Accurate module performance characterisation using novel outdoor matrix methods

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8D: Characterization and Monitoring of Modules and Systems 4:15 PM eastern time.
How linearly do PV modules behave?

1. Do modules perform linearly?
2. If there are non-linearities, what causes them and how non-linear are they?
3. How can we best model them?

A module that behaves linearly can be fitted just by functions of irradiance G or temperature T independently

\[
PR_{DC} = f(G) + f(T)
\]

i.e. without any “\(f(G,T)\) non_linear terms”
Measuring matrices of $PR_{DC}(G,T)$

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

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

**(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=5°C bins)
→ Better analysis possible e.g. any non linearities

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

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**PR$_{DC}$**

$$PR_{DC} = \frac{P_{MP_{MEAS}}}{P_{MP_{REF}}} / G_{SUNS}$$

**Outdoor measurements:**

1. Cheaper than indoor?
2. More matrix bins better for coefficient extraction
3. Quick results with insulation/heating, mesh cover, 2D mistrack
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
Derived parameters using Loss Factors and Mechanistic Performance Models
Integrates 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

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>GH</td>
<td>Global Horizontal Irradiance</td>
<td>kW/m²</td>
</tr>
<tr>
<td>DH</td>
<td>Diffuse Horizontal Irradiance</td>
<td>kW/m²</td>
</tr>
<tr>
<td>BN</td>
<td>Beam Normal Irradiance</td>
<td>kW/m²</td>
</tr>
<tr>
<td>GI</td>
<td>Global Inclined Irradiance (Pyranometers and c-Si ref cells)</td>
<td>kW/m²</td>
</tr>
<tr>
<td>TAMB</td>
<td>Ambient Temperature</td>
<td>°C</td>
</tr>
<tr>
<td>TMOD</td>
<td>Back of Module Temperatures</td>
<td>°C</td>
</tr>
<tr>
<td>WS</td>
<td>Wind Speed</td>
<td>ms⁻¹</td>
</tr>
<tr>
<td>WD</td>
<td>Wind Direction</td>
<td>°</td>
</tr>
<tr>
<td>RH</td>
<td>Relative Humidity</td>
<td>%</td>
</tr>
<tr>
<td>G(λ)</td>
<td>Spectral Irradiance G(350–1050nm)</td>
<td>W/m²/µm</td>
</tr>
</tbody>
</table>

2D Tracker
Sensors
2D Tracker
Sensors
Fixed orientation 25deg, South
CdTe, CIGS, aSi etc.
CdTe, CIGS, aSi etc.
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?

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Irradiance $G_{T1}$ [W/m²] →

$PR_{DC\_max}$

$PR_{DC\_min}$

‘outlier’

‘bad point’

$T_{MOD\_\text{[C]}}$
How to generate dense performance matrices from good outdoor data 2/3

A) Raw \( \text{PR}_{\text{DC}}(G,T) \)

- Good points 1 year random 4000 shown

B) Filter into \((G,T)\) bins

- Filter by steady weather,
- Sanity check e.g. 3sigma,
- Group into \((G,T)\) bins

\[ T_{\text{MOD}} [\text{C}] \]

\[ \text{Irradiance } G_{\text{T1}} [\text{W/m}^2] \]

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 = $\text{Avg}(PR_{DC}) / \text{bin}$

Area = $\sum (H \text{ kWh/m}^2) / \text{bin}$

- Usefult standard graph format to be used often showing
  Performance (colour), Insolation (area) vs. Irradiance $\rightarrow$ and
  $T_{\text{module}} \uparrow$ bins

- Generated accurate dense measurement matrix with ~100 useful points

Irradiance $G_{\text{T}_\text{I}}$ [W/m$^2$] →
‘PR<sub>DC</sub> vs. irradiance’ from outdoor matrix

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

How does PR<sub>DC</sub> vary with irradiance?

Logarithmic fall @ low light

Linear drop @ high light

Small scatter only at extreme weather?
‘PR_{DC} vs. irradiance’ for four technologies

M78 cSi
- Smooth lines, regular

M31 HIT
- Similar shape vs. G to cSi, lower separation vertically

M72 CdTe
- Similar vs. G to cSi, degraded, lower separation vertically, higher scatter

M81 CIGS
- This CIGS has a different shape rising PR_{DC} at high G and larger gamma separation at high temperatures which indicates non-linearity

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cSi, HIT and CdTe look quite linear over the matrix area (Extreme weather points may have a little scatter)
‘PR\textsubscript{DC} vs. Temperature’ from outdoor matrix

Datasheets usually report \textbf{1 constant gamma value}.

This plot will quantify any \textbf{non-linear behaviour}.

\textit{How does PR\textsubscript{DC} vary with temperature?}
Gamma(G,T) heatmaps for four modules

M78 cSi

~Constant
\[-0.47\%/K\]

Datasheet
\[-0.45\%/K\]

cSi, HIT : ~constant $\gamma(G,T)$

→ “A constant temperature coefficient means a linear device”

M31 HIT

~Constant
\[-0.35\%/K\]

Datasheet
\[-0.30\%/K\]

M72 CdTe

Better
\[-0.25\%/K\]

Worse
\[-0.34\%/K\]

Weighted Ave
\[-0.26\%\]

\[\gamma(G,T)\, [%/K]\]

CdTe, CIGS : can have Non-linear temperature coefficients which will affect $PR_{DC}(G,T)$

M81 CIGS

Worse
\[-0.52\%/K\]

Datasheet
\[-0.45\%/K\]

Weighted Ave
\[-0.50\%\]
1st Pass: Fitting performance matrices with a linear model (mpm6)

```python
def mpm_6(G, dT, WS) = (c_1 + # constant
c_2 * dT + # temp. coeff
      c_3 * log_{10}(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/m²]
- dT = delta temperature (Tmod – 25) [°C]
- WS = windspeed [ms⁻¹]

PR<sub>DC</sub>

80% to 100%

< ±0.2% fit/bin

MPM6 FIT

Weighted by insolation

PR<sub>DC_MEAS</sub>

PR<sub>DC_FIT</sub>

PR<sub>DC_RESIDUAL</sub>

Residual norm_prdc_selfref [%]
Typical outdoor linear model residual fit error $\text{PR}_{\text{DC(MEAS-FIT)}}$ for four modules

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

This CIGS module has a $\leq 0.5\%$
Monotonic residual error between high $\leftrightarrow$ low temperature indicating a Non-linearity
(as expected from the gamma heatmap)
Many more modules were studied linear mpm6 residual fit error

5 x cSi

2 x HIT

2 x CdTe

4 x CIGS

Good fits $PR_{DC}(G,T) <\pm 0.2\%$ for all c-Si and HIT tested

CdTe $<\pm 0.3\%$ almost linear

AZ has “little insolation at low light” 2D tracker worse choice for matrix unless mistracked

Non-linearities for some CIGS
Different shapes #1, #2 shown
Which LFM parameter(s) cause non-linearity #1?

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

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

(3) Cause found: Atypical \( R_{SERIES} \sim T_{MOD} \) Only at High Light

Find cause of non-linearity from pattern matching PR_{DC} with LFM fits
>3 Different types of “<1%/bin” perturbations have been seen so far

(1\textsuperscript{st} Pass) use linear fit to identify and quantify any non-linearities

(2\textsuperscript{nd} Pass) simple device dependent corrections <~0.5-1.0% if needed

Perturbation #1:
High temperature

Perturbation #2:
“Sinusoid vs. irradiance?”

Perturbation #3:
“Low light and High light”

No single non-linear model can fit all different behaviours perfectly

Small technology dependent perturbation coefficients can be added to mlfm6 for optimum fit if needed as most fits are < ±0.5-1.0%/bin
Summary of this work

1) From high Quality outdoor data (e.g. Gantner’s OTF)

2) 100+ point matrices of PR<sub>DC</sub> or any LFM e.g. nR<sub>SC</sub>, nV<sub>OC</sub>

3) 1<sup>st</sup> pass Linear Model fit = f(G) + f(T) ...

4) Residual (measured-fit) matrices

5) Linear : cSi, HIT

6) ~Non_Linear : Some cigs

7) Database of normalised coefficients

8) Temperature coefficient heatmaps

9) 2<sup>nd</sup> pass with non-linear coeffs

10) Quantify small perturbations Identify cause

Thank you for your attention!

Contact us for OTF enquiries and high-quality data sets for your own research

www.gantner-instruments.com/products/software/gi-cloud/

26-Jun-21

www.steveransome.com

Steve Ransome Consulting Limited
1) GOOD OUTDOOR MEASUREMENTS
PR DC vs. Time, Irrad G, Tmod T, Wind W) (+ LFM)

2) PERFORMANCE MATRICES (G,T)
PR DC or any LFM e.g. nR SC, nV OC ~ 100 bins

3) FIT WITH LINEAR MODEL MPM6
Meaningful orthogonal robust normalised Fit = f(G) + f(T) … + γ x f(G,T)
Lowest RMSE (weighted by H)

4) DATABASE NORMALISE COEFF

4A) ENERGY YIELD PREDICTIONS kWh/kWp/y
Sum PR DC * H * T

4B) PERFORMANCE VALIDATION FIND FAULTS AND CAUSES

5) OPTIONAL NON-LINEAR FIT

5) OPTIONAL NON-LINEAR FIT

6A) DEGRADATION RATE vs. time and CAUSE

6B) PERFORMANCE LOSS LIMITS and CAUSE vs. Technology e.g. high Rs, low Voc

Binned PR DC (G,T)

Residual Meas - Fit PR DC (G,T)

Tcoeff map γ (G,T)
γ = variable

2A) GAMMA (G,T)
dPR DC /dT

1/FF → Sum(Losses) → PR DC
Show (Isc, Rsc, Ffi, Ffv, Roc, Voc)

γ = constant

1A) SPECTRAL G(350..1050nm)

0) NORMALISED IV CURVE ANALYSIS
0) NORMALISED IV CURVE ANALYSIS

3B) > ± 0.5% → NON-LINEAR