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University of Cyprus
PV Technology

Innovative Performance Monitoring System for Improved Reliability and Optimized Levelized Cost of Electricity (IPERMON)

Jürgen Sutterlüti

Gantner Instruments GmbH, Austria

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Introduction

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- Key factor for future PV uptake is the reduction of the Levelized Cost of Electricity (LCoE)
- This can be achieved by increasing lifetime performance and reducing operation and maintenance (O&M) costs

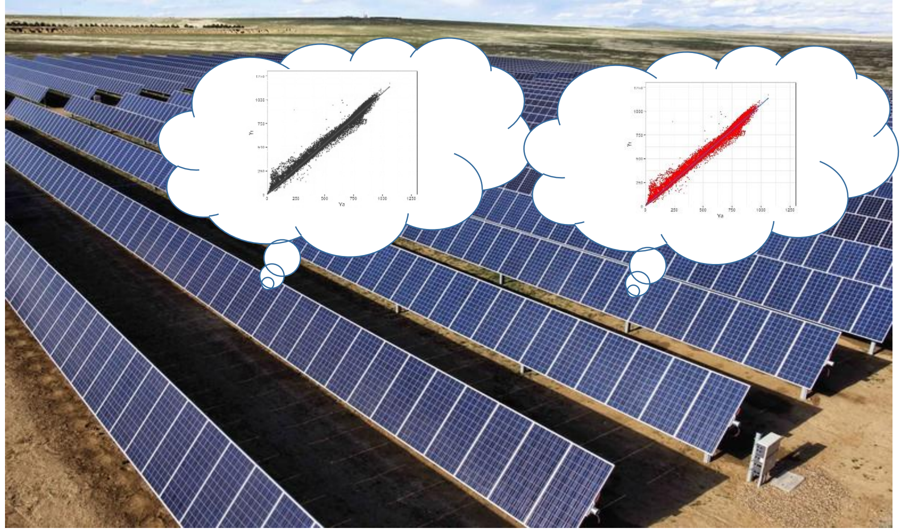
$$\downarrow LCoE(€/MWh) = \frac{(CapEx) + O\&M}{(Energy\ yield)} \begin{matrix}\downarrow \\ \uparrow\end{matrix}$$

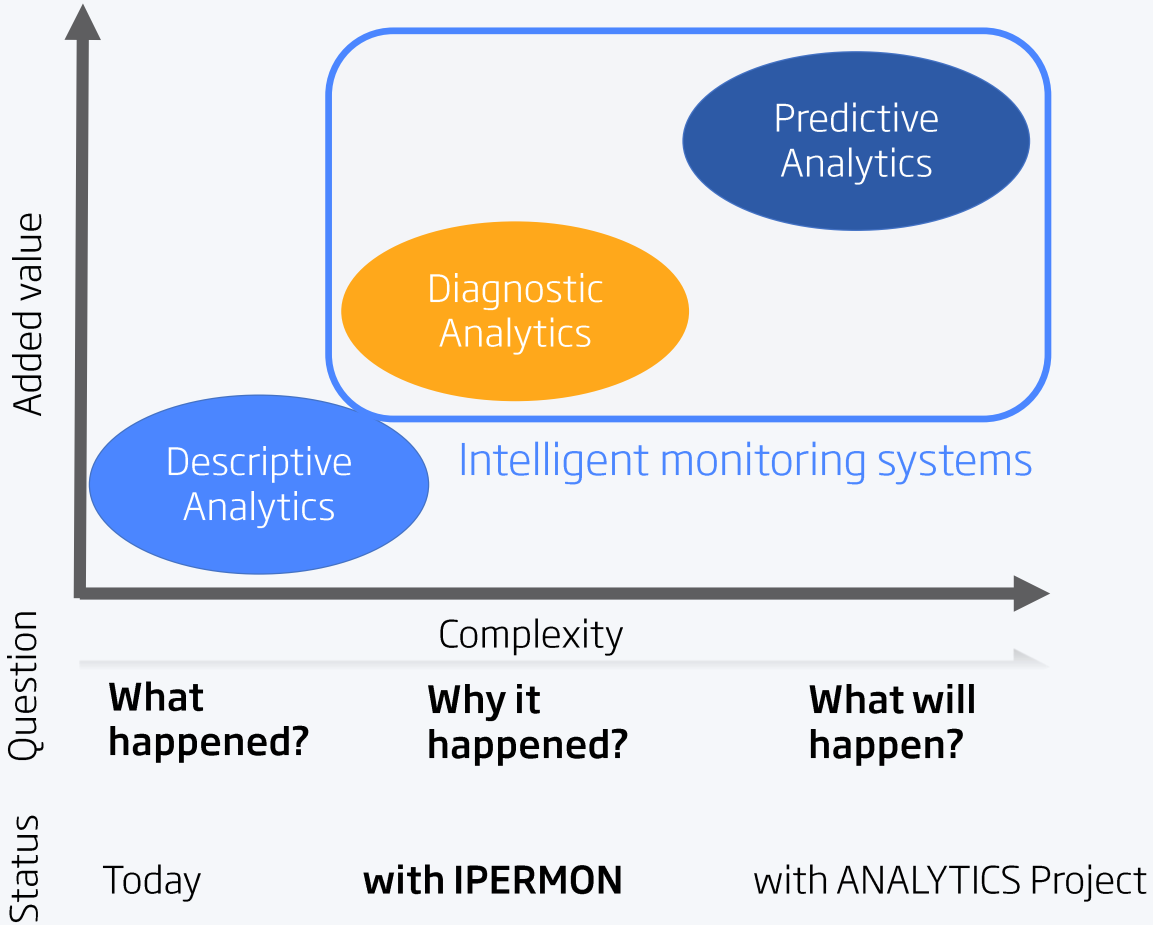
Example:
100 MWp plant
LCoE of 0.08 €/kWh
160,000 MWh/yr (M€ 12.8/yr)

5 % performance improvement
(availability and proactive O&M) equivalent to more income.
~0.64 M€/year

Data-driven approaches for PV & Energy monitoring

- Change from current Descriptive to novel Diagnostic/Predictive Analytics.
- Algorithms can **operate for any application** (Electrical and mechanical parameters, failures).



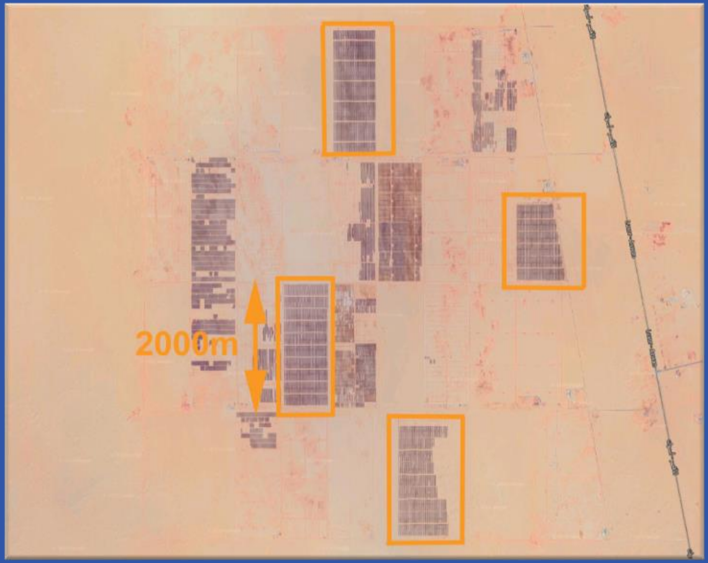


Outcome:
Full performance visibility
Quality control
Automated process

Benefits:
Reduced LCOE
Increased Return on Investment (ROI)
Risk reduction

Utility Scale Example

- Ben Ban, Egypt; Monitoring and grid control
- Project size: 230 MW, 1-axis tracking
  - 1400 Combiner boxes, 60 x 2.5 MW Inverters, 24 Irradiance sensors/weather stations
  - DC side: 30,000 String currents, 1,400 voltages
- Parameters:
  - 70,000 measured
  - 140,000 Normalized and calculated parameters
    - E.g. PR per component, Aggregation of I, V for each level, limit checks, warning for degradation, temperature limits, …
    - Each parameter has different aggregation methods per time interval (Average, Min, Max, Standard deviation) for direct Loss Factor Model use
- Raw data volume:
  - 400 GB per year
  - 8 TB for 20 years

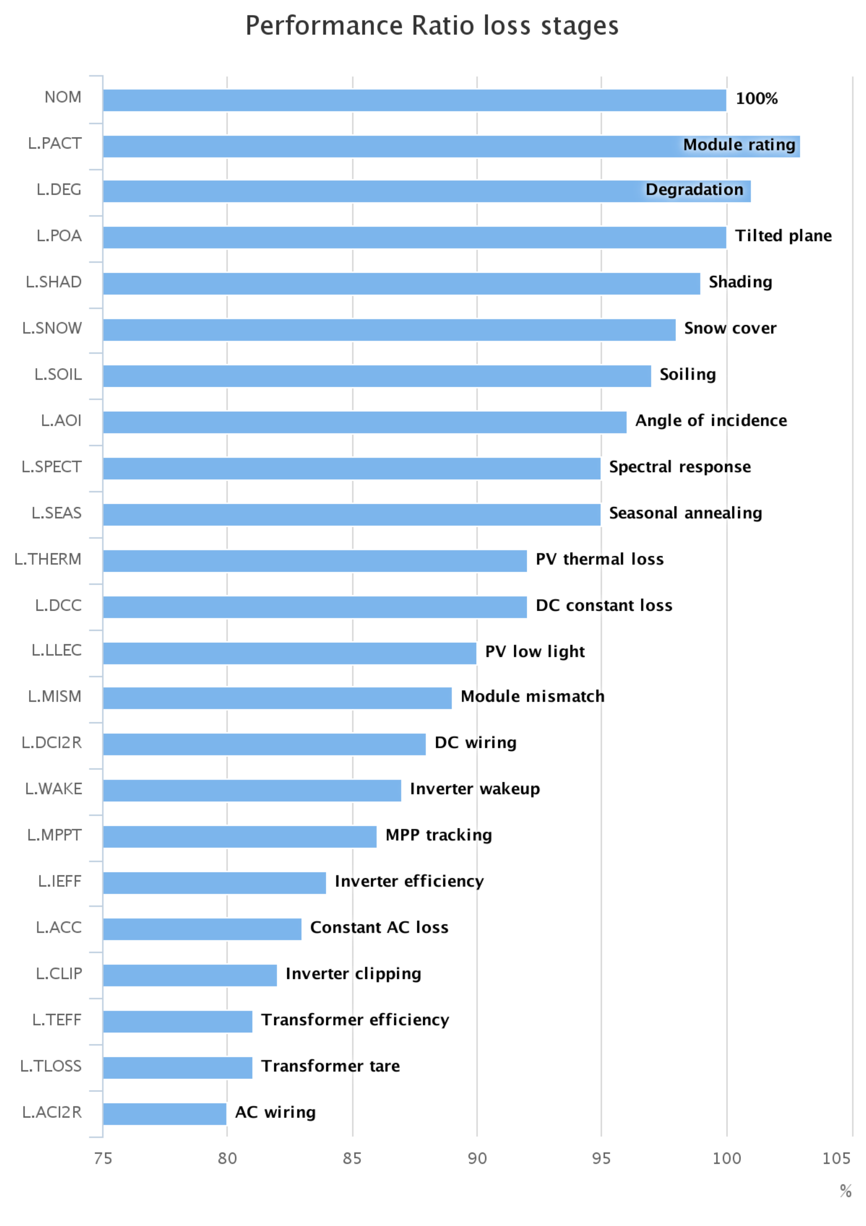


How to store and process very large datasets cost efficiently?

Results & Methodology

Performance Loss Stages

- Performance losses and failures can occur during the operational lifetime of PV systems
- Such losses and failures decrease the output power of the PV system

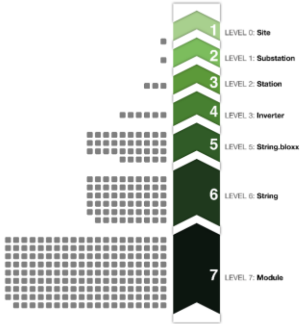


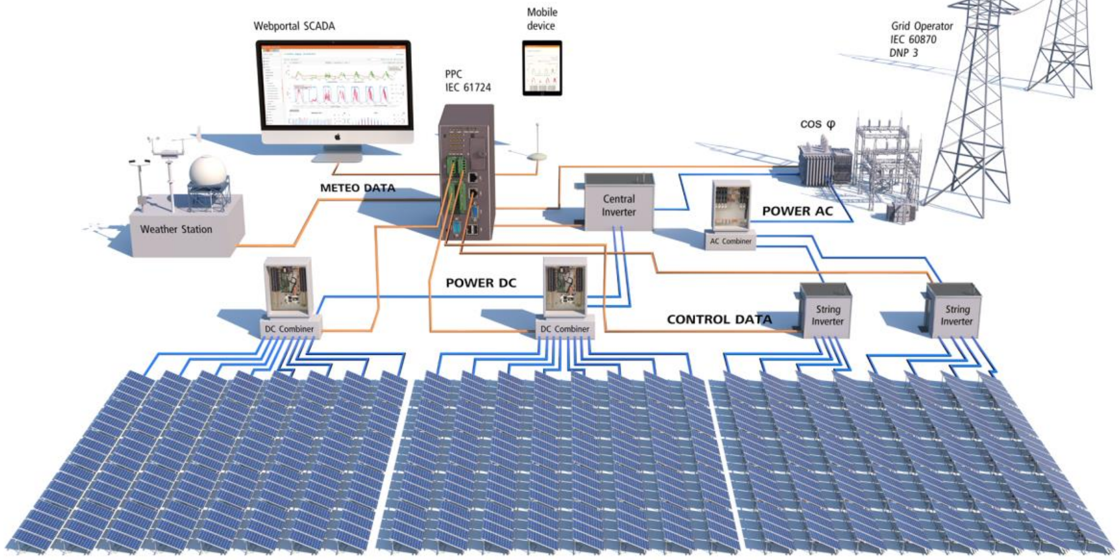
Key method:
Identification and accurate quantification
of losses and failures
in PV systems

Robust performance monitoring

- Reliable Data collection (weather, inverters, grid, …)
- Synchronized data acquisition
- Data reduction & filtering on the edge
- Real time calculation: Aggregation – from PV Module up to site level

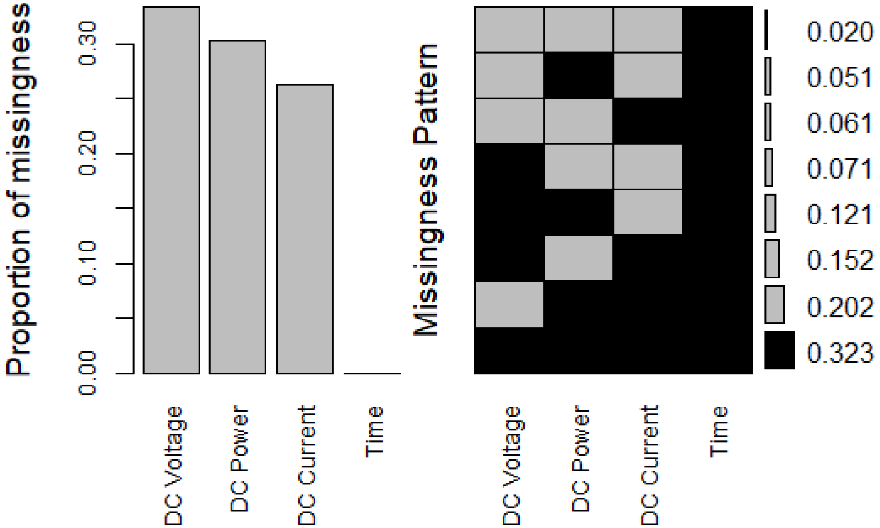


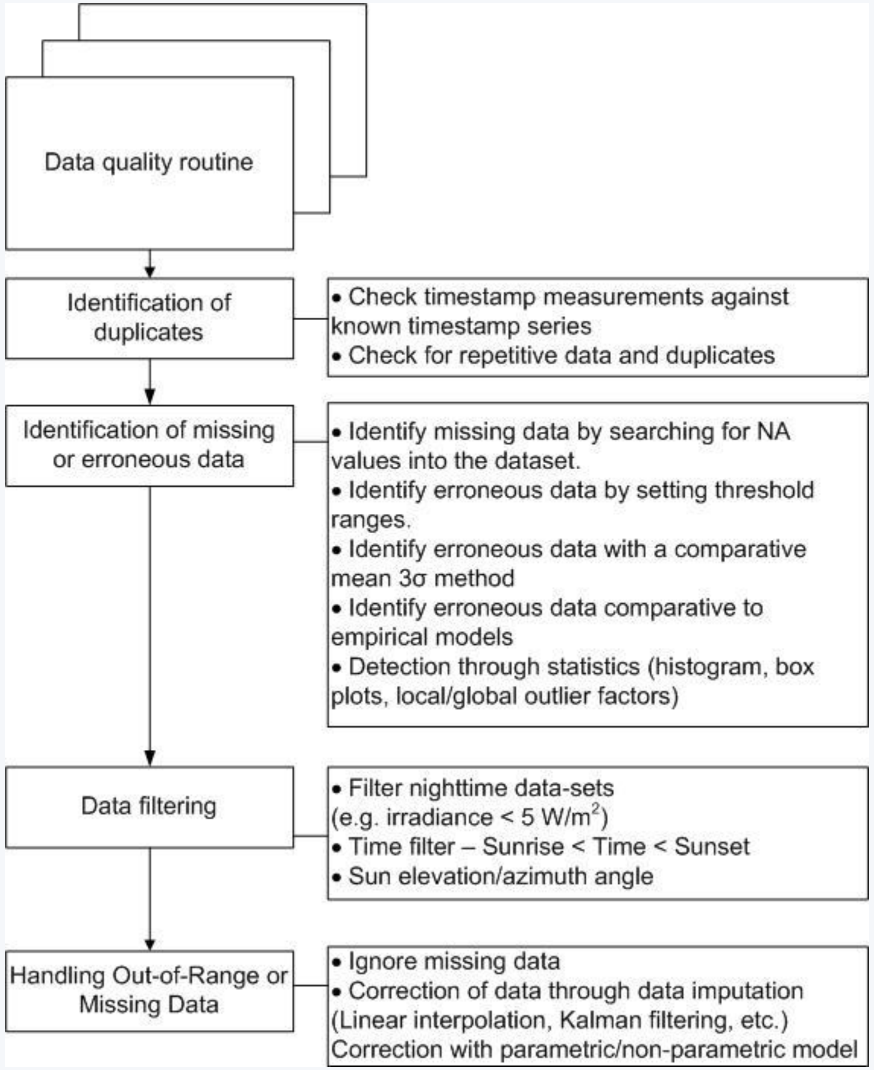




Data quality routines (DQRs)

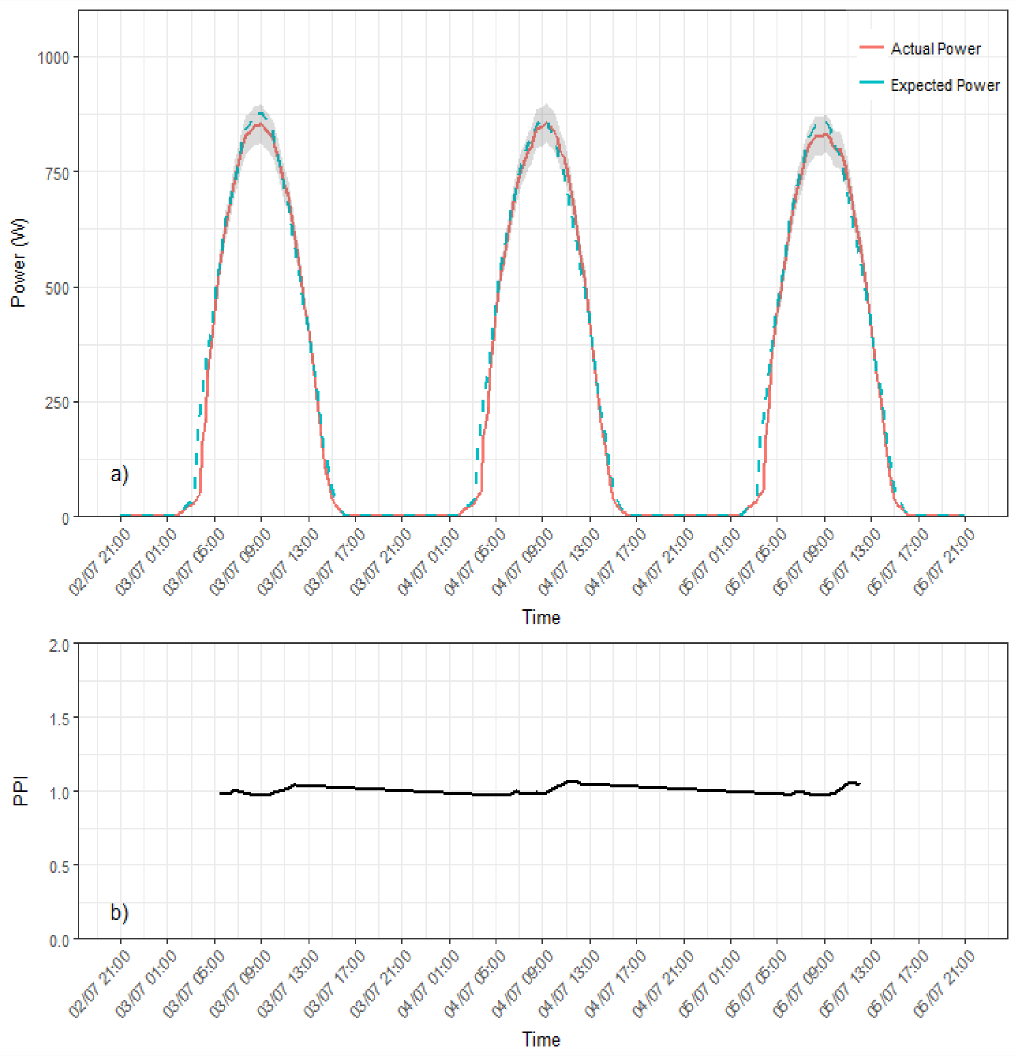
- Identification of repetitive data and duplicates
- Identification of missing or erroneous data, outliers and outages, Sensor drifts
- Correction of erroneous/missing data through data imputation techniques





Capacity Test

- Power performance Index (PPI) for commissioning of PV system according to IEC 61724-2
- Automated process with notifications when test was completed
- Different methods used:
  - ASTM Regression Method
  - IEC 61724 method
  - Mechanistic performance model (MPM)

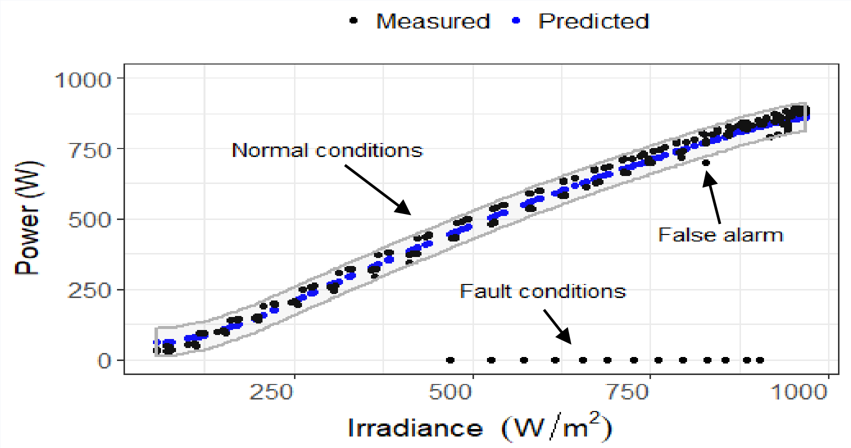


Failure detection & verification

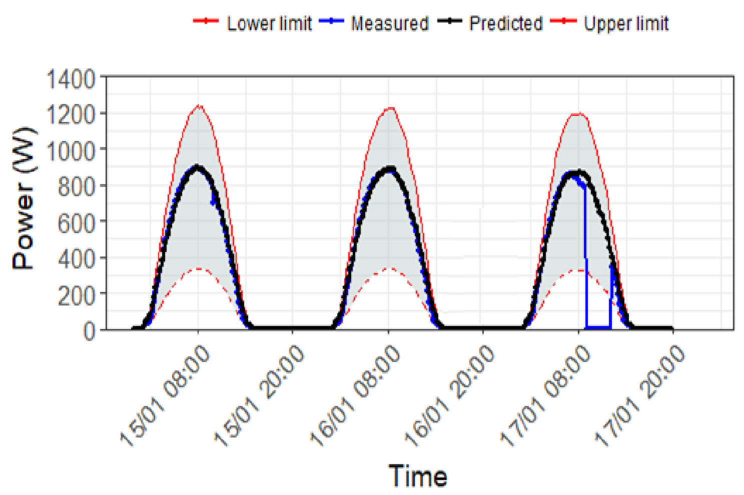
Detailed verification and bench marking of failure detection and classification events at test-bench systems at the University of Cyprus and actual power plants administered by GI

- Detect faults
- Diagnose the problems
- Comparative to thresholds, ratio
- Outlier detection rules

Power irradiance diagnostic plot

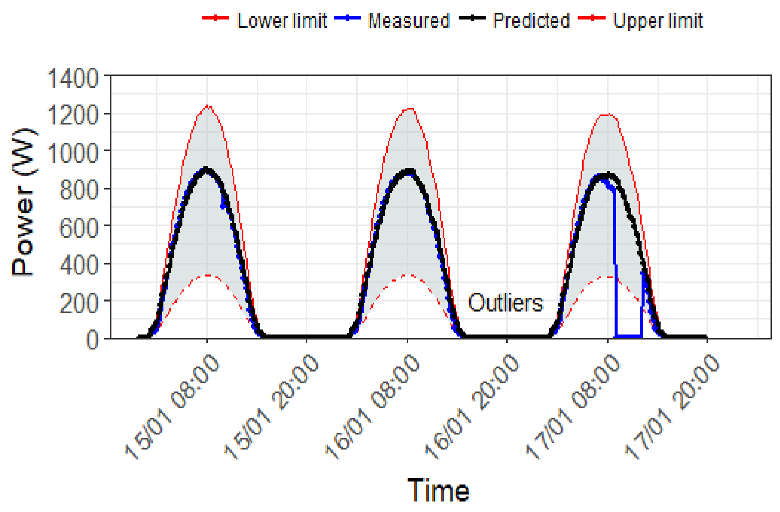


Sigma rule limit method



Real Time Health state detector

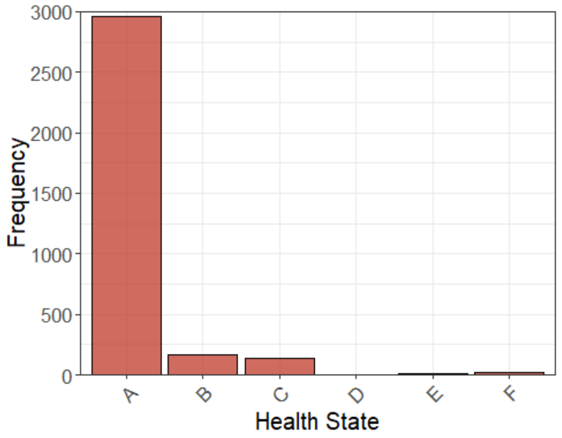
Health-state detector to quantify the performance on a daily basis of PV power plants against a digital twin accurate performance replica (mechanistic performance model). The monitor can detect and classify commonly exhibited failures with over 98 % accuracy.



System health state detector:

- Comparative assessment between measured and predicted daily PV performance
- Classification of the relative error in ranked categories

Grade A:	RE ≤ 10 %
Grade B:	10 % < RE ≤ 20 %
Grade C:	20 % < RE ≤ 30 %
Grade D:	30 % < RE ≤ 40 %
Grade E:	40 % < RE ≤ 50 %
Grade F:	RE ≥ 10 %



Degradation Rate analysis.

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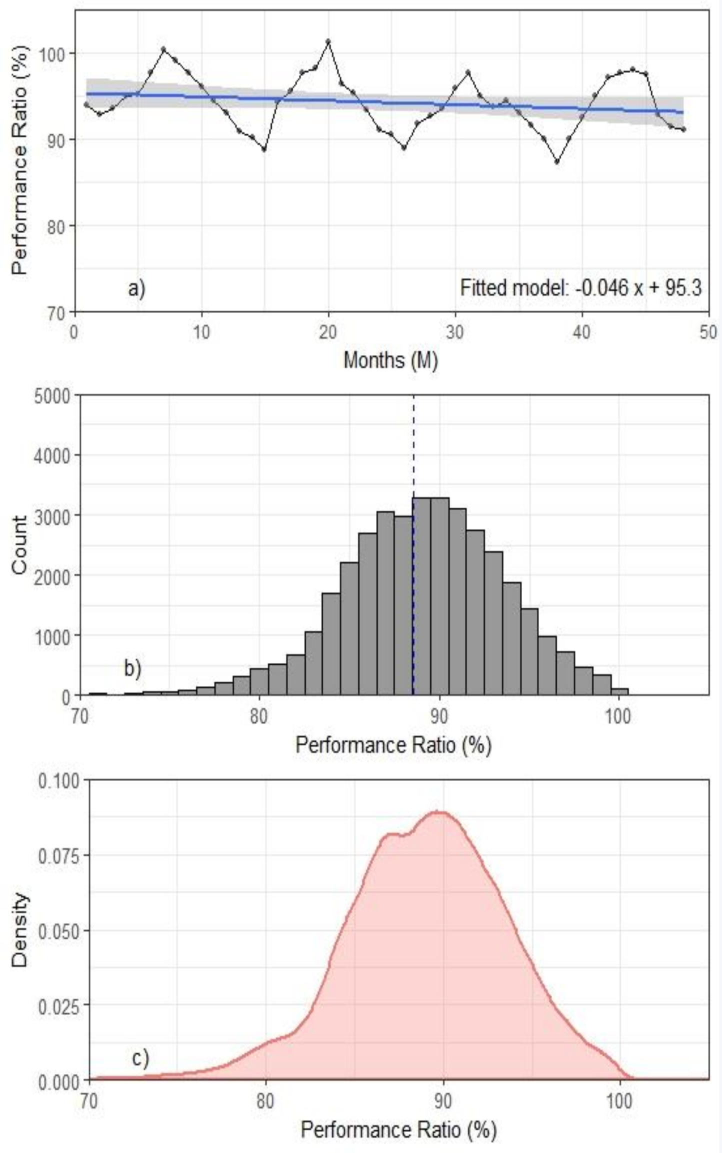
Comparison of different methods with 8 years of long term data from OTFs

Statistical and comparative techniques for trend extraction

- Ordinary Least Squares (OLS)
- Classical Seasonal Decomposition (CSD)
- Year-on-Year (YOY)
- Seasonal Trend decomposition (STL)
- Autoregressive Integrated Moving Average (ARIMA)
- Estimation of the annual degradation rate (YOY)



Development of Prediction models (mechanistic and Machine learning based)

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Important steps

- Use different types of data source (locations, concept)
- Select different models (empirical , machine learning, ...)
- Train and optimize
- Benchmark & conclude

Experimental Setup for Model training (PV arrays, PV Module IV scans), Location: Arizona/US, Cyprus, others

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Gantner's PV Outdoor Test Facility in Arizona has 30 individual PV Module testing channels

- Fixed and 2D track; IV curve every minute, all environmental, spectral parameters
- PV Module Power up to 500 W/800 W
- High quality digitalization, accuracy 0.1 % FS (current), 0.05 % FS (voltage)
- Scalable system (4 .. 48 channels; raw data access
  Derived parameters using Loss Factors and Mechanistic Performance Models. Local or cloud-based data streaming
  Integrated Python Jupyter Lab for direct analysis and automatic reporting

Continuous measurements in Arizona since 2010; other sites available around the world

GI OTF MEASUREMENTS

Name	Description	Units
G_H	Global Horizontal Irradiance	kW/m²
D_H	Diffuse Horizontal Irradiance	kW/m²
B_N	Beam Normal Irradiance	kW/m²
G_I	Global Inclined Irradiance (Pyranometers and c-Si ref cells)	kW/m²
T_{AMB}	Ambient Temperature	C
T_{MOD}	Back of Module Temperatures	C
WS	Wind Speed	ms^{-1}
WD	Wind Direction	°
RH	Relative Humidity	%
G(λ)	Spectral Irradiance G(350– 1050nm)	W/m²/nm

Trusted by leading PV Module manufacturers, Technology providers and Research Labs

Machine Learning
Different Algorithms

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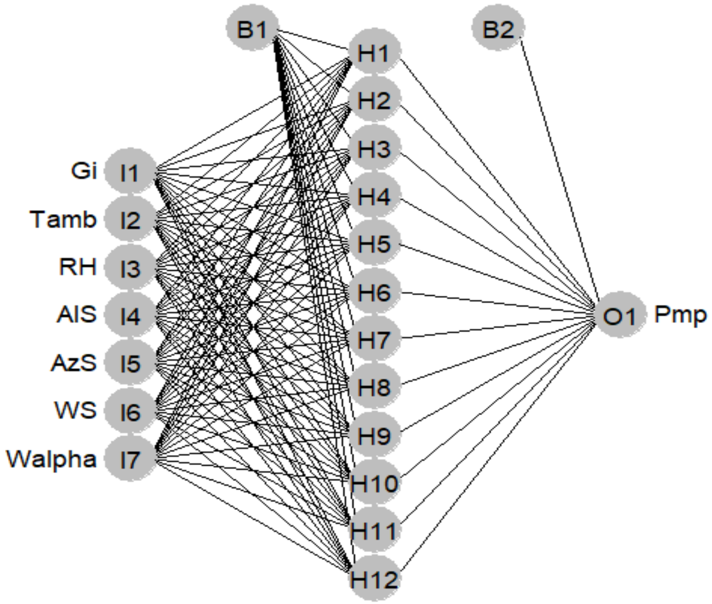
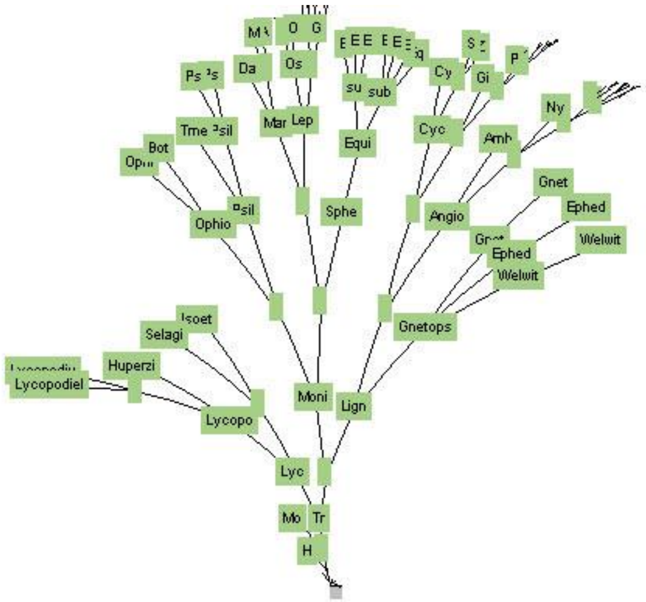
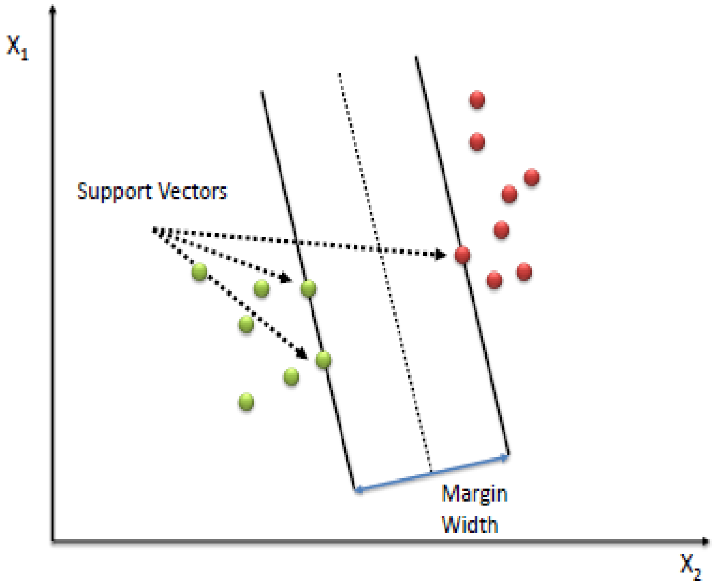
- Machine Learning Algorithms: **Artificial Neural Networks (ANN), Decision Trees (DT), Support Vector Machines (SVM).**
- Many machine intelligence developers prefer neural networks because of their high accuracy and fast operation. However, this is problem dependent.



ANN



DT



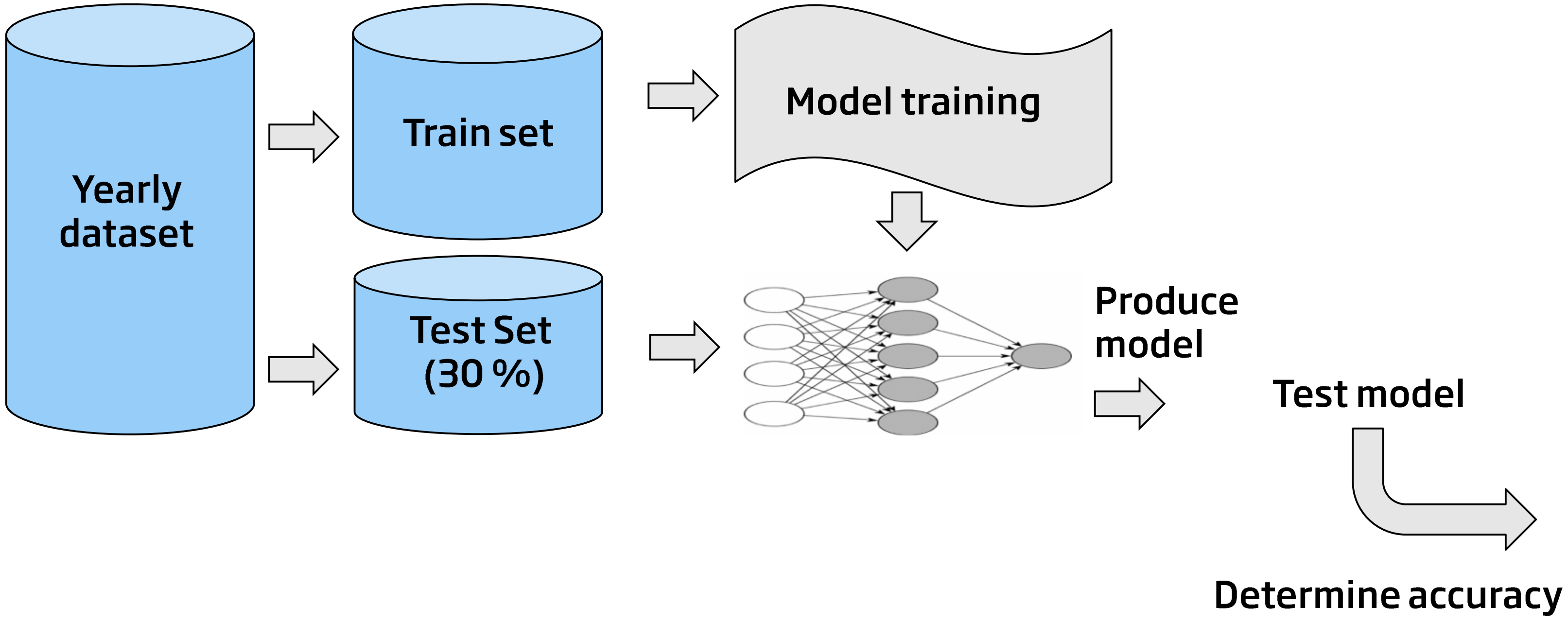
SVM

Methodology for Model training

Experimental setup – Data acquisition system (DAQ)
- Test-bench PV system in Cyprus
- Test-bench PV module in Arizona

Data quality routines (DQRs)
- Data filtering ($G_I > 0.1\ kW/m^2$)
- Identify missing/erroneous values
- Correction/Imputation of data

Train, test and improve the model
- Train model
- Evaluate performance

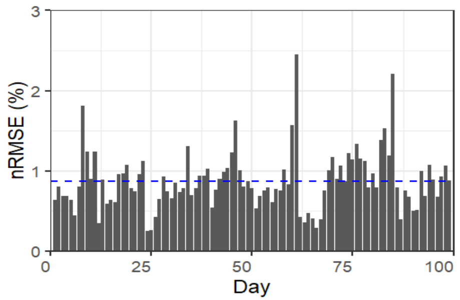


Performance metrics

$$Error\ (\%) = 100 \cdot \frac{\hat{Y}_j - Y_j}{Y_j}$$

$$MAPE\ (\%) = \frac{100}{n} \cdot \sum_{j=1}^{N} \left| \frac{\hat{Y}_j - Y_j}{Y_j} \right|$$

$$nRMSE\ (\%) = \frac{100}{P_{STC}} \cdot \sqrt{\frac{1}{n} \sum_{j=1}^{N} (\hat{Y}_j - Y_j)^2}$$



Data driven improvement
Benchmarking different Machine Learning Algorithms

Mechanistic Performance Model (MPM)

MECHANISTIC PERFORMANCE MODEL "MPM"
with 6 physical and normalised coefficients

$$PR_{DC} = C_1 + C_2 * dT_{MOD} + C_3 * \log_{10}(G_I) + C_4 * G_I + C_5 * WS + C_6 / G_I \quad (3)$$

Quality
Gamma
LogGi
Gi
Windspeed
1/Gi

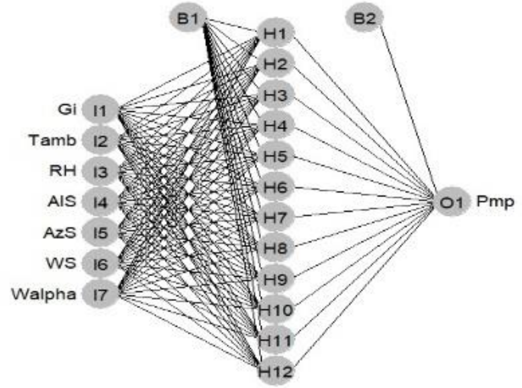
Meaningful normalised MPM coefficients

Typical power plant values

	C_1	C_2	C_3	C_4	C_5	C_6	RMS
Stn_1	102.2%	-0.69%	-0.004%	5.8%	-0.65%	-1.28%	0.97%
ACCB_1.01	103.8%	-0.43%	-0.004%	1.1%	-0.32%	-1.18%	1.18%
Inv_1.01.03	103.3%	-0.39%	-0.004%	0.4%	-0.28%	-1.15%	1.18%
Inv_1.01.03.1	105.4%	-0.33%	-0.004%	-0.5%	-0.13%	-1.18%	1.22%

Quality C1 ~ 100%
Other coefficents are small corrections ~<2%

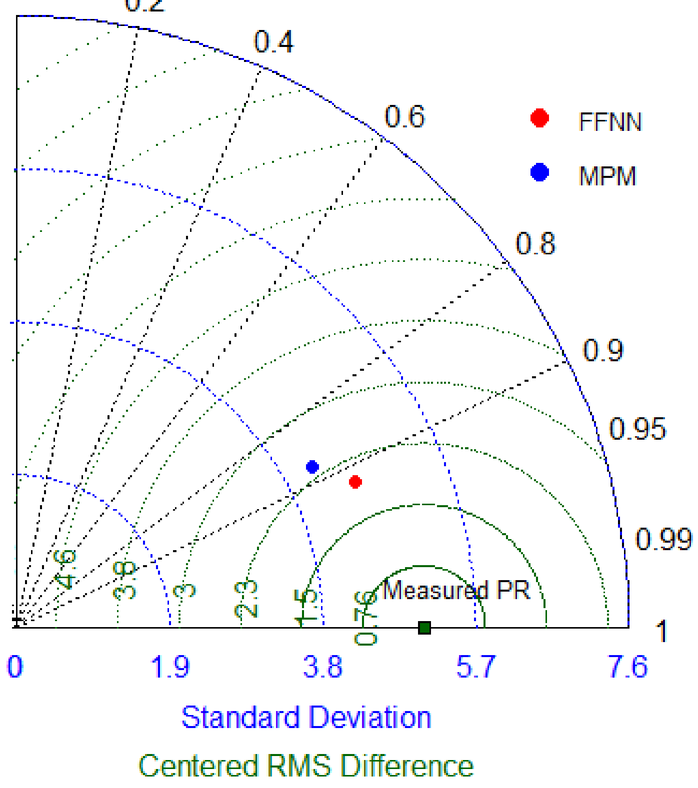
Machine Learning



- Feed forward /Artificial Neural Networks (ANN)
- Decision Trees (DT)
- Support Vector Machines (SVM)

Model fit robustness:
Machine learning (FFNN) vs. MPM

Random 70:30 % - GI OTF

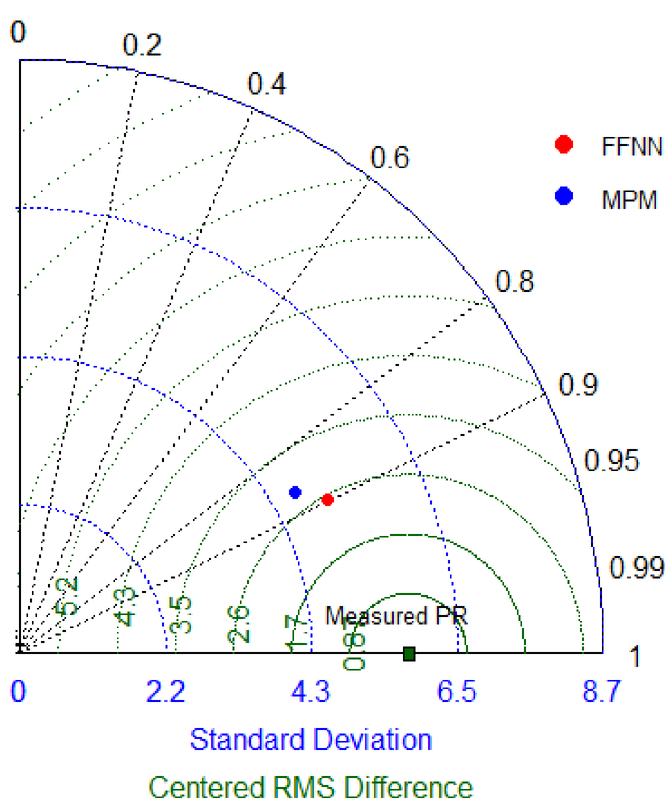


Good predictive quality using both instantaneous and average measurements

ML – Lower SD, RMSE error and higher R

MPM – Should have been corrected for AOI and Beam fraction (UCY OTF)

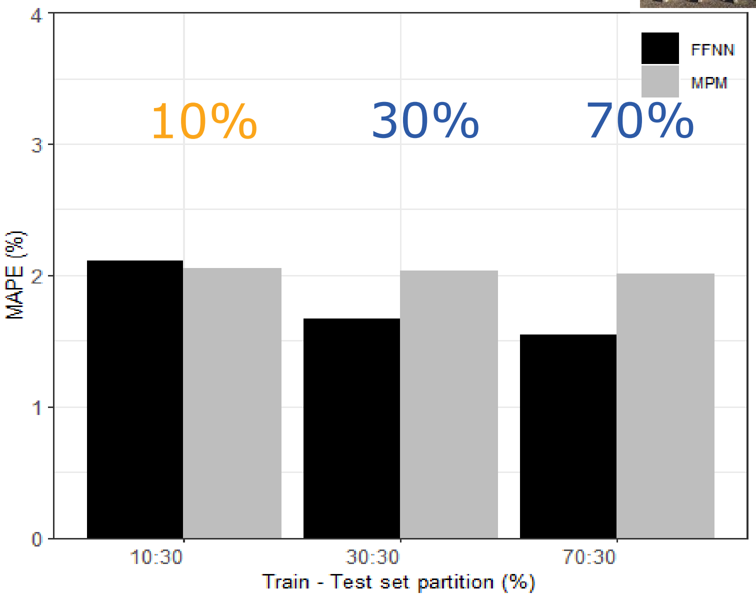
Random 70:30 % - UCY OTF



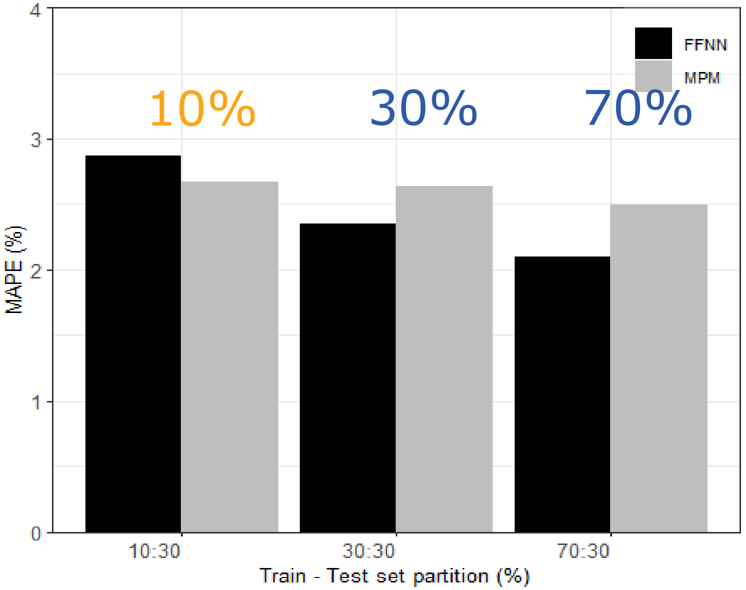
Model benchmarking
Train subset duration

Train subsets of 10, 30 and 70 % of the entire dataset

GI OTF - Arizona, USA



UCY OTF - Nicosia, Cyprus



ML
More accurate when using larger train subsets

MPM
Robust model for low availability duration datasets

Data driven improvement

Benchmarking different Machine Learning Algorithms

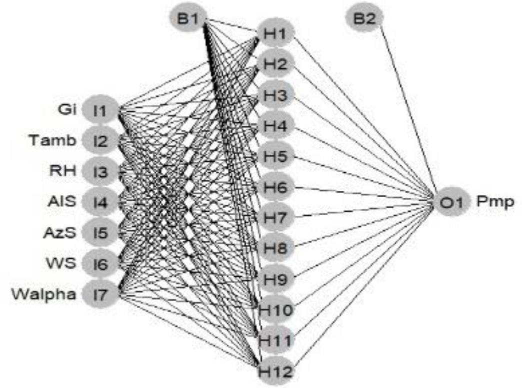
Mechanistic Performance Model (MPM)

MECHANISTIC PERFORMANCE MODEL "MPM"
with 6 physical and normalised coefficients

$$PR_{DC} = C_1 + C_2 * dT_{MOD} + C_3 * \log_{10}(G_I) + C_4 * G_I + C_5 * WS + C_6 / G_I \quad (3)$$

Quality   Gamma   LogGi   Gi   Windspeed   1/Gi

Machine Learning



- Feed forward /Artificial Neural Networks (ANN)
- Decision Trees (DT)
- Support Vector Machines (SVM)

Models	MAE	nRMSE (%) (trainset 70 %)	nRMSE (%) (trainset 10 %)
Artificial Neural Network (ANN)	1.04	2.23	11.74
MPM (physical)	1.63	2.79	2.57
Parametric (physical)	2.44	4.11	6.72
Regressive Tree (RT)	1.55	2.82	4,53
Support Vector Regression (SVR)	1.32	2.73	21.56

Accuracy of 2.5 % achieved at 30MW power plant level

Platform for data storage, processing and analytics

Real time data visualization

- From controller to cloud platform
- Create our own dashboards (read only, read/write)
- Display Real time charts (different controllers, merged data streams)
- Cockpit: see device location, status, warnings, meta data
- Efficient storage of full life cycle data streams, e.g. 30 years of device data
- Store and visualize triggered data and different sampling intervals
- Analytics powered by JupyterLab

Determining performance stability PR_{DC} by time of day and month

Average PRdc by hour of day 1…24 HOD🡅 and Year Month 1401…1612 MOY🡆

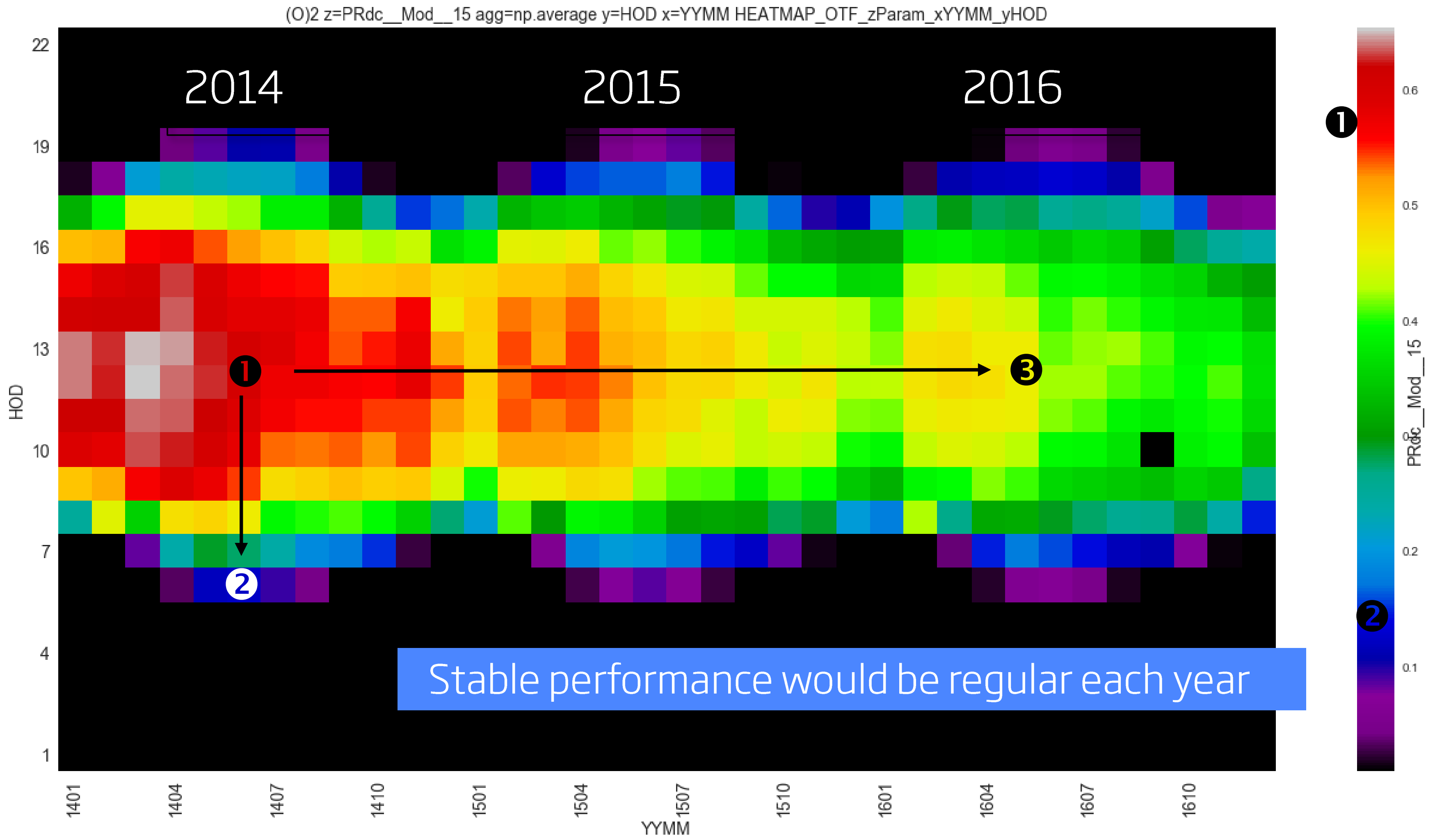
❶1st Summer 1406 Module performance although poor was highest during the day ~0.6

❷ it was worse at lower irradiance ~0.2

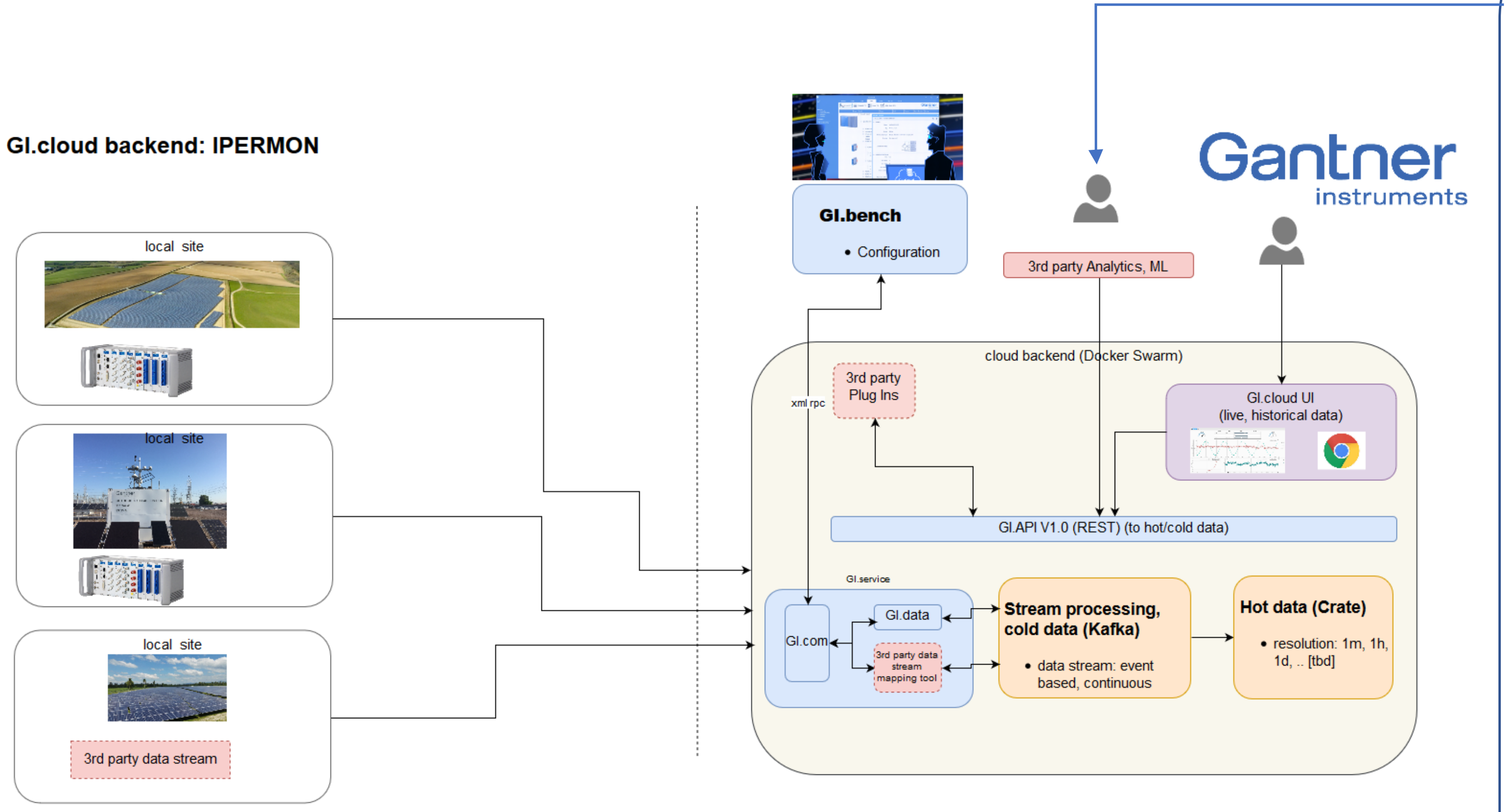
❸ >2 years later 1606 this module has degraded badly and is below 0.45

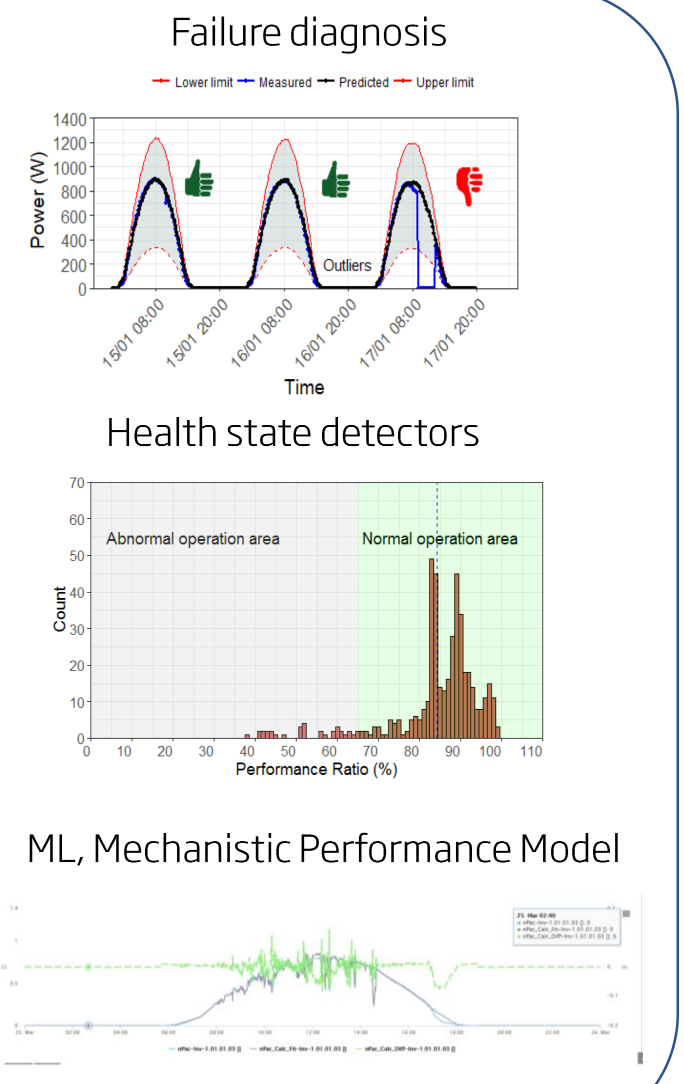
Degradation rates can be obtained by the fall per year from ❶ to ❸ e.g. 0.6 to 0.45

Note longer summer days give “taller” datasets 06:00 to 19:00



Integration of diagnostic plus predictive analytics
Machine learning with Project IPERMON





Project "IPERMON", joint project between University of Cyprus and Gantner Instruments for predictive analytics based on scalable platform.

Example of empirical model (MPM) in platform

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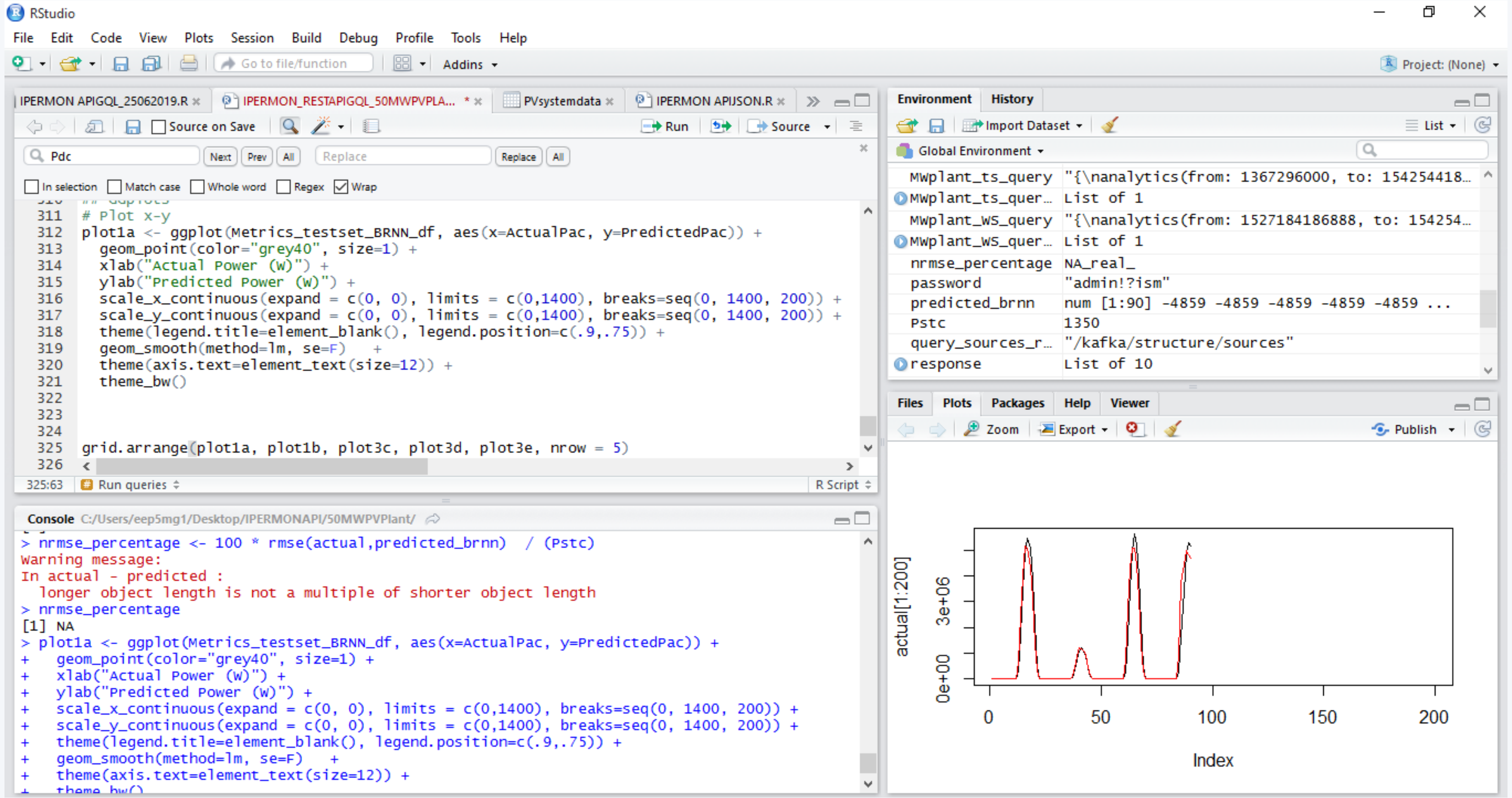
Machine Learning

- Example with connection to GI.cloud via API
- Executing Machine learning model with R, Jupyter, …
- Service runs on Gantner Instruments data backend



Conclusion & summary

Conclusion Model selection

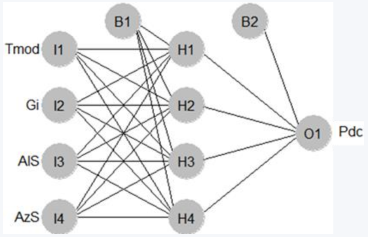
Mechanistic Performance Model

- Simple implementation (low complexity)
- 3 inputs parameter to get *PR_dc* output (+/-2.5%)
- More accurate at high irradiance conditions
- Robust model at low availability duration datasets
- Useful, meaningful coefficients (C1-C5)

$$\mathrm{PR}_{DC} = \underbrace{C_1}_{\text{Tolerance}} + \underbrace{C_2 \times dT_{MOD}}_{\text{Temperature coeff}} + \underbrace{C_3 \times \mathrm{Log}_{10}(G_I)}_{\text{Low light} \sim V_{OC},\ R_{SHUNT}} + \underbrace{C_4 \times G_I}_{\text{High light } R_{SERIES}} + \underbrace{C_5 \times WS}_{\text{Wind}}$$

Machine Learning

- Higher complexity for implementation
- 4-5 inputs parameter, output
- More accurate at low and medium irradiance conditions
- Higher training data partitions yield more accurate predictions
- No direct usable coefficients



Summary Project IPERMON

- Monitoring systems improve the LCoE of PV, Project IPERMON created helpful routines and algorithms for practical use
- Diagnostic data analytic functionalities (next to descriptive) make sure that optimal levels of PV performance can be maintained
- O&M contractors are enabled to take preventive and corrective actions to minimize power losses immediately
- Machine learning is one of the most important enables for Energy asset performance optimization
- Gantner Instruments data platform offers the Integration of data analytic algorithms and machine learning models for customer so they can utilize this competitive advantage for their asset services

Data quality routines, guidelines

Failure diagnosis

Capacity Test for Commissioning

System health state

Predictive models

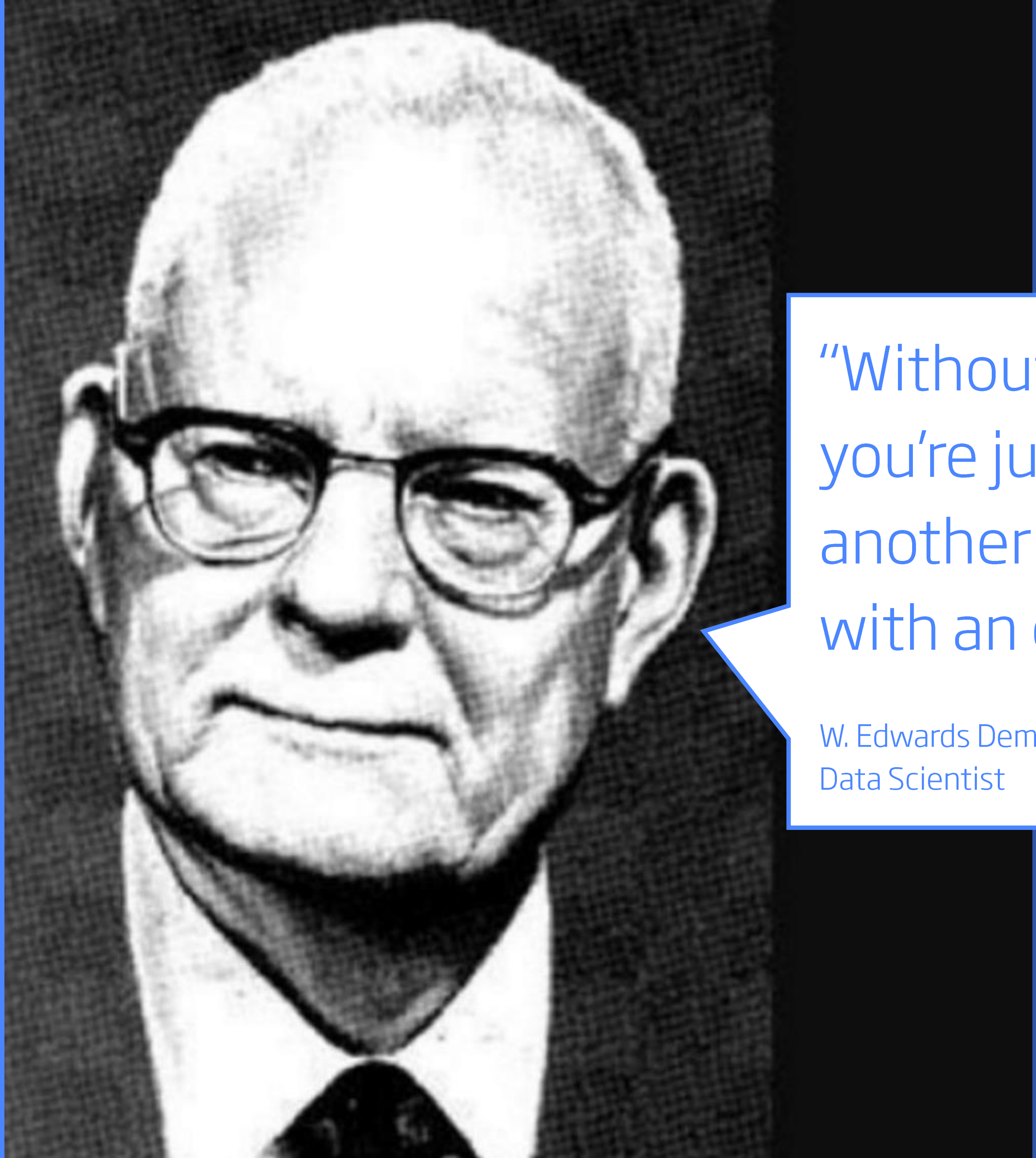
Performance loss quantification

Degradation rate estimation

Outlook

Future work will involve integration of new data analytic algorithms for:

- Full asset digitalization
- Predictive maintenance
- Operation at higher resolution time series (10Hz, 100Hz, …)
- Interoperability



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

W. Edwards Deming,
Data Scientist

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Turn Data Into Information.

Turn Information Into Customer Benefits

Thank you very much!

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Appendix

About Gantner Instruments

Gantner Instruments is a global leader in the development
of high precision measurement and control systems.

Founded in 1982, the company excels in delivering products
and services in the fields of electrical, mechanical and thermal measurement, always prioritizing flexibility,
usability, and accessibility.

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Mobility

Aerospace

Smart Energy & Condition Monitoring

Civil Engineering

Substantial demand for high performance edge computing in a growing market

Drivers:

- Industry 4.0, big data, AI, ML all need high quality data sources
- More distributed and adaptive monitoring and control applications
- Requires better and faster utilization of data streams
- Flexible data architecture to meet customer needs

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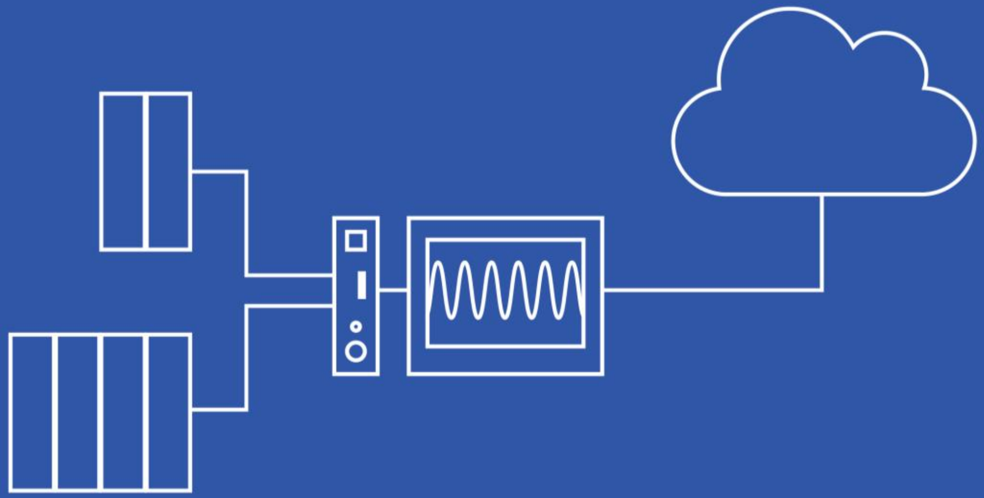

Technology and market designers understand the need for powerful cloud and edge computing in combination with adaptable high resolution measurement down to micro-seconds (µs).

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- more at https://www.researchgate.net/scientific-contributions/Juergen-Sutterlueti-2133552590

How to find faults automatically

Analytic Snapshot based on GI.cloud data backend

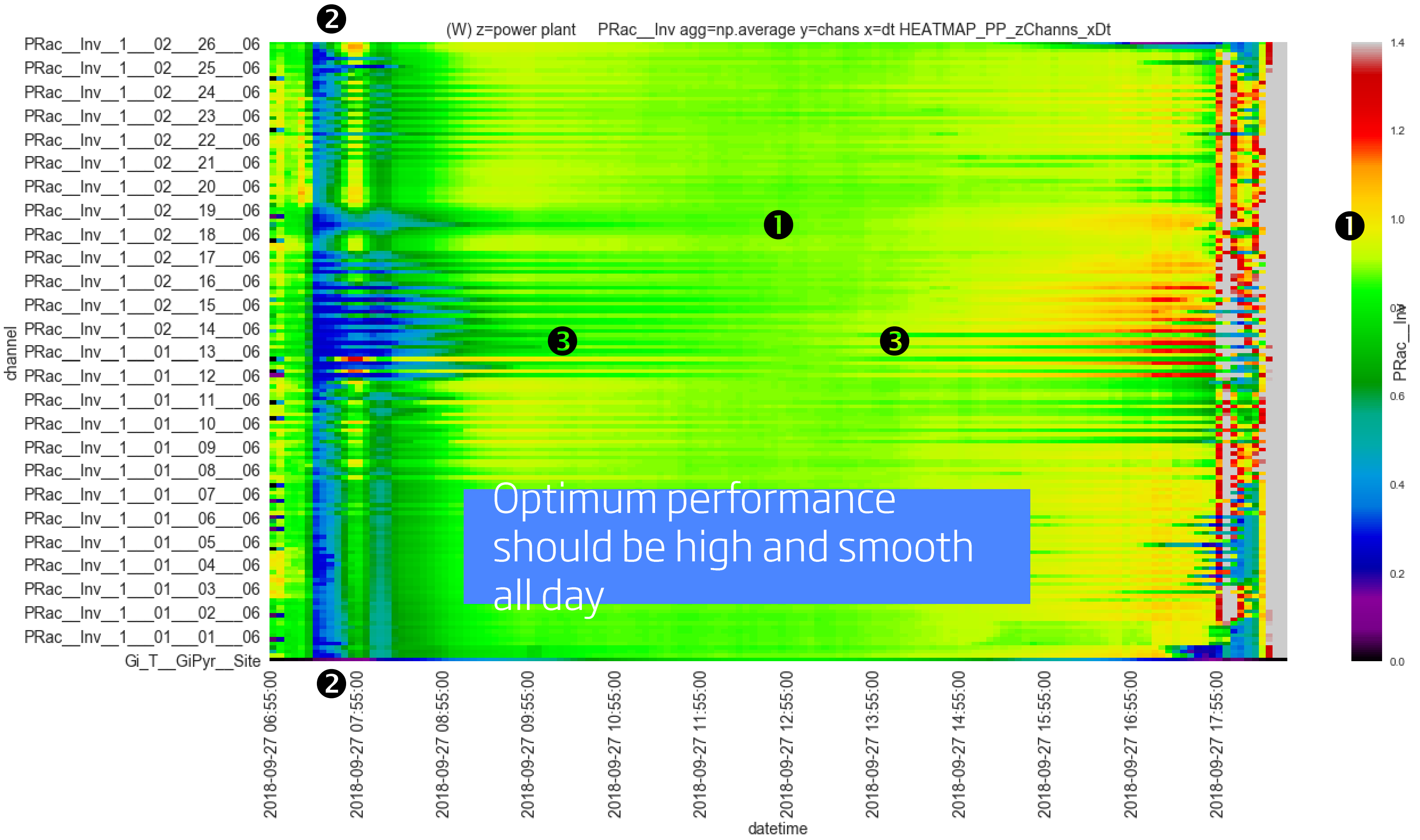
- How to find faults automatically

How to compare PV Performance for many different components over time

Performance ratio (colours red=best blue=worst) for 156 inverters↑ and time→

PR = Pmeas/Pnom/G

- ❶High performance ratio (near 100%) is light green to yellow
- ❷Early morning <08:00 there may be some problems of shading or turn on (blue)
- ❸ Some inverters that are worse in the morning are better in the afternoon>15:00 – it's likely that these arrays are facing westwards



Optimum performance should be high and smooth all day

Comparing standard deviation of similar components – use to find faults

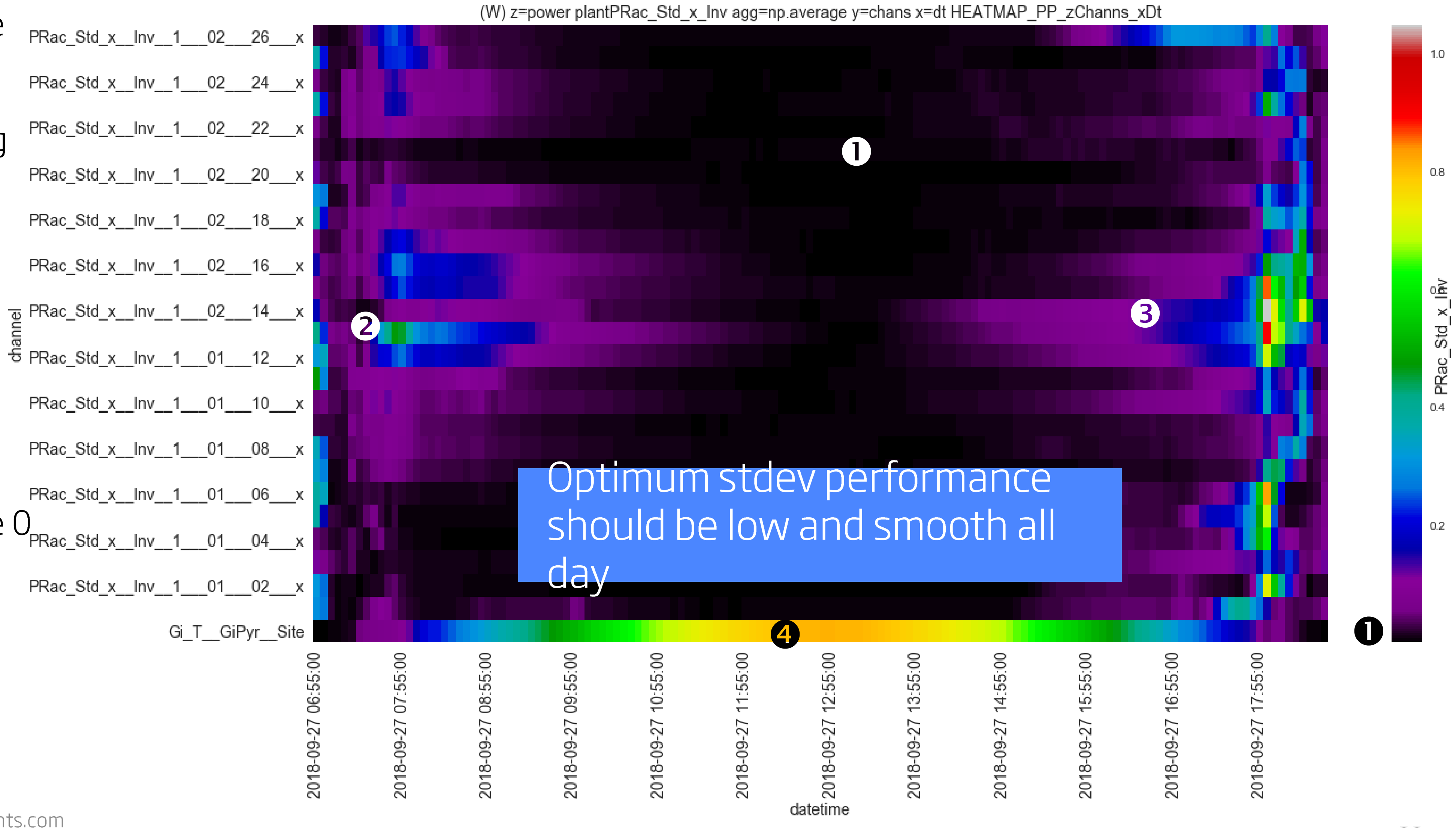
StdDev of PR (colours blue=worst black=best) for 6x26 inverters ↑ and time ➔

❶ Uniform performance has low stdev (black)

❷ Higher stdev morning from the inverters including some west facing

❸ Higher stdev from same inverters in the afternoon

❹ Lowest trace shows normalised irradiance 0 to 0.8kW/m2



How to compare Inverter Efficiency for many different components over time

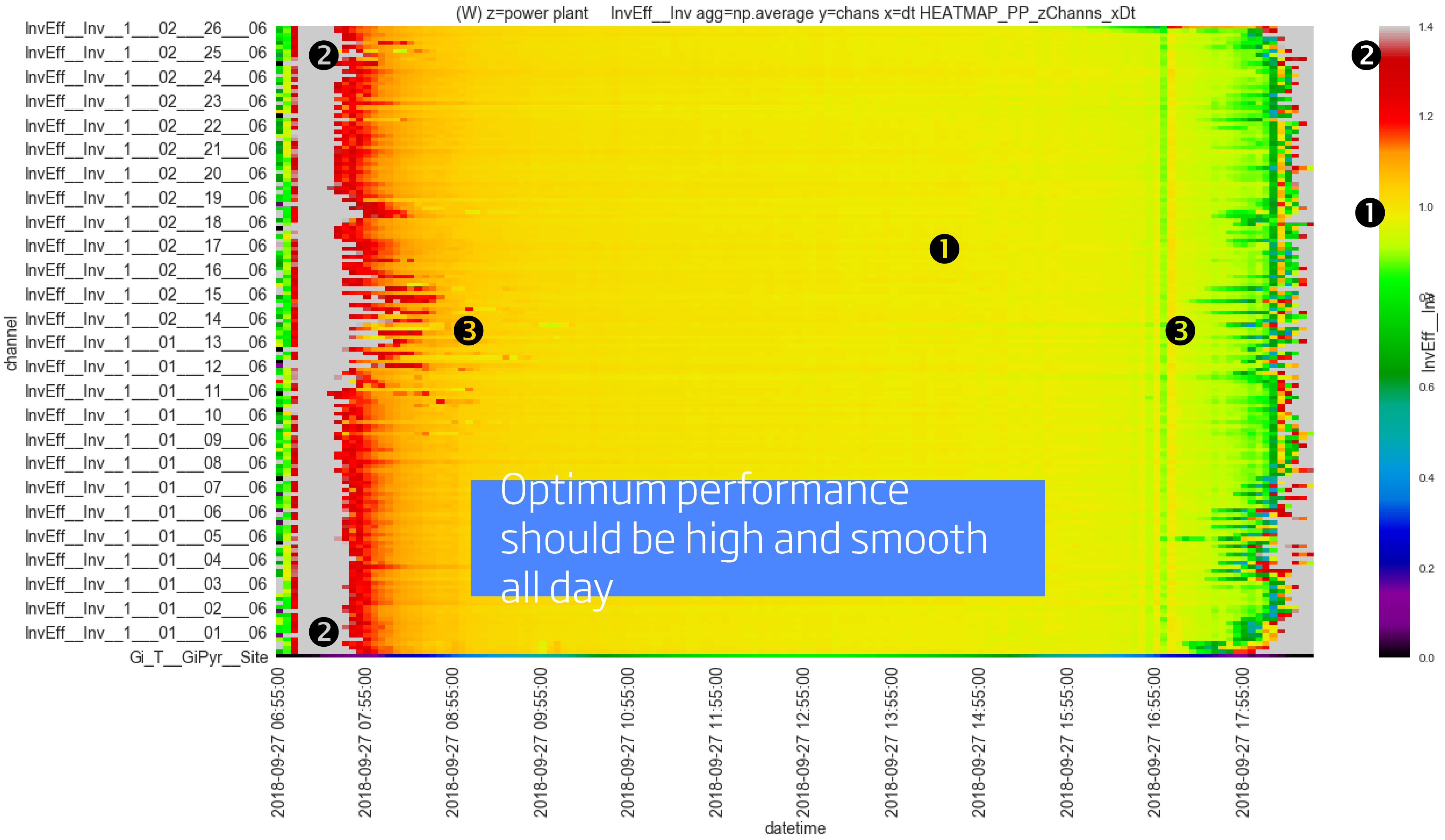
Inverter Efficiency (colours red=best blue=worst) for 156 inverters↑ and time➔

❶High Inverter efficiency (near 100%) is yellow

PR = Pmeas/Pnom/G

❷Very early morning there appear to be reports of <100%

❸ Some inverters that are better in the morning are worse in the afternoon



Determining performance stability PR_{DC} by time of day and month

Average PRdc by hour of day 1…24 HOD🡩 and Year Month 1401…1612 MOY🡪

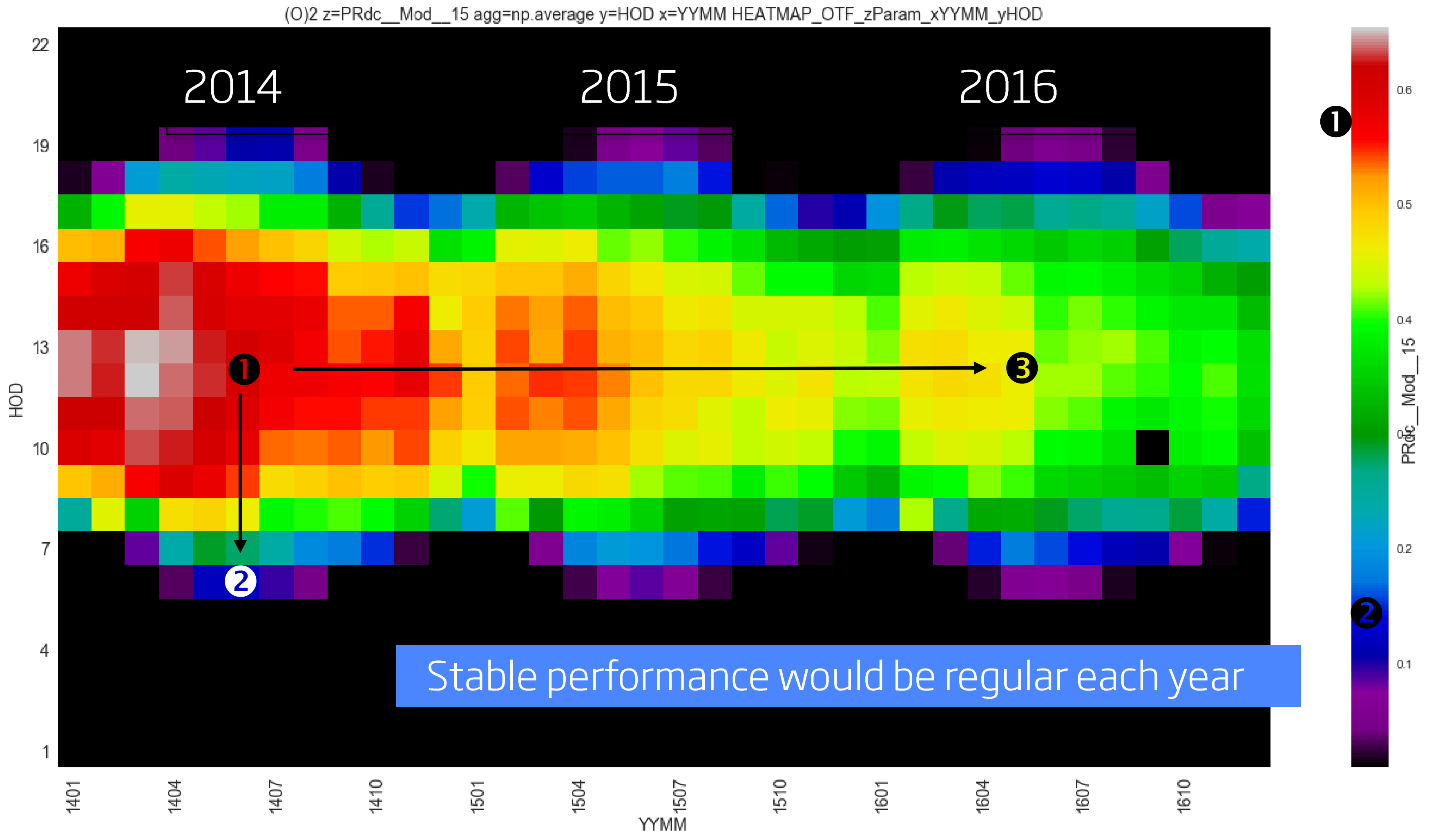
❶1st Summer 1406 Module performance although poor was highest during the day ~0.6

❷ it was worse at lower irradiance ~0.2

❸ >2 years later 1606 this module has degraded badly and is below 0.45

Degradation rates can be obtained by the fall per year from ❶ to ❸ e.g. 0.6 to 0.45

Note longer summer days give "taller" datasets 06:00 to 19:00



Determining performance stability PR_{DC} by irradiance and month

Average PR_{DC} by Irradiance 0 … 1200W/m² G_i↑ and YearMonth 1401…1612 MOY➔

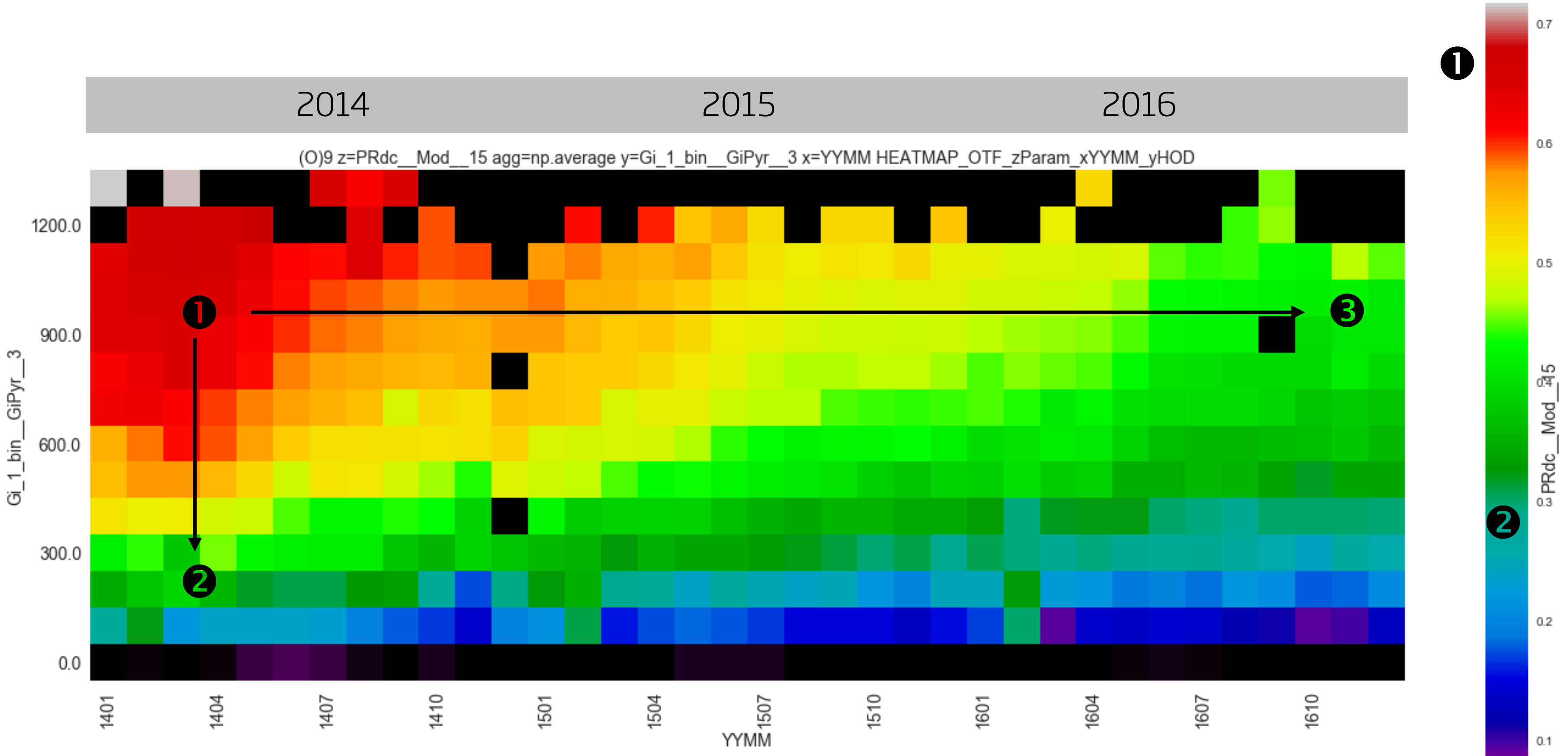
❶Initially Module performance was quite good PR~0.7 at high irradiance 1000W/m2

❷ and worse PR~0.3 at lower irradiance 200W/m2

❸>2 years later this module has degraded badly

Degradation rates can be obtained by the fall per year from ❶ to ❸

Low light performance LLEC can be got from ❷ / ❶



Optimum performance would be high everywhere

Predictive Model: MPM Section

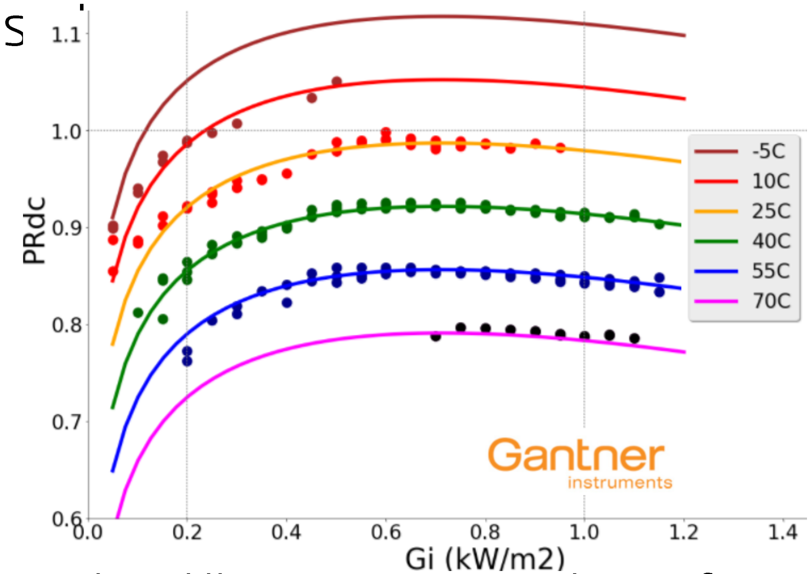
… use the Mechanistic Performance Model (MPM)

- … to fit measured PR vs. Irradiance and Tmodule
- look for discrepancies or poor fit coefficients

$$\mathbf{PR_{DC} = C_1 + C_2 \times dT_{MOD} + C_3 \times Log_{10}(G_I) + C_4 \times G_I + C_5 \times WS}$$

MPM Coefficients are meaningful, orthogonal, robust and normalis

	Usual approx. Range	Coefficient Dependency	Comment	Unit
C_1	80% to 100%	Performance Tolerance	Actual/Nominal	%
C_2	-0.2% to -0.5%/K	(Tmod-25)C	Temperature Coefficient	%/K
C_3	0 to 20%	$log_{10}(G_I)$	Low light fall (~Voc, Rshunt)	%
C_4	-20% to 0%	G_I	High light fall (~Rseries)	%
C_5	-2% to 2%	Windspeed	Windspeed correction	%/(ms-1)



Fitted lines to measured PR_{DC} for c-Si module at GI OTF in AZ with good agreement

... use the Mechanistic Performance Model (MPM)

- ... to fit measured PR vs. Irradiance and Tmodule
- look for discrepancies or poor fit coefficients

$$\mathbf{PR_{DC} = C_1 + C_2 \times dT_{MOD} + C_3 \times Log_{10}(G_I) + C_4 \times G_I + C_5 \times WS}$$

MPM Coefficients are meaningful, orthogonal, robust and normalised

	Usual approx. Range	Coefficient Dependency	Comment	Unit
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C_5	-2% to 2%	Windspeed	Windspeed correction	%/(ms-1)