Degradation Rates

NREL

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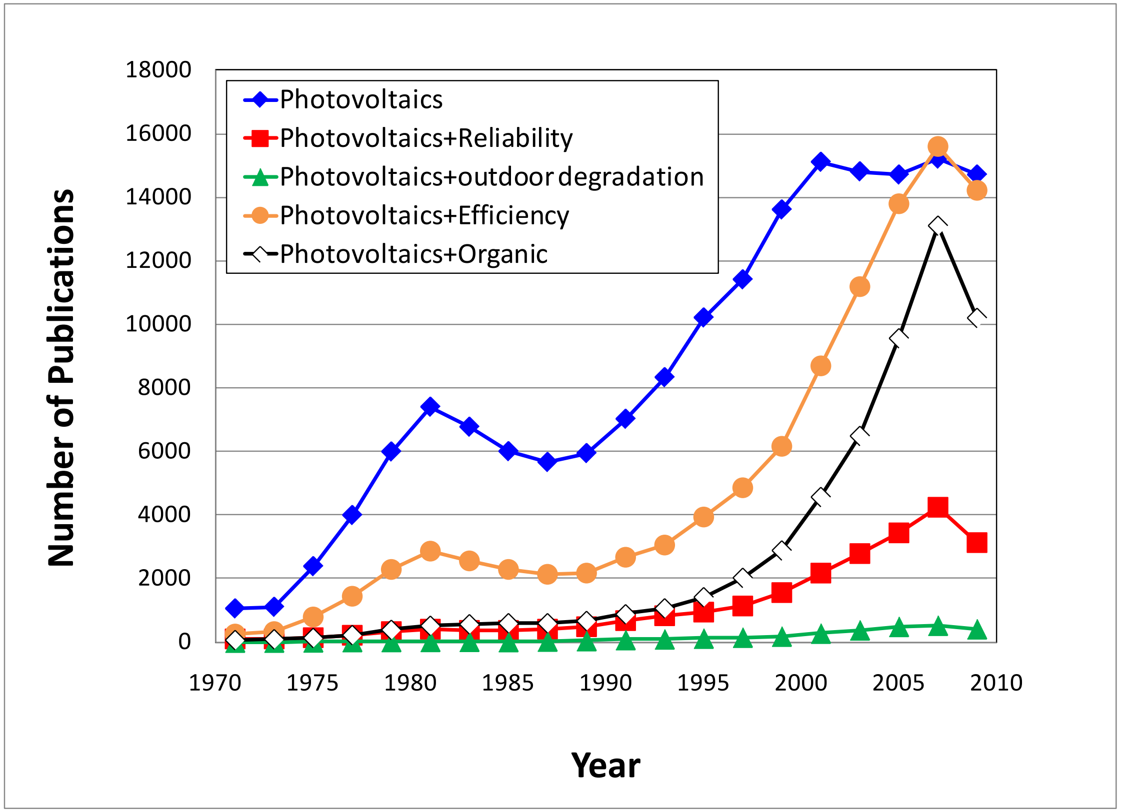
This presentation does not contain any proprietary or confidential information.

Outline

- Historical Degradation Rates (R_d)
- Importance of Uncertainty
- Traditional way to determine R_d
- Alternative methodologies - Classical Decomposition , ARIMA
- Impact of outliers, data shifts, missing data
- Correction for data shifts
- Determination of R_d in shorter time

Introduction - PV Publications

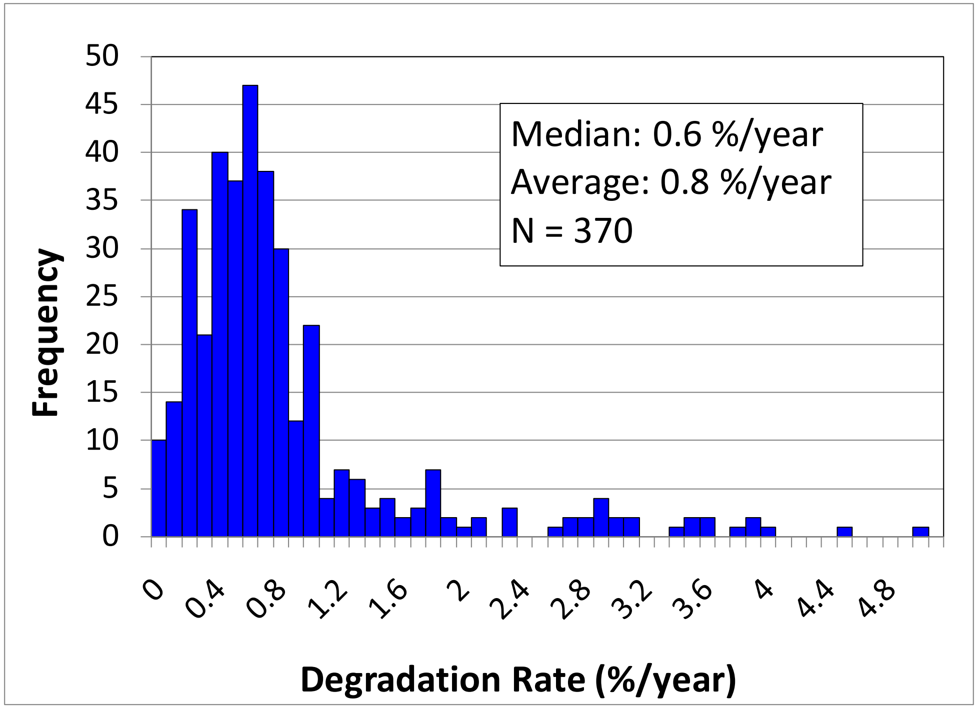


Number of Publications on Google Scholar

Different search engine. Web of Science, Scirus, INSPEC etc. → vertical axis will be different

Historical Degradation Rates

Degradation Rates (R_d) most often reported



Ref
Perfor & Reliability_Adelstein_NREL_PVSC_2005
A-Si in Kenya_Jacobsen_Berkley_ASES_2000
Outdoor testing at ASU_Mani_ASU_2006
Measuring Degradation Rates without Irradiance Data_Pulver_UofA_PVSC_2010
DegRate for c-Si_Osterwald_NREL_2002
Outdoor PV on Cyprus_Makrides_Cyprus_2009
Field test in Mexico_Foster_New Mexico State_2005
PV Power production after 10 years_Cereghetti_Switzerland_2003
Predicted long-term PV performance_Muirhead_Australia_PVScienceConf_1996
Outdoor PV on Cyprus_Makrides_Cyprus_2009
CIGS Outdoor degradation_Jordan_NREL_2010
Measuring Degradation Rates without Irradiance Data_Pulver_UofA_PVSC_2010
Field PV reliability_Vazquez_Spain_2008
PV Power production after 10 years_Cereghetti_Switzerland_2003
DegRate for c-Si_Osterwald_NREL_2002
Long-term field age_Skoczek_Italy_2009
PV performance_Carr_Australia_2005
Outdoor testing at ASU_Mani_ASU_2006
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Predicted long-term PV performance_Muirhead_Australia_PVScienceConf_1996
PV performance_King_Sandia_2004
Outdoor PV on Cyprus_Makrides_Cyprus_2009
PV Korea_So_Korea_2006
PV Korea_So_Korea_2006
PV in Saxony_Decker_Germany_1997
25 yearold PV modules_Hedstroem_Sweden_2006
PV degradation_Vignola_UofOregon_2008
C-Si degradation_Morita_Japan_PVenergyconv_2003
PV degradation_King_Sandia_2003
Field test of c-Si in 1990_Sakamoto_Japan_PVenergyconv_2003
c-Si of 22 years_Dunlop_EU_2006
PV performance_Carr_Australia_2005
DegRate for c-Si_Osterwald_NREL_2002
PV Power production after 10 years_Cereghetti_Switzerland_2003
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PV performance_Carr_Australia_2005
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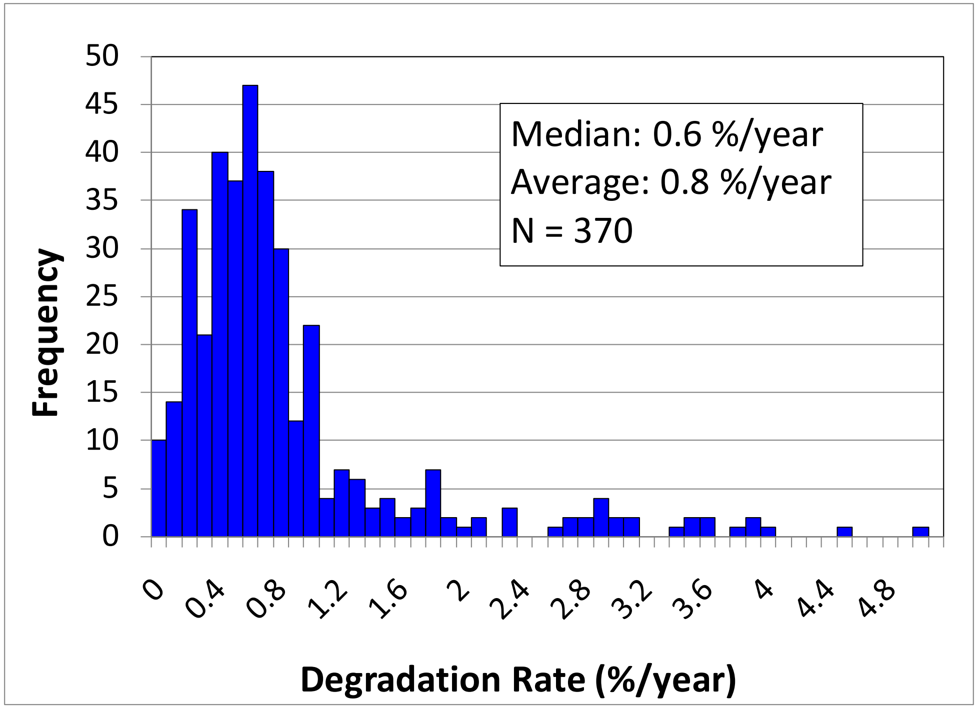
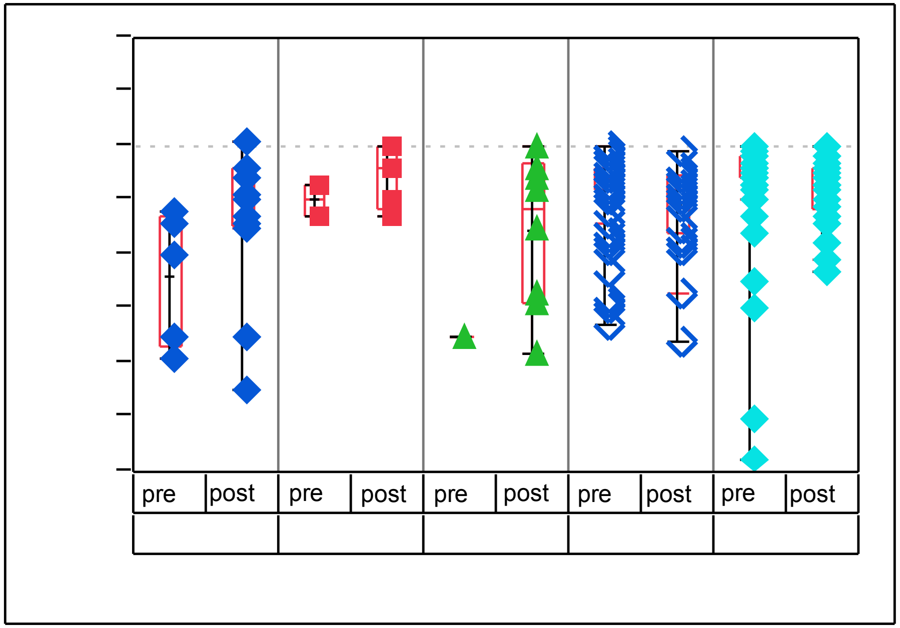
PV Korea_So_Korea_2006
PV Greece_Kalykakis_Greece_2009
PV degradation_Vignola_UofOregon_2008
Measuring Degradation Rates without Irradiance Data_Pulver_UofA_PVSC_2010
Long-term reliability_Wolgemuth_BP-1999
Common degradation mechanism_Quintana_Sandia_IEEE_2003
PV degradation_King_Sandia_2003
C-Si degradation_Morita_Japan_PVenergyconv_2003
C-Si degradation_Morita_Japan_PVenergyconv_2003
Field test of c-Si in 1990_Sakamoto_Japan_PVenergyconv_2003
PV performance_Carr_Australia_2005
Improved Power ratingsd_Kimber_PVSC_2009

Historical Degradation Rates

Degradation Rates (R_d) most often reported

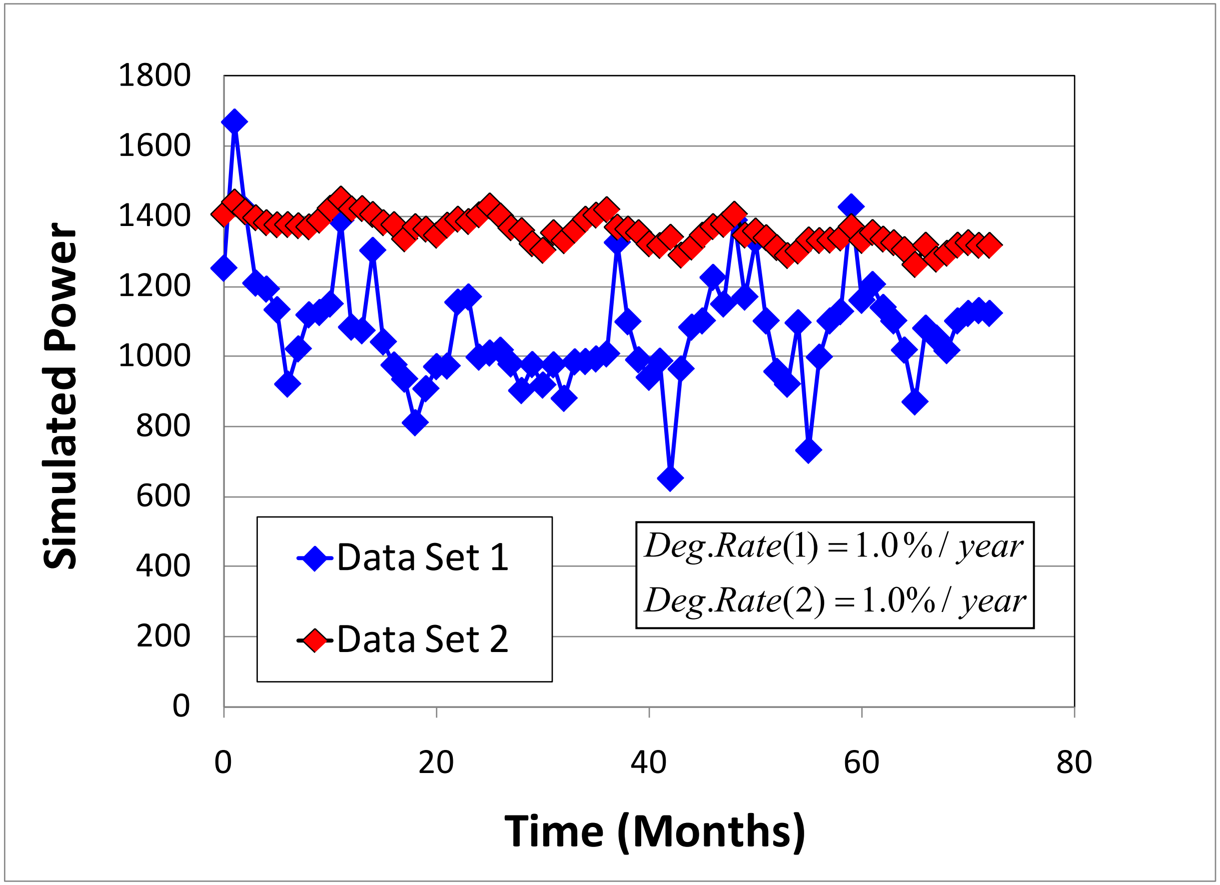


Installation
Pre: before 2000
Post: after 2000



All technologies show some degradation rates around 0 %/year for modules installed after 2000.

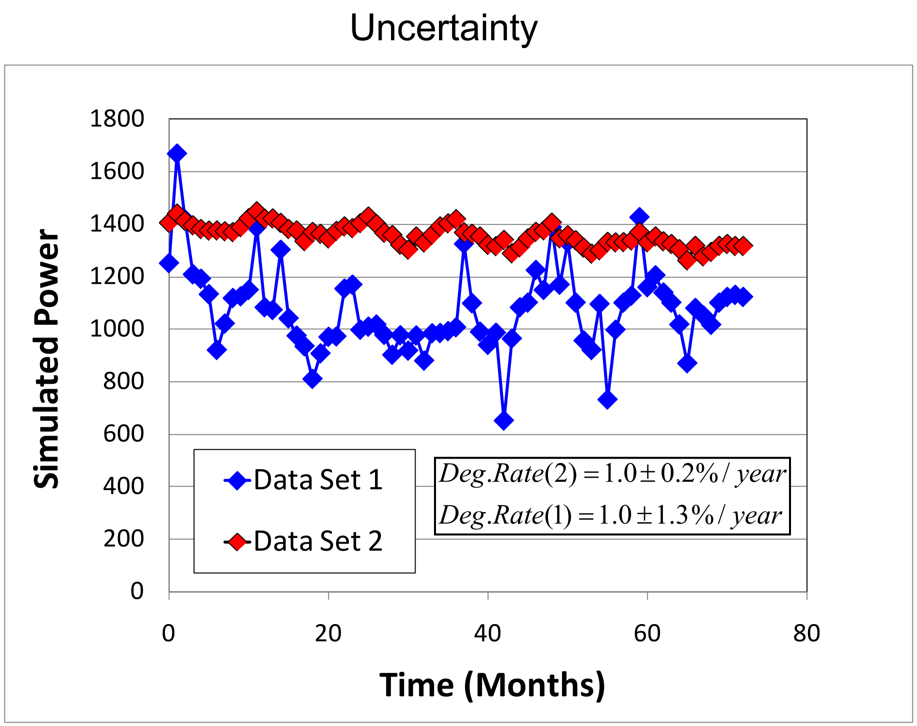
Degradation Rates



Both data sets have the same degradation rate!

How can you distinguish the 2 data sets?

Degradation Rate Uncertainty Impact

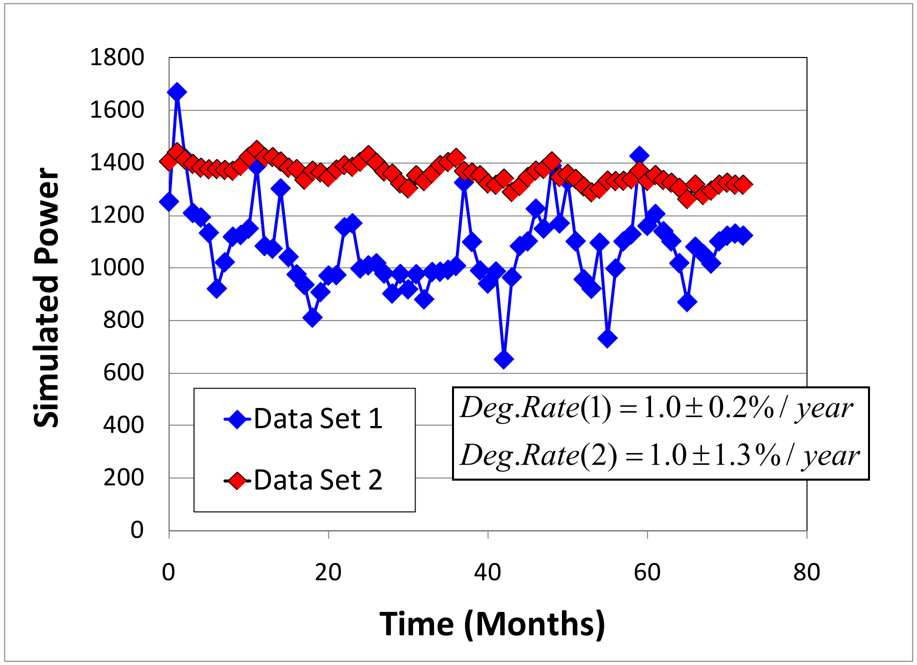


Uncertainty for Data set(1) small → R_d looks believable

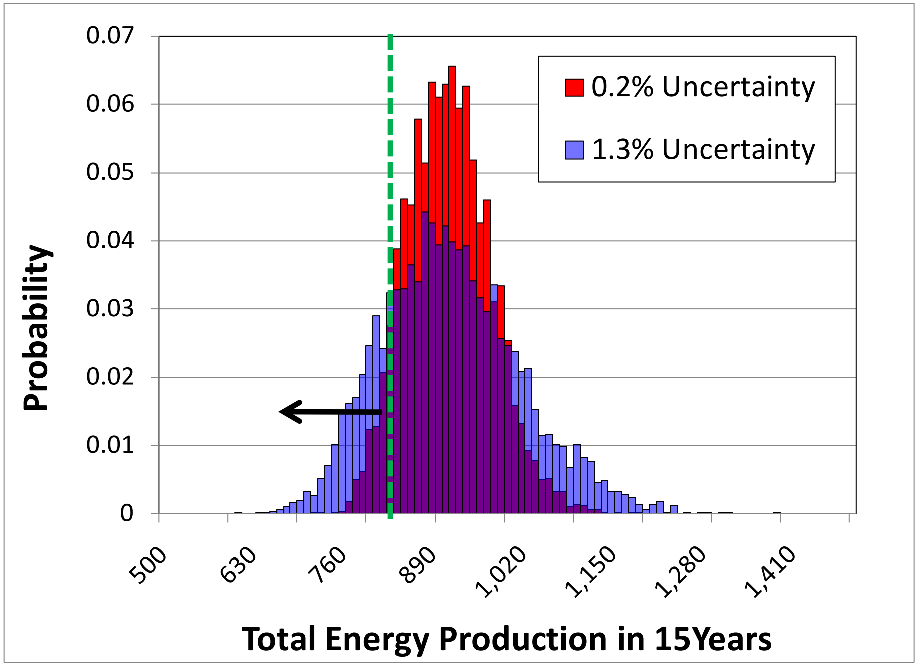
Uncertainty for Data set(2) large → 2 different slopes

Degradation Rate Uncertainty Impact

Uncertainty



Monte Carlo Simulation of Energy Production



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Uncertainty for Data set(2) large → 2 different slopes

$$Energy(Year_N) = \sum_{n=1}^{N} \frac{Energy(Year_1) \cdot (1 - R_D)^n}{(1+r)^n}$$

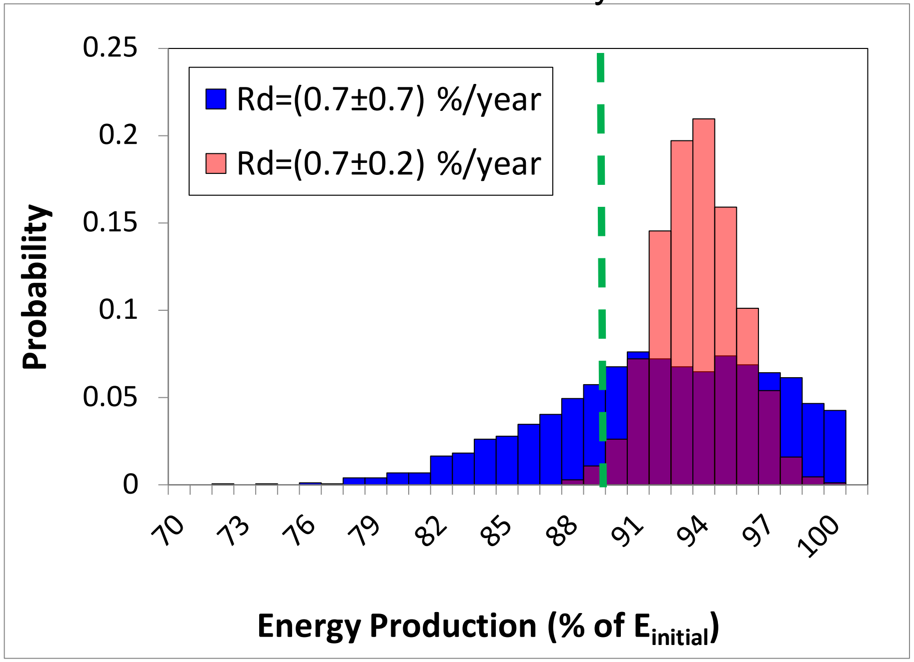
Energy production → Levelized Cost of Energy
Assumption:
Same Degradation Rate: 1.0%/year
Energy production for 15 year lifetime system
1st-year production 100%
Discount rate: 6%±1%

Larger Uncertainty leads to broader distribution → higher risk

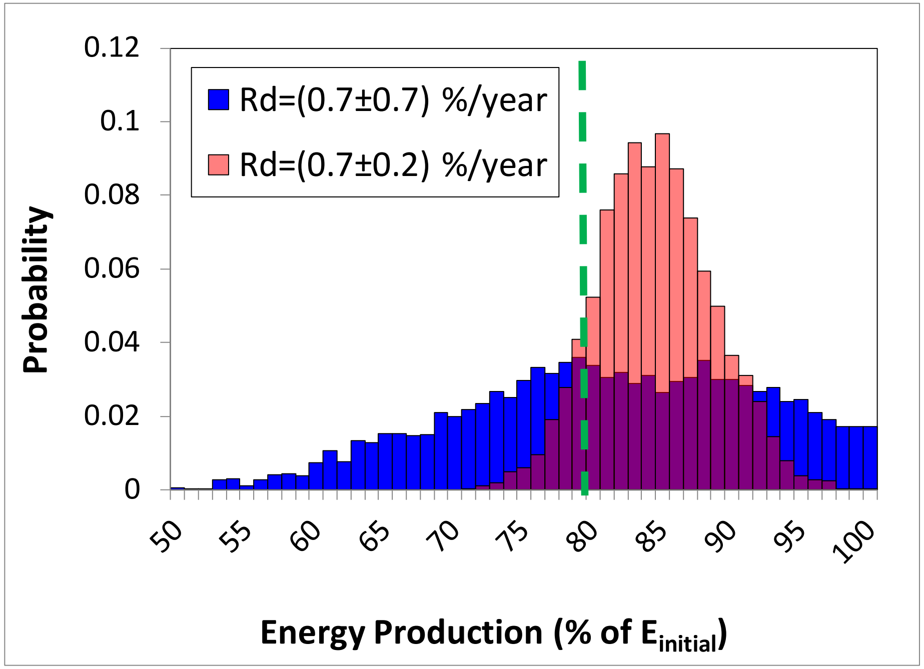
R_D Uncertainty Impact on Warranty

Warranty often twofold: 90% after 10 years, 80% after 25 years

Power Production after 10 years



Power Production after 25 years



Chance to invoke warranty:

0.7 %/year uncertainty = 36%
0.2 %/year uncertainty = 4%

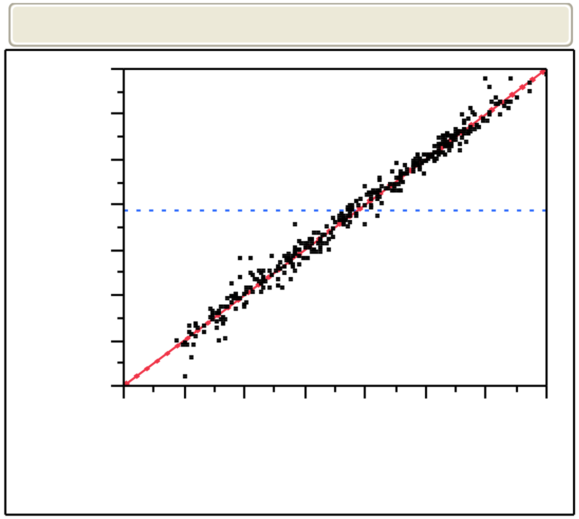
Chance to invoke warranty:

0.7 %/year uncertainty = 47%
0.2 %/year uncertainty = 16%

Degradation Rate Determination

1. Step

Rating



1. PVUSA equation

$$P = E\cdot\left(a_1 + a_2\cdot E + a_3\cdot T_{ambient} + a_4\cdot ws\right)$$

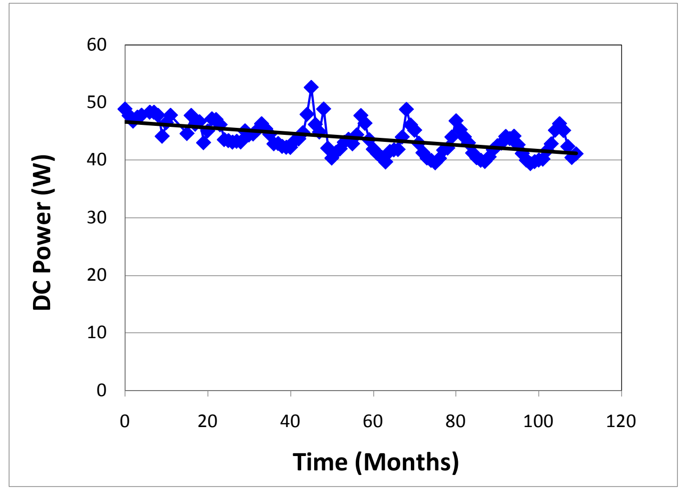
PTC conditions:
E=1000 W/m^2, Tamb=20ºC, w=1m/s

2. Sandia Model

3. BEW Model

2. Step

Time series + Linear Fit, Standard Least Squares



$$P = b + m\cdot t$$

$$m = \frac{n\left(\sum P\cdot t\right) - \left(\sum P\right)\left(\sum t\right)}{n\left(\sum t^2\right) - \left(\sum t\right)^2}$$

$$b = \frac{\left(\sum P\right)\left(t^2\right) - \left(\sum t\right)\left(\sum P\cdot t\right)}{n\left(\sum t^2\right) - \left(\sum t\right)^2}$$

$$SE_b = RMSE\cdot\sqrt{\frac{1}{\sum(x_i - \bar{x})^2}}$$

$$SE_m = RMSE\cdot\sqrt{\frac{1}{n} + \frac{\bar{x}^2}{\sum(x_i - \bar{x})^2}}$$

$$R_d = \frac{\left[\dfrac{P(t_0) - P(t)}{t}\cdot 12\right]}{P(t_0)} = \frac{m\cdot 12}{b}$$

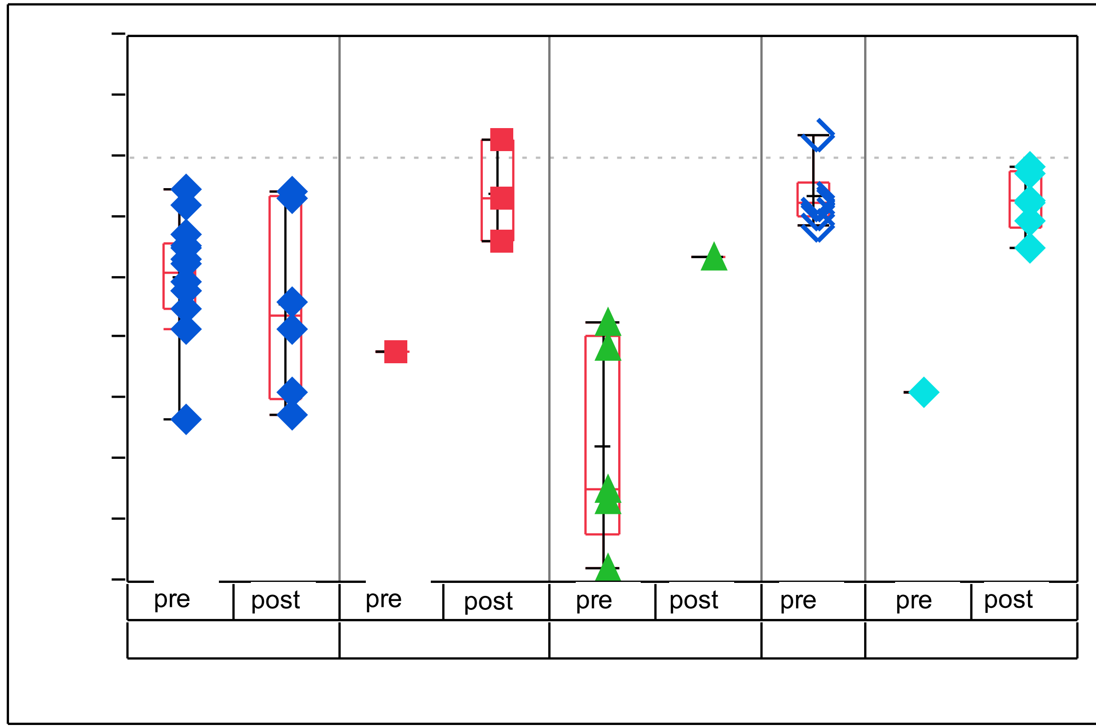
$$\Delta R_d = \sqrt{\left(\frac{\partial R_d}{\partial m}\Delta m\right)^2 + \left(\frac{\partial R_d}{\partial b}\Delta b\right)^2}$$

Linear Fit using Standard Least Square → Method 1

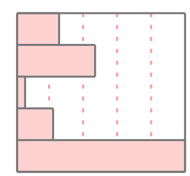
Kimber A, Dierauf T, Mitchell L, Whitaker C, Townsend T, Newmiller J, King D, Granata J, Emery K, Osterwald C, Myers D, Marion B, Pligavko A, Panchula A, Levitsky T, Forbess J, Talmud F. Improved Test Method to Verify the Power Rating of a Photovoltaic (PV) Project. Proceedings of the 34th IEEE PV Specialist Conference, Philadelphia, 2009.

PERT – Degradation Rates

Performance Energy Rating Testbed = PERT



More than 40 Modules,
> 10 manufacturers,
Monitoring time: 2 yrs-16 yrs

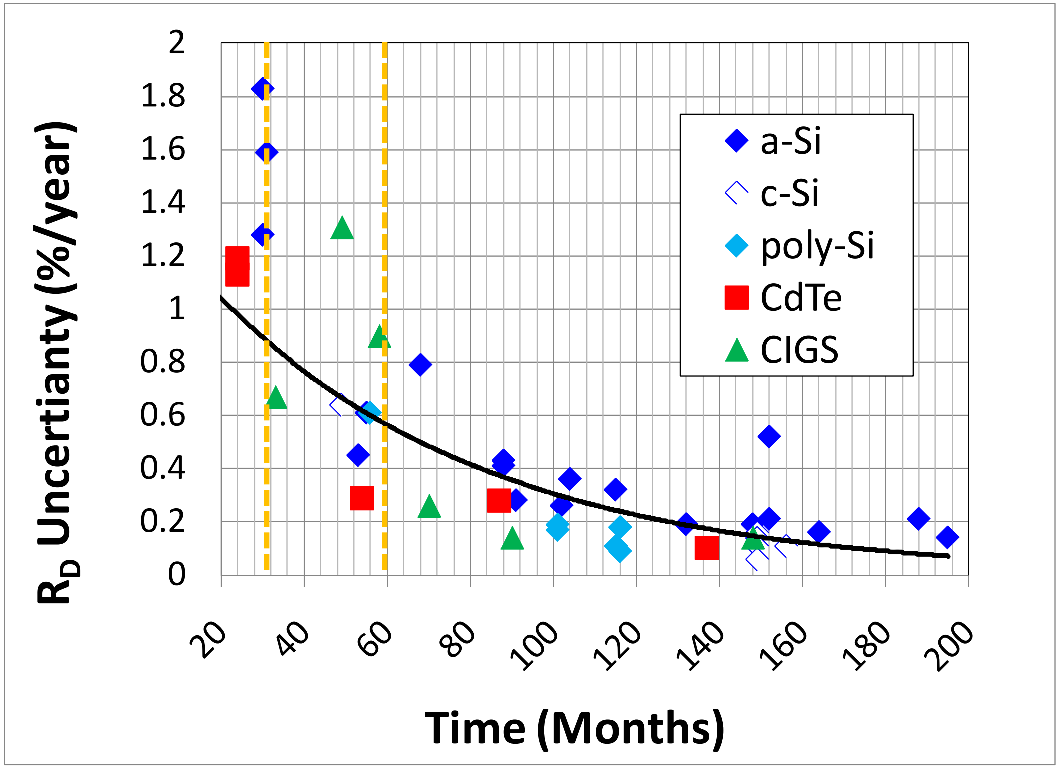


Appears that CdTe, CIGS & poly-Si improved, although sample size is small

PERT – Degradation Rate Uncertainty

Performance Energy Rating Testbed = PERT

Pmax + PVUSA multiple regression → Degradation Rate



Traditional Method → need 3-5 years to determine degradation rate*.

3-5 Years: Uncertainty is between (0.9-0.6) %/year

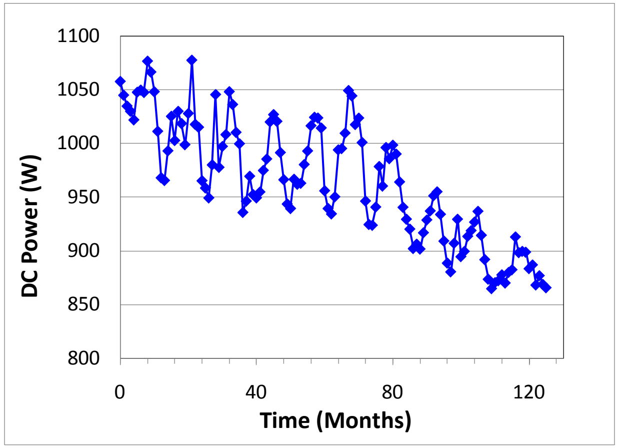
*Osterwald CR, Adelstein J, del Cueto JA, Kroposki B, Trudell D, Moriarty T. Proc. of the 4th IEEE World Conference on Photovoltaic Energy Conversion, Hawaii, 2006.

Classical Decomposition

Signal = Trend + Seasonality + Error

$$P_t = T_t + S_t + E_t$$ Additive Model

Original Data



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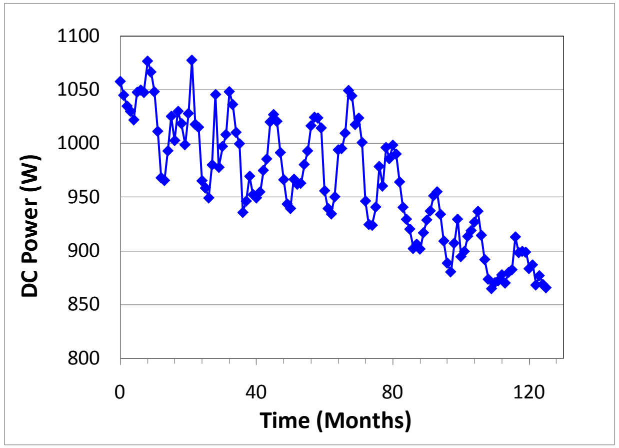
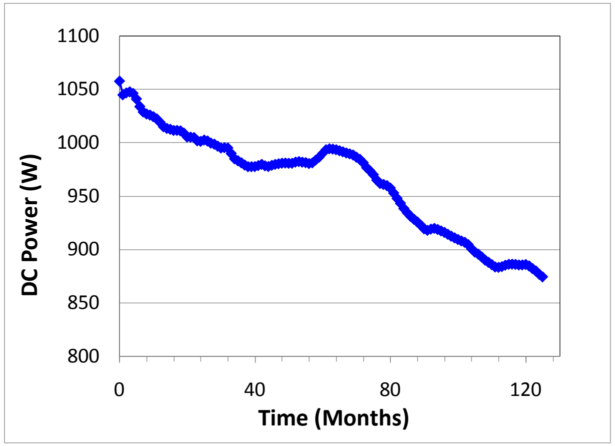




Trend

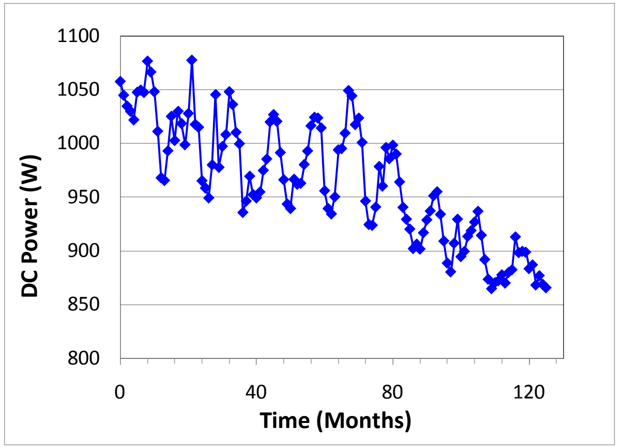
12-month centered-Moving Average

Classical Decomposition

Signal = Trend + Seasonality + Error

$P_t = T_t + S_t + E_t$ Additive Model

Original Data



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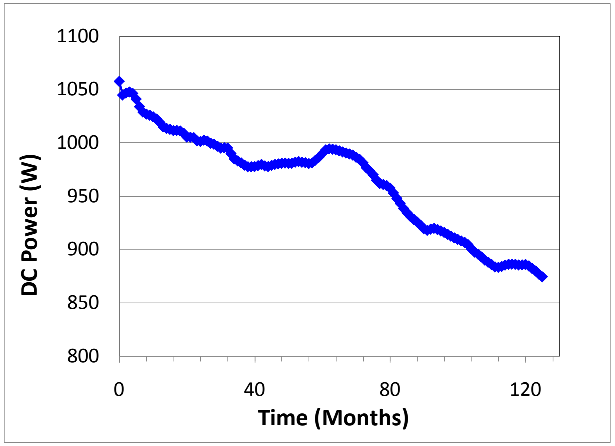
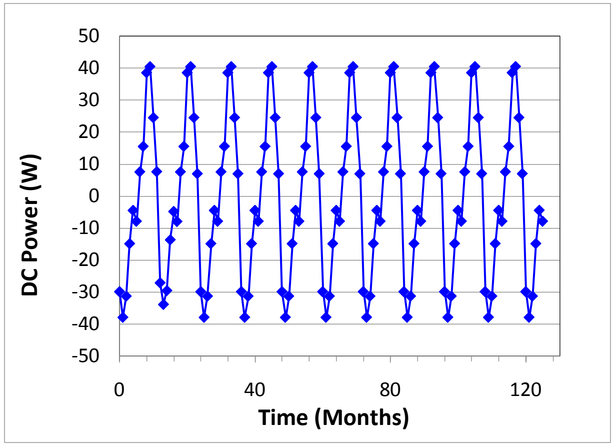


Seasonality

Average of each month for all years of observation



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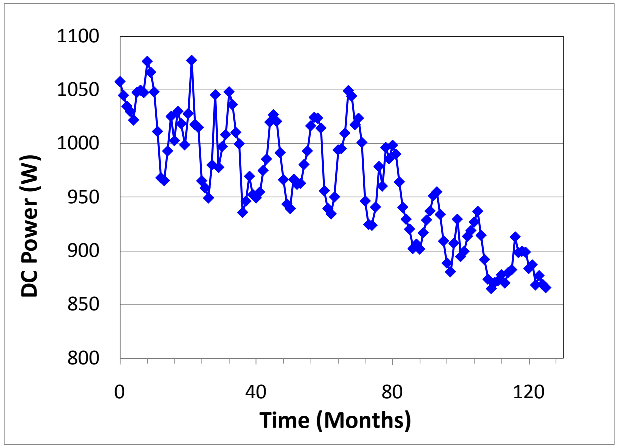

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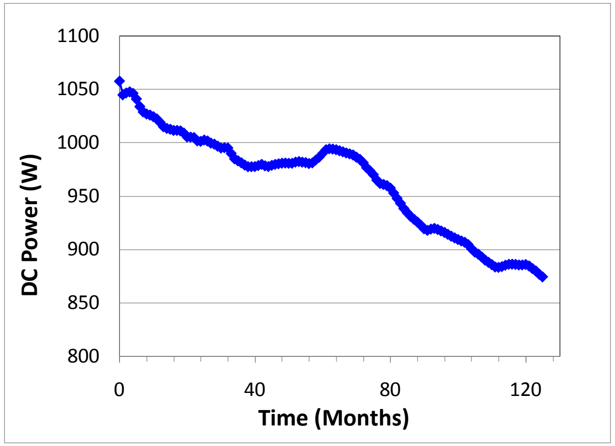

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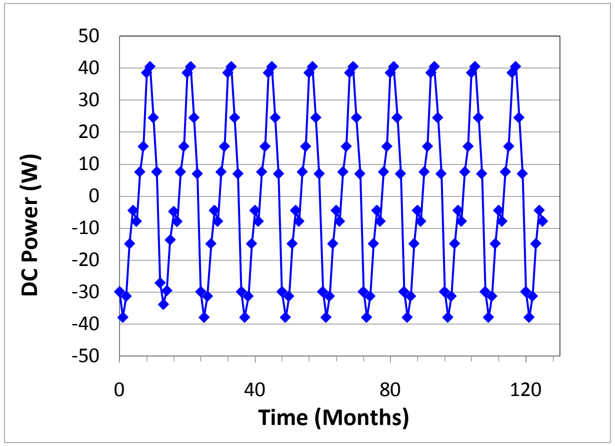
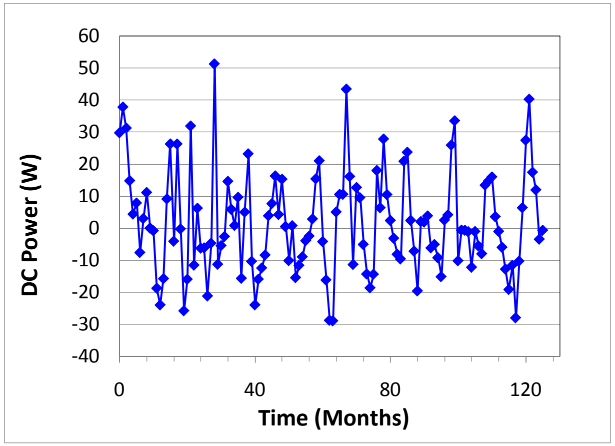


Error



Determine R_d from Trend graph only using SLS

Power Decline as Difference Equation

$$\frac{dP}{dt} = a_0 P(t) + c + e(t)$$

Stochastic differential equation

$$\left(P_t - P_{t-1}\right) = a_0 P_t + c + e_t$$

Discrete difference equation

$$P_t = \frac{1}{1-a_0} P_{t-1} + \frac{c}{1-a_0} + \frac{e_t}{1-a_0}$$

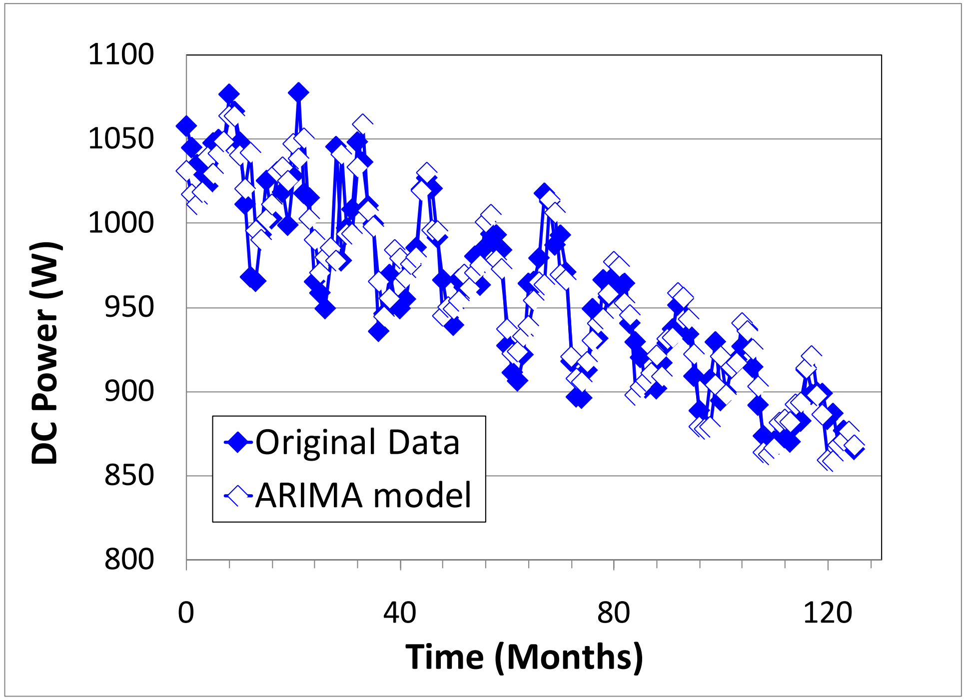
$$\phi = \frac{1}{1-a_0}, \quad \mu = \frac{c}{1-a_0}, \quad and \quad \varepsilon_t = \frac{e}{1-a_0}$$

$$P_t = \phi \cdot P_{t-1} + \mu + \varepsilon_t$$

- Regression of it's lagged self → auto-regression
- Because only 1 time lag is included → AR(1)

- AR(1) subset of larger class of ***A***uto***R***egressive ***I***ntegrated ***M***oving ***A***verage (ARIMA)

ARIMA + Decomposition



Commercial software:
(i) US Census Bureau
(ii) Bank of Spain
Complete solution

Statistical software:
User has to select model

Equation for ARIMA : $$P_t - P_{t-12} - \phi \cdot P_{t-1} + \phi \cdot P_{t-13} = \varepsilon_t - \theta \cdot \varepsilon_{t-12}$$

Autoregressive coefficient

Seasonal Moving average coefficient

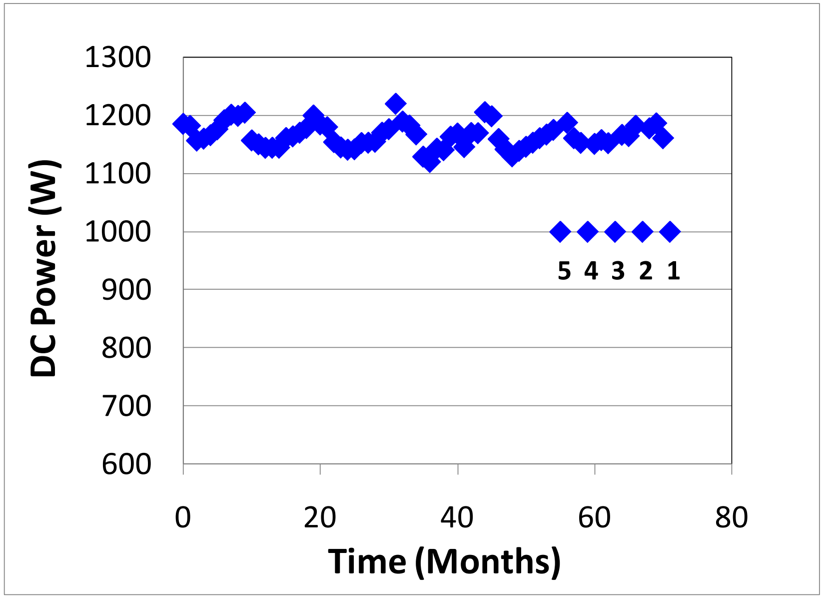
ARIMA(100)(011)

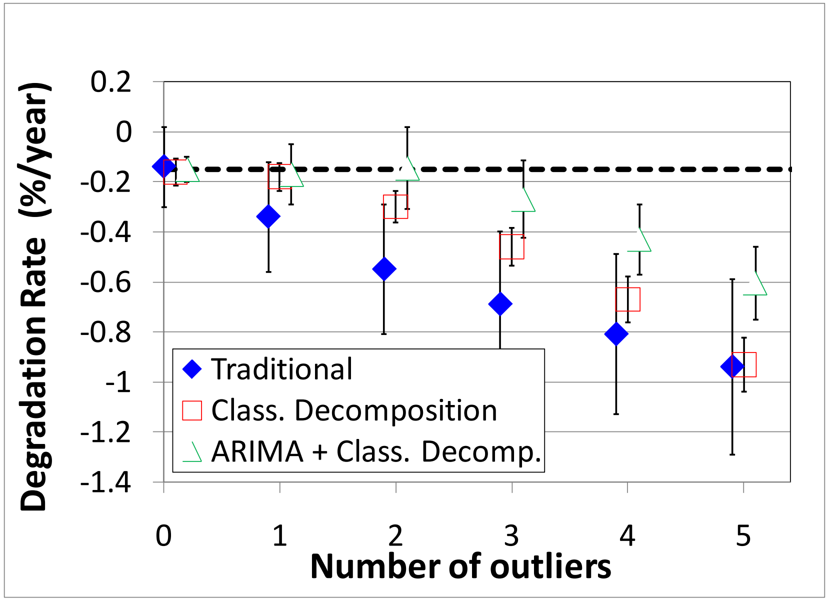
Analytical problems leading to longer observation times: Outliers, Data shifts, Missing Data

Outlier Sensitivity

Data set from OTF
Deliberately introduce outliers
Calculate Rd

(i) Linear Fit w/ SLS = traditional
(ii) Classical Decomposition
(iii) ARIMA + Decomposition





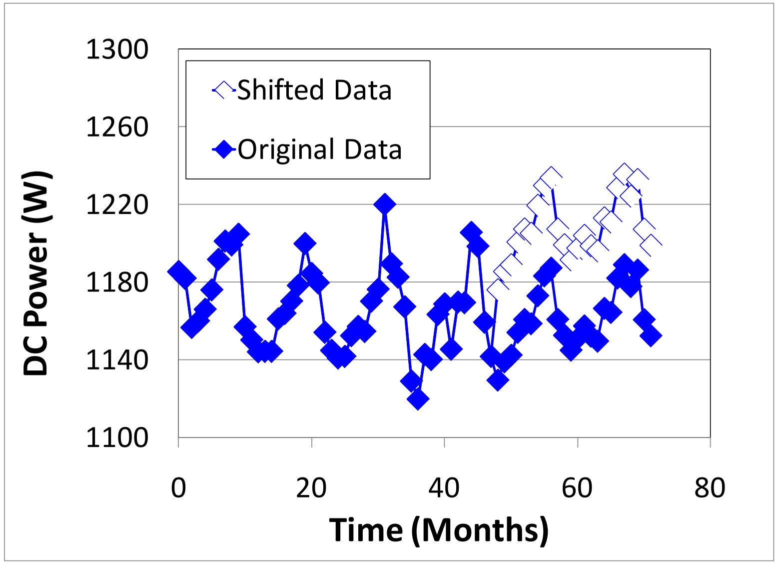
Traditional: 1 outlier → R_d changed significantly

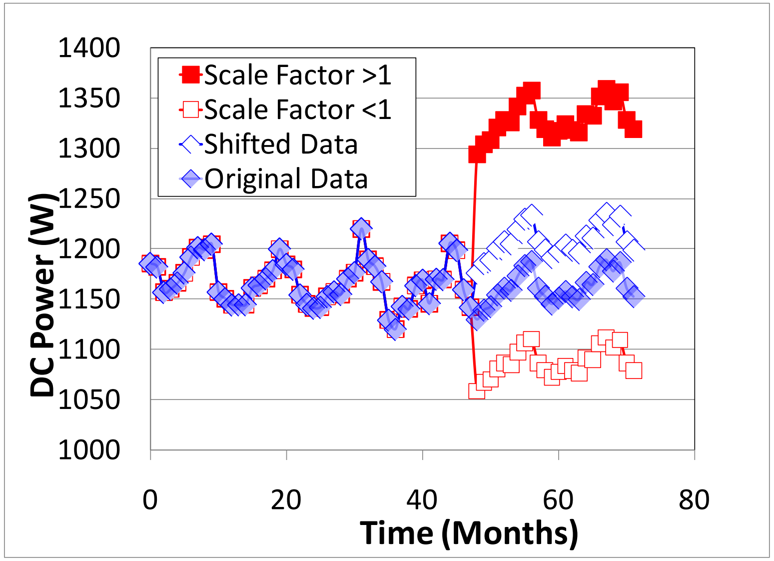
Class. Decomposition: 1 outlier → R_d does not change significantly, 2 outliers → significant change

ARIMA+Decomposition: Least sensitive to outliers → even 3 outliers

Method to correct Data Shifts

Data shifts often occur due to hardware changes



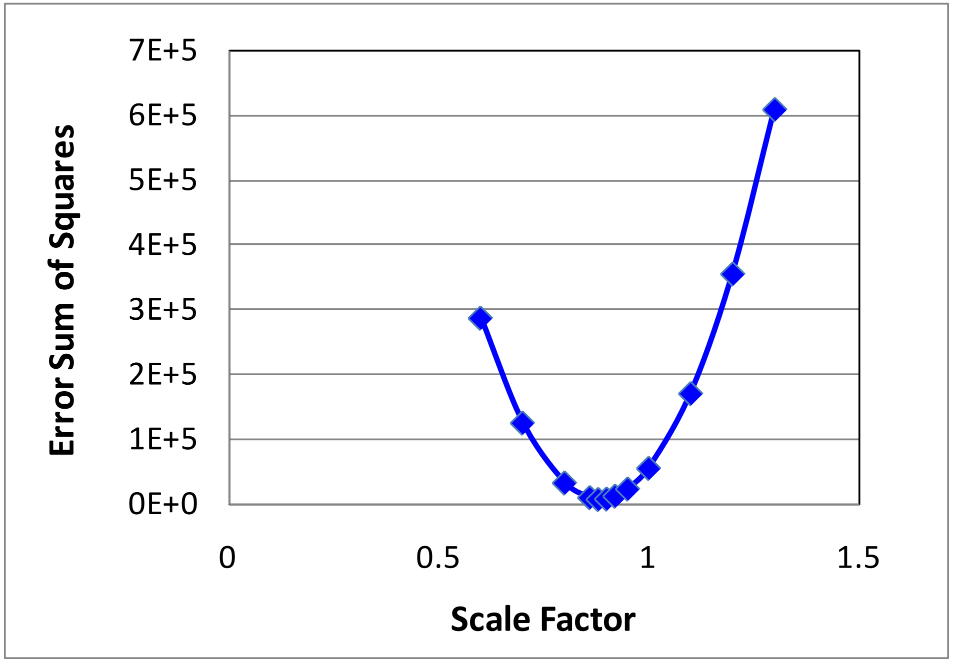


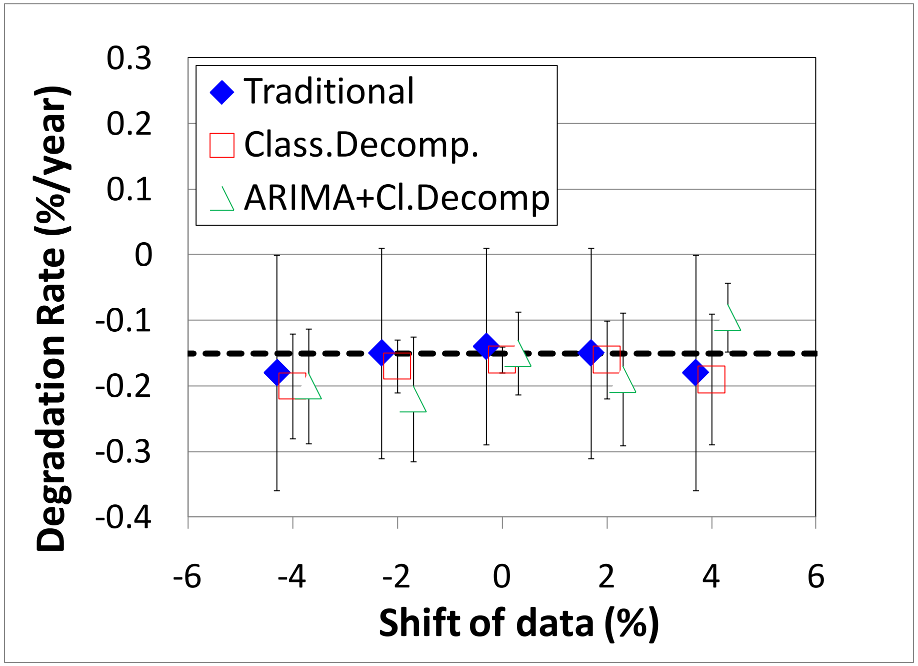
Method:

- Multiply shifted section by a scaling factor
- Plot Residual sum of squares vs. scaling factor

Method to correct Data Shifts

Example: Minimization of Error Sum of Squares of Errors (ESS)

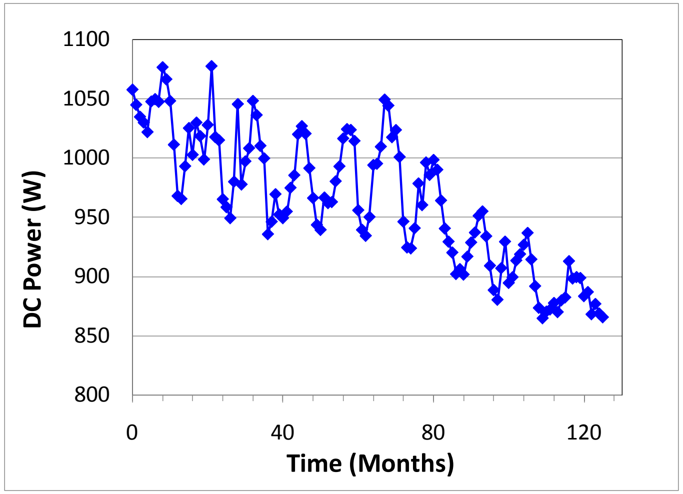




Data shift correction procedure is successful for all 3 approaches.

Data Shift – blind test

Data set with marked hump in the c-12-Month Moving Average



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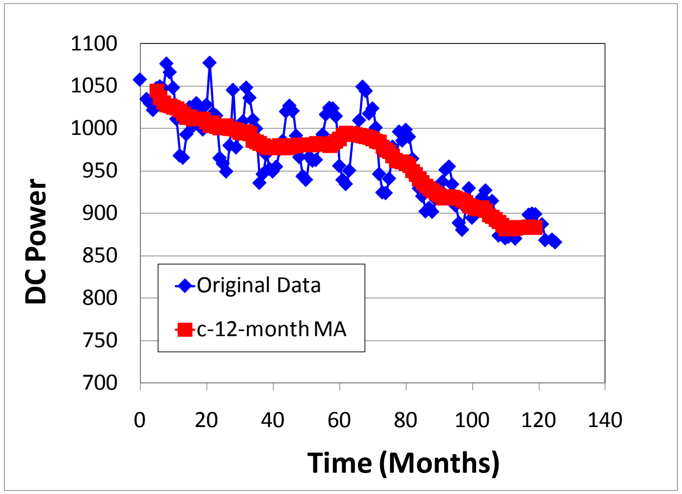

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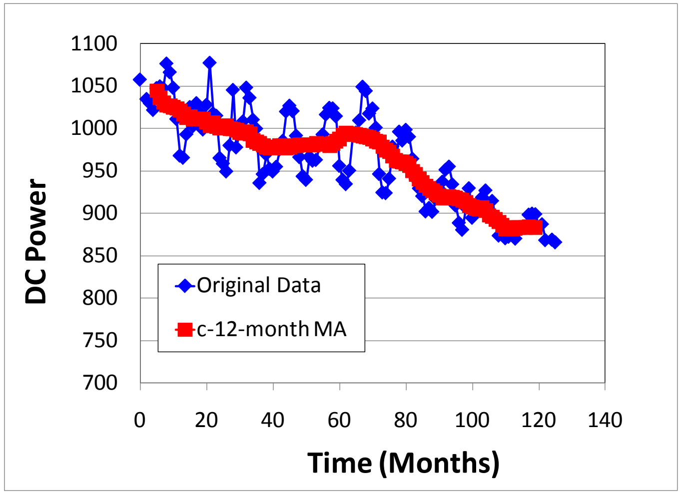
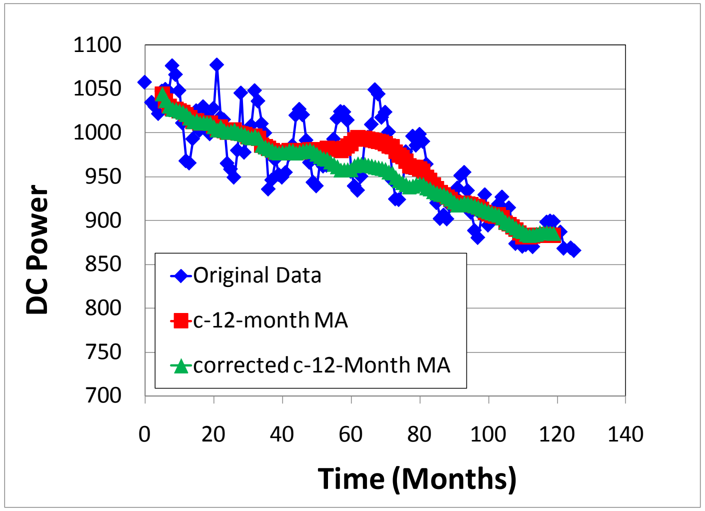


c-12-Month Moving Average after shift correction → no peak anymore



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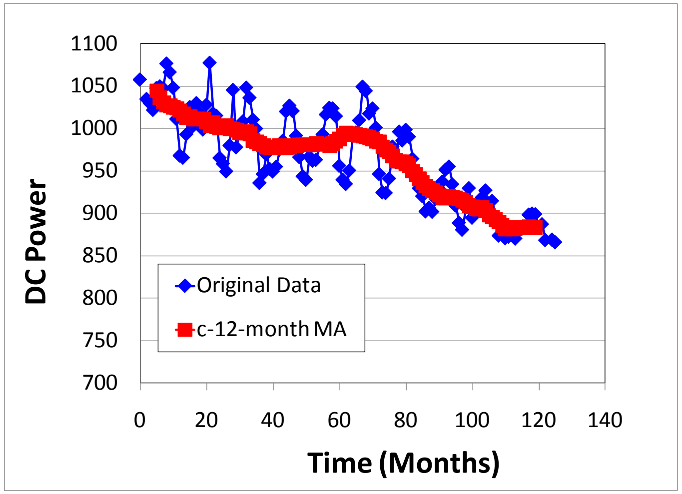

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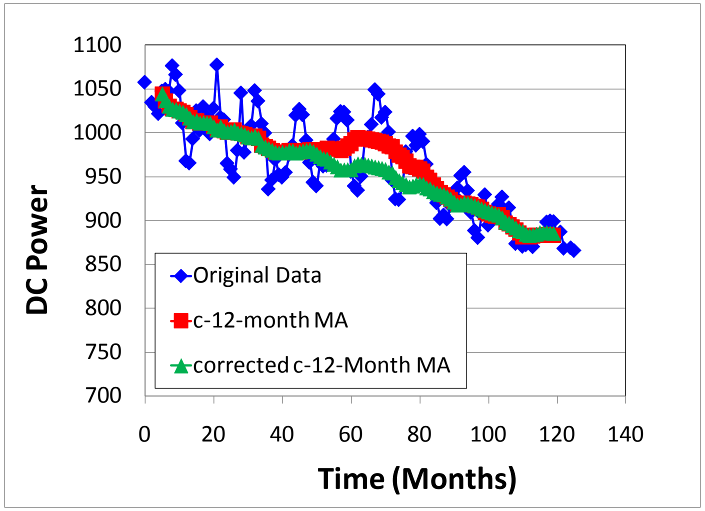


Methodology	Degradation Rate (%/year)	Error
SLS original	1.47	0.12
ARIMA+Classical Decomp.	1.44	0.06
SLS till 81 month (after hump)	0.86	0.24
SLS till 81 month (after hump) corr	1.41	0.22

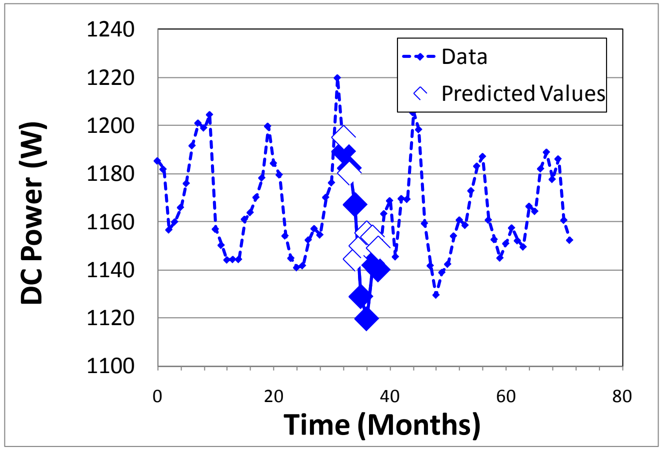
Cause: Ambient temperature sensor was reading erratically and was replaced.

Standard Least Square and ARIMA+Decomposition give the same result for degradation because almost 4 years of good data after shift.

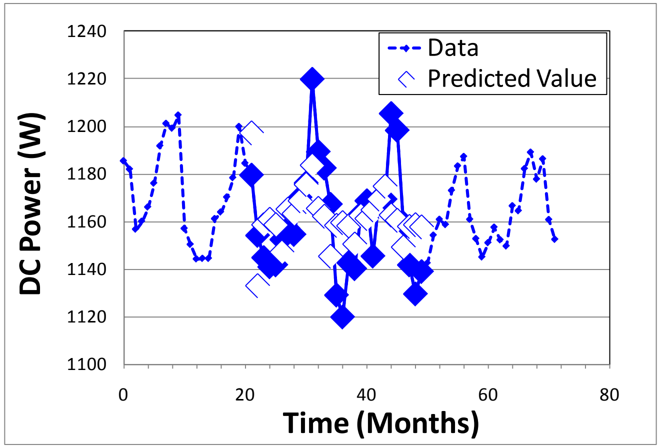
If degradation had been after shift, uncorrected → degradation rate would have been misleading.

ARIMA Modeling and Missing Data

10% missing data



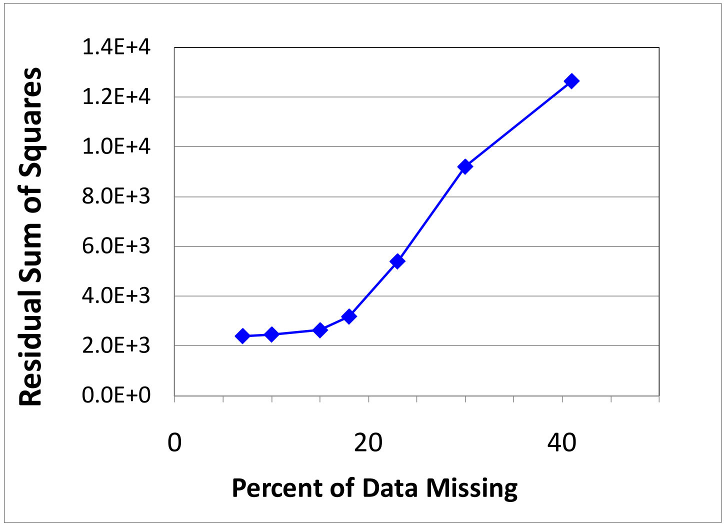
40% missing data



Actual data points: solid diamonds
Modeled points; open diamonds

Procedure:

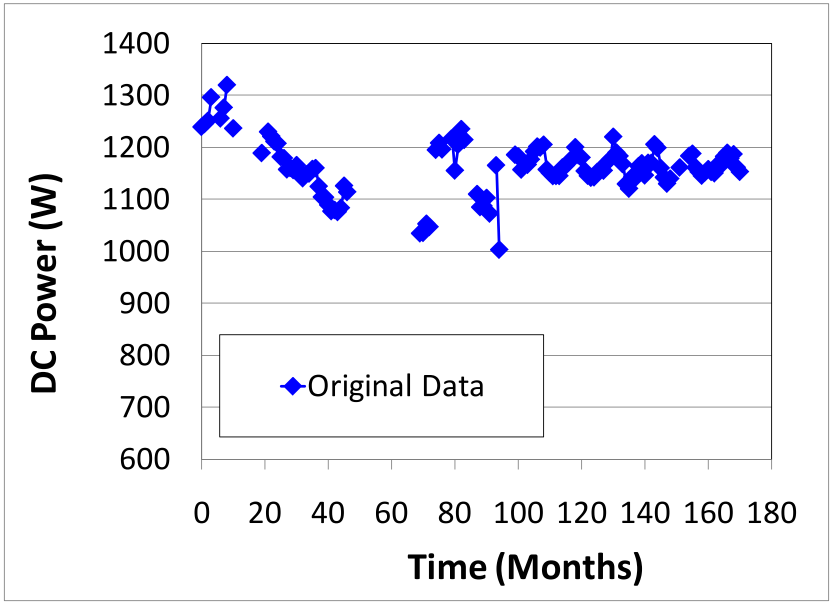
1. Remove x number of data points from time series.
2. Substitute w/ average value
3. Fit ARIMA model and predict missing data points
4. Compare with actual data points



Error does not increase significantly until >20% data missing (i.e. > 1 year of data missing)

Problematic Data Set

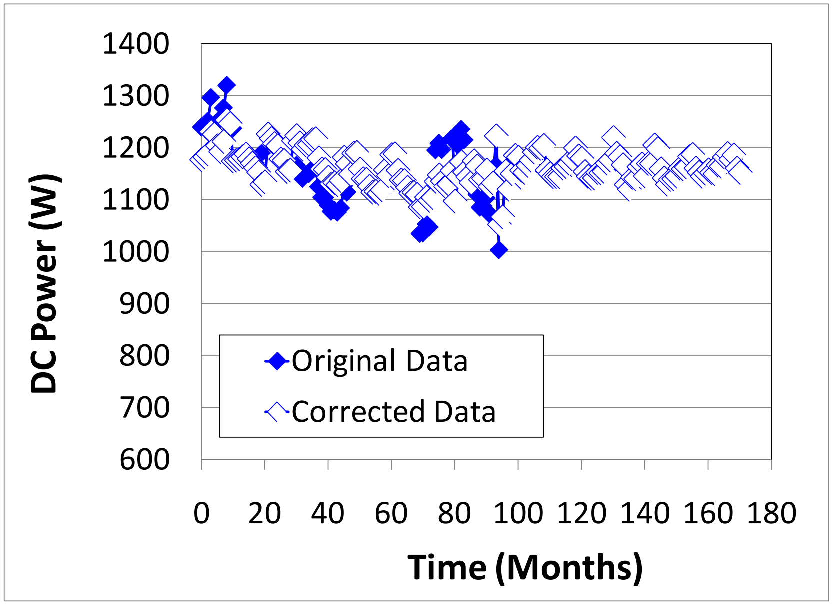
Degradation Rate determination difficult due to Data shifts, outliers & missing data



Data stabilize at > 100 months!

Data Shift - all data

Degradation Rate determination difficult due to Data shifts, outliers & missing data



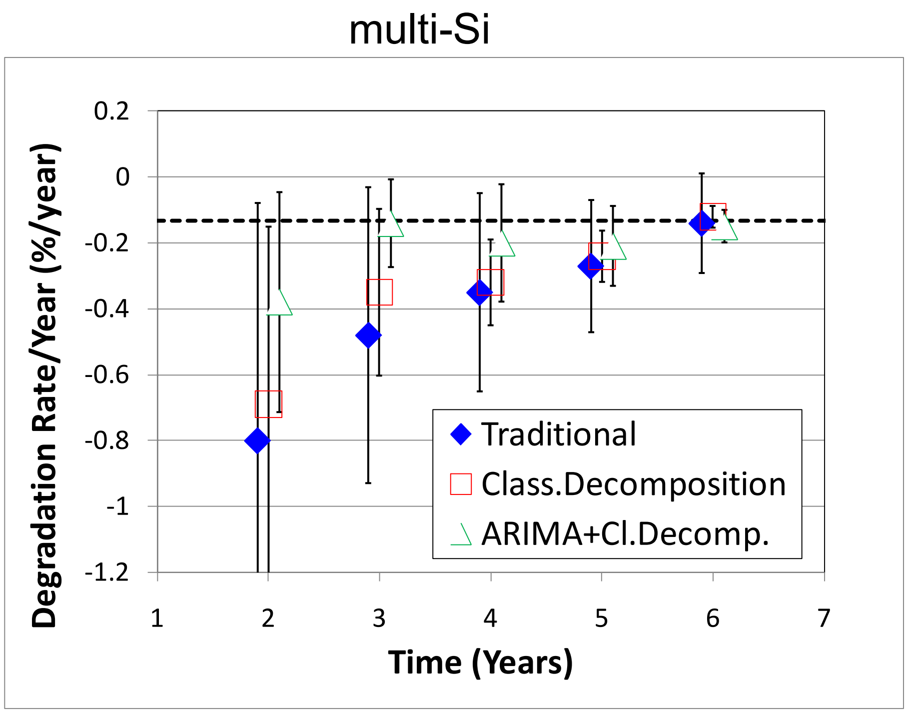
Methodology	Degradation Rate (%/year)	Error
SLS, all data	0.14	0.13
SLS, all data Shift-corrected	0.14	0.07
Class.Decomp. Shift-corrected	0.13	0.07
ARIMA+Class.Decomp Shift-corrected	0.15	0.04

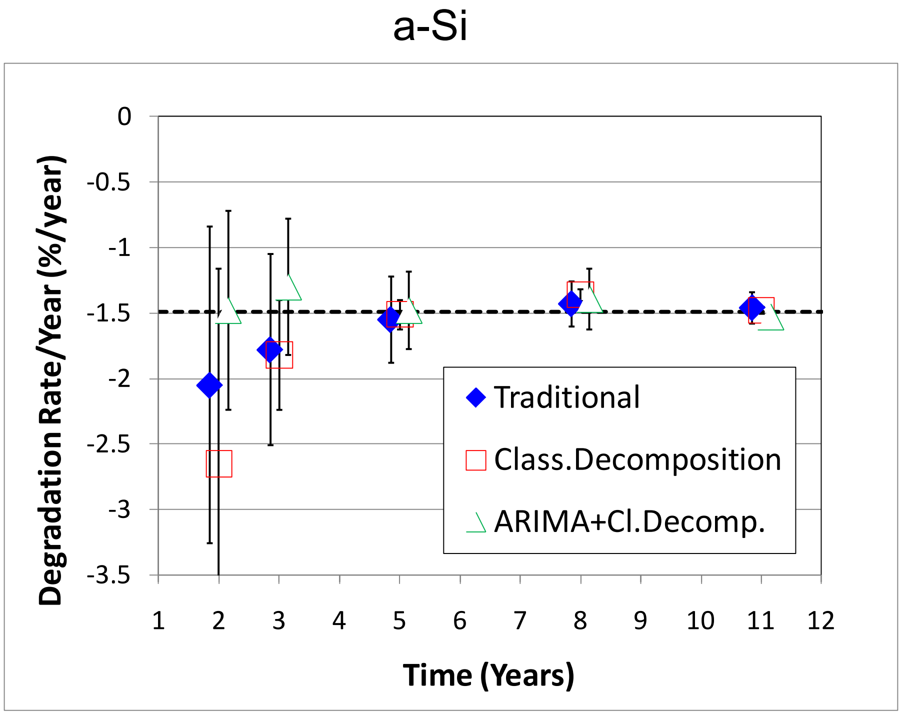
Data stabilize at > 100 months!

All 3 methodologies determine ultimate degradation rate after data are corrected.

Correction procedure enables to determine degradation rate with small enough uncertainty

Degradation Rate in shorter Time



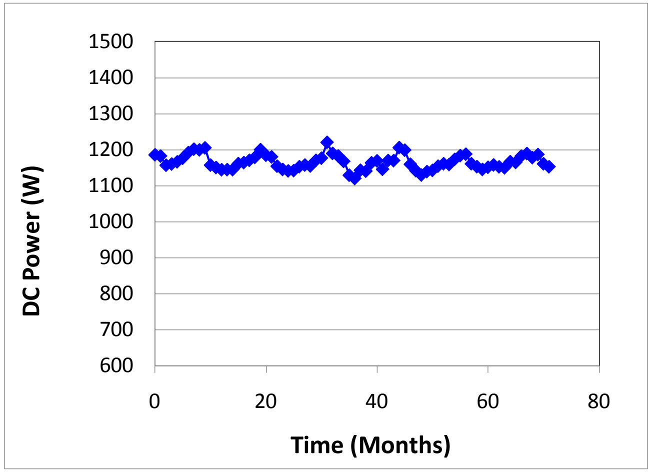


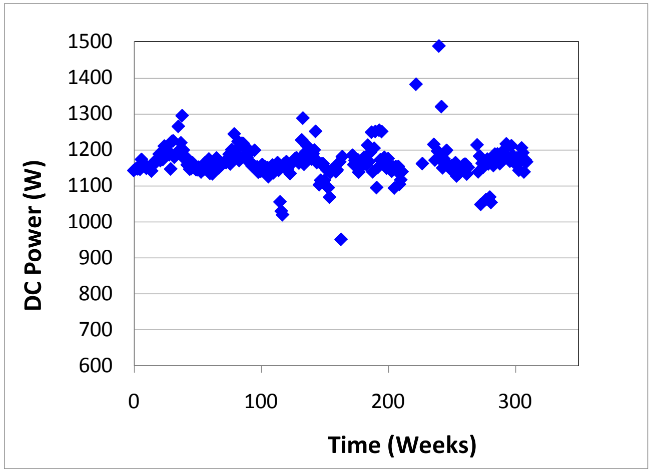
- Degradation rates were calculated for each method starting with the first 2, 3 years etc.
- The a-Si module was in the field for over 6 months before data collection commenced.
- For longer times all three methodologies converge to the same rate.
- Traditional & Cl.Decomp. show increasing bias for shorter time but w/in uncertainty.
- ARIMA approach shows lowest bias close to ultimate degradation rate.

PVUSA – Weekly Intervals

PVUSA Method – multi-crystalline Si

Monthly Intervals



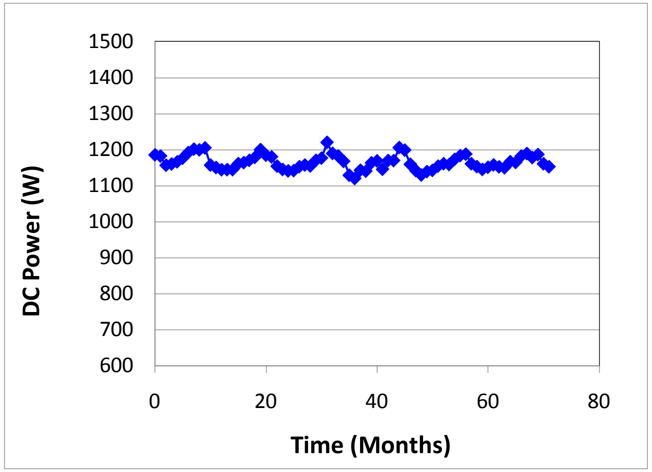


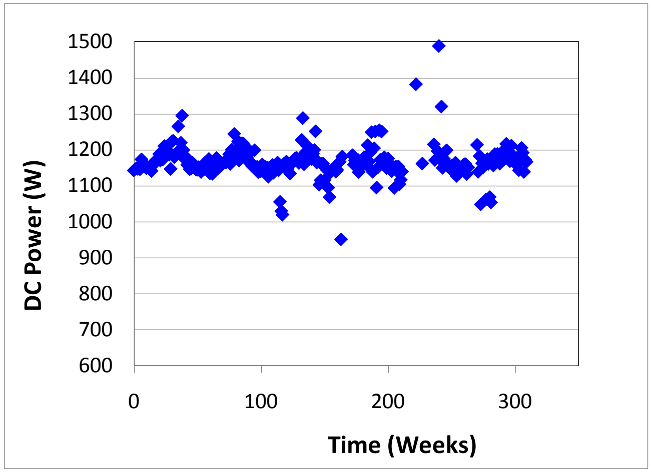
Weekly Intervals

PVUSA – Weekly Intervals

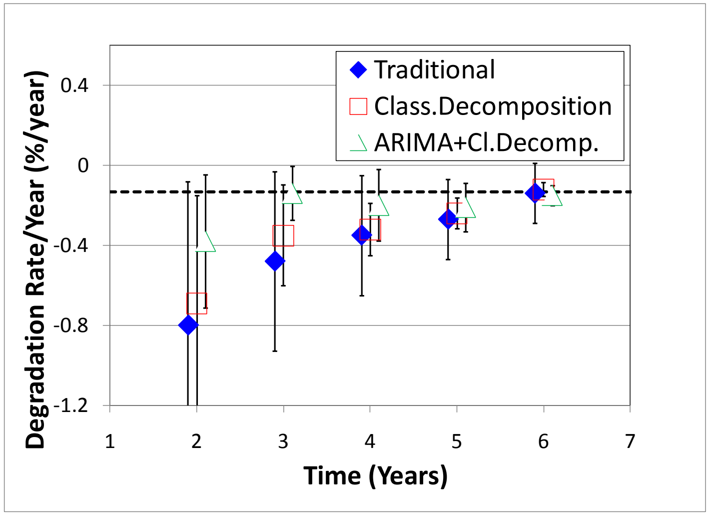
PVUSA Method – multi-crystalline Si

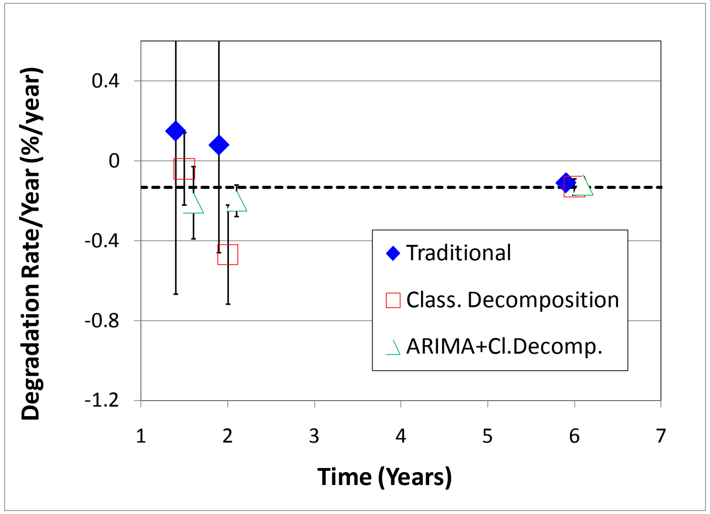
Monthly Intervals





Weekly Intervals





Weekly intervals → more data, degrees of freedom

Conclusion

- Analysis of >40 modules showed why 3-5 years traditionally required to determine R_d
- Introduced 2 new methods to determine R_d (Class.Decomp., ARIMA+Decomp.)
- ARIMA most robust against outliers
- Introduced method to correct data shifts
- ARIMA seems to able to determine R_d more quickly → limited by numbers of degree of freedom → need more data points → sample weekly
- Using shorter time intervals increases noise but holds promise

Conclusion

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"All Models are wrong………but some are useful!"

-- G.P.P. Box