

PV Plant Variability, Aggregation, and Impact on Grid Voltage

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SunEdison, Belmont, California

PV Grid Integration Workshop
19 April, 2012

MEMC
TECHNOLOGY IS BUILT ON US



SunEdison Overview

We develop, build, finance, and operate turnkey solar power plants to provide our customers electricity at predictable and competitive prices.

One of the largest solar energy service providers in the world

- Over 600 solar power plants, built, financed, and/or under O&M
- ~600 MW of 100% renewable electricity installed
- One of the Europe's largest utility scale solar plants (70 MWp)

Demonstrated track record with financial institutions

- Over \$2.5bn in financing experience
- Ground-breaking \$1.5 billion fund with private equity investor, First Reserve
- Systems operating at 100% of underwritten investment

Pioneer provider of solar systems and services

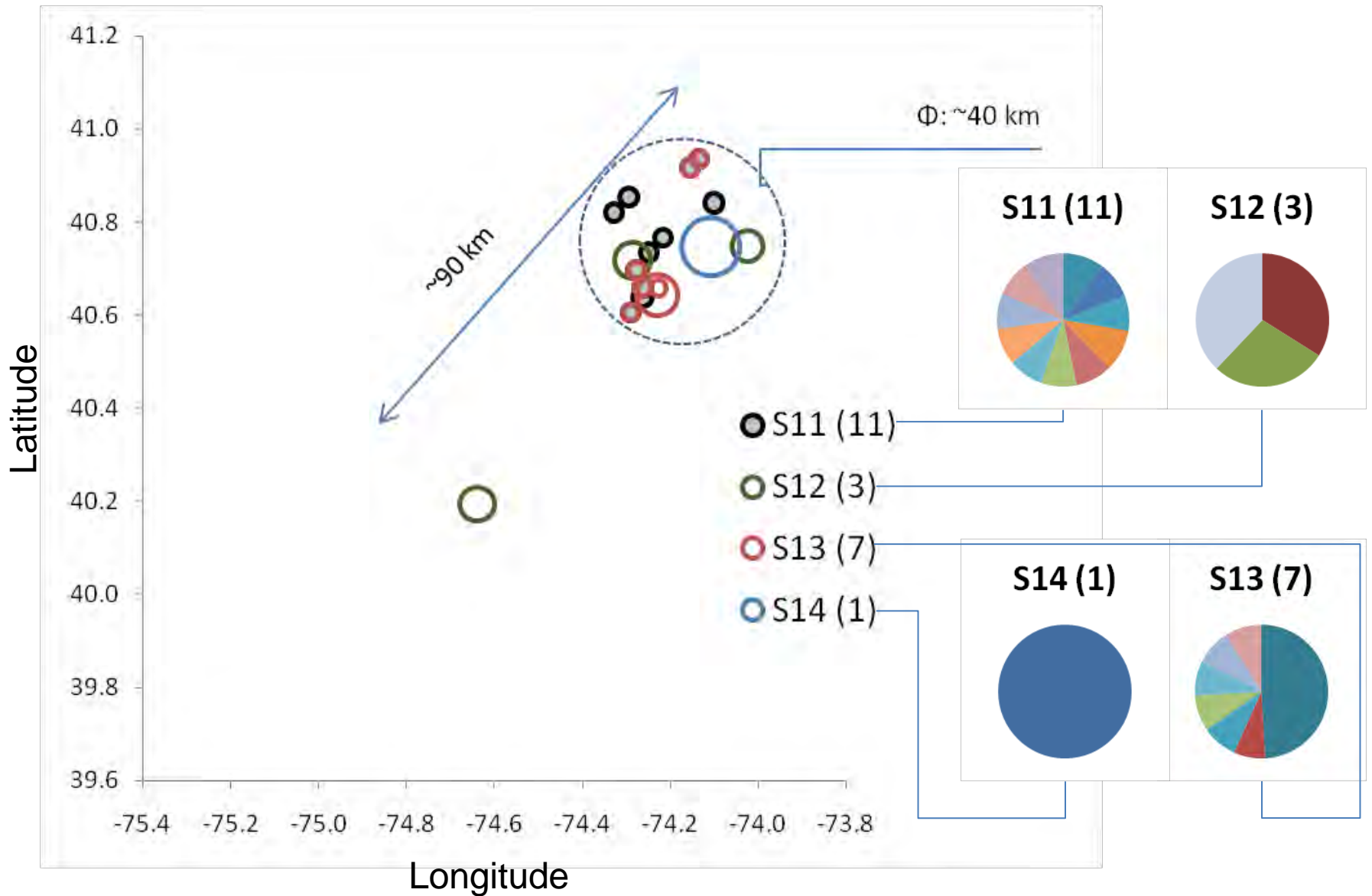
- Founded in 2003 to make solar energy a competitive alternative
- First to provide solar PPA - commercial turnkey solar power plants



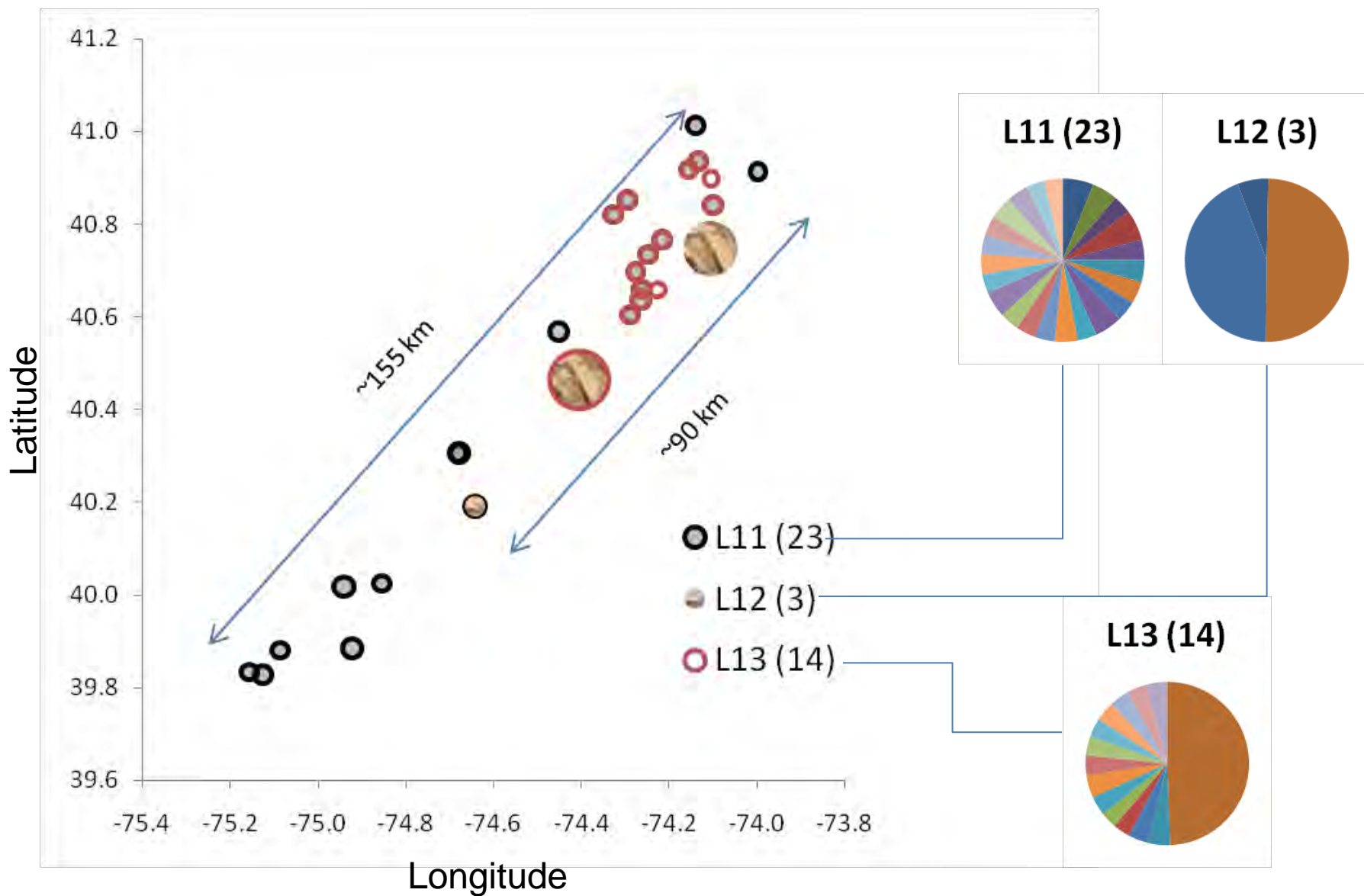
Rationale

- Real-world examples of variability metrics
 - across an extended period (11-months: Sep 1, 2010 – Jul 31, 2011)
 - across different time-scales (1-, 10-, 60-minutes)
 - based on peak production hours (10:00 – 14:00 local standard time)
- Impact of fleet composition on the variability metrics
- Potential impact on grid planning/operating reserve
- Output variability of large utility scale solar plants
- PV output variability and grid voltage

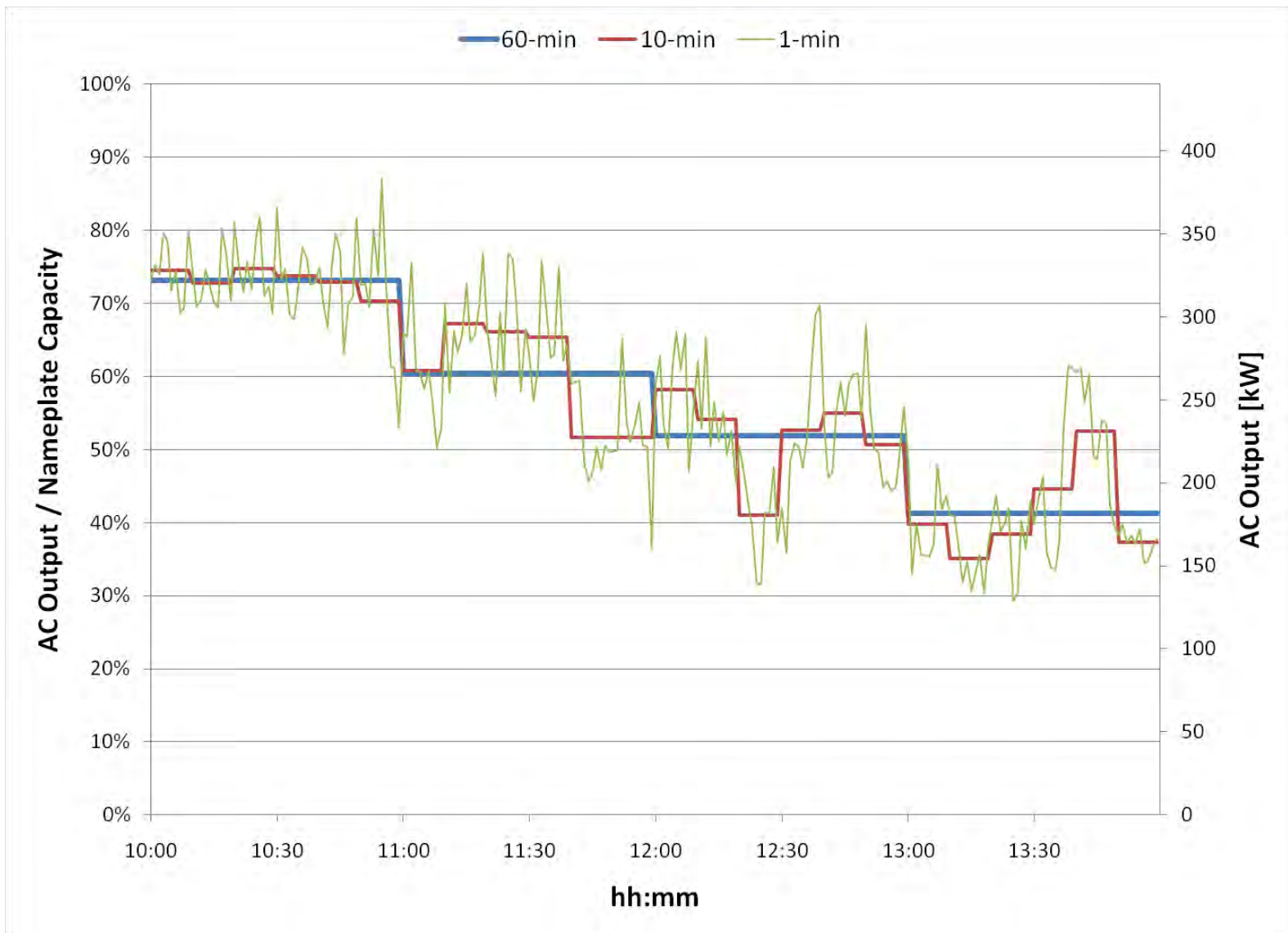
PV system map – small ensembles (~440 kWp)



PV system map – large ensembles (~1000 kWp)



Measured AC output aggregated over 11 systems (2011-04-29)



Variability metrics

Goal:

Characterize the distribution of step changes in power output

$$\Delta P = P(t+\Delta t) - P(t)$$

– Δt : 1, 10, 60 minutes

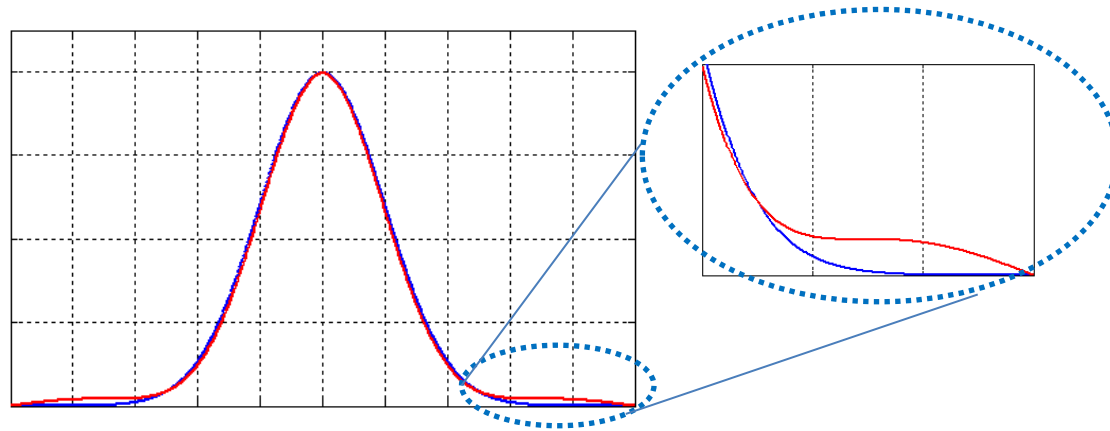
- Standard deviation of step changes
 - Most common metric
 - Intuitive but of limited practicality
- **$\kappa_{3\sigma}$: likelihood of extreme events compared to normal dist.**

$$\kappa_{3\sigma} = \frac{99.7^{\text{th}} \text{ percentile}}{\sigma}$$

- **Maximum step change for a given probability**
- **Probability of exceeding a ramp rate threshold**

High-frequency step changes exhibit longer tails

- The distribution of step changes in the output of a PV plant is not normal:
 - Its tails contain more events than the tails of a normal distribution

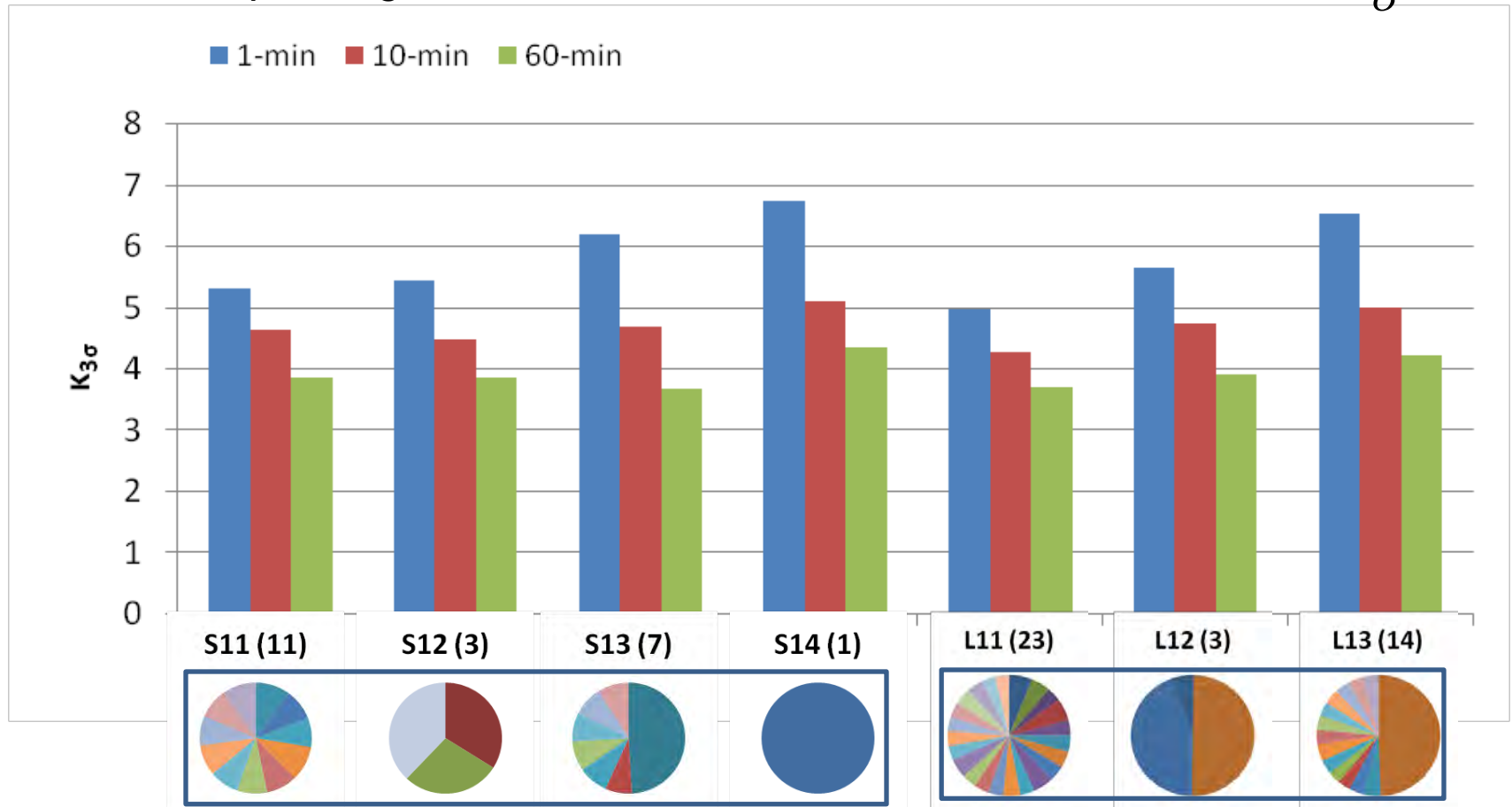


- Widely distributed fleets => fewer “extreme” events

Is the standard deviation of step changes a practical metric?

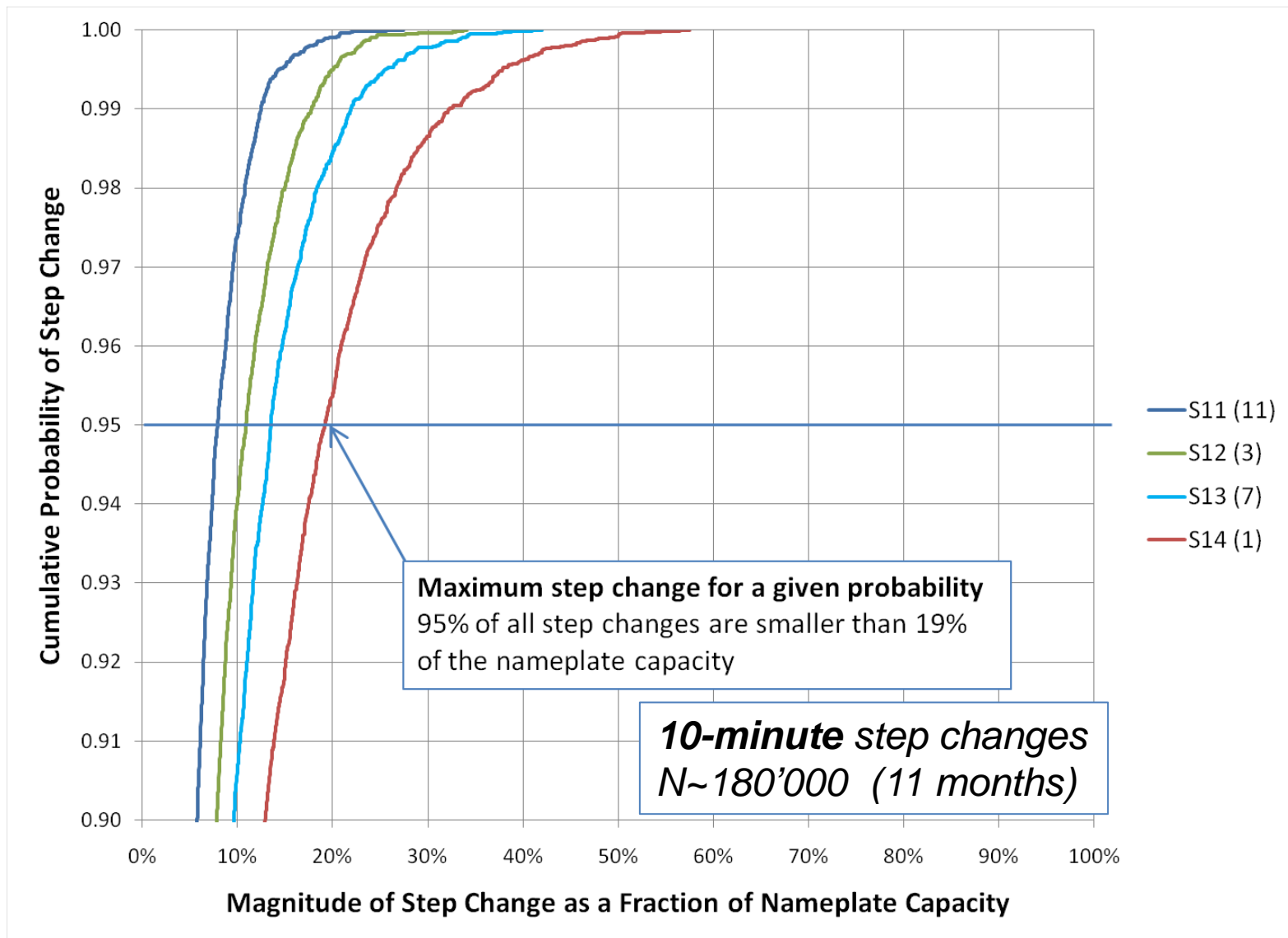
$K_{3\sigma} > 3$ means that a $\pm 3\sigma$ interval contains fewer than 99.7% of step changes

$$K_{3\sigma} = \frac{99.7^{\text{th}} \text{ percentile}}{\sigma}$$

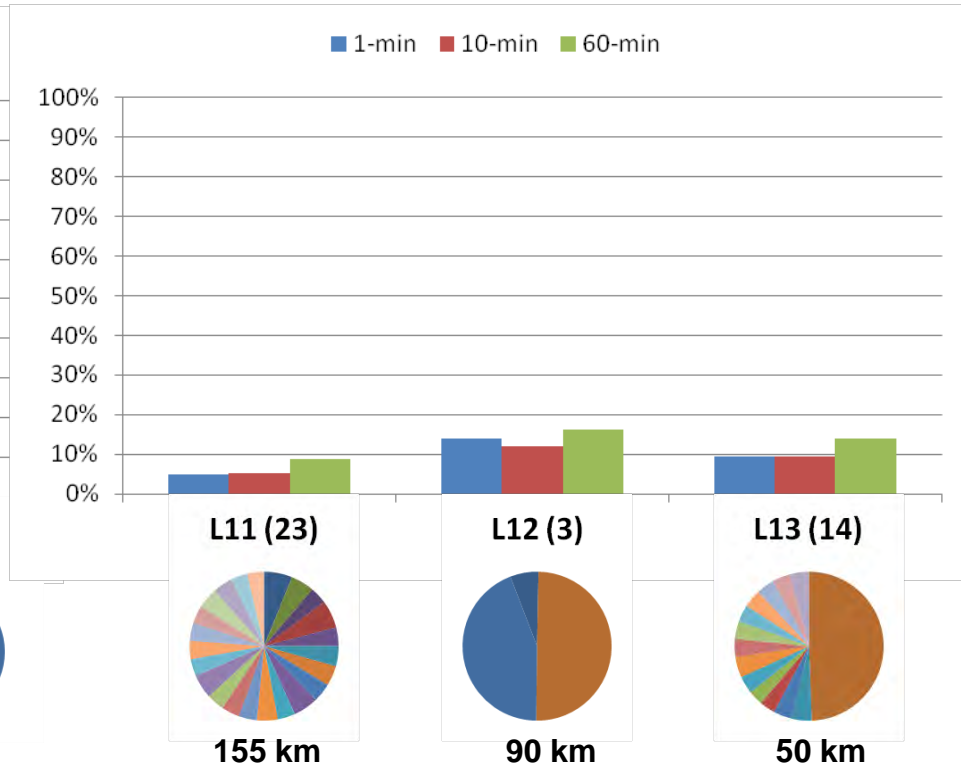
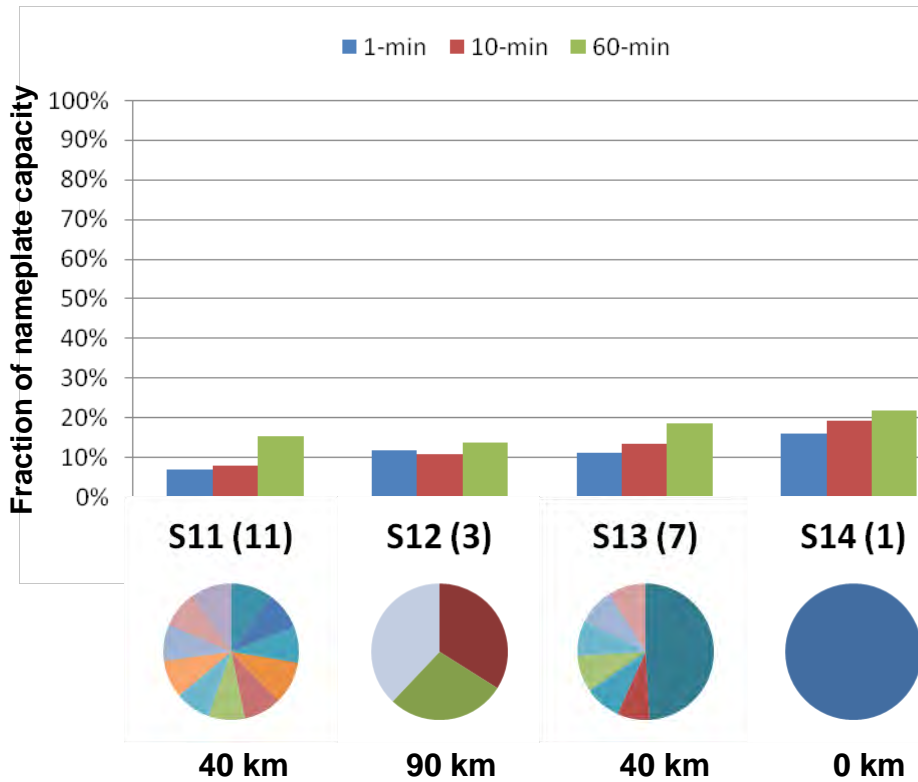


† A. Mills, R. Wiser, "Implications of Wide-Area Geographic Diversity for Short-Term Variability of Solar Power", LBNL-3884E, Lawrence Berkeley National Laboratory, 2010.

Maximum step change for a given probability



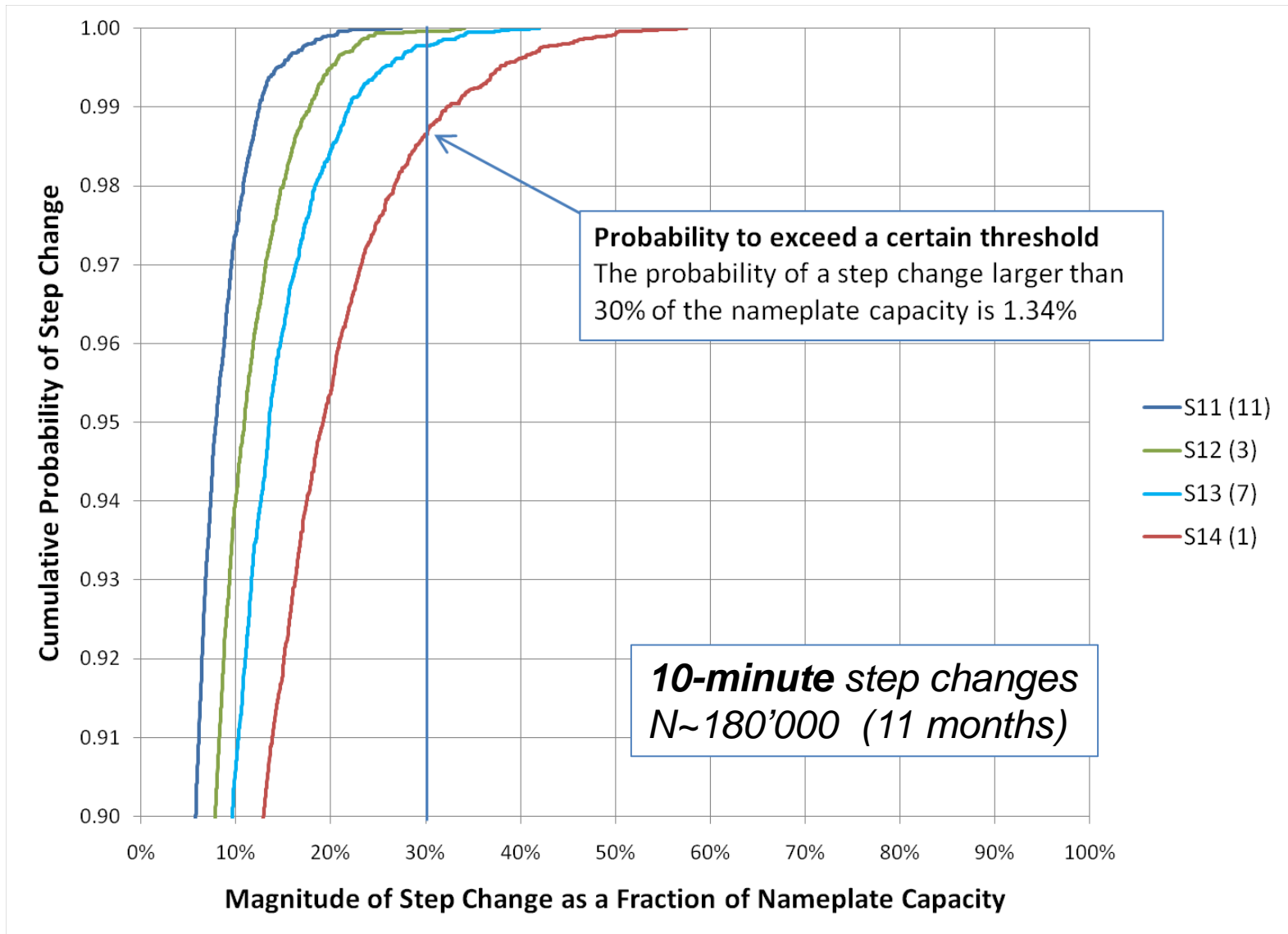
Planning for reserves based on probabilities (p95)



440 kWp

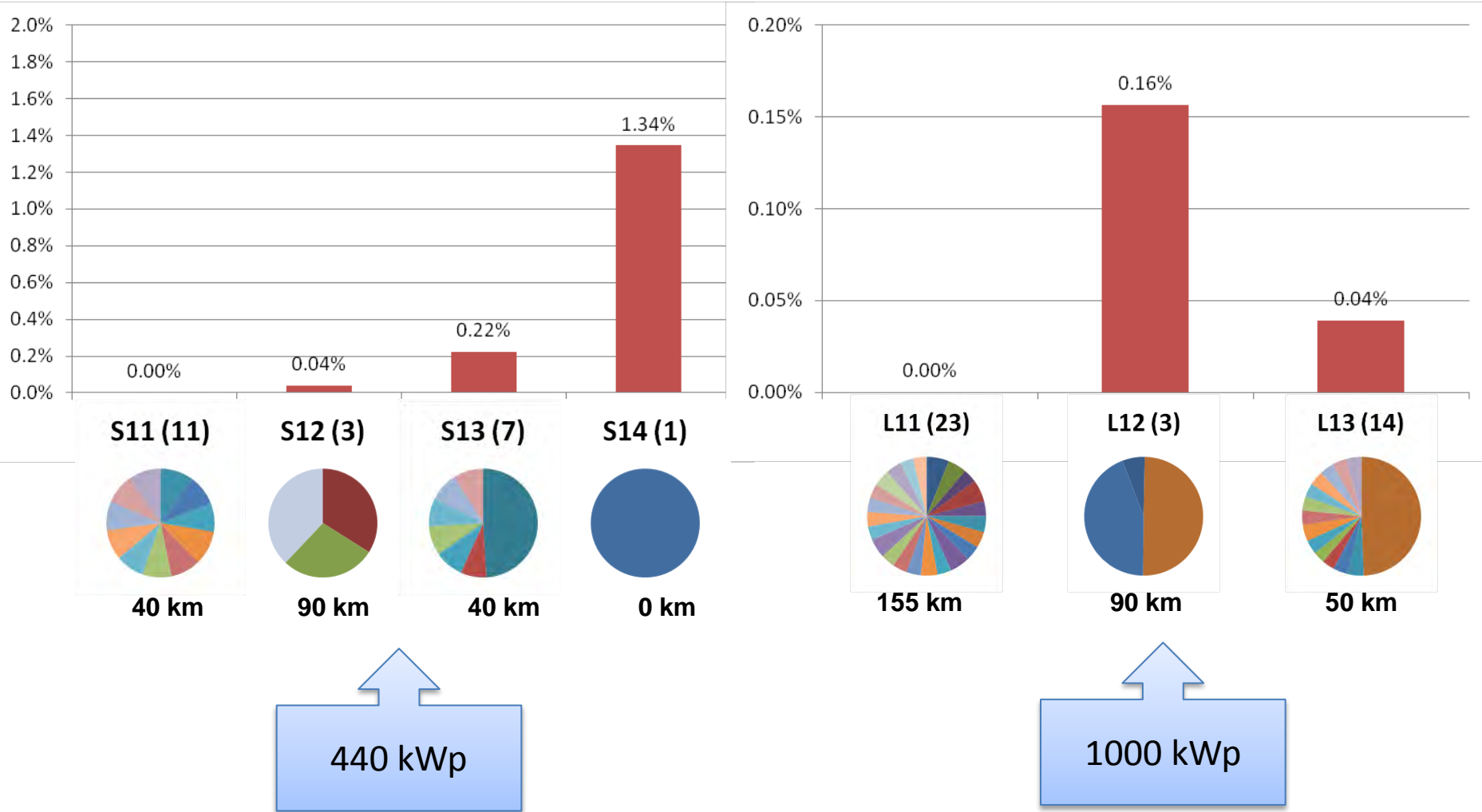
1000 kWp

Fraction of step changes (ramp rates) above a threshold



Fraction of ramp rates > 3% per minute ($\Delta t = 10$ min)

*A steam plant can ramp at ~3% per minute**



(*) CEC Intermittency Analysis Project Study "Appendix B—impact of intermittent generation on operation of California power grid," Jul. 2007

Potential impact on grid planning/operating reserves

▪ **Fleet topology:**

- Easiest to mitigate: The aggregate output variability of a geographically distributed fleet of “many” similarly sized systems.
- If a large system accounts for most of the fleet’s capacity it will dominate the aggregate variability behavior.

▪ **Reserve planning:**

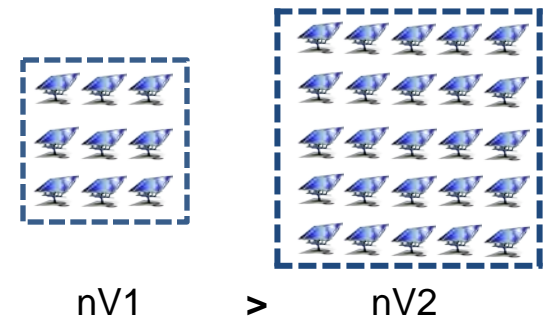
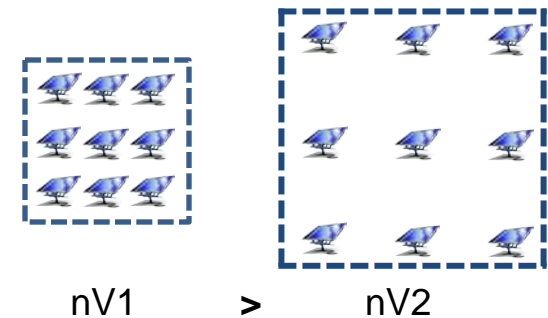
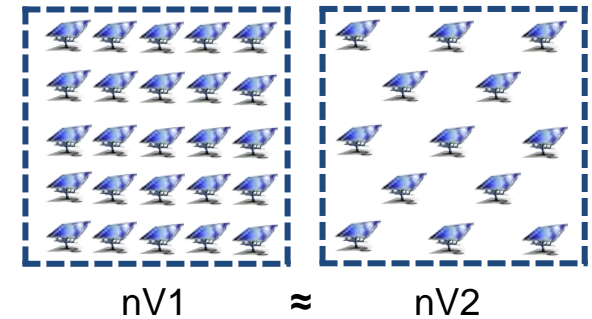
- Regulation and load following: 95% of the step changes in aggregated PV output are less than 5-10% of the fleet’s nameplate capacity for a fleet with many similarly sized systems, depending on the fleet topology
 - At 20-30% PV penetration (wrt peak load) this is equivalent to a 1-1.5% of the load, which is comparable to typical regulation reserve considered for the load.
 - The maximum delta jumps by about 2x as the confidence interval is increased from 95% to 99.7%.
- Contingency reserve : Because individual solar systems are relatively small, they may not affect the contingency reserve requirement.
- Ramp rate: In theory, a steam plant could respond to 99.7% of the 10-min deltas (and 100% of the 60-min deltas) of a PV fleet of equal nameplate capacity, if adequate forecasting and spare capacity were available, but a smaller gas-fired plant would be a far more practical choice.

Power Output from Rovigo (70 MWp)



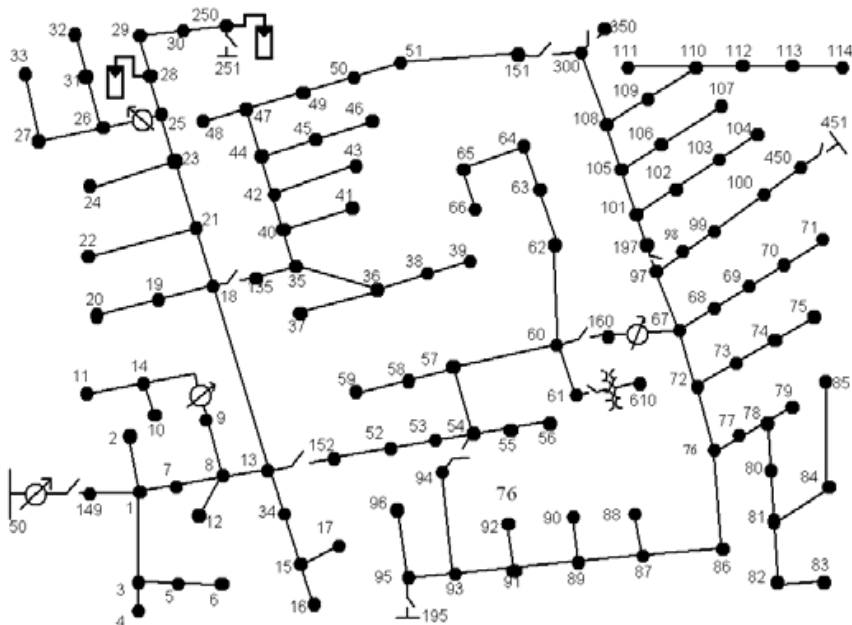
What happens to variability from 1 MWp to 70 MWp?

- For constant area, normalized variability is independent of density (Wp/m^2),.
 - Covering 200 acres with more systems will not have a dramatic impact on normalized variability (as a percentage of nameplate capacity).
- For constant capacity, variability is proportional to density (Wp/m^2),.
 - Distributing 40 MW over more acres (e.g. 200 vs 100) will reduce variability.
- For constant density (Wp/m^2), normalized variability is inversely proportional to area.
 - A 20-MW system will have lower normalized variability than a 10-MW system (as a percentage of nameplate capacity).

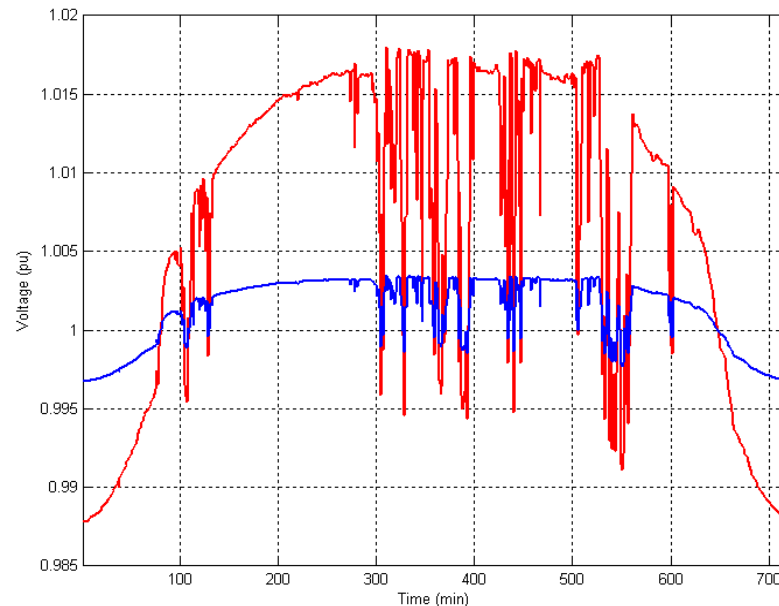


PV output variability and grid voltage*

$$\begin{cases} P_k = \sum_{n=1}^N |V_k| |V_n| |Y_{kn}| \cdot \cos(\theta_{kn} + \delta_n - \delta_k) \\ Q_k = \sum_{n=1}^N |V_k| |V_n| |Y_{kn}| \cdot \sin(\theta_{kn} + \delta_n - \delta_k) \end{cases} \quad \begin{vmatrix} \Delta\delta \\ \Delta V \end{vmatrix} = \begin{vmatrix} S_{\delta P} & S_{\delta Q} \\ S_{VP} & S_{VQ} \end{vmatrix} \cdot \begin{vmatrix} \Delta P \\ \Delta Q \end{vmatrix} \quad PF_s = \frac{|S_{VQ_{vs}}|}{\sqrt{S_{VP_{vs}}^2 + S_{VQ_{vs}}^2}}$$



IEEE 123-bus distribution system



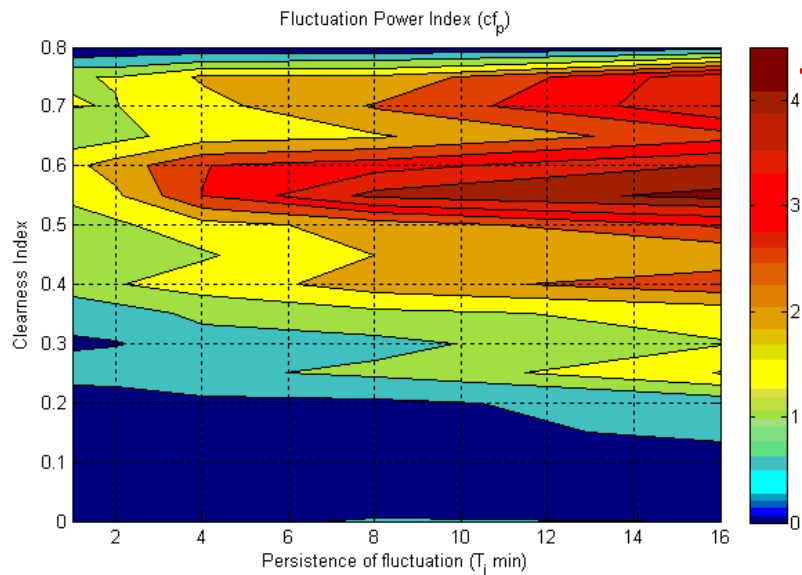
Bus 28 voltage
UPF (red), APF(blue)

* R. Aghatehrani and T Golnas, "Reactive power control of photovoltaic systems based on the voltage sensitivity analysis," Accepted for *IEEE PES GM 2012*.

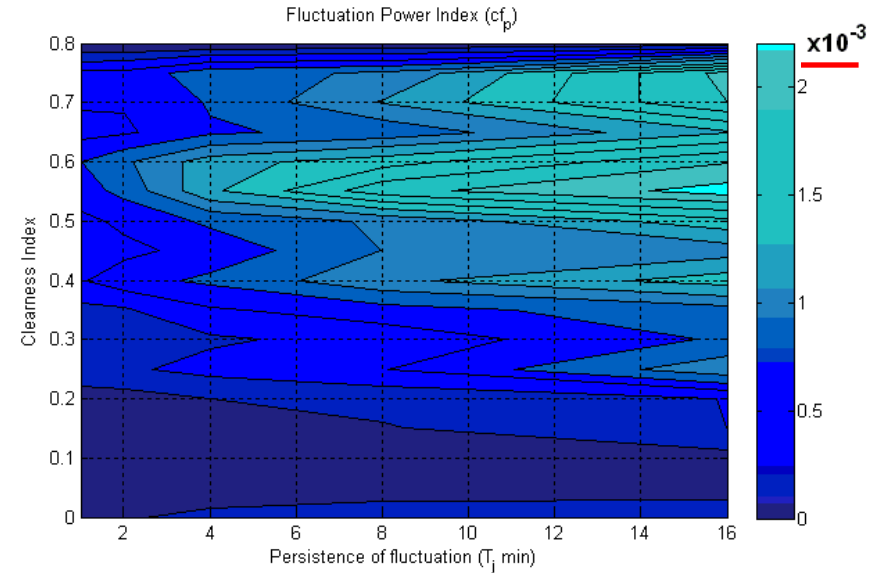
Wavelet based voltage fluctuation power index (cf_p)

Fluctuation Power Index (cf_p): mean value of square of wavelet coefficients ($W_{j,q}$) on each scale (j)*.

$$\text{Wavelet transform: } W_{2^j}^\theta(x(t)) = \int_{-\infty}^{\infty} x(t) \frac{1}{2^{\frac{j}{2}}} \psi\left(\frac{t-\theta}{2^j}\right) dt$$



Voltage cf_p with unity power factor



Voltage cf_p with adjusted power factor

* A. Woyte, V. Thong, R. Belmans and J. Nijs, "Voltage fluctuations on distribution level introduced by photovoltaic systems," *IEEE Trans Energy Convers.*, vol. 21, pp. 202-209, Mar. 2006.

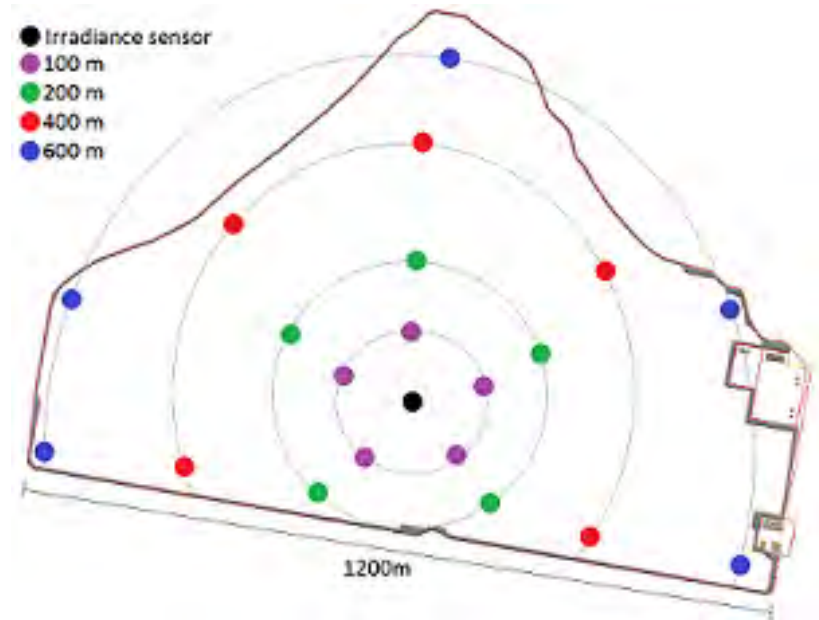
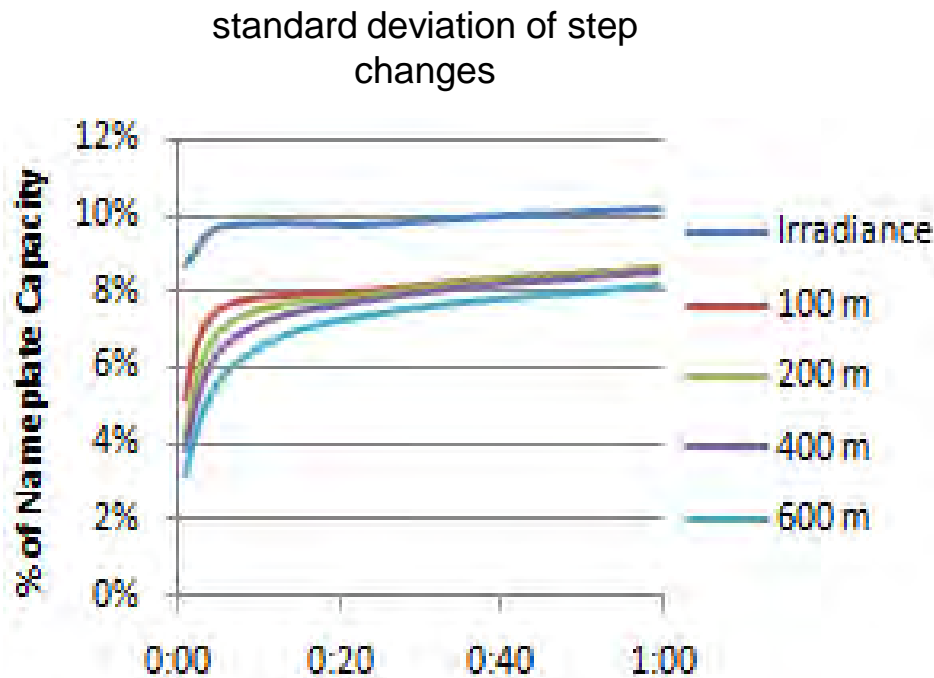
Conclusions

- Fleets of widely distributed, uniformly sized PV power plants provide natural mitigation against variability.
- Study of fleets with different characteristics yields information that can be used in optimal-cost planning of reserves.
- Study of large contiguous PV plant in Europe shows that the outer extent of the area occupied by an array is the biggest determinant of variability.
- Methodical Power Factor adjustment of an inverter can reduce voltage variability caused by the variability of PV systems.

Thank you for your attention!

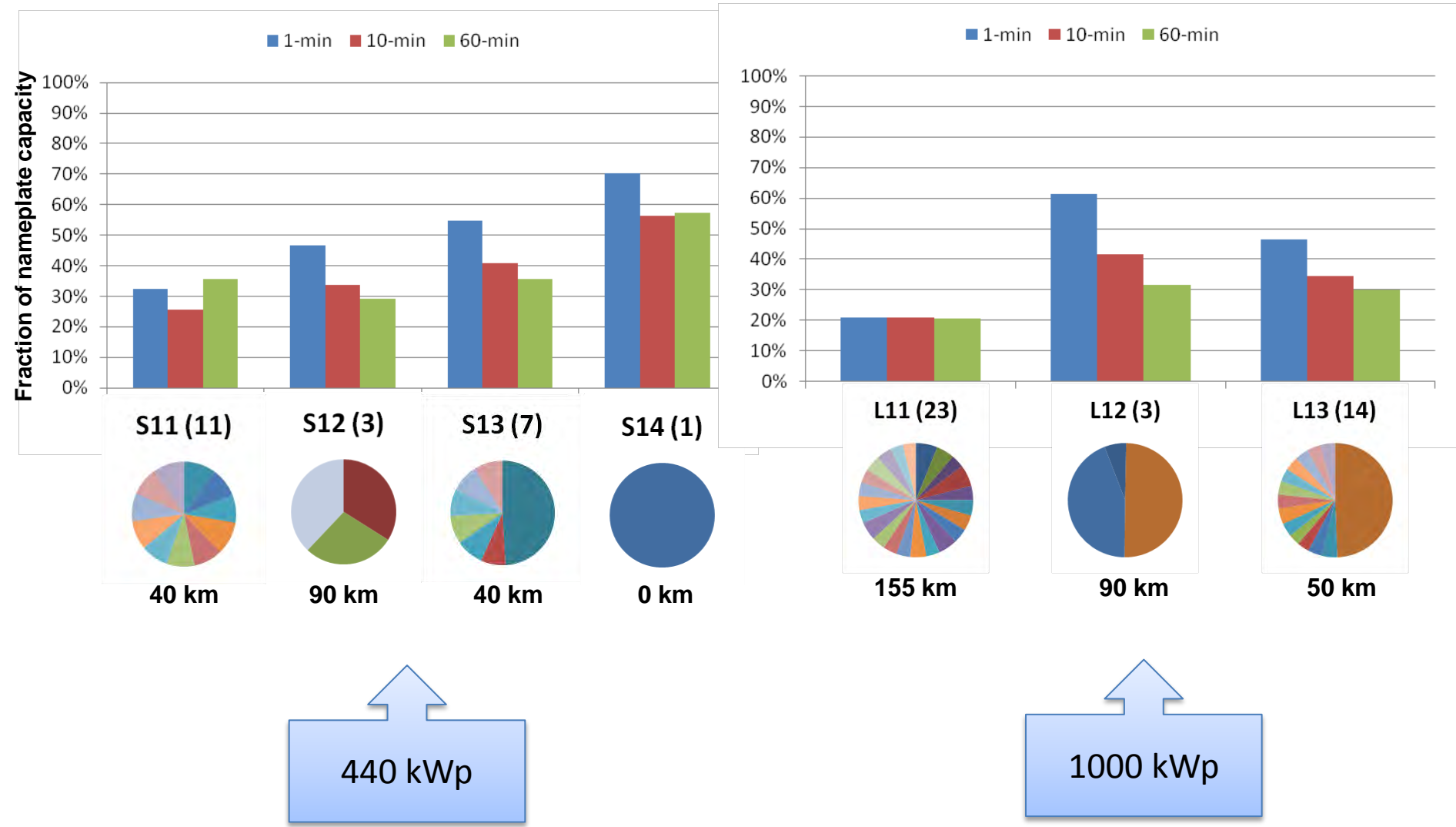
What happens to variability from 1 MWp to 70 MWp?

- **The area covered by the fleet or the plant determines the normalized variability.**
 - Normalized variability: variability (standard deviation of step changes) normalized by the nameplate capacity of the power plant or fleet.



Rovigo PV plant (70MW)

Maximum step change



440 kWp

1000 kWp



Session 2A. Data & Models for High Penetration

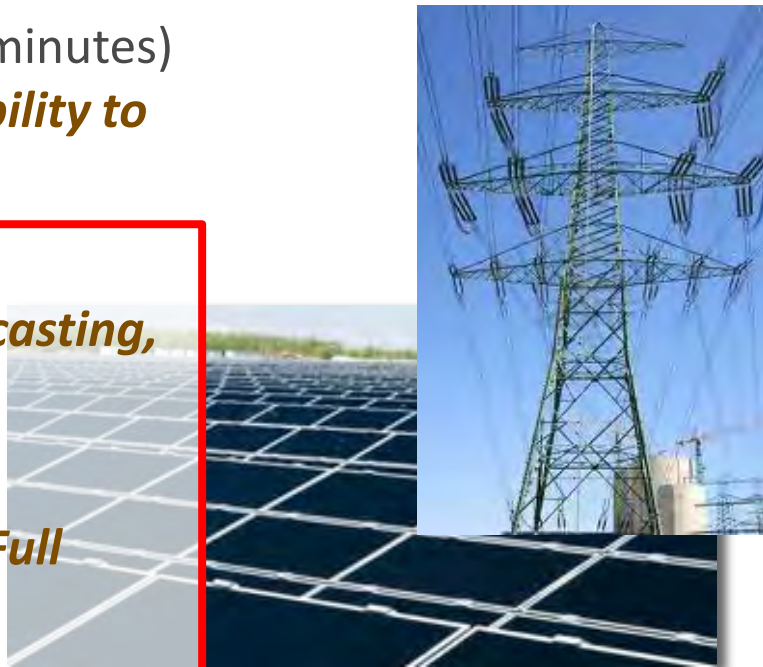
Tucson, April 19th 2012



Grid Integration Impacts

Strategy at Different Timescales

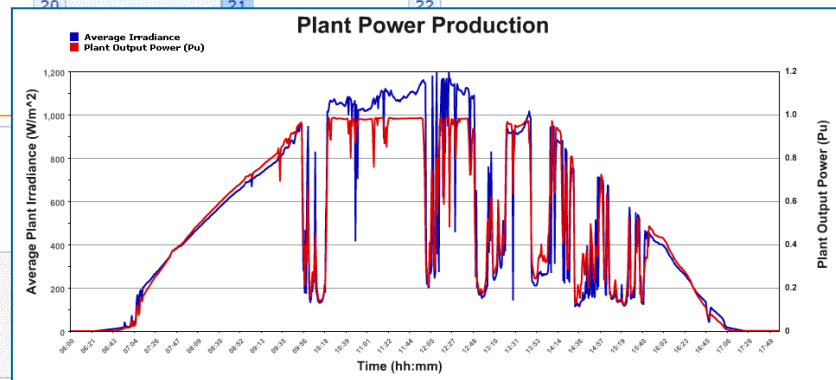
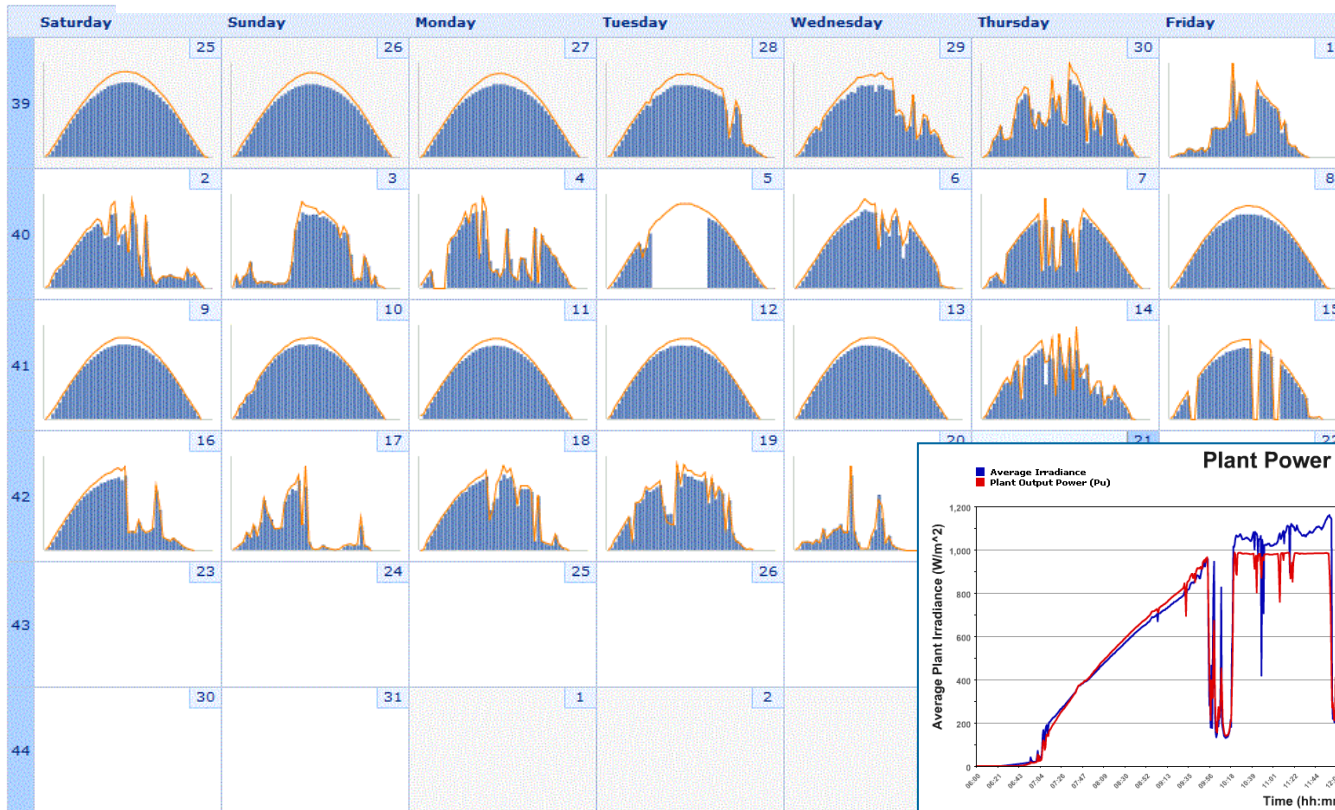
- Immediate Grid Stability (milliseconds to minutes)
... Develop Grid Controls & Inverter capability to Support Grid Reliability & Stability
- Fleet Operation (hours to days)
... Address PV Variability Issues e.g., forecasting, ramp rates
- Long Term Resource Planning (years)
... Address integration of PV as part of a Full Generation Resource Portfolio



PV Variability ... what does it look like?



El Dorado - Solar Expansion 1 - October 2010 - Generation



Costs to Manage Short-Term Variability of Solar Dramatically Impacted By Geographic Diversity; Costs Similar to Wind for Diverse Sites

Time Scale	Increased Balancing Reserve Costs (\$/MWh)				
	Reserves Constant Throughout Year				Reserves Change with Position of Sun
	Solar		Wind	Solar	
	1 Site	5 Sites	25 Site Grid		
1-min Deltas	\$16.7	\$4.8	\$1.2	\$0.9	\$0.8
10-min Deltas	\$17.3	\$4.4	\$1.0	\$0.2	\$0.7
60-min Deltas	\$5.0	\$1.6	\$0.6	\$0.5	\$0.5
Total Cost	\$39.0	\$10.8	\$2.7	\$1.6	\$1.9

These costs address only short-term variability and do not include many other costs and benefits associated with solar and wind

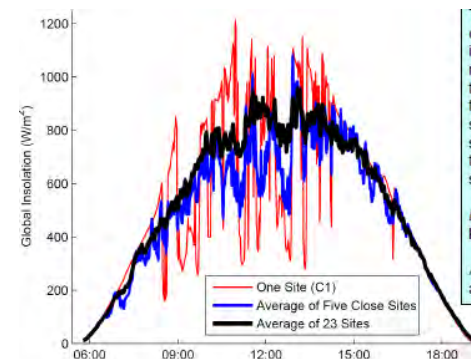
Cost estimates are developed using simple approximations and are only meant to illustrate relative changes in cost

Example costs based on 10% penetration of solar or wind on capacity basis

Why are solar and wind costs comparable?

Reserves can be held in proportion to clear-sky insolation for solar

Reserves assumed to be held at same level all year for wind



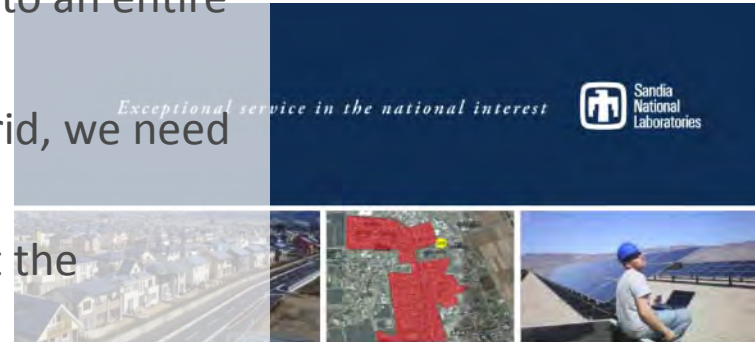
Source: "Implications of Wide-Area Geographic Diversity for Short-Term Variability of Solar Power";

Andrew Mills and Ryan Wiser
Lawrence Berkeley National Laboratory
September 2010

Need to Solar Power Variability Model

Wouldn't it be nice

- to be able to determine how much of a reduction in variability will occur in transitioning from a GHI point sensor to an entire power plant for any plant?
- In order to address how to integrate PV into the grid, we need to have an understanding of the variability.
- How does plant size (footprint and capacity) affect the reduction in variability?
- What is the difference between central and distributed plants?
- How does this relationship vary geographically (coastal vs. inland, by latitude, etc.)? To answer these questions, a solar power variability model is needed.



Simulating Solar Power Plant Variability for Grid Studies: A Wavelet-based Variability Model

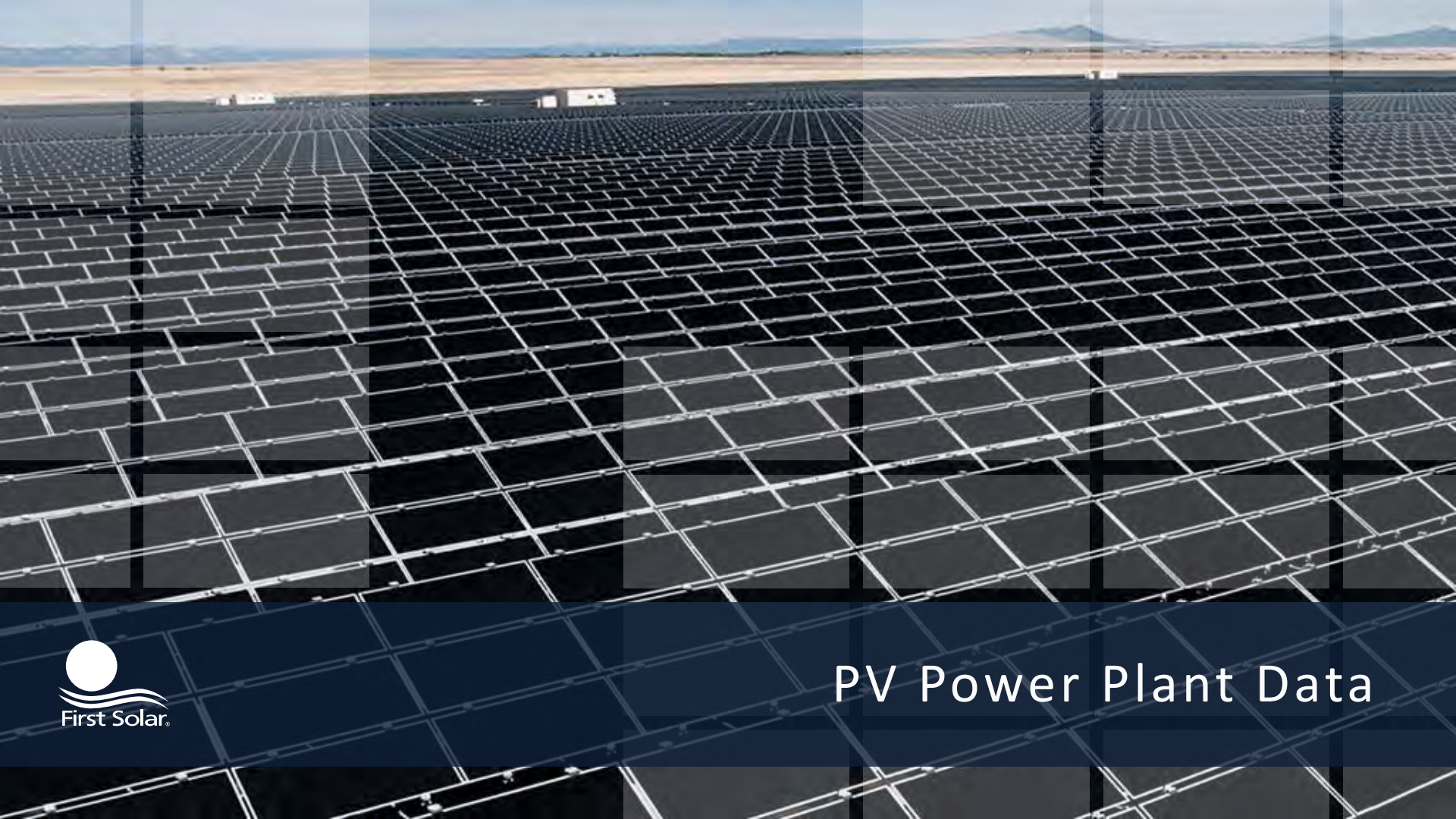
Matthew Lave^{1,2}, Joshua Stein¹, Jan Kleiss², Abraham Ellis¹, Clifford Hansen¹, Yusuke Miyamoto³
mlave@sandia.gov

UWIG Solar User Group Fall 2011, Maui, HI

¹Sandia National Laboratories; ²University of California, San Diego; ³Kandenko, Ibaraki, Japan

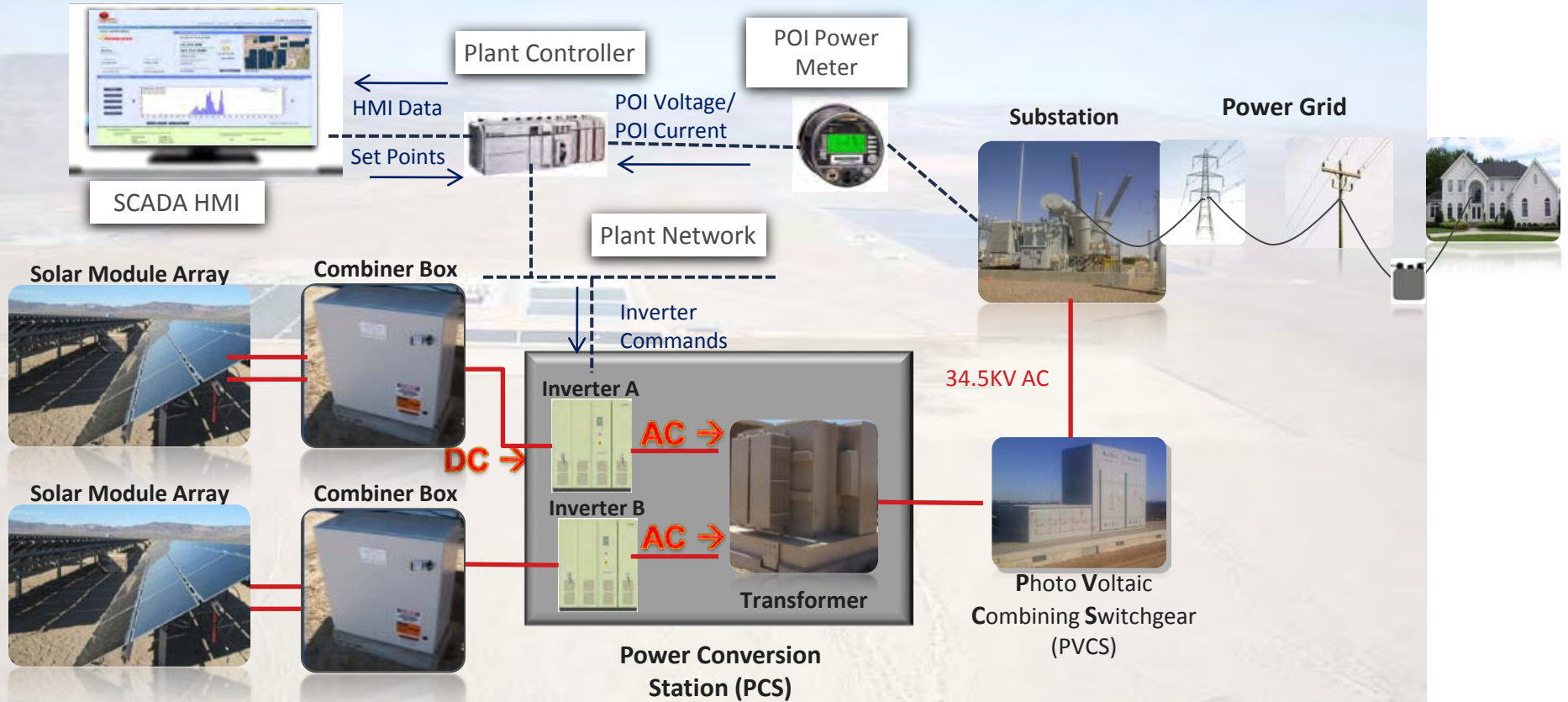
Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC02-04OR21400.

- Source: Lave et al of Sandia Labs



PV Power Plant Data

Power Plant Overview

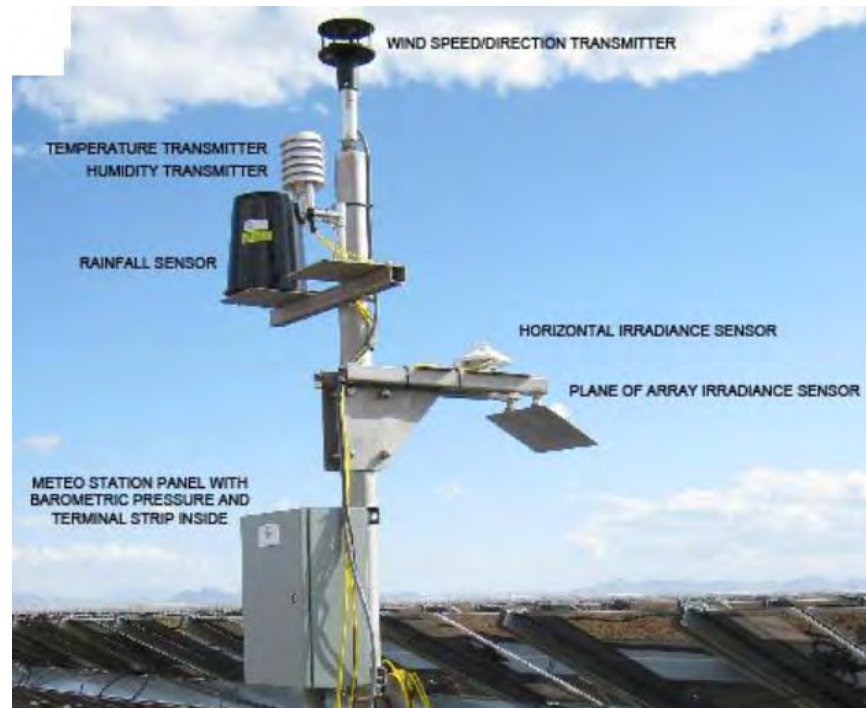


Meteorological & Other Instrumentation

- Plane of Array and Global Horizontal Solar Irradiance) Accuracy: +/- 2%
- Temperature Accuracy: +/- .3°C
- Humidity Accuracy : +/- 2%
- Wind Speed Accuracy +/- 2.0 %
- Wind Direction Accuracy +/- 3.0 %
- Barometric Pressure
- Rainfall

- Reference Module (~3 per block)
- Module Surface Temperature Sensors
- DC Current Transducer

- Energy Meter at Various Levels



plant

Plant Level Data

- Avg Plant POA Irradiance
- Avg Plant Global Horizontal Irradiance
- Avg Plant Panel Temperature
- Avg Plant RM Temperature
- Avg Plant Ambient Temp
- Avg Plant Wind Speed
- Total Energy Meter Reading
- Total Energy Delivered
- Total Energy Received
- Total Plant Power
- Total Reactive Power of the plant
- Total Plant kVA

Inverter Data

- DC Current on CB1 ... CB9
- Fault Status
- Line Frequency
- Inverter Phase A/B/C Current
- Inverter State
- AC Output kWh
- AC Output kW
- Inverter kVAR
- Matrix Temperature
- inverter Internal Air Temp
- PV Current
- PV kW
- PV Voltage
- Operating Time

Other Data

- Pressure
- Rainfall
- Relative Humidity
- POR Irradiance
- Global Irradiance
- Air Temperature
- Wind Direction
- Wind Speed
- Module Surface Temperature
- RM Irradiance
- RM Temperature
- Main Breaker Status

EPC Project Overview

NRG – Agua / 392 MW dc



Project Details

Yuma County

Dateland, AZ

2,400 Acres

39,000 Tons Steel

PPA – PG&E

EPC/O&M - NRG

EPC Project Overview

NextEra / GE – Desert Sunlight – 570 MWac (725 MWdc)

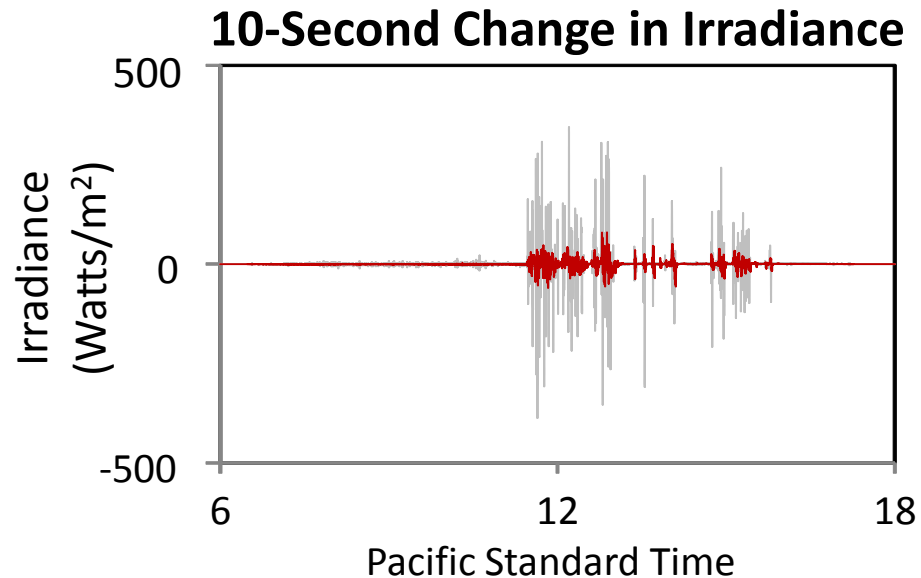
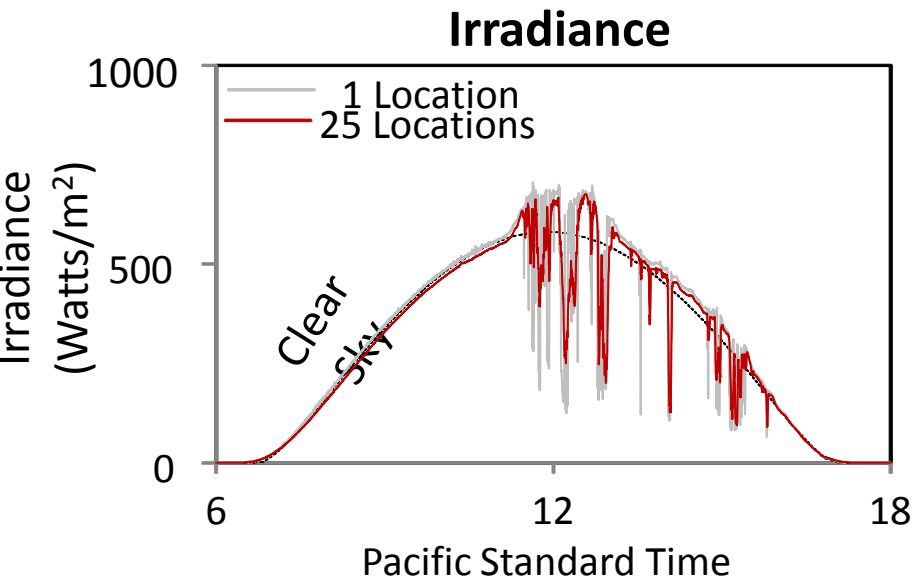




Data Analysis and Models

Power Output Variability Analysis (Hoff & Perez)

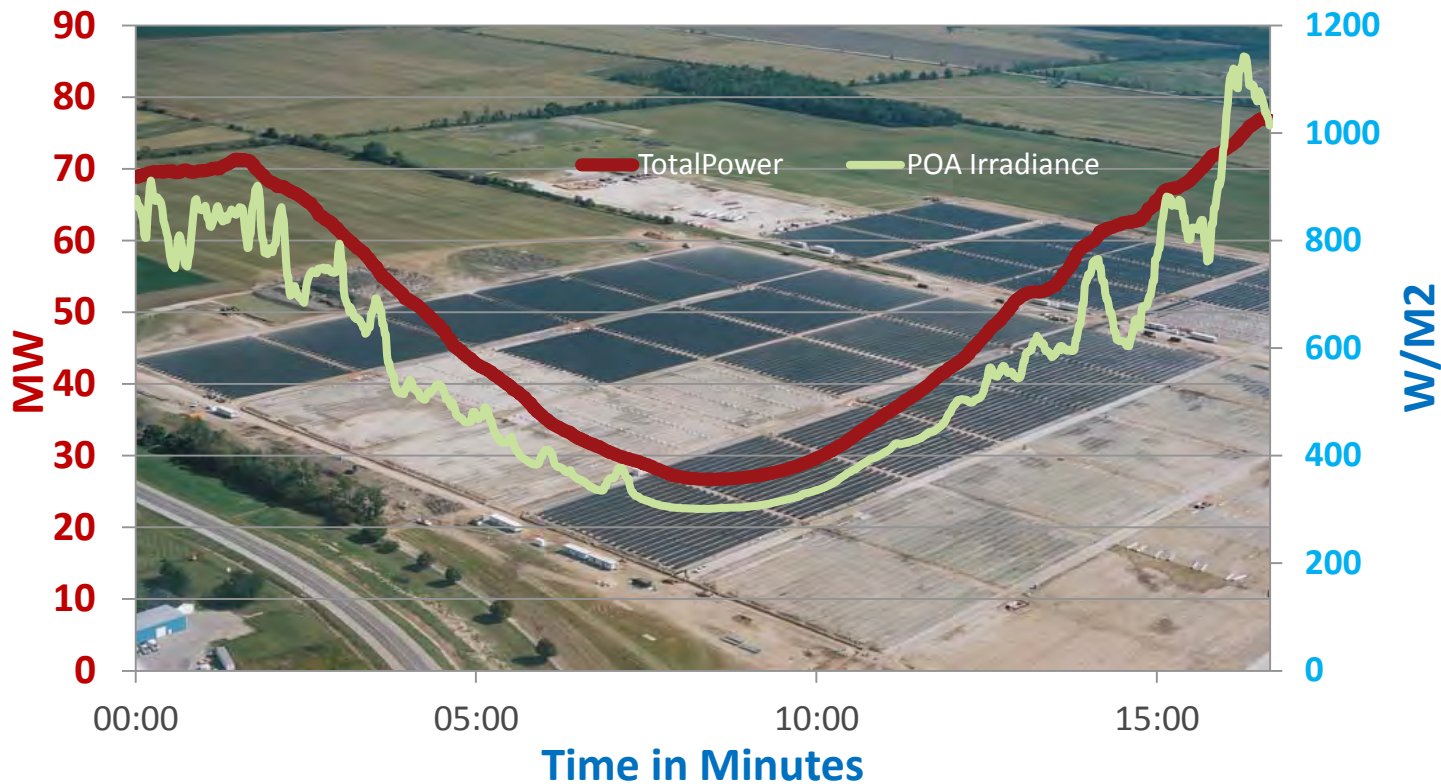
Measured 10-second data from high-density, 400 meter x 400 meter grid in Cordelia Junction, CA on November 10, 2010



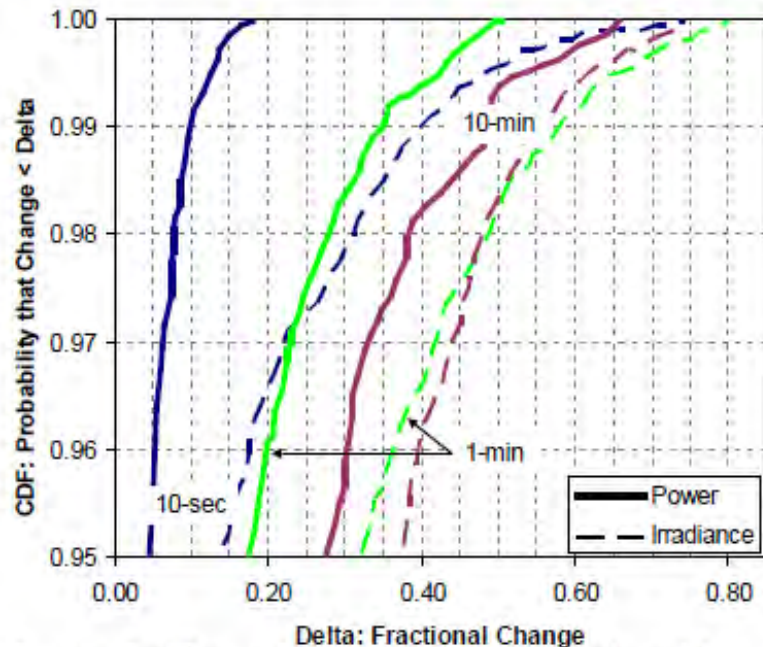
Source: Incorporating Correlation into a PV Power Output Variability Analysis, Thomas E. Hoff and Richard Perez, Clean Power Research, *Preliminary Results*

Plant Data Sample

One Second Plant Level Data



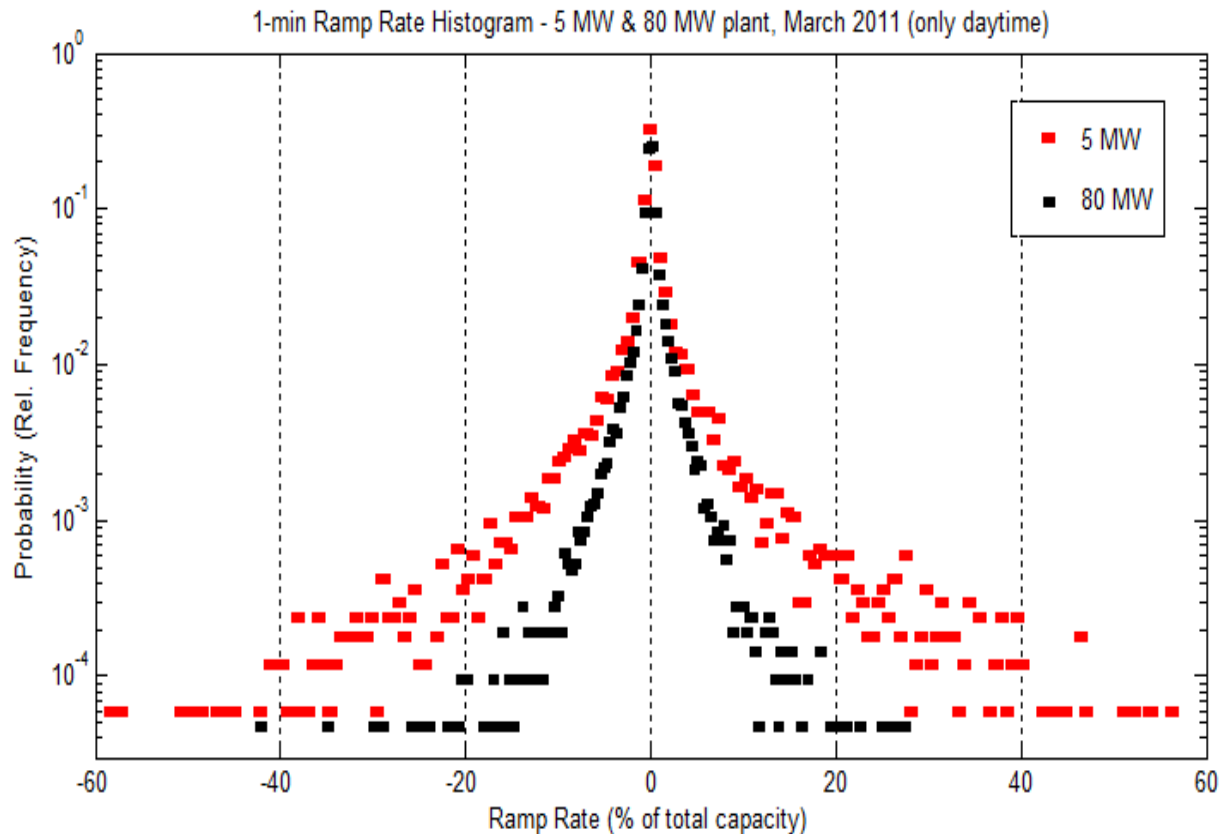
What is the smoothing effect in a large PV system



Source: Carl Lenox, SunPower Corporation, adapted from presentation at PV Variability Workshop

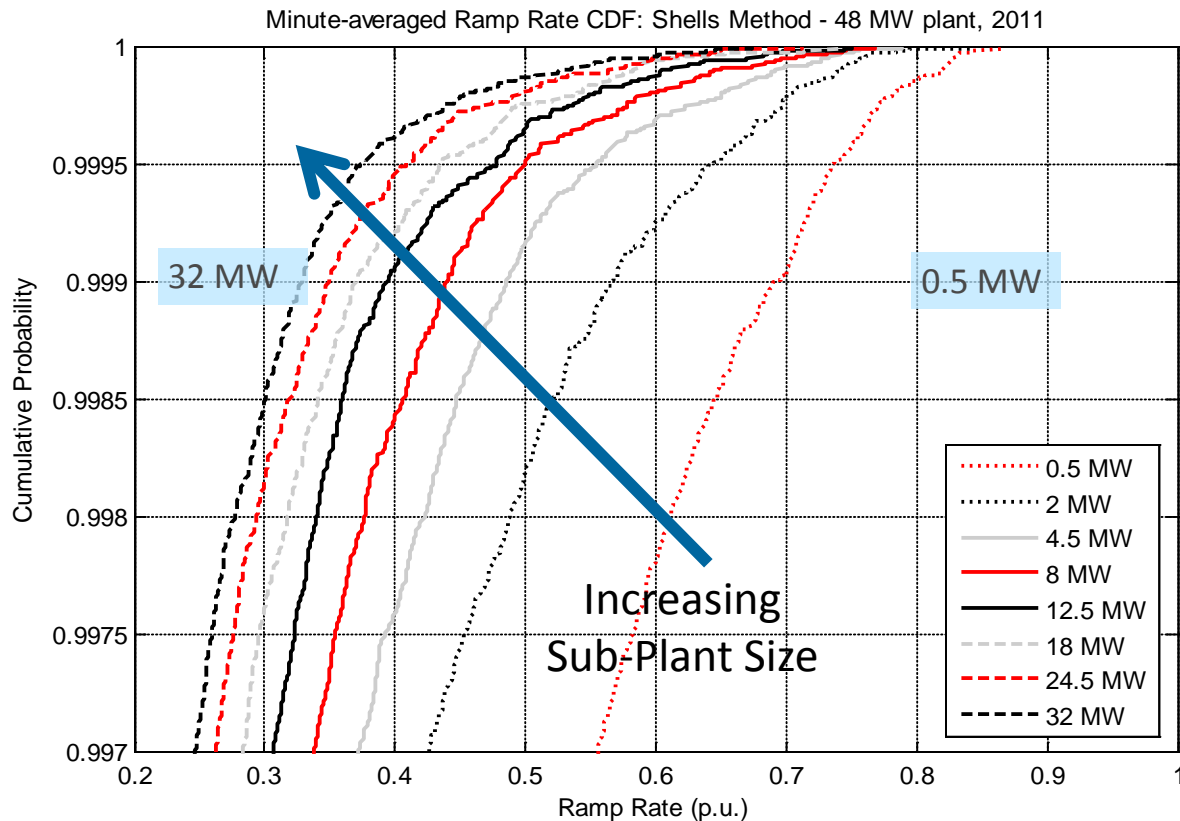
Cumulative distributions (95th to 100th percentiles) of irradiance and PV power changes over various time periods during a highly variable day for a 13.2-MW system.

One-Minute Ramps for 5 and 80 MW Plants



**Source: Empirical Assessment
of Short-term Variability from
Utility Scale Solar-PV Plants**
Rob van Haaren^a, Mahesh
Morjaria^b and Vasilis Fthenakis^a

One-Minute Ramps Using Sub-Plant Data



Source: Empirical Assessment of Short-term Variability from Utility Scale Solar-PV Plants
Rob van Haaren^a, Mahesh Morjaria^b and Vasilis Fthenakis^a

Session 2A. Data & Models for High Penetration

- Opening Remarks
- Solar Data Inputs
- Distributed PV Monitoring
- PV Plant Variability, Aggregation, & Impact on Grid Voltage

Mahesh Morjaria, First Solar

Josh Stein, Sandia

Kristen Nicole, EPRI

Rasool Aghatehrani, SunEdison



A Solar Future for World

A large array of solar panels is shown from a low angle, looking up. The panels are dark and highly reflective, mirroring the bright blue sky and scattered white clouds. The perspective creates a strong sense of depth and scale, with the lines of the panels converging towards the top of the frame. The overall tone is clean, modern, and optimistic.

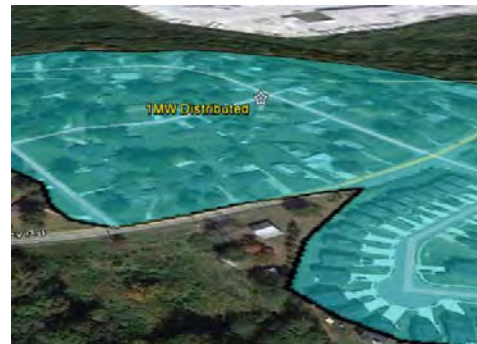
Reliable

Local

Abundant

Cost Effective

Exceptional service in the national interest



Solar PV Data for Distributed Grid Integration Modeling

Joshua Stein, Matthew Lave, Matthew Reno, Robert Broderick, and Abraham Ellis

April 19, 2012 Tucson, AZ



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Outline

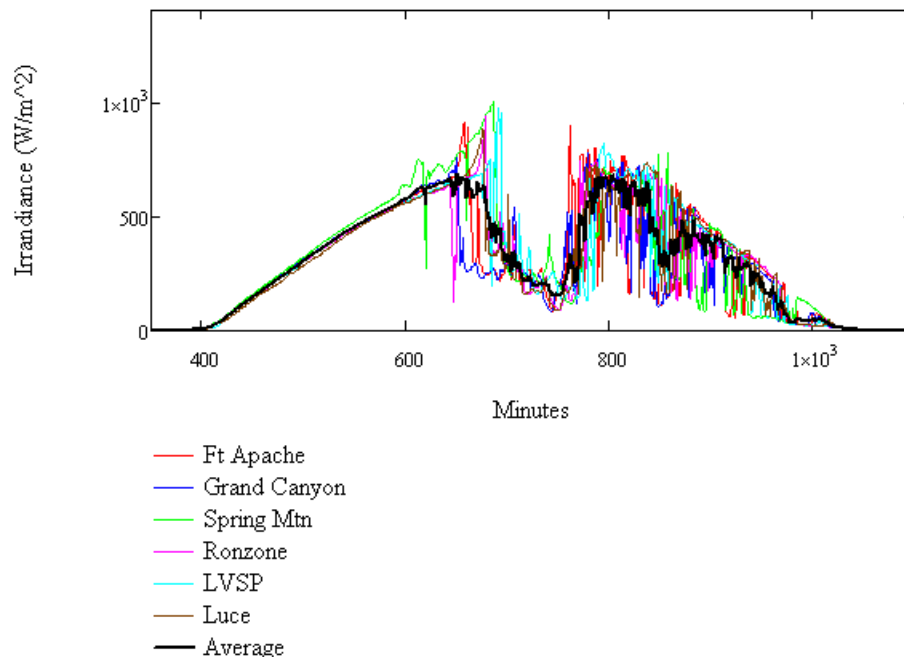
- Introduction
 - Why is solar variability important for distribution planning?
- What information is needed for distribution planning studies?
- What do we know about PV output variability?
- How to describe and classify PV and irradiance variability?
- Example application of the Wavelet Variability Model
 - Generation of PV output profiles
 - Project involving Sandia, EPRI, and Georgia Power (Southern Company)

Why is solar variability important?

- Solar Variability is important to study because it can cause problems on electric grids with high penetrations of PV (Flicker, Voltage changes, equipment wear, etc.)
- Geographic diversity reduces variability but does not eliminate it.

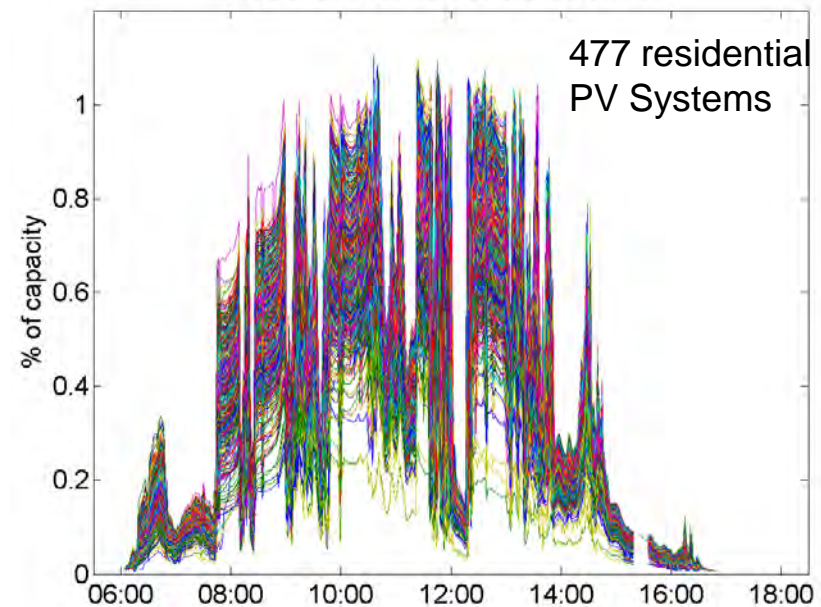
Las Vegas, NV

Horizontal Irradiance at Six LVVWD Sites



Ota City, Japan

12-Oct-2007 sites that passed filter



What information is needed?

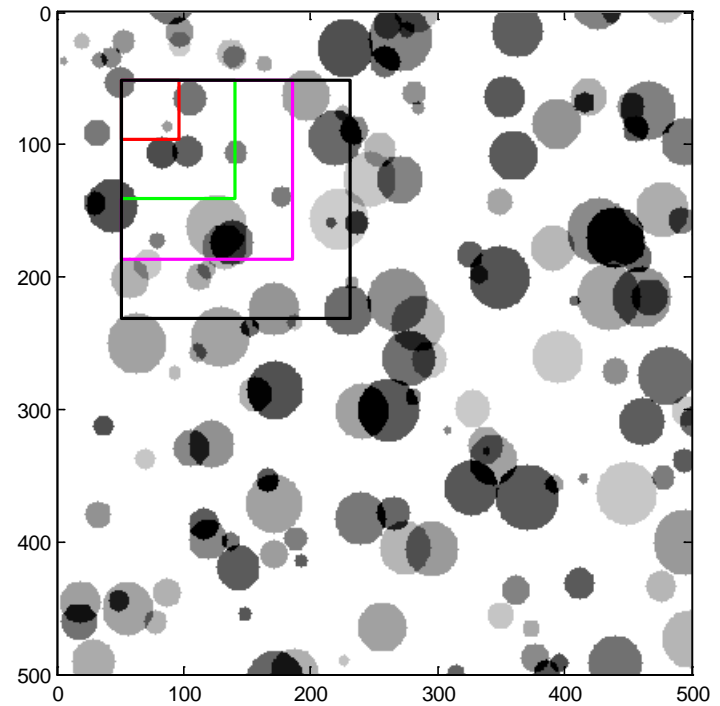
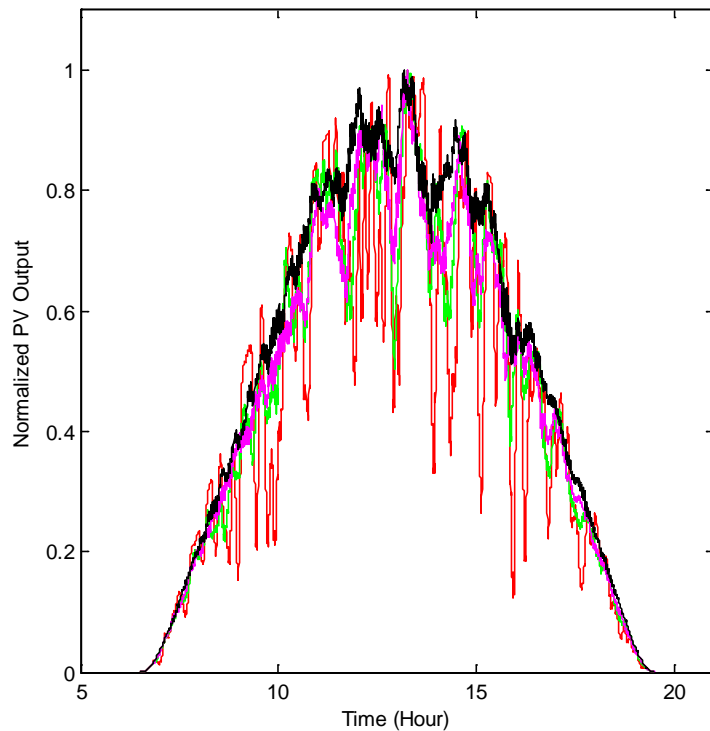
- Answer: PV power output as a function of time and space (correlated with load).
- Grid integration studies need estimates of PV power output in space and time for a period in the past when load data is available.
- This is difficult because:
 - High frequency (1-sec) irradiance data is rarely available when and where you want it (EPRI is beginning to address this).
 - Geographic diversity reduces variability in complex ways (time and space dependent)
 - PV performance is influenced by many variables other than irradiance (design, technology (module, inverter, BOS), weather, and environment).
 - Tracking and orientation can significantly affect variability magnitude and timing

What do we know about PV variability?

- On clear days PV variability can be predicted quite accurately (diurnal, temperature and atmospheric factors)
 - Even without detailed design information
 - Clear Sky Irradiance Modeling (Reno et al., 2012)
 - Neural Networks: (Riley et al., 2011)
- On partly cloudy days PV variability is primarily controlled by cloud shadows
 - Point irradiance measurements overestimate variability from PV systems and fleets
 - Ota City study of 553 homes (Lave et al, 2011)
 - NV Energy integration study (e.g., Hansen et al., 2011)
 - Need methods to represent geographic diversity and smoothing
- On overcast days PV variability is low

Geographic Diversity

Larger PV plant footprints or distributed PV reduces variability



Simulated Effect of Cloud Shadows

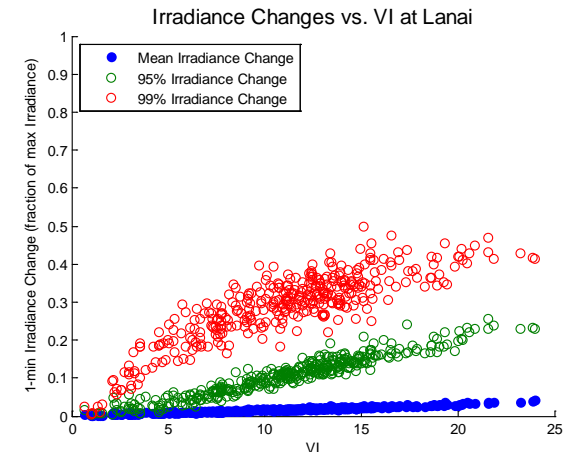
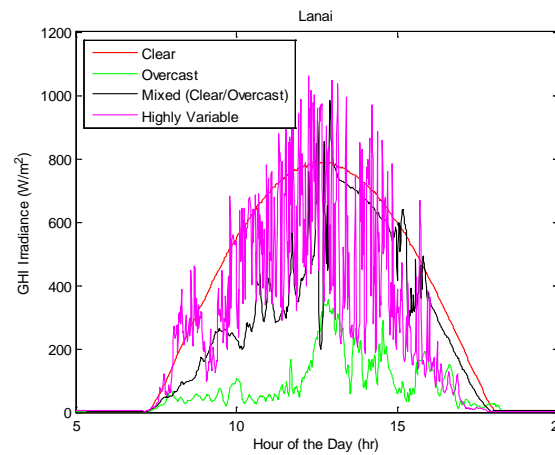
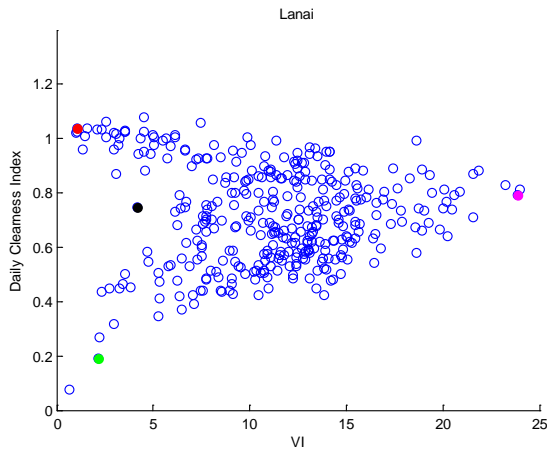
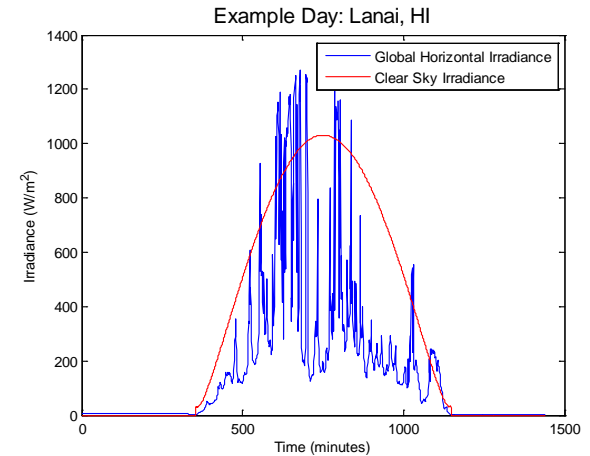
Describing Irradiance Variability

Ramp rate distributions and statistics

- Mean and standard deviation
- Cumulative distribution functions

Correlation with distance and time scale

▪ Variability Index
$$VI = \frac{\sum_{k=2}^n \sqrt{(GHI_k - GHI_{k-1})^2 + \Delta t^2}}{\sum_{k=2}^n \sqrt{(CSI_k - CSI_{k-1})^2 + \Delta t^2}}$$

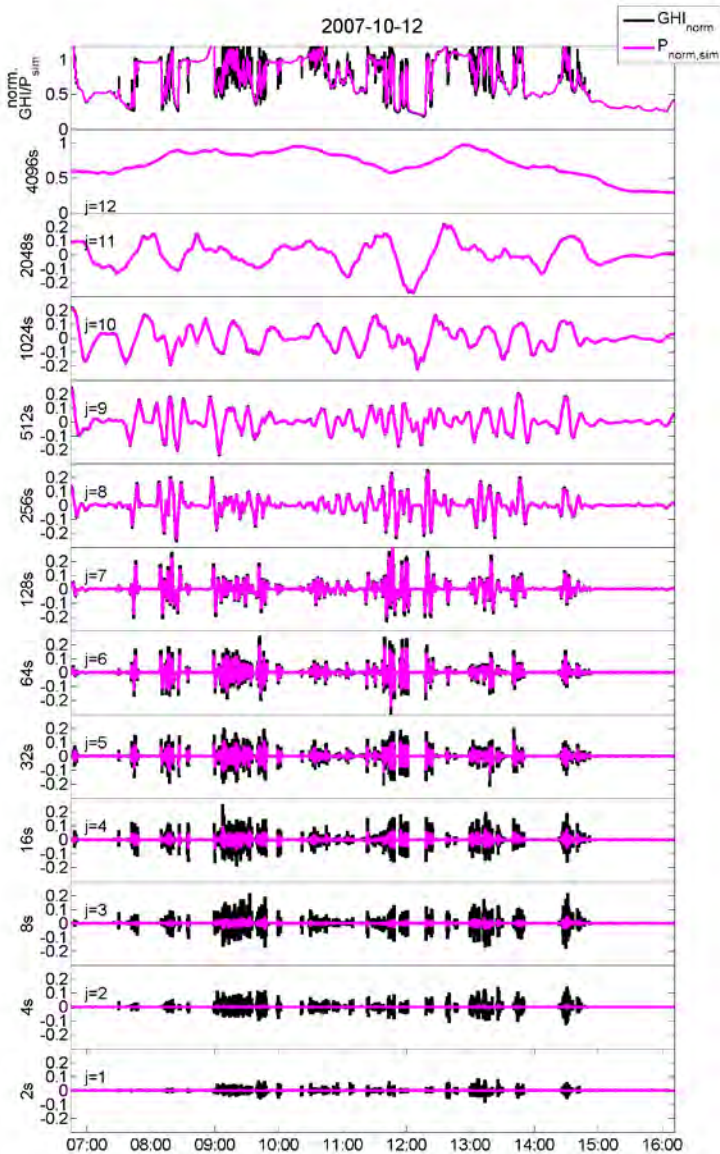


Variability Index metric described Stein et al. (2012)

Example application of the Wavelet Variability Model

- Uses EPRI's Distributed PV Monitoring (DPV) system data from a single feeder
- Wavelet Variability Model (WVM)(Lave et al, 2012)
 - Developed at UCSD as part of Matthew Lave's Ph.D. dissertation
 - Refined and validated in partnership with Sandia National Labs
- Predict PV output power time series that reflect expected geographic smoothing

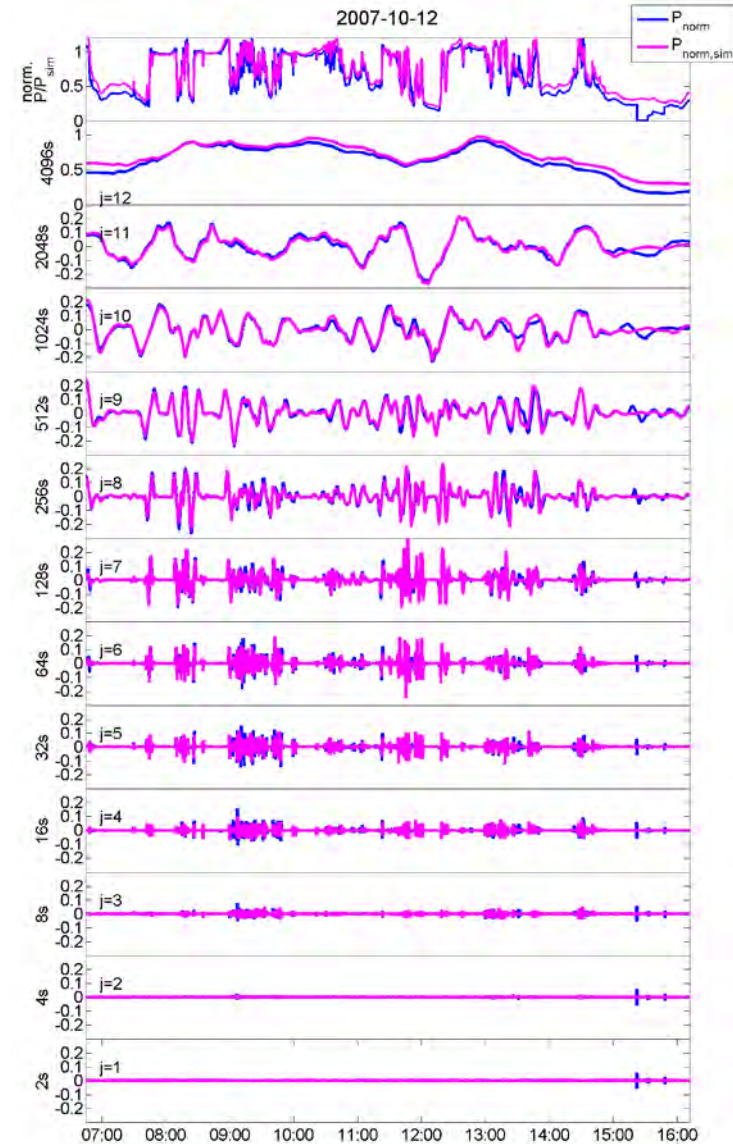
Wavelet Modes Example



Simulated wavelet modes derived from GHI wavelet modes

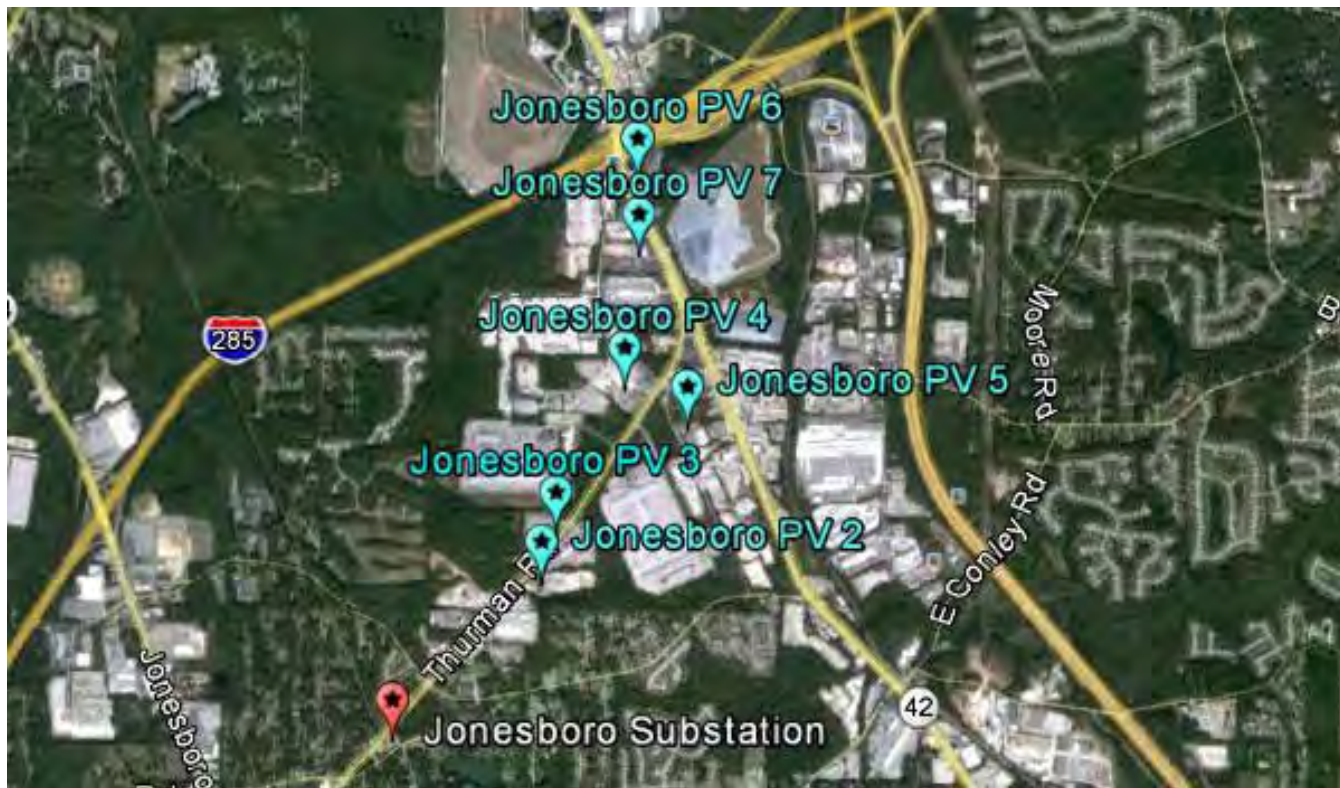


Modeled and measured power compare well



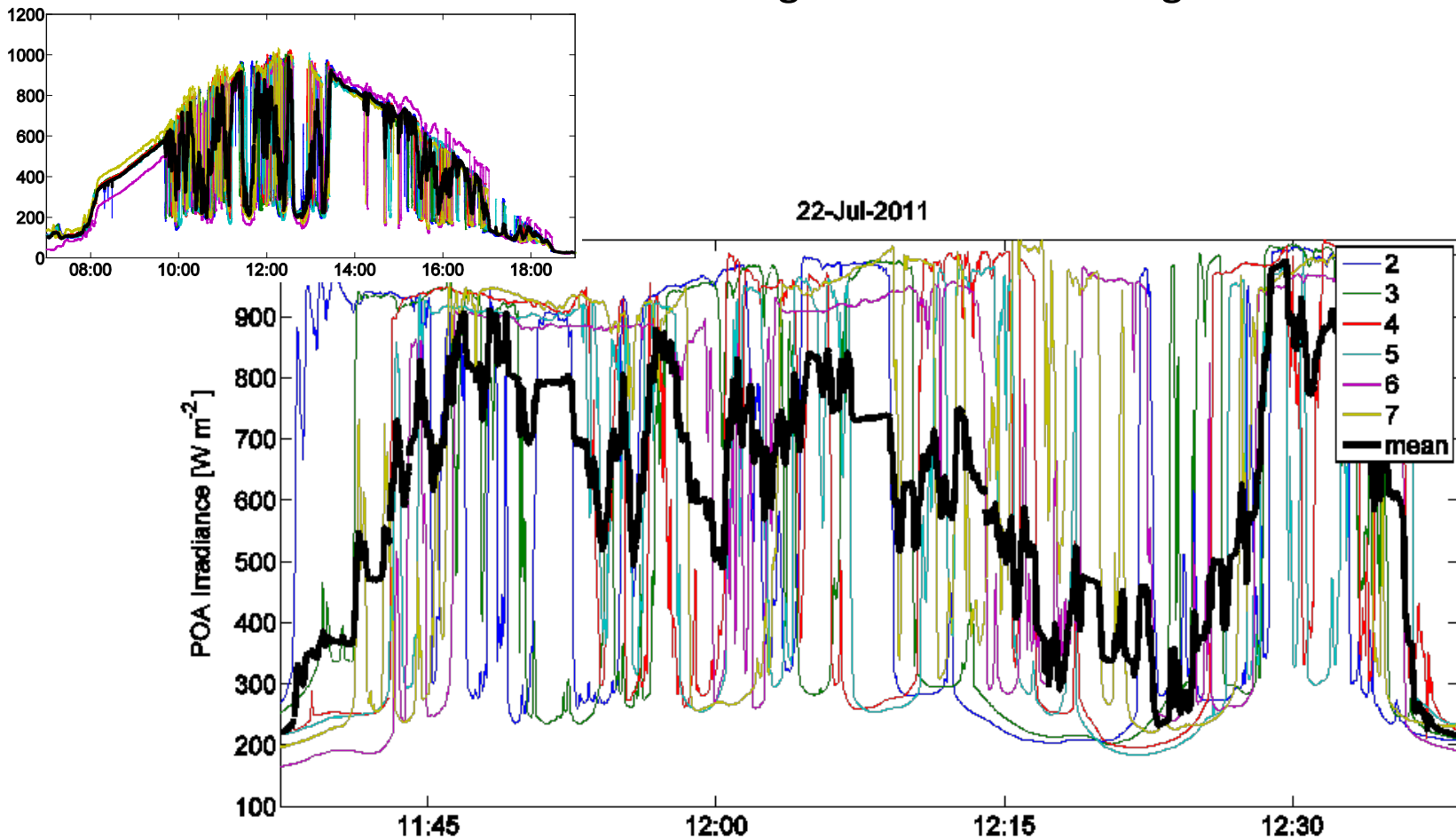
Layout

- 6 PV sensors provided by EPRI
- Plane of array (POA) irradiance at 1-sec resolution for 1-year (2011)
- Maximum distance between sensors ~2km



Geographic Diversity

- Even at such short distances between sensors, we see a large amount of geographic diversity.
- Mean of all 6 sensors shows a strong reduction in average and maximum RRs



Wavelet Variability Model (WVM)

Model Inputs

PV Footprint

PV Plant Density

Point Sensor Timeseries

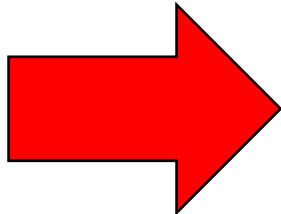
Correlation Structure
Location/day dependent
“A” coefficient

Model Outputs

Plant Areal Average
Irradiance

irradiance to
power model

Plant Power Output



determine variability reduction
(smoothing) at each wavelet timescale

$$\rho(d_{m,n}, \bar{t}) = \exp\left(-\frac{d_{m,n}}{At}\right)$$

$d_{m,n}$ is distance between two sites, m and n , and t is the timescale
 $\rho=0$ when $d_{m,n}$ is very large or t is very small
 $\rho=1$ when $d_{m,n}$ is very small or t is very large

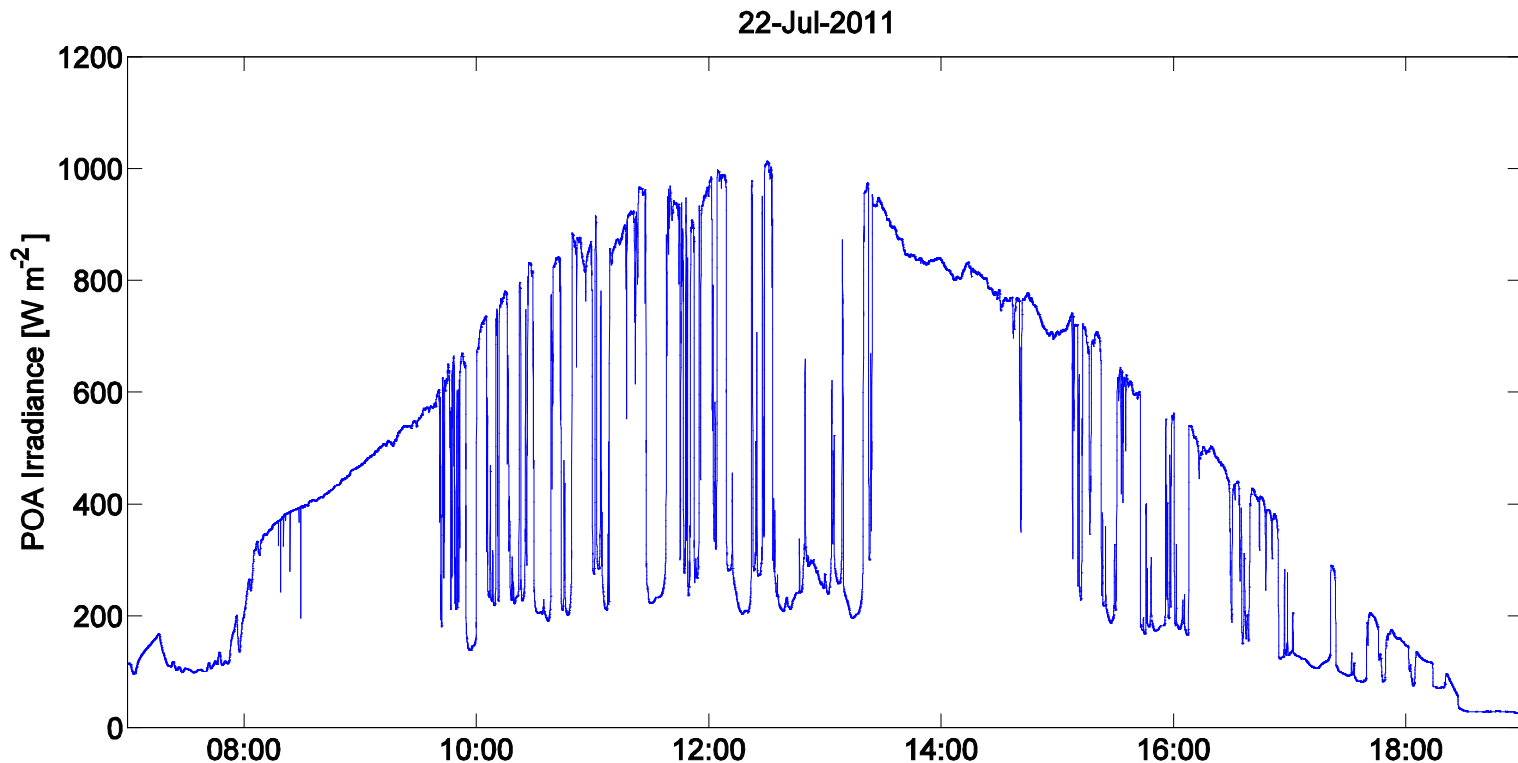
Pick PV Scenarios

- 7MW central (yellow), 3MW central (red), and 1MW distributed (blue) PV plants were simulated. Central densities were about 30 W/m^2 and distributed about 8 W/m^2 , consistent with previous PV plants. Plants are assumed to have PV modules at fixed latitude tilt.



Pick input point sensor

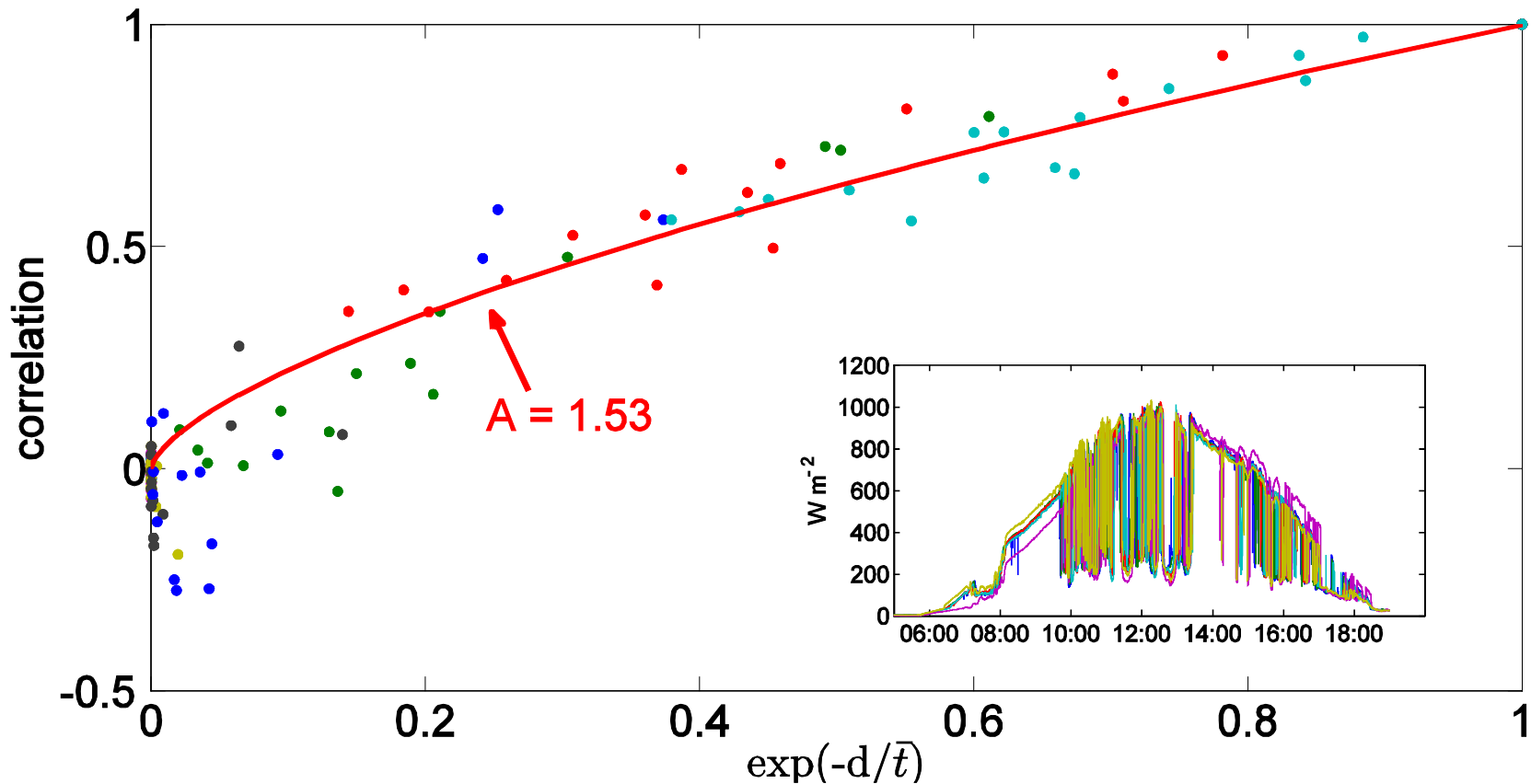
- Choose July 22nd, 2011 as a test day since it is highly variable.
- Use PV sensor 2. This is the closest sensor to both the 7MW central and 1MW distributed plants. It was also used at the 3MW distributed plant to allow for easy comparison between the 3 scenarios.



Determine A value

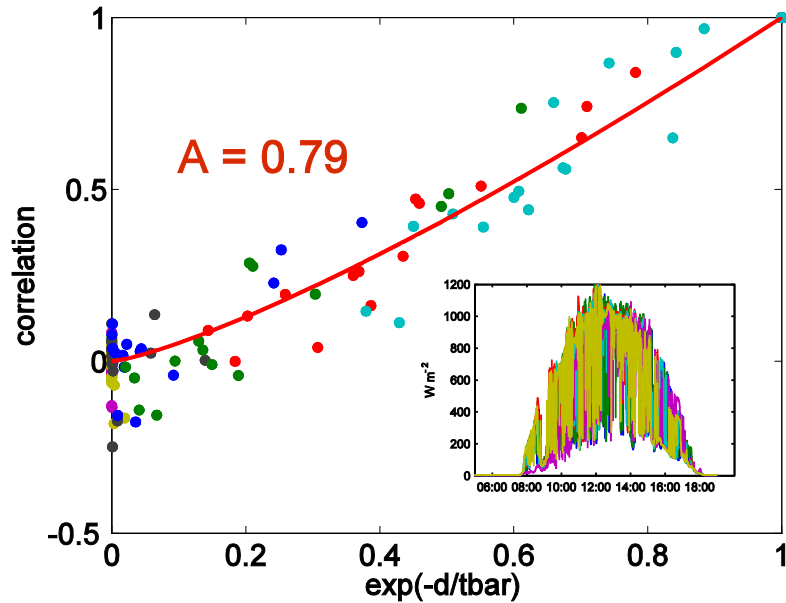
- Research has shown that correlations between sites are related to the distance (d) between sites and time averaging interval (\bar{t}).

22-Jul-2011

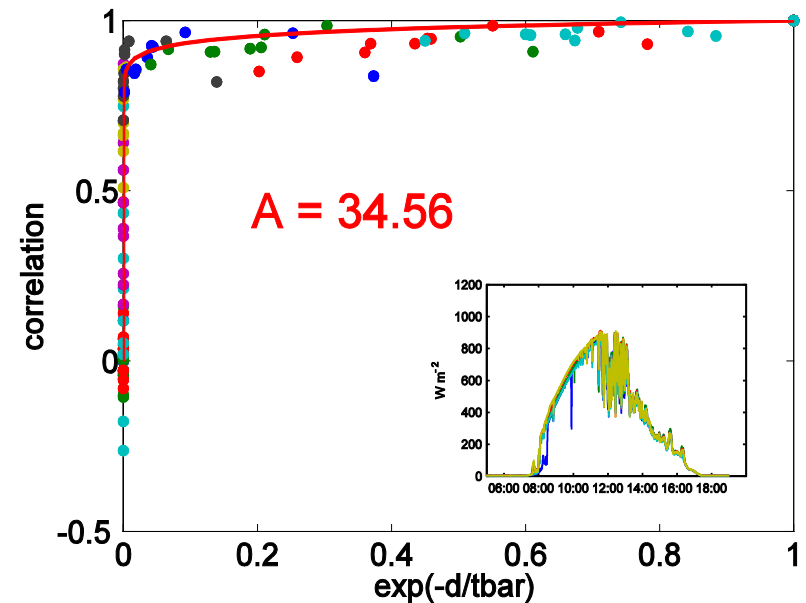


A value changes by day

small A value
10-Feb-2011



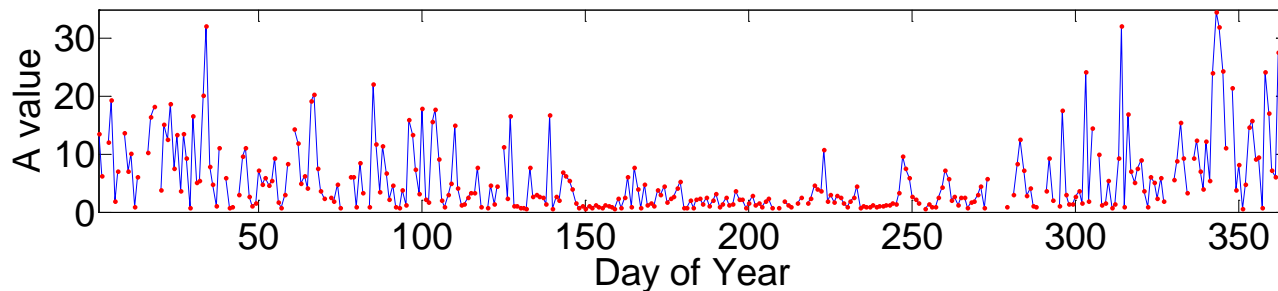
largest A value
09-Dec-2011



- Sites weakly correlated – small clouds.

- Sites highly correlated – large clouds.

Jonesboro 2011 A values

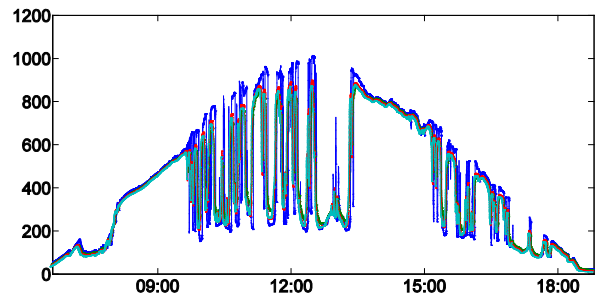


Notes: (1) missing values are clear days, when A is meaningless (no cloud fluctuations to correlate).

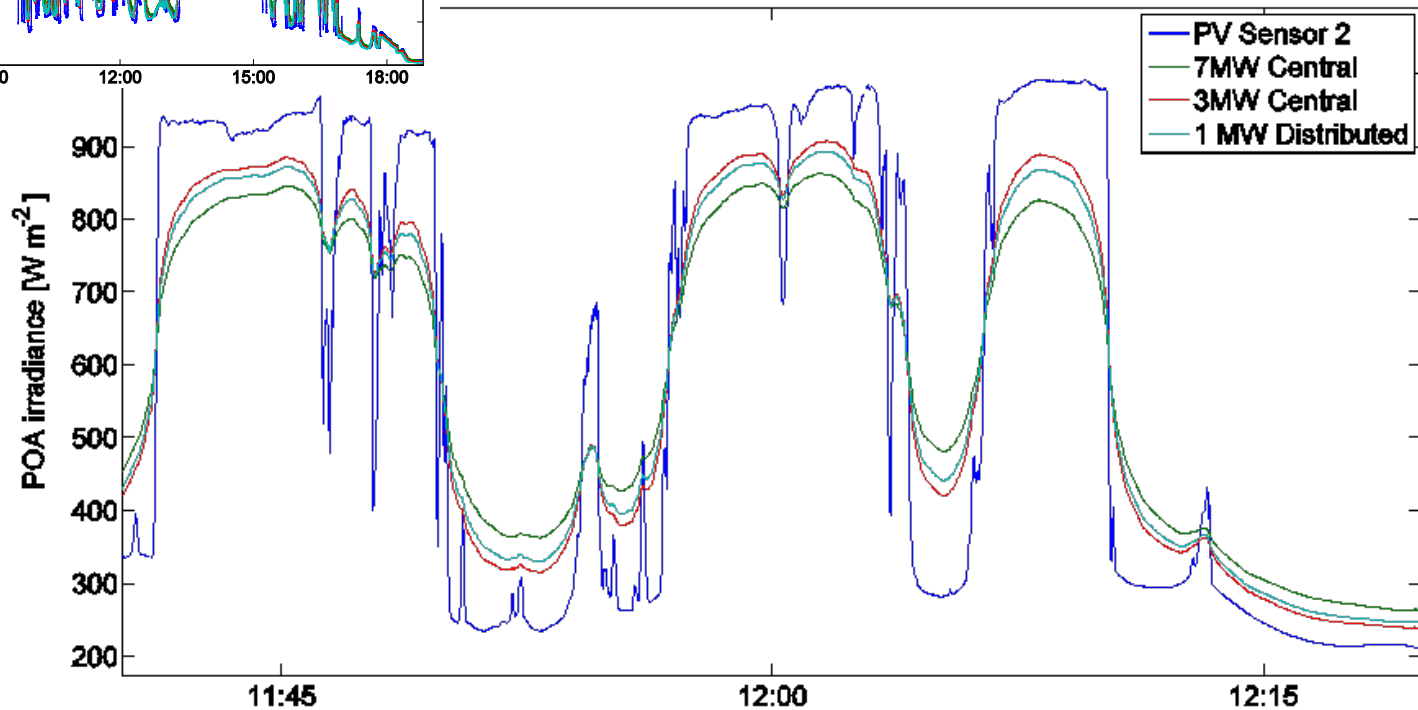
(2) A values relate to correlation by $\rho = \exp\left(\frac{1}{A} - \frac{d}{t}\right)$, so the effect of a larger A is not linear (i.e., A=1 and A=3 are very different; A=25 and A=30 very similar)

Plant Average Irradiance

- WVM simulates plant average POA irradiance.
- 7MW plant is most smoothed due to its size. 1MW distributed is slightly more smooth than 3MW central, due to added geographic diversity.

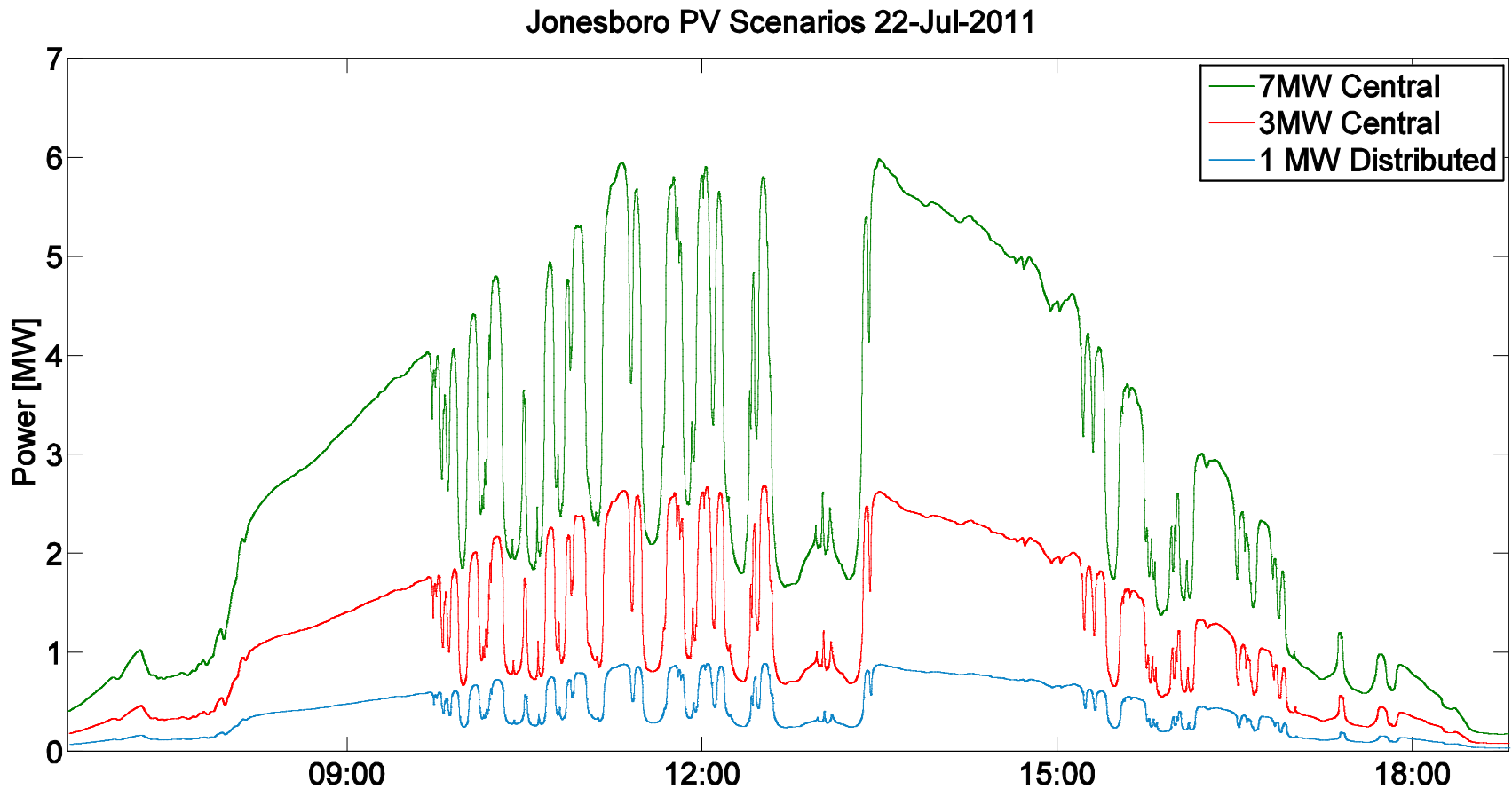


Jonesboro PV Scenarios 22-Jul-2011



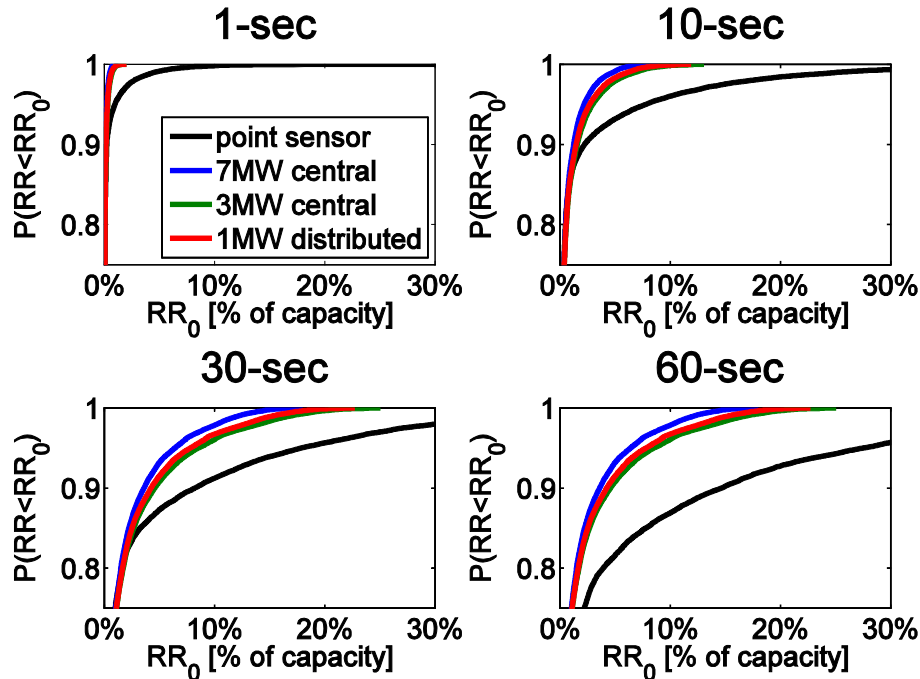
Plant Power

- For this example, we simulate plant power output using a simple linear irradiance to power model*.



*A more complicated irradiance to power output model may be used to increase accuracy.

Look at RRs



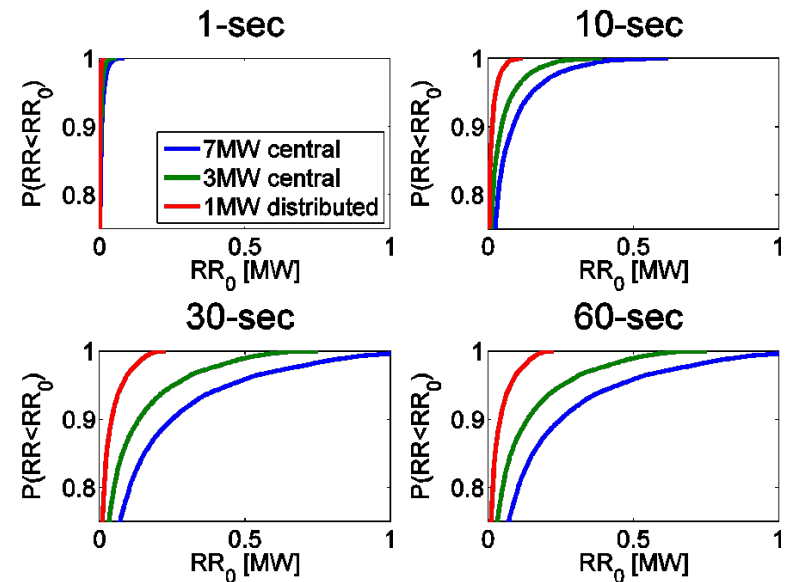
Relative RRs

- Relative RRs show strong difference between point sensor and area averaged irradiance.

cdfs of extreme RRs (>75th percentile) on July 22nd, 2011

Absolute RRs

- Absolute RRs increase with increasing capacity.



Summary

- Prediction of PV output variability is important to support increased penetration of PV on distribution feeders
- High frequency irradiance and PV data are needed as input for these predictions and for validation of models.
- Models such as WVM can be used to simulate nearly any PV scenario if irradiance data is available.
- If measured irradiance data is not available, methods exist to simulate irradiance (adds to the uncertainty)
- Classification schemes (e.g., Variability Index) provide a way to represent variability for a range of representative conditions without needing to run every day and location.



References

- Reno, M. J., C. W. Hansen and J. S. Stein (2012). Global Horizontal Irradiance Clear Sky Models: Implementation and Analysis. Albuquerque, NM, Sandia National Laboratories, SAND2012-2389. (http://energy.sandia.gov/wp/wp-content/gallery/uploads/SAND2012-2389_ClearSky_final.pdf)
- Riley, D. and G. K. Venayagamoorthy (2011). Comparison of a Recurrent Neural Network PV System Model with a Traditional Component-Based PV System Model. 37th IEEE Photovoltaics Specialists Conference, Seattle, WA. (http://energy.sandia.gov/wp/wp-content/gallery/uploads/NeuralNetworkPaper_Riley.pdf)
- Lave, M., J. Stein, A. Ellis, C. Hansen, et al. (2011). Ota City: Ota City: Characterizing Output Variability from 553 Homes with Residential PV Systems on a Distribution Feeder. Albuquerque, NM, Sandia National Laboratories, SAND2011-9011. (http://energy.sandia.gov/wp/wp-content/gallery/uploads/Ota_City_Analysis-SAND2011-9011.pdf)
- Lave, M., J. Kleissl and J. Stein (2012). "A Wavelet-based Variability Model (WVM) for Solar PV Powerplants." IEEE Transactions on Sustainable Energy. (in review).
- Hansen, C., J. Stein and A. Ellis (2011). Simulation of One-Minute Power Output from Utility-Scale Photovoltaic Generation Systems. Albuquerque, NM, Sandia National Laboratories, SAND2011-5529. (<http://energy.sandia.gov/wp/wp-content/gallery/uploads/SAND2011-5529-final.pdf>)
- Stein, J., C. Hansen and M. Reno (2012). The Variability Index: A New and Novel Metric for Quantifying Irradiance and PV Output Variability. World Renewable Energy Forum, Denver, CO.

Southern Company

Will Hobbs



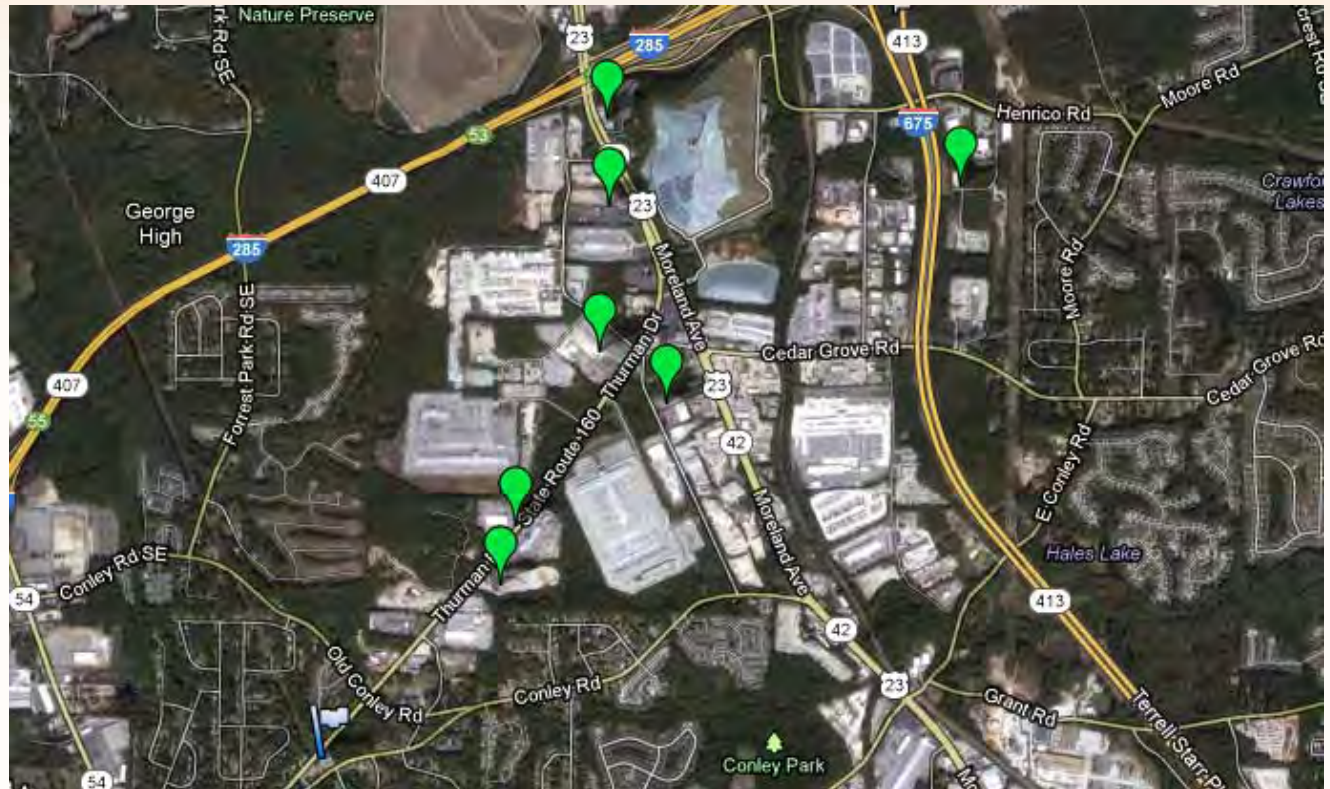
Hickory Ridge Landfill

- Customer owned
- $\sim 1\text{MW}_{\text{dc}}$ thin film laminated on cap membrane



DPV Feeder

- Happens to be on a DPV feeder
- Feeder will be modeled in Open DSS
- 1 sec power and PQ events will be metered



Other perspectives on DPV

- Significant resource data
 - Validate weather models
 - Forecasting?
- Interconnection study validation



Distributed PV Monitoring

*Highlights for PV Grid Integration Workshop
Tucson, Arizona*

Kristen Nicole
Tom Key
Chris Trueblood

19 April 2012

Overview of EPRI's DPQI and DPQII Power Quality Monitoring Studies

	DPQ Phase I	DPQ Phase II
Number of Sites	277*	480**
System Level Monitored	3	8
Monitor•Days	146,661	541,399

* 300 sites were selected during site selection

** 493 sites were selected during site selection

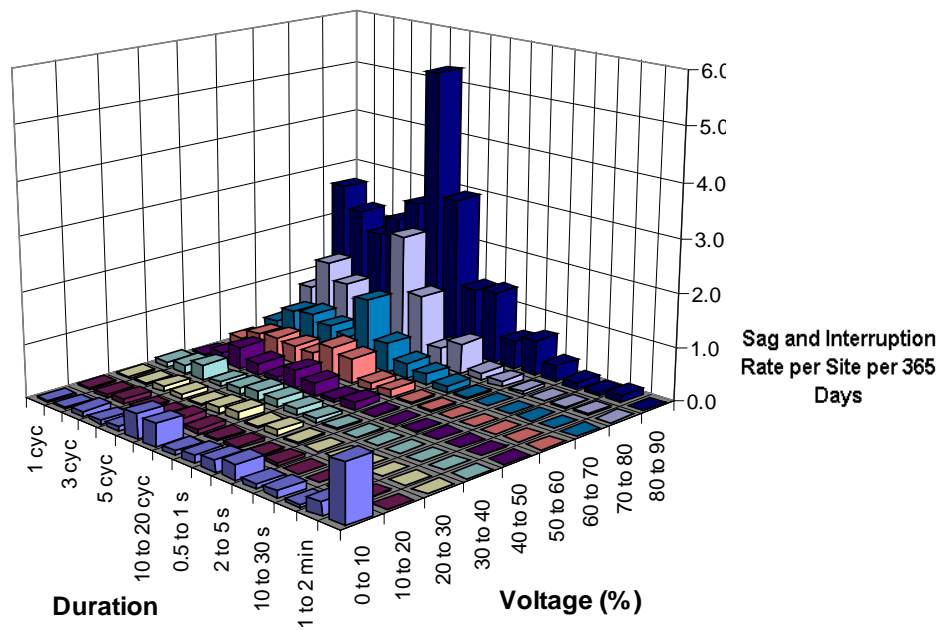
EPRI's DPQI and DPQII Power Quality Monitoring Studies

- Since DPQI Phase I completion in 1995, many utilities have implemented system-wide PQ monitoring programs on distribution and transmission.
- Wealth of data provided unique opportunity for Round II, DPQ. (2001-2002)
- DPQI PQ along the feeder (sub, middle, end), DPQII (various locations on feeder)

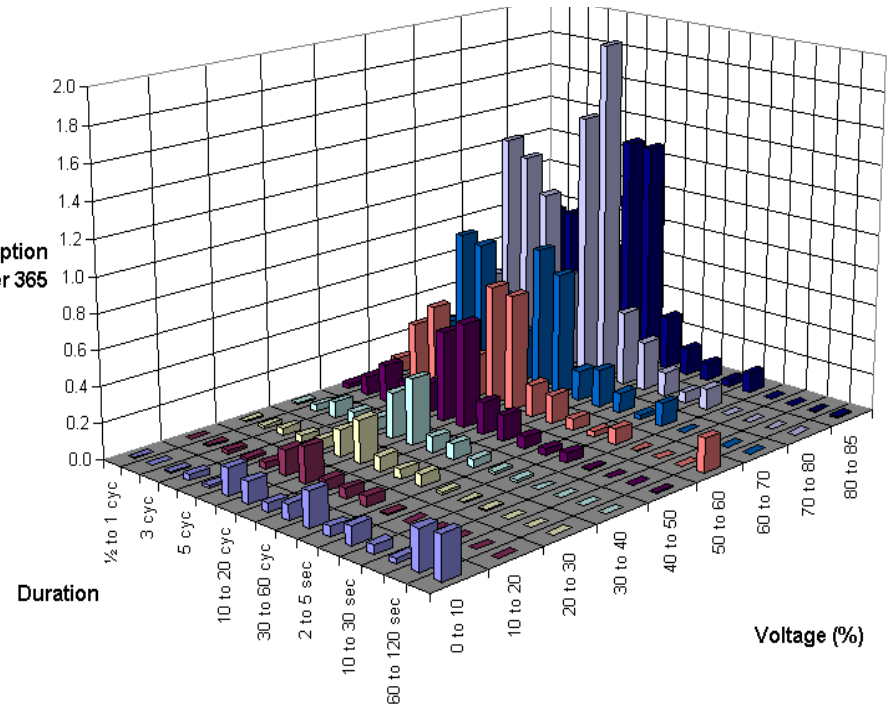
Sag and Interruption Annual Rates (Magnitude/Duration Histogram)

DPQ Phase I, 0 – 90% Voltage

RMS Voltage Variation Sag and Interruption Rate



DPQ Phase II, 0 – 85% Voltage

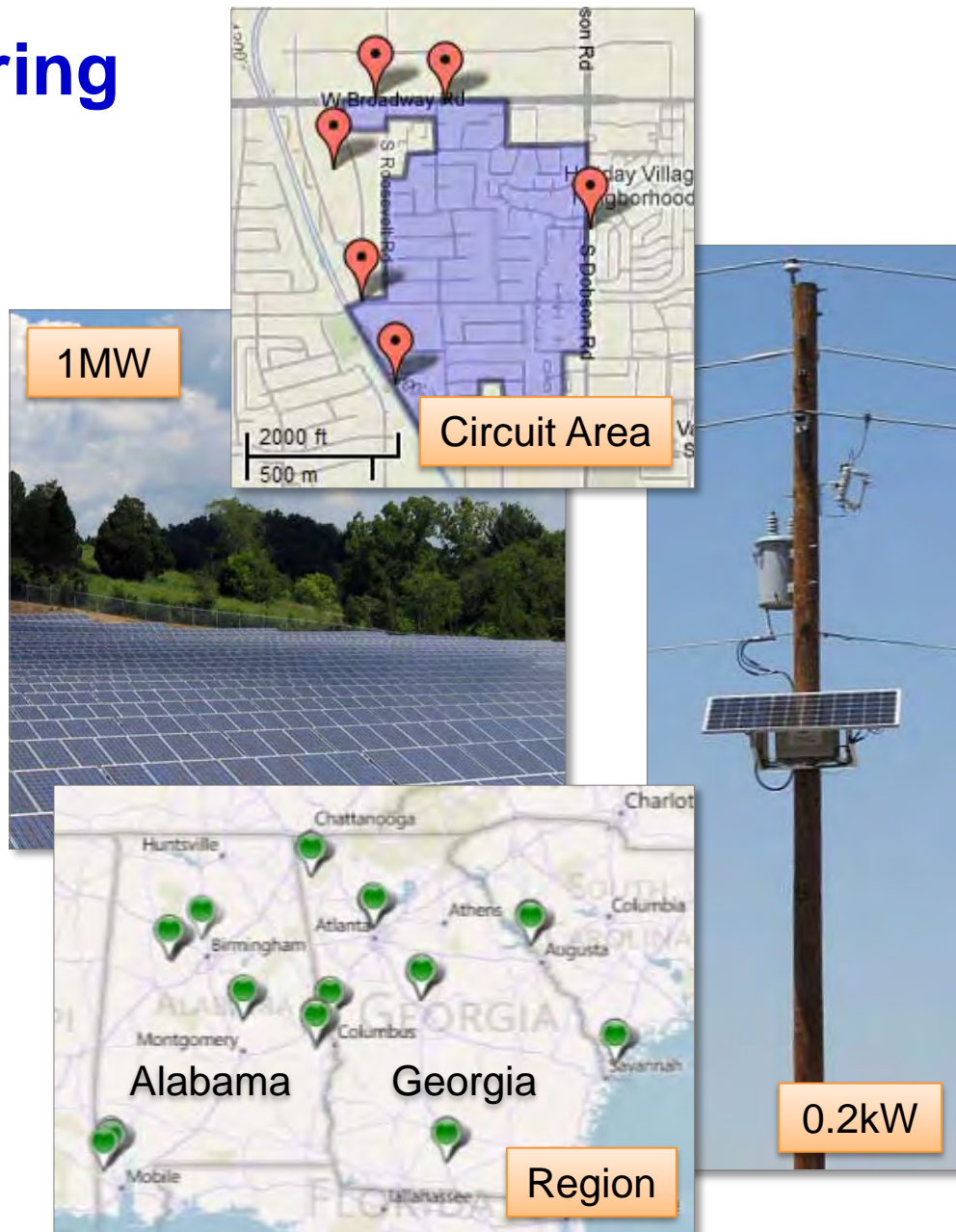


Distributed PV Monitoring

An EPRI Research Project

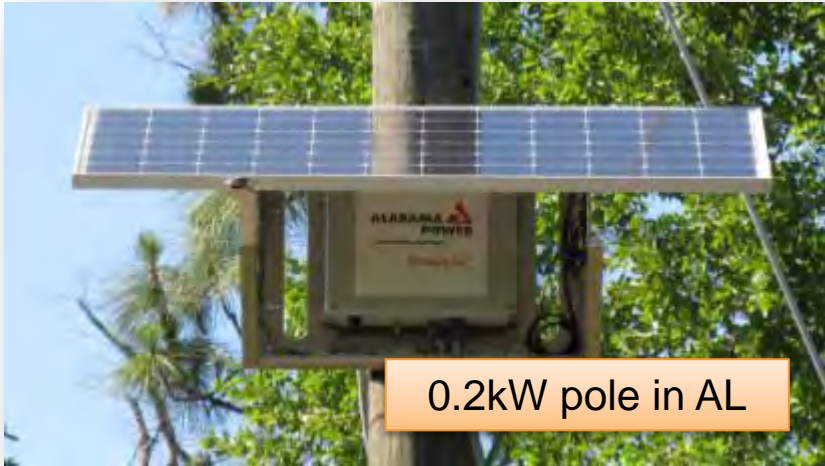
Field monitoring to characterize PV system performance & variability

- **Utility interactive PV systems**
 - ✓ Single modules on poles
 - ✓ 1MW plants
 - ✓ 200+ sites committed nationwide
- **Field measurements for 1+ years**
 - ✓ AC power meter
 - ✓ Plane-of-array pyranometer
 - ✓ Module surface temperature
 - ✓ ...More sensors on select sites
- **Data acquisition**
 - ✓ 1-second resolution
 - ✓ Time synchronized
 - ✓ Automated uploads to EPRI
 - ✓ Structured data storage at EPRI



PV systems small and large are monitored

High definition monitoring captures 1-sec data on any size PV system



Monitoring for Central Inverter PV Systems

Instrumentation for solar resource, selected dc points, and ac output

Data acquisition: up to 1-second recording, automatic data transfers, internet time synchronization, remote login

Solar Resource

- **Irradiance:** plane-of-array, global horizontal
- **Weather:** temperature, humidity, wind, rain

PV Array

- **Module:** dc voltage, current, back temperature
- **Combiner box:** dc voltage, string currents

Inverter

- **Input:** dc voltage, current
- **Output:** ac power, energy totals (real & reactive), voltage, current



Instrumentation designed, assembled, configured, and tested by EPRI for field installation

High Resolution Field Data & Geospatial Analytics

Distributed PV Monitoring supports EPRI's core PV research areas

Utilities &
System
Operators

Forecasting

Bulk
System

Distribution
System

**Distributed
PV
Monitoring**

Renewable
Generation

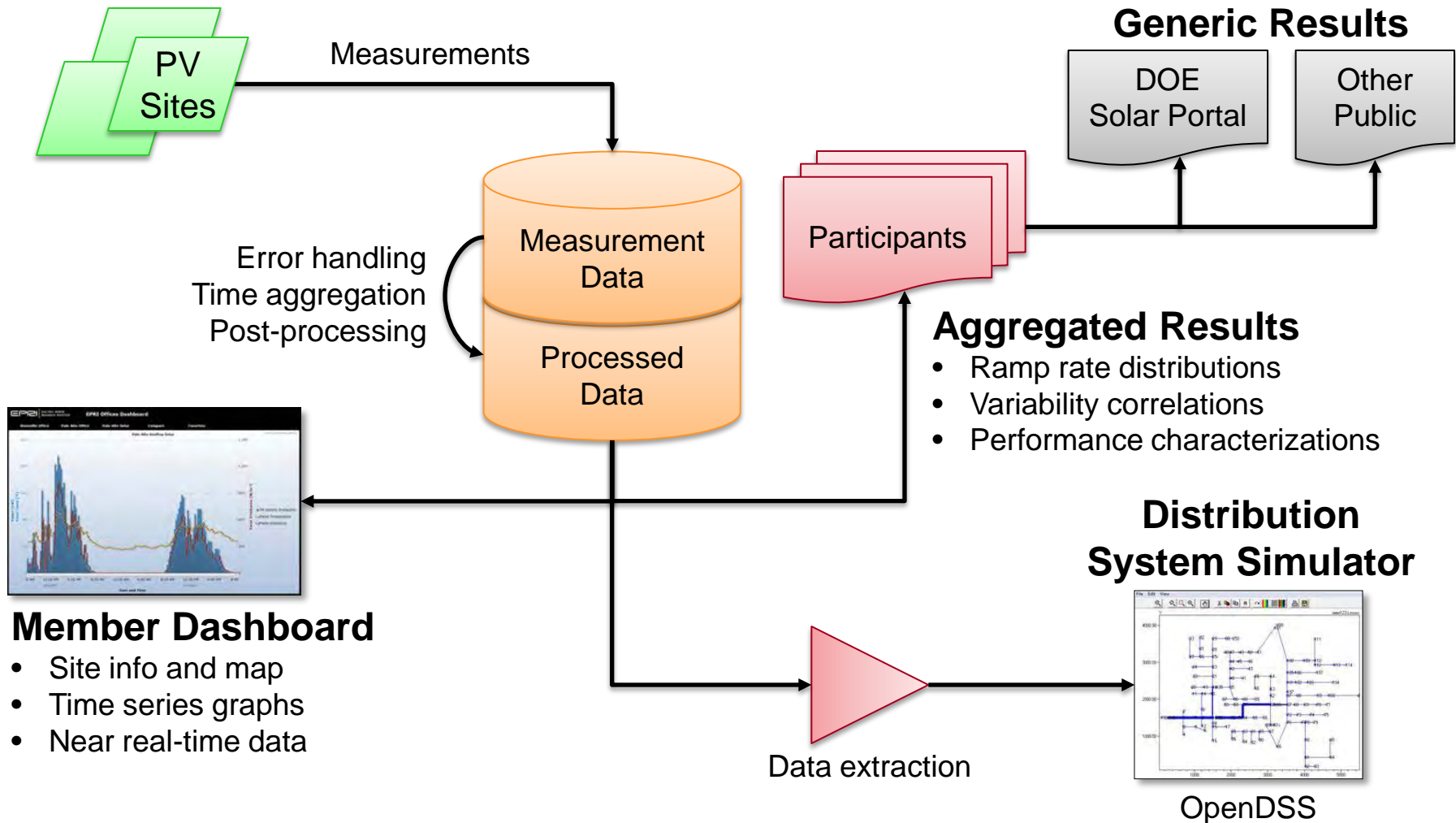
Operations &
Maintenance

Prediction

PV System
Owners &
Stakeholders

Analysis and Reporting Plan - DPV Data Flow

Measurement data feeds website, site analysis, and OpenDSS



Site Analysis of Distributed PV Systems

Many sites have 1+ year of field data, ripe for site-level analysis


EPRI ELECTRIC POWER RESEARCH INSTITUTE

Distributed Photovoltaic (DPV) Monitoring - Site Analysis

April 2012

This is the first monthly update for the collaborative Distributed PV Monitoring project. Thank you to the 8 utilities that have joined the project and selected and instrumented PV sites in 26 cities across the country. As we focus on site-level analysis, EPRI will provide monthly updates on interesting results and learnings. This update offers a summary of the planned site analysis.

Project Overview
EPRI has partnered with utilities to monitor distributed PV systems and characterize solar variability in a variety of locations and along specific distribution circuits. Detailed, high resolution (one-second) solar input and ac output data is being collected at several PV plants and 150+ single-module monitoring sites (see map below for locations). The project has several phases: site selection, equipment installation, data collection, site analysis, and reporting.



Site Analysis Plan
EPRI is analyzing variability and performance of each site over multiple time steps and site groupings. Results will broaden utilities' knowledge of PV system dynamics as grid-connected solar becomes more prevalent. While site-level analysis is the focus of this project, other related EPRI projects focus on distribution feeder impacts and bulk system studies through extensive circuit modeling and simulation. A summary of the planned site analysis with examples is provided below and on the next page.

Ramp Rate Characteristics
Approach: Quantify the prevalence of solar variability and compute probability distributions of ramp events. Participants can enhance power system studies by incorporating sub-minute to hourly statistics of measured solar variability.

Example: Monthly ramp rate extremes are charted for a group of single-module monitoring systems in Arizona (Figure 1). The 6 sites cover 300 acres (1.0x1.2 km) and are located on the perimeter of a specific distribution circuit. Observed ramp rate magnitudes are shown as a percentage of normalized system ratings. For the 3 months shown, maximum 10-second changes are about 33% of rated power. At 1 minute time steps, maximum ramp rates increase to about 55%.




Figure 1. Maximum ramp rates from a cluster of Arizona single-module PV monitoring sites

These sites are distributed across the country, allowing for correlation activities by knowing the geographic location of dispersed PV systems.

Interpolation is provided for single-module monitoring systems. One site appears to be in a neighboring system with high cloud cover. When the sun will rise and fall as clouds pass.



Figure 2. Surface mesh showing PV output diversity for a moment in time in Georgia

PV System Performance
Approach: Tabulate measured energy production, solar insolation, and normalized performance metrics. Participants can validate expected output and refine predictions when siting new PV systems or evaluating solar resources.

Example: The calendar in Figure 3 shows daily ac power output profiles from a LOMW PV plant in Tennessee. The thin green line represents the PV system rating. February 1, 4, and 7 are overcast days, while February 7 and 12 are cloudier days. High variability days, such as February 6, 8, 11, 21, and 25 are of particular interest.



Figure 3. Daily ac power output profiles from a LOMW PV plant in Tennessee

View of monitoring site operations
Participants can leverage hands-on knowledge when siting new PV systems or evaluating solar resources.

View of the inside of a single-module monitoring site in North Carolina. EPRI on-site personnel and involve at



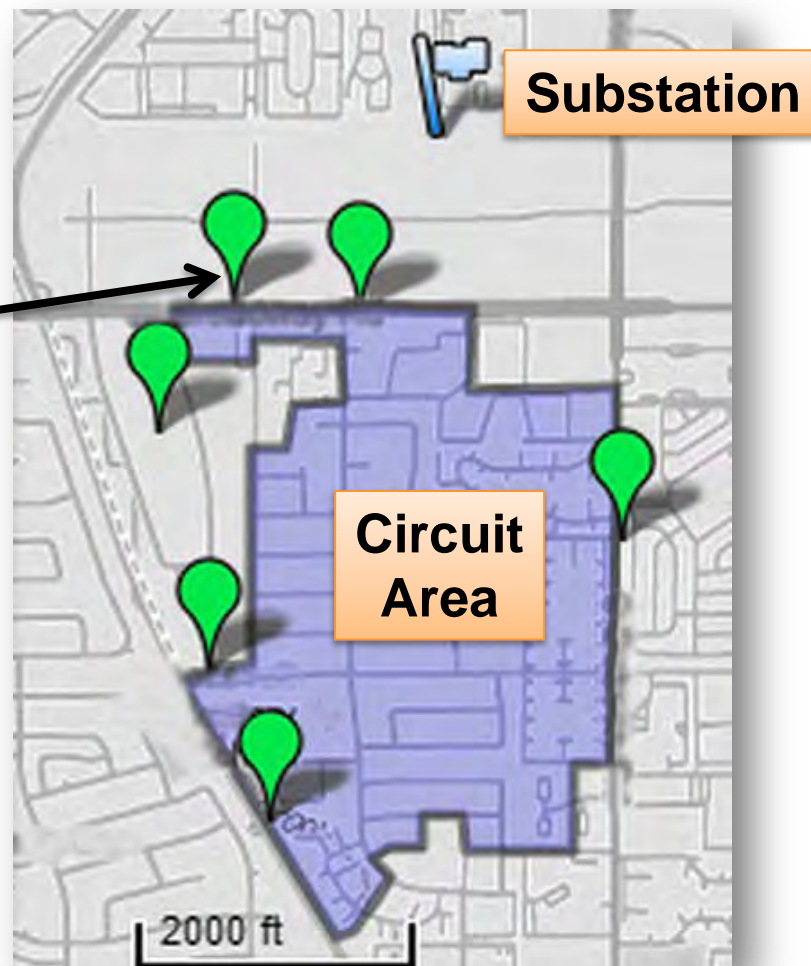
Figure 4. View of EPRI's instrumentation enclosure and an installation on a pole in North Carolina

2012, first week of each month
Site details, time-series charts, and data downloads - June 2012
Project summary and generalized results - December 2012

Distributed PV Monitoring project as a collaborator or would like more information, contact ctruelwood@epri.com, 865-218-8118.

Distributed pole-mount PV sites in Arizona

Six single-module systems installed, data collection began June 2011

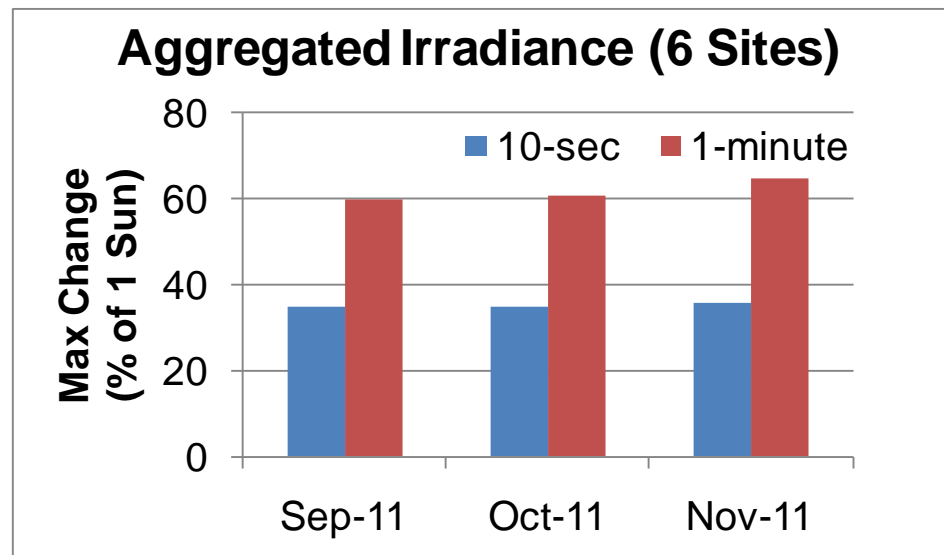
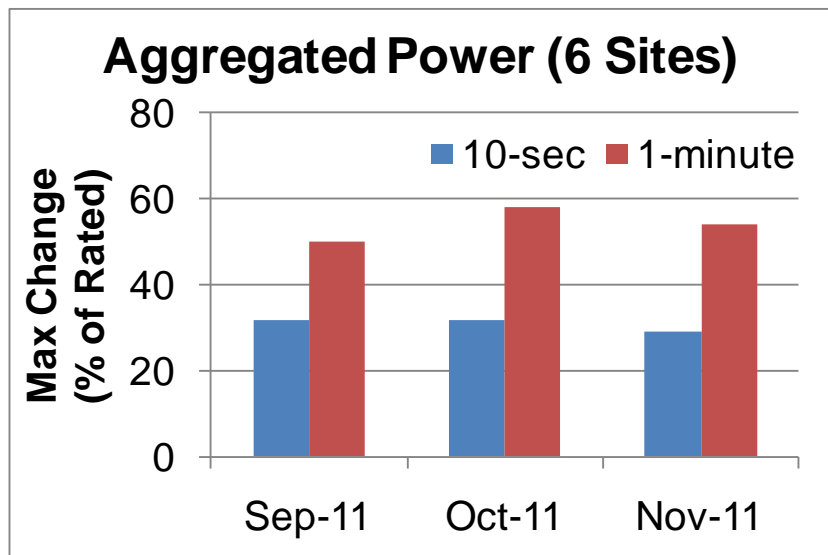


Map data © 2012 Google

Daily Maximum Changes in Power, Irradiance

Aggregated from 6 pole-mount PV sites on an Arizona distribution circuit

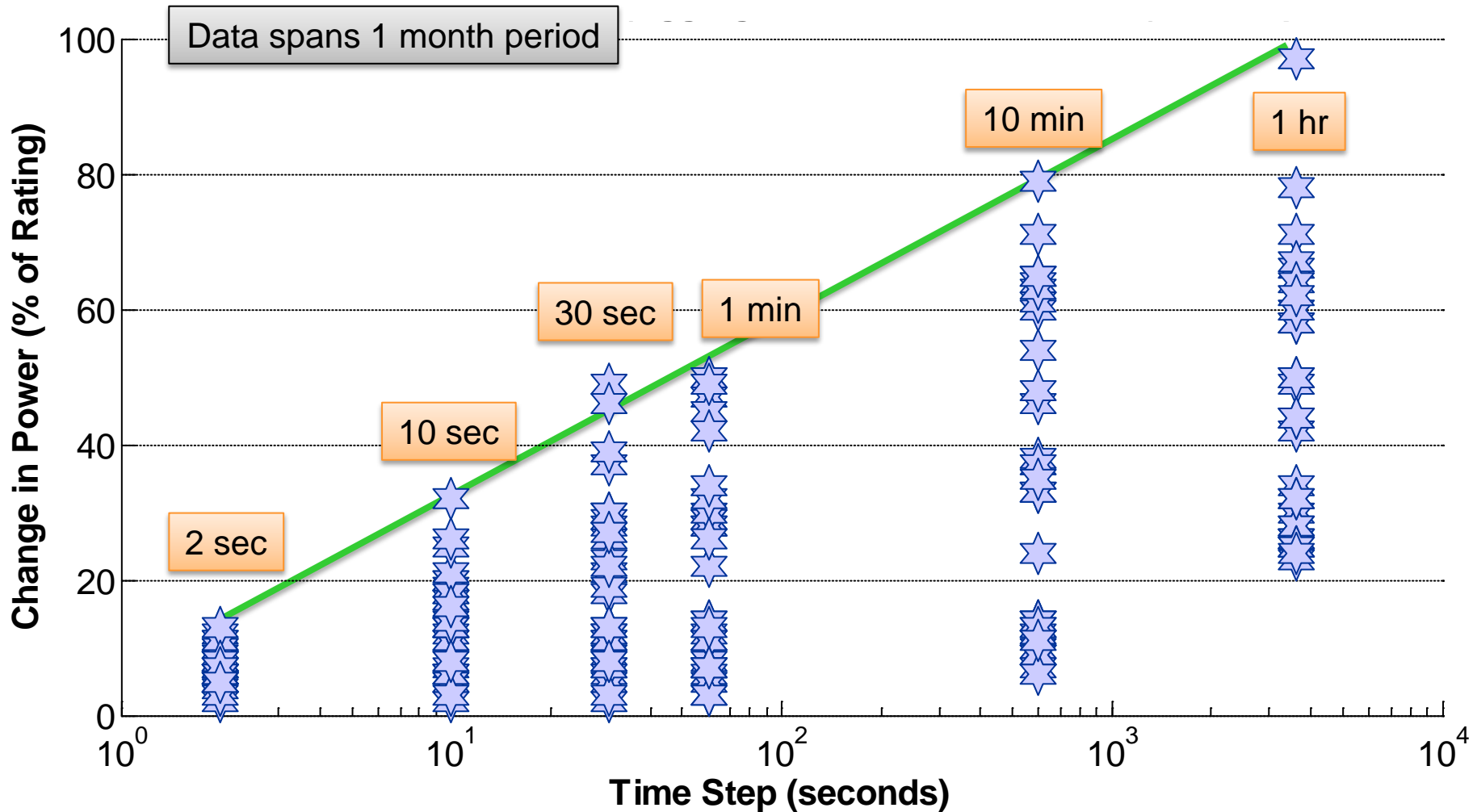
- **Aggregated Power (from six 190W PV modules)**
 - Max 10-sec change about **30%** of rated power
 - Max 1-minute change about **55%** of rated power
- **Aggregated Irradiance (plane-of-array pyranometers)**
 - Max 10-sec change about **35%** of full sun (1000 W/m²)
 - Max 1-minute change about **60%** of full sun



Max changes in power/irradiance are consistent across fall months Sept-Nov 2011

Daily Maximum Changes in AC Output Power

Aggregated from 6 pole-mount PV sites on an Arizona distribution circuit



1MW PV System in Tennessee

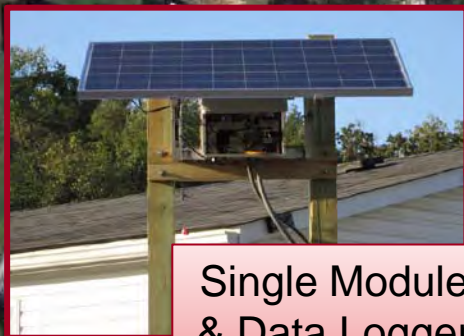
Solar resource and AC output recorded at 1-sec resolution

1.0 MW_{dc}

- 3.5 acre property
- 4,608 PV modules
- Four 260kW inverters
- Installed Aug 2010
- Data began Oct 2011

8 Pyranometers

- 7 on PV system
- 1 on single-module
- Plane-of-array
- 25° fixed tilt, south



Single Module
& Data Logger

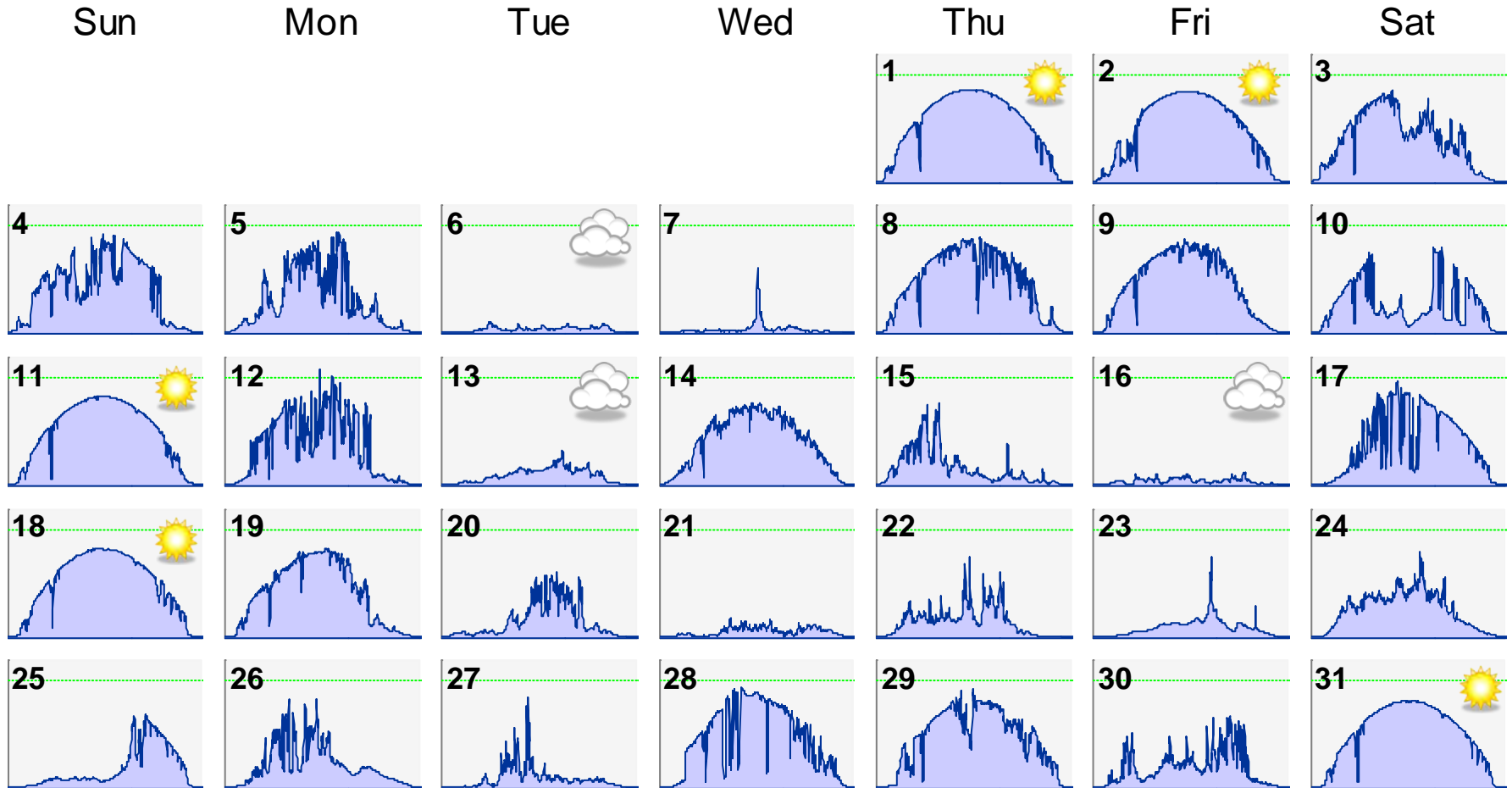


Pyranometer

Solar Resource Calendar – Single Pyranometer

December 2011 at 1MW PV site in Tennessee

December 2011: Tennessee Plane-of-Array Irradiance

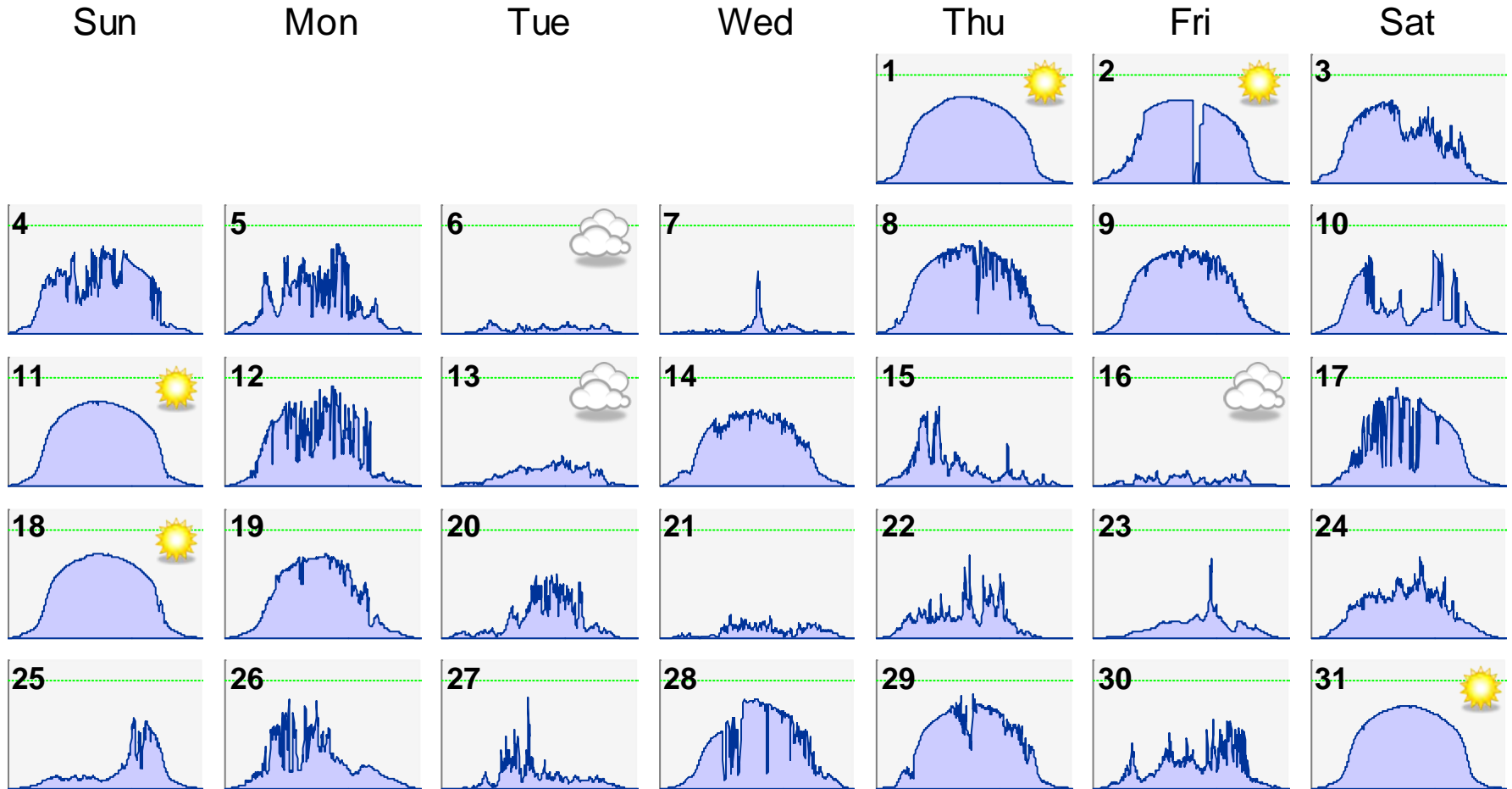


Calendar profiles are 1-minute averages derived from 1-sec data

Solar Resource Calendar – 1MW_{AC} Output Power

December 2011 at 1MW PV site in Tennessee

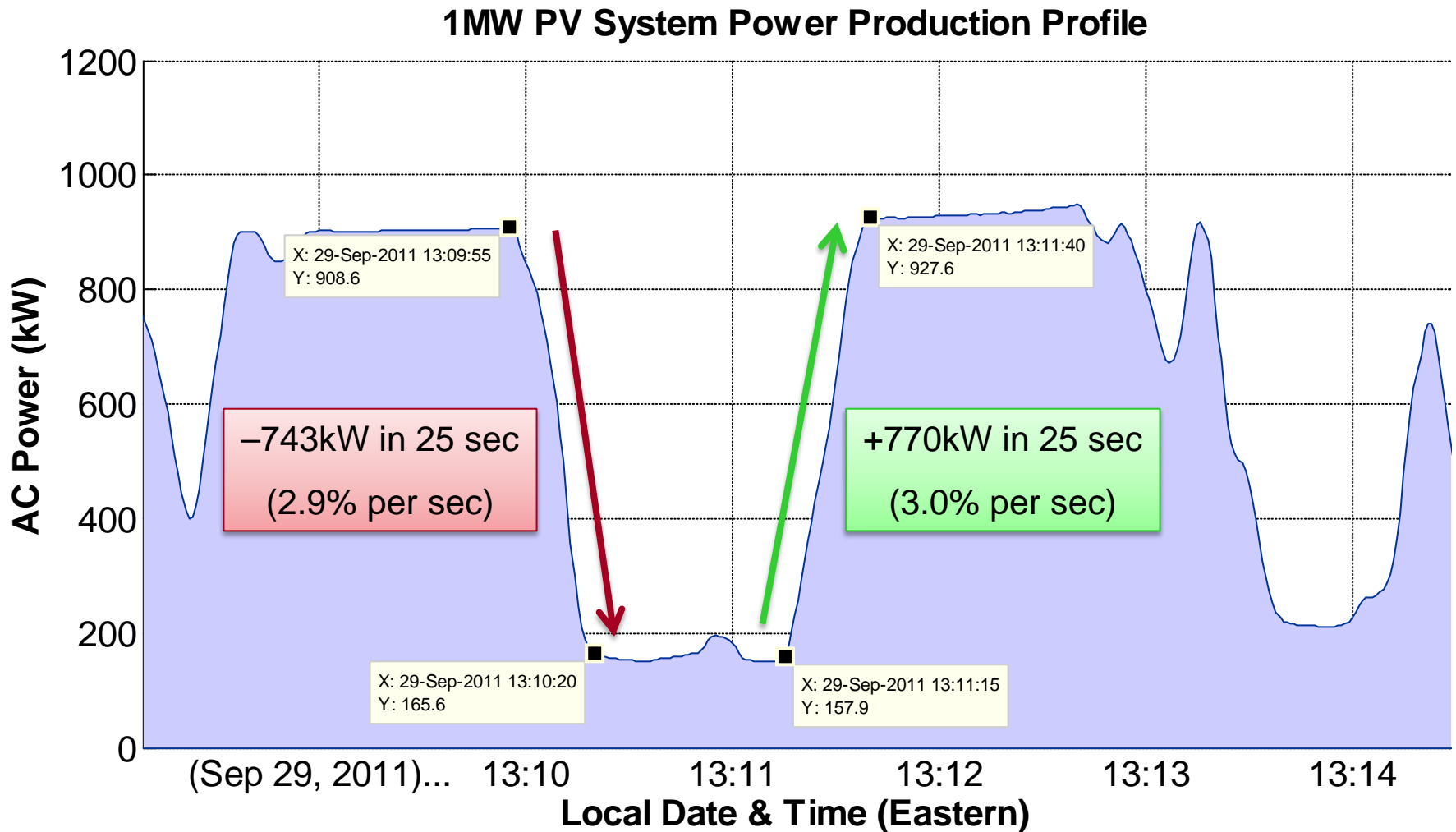
December 2011: Tennessee 1MW PV System Power



Calendar profiles are 1-minute averages derived from 1-sec data

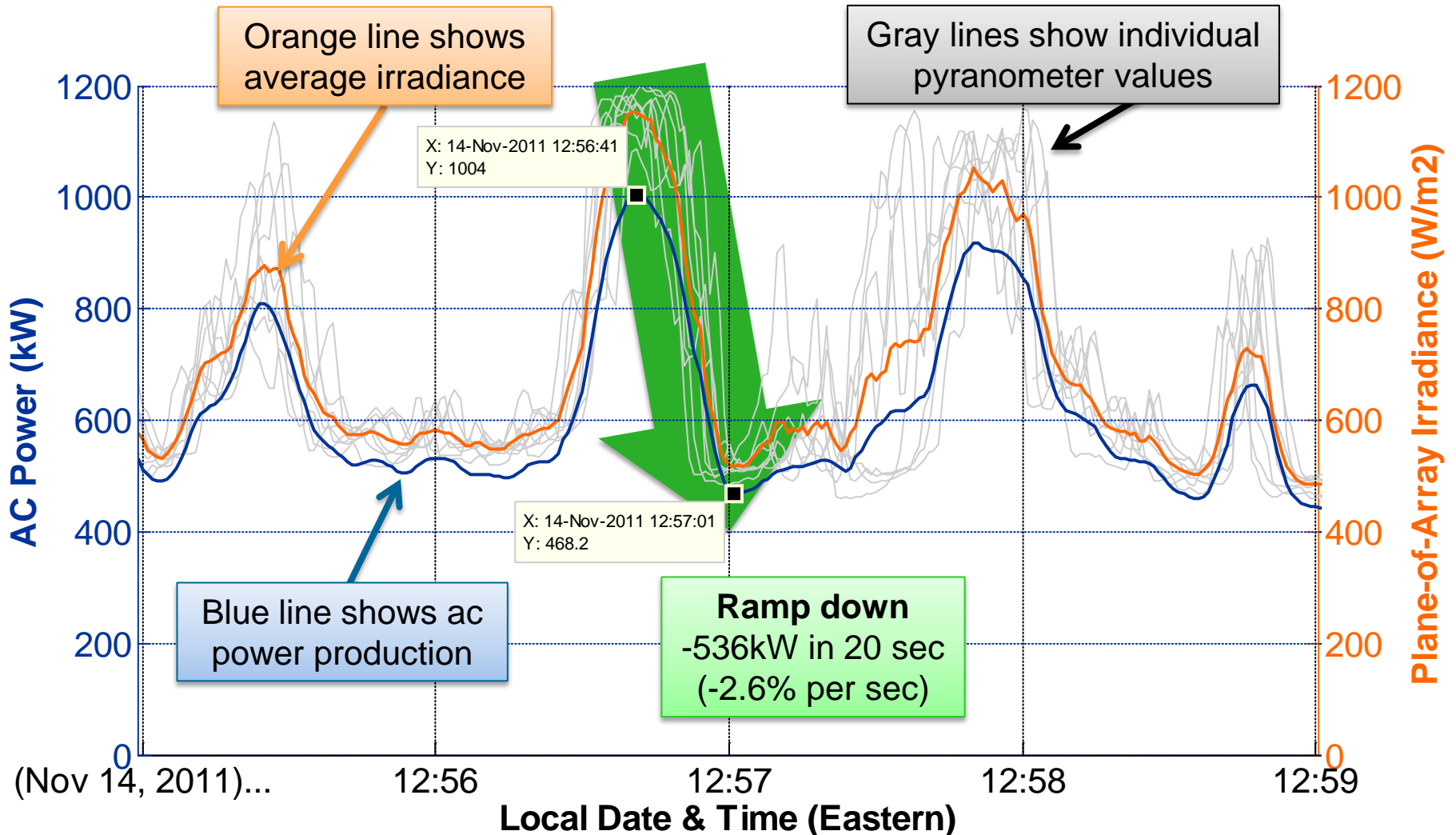
Example Ramp Events on Partly Cloudy Day

Six-minute view of AC power profile of 1MW system at 1-sec resolution



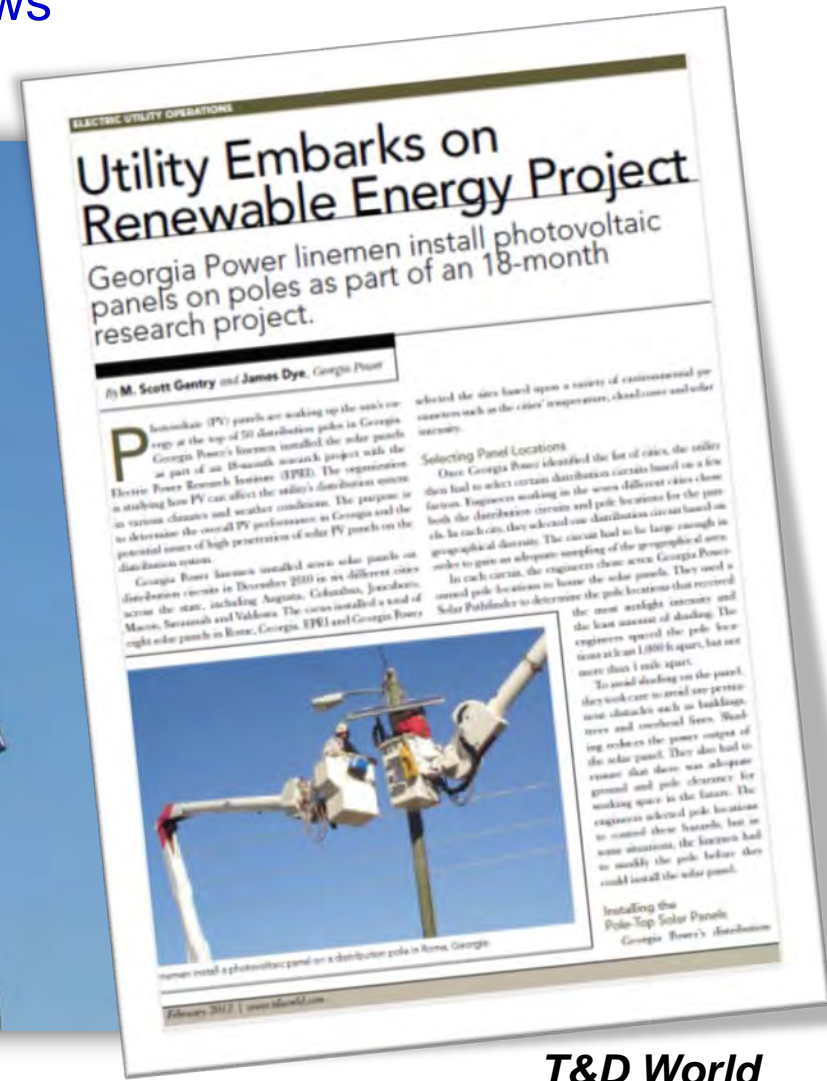
AC Power and Irradiance on Partly Cloudy Day

4-minute period shows time-shifted effect of passing clouds over 1MW



Added Value with Utility Line Crew Participation

Hands-on approach yields PV savvy crews



Georgia Power installs project's first pole-mount systems in Dec 2010

T&D World
February 2012

Together...Shaping the Future of Electricity