TÜV Rheinland PTL

STATISTICAL LIFETIME PREDICTION FOR PHOTOVOLTAIC MODULES

Joseph M. Kuitche

Arizona State University &
TUV Rheinland PTL
Arizona, United States

ARIZONA STATE UNIVERSITY

TÜV Rheinland PTL

OUTLINE

- Introduction & Scope
- Conventional Approach: Time-To-Failure Analysis
- Degradation Analysis with non-constant model parameters

ARIZONA STATE UNIVERSITY

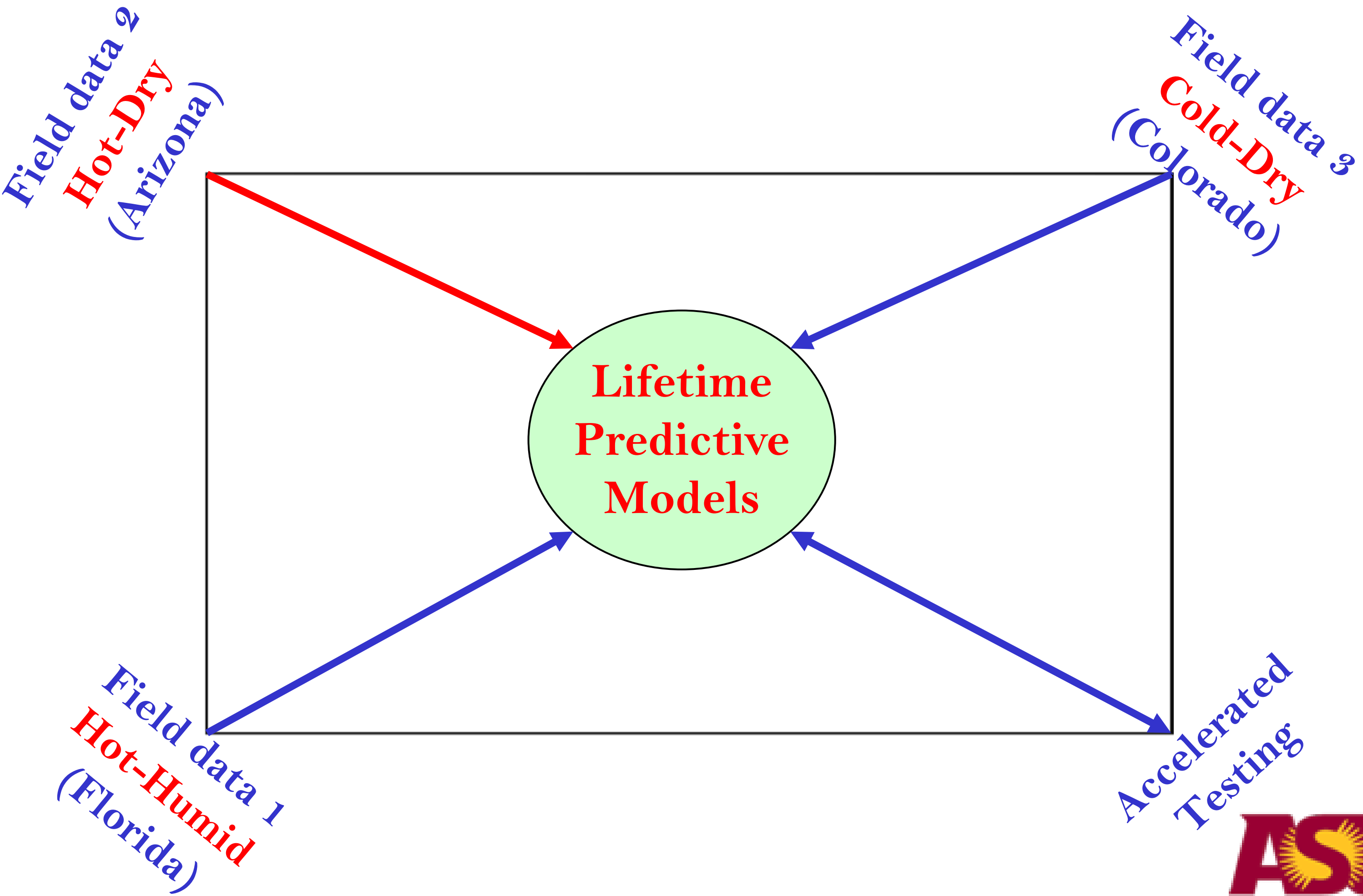
TÜV Rheinland PTL

INTRODUCTION & SCOPE

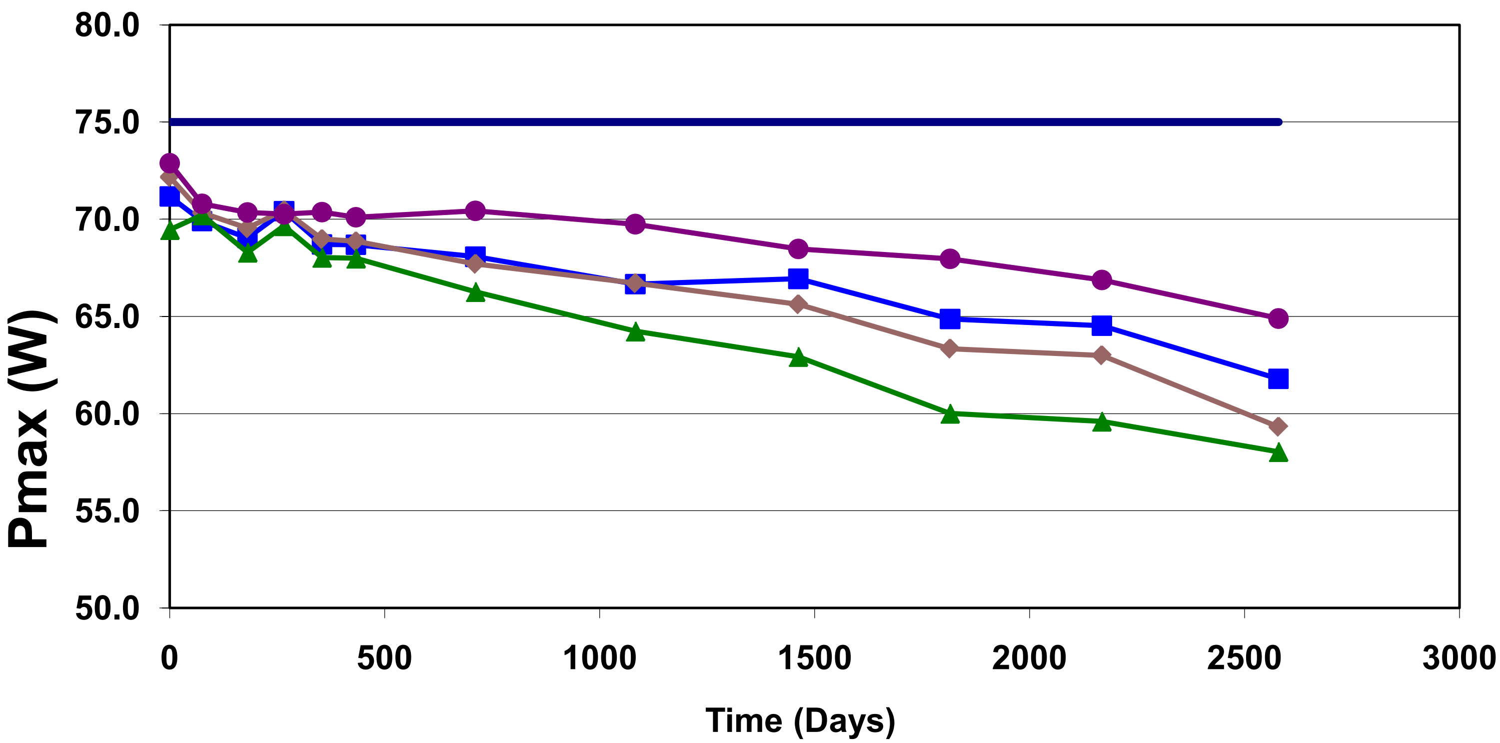
Arizona State University

Our approach to lifetime prediction

- Field data analysis from different climates
- Accelerated test data analysis
- Correlation between field and accelerated data



- The purpose of this presentation is to provide our statistical approach to predicting lifetime of of PV modules undergoing long-term outdoor exposure at TUV Rheinland PTL, located in Tempe, Arizona.
- Two groups of c-Si modules are used: One installed at latitude tilt and the other on a two-axis tracker.
- Both groups have been installed for at least 8 years
- The plot below is an example of the max power output over time as reported.



TÜV Rheinland PTL

TIME-TO-FAILURE ANALYSIS

Arizona State University

TÜV Rheinland PTL

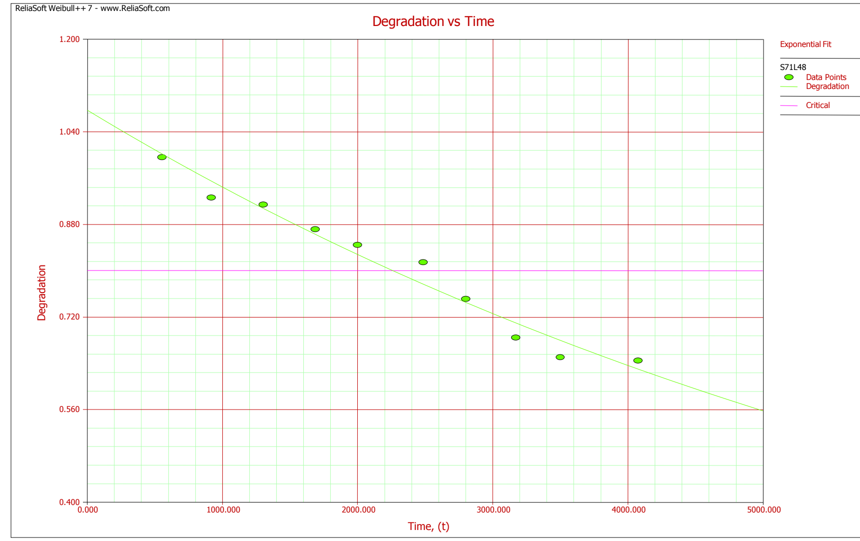
- Sample Power output data for modules installed on a two-axis tracker
- Data are shown as fraction of measured initial power output

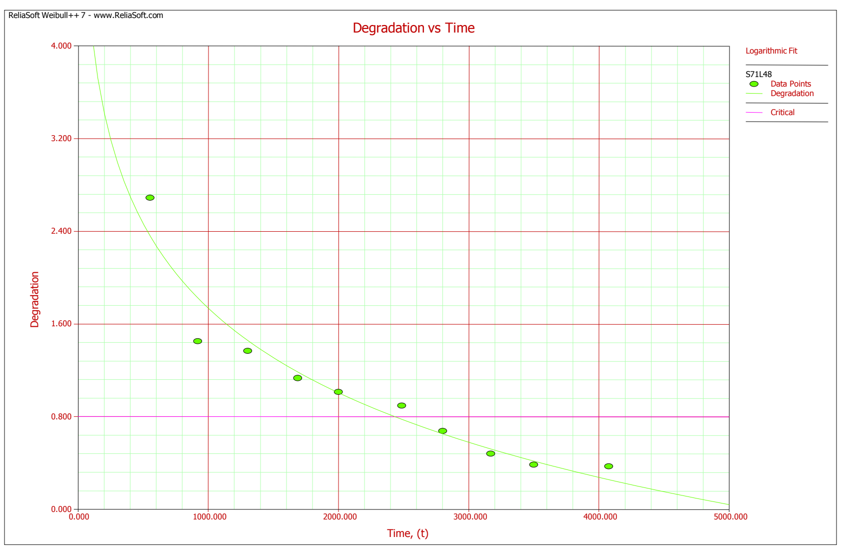
Test Date	S70L45	S72L46	S73L47	S71L48
9/24/1998	100	100	100	100
3/23/1999	98.13371	97.99541	98.08094	99.05143
3/29/2000	98.56707	98.30695	98.13213	99.64207
3/30/2001	96.17613	95.50743	99.06003	92.65495
4/18/2002	95.99587	93.96017	97.29334	91.41772
5/7/2003	94.70425	91.75761	97.08592	87.15466
3/16/2004	92.98966	88.53482	95.50054	84.47388
7/14/2005	86.65919	88.54046	93.44639	81.48294
5/25/2006	76.14737	77.13774	88.38811	75.11946
5/29/2007	69.60249	71.62216	82.89079	68.44898
4/23/2008	69.07595	72.03201	83.63877	64.46939
11/20/2009	58.31153	63.49378	76.61548	65.06237

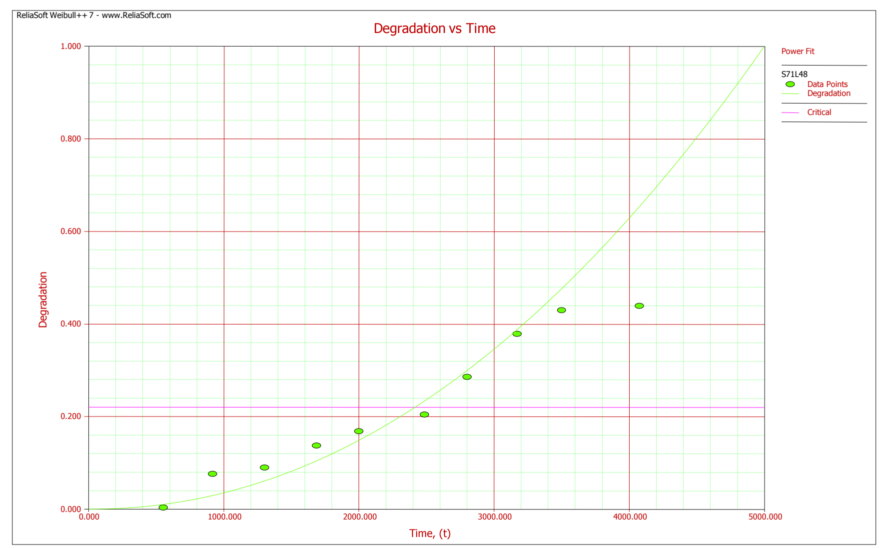
Arizona State University

From Degradation to TTF Data

- Mathematical models (Linear, exponential, power, and logarithmic) were used on each unit of test to extrapolate the degradation measurements to the defined (80%, 50%) failure level
- Time-to-failure (TTF) of each unit was estimated from the best fit.
- These failure times can now be used for reliability estimations







Extrapolated TTF at 80% degradation

Samples at Latitude tilt		Samples on the Tracker	
Unit	Failure time (years)	Unit	Failure time (years)
3801	33.41386	S64L38	8.270246
4821	26.93645	S66L40	48.78274
DG22	25.60665	S67L39	9.783445
DG822	20.84669	S68L37	9.667831
RA240	32.01457	S70L41	8.06494
		S70L45	7.041274
		S71L44	11.47928
		S71L48	6.419939
		S72L42	8.141393
		S72L46	7.273979
		S73L43	7.866981
		S73L47	10.91259

Fitting the TTFs to a distribution

Three types of statistical failure (distribution) models are generally appropriate for PV reliability analysis:

- Exponential distribution

$$f(t) = \lambda e^{-\lambda t}$$

- Weibull distribution

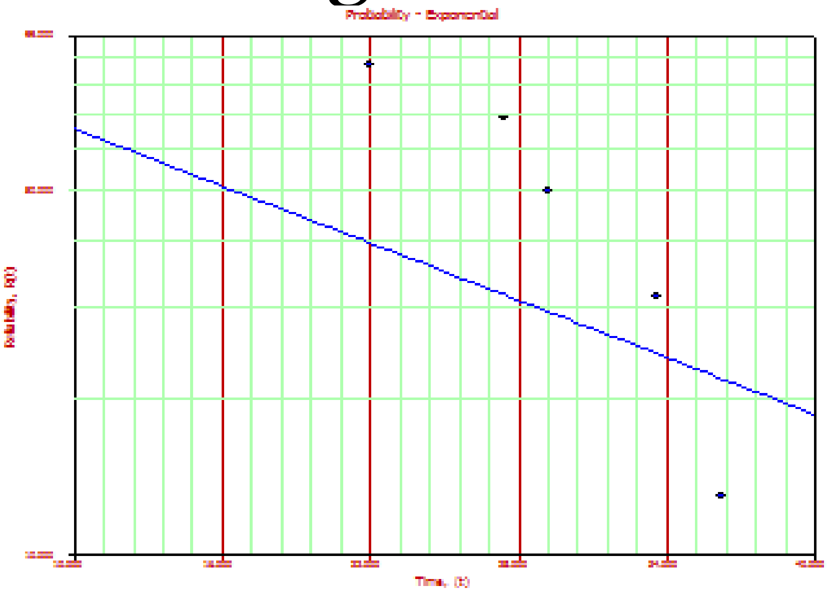
$$f(t) = \frac{m}{c}\left(\frac{t}{c}\right)^{m-1} e^{-\left(\frac{t}{c}\right)^{m}}$$

- Lognormal distribution

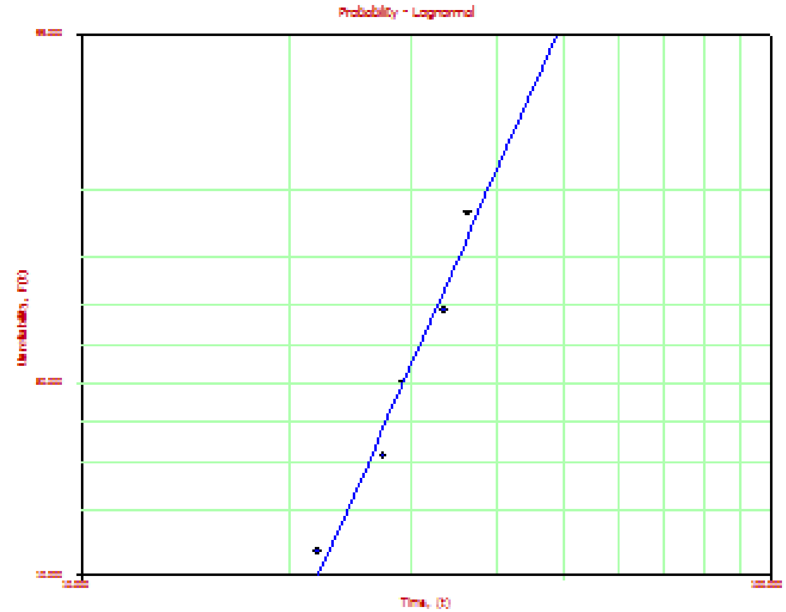
$$f(t) = \frac{1}{\sigma t\sqrt{2\pi}} e^{-\left(\ln t - \ln T_{50}\right)^2 / 2\sigma^2}$$

To determine what distribution will adequately represent the data, we used graphical methods. This consists of linearizing the above functions and plot the relevant quantities.

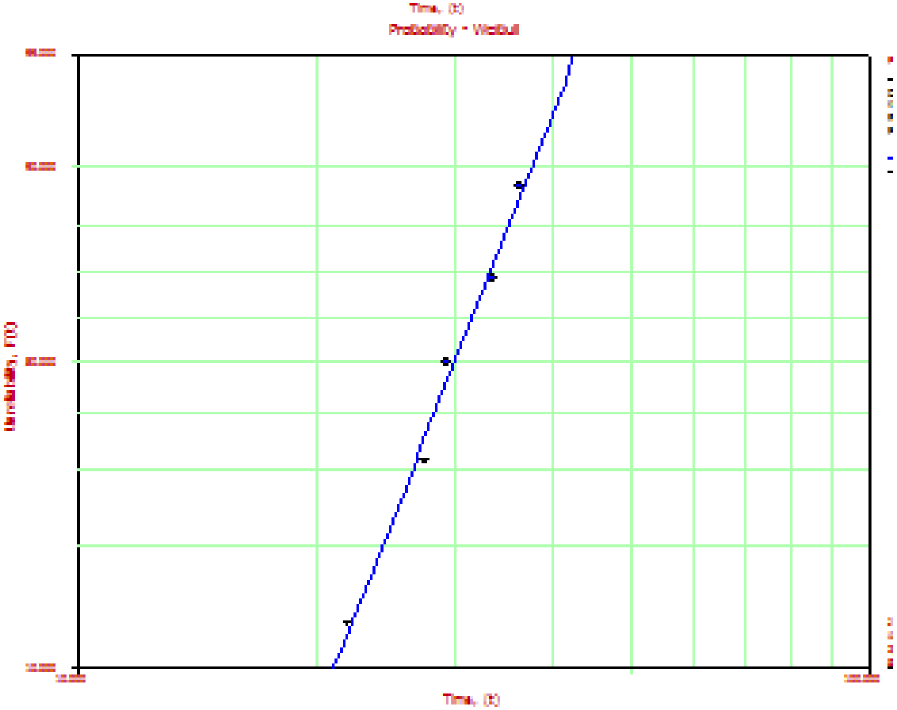
Fitting the TTFs of the fixed latitude data



Exponential distribution

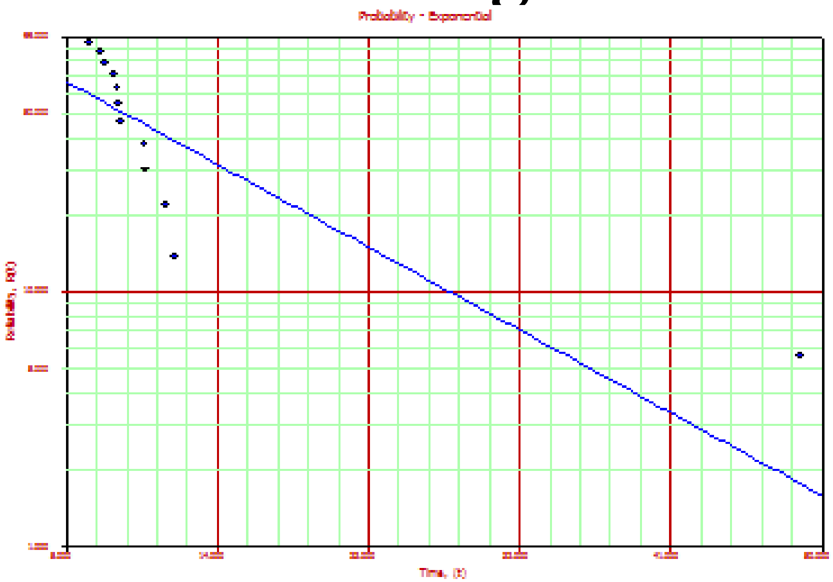


Lognormal distribution

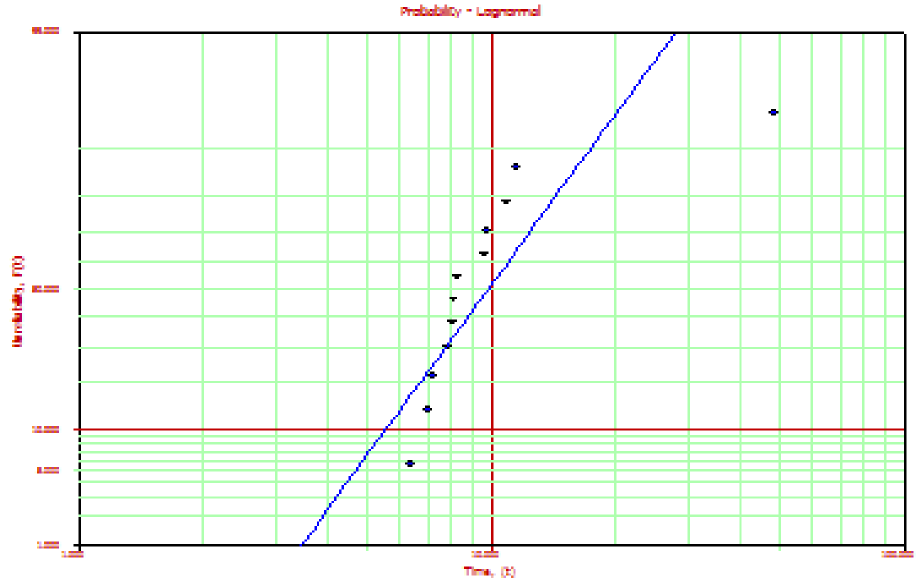


Weibull distribution

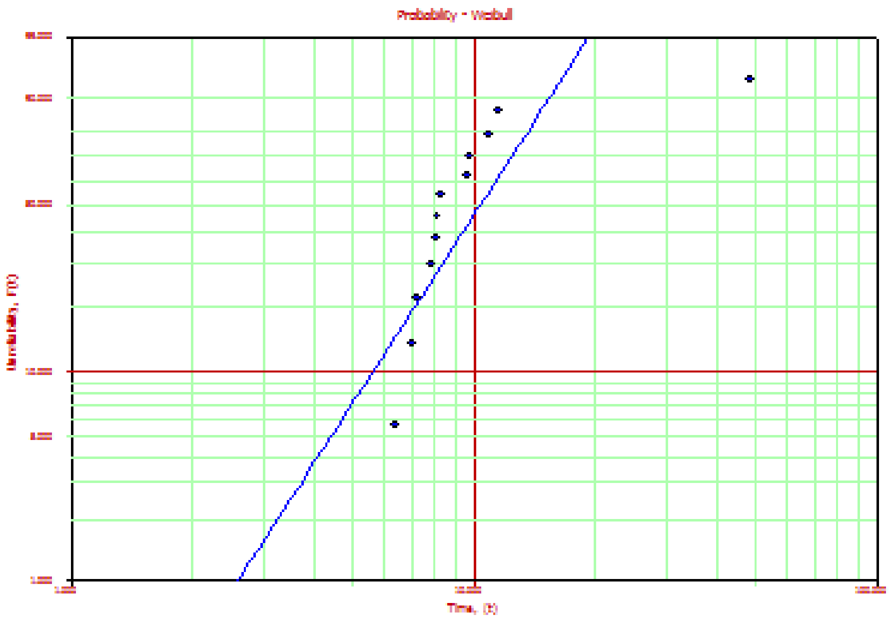
Fitting the TTFs of the tracker data



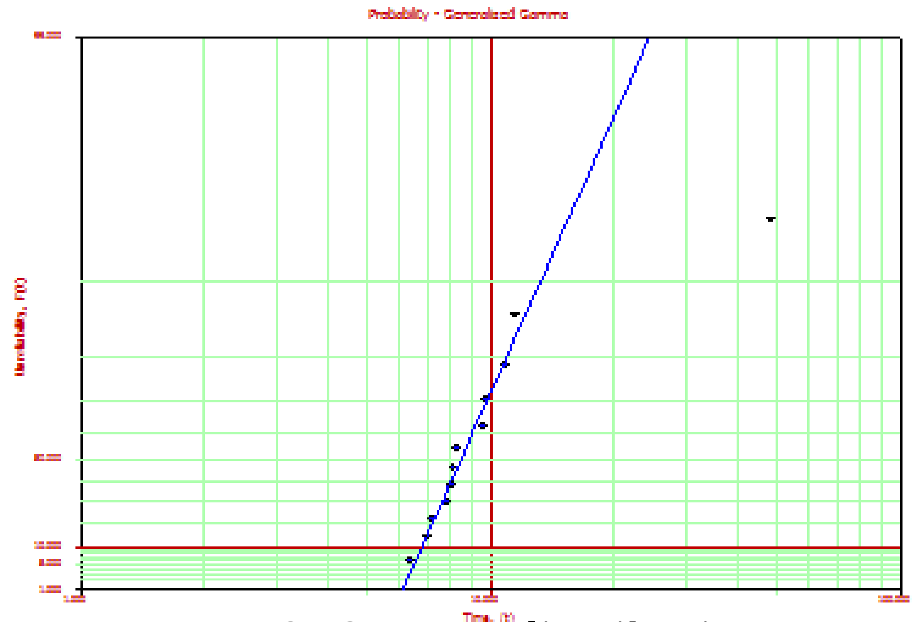
Exponential distribution



Lognormal distribution

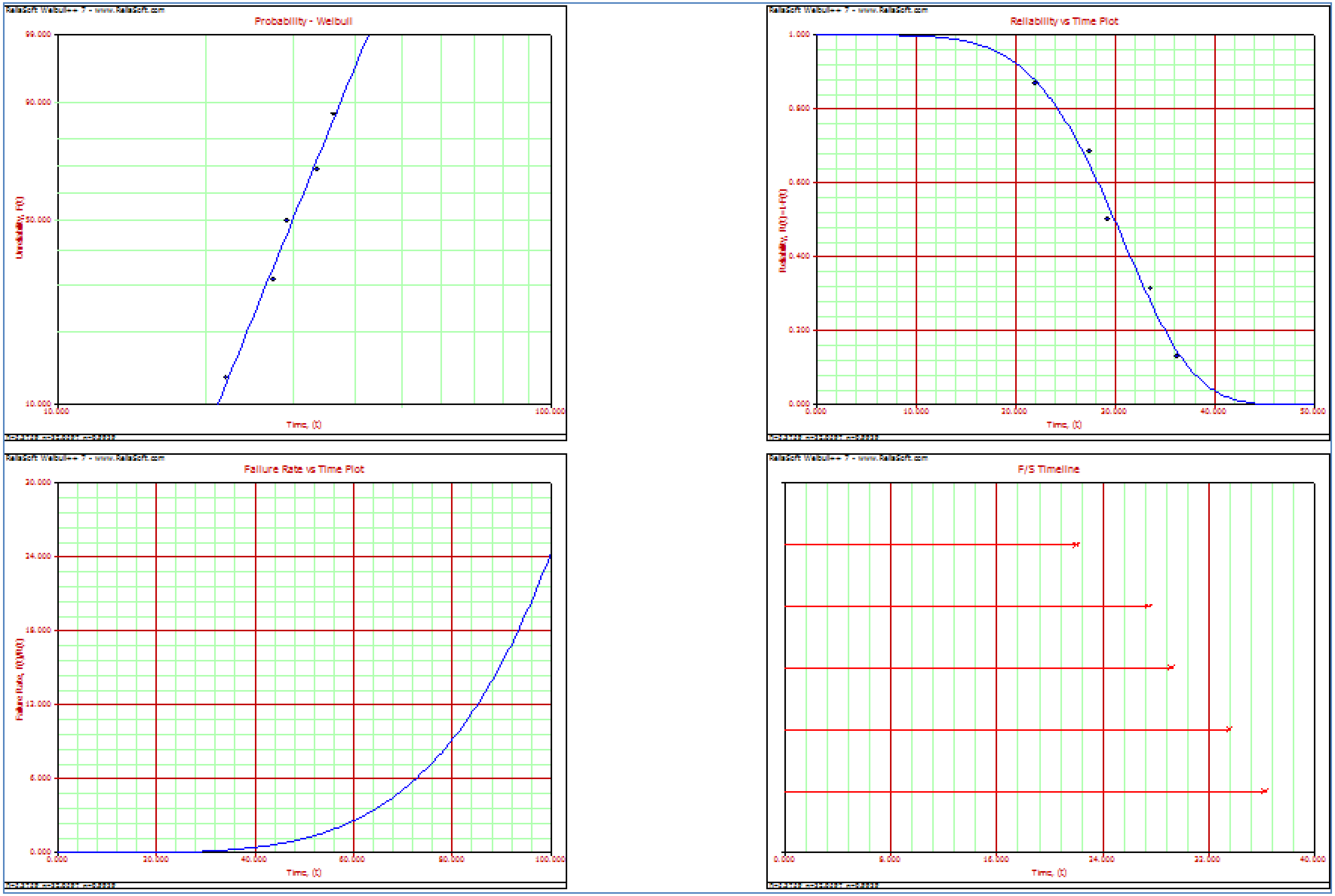


Weibull distribution



G-Gamma distribution

Analysis of fixed latitude data



Analysis of fixed latitude data

- The 2-parameter Weibull distribution was selected
- The output below was obtained from Weibull++7 software

	Value	Lower Bound	Upper Bound
Beta (m)	5.3759	3.3	8.7484
Eta (c)	32.0597	28.5706	35.975
Mean Life	29.5591	25.2656	34.5821
Failure Rate	24.3424	0.2683	2208.7097

- A module from that batch would need an average of 29 years before seeing its power output drop below 80%
- An average of 24 of those samples are expected to fail per year

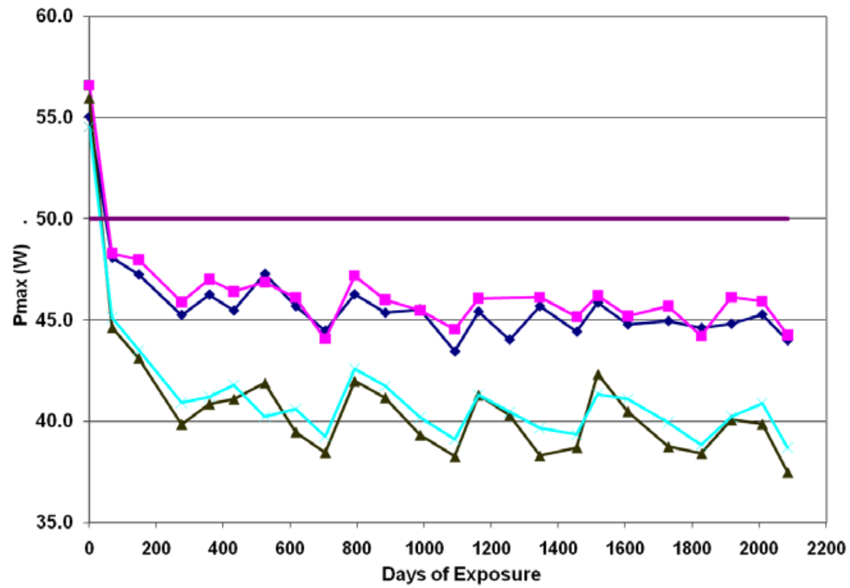
TÜV Rheinland PTL

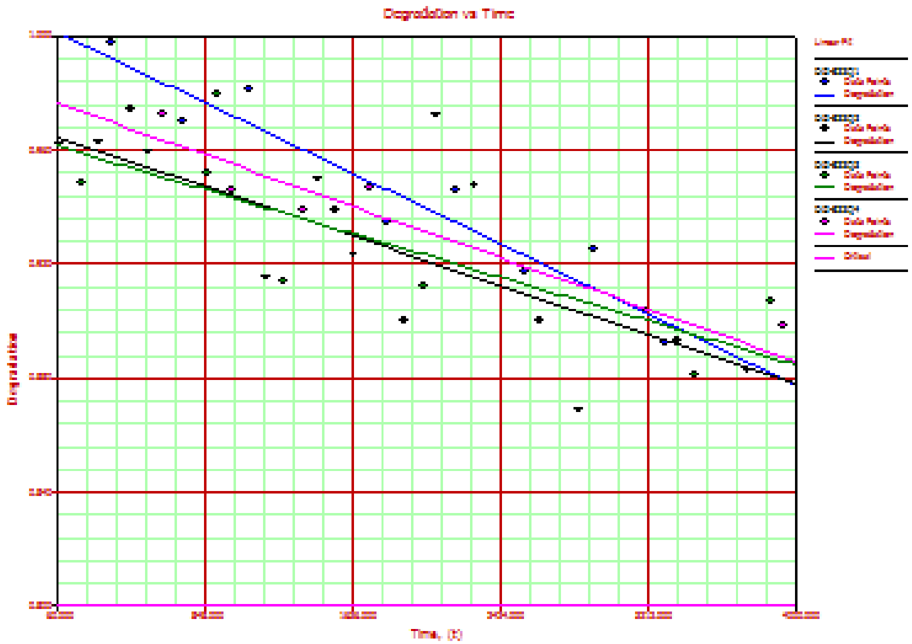
DEGRADATION ANALYSIS WITH NON-CONSTANT MODEL PARAMETERS

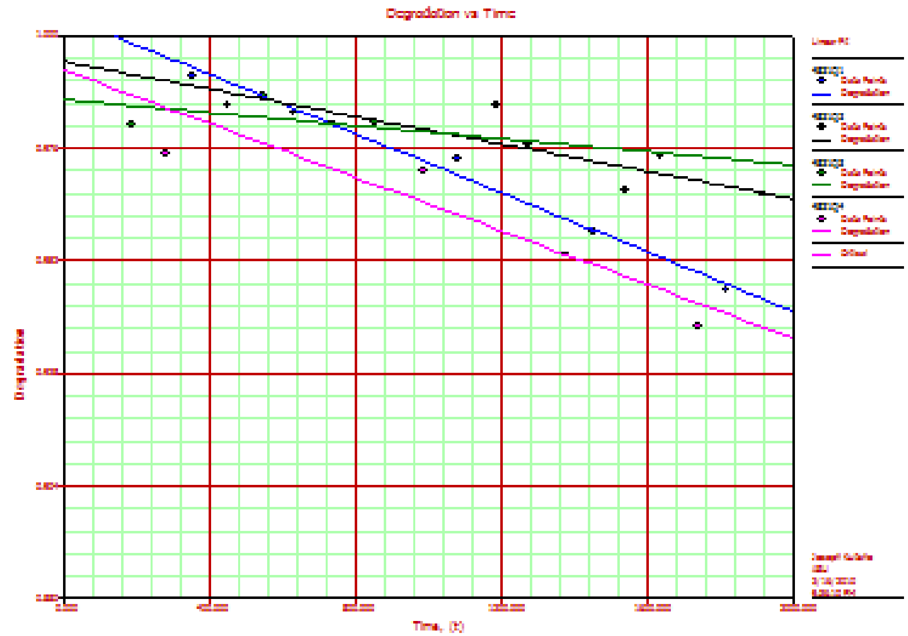
ARIZONA STATE UNIVERSITY

Non-linear degradation of PV Modules

- PV modules degradation is not really linear
- Such behavior makes it difficult to use the approach just described to adequately model module degradation
- The two figures below show how modules behave by quarters.







Accounting for Environmental Variables

- PV degradation analysis must account for environmental effects
- Assuming an end-of-life criterion of 50%
- Let R be the likelihood that an item is still functioning at time t;

  i.e. degradation of power output < 50%

  R = Pr [fraction of initial Pmax > 0.5]
- We make the following assumptions:

R = fraction of initial power if > 0.5;

= 0 otherwise

Non-Constant parameters approach

- Fit the data to a mathematical model → choose a distribution.
- The fraction of power output can be written as a function of that model, with non-constant parameters; say, a & b
- The parameters of the model above are function of environmental parameters

  a, b = f(Insolation, Tambient, RH, WS, etc.);

  $(\text{insolation, Tambient, RH, WS, etc.})_i$ = environmental cell i
- From the weather data, define a "typical day" of a month as a series of x hours period.

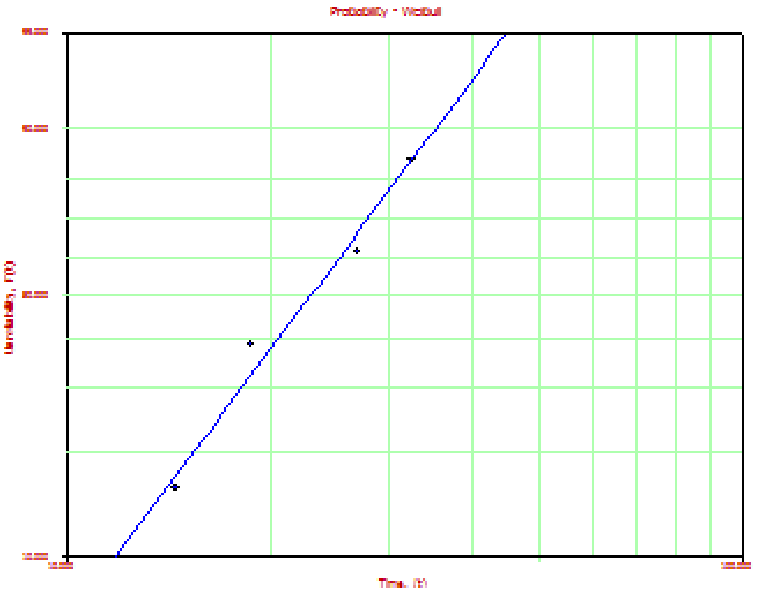
Non-Constant parameters approach

	1006	1012	4425	4510	Days	Average R	ln (1/R)	Month
4/9/2004	0.840257667	0.83049	0.73012	0.75569	359	0.789139	0.23681	A
4/12/2006	0.78911445	0.78723	0.68367	0.71686	1092	0.74422	0.29542	A
4/11/2007	0.806853207	0.79791	0.69166	0.72138	1456	0.754453	0.28176	A
4/17/2008	0.810279984	0.78122	0.68636	0.71219	1828	0.747514	0.291	A
12/23/2004	0.829707377	0.81488	0.70536	0.74428	617	0.773555	0.25676	D
12/29/2005	0.826896293	0.80344	0.70281	0.73692	988	0.767515	0.2646	D
12/21/2006	0.829814596	0.81501	0.68434	0.72719	1345	0.764091	0.26907	D
12/30/2008	0.799022942	0.78191	0.66973	0.7096	2085	0.740065	0.30102	D
6/24/2003	0.873406436	0.85342	0.79745	0.82749	69	0.837942	0.17681	J
6/21/2004	0.825861406	0.82025	0.73449	0.76658	432	0.786798	0.23978	J
6/16/2005	0.840483675	0.83395	0.75017	0.78105	792	0.801412	0.22138	J
6/21/2006	0.824962664	0.8139	0.73793	0.75718	1162	0.783494	0.24399	J
6/13/2007	0.832947475	0.81657	0.75642	0.75829	1519	0.791058	0.23438	J

Non-Constant parameters approach

- The data were found to best fit a Weibull
- Thus, ln(1/R) can be defined by a power function

  $Ln(1/R) = bt^{a}$
- The fit yields the parameters (a, b) showed in table



Test Month	Parameter a	Parameter b	Avge Max Tamb
A	0.1298	0.112	35.03
D	0.12	0.113	24.95
J	0.095	0.122	43.02
S	0.114	0.113	41.03

- Average Max Tamb obtained from weather data
- For simplicity, we consider only thermal effect; i.e. (a,b)=f(Tamb)
- Assuming a linear relationship with natural temperature:

$(a, b) = C_1 + C_2/T$

Non-Constant parameters approach

- The data were found to best fit a Weibull
- If a is constant, we have for a day:

  $Ln(1/R) = [b_{7-9}^{(1/a)}(2/24) + b_{9-11}^{(1/a)}(2/24) + \ldots]^a$

- We can now predict over a given time frame.

Parameter	C2	C1
a	126.94	-0. 295
b	-31.8	0.218

Typical Day	7a - 9a	9a - 11a	11a - 1p	1 - 3 p	3 - 5p
Avge Max Temp	20.87	39.37	50.65	50.12	43.7
$b = C1+C2/T$	0.109842813	0.11626	0.11981	0.11965	0.11766
$b_i^{(1/a)}$	5.39131E-09	8.8E-09	1.1E-08	1.1E-08	9.7E-09
$Ln(1/R) = [Sum(\ldots)]^a *(kt)^a$					

Thanks for Your Attention!