ADAPTABLE PV PERFORMANCE MODELLING FOR INDUSTRIAL NEEDS

Steve Ransome[1] and Juergen Sutterlueti[2]

[1]Steve Ransome Consulting Ltd, Kingston upon Thames #99 KT2 6AF, U.K.

[2]Gantner Instruments GmbH, 6780 Schruns / Austria

ABSTRACT: Precise PV measurements and accurate performance models are vital in understanding and optimizing the system energy yield. An adaptable combination of features from the "Loss Factors Model" (used to define the normalised parameters) and the "Mechanistic Performance Model" (which determines the optimized fitting method) has been used on performance measurements such as individual module full IV curves (8 derived parameters in Arizona) and monitored large arrays (I_{MP} and V_{MP}) from Gantner Instruments at other sites with similar algorithms. It allows PV performance to be predicted and measurements to be validated with reasons for any underperformance or degradation to be identified and quantified.

Keywords: Energy Rating; Energy Performance; Modelling

1 INTRODUCTION

Electrical measurements of individual modules or string connected arrays on site are made with differing numbers of parameters depending mainly on whether the monitoring system sweeps between I_{SC} and V_{OC} (IV curves) or just measures at maximum power point tracking (MPPT).

As it is easier to measure IV curves of single modules than for strings of arrays, more parameters (6 or more) are available for individual modules.

For multi MW_P solar plants either one (just P_{MP}) or two (I_{MP} and V_{MP}) measured values are usually available for strings.

Performance modelling needs to be adaptable to make the best use of whichever data parameters are available.

Figure 1 and table I give the optimum parameters to measure vs. the number of parameters. They are as independent as they can be from each other, are meaningful and they cover the full IV curve.

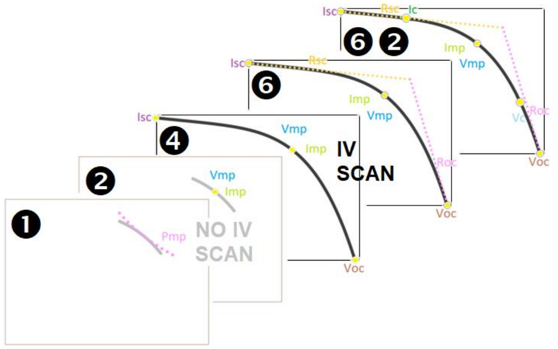

Figure 1: Optimum parameters to measure at increasing levels of detail from MPPT (❶ and ❷) to IV curve (❹ to ❻+❷).

Table I: Optimum parameters to measure (as in figure1)

#Params	Parameter names
(just MPPT)	
❶	P_{MP}
❷	I_{MP}, V_{MP}
(full IV curves)	
❹	I_{SC}, I_{MP}, V_{MP}, V_{OC}
❻	I_{SC}, R_{SC}, I_{MP}, V_{MP}, R_{OC}, V_{OC}
❻+❷	Add I@V_{MP}/2 (check mismatch), and V@I_{MP}/2 (Schottky contact rollover)

An explanation for the choice of parameters is as follows – (see Python Code 1 for glossary).

- ❶ The simplest PV performance measurements (1 parameter P_{MP}) can give PR_{DC} (=$mP_{MP}/rP_{MP}/G_I$).
- ❷ 2 parameters (I_{MP} and V_{MP}) can be analysed to give more information on I and V separately.
- ❹ If IV curves are taken, then I_{SC} and V_{OC} can be also be found and analysed (to make 4 parameters)
- ❻ If IV curves are good quality (i.e. smooth and high precision) then R_{SC} and R_{OC} can also be fitted (6 parameters).
- ❻+❷ For the highest quality IV measurements check "curvature parameters" can be taken such as I@V_{MP}/2 and V@I_{MP}/2 (and comparing these with expected values from extrapolating I_{SC} and R_{SC} or V_{OC} and R_{OC}) to make 8 in total.

These parameters are illustrated in Table I and figure 2.

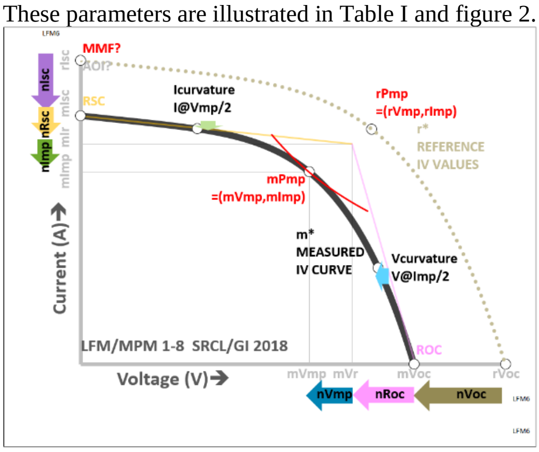

Figure 2: Measured parameters from a 6+2 IV curve used for LFM/MPM analysis

The LFM [1-5] had previously only been used to analyse 6 independent parameters from an IV curve, but in this study it is shown how it can analyse fewer values as in figure 1 depending on what data is available.

The following python code shows how to normalise the measured parameters in figure 1 such that their product equals PR_{DC}.

Python Code 1:

```
# CALCULATIONS IN PYTHON SRCL and GI Sep 2018
# Key to naming convention
# m* = measured value
# r* = reference value at STC
# d* = difference measured - reference
# *_U = not temperature compensated
# *_T = temperature compensated
# alpha, beta, gamma = temperature coeffs
# Gi = POA irradiance kW/m^2
Tstc = 25 # STC temperature celsius
# 1 parameter
PRDC = mPmp / rPmp / Gi
# 2 parameters named to distinguish dc or ac
nIdc = mImp/rImp / Gi
nVdc = mVmp/rVmp
# 4 parameters (note nFFI * nFFV = FF)
nFFI = mImp/mIsc
nFFV = mVmp/mVoc
# temporary calcs for easier maths
# (= intercept of RSC and ROC tangents)
mIr = (mIsc*mRsc-mVoc)/(mRsc-mRoc)
mVr = mRsc*(mVoc-mIsc*mRoc)/(mRsc-mRoc)
# 6 parameters default for LFM
dTmod = mTmod - Tstc
nIsc = mIsc/rIsc/Gi
nRsc = mIr/mIsc
nImp = mImp/mIr*rIsc/rImp
nVmp = mVmp/mVr*rVoc/rVmp
nRoc = mVr/mVoc
nVoc_U = mVoc/rVoc
# correct V by beta_Voc and (temp - 25C)
nVoc_T = nVoc_U * (1-beta_Voc * dTmod)
# curvature parameters for 6+2 check
nIc = mI(@Vmp/2)/(mIsc-mVmp/2/mRsc)
nVc = mV(@Imp/2)/(mVoc-mImp/2*mRoc)
```

The LFM PR_{DC} definitions for 2, 4 and 6 parameters respectively are given in equations below (where $PR_{DC}x$ means the equation is for x parameters).

$$PR_{DC2} = [\quad nI_{DC} \quad] \times [\quad nV_{DC} \quad] ❷$$
$$PR_{DC4} = [nI_{SC} \times nFF_I] \times [nFF_V \times nV_{OC}] ❹$$
$$PR_{DC6} = [nI_{SC} \times nR_{SC} \times nI_{MP}] \times [nV_{MP} \times nR_{OC} \times nV_{OC}] ❻$$

Figure 3 illustrates visually how these values all multiply to give the usual PR_{DC}.

(Note the 6+2 version has two extra parameters to quantify the curvature from cell mismatch or rollover.)

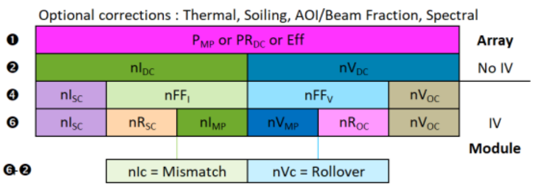

Figure 3: Showing how the PR_{DC} is the product of different numbers of parameters from 2 to 6.

The MPM was originally developed to characterise only the PR_{DC} but has been generalised to be able to fit any of the normalised LFM parameters in code 1 e.g. nR_{SC}, nV_{OC} as in equations for $PR_{DC}x$ and table II where

$dT_{MOD} = (T_{MOD} – 25)$;

G_I = plane of array irradiance (kW/m^2),

WS = wind speed (ms^{-1}).

The MPM equation to fit any normalised LFM parameter is -

$$nLFM = C_1 + C_2 \times dT_{MOD} + C_3 \times Log_{10}(G_I) + C_4 \times G_I$$

Table II: Explanation of MPM coefficients

Coefficient	Dependency	Comment	Unit
C_1	Performance Tolerance	Actual/ Nominal	%
C_2	Delta T_{MOD}	Temperature Coefficient	%/K
C_3	log_{10}	low light fall	%
C_4	G_I	high light fall	%

The fitting modelling of the MPM has therefore been combined with the LFM parameters [3].

Figure 4 shows the effect of monitoring and modelling a large array in the UK at 1-minute instantaneous intervals using just the measured parameter nP_{AC} and then modelling the fits with the MPM vs time, irradiance and module temperature then calculating the residual error “Difference” which is very low usually <±2.5%. The only discrepancies are during quickly changing irradiance periods as the array is large and the irradiance sensor is small, so cloud fronts do not pass over the sensor and modules at the same time.

The same methods can be used to fit individual modules with full measured IV curves (so up to 8 parameters can be extracted, the usual 6 LFM plus the curvature coefficients).

Figure 5 has plots of measured vs. fitted values for four parameters nI_{SC}, nFF_I , nFF_V and nV_{OC} (left) for a CdTe module (top) vs. a c-Si (bottom) showing good accurate fits but different behaviour e.g. the CdTe has a worse low light nV_{DC}.

The other columns show the greater detail from analysing more parameters centre (measured) and right (fitted) for the same two modules. Here we can see the nR_{OC} is worse for the CdTe at high light levels (caused by the higher $I^2.R_{SERIES}$ loss) and the CdTe also has a poorer low light nR_{SC} (caused by a collapse in R_{SHUNT}). This is partially offset by a better nV_{MP}

Figure 6 shows a module with both poor low light and high light PR_{DC} behaviour.

Adding more coefficients to the analysis the reasons for this can be found, here the causes are found to be nR_{SC} (~R_{SHUNT}) and nV_{OC_T} at low light whereas it is due to nR_{OC} (~R_{SERIES}) at high light. These values can be identified and quantified.

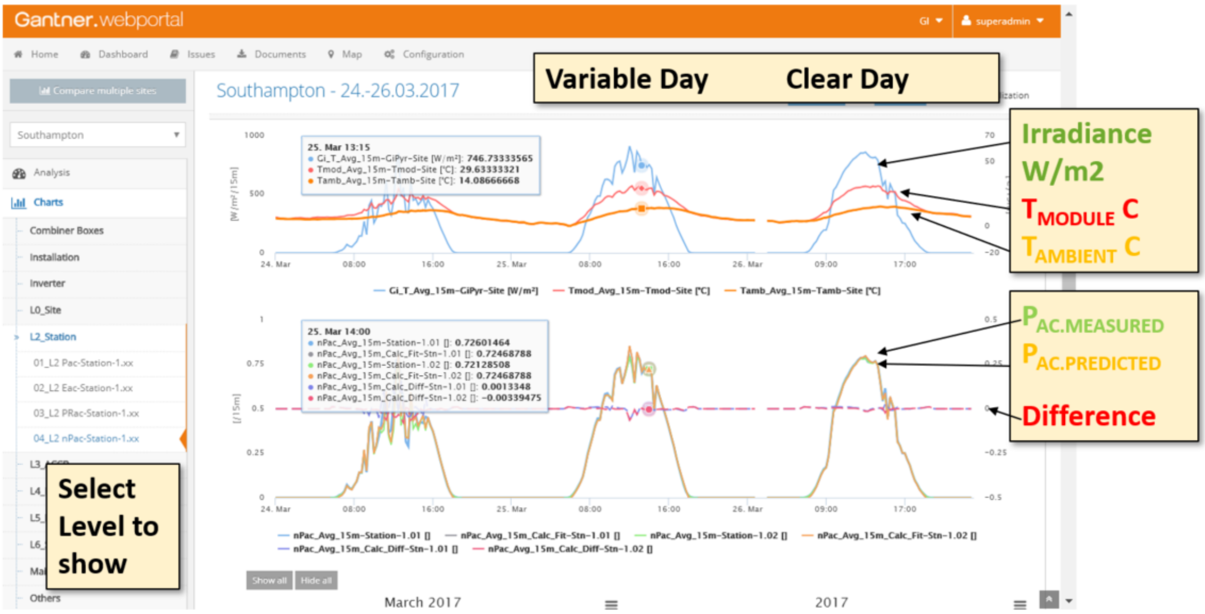

Figure 4: Analysis of a large array measured in the UK for (left to right) poor, variable weather and clear days showing weather (top) and predicted vs. measured nP_{AC} (bottom) with good agreement < ±2.5%.

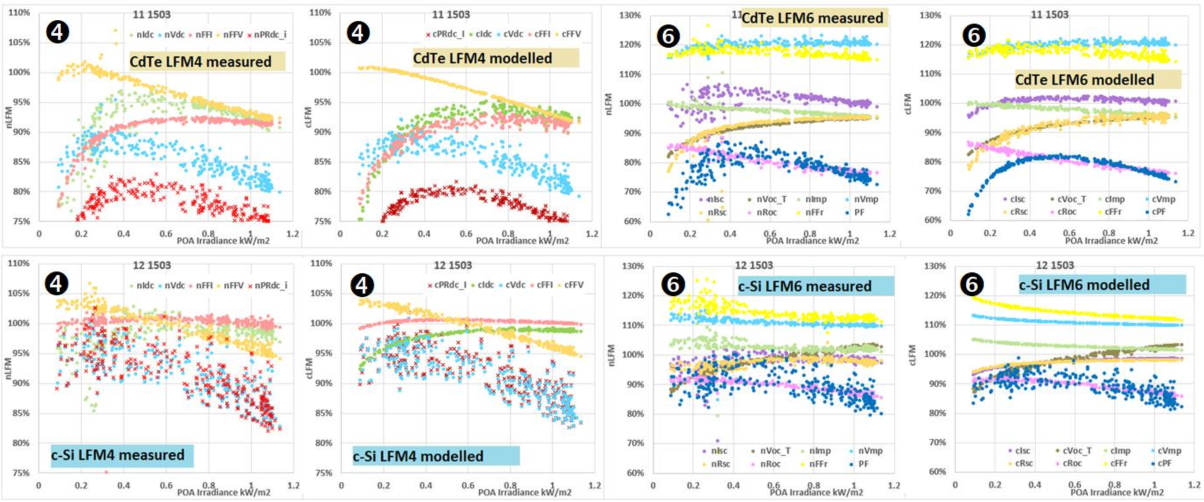

Figure 5: Extended LFM parameters fitted by MPM methods at different irradiances (left to right: LFM 4 measured vs. modelled; LFM 6 measured vs. modelled) for a CdTe module (#11 top) and vs. a c-Si module (#12 bottom) for one-month March 2015 at Gantner Instruments' data at their OTF in AZ.

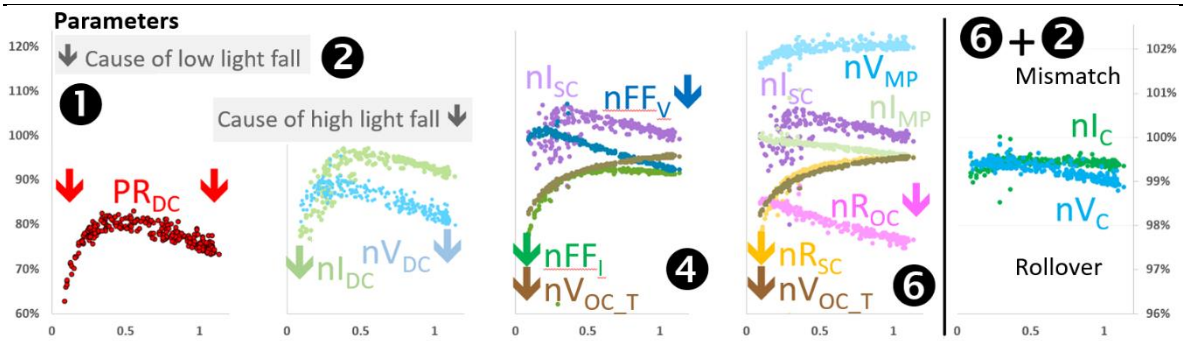

Figure 6: As more parameters are analysed the causes and rates of performance changes can be identified more closely.

	Cause of Low light drop	Cause of High light drop
❶	PR_{DC} no cause known	PR_{DC} no cause known
❷	nI_{DC} could be I_{SC} or R_{SHUNT}	nV_{DC} could be V_{OC} or R_{SERIES}
❹	nFF_I (possibly R_{SHUNT}?) and nV_{OC_T} (V_{OC})	nFF_V (possibly R_{SERIES}?)
❻	nR_{SC} (definitely R_{SHUNT}) and nV_{OC_T} (V_{OC})	nR_{OC} (definitely R_{SERIES})
❻+❷	None Both are flat so this module has no problems with cell mismatch (nI_C) or Schottky back contact (nV_C)	

Another advantage of using normalised coefficients for the MPM is that it is easy to calculate expected performance at the standard PV module test conditions as in Table III.

Table III: Definitions of test conditions

	standard test	PVUSA	nom. operating cell temp	low temp.	low irrad	high temp
	STC	PTC	NOCT	LTC	LIC	HTC
G_I (kW/m^2)	1	1	0.8	0.5	0.2	1
T_{AMB} (C)	-	20	20	-	-	-
T_{MOD} (C)	25	-	-	15	25	75
WS (ms^{-1})	0	1	1	0	0	0
Tilt (degrees)	-	-	45	-	-	-
AM (#)	1.5	1.5	1.5	1.5	1.5	1.5

The MPM fit can be used to estimate the module's performance under specific conditions such as STC (1kW/m^2, Tmod=25C) and Low Irradiance (0.2kW/m^2, Tmod=25C).

The following tables IV and V show the differences between the some of the parameters for the cSi and CdTe modules analysed for each 6 months 2014 to 2016 to evaluate degradation. (Column "yymm" is 2 numbers for the year and 2 numbers for the month").

Table V shows the CdTe module has a degrading nR_{SC} at low light caused by a drop in low light R_{SHUNT}

Table IV: A slight fall in nR_{SC} for CdTe only at high light levels (STC)

STC	yymm	nVoc	nRsc	nRoc
12 c-Si	1403	100.0%	96.5%	88.6%
12 c-Si	1409	99.8%	96.5%	88.7%
12 c-Si	1503	100.0%	98.0%	88.9%
12 c-Si	1509	99.7%	97.1%	88.5%
12 c-Si	1603	99.9%	97.6%	88.9%
12 c-Si	1609	100.2%	95.8%	88.5%
11 CdTe	1403	95.8%	95.8%	75.2%
11 CdTe	1409	96.0%	95.0%	75.8%
11 CdTe	1503	95.0%	94.9%	74.4%
11 CdTe	1509	94.9%	93.8%	76.0%
11 CdTe	1603	95.1%	94.9%	75.0%
11 CdTe	1609	95.1%	93.4%	78.3%

Table V: A worse fall in nR_{SC} for CdTe only at low light levels (LIC)

LIC	yymm	nVoc	nRsc	nRoc
12 c-Si	1403	92.4%	96.1%	91.7%
12 c-Si	1409	92.3%	95.9%	91.7%
12 c-Si	1503	92.3%	95.9%	92.0%
12 c-Si	1509	92.2%	96.2%	91.9%
12 c-Si	1603	92.2%	95.7%	91.6%
12 c-Si	1609	92.4%	95.7%	91.9%
11 CdTe	1403	89.1%	91.1%	85.3%
11 CdTe	1409	88.7%	91.0%	85.3%
11 CdTe	1503	87.6%	86.9%	84.7%
11 CdTe	1509	87.4%	86.4%	85.2%
11 CdTe	1603	87.7%	86.7%	85.0%
11 CdTe	1609	87.5%	86.2%	86.3%

Figures 7 and 8 give the differences between the STC and LIC values of nR_{SC} and nR_{OC} for c-Si (7) and CdTe modules (8)

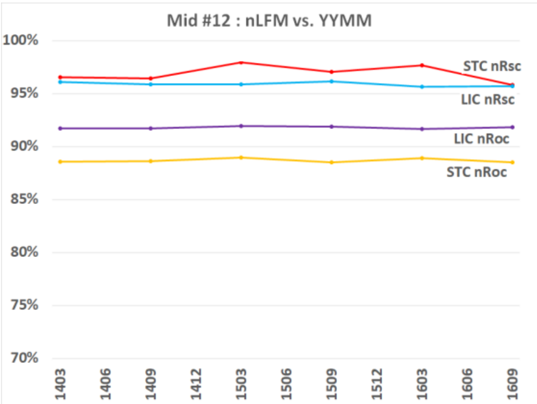

Figure 7: LFM parameters for a c-Si module every 6 months with good(high) and stable(flat) performance.

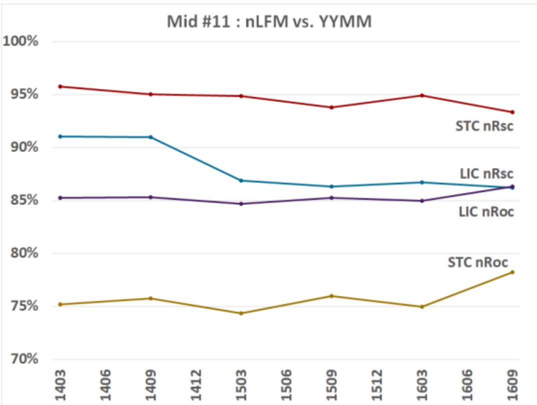

Figure 8: LFM parameters for a CdTe module every 6 months with poorer(lower) and unstable(sloped) performance with worsening nR_{SC}.

3 CONCLUSIONS

- The Loss Factors Model (LFM) and Mechanistic Performance Model (MPM) have been combined to give an advanced analysis of MPPT or IV data using the same procedure.
-

- Optimised coefficients used are “Meaningful, Orthogonal, Robust and Normalised” (MORN).

- Instantaneous measurements can be validated in real time.

- The reasons and magnitudes for any faults/underperformance can be easily found.

- Seasonal effects and degradation can be identified and quantified (e.g. %/year V_{OC}).

- This procedure confirms optimum output behavior or else identifies faults which should be quickly rectified to minimise any downtime or errors.

- The LFM/MPM method has been added to Gantner Instruments’ SaaS platform for advanced analysis and fault detection.

- For further data see www.gantner-instruments.com, www.gi-cloud.io, www.otf.gantner-instruments.com.

References

[1] Ransome et al, 44th PVSC (2017) Washington DC "How to Choose the best Empirical Model for Optimum Energy Yield Predictions" https://de.slideshare.net/sandiaecis/21-gi-8thpvpmctalkabqfinalext170508t19new

[2] Ransome et al, PVSEC27 (2017), “7TuPo Quantifying and analysing the variability of PV module resistances R_{SC} and R_{OC} to understand and optimise kWh/kWp modelling"

[3] Ransome et al, PVSEC27 (2017), “7MoO.5.4 "Optimised fitting of indoor (e.g. IEC 61853 matrix) and outdoor PV measurements for diagnostics and energy yield predictions"

[4] http://www.gantner-webportal.com www.gi-cloud.io www.otf.gantner-instruments.com

[5] Sutterlueti, PVPMC8 (2017), “Optimized PV Performance using State of the Art Monitoring for Increased Asset Value”