Modelling of PV modules and systems

Steve Ransome (SRCL, UK)

https://www.pearlpv-cost.eu/wp-content/uploads/2020/05/PEARL-PV-CA16235-Training-School-Brasov-July-2021-provisional04062021.pdf

Papers : www.steveransome.com   mailto: steve@steveransome.com

Acknowledgements :

Juergen Sutterlueti (Gantner Instruments)

http://www.Gantner-instruments.com/

PVCost : Mon, 6th Jul 2021

Contents of this talk

Normalise measurements and modelling!

Normalised = Measured / Reference STC values

Raw Measured data			Measurement Stage	Normalised data		
meas_Imp [A]	meas_Vmp [V]	meas_Pmp [W]		norm_Imp [%]	norm_Vmp [%]	PRdc [%]
			Ref module STC →	8.23 A	30.4 V	250 W
0.034 A	0.51 V	0.017 W	1 cm^2 sample	100%	100%	100%
8.23 A	0.51 V	4.20 W	1 cell ~ 156x156 mm = 243 cm^2	100%	100%	100%
8.23 A	30.4 V	250.2 W	1 module = 60 cells	100%	100%	100%
8.23 A	729.6 V	6004. W	1 string = 24 modules	100%	100%	100%
57.6 A	729.6 V	42025. W	1 combiner box = 7 strings	100%	100%	100%

Measured values vary by >3 orders of magnitude

Normalised values should be near 100%. Errors and/or degradation are easily spotted

- Modelling from 1cm^2 samples through cells, modules, strings and large arrays can be performed far easier if data is normalised

- 1) Modelling of PV performance from IV curves

LFM first developed in 2011 at 26th EU PVSEC
http://www.steveransome.com/pubs/2011Hamburg_4AV2_41.pdf

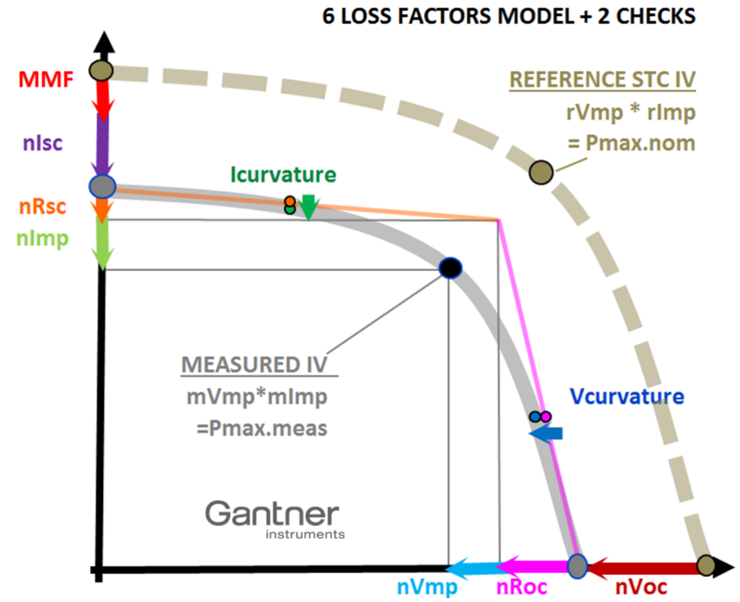
Overview of The Loss Factors Model (LFM)
E.g Stein et al 28th PVSEC Paris 2013 for comparison with 1-diode and SAPM

- The Loss Factors Model "LFM" provides a powerful analysis of indoor or outdoor IV curves

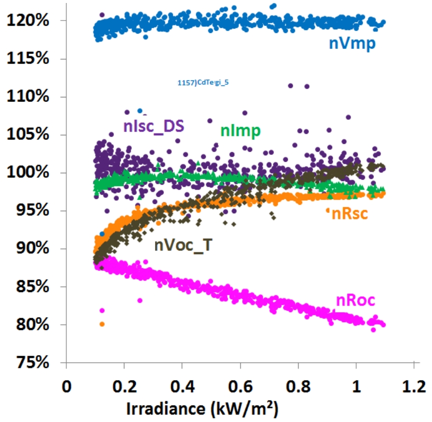
$$PR_{DC} = nI_{SC} * nR_{SC} * nI_{MP} * nV_{MP} * nR_{OC} * nV_{OC}$$

Old naming convention but same approach used

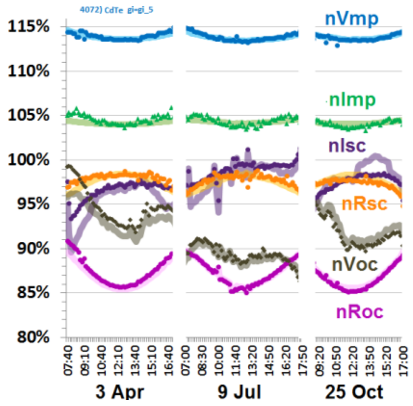
- Two other parameters **nI_C** and **nV_C** show the deviation from expected $I@V_{MP}/2$ and $V@I_{MP}/2$ and give measured values indicating amounts of cell current mismatch and roll over respectively



Characterise a module vs. G_I, Tmod etc.



Predict performance vs. time and weather



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

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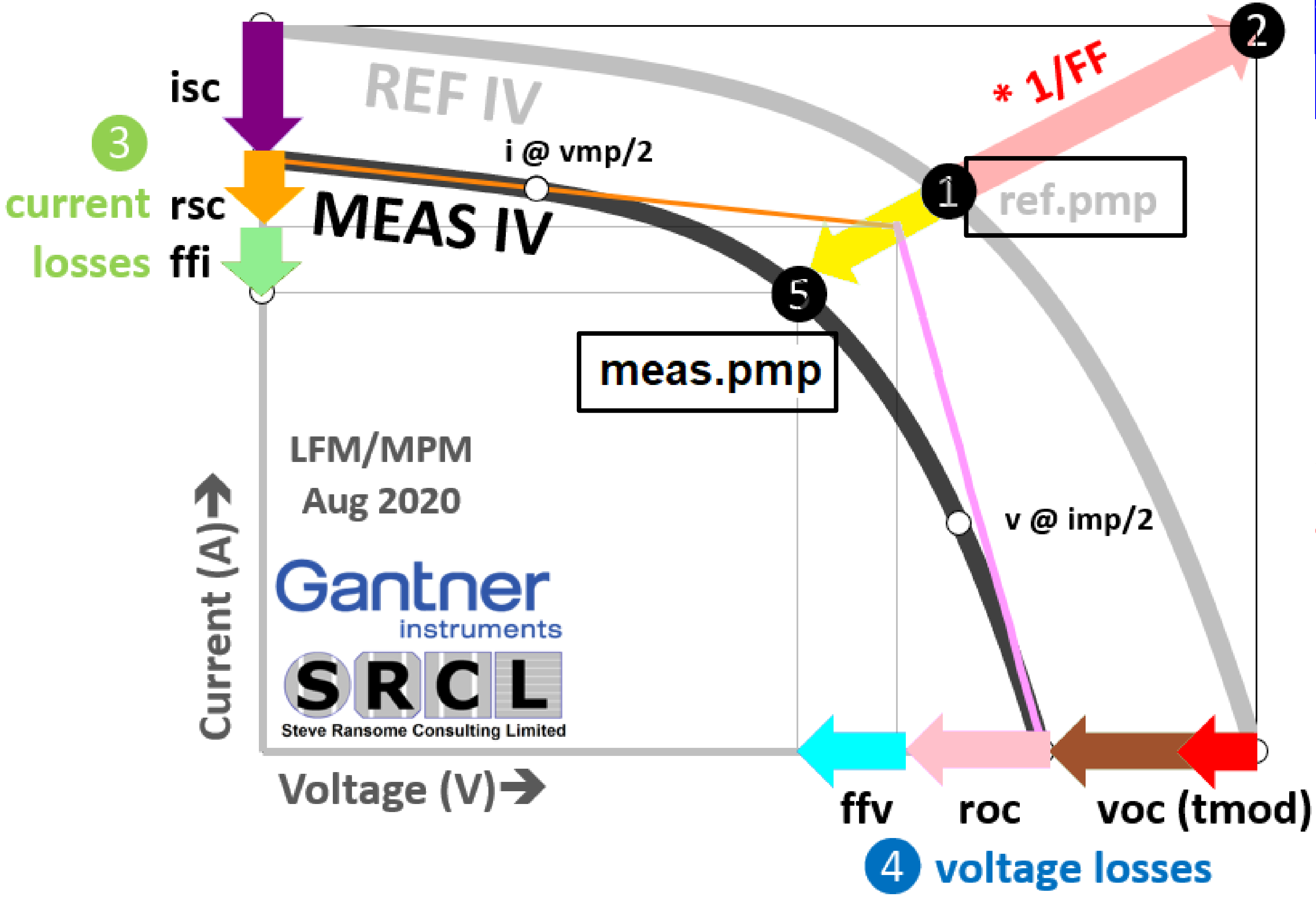
Calculating PR_{DC} from the Loss Factors Model (LFM) Latest naming convention

PR_{DC} = [Pmax at Point 5] / [Pmax at Point 1]



The LFM extracts normalised, orthogonal losses from IV curves

- I_{SC}
- R_{SC} (~ Rshunt)
- ffi (Fill Factor Current dependence)
- ffv (Fill Factor Voltage dependence)
- R_{OC} (~ Rseries)
- V_{OC} (Temperature corrected)
- $T\text{-}_{corr}$ Temperature losses

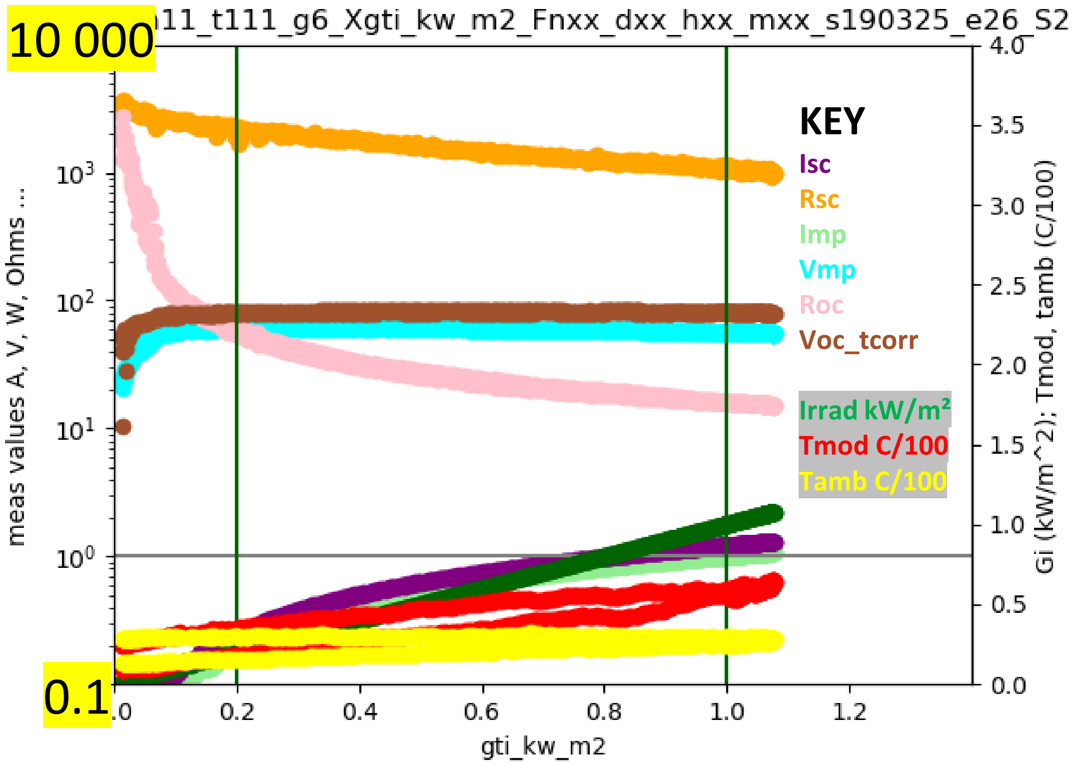
Also quantifies current mismatch and rollover

Typical Measured IV vs. Normalised LFM parameters

Absolute values depend on module technology, cell numbers, module area, series strings etc.

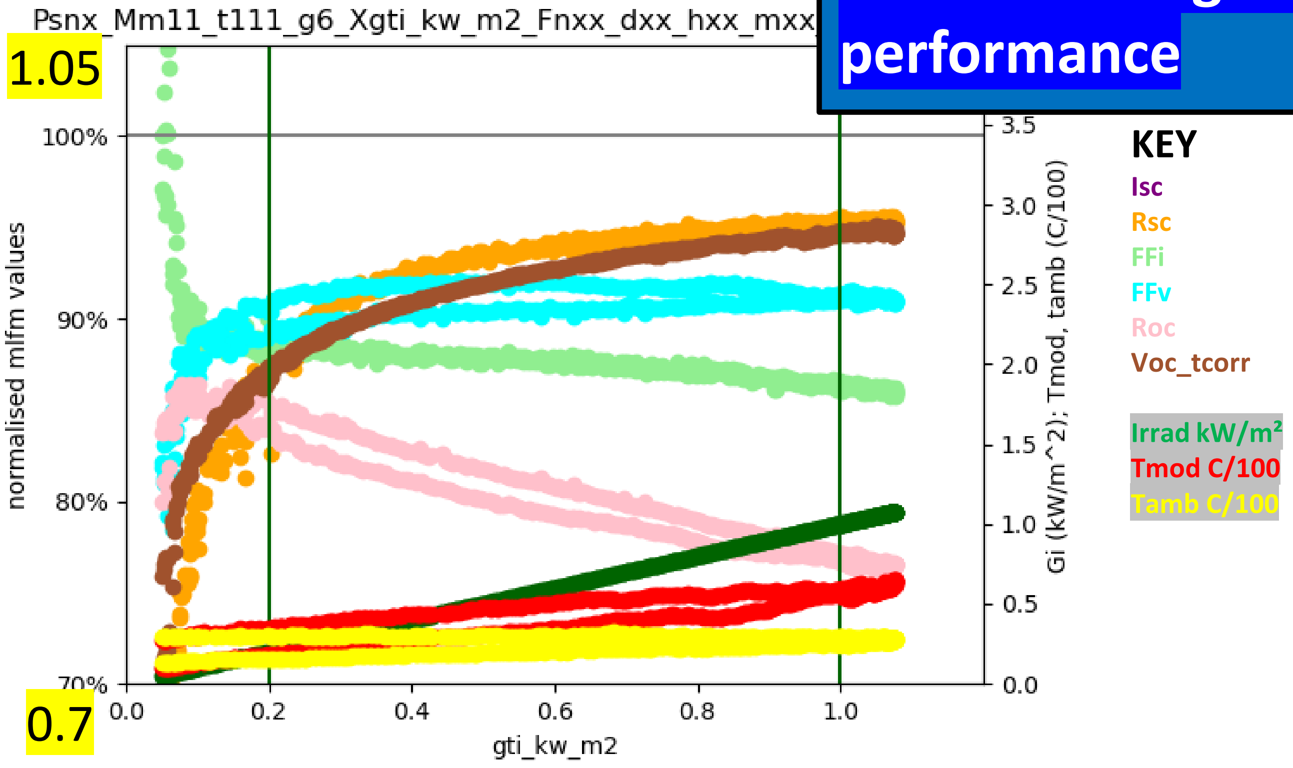
#11 Thin film vs. irradiance
Measured (log)

Yaxis >5 orders of magnitude



#11 Thin film vs. irradiance
Normalised (linear)

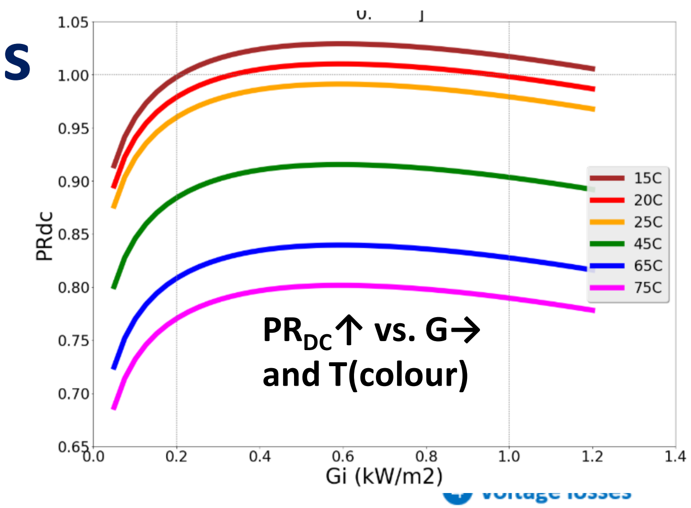
Yaxis just 0.7 to 1.1

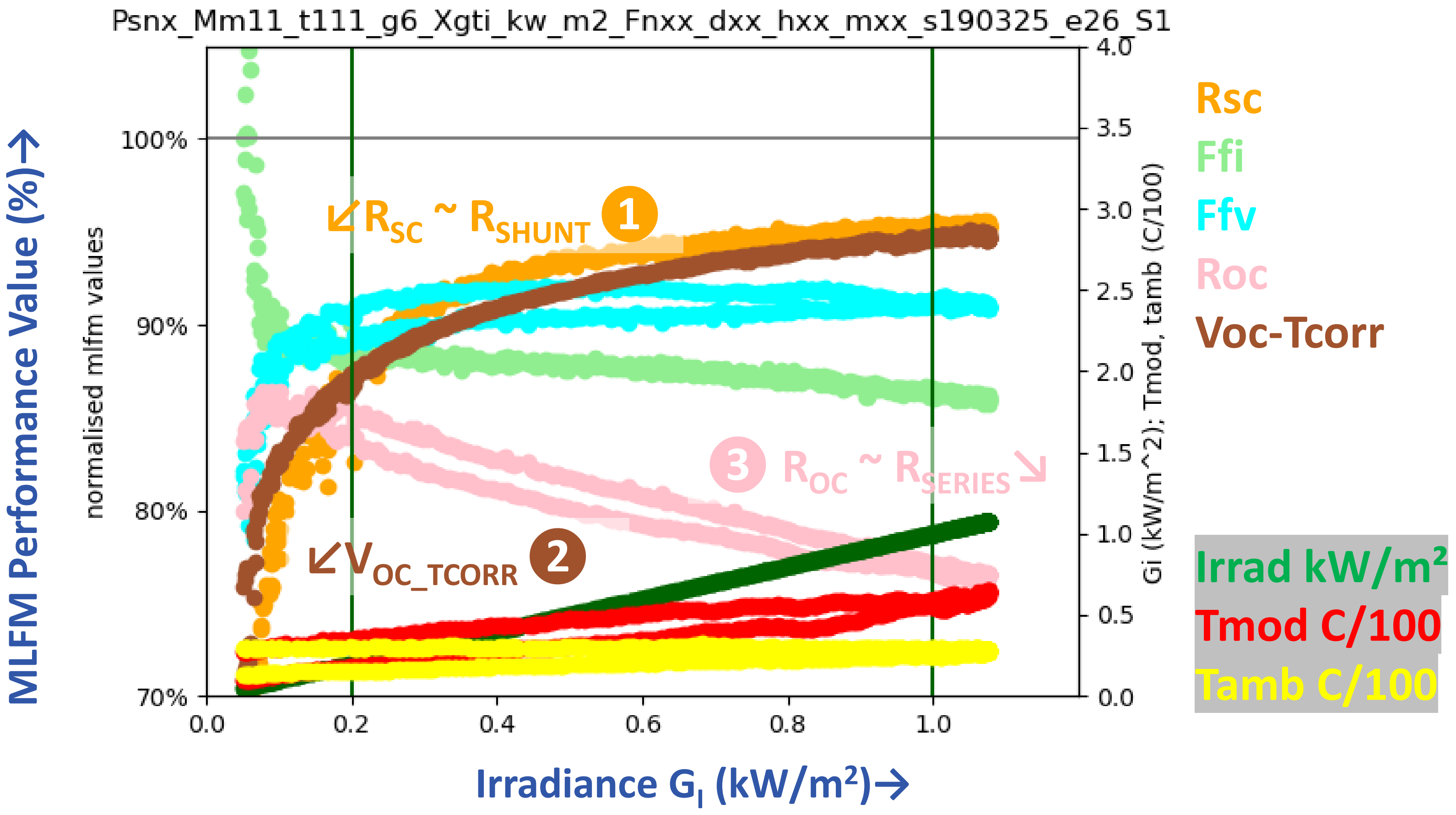


Normalised data gives far better understanding of performance

LFM vs. irradiance identify performance limits and changes

PRdc ∝ 1/FF_ref * norm[(~~isc~~ * rsc * ffi) * (ffv * roc * voc_Tcorr * t_corr)]





The shape of PR_{DC} vs. irradiance is mainly determined by drops in 3 coefficients

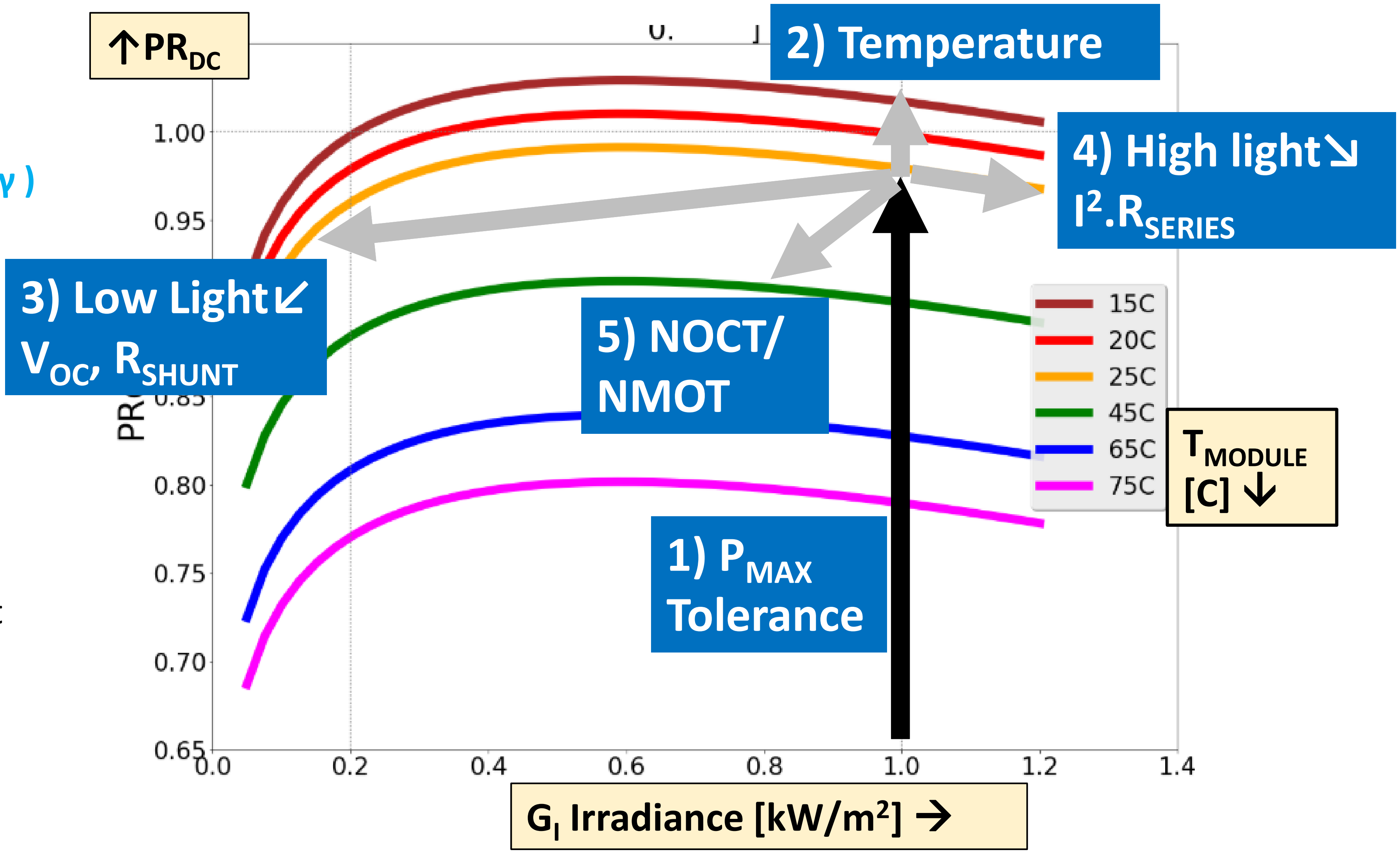
1. R_{SC} at low light↙
2. V_{OC} at low light↙
3. R_{OC} at high light↘

Hysteresis on 3 shows Roc temperature dependency am to pm

5 independent values are needed to characterise PV Efficiency vs. Irradiance and Tmodule curves

1. **Pmax Tolerance at STC**
   $=P_{MAX}/P_{MAX.NOM}$ @ 25C, 1000W/m^2
2. **Thermal Pmax coefficient (γ)**
   $=1/P_{MAX}*dP_{MAX}/dT_{MOD}$ %/K
3. **Low light loss LLEC ($\sim V_{OC}$, R_{SHUNT})**
   $=PR_{DC.200}$ / $PR_{DC.1000\ W/m^2}$
4. **High light loss ($\sim R_{SERIES}$)**
   $= I_{MAX}^2.R_{SERIES}$
5. **Temperature rise (~NOCT or NMOT)**
   thermal rise above ambient

(Not shown : I_{SC} losses from AOI reflectivity, Spectral Response and soiling.
Note temperatures are not linear)



Gantner instruments

www.steveransome.com

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A mechanistic performance model (MPM) for PR_{DC}

How does PV performance depend on weather inputs?

1. $I_{MAX} \propto G_I$ — Module STC rating actual/nominal
2. $P_{MAX} \propto (1+\gamma*(T_{MOD}-25))$ … — Power temperature coefficient
3. $V_{MAX} \propto Log_{10}(G_I)$ — From diode equation
4. $\Delta P_{MAX} \propto I_{MAX}^2 * R_{SERIES}$ — $I^2.R_S$ loss
5. $T_{MOD} \sim T_{AMB}$ – fn(Windspeed) — NOCT/NMOT Thermal rise
6. $R_{SHUNT} \propto$? — "looks similar to V_{OC} low light drop"
7. ? — 2nd Order non-linear effects if needed (some thin film)

Mechanistic model = (Meaningful, Orthogonal, Robust and Normalised) coefficients

$$PR_{DC} = C_1 + C_2*(T_{MOD}-25) + C_3*Log_{10}(G_I) + C_4*G_I + C_5*WS + C_6/G_I + «?2nd\_order»$$

$P_{MAX.ACTUAL}$ | Tolerance | Temperature | Voc and Rshunt | R_{SERIES} | NOCT | Other low light | 2nd order effects

C_3 models both V_{OC} and R_{SHUNT}

Also allow some 2nd order non-linear coefficients if needed

All measurement data is from Gantner Instruments' OTF Solutions Tempe, AZ

Further info in published paper, otf@gantner-instruments.com or email authors

PV Module Measurements:

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

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

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

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

Example
OTF 8 Channel IV Scan Outdoor

IV Scan:

- 8 Channels, 4wire

Environment:

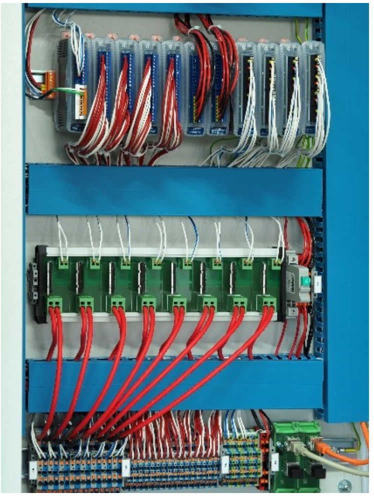
- Irradiance: tilted, horizontal, albedo, 3 spare
- Temperature: 16x PV Module, 1x Cabinet
- Wind speed, direction; Rel. Humidity; Air pressure

Location:

UAE, China (Gobi Desert), California, USA

Cooling:

Active, 20000 BTU



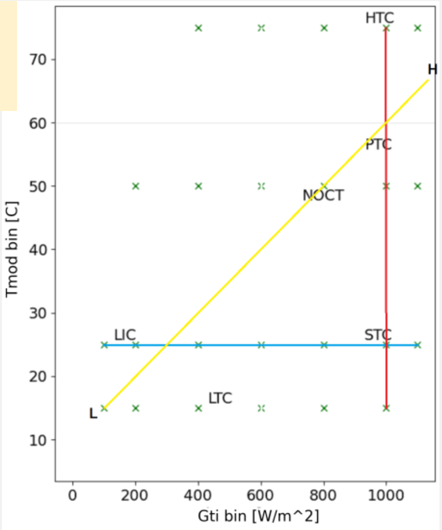
- 2) Characterising PV module performance with matrix methods (IEC 61853) using high quality outdoor measurements

Measuring matrices of $PR_{DC}(G,T)$

$PR_{DC} = P_{MP\_MEAS}/P_{MP\_REF}/G_{SUNS}$

(A) INDOOR (IEC 61853:2011-2018)

(1) IEC 61853
23 point (G,T) Matrix



Temperature Coefficients up to 4 T values ↕

PR_{DC} vs. irradiance Up to 5 G values ↔

Specifies 23 points – could reduce costs with fewer e.g. 6

→ Gives worse modelling accuracy

→ Poorer fitting with inter/extrapolation from only 6 points.

→ No understanding of non linearities

COSTS :
Indoor Matrix ~ \$2800/€2300 + \$700/€580 for AOI

Outdoor measurements :

1. Cheaper than indoor ?
2. More matrix bins better for coefficient extraction
3. Quick results with insulation/heating, mesh cover, 2D mistrack

(B) OUTDOOR (GI OTF, Tempe AZ)

From IV curves or P_{MPP} with real weather

→ 260k measurements/year (if every 1m)

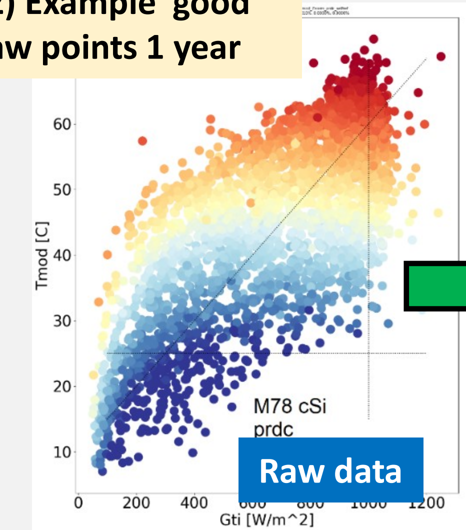
→ Needs data sanitizing and filtering

→ Can give ~100 matrix points (G=100W/m²,T=5C bins)

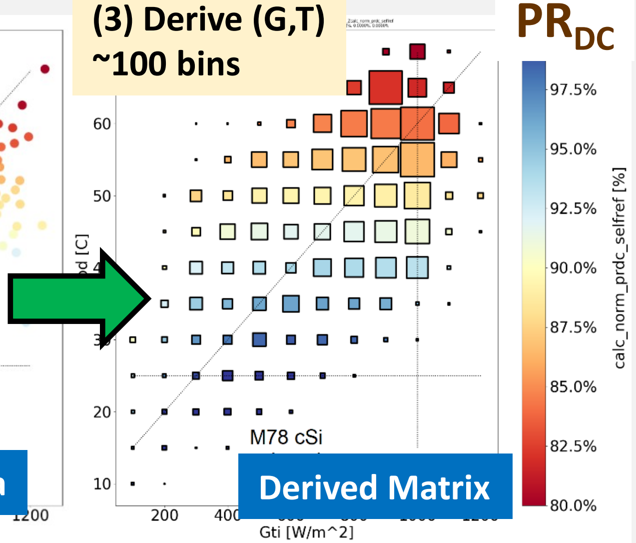
→ Better analysis possible e.g. any non linearities

COSTS:
Outdoor /module \$1000/6 months with spectral, AOI

(2) Example good raw points 1 year



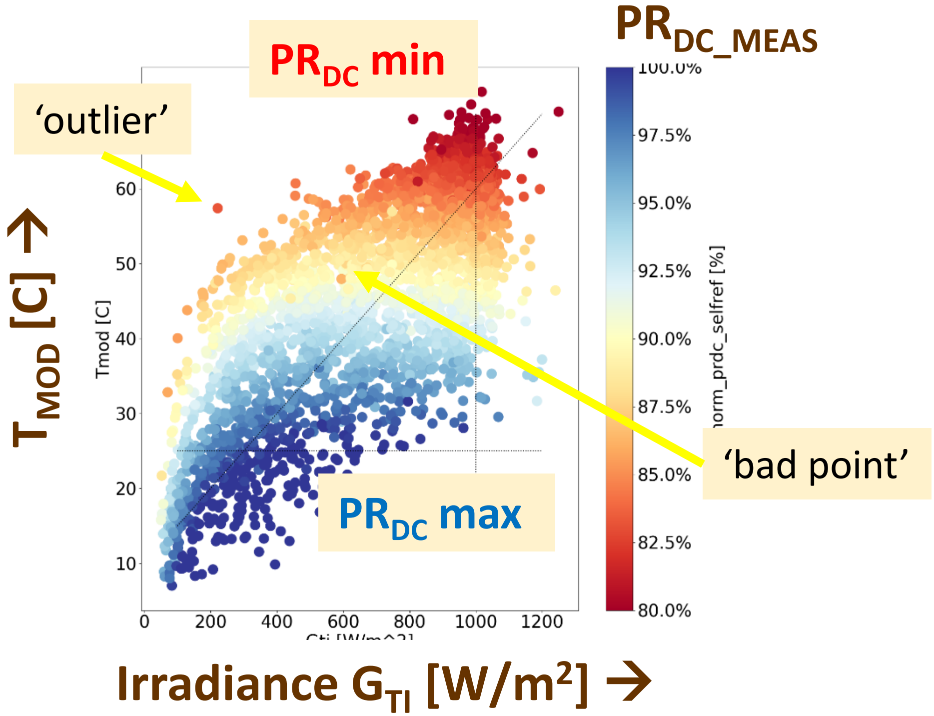
(3) Derive (G,T) ~100 bins



How to generate dense performance matrices from good outdoor data 1/3

A) Raw $PR_{DC}(G,T)$

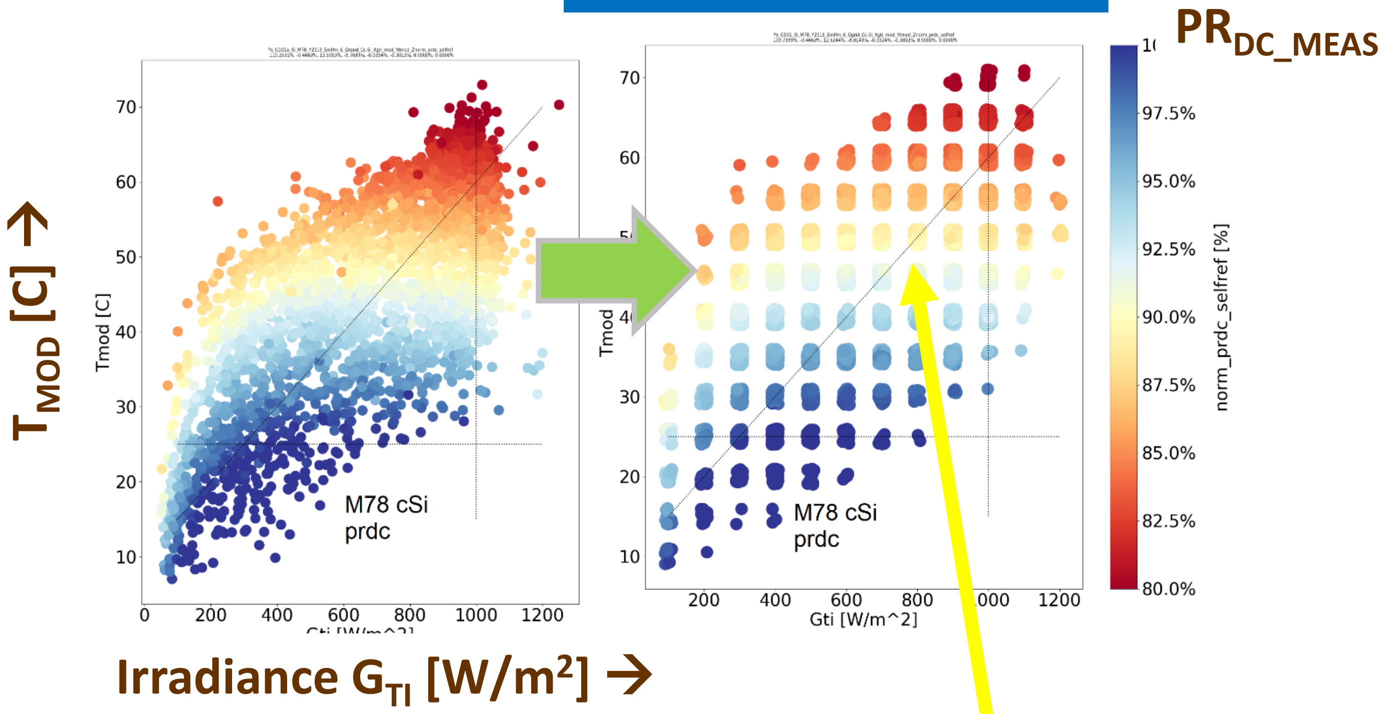
Good points 1 year random 4000 shown



How to generate dense matrix points?

How to generate dense performance matrices from good outdoor data 2/3

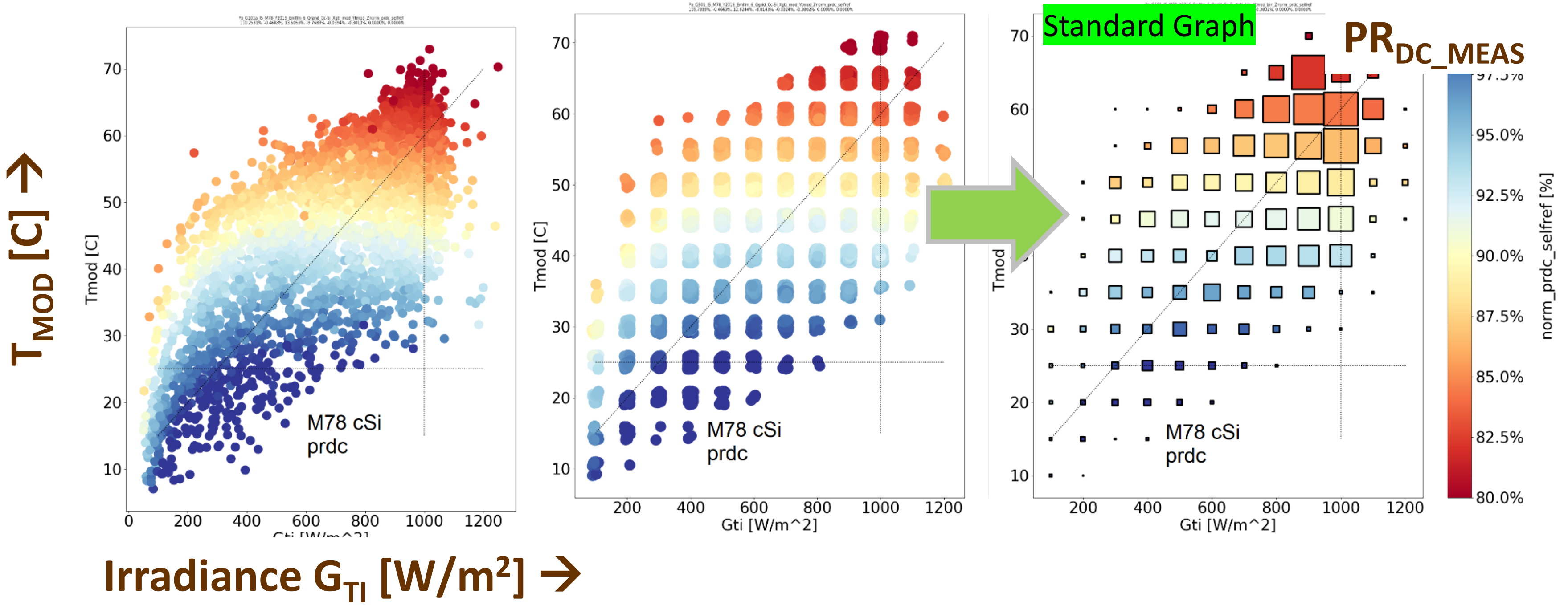
A) Raw $PR_{DC}(G,T)$	B) Filter into (G,T) bins
Good points 1 year random 4000 shown	Filter by steady weather, Sanity check e.g. 3sigma, Group into (G,T) bins



Uniform colour bins prove good non-scattered data

How to generate dense performance matrices from good outdoor data 3/3

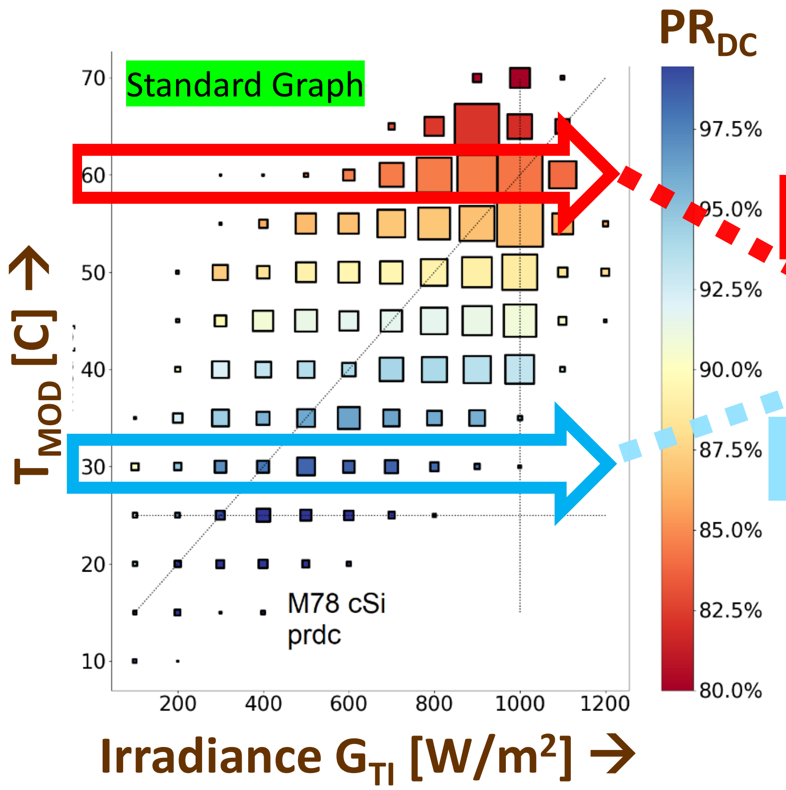
A) Raw $PR_{DC}(G,T)$	B) Filter into (G,T) bins	C) Average, sum per (G,T) bin
Good points 1 year random 4000 shown	Filter by steady weather, Sanity check e.g. 3sigma, Group into (G,T) bins	Colour = Avg(PR_{DC}) /bin Area = Σ(H kWh/m^2) /bin



Useful standard graph format to be used often showing Performance (colour), Insolation (area) vs. Irradiance→ and Tmodule↑ bins

Generated accurate dense measurement matrix with ~100 useful points

‘PR_{DC} vs. irradiance’ from outdoor matrix

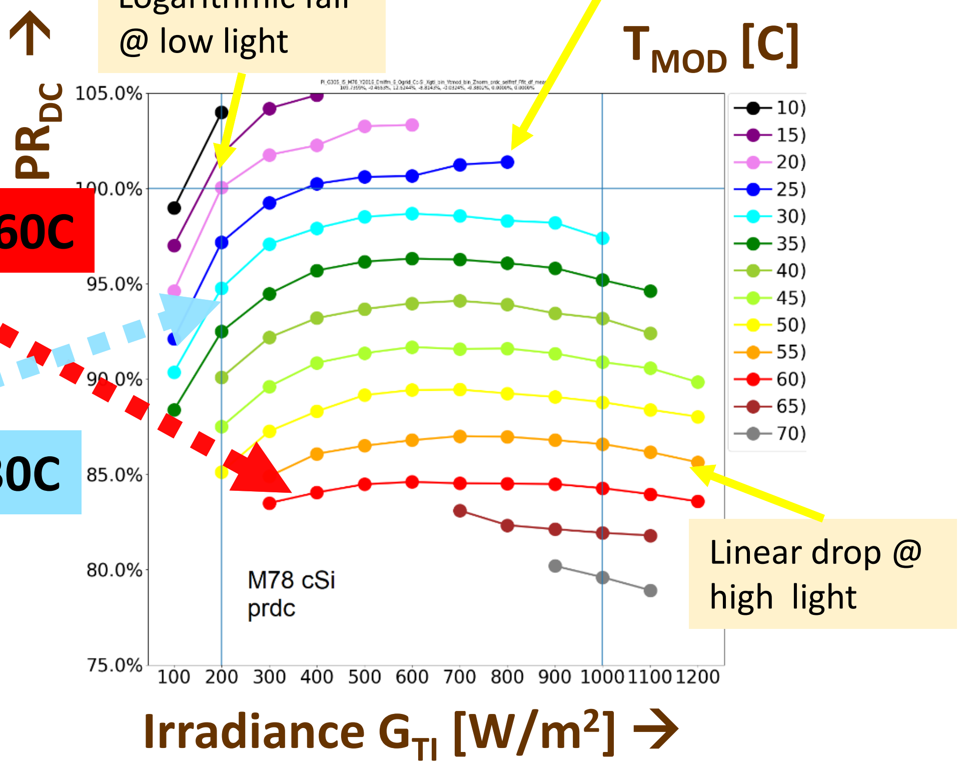


(A) 60C

(B) 30C

Logarithmic fall @ low light

Small scatter only at extreme weather?

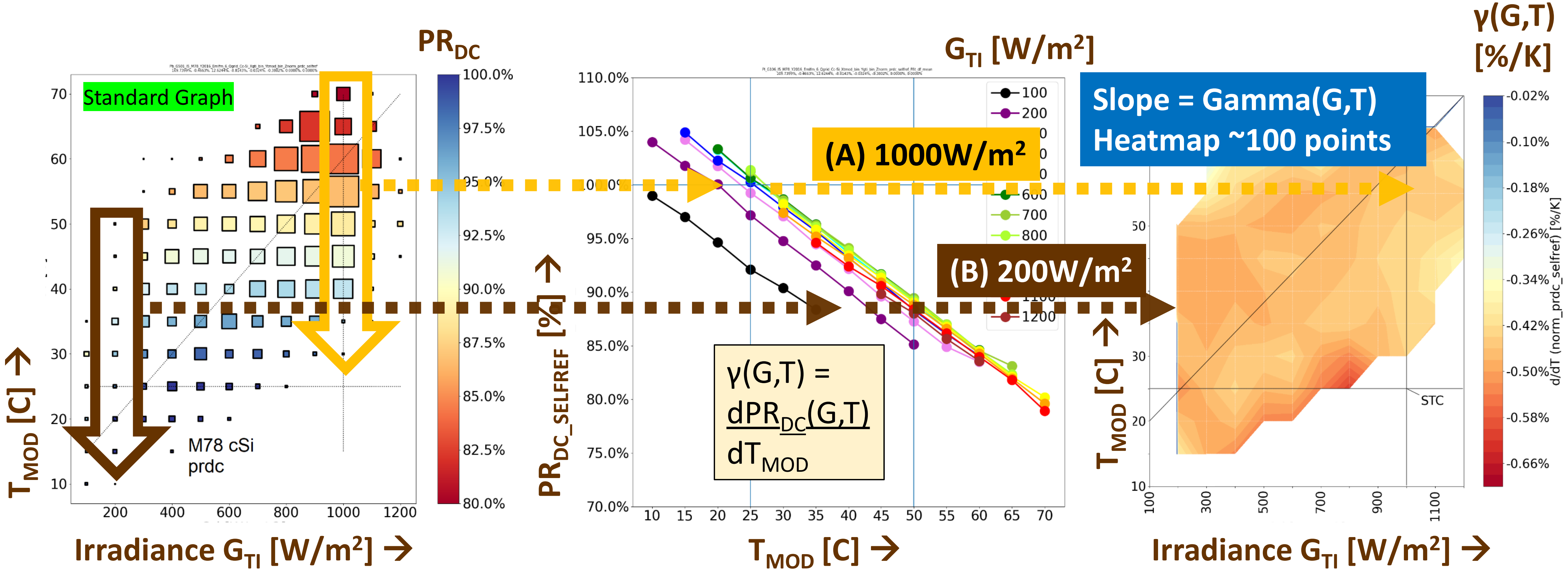


Linear drop @ high light

How does PR_{DC} vary with irradiance?

Smooth plots can be generated from good quality outdoor measurements which allow accurate characterisation

‘PR_{DC} vs. Temperature’ from outdoor matrix



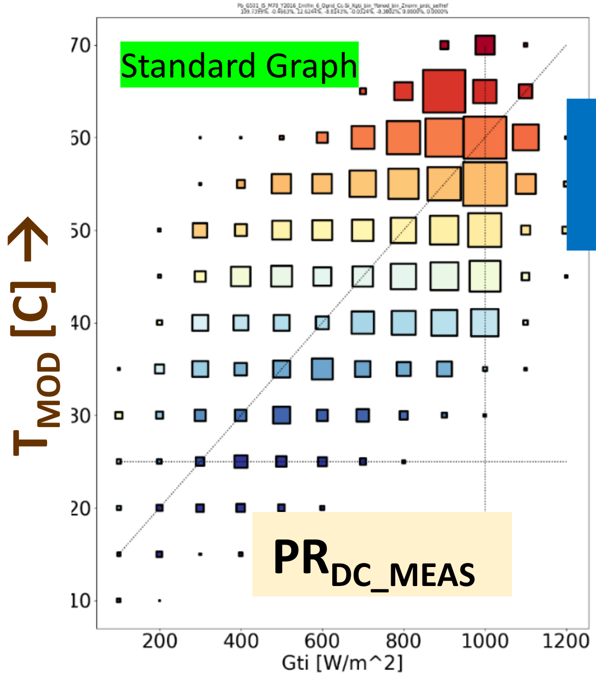
How does PR_{DC} vary with temperature?

Datasheets usually report 1 constant gamma value
This plot will quantify any non-linear behaviour

1st Pass : Fitting performance matrices with a linear model (mpm6)

```
def mpm_6(G, dT, WS) = (
    c_1 +                  # constant
    c_2 * dT +             # temp. coeff
    c_3 * log10(G) +       # low light ~Voc, Rshunt
    c_4 * G +              # high light ~Rseries
    c_5 * WS +             # windspeed ~0
    c_6 / G                # c_6 <= 0 low light
)
```

MPM6 is a linear model :
(each coefficient is only a function of G , T or WS)
G = irradiance [kW/m^2] ;
dT = delta temperature (Tmod – 25) [C] ;
WS = windspeed [ms^{-1}]

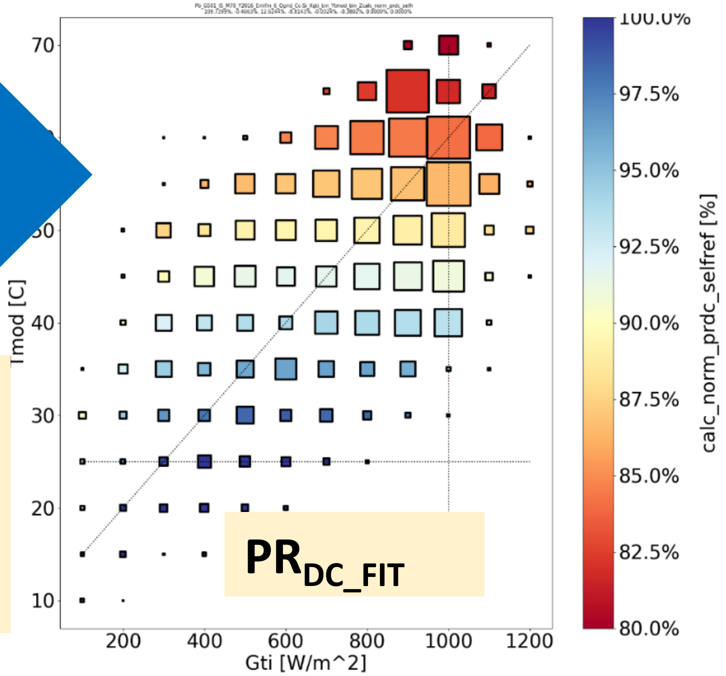


MPM6 FIT

Can weight by insolation for more realistic results

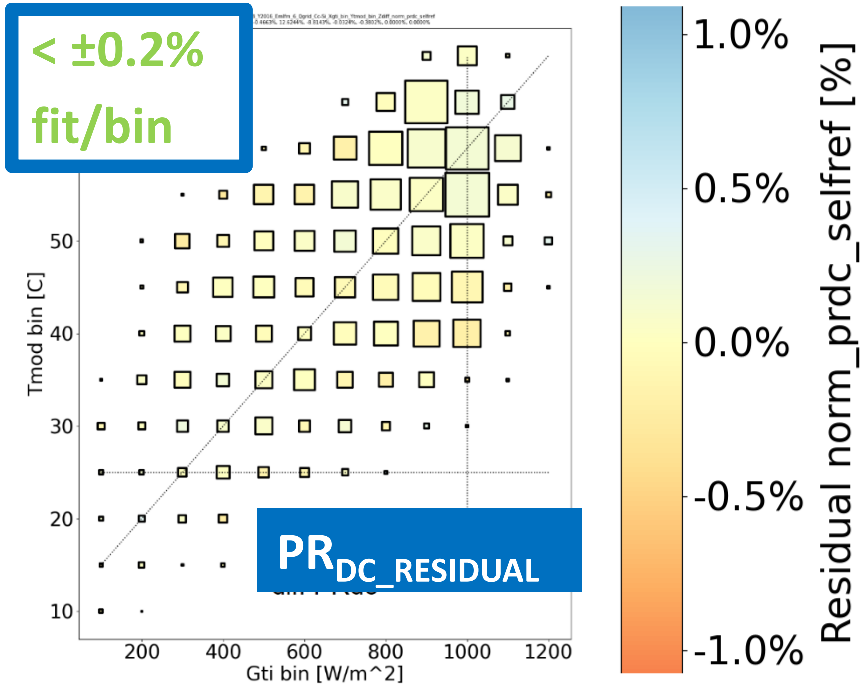
PR_{DC}

80% to 100%



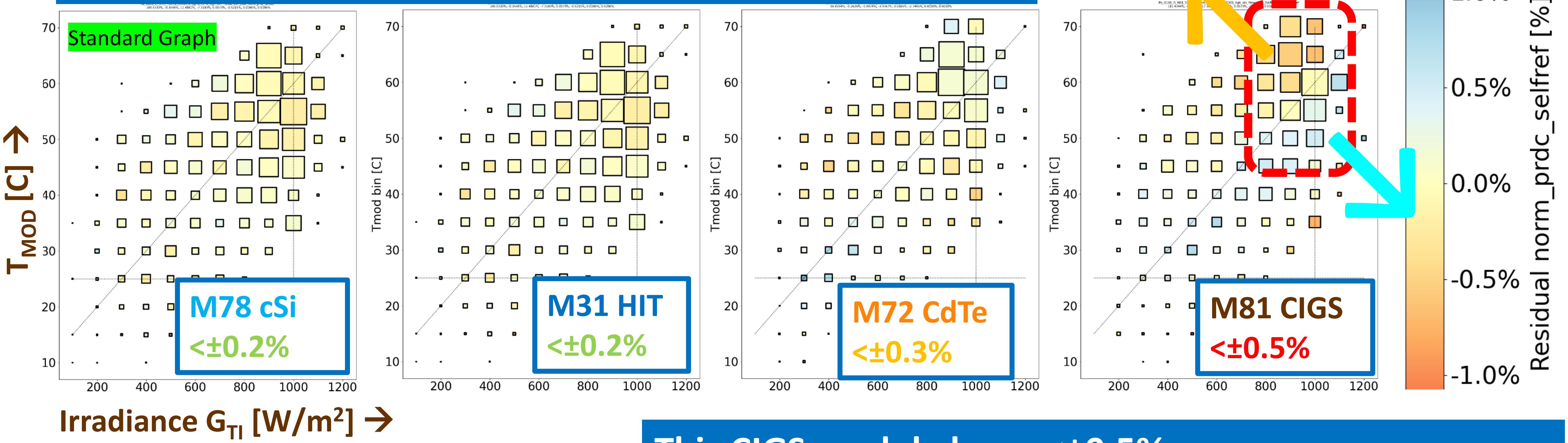
< ±0.2% fit/bin

$PR_{DC\_RESIDUAL}$



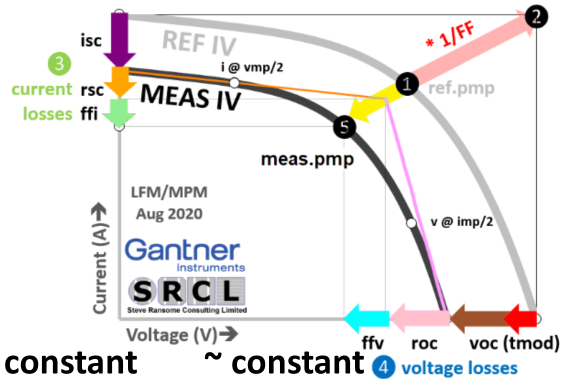
Typical outdoor linear model residual fit error $PR_{DC(MEAS-FIT)}$ four technologies

cSi, HIT, CdTe :
Fit very well (because they are linear)



This CIGS module has a <±0.5%
Monotonic residual error between
high ↔ low temperature indicating a Non-linearity
(as expected from the gamma heatmap)

Which LFM parameter(s) cause non-linearity #1 ?

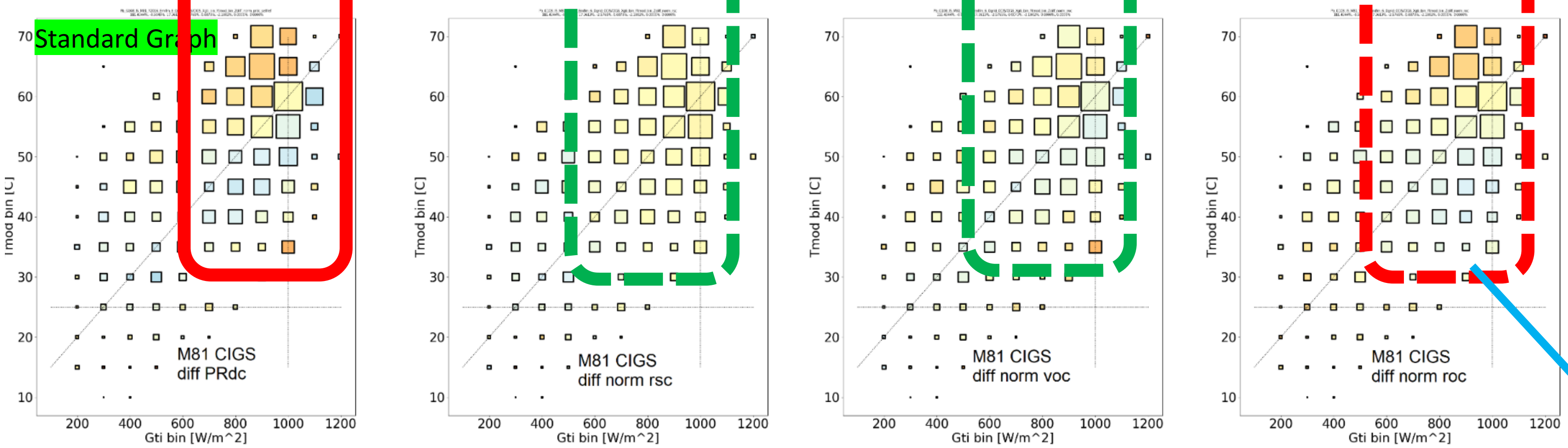


(2) Correlating shapes of colours 'Cause' PR_{DC} behaviour

Dependency	~ Rshunt	~ Voc	~ Reseies	~ constant	~ constant	~ constant

(1) $PR_{DC} = [\ nR_{SC} \times nV_{OC} \times nR_{OC} \times nI_{SC} \times nFF_I \times nFF_V\ ]$

Tmodule [C] →



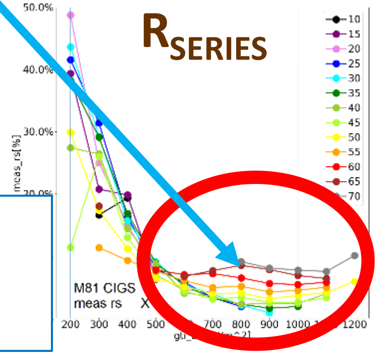
Irradiance G_{TI} [W/m²] →

No correlation

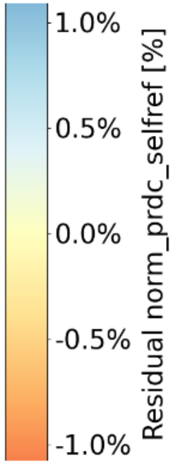
Little correlation

Correlation !

Can find cause of any non-linearity from pattern matching PR_{DC} with LFM fits



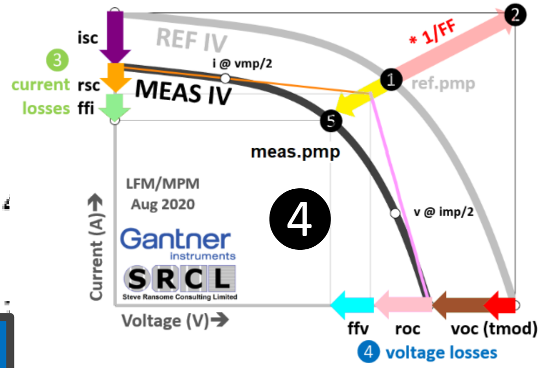
(3) Cause found :
Atypical R_{SERIES}~T_{MOD}
Only at High LIght



$PR_{DC\_RESIDUAL}$
-1% to +1%

- 3) Stacked loss charts of performance

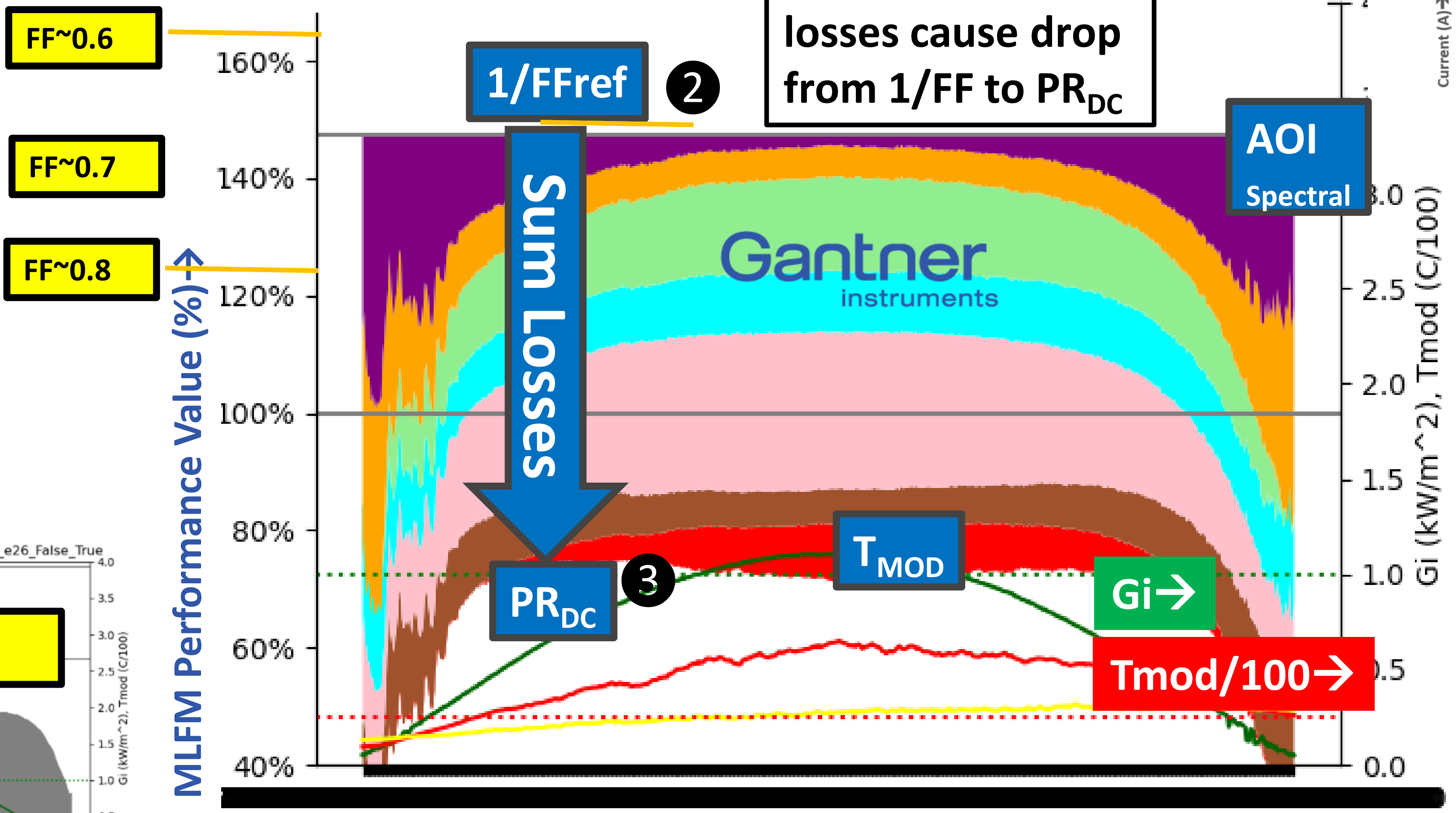
LFM losses causing measured behaviour from 1/FF → PR_{DC}



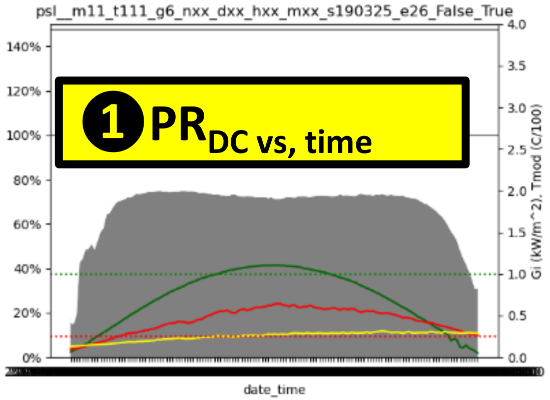
Lossless performance starts at 1/FF.

Heights are shown for FF 0.6 to 0.8

7 different LFM losses cause drop from 1/FF to PR_{DC}



(1 clear day) Time of day→



KEY

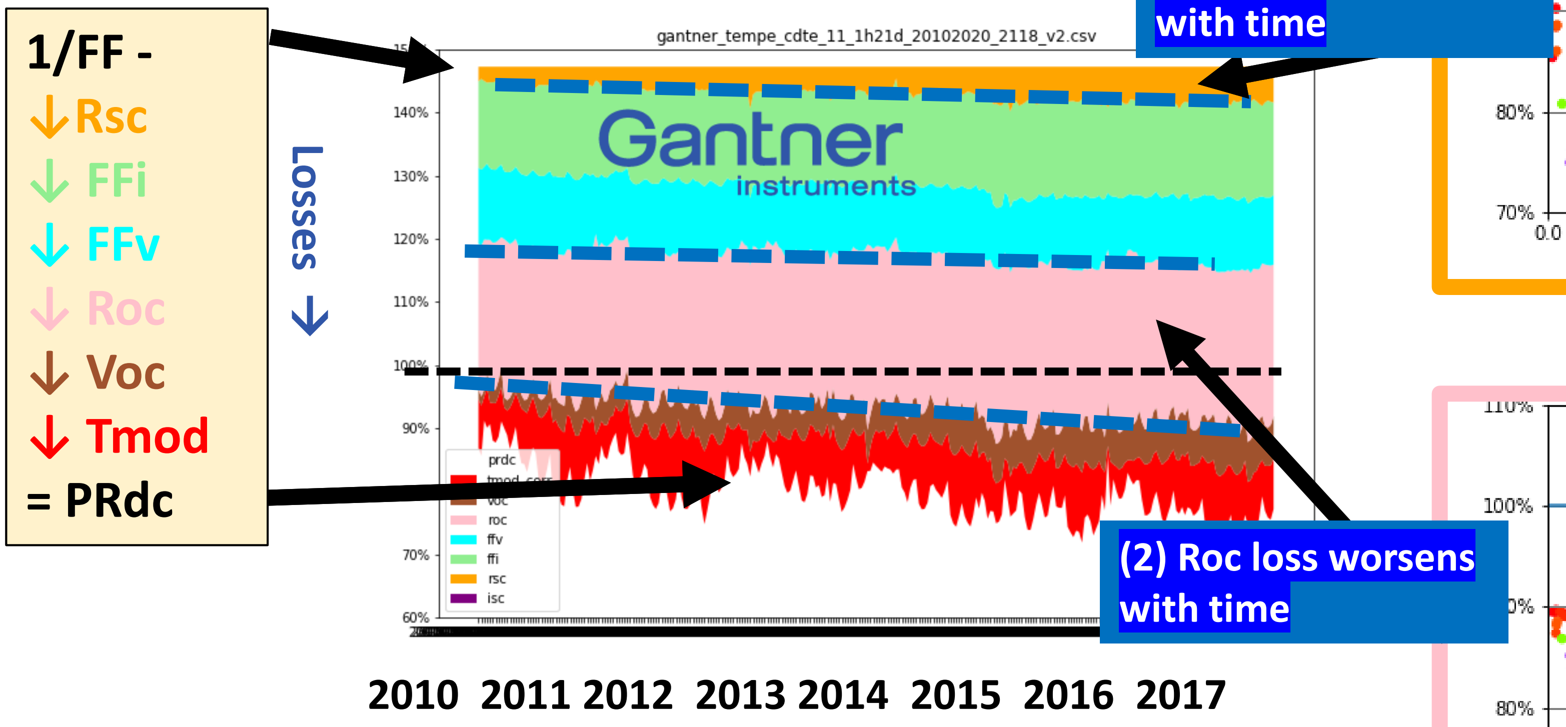
- Isc
- Rsc
- Ffi
- Ffv
- Roc
- Voc-T
- T-corr

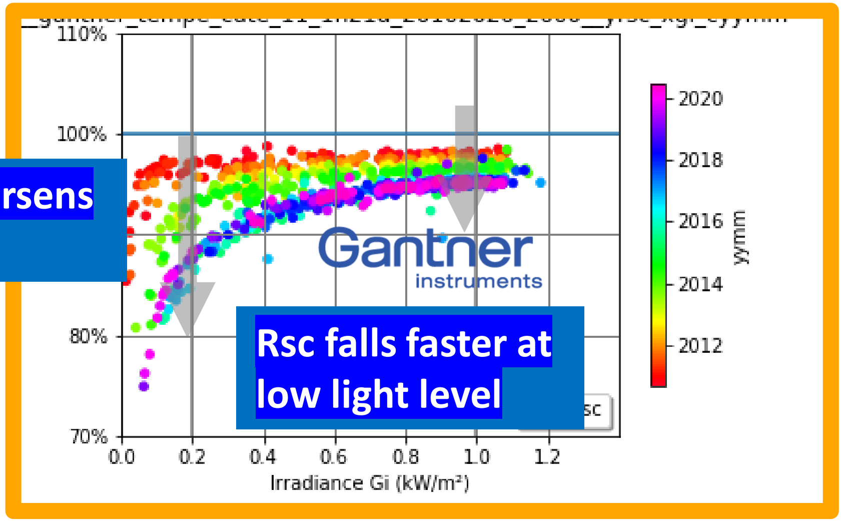
- Irrad kW/m²
- Tmod C/100
- Tamb C/100

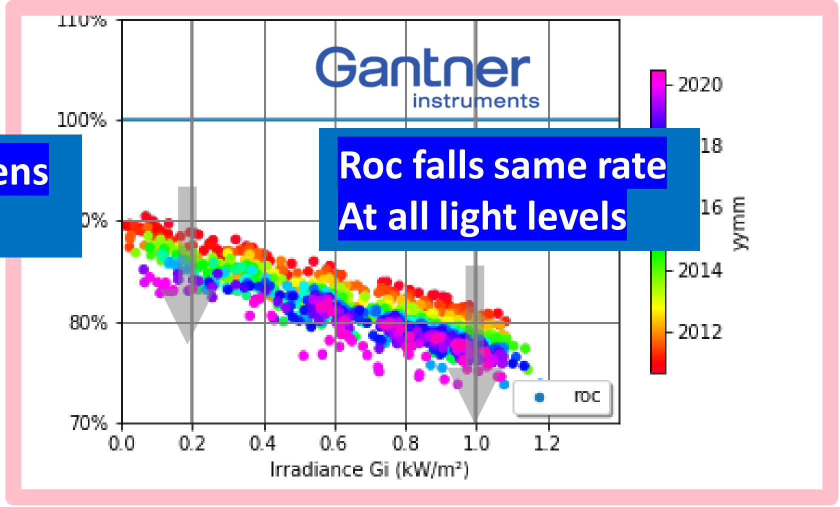
Stacked loss graphs identify causes and rates of any long-term degradation –

Gantner 2010-2017+ (self referenced Isc) Unstable

PRdc ∝ 1/FF_ref – stacked_loss[(~~isc~~ + rsc + ffi) + (ffv + roc + voc_Tcorr + t_mod)] <5>





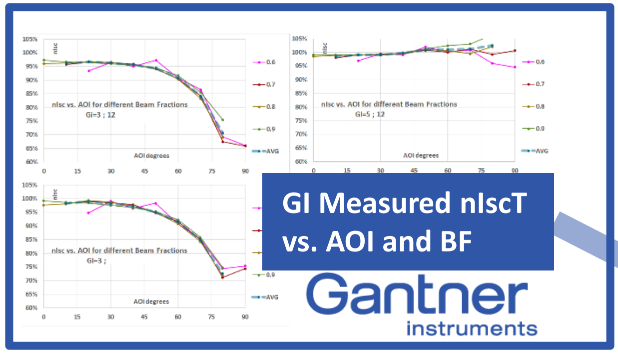


- 4) Predicting Energy Yield vs. Climate worldwide

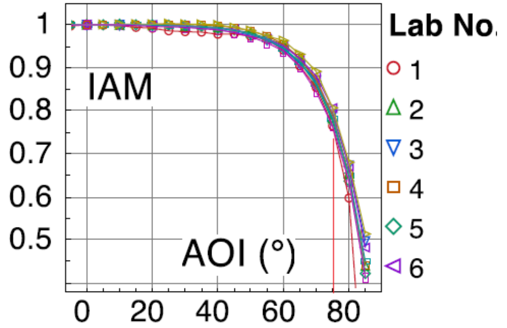
Some 24 modelling steps needed for Energy Yield … (see also pvpmc for more definitions)

	Step	Comment
Site Defin-itions	Site Location	Latitude, Longitude, Altitude, TimeZone
	Array orientation(s)	Tilt,Azimuth or Tracking (Fixed tilt vs. Tracking 1D or 2D, limits, backtrack)
	Array Shading – 3D model?	Self (by other rows); near (e.g. chimneys); horizon (e.g. mountains)
	SENSORS	Pyranometer/Reference cell; Temperature; Wind speed, RH, Spectrum etc.
Met Data	Weather hourly series	Global horizontal irradiance, Tambient, Wind Speed and variability /year
	Snow	Depth, frequency distribution. (Note will melt and fall off)
	Soiling	Dust increase/dry day (~0.1-0.25%/d?); cleaning; rain event washing
Calcu-lations	Solar angle of incidence (AOI)	(reflectance losses increases with clear sky and high AOI).
	Solar spectrum	APE or Blue fraction (from Solar altitude and clearness index)
	Module Temperature	From Irradiance, Tambient, Windspeed and NOCT
	Tilted plane irradiance Gi from Gh, Dh, Rh	Needs ground albedo, extra calcs for Bifacial?
PV Perfor-mance	Initial Wp nominal/nameplate	LID, "marketing tolerance", distribution within bins
	Degradation/LID/Astability	Yearly steady decline/sudden decline/variability
	PV vs. Angle of Incidence AOI	Anti reflection coating, glass or cell texturing
	PV vs Spectral response SR AM<>1.5	(Usually smaller effect for c-Si than Thin Film and Multi Junctions)
	PV Efficiency vs. Tmodule	NOCT/NMOT; mounting (distance from roof); wind, dPmax/dT Gamma
	PV Efficiency vs. Irradiance	Low light drop (Rshunt and Voc); High light drop from module $I^2.R_{SERIES}$
DC loss	Module mismatch strings	Current in string can be dominated by lowest Imp
	dc wiring loss	DC Cabling loss ~ $I^2.R_{SERIES}$
	Inverter "Wake up"	Turn on at low Pin or Vin
AC loss	Max power point tracking	find I=fn(V) when $V<>V_{MP}$
	Inverter efficiency	Inv.eff = $f(P_{IN}, V_{IN,} T_{INV})$ maybe multi stages to improve low light eff. Tare
	Inverter Clipping	(e.g. P_{OUT} when $P_{PV}> P_{INV.MAX}$)
	Transformer efficiency	Transf.eff = $f(P_{IN}, V_{IN,} T_{INV})$
	ac wiring	DC Cabling $I^2.R_{SERIES}$

REFLECTIVITY vs. AOI

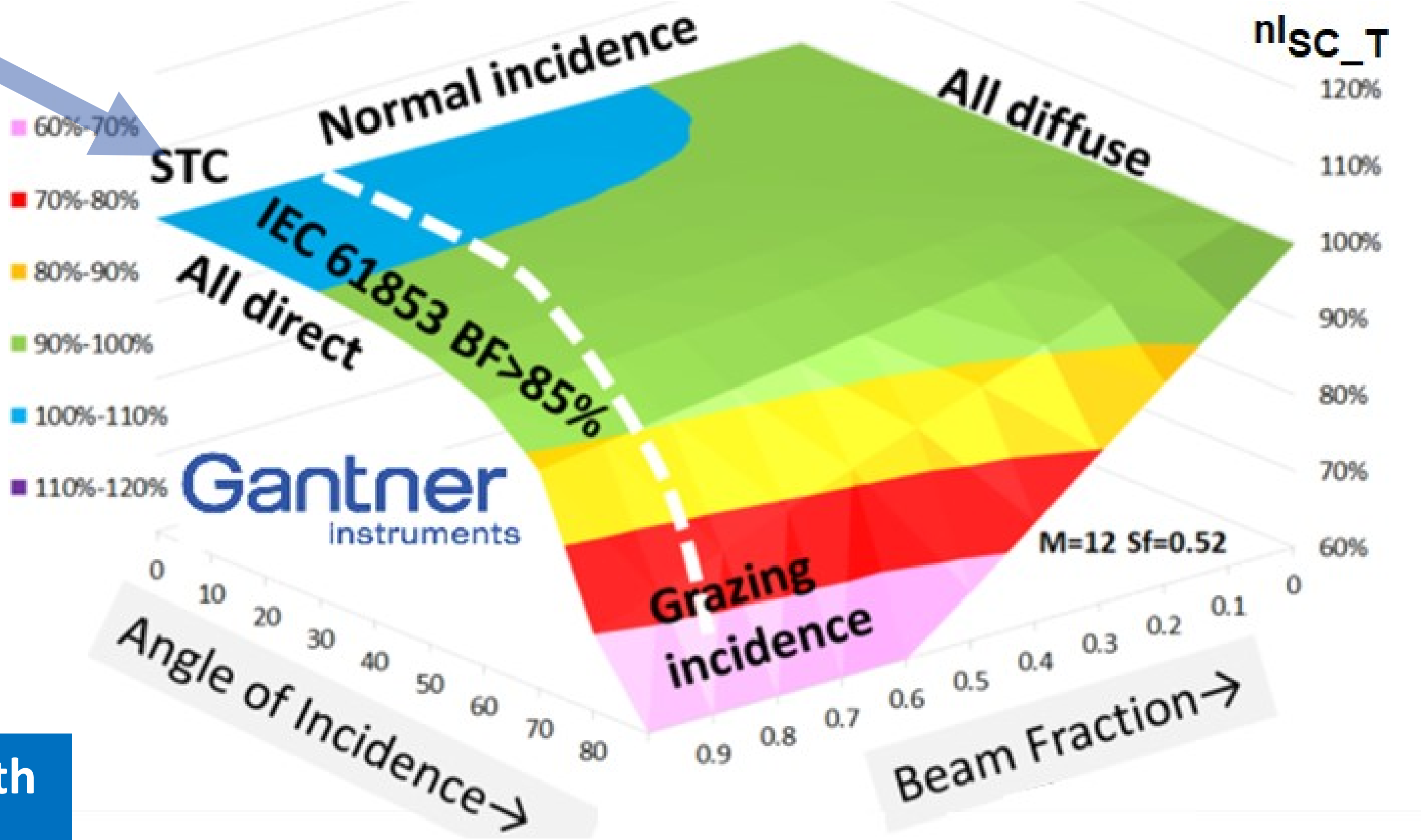


Compare with
Riedel et al 12th PVPMC 2019
"Incident Angle Modifier (IAM) Round Robin Updates"



GI OTF agrees well with round robin

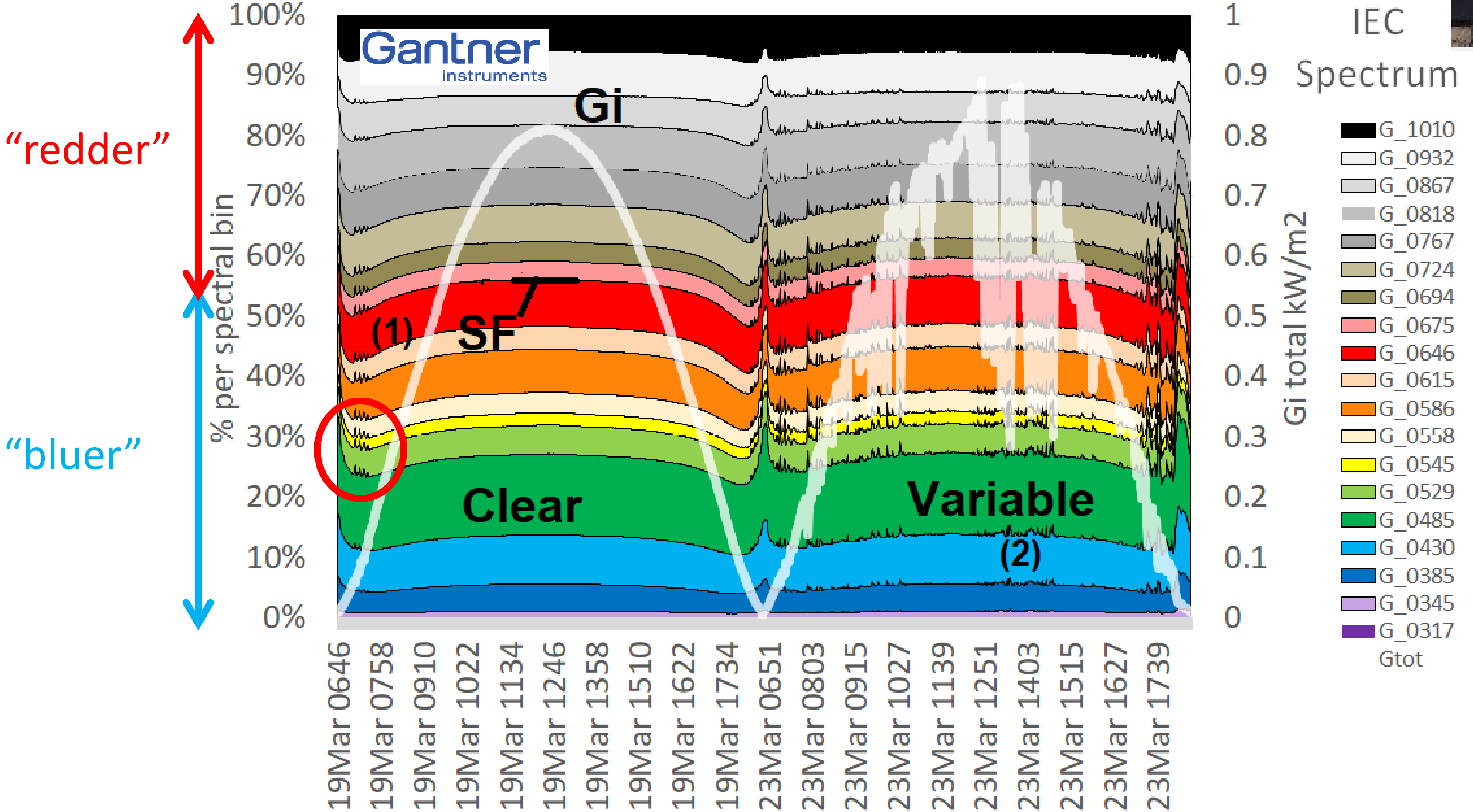
$$nI_{SC_T} = \frac{I_{SC.MEAS}}{I_{SC.NAMEPLATE}} \times (1 - \propto_{ISC} \times (T_{MOD} - 25))$$

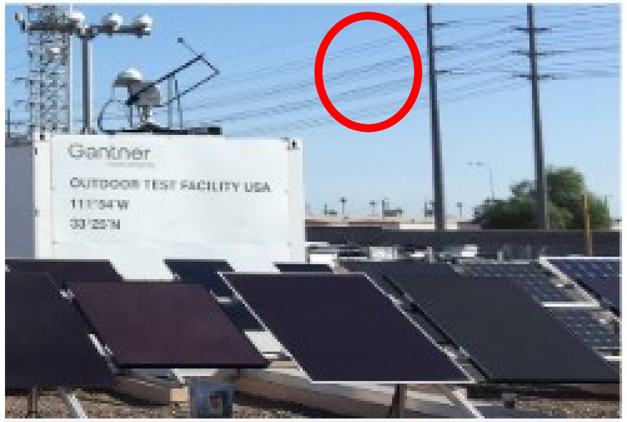


SPECTRAL :

GI OTF every 3.3nm → 61853 bins

- Clear (left) day and Variable (right) days
- Most PV only sensitive ~350 to <=1050nm





Spots morning shading from transmission lines

Spectral Fraction

=(bluer)/(bluer+redder)

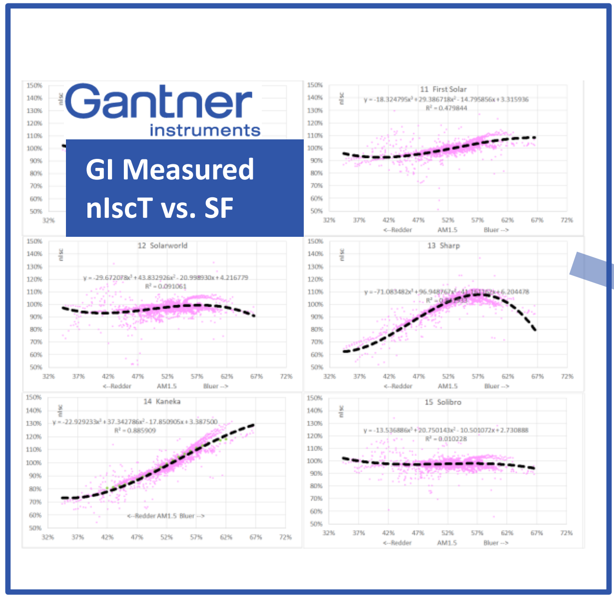
$$SF = \sum G_{350...650nm} / \sum G_{350...1050nm}$$

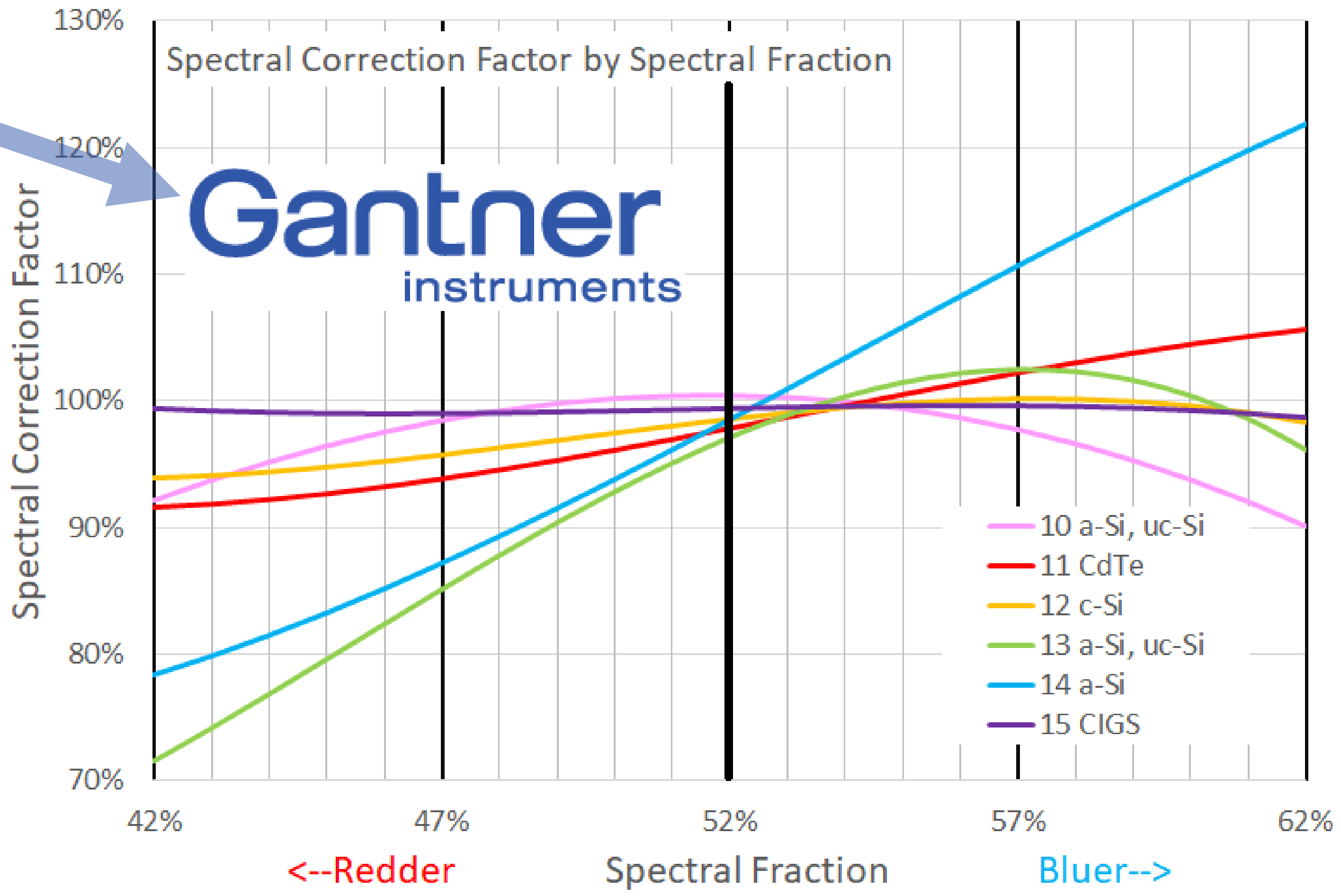
GI OTF measurements are accurate and can be used 350-1050nm

Spectral correction factor SCF vs. Spectral fraction SF

Spectral Fraction
=(bluer)/(bluer+redder)

$$SF = \sum G_{350\ldots650nm} / \sum G_{350\ldots1050nm}$$





simple fits SCF vs. SF

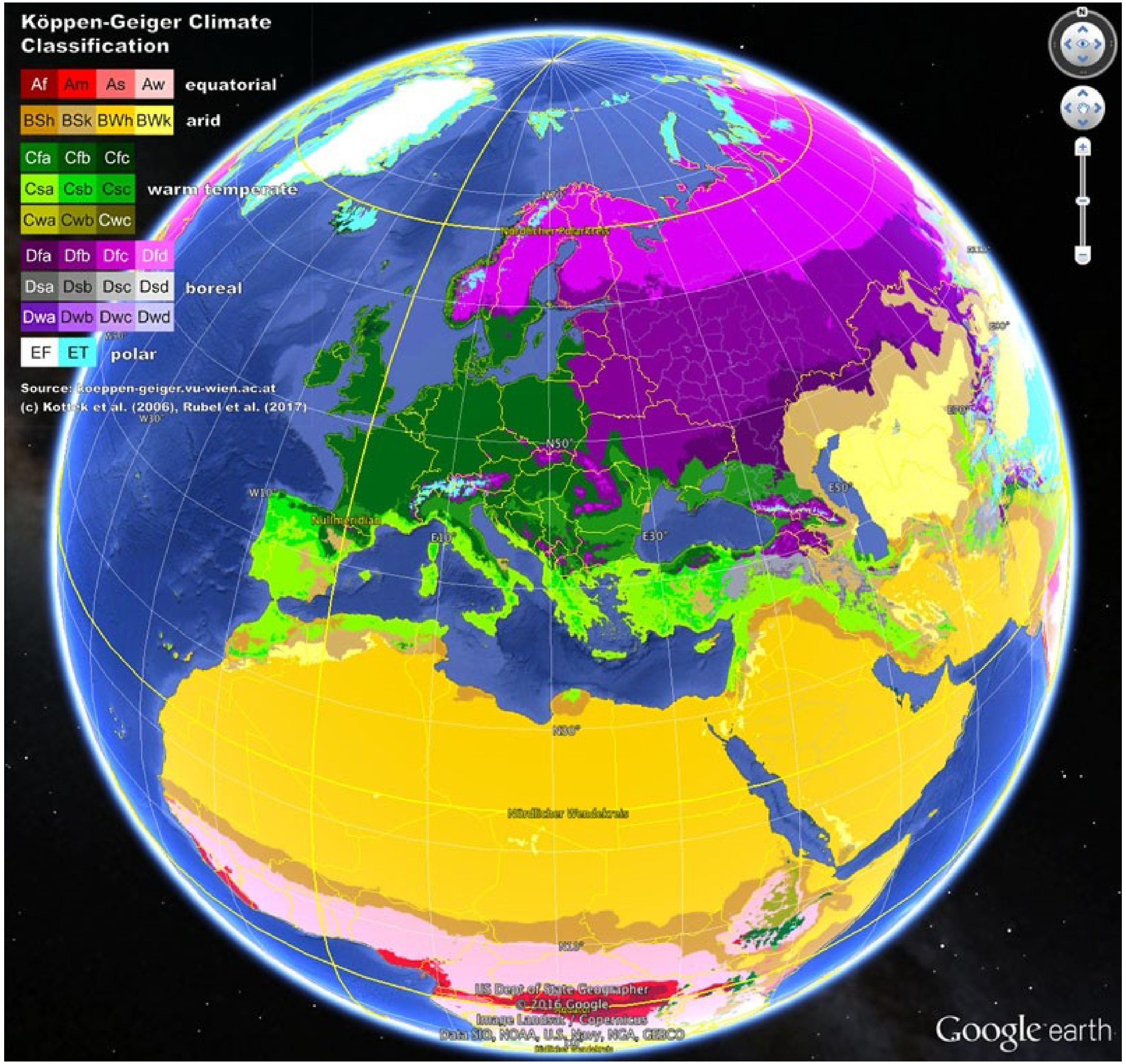
1 Junction = Linear fit
a-Si, CdTe, c-Si

2 Junction = Concave down
a-Si:uc-Si a-Si:uc-Si

Koeppen climate classification

http://koeppen-geiger.vu-wien.ac.at/

Shows "similar" climates



Polar

Boreal

(or Cold Continental)

Temperate

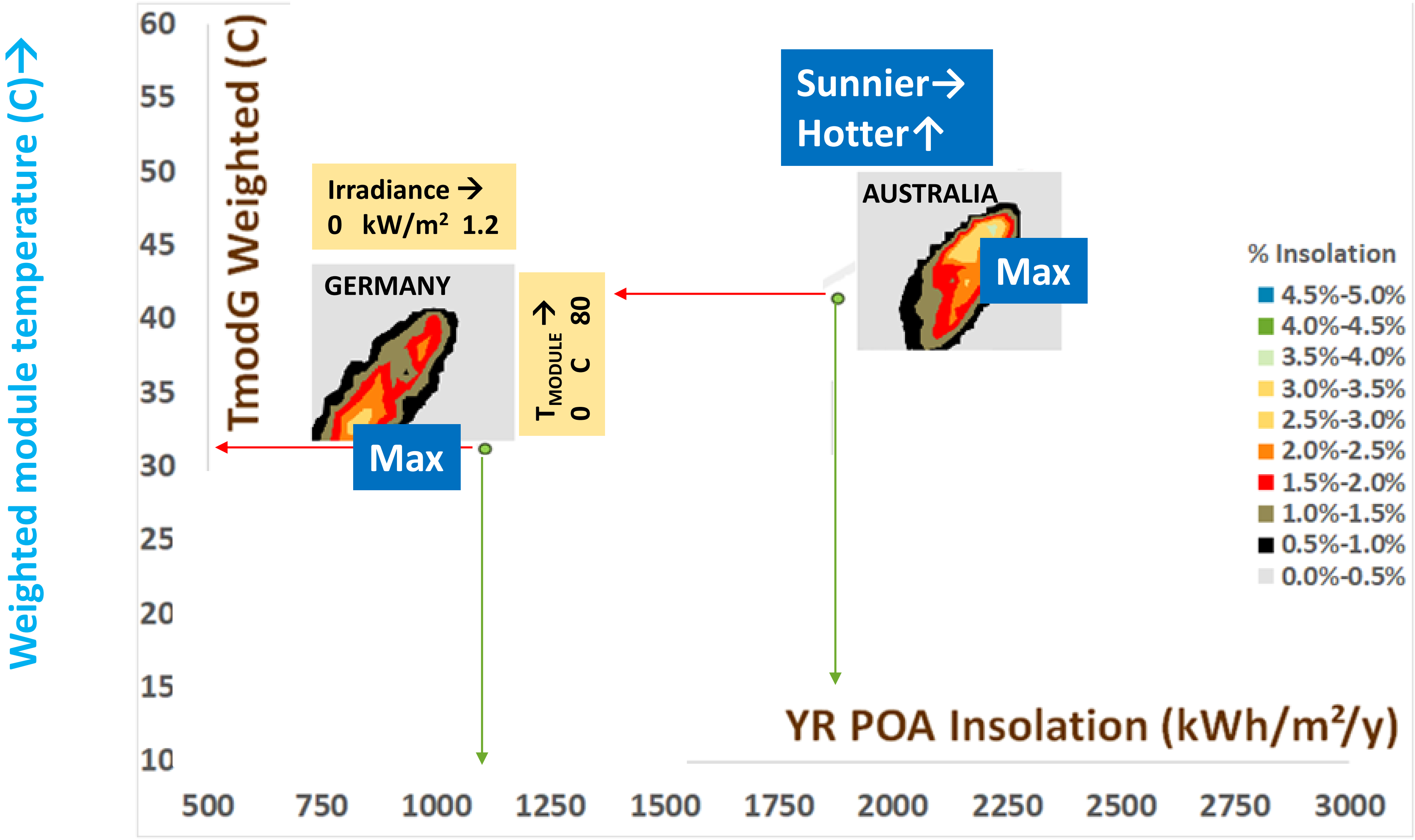
(Cooler vs. Hotter)

Arid

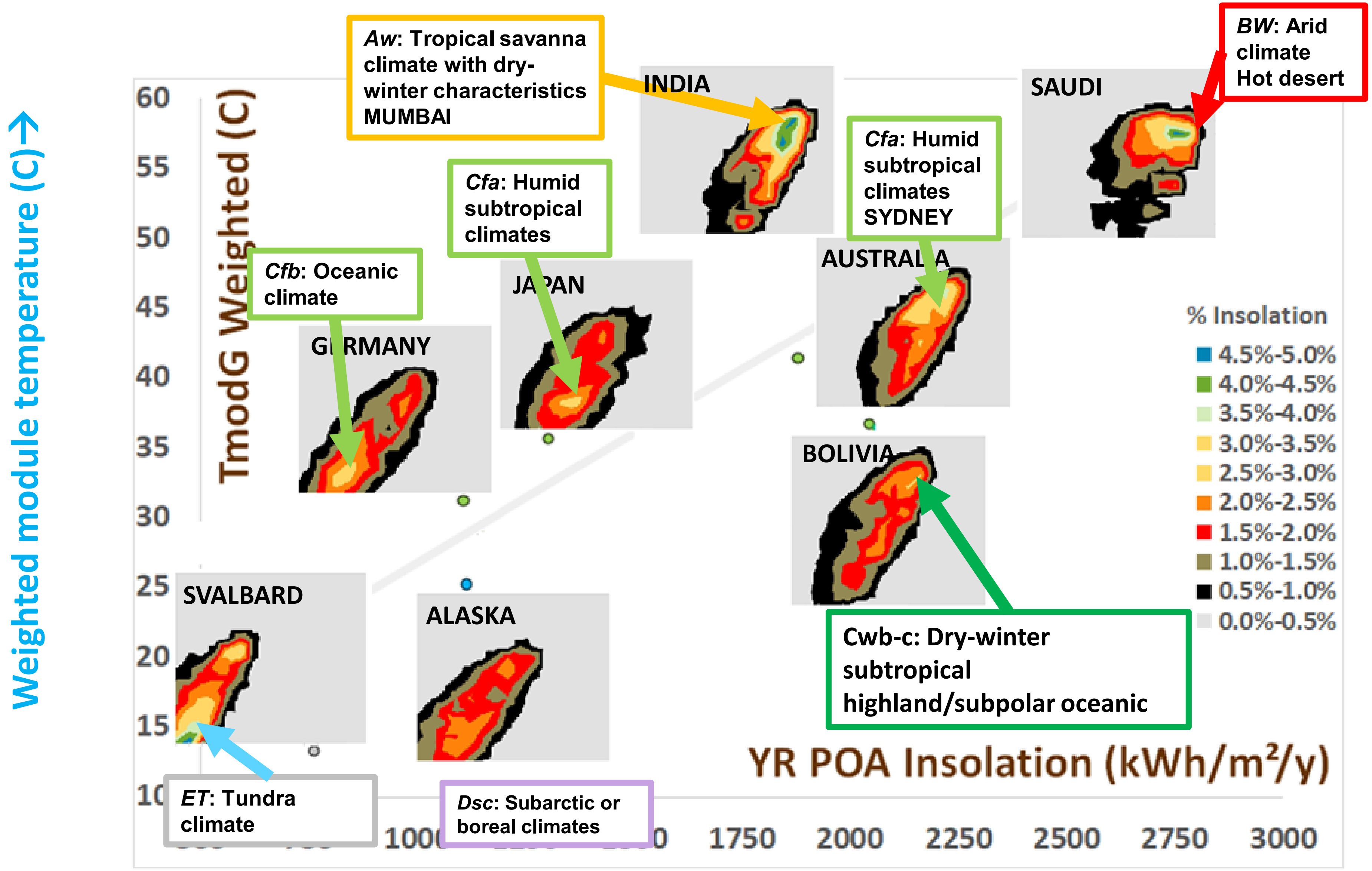
Equatorial

Insolation fraction %kWh/m² vs. Irradiance➲ and Module Temperature⬆

Site insolation distribution kWh/m²/y vs. Irradiance and Tmodule

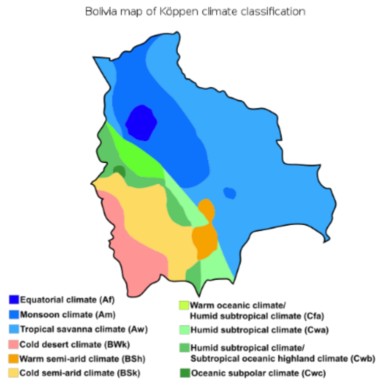


Insolation fraction %kWh/m² vs. Irradiance➔ and Module Temperature⬆



Note Insolation distribution vs. irradiance and temperature.

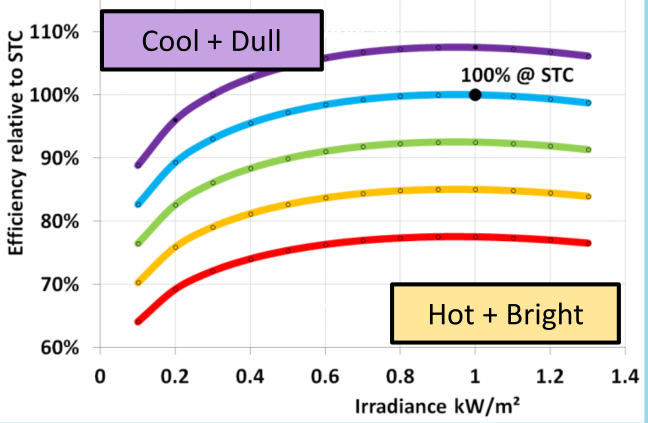
https://commons.wikimedia.org/wiki/File:Bolivia_map_of_K%C3%B6ppen_climate_classification.svg



PV Modelling vs. site dependent climate

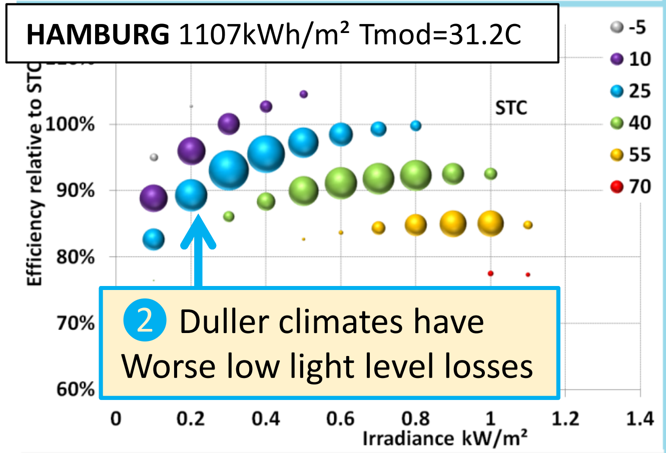
Module efficiency (y) vs. Irradiance (x) and temperature (colours)

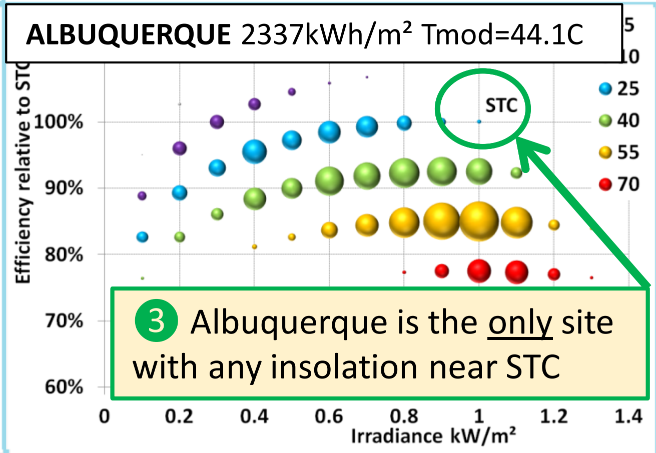
❶ Typical Efficiency vs. Irradiance and Tmodule model

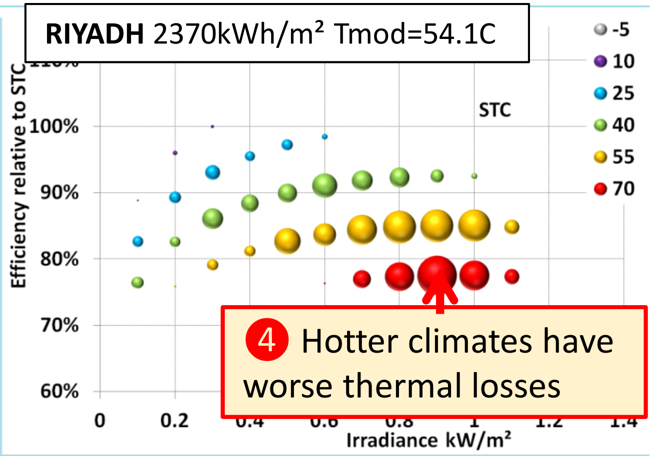


Energy yield sensitivity to Low light and Temperature coefficients is site dependent

Circle Size ~ Fraction of Insolation at each bin (Irradiance, T_{MODULE})







Modelling some PV loss stage sensitivities per site

Procedure

1) Give most loss stages nominal inputs

2) Change chosen loss inputs individually by fixed amounts

3) Calculate new energy yields YF kWh/kWp at each site worldwide

4) Determine site sensitivity ΔYF vs. "loss input change"

Loss stages		Nominal Value	"Improved Value"	INSOLATION kWh/m²
Rating Loss		Modelled as Constant		
DC Losses e.g. Degradation, Tilted plane, Shading, Snow cover, Soiling, Angle of Incidence, Reflectivity, Spectral response, Thermal annealing, Module mismatch, DC wiring I²R loss		Modelled as Constant		
THERMAL LOSSES	**GAMMA**	-0.45%/K	-0.35%/K	
	NOCT	47C	37C	
IRRADIANCE LOSSES	**LLEC**	95%	100%	
	I².RS	95%	100%	
AC Losses e.g. Inverter wake up, MPP tracking, Eff. vs Vin, Clipping, Transformer, AC wiring I²R loss		Modelled as Constant		kWh/kWp / LOSS

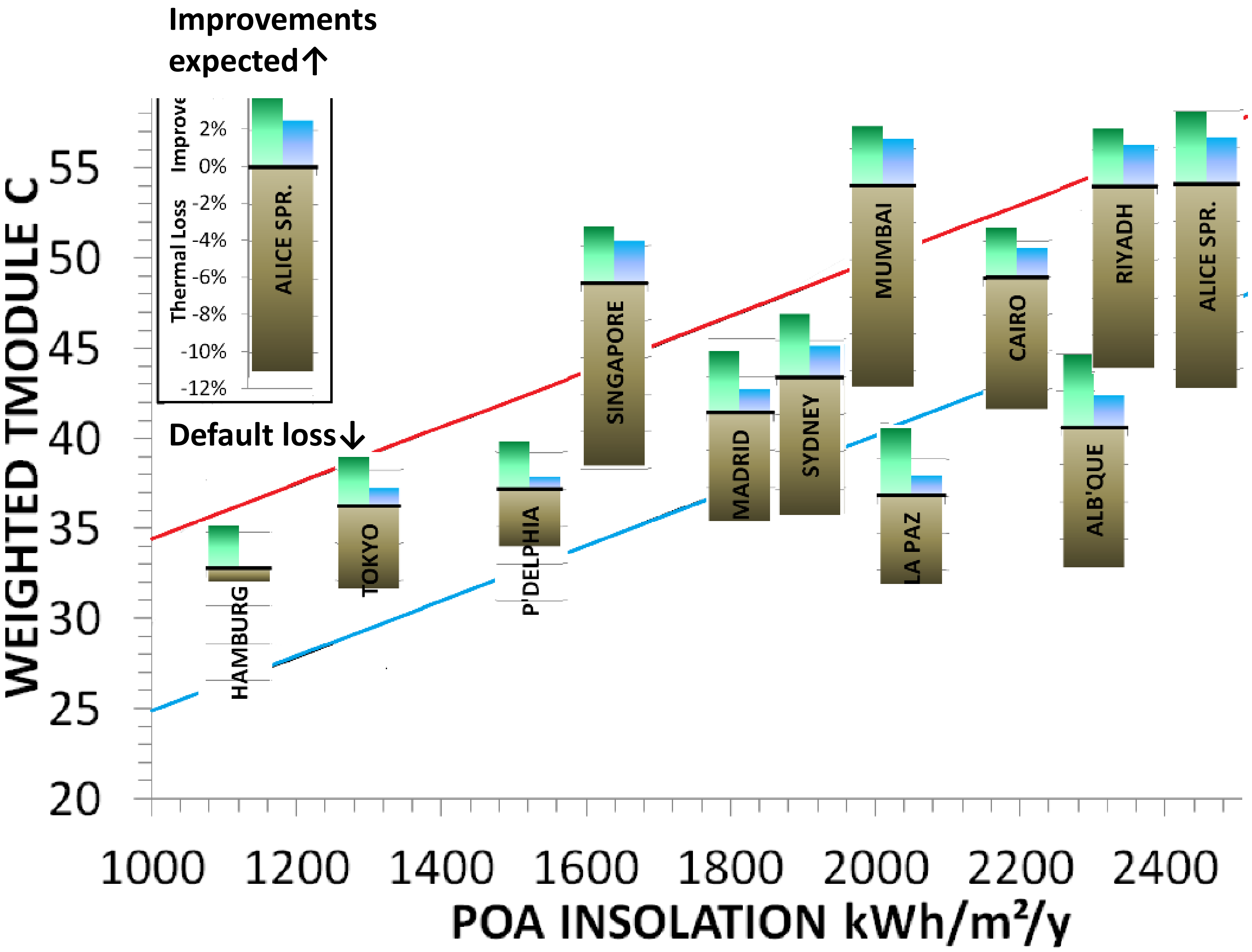
Pmax temperature coefficient

Module heating up

Low light efficiency drop

High light Rseries worse

Energy yield sensitivities per site – Thermal effects



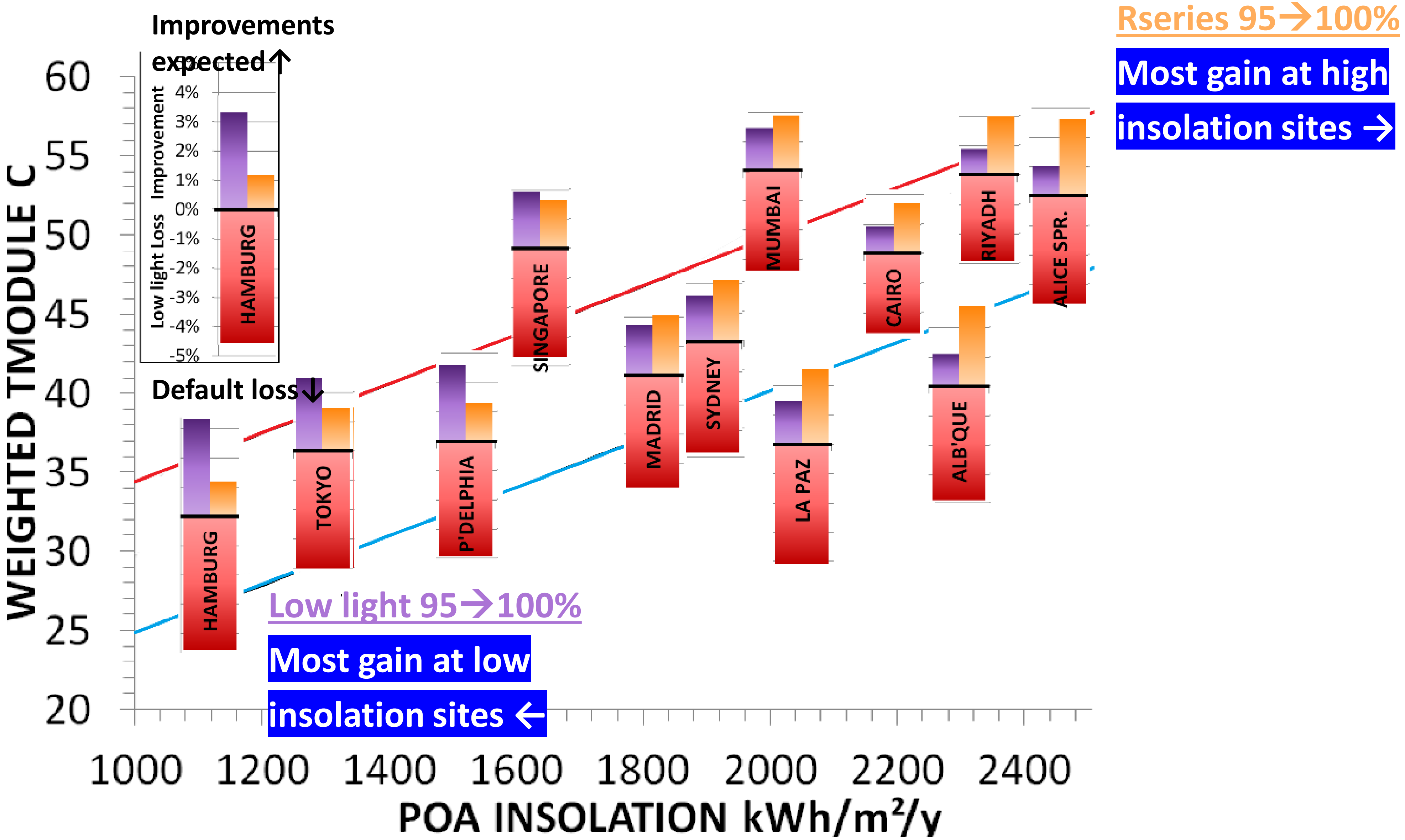
NOCT 47→37C

most gain at high temp. sites ↑

Gamma -0.45→-0.35

most gain at high temp. sites ↑

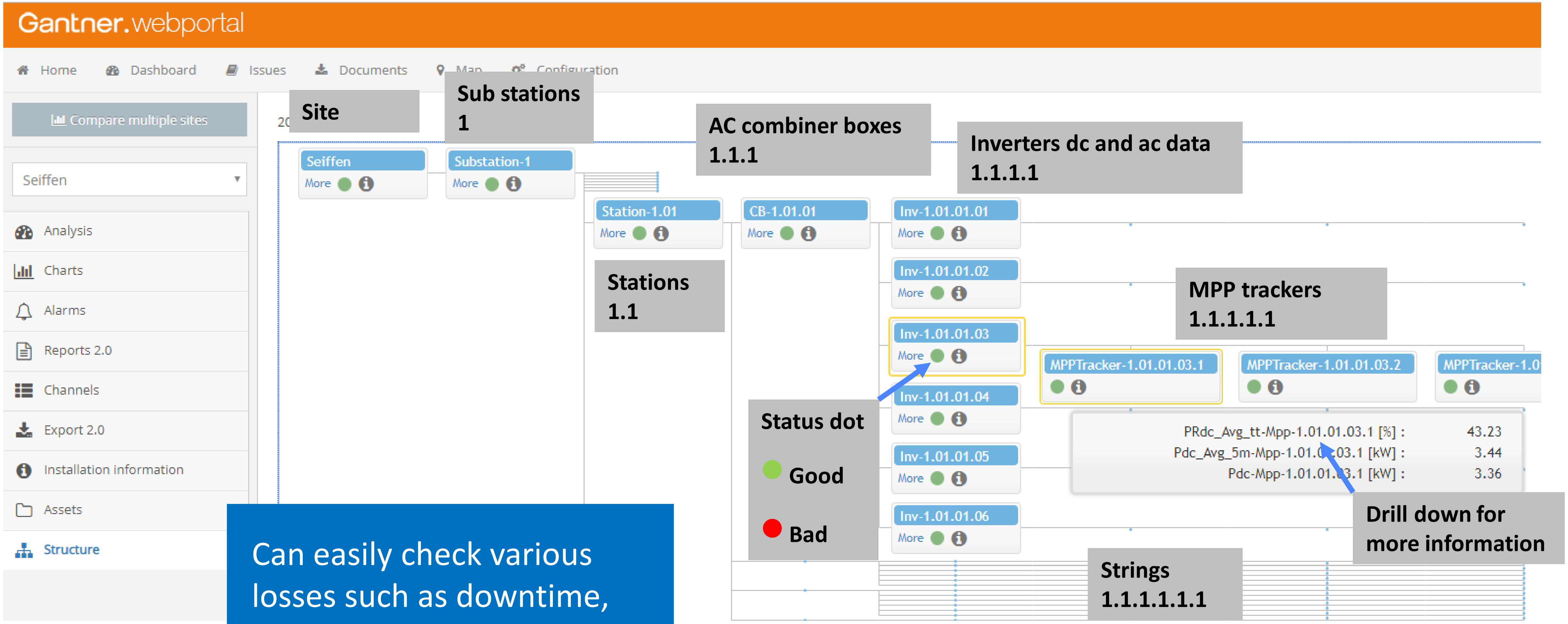
Energy Yield sensitivities per site – Irradiance effects



- 5) Analysing array data from Gantner

Checking performance at 7 different levels on a power plant

~~module~~, 1=string, 2=mppt, 3=inverter, 4=accb, 5=station, 6=substation, 7=site



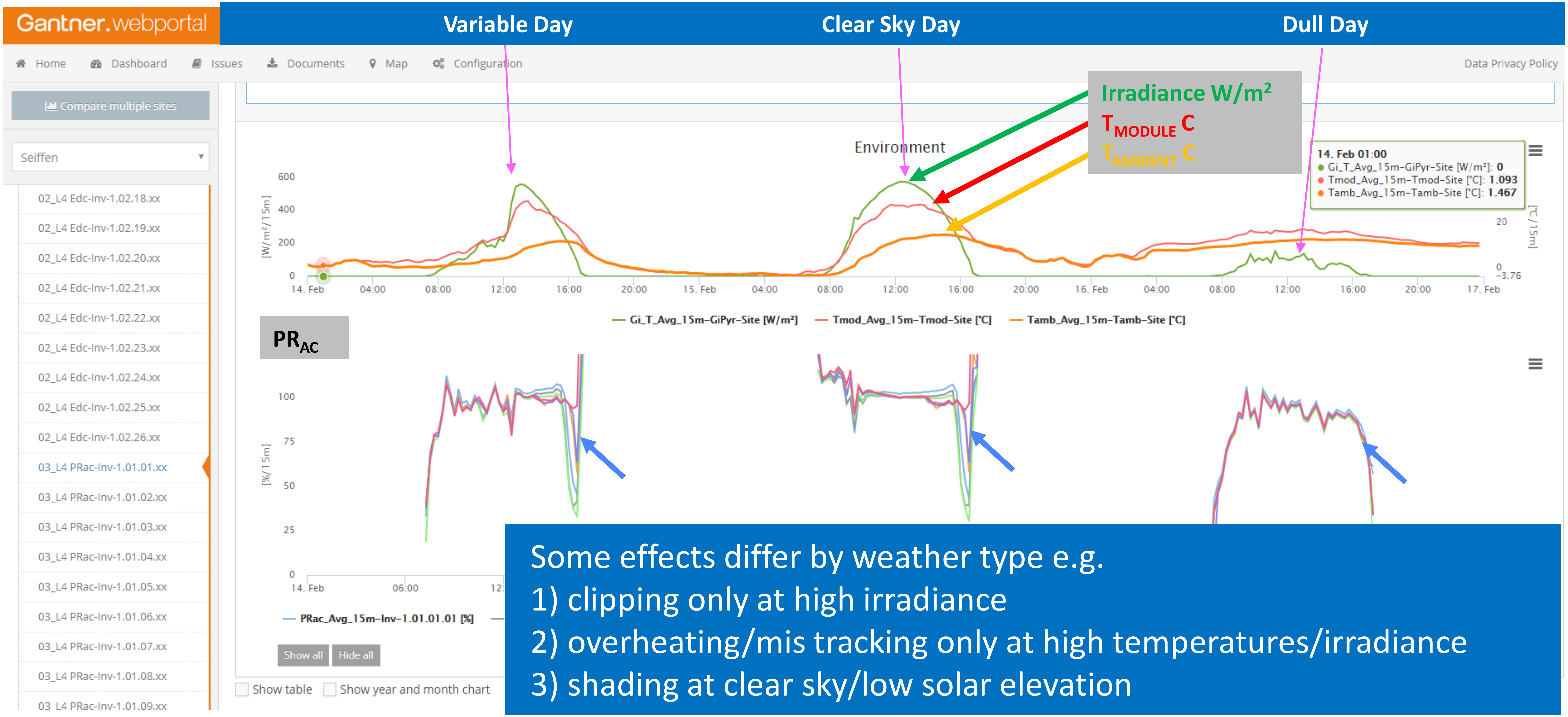
Can easily check various losses such as downtime, mismatch, shading, tracking per component …

Gantner instruments

http://www.Gantner-instruments.com/

SRCL Steve Ransome Consulting Limited

Monitoring a large array – looking at different weather type days



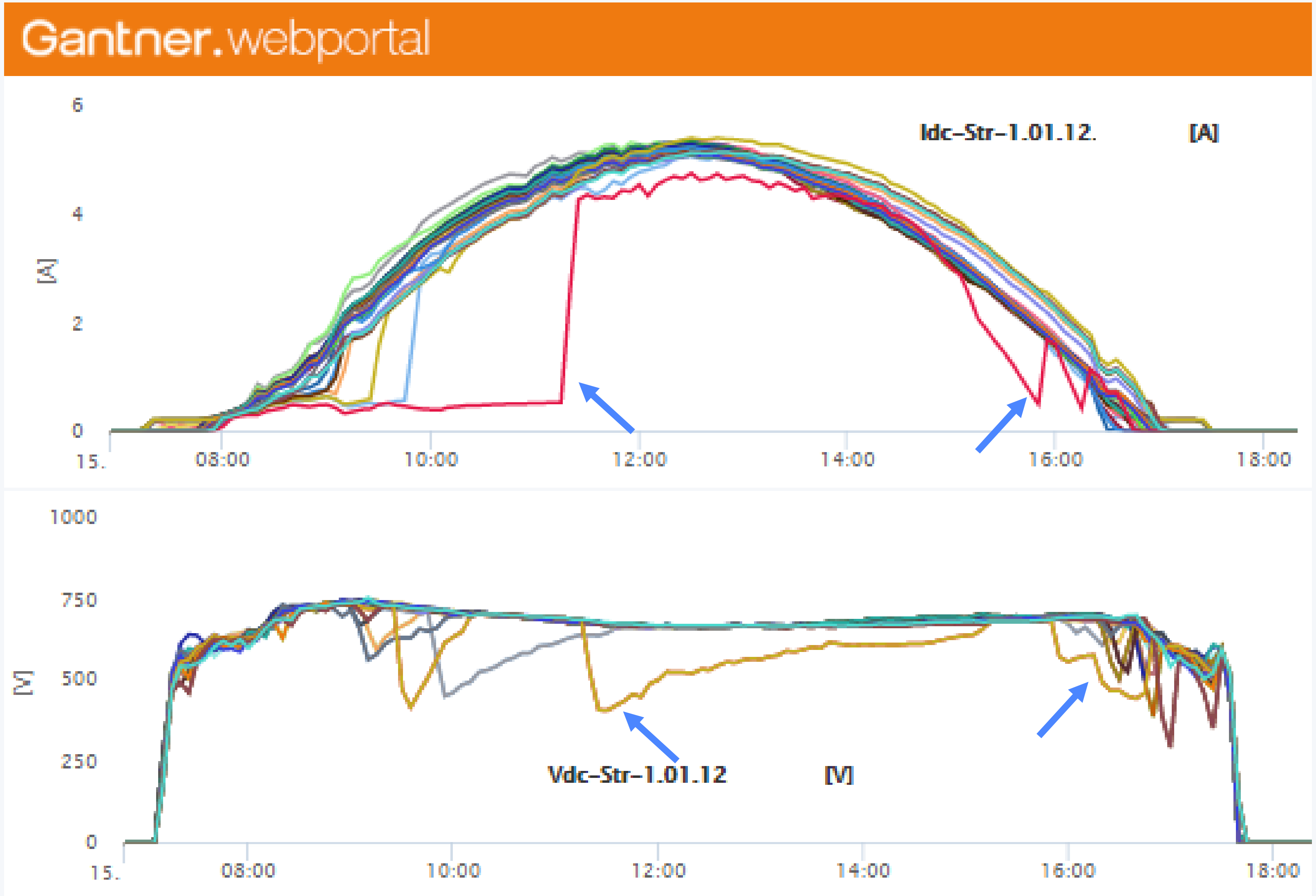
Some effects differ by weather type e.g.
1) clipping only at high irradiance
2) overheating/mis tracking only at high temperatures/irradiance
3) shading at clear sky/low solar elevation

Idc(top) and Vdc(bottom) for Strings in Inverter 1.01.12

Faults get more apparent as we zoom in closer with fewer modules

Can now investigate at string level reason for unusual behaviour

Level 6: String
1.1.12.6.01.xx



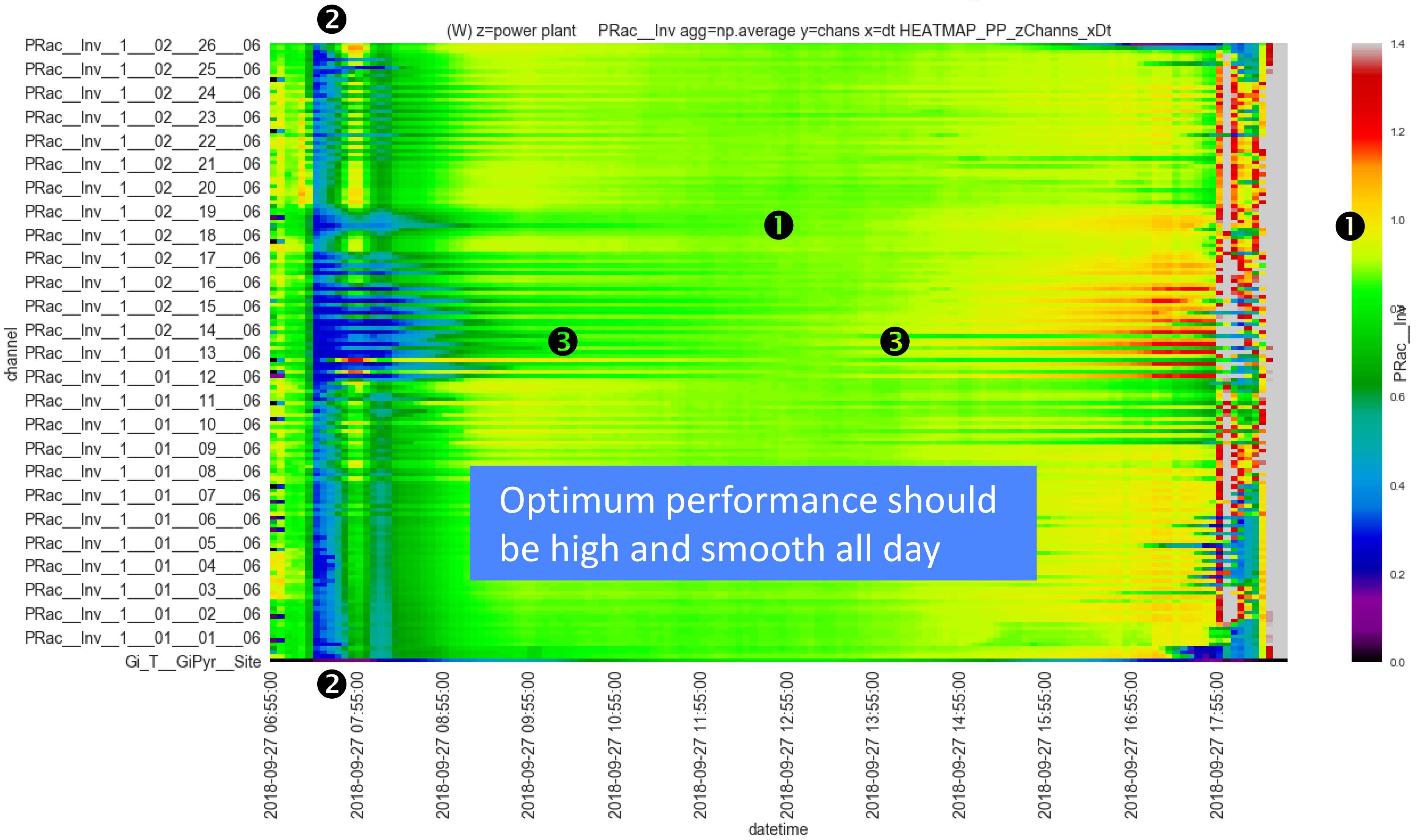
How to compare PV Performance for many different components over time
Performance ratio (colours red=best blue=worst) for 156 inverters↑ and time➔

PR = Pmeas/Pnom/G

❶ High performance ratio (near 100%) is light green to yellow

❷ Early 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



Determining performance stability PR_{DC} by time of day and month
Average PRdc by hour of day 1…24 HOD↑ and YearMonth 1401…1612 MOY→

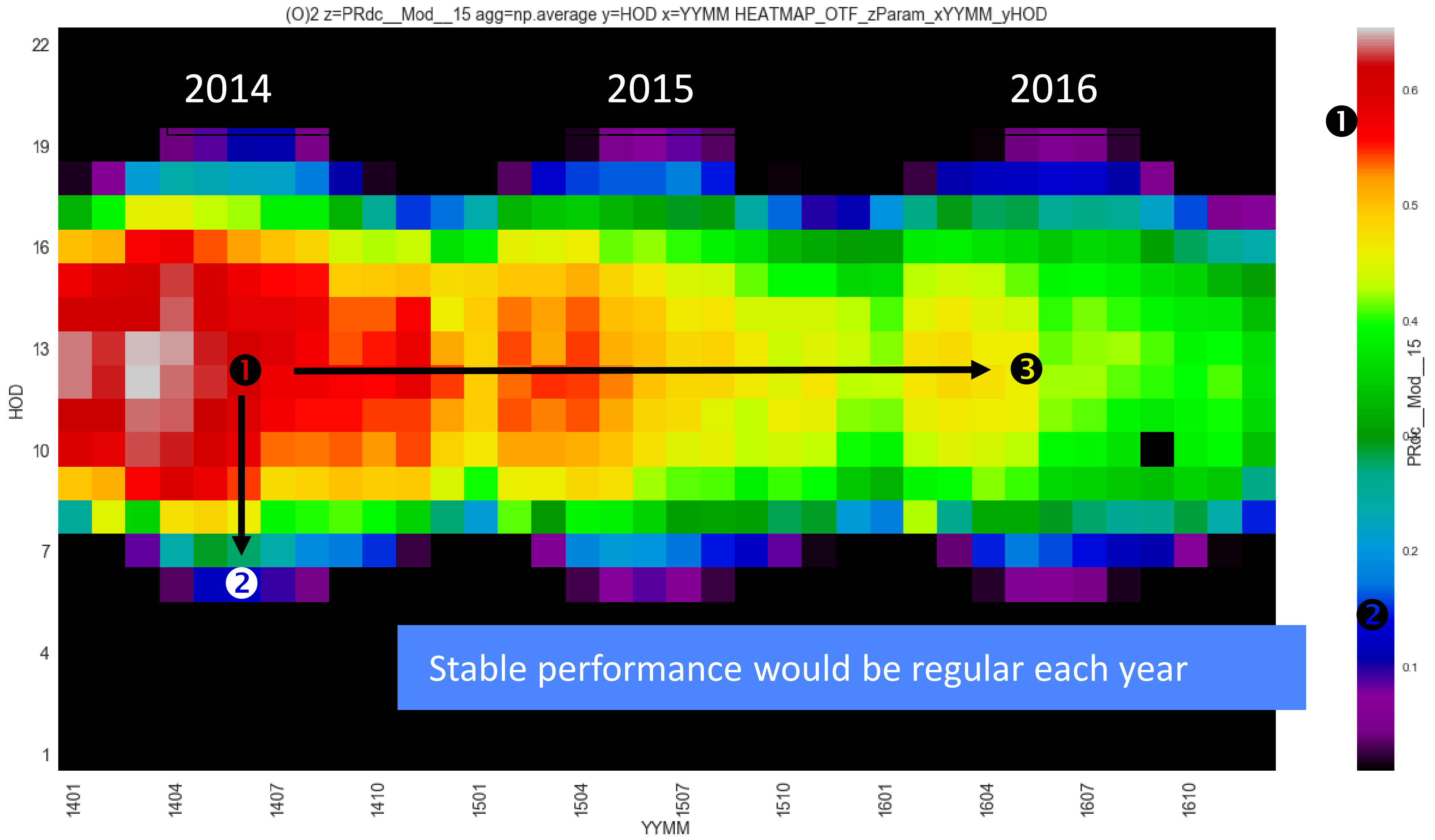
❶1st Summer 1406 Module performance although poor was highest during the day ~0.6

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

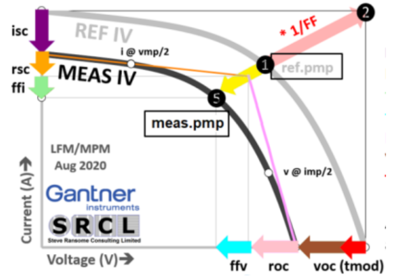


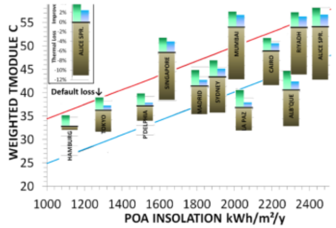
Gantner instruments

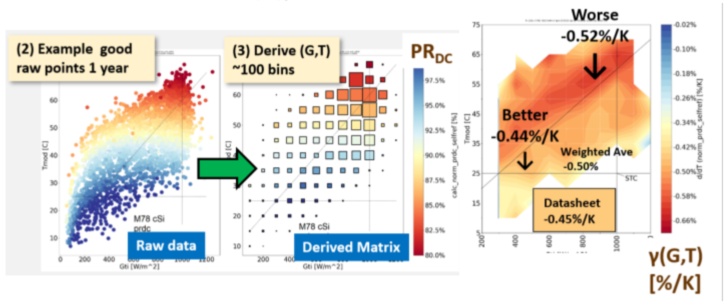
http://www.Gantner-instruments.com/

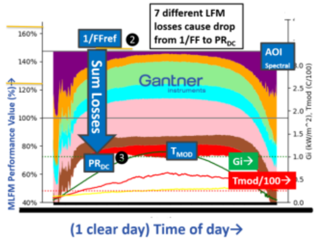
SRCL Steve Ransome Consulting Limited

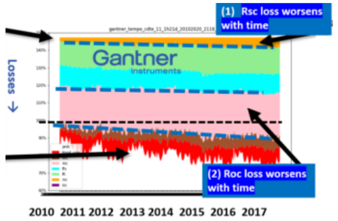
CONCLUSIONS











1. **Accurate modelling of outdoor modules and arrays with normalised models has been shown**
2. **Analysed Module Energy yield worldwide with sensitivity to insolation and module temperature**
3. **Advanced matrix methods have been used to derive temperature coefficient maps vs. irradiance and module**
4. **Independent loss factors (e.g. for Rshunt or Voc) have been characterised vs. irradiance, temperature, solar position etc.**
5. **Degradation or astability causes and rates %/y have been quantified**

Thank you for your attention !

- 7) Appendix : More details from Gantner Instruments

Connectivity from Edge to cloud

Adaptive and Scalable Platform for High Performance Edge Computing Services

DAQ Controller

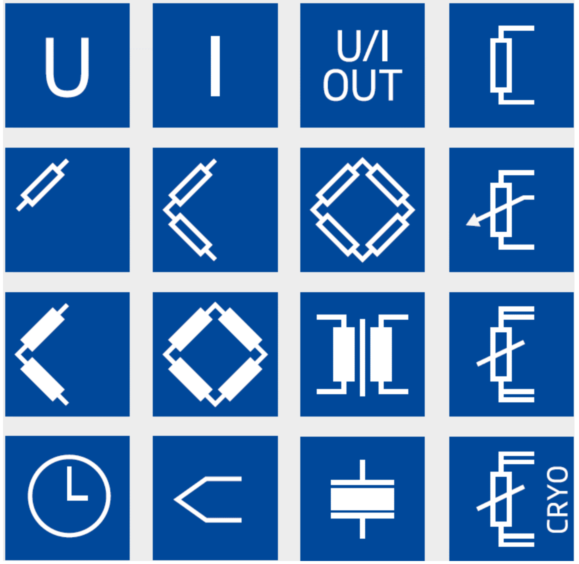
Q.monixx A117 D

- For computer independent data logging
- 6x RS485 serial channels, all galvanic isolated
- 4 configurable data loggers with individual selectable logging rate 0.01 s (100 Hz) up to 24 h
- Data storage 16 GB SD Card (exchangeable)
- 1 UART Interface for connection of Q.bloxx I/O Modules
- 14 Digital I/Os
  - 8 inputs (2 kHz) for status
  - 4 outputs (10 Hz) for status
  - 2 relay
- TFT Touch Display 5” WVGA (800 + 480)
  - Auto-off selectable
  - User defined HMI with test.con
- 8 analog universal inputs
  - For voltage, current, resistance, Pt100/Pt1000

Click on image to download datasheet

Q.series X

Measurement and I/O Modules for all Relevant Signals



Dedicated Modules

- 8 strain gage quarter, half, and full-bridge
- 16 strain gage quarter bridge
- 8 thermocouples
- 8 voltages or current
- 4 Piezoelectric sensors

Multi-purpose Modules

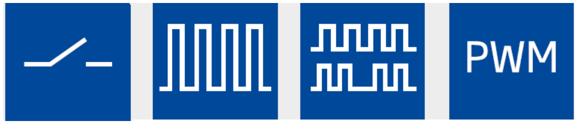
- 2 or 4 inputs for almost all sensors
- Strain gage module with DC and CF excitation

Digital Modules

- Frequency and PWM in and outputs
- Quadrature and up/down counter
- Specials like missing tooth detection and Chronos method

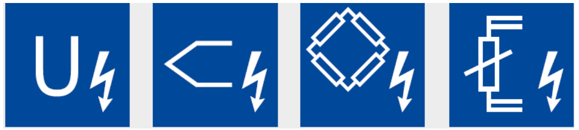
OPC UA

Modbus



High Isolation Modules

- Isolation 1200 VDC
- Inputs for voltage, current, thermocouples, Pt100, NTC, IEPE, strain gage full- and half-bridge
- LEM current transducers



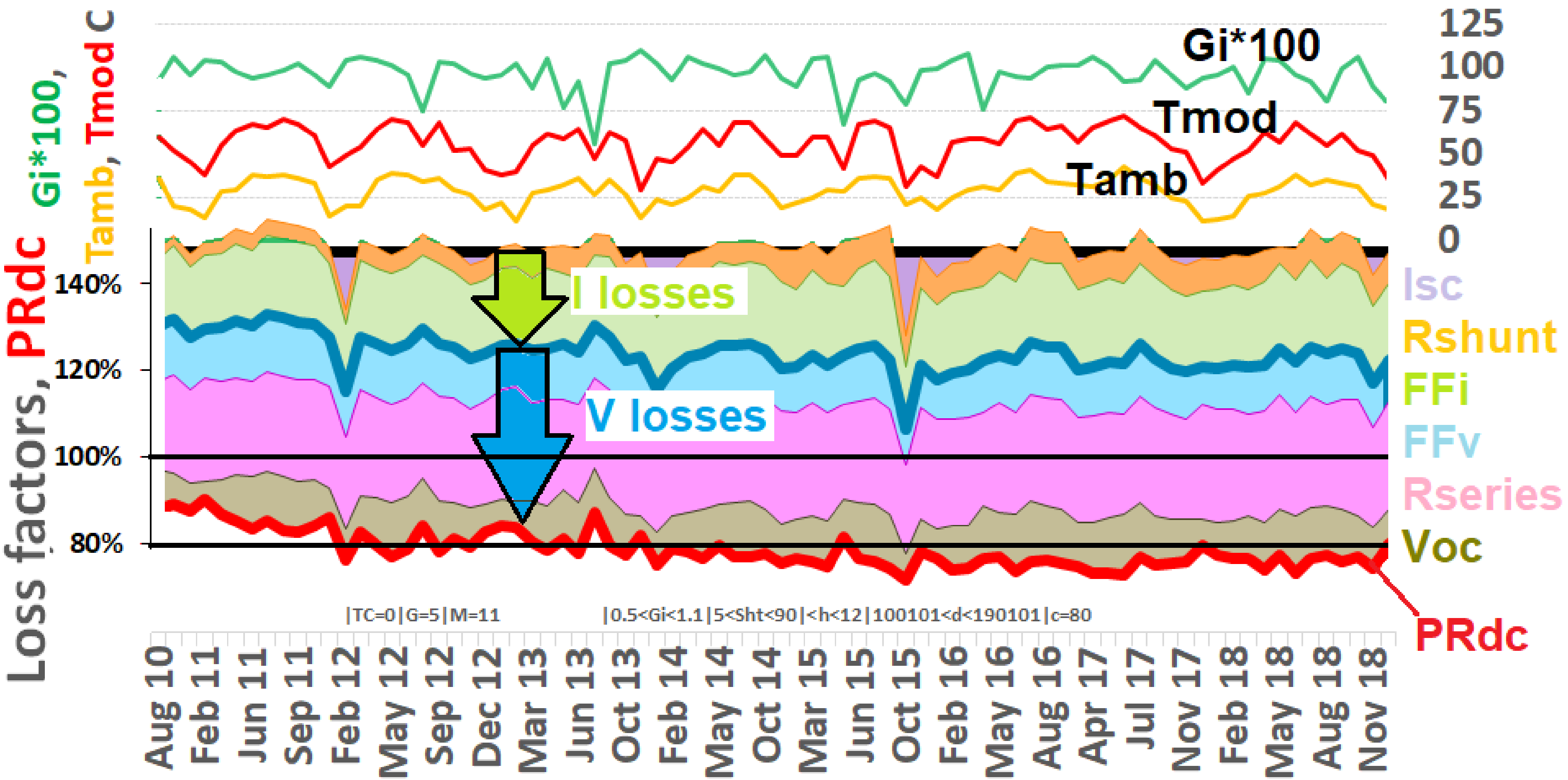
Compare individual P_{AC} with mean of >150 Inverters (usually look for faulty or worst ones for more analysis)

Gantner.webportal

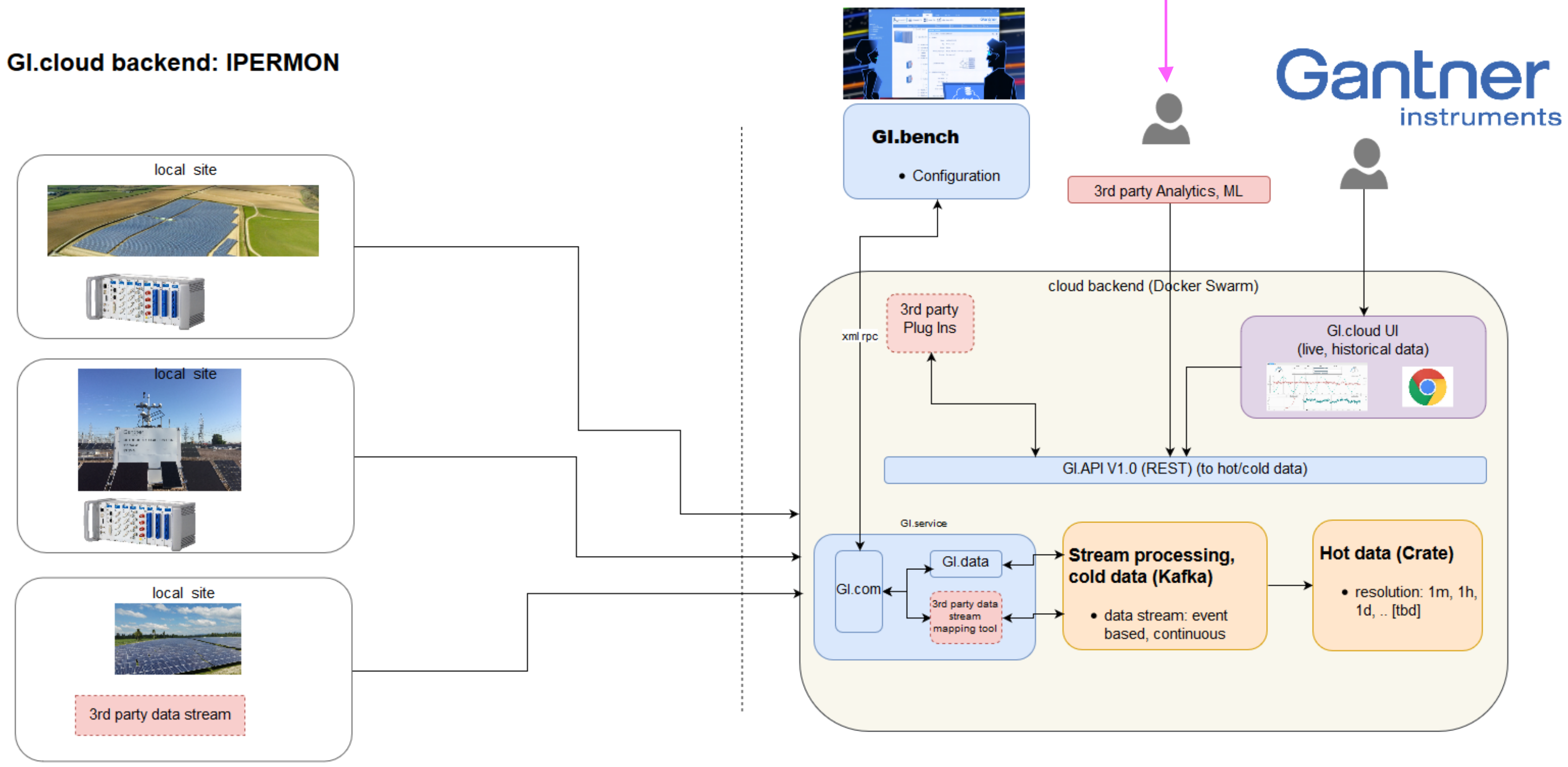
Count	Mean	Std. deviation (k=2)	Rel. deviation [%] min/max	OK range (from mean) [%] [abs]	Median
156/156	6.98	0.35355	-20.53 / 5.31	90.0000	7.08

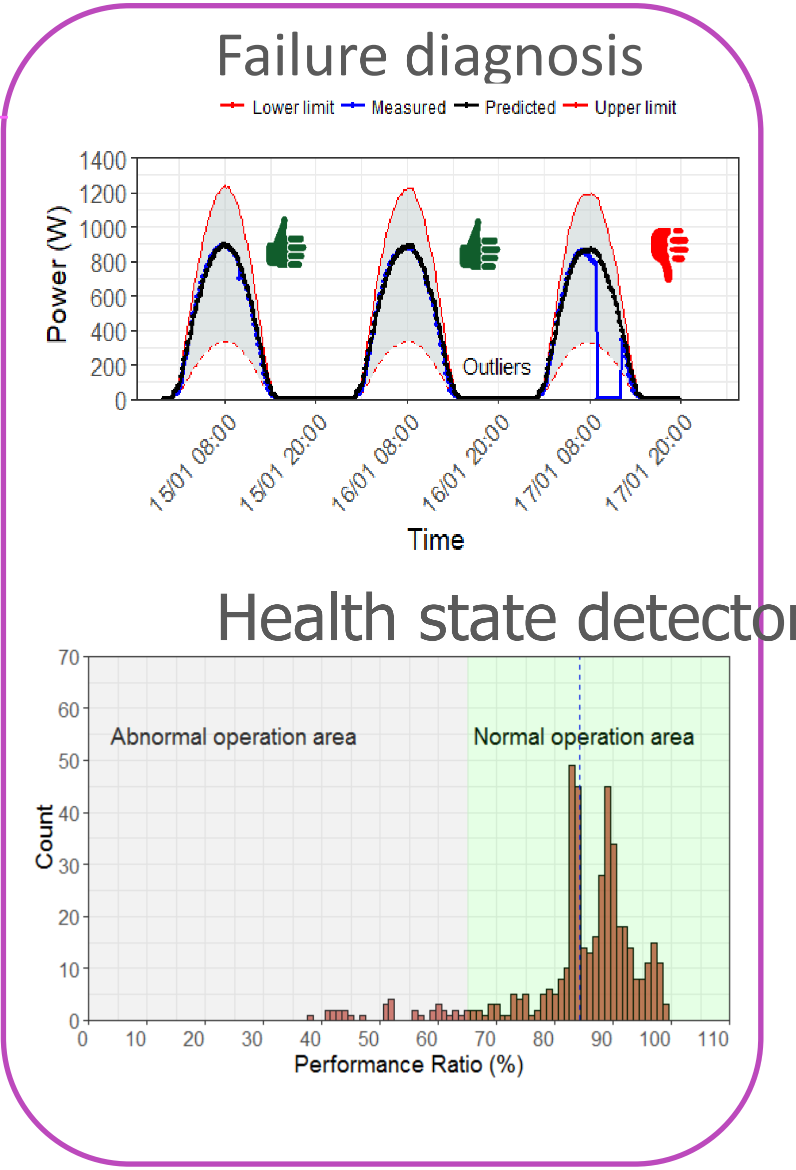
Component	Pac [kW]	Pac Difference [kW]	PacRel. deviation [%]	Range [%]	PacStatus []
Inv-1.02.19.05	5.549	-1.433	-20.53		low
Inv-1.01.08.04	5.603	-1.379	-19.75		low
Inv-1.02.19.02	5.608	-1.374	-19.68		low
Inv-1.02.19.04	5.673	-1.309	-18.75		low
Inv-1.02.19.03	5.764	-1.218	-17.45		ok
Inv-1.02.19.06	6.031	-0.951	-13.63		ok
Inv-1.02.19.01	6.233	-0.749	-10.73		ok

Degradation analysis
Drill down to responsible parameter to get meaningful conclusions



Integration of diagnostic plus predictive analytics
Machine learning with Project IPERMON



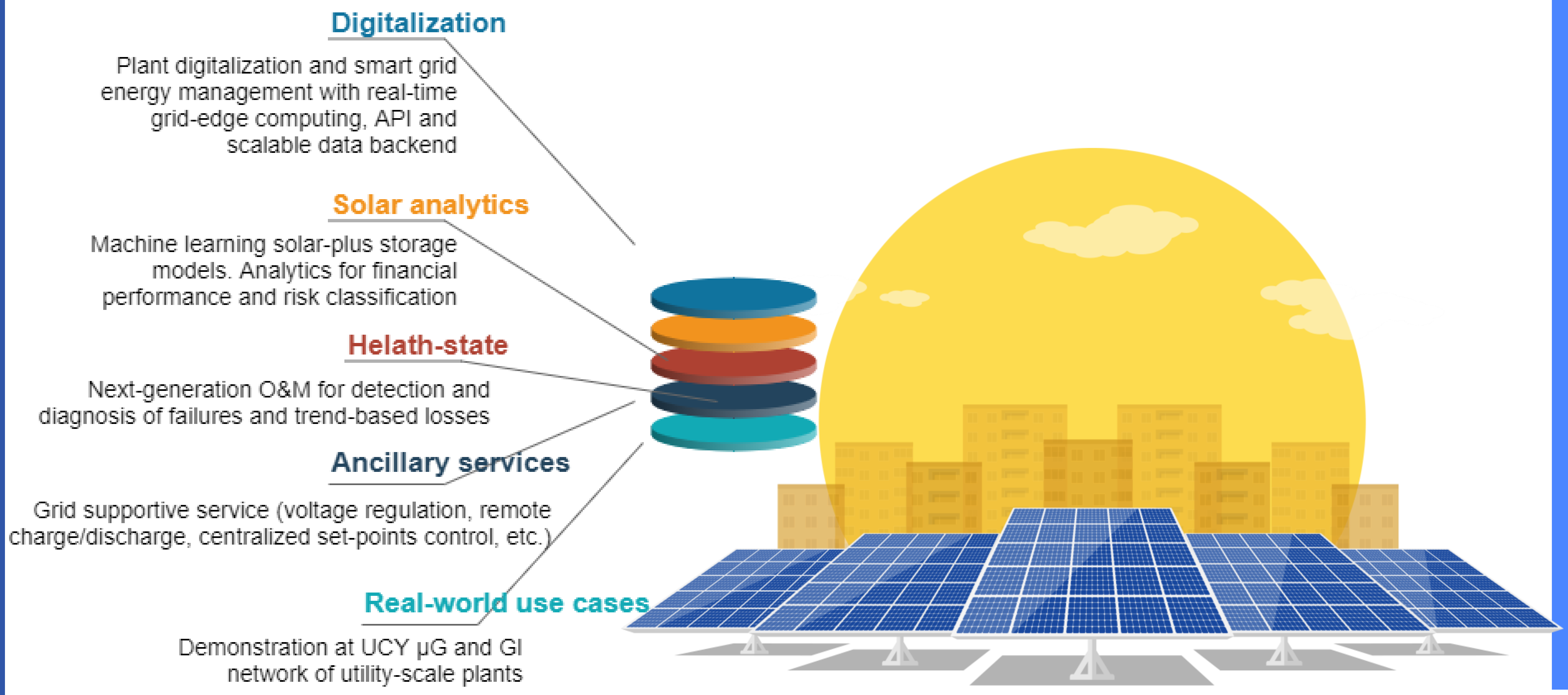


See next talk from Marios Theristis (University of Cyprus):
"Performance Evaluation of PV Power Predictive Models for Realtime Monitoring"

PV-Analytics

Gantner instruments | FOSS Research Centre for Sustainable Energy | Analytics

- Increase the value and competence of solar and energy storage by developing a next-generation multi-service monitoring and control system with real-time edge control and AI for tomorrows smart grid services



FUNDING
SOLAR-ERA.NET
P2P/SOLAR /0818/0012
€460,080

Consortium
Gantner Instruments
University of Cyprus

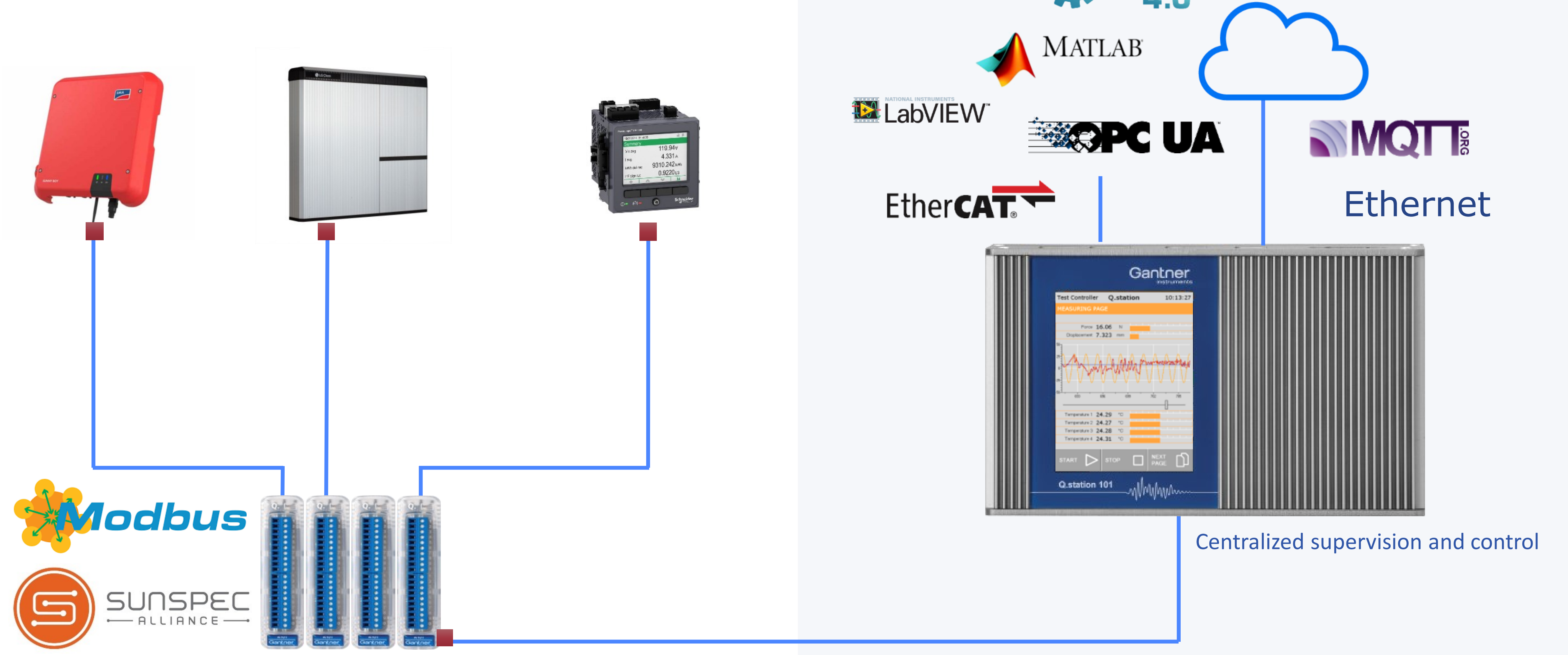
Duration
Nov 2019 – Nov 2022

APPLICATION
AI-driven supervision and control of distributed energy resources

MARKET
Smart Grid

“Next-generation multi-service monitoring system for grid-edge control and AI-driven smart grid services“

Analytics



Digitalization and interoperability with open communication standards

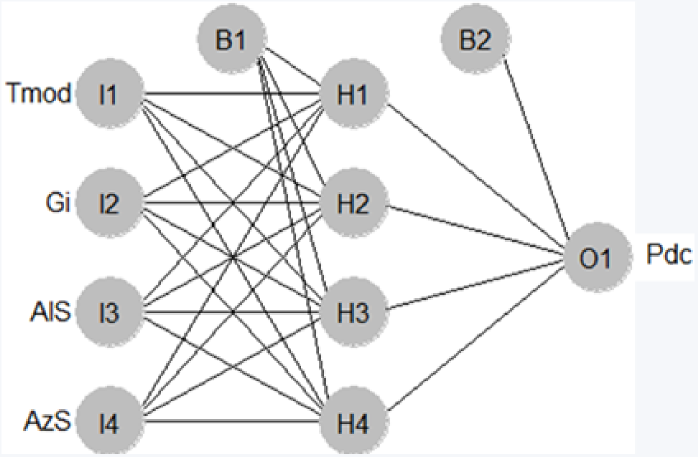
Real-time datastream flow

Use cases

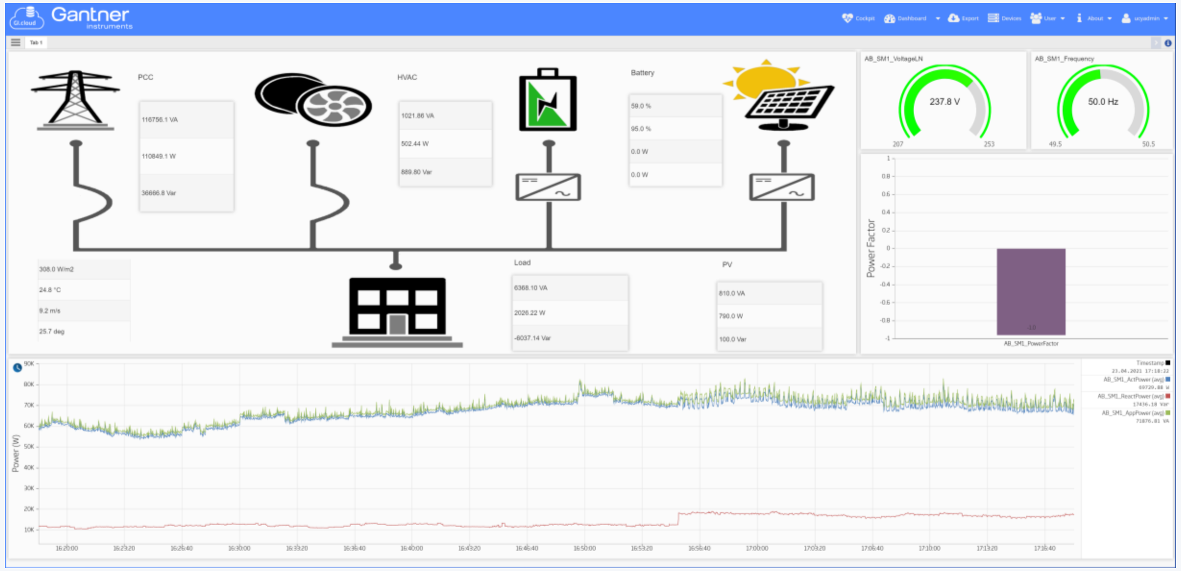
AI for tomorrows smart grid services

- PV power plants
  - Optimally performing digital twin replica
  - Predictive maintenance analytics
  - Data-driven failure diagnosis
  - Interoperable centralized PV power plant controls
- Battery storage
  - Battery performance models
  - Storage system remote charge/discharge control
- Microgrid (UCY microgrid pilot)
  - Enhanced real-time supervision and observability of DER assets
  - Event-triggered fault detection and power quality alerts
  - Smart grid energy services and controls
- More: https://www.gantner-instruments.com/research/advanced-system-monitoring-analytics-smart-grid/

Analytics



PV power plant machine learning digital twin (Accuracy of ~1%)



Microgrid and DER assets real-time supervision (GI.cloud dashboards)