "outliers" (<0.1%)

Non-weighted  $pr_{\text{dc}}$  fit vs Weighted  $pr_{\text{dc}}$  fit

MLFM fits both weighted and unweighted well

### MLFM COEFFICIENTS ARE INDEPENDENT FOR UNIQUE MATRIX FITS

- Alter each of the  $mfm4+$  coefficients ( $c_{\text{c}}, c_{\text{t}}, c_{\text{lg}}, c_{\text{hg}}$ ) separately
- Show sensitivity: shape and magnitude of apparent performance change (red arrows)
- Changes are independent meaning there's a unique best fit

4 independent terms are needed to model matrix behaviour

### A BETTER METHOD TO FIND TEMPERATURE COEFFICIENTS

Temperature coefficients can be more simply and accurately derived using  $c_{\text{t}}$  from  $mfm$  matrix fits without needing extra measurements and trend fits as used in IEC 61853

IEC 61853 values and linear trend fits (Not needed)

### MLFM FITTING $v_{\text{oc}}, v_{\text{mp}}, pr_{\text{dc}}$ : INDOOR vs. OUTDOOR

Indoor: CFV IEC61853 Module #5 Canadian Solar : rmsc  
Outdoor: Gantner Tempe AZ, 1year Module #78 Solar World : wrmsc

Fitting good indoor vs good outdoor data:

- Weight outdoor data by occurrence
- Outdoor weighted  $v_{\text{mp}}$  and  $v_{\text{oc}}$  fits can be as good as indoor!
- Higher  $pr_{\text{dc}}$  variability outdoors (soiling, aol, beam fraction and spectrum affect  $i_{\text{sc}}$ )
- MLFM fits matrices well

### SUMMARY

- MLFM is better than SAPM or PVGIS fitting matrices for all parameters with only 50% of their rmse (they don't model  $r_{\text{series}}$ ) [see PVSC49]
- MLFM has optimised fits to indoor measurements and fits good outdoor measurements well
- Weighting outdoor measurements by occurrence mean infrequent extreme or transient data don't affect the fits
- The MLFM matrix fit  $c_{\text{t}}$  parameter is an accurate temperature coefficient (without needing extra measurements at  $1000 \text{ W/m}^2$ )

References : www.steveransome.com email : steve@steveransome.com  
 [PVSC 49] http://www.steveransome.com/pubs/2006\_PVSC49\_philadelphia\_4\_presented.pdf  
 PVPMC/PVLIB : https://pvpmc.sandia.gov/ https://github.com/pvlib/pvlib-python

Acknowledgements : Gantner Instruments and CFV for measurement data https://pvpmc.sandia.gov/download/7791/

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- 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
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- 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?

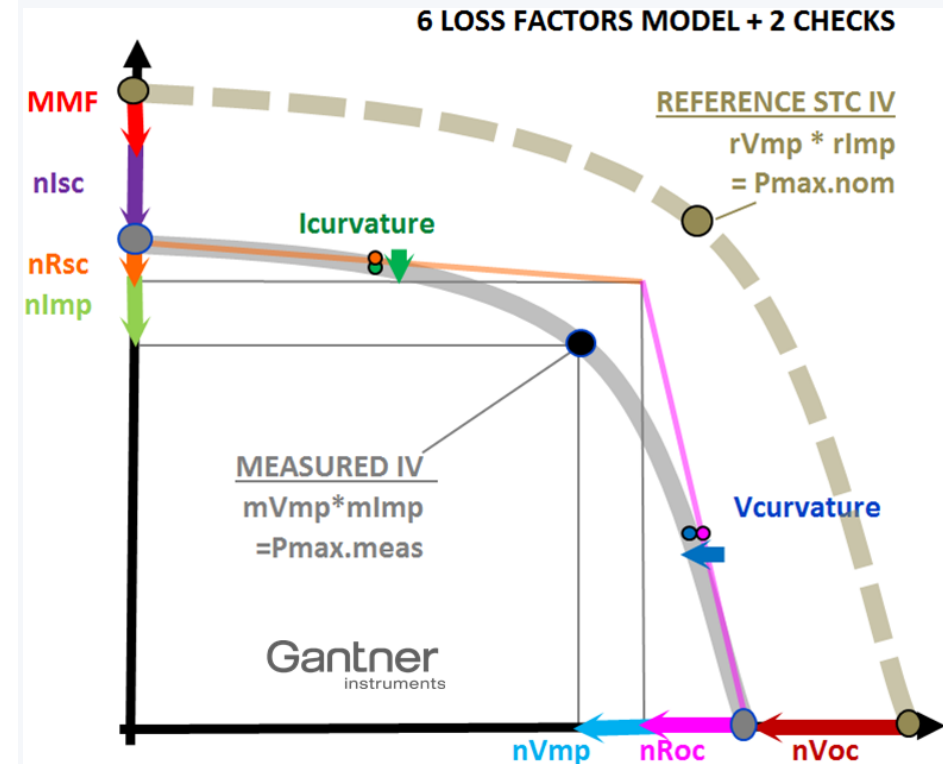
Contact us for any data sharing, validation, PV Module testing or  
IV scan solution at [otf@gantner-instruments.com](mailto:otf@gantner-instruments.com)



# 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

