PV Output Variability, Characterization and Modeling

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Outline

- Introduction
  - Why is solar variability important?
- What information is needed to address integration costs for PV?
- What do we know about PV output variability?
- What model forms are available and promising?
- Two example applications
  - Using satellite imagery to predict short-term variability
  - Generation of PV output profiles for grid integration study

System Impacts of Variability

- **Increases in variable generation can affect operations over all time frames**
  - **Regulation**
  - **Unit Commitment and Economic Dispatch**
  - **Resource Adequacy**
- **Increases in overall variability and uncertainty adds to costs**

“Easy” Week

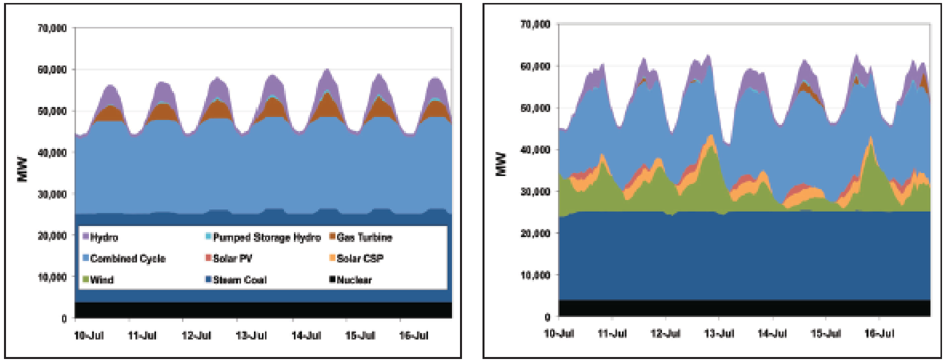


Figure 3 – 35% renewables have a minor impact on other generators during an easy week in July, 2006. WestConnect dispatch - no renewables (left) and 30% case (right)

“Hard” Week

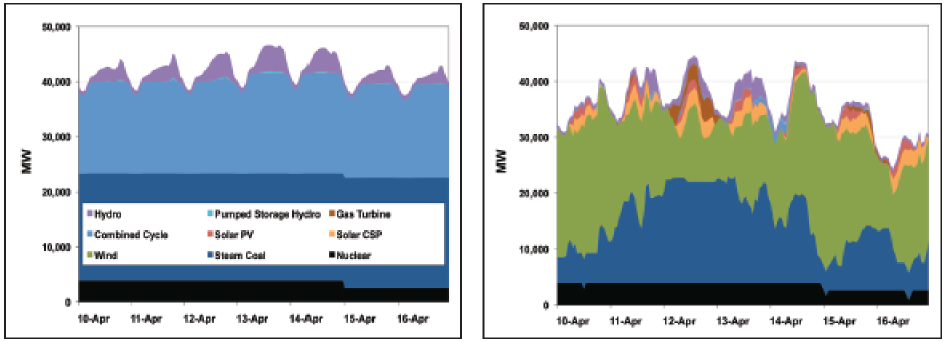
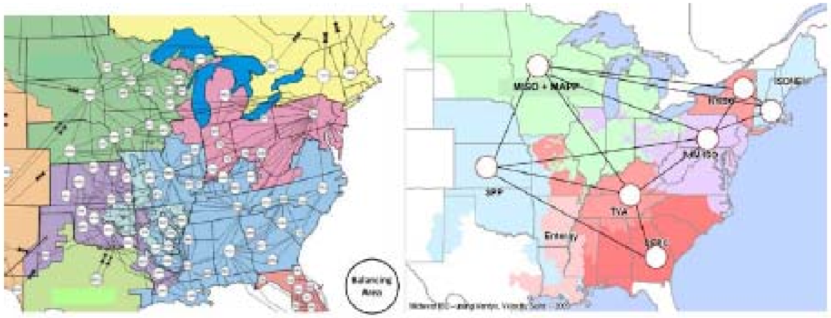


Figure 4 – 35% renewables have a significant impact on other generation during the hardest week of the three years (mid-April 2006). WestConnect dispatch - no renewables (left) and 30% case (right)

Figures from Western Wind and Solar Integration Study, 2010

Integration Costs are System Dependant

- **Solar resource variability is geographically dependent**
- **Solar generation deployment scenarios**
  - **Penetration level**
  - **Large central-station plants vs. distributed deployment**
- **Every balancing area has a unique characteristics**
  - **System flexibility (generation & market), size, and transmission constraints are different**
  - **Operations practices, performance requirements differ**
    - **E.g., Control performance standards**
    - **Frequency tolerance**



As of August 1, 2007 | Assumption for 2024

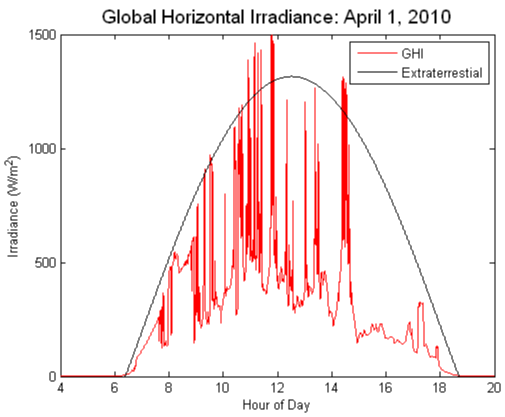
What is Needed?

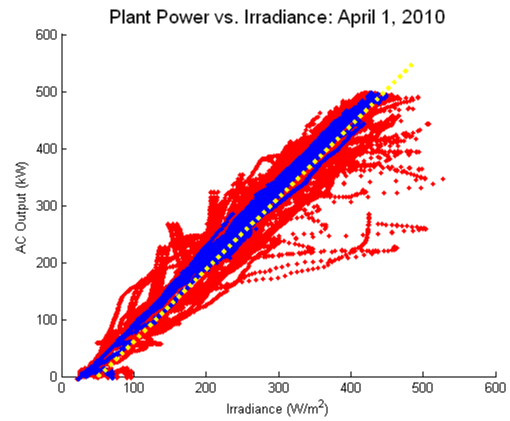
- **Validated methods to estimate and predict single and aggregated PV plant output profiles for historical periods with minimal ground based measurements**
  - **Plants of any size, any location, any deployment pattern**
    - **Ground measurements of irradiance**
    - **Satellite imagery**
    - **Weather data and forecasts**
  - **High time resolution (sub-hourly)**
  - **Reasonable forecast estimates**
- **These estimates provide inputs to grid integration studies that can help determine how large amounts of PV can be accommodated most cost-effectively.**

What Do We Know?

1. Spatial Average of POA Irradiance is the Key

- **PV output is a function of plane of array irradiance and temperature**
- **Irradiance sensor network at “La Ola” 1.2 MW_{AC} PV plant in Lanai, HI has demonstrated that short-term PV output (1-sec) is linearly proportional to the *spatial average of irradiance* (Kuszmaul et al. 2010)**





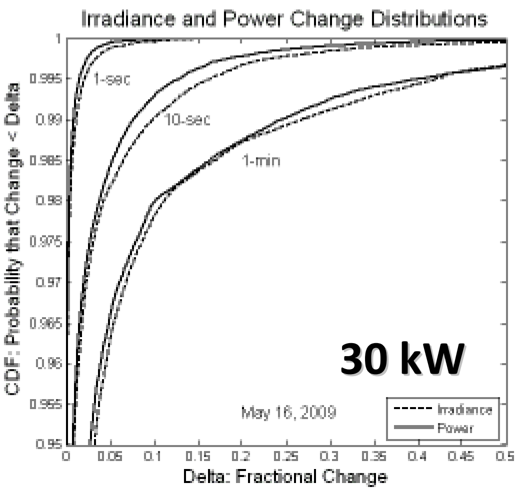
Red = Single Irradiance Sensors (5)

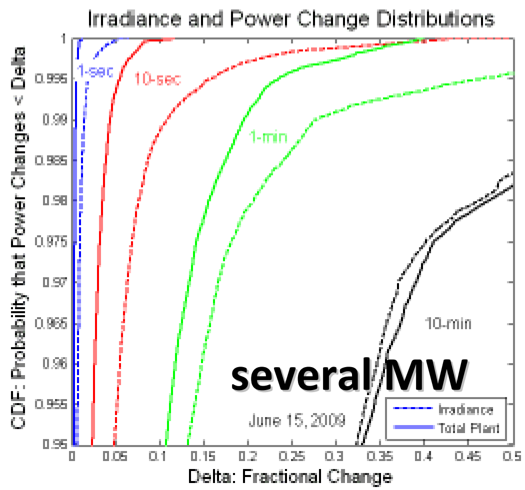
Blue = Network Average Irradiance

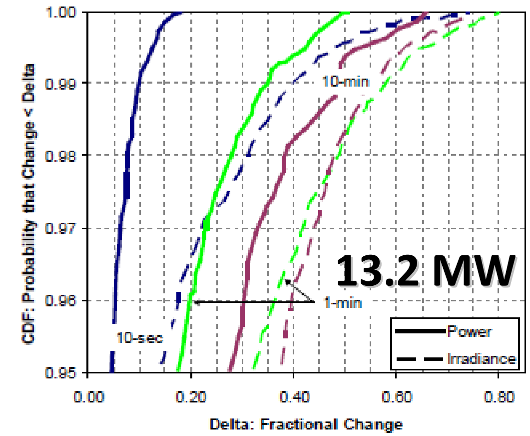
Sandia and SunPower are working together to validate this for larger PV plants

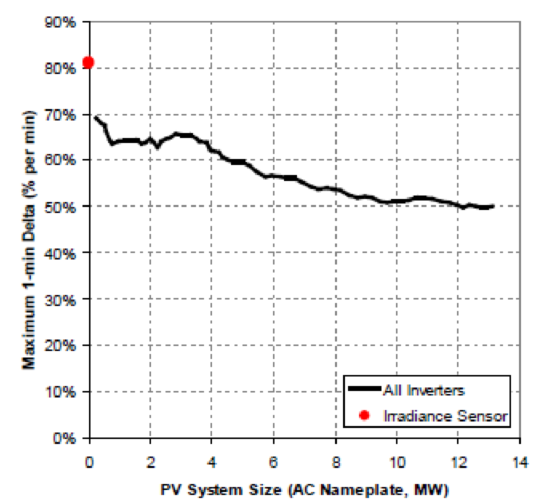
What Do We Know?:
2. Plant Size Affects Ramp Rate Distribution

- **As PV plants get bigger, ramp rates decrease**







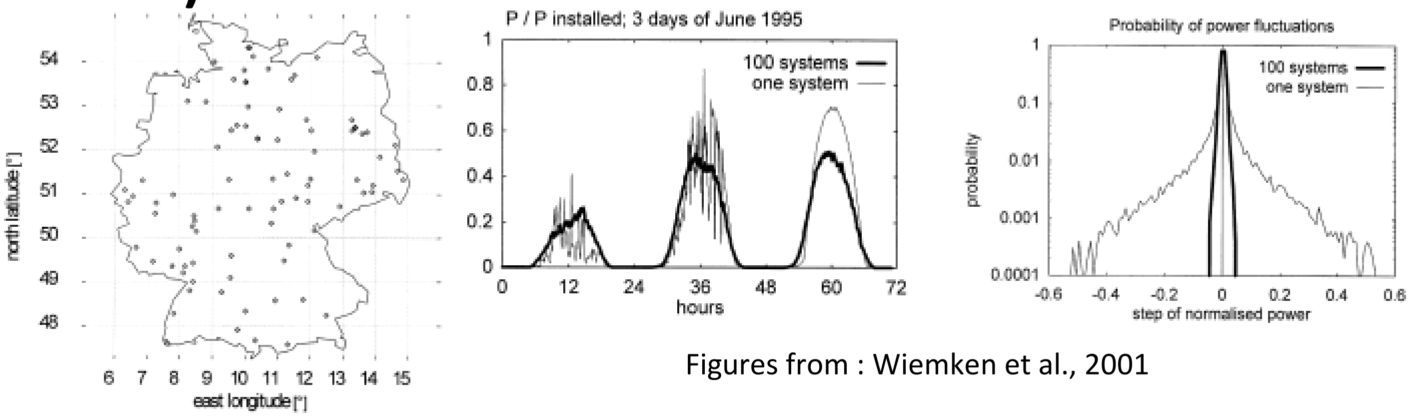


- **No model yet exists to predict these relationships.**
- **Function of plant efficiency, tracking, weather patterns, etc….?**

Figures from Mills et al., 2009

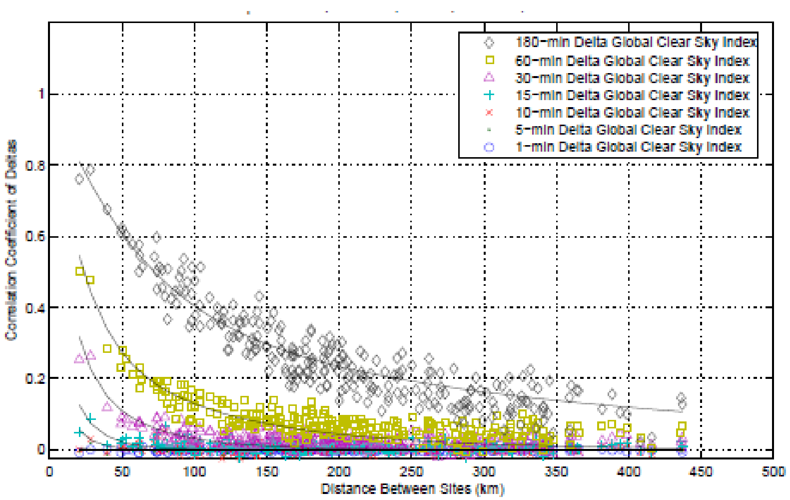
What Do We Know:
3. Geographic Diversity Reduces Ramp Rates

- **As multiple PV plants are aggregated over large geographic areas ramp rates decrease (Wiemken et al., 2001)**



Figures from : Wiemken et al., 2001

- **Correlation between ramp rates at different sites decreases with separation distance**
  - **Mills and Wiser (2010)**

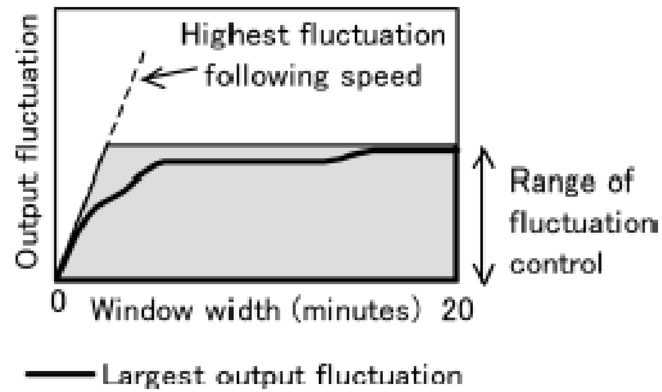


Model Forms: Point Irradiance to Spatial Average

- Longhetto et al, 1989 suggested a model form that reduces high frequency power variations as plant size increases
  - Clouds take time to pass over plant footprint and power changes are slower as plant size increases
- Beyer et al. (1994) used sky imagery and a 16 node irradiance sensor (1 sec) to develop a model based on the fractal dimension of clouds.
  - Model was applied to estimate point irradiance time series (~5 min in length), but model form potentially could work for spatial averages too.
- Model validation studies are needed
  - New Sandia report describes validation metrics (Hansen et al., 2010)

Model Forms: Geographic Diversity

- Wiemken et al. (2001) examined 5-min output profiles from 100 PV systems in Germany
  - Described decrease in cross correlation with increasing distance between sites.
- Murata et al. (2009) presents a model of geographic diversity based on the "Largest Output Fluctuation"



- Hoff and Perez (2010)
  - Model based on 'dispersion factor' (number of time intervals for clouds to pass over PV fleet)
- Bottom line: Existing model forms do not tell us what we need to know: Frequency and Magnitude of ramp rates

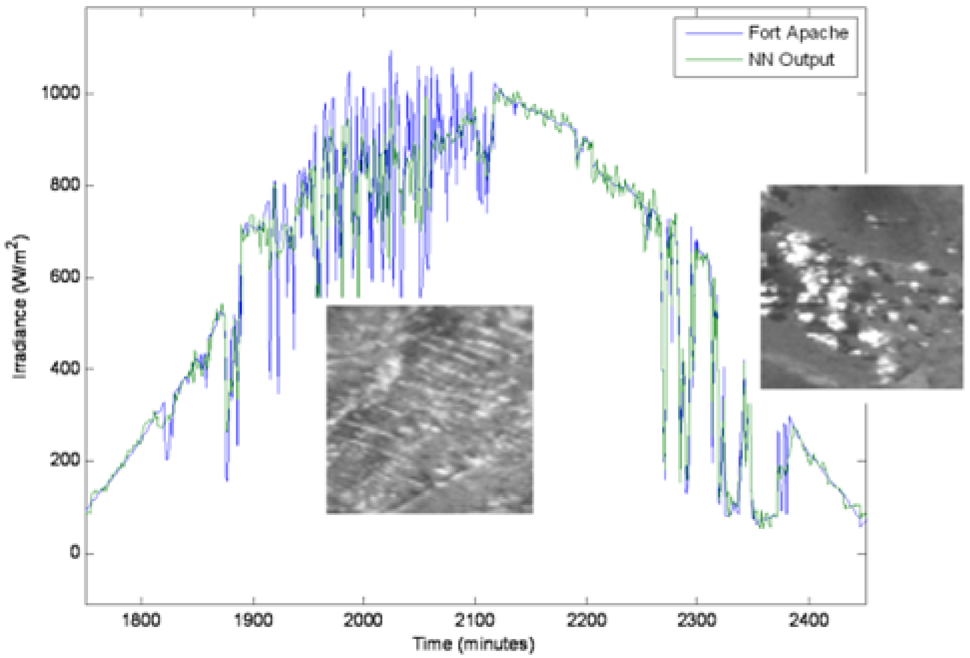
Example Applications at Sandia

1. **Using satellite imagery to estimate variability in areas with no ground data.**
2. **Generate PV output datasets (1-min) for grid integration study in southern Nevada.**

Example Application 1: Novel Use of Satellite Data

- **Sandia working on method to estimate 1-min irradiance variability from satellite imagery (Reno et al. 2010)**

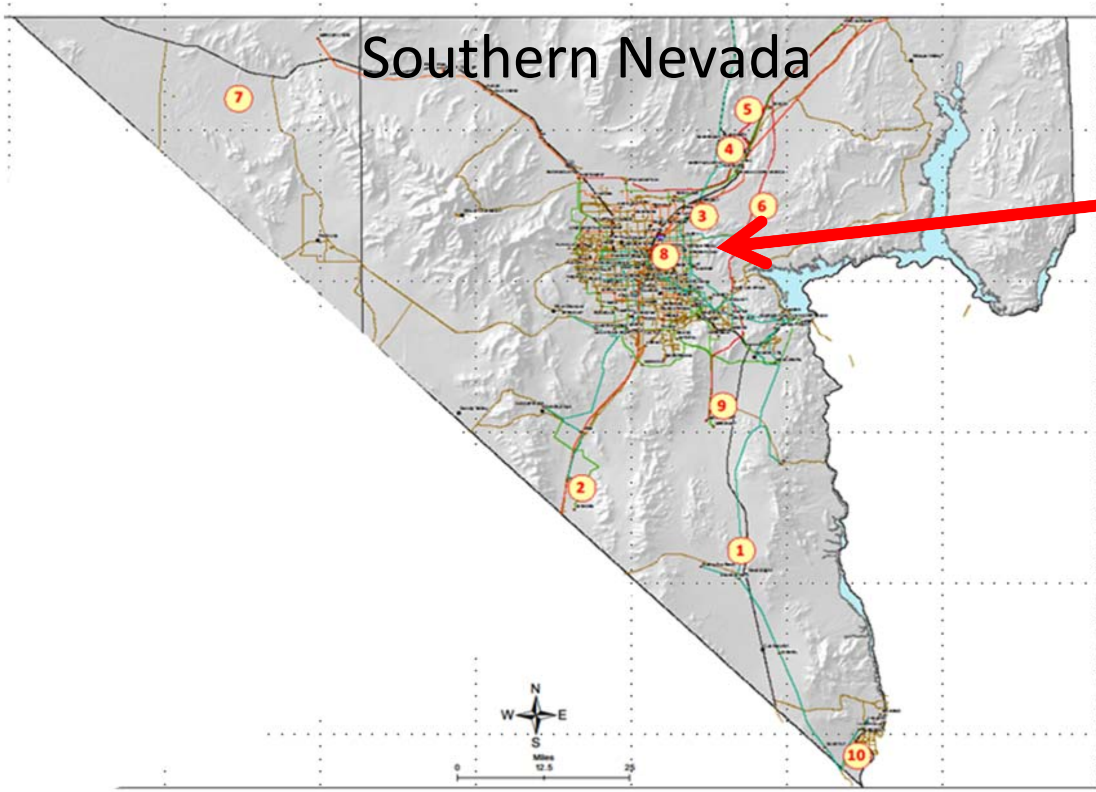
- **Clouds are identified using background subtraction**
- **Variability estimated from images using artificial neural network**



This project is described in poster session

Example Application 2:
NV Energy Solar Integration Study

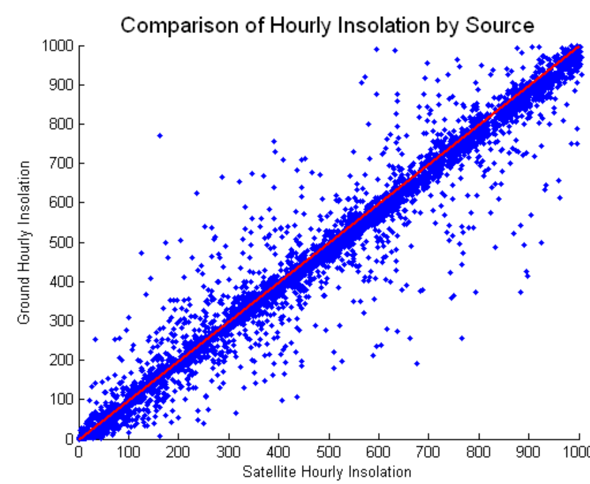
- **Sandia is preparing 1-min PV output profiles for 2007 for 10 sites in southern Nevada for a Solar Grid Integration Study.**



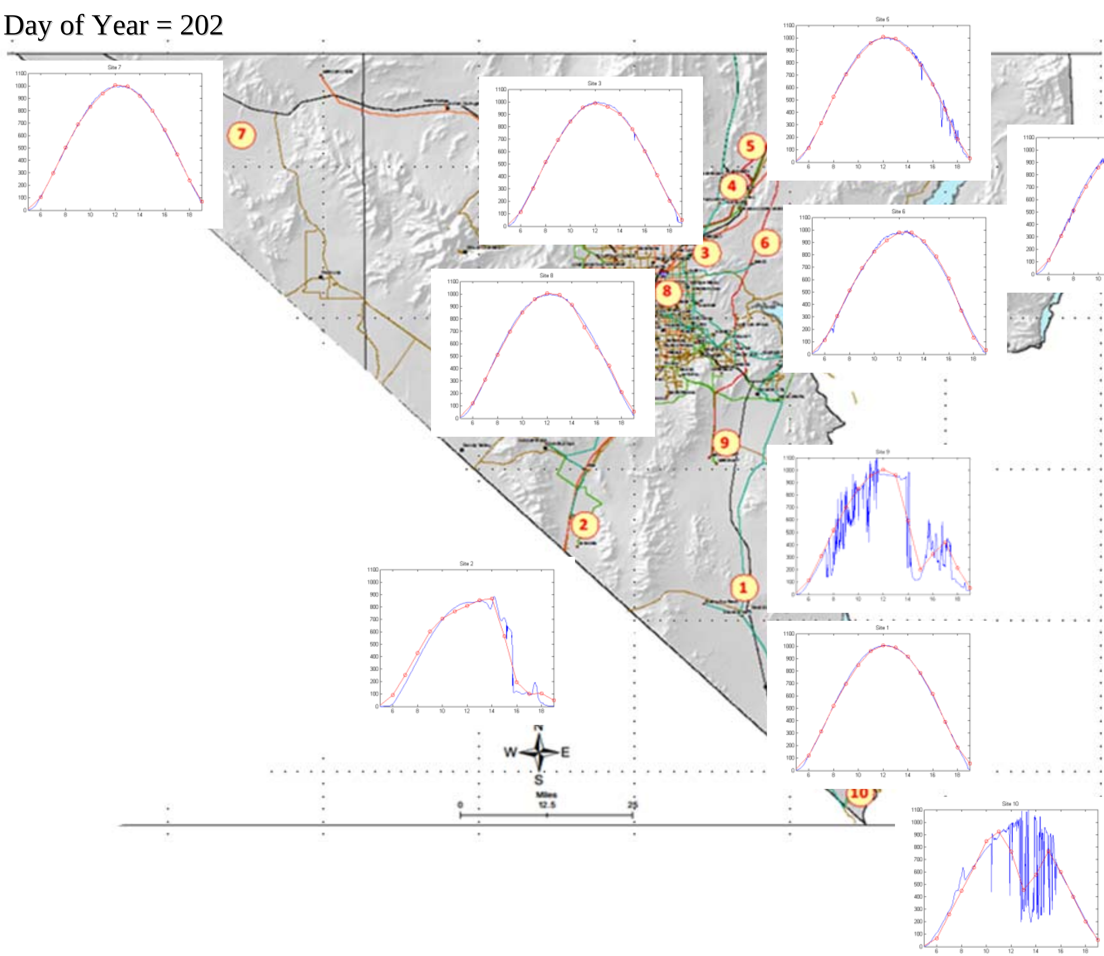
6 ground irradiance sensors in Las Vegas Valley with data from 2006 onward.

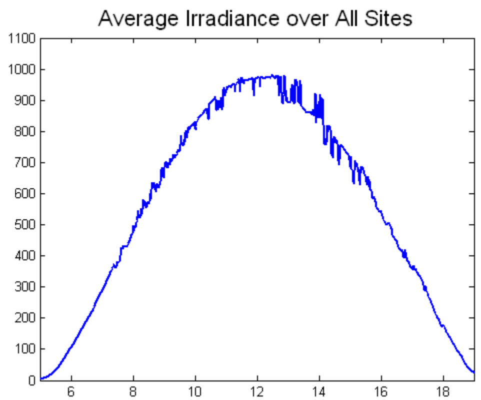
Example Application 2: NV Energy Solar Integration Study

- Limited geographic extent allows us to assume similar general weather patterns across area
- Satellite (SolarAnywhere) data used to estimate hourly irradiance at each of the 10 sites.
  - Good match with ground data in Las Vegas
- Ground stations used to develop library of irradiance days classified by hourly averages
- Satellite day used to choose best-fit ground day based on sum of squared irradiance differences



Example Application 2:
NV Energy Solar Integration Study

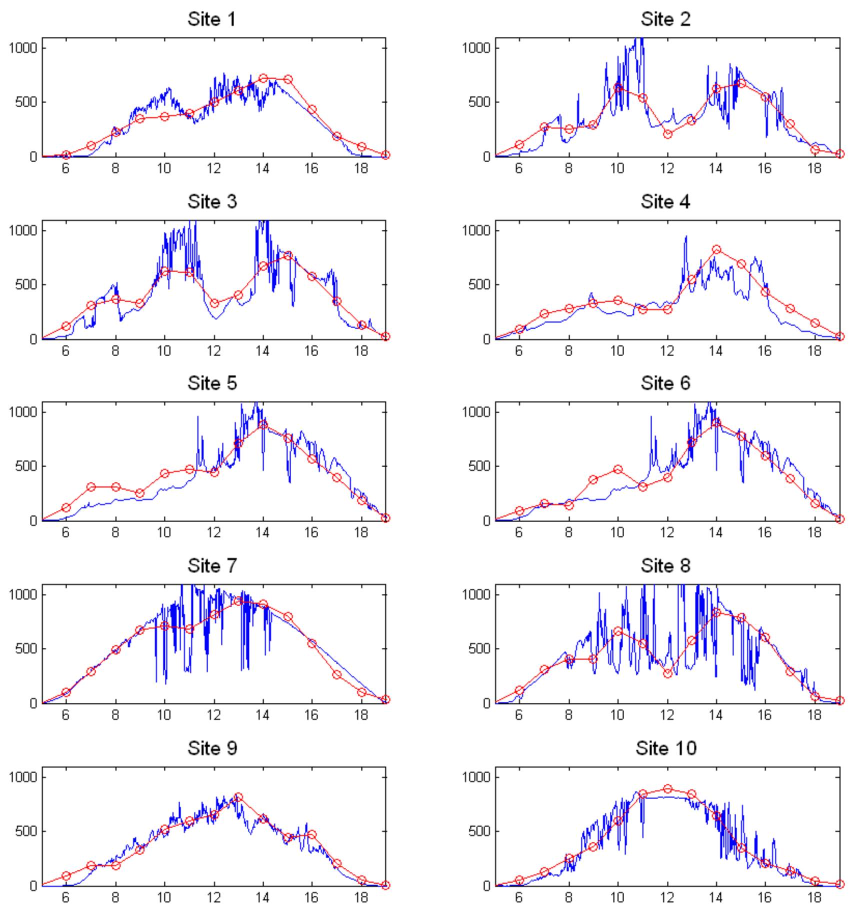




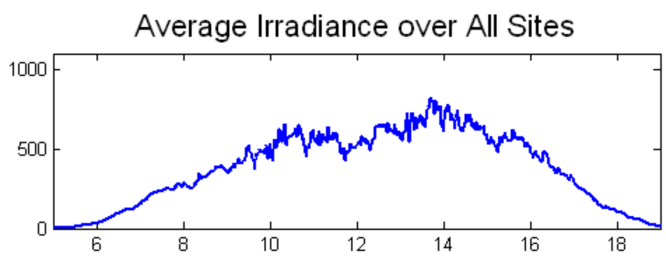
This example shows model represents days when only part of domain has clouds.

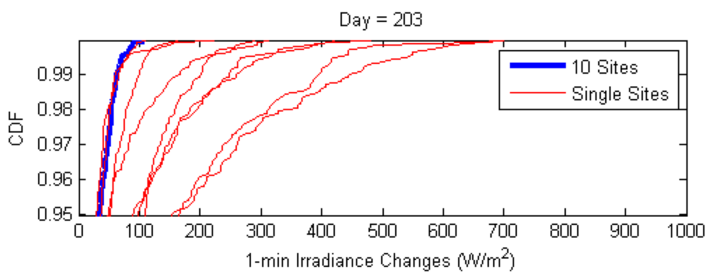
Example Application 2:
NV Energy Solar Integration Study

Day of Year = 203



Model shows potential for ramp rate reduction with geographic diversity across 10 sites.





Summary

What we know

1. **Spatial Average of POA Irradiance is the Key**
2. **Plant Size Affects Ramp Rate Distribution**
   - **Especially short-term ramps (< 1-min)**
3. **Geographic Diversity Reduces Ramp Rates**

What we need to do next

1. **Irradiance -> irradiance field**
   - **Ground measurements to spatial average**
   - **Use of satellite information to expand coverage**
2. **Validation is critical**
   - **Need appropriate standard metrics**

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