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Modeling Solar Power Plant Variability:

Benefits of Geographic Smoothing at Various Timescales

Matthew Lave, Joshua Stein, Abraham Ellis, Cliff Hansen

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Background

- Solar Variability is important to study because it can cause problems on electric grids with high penetrations of PV
  - Flicker
  - Voltage rise
  - Balancing issues

- Variability in power output occurs at various timescales
  - Rising and setting sun (long timescales, precisely predictable)
  - Changes in atmospheric content (long timescales, somewhat predictable)
  - Temperature and soiling (long timescales, less predictable, small effects)
  - Clouds (short timescales, big effects, only large cloud effects are predictable)

Research Questions

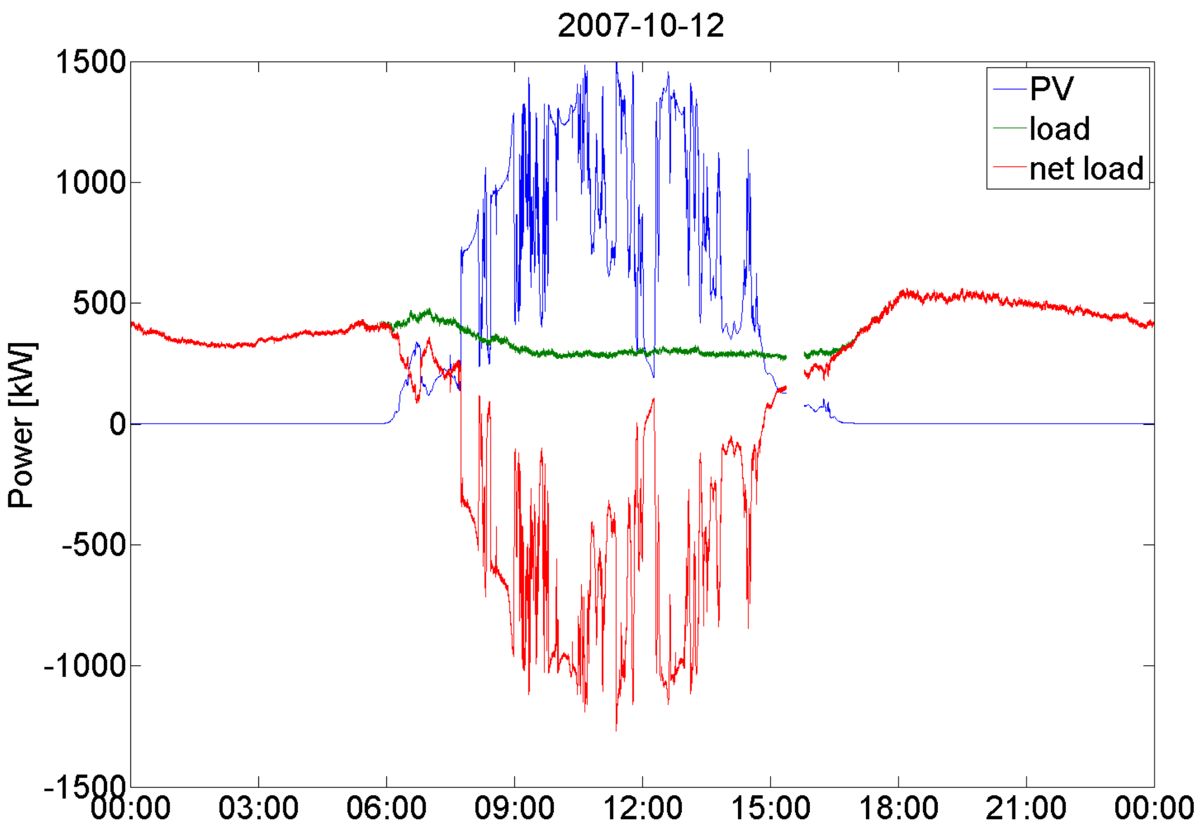
- How does solar power variability change at various timescales?
  - When aggregating many PV sites, is the same reduction in variability seen at all timescales?
  - Is there a relationship between the reduction in variability and the timescale?
- How does solar power variability scale with increasing PV penetration?
  - Adding more PV will always increase absolute variability (MW), but will it decrease relative variability (% of capacity)?
- Most of these questions have been answered for solar irradiance, but not directly for solar power.

Ota City, Japan

- There is interest in understanding the effects of high penetration PV on distribution circuits
- Ota City data is a unique data set to analyze (high density of residential PV, all on 1 feeder, data recorded every 1-sec)
- Sandia conducted analysis with assistance from Kandenko (Tokyo, Japan)
- Purpose of Ota City analysis is to understand how PV variability scales on a residential feeder scale
  - What is a meaningful measure of variability?
  - How is variability over different time scales reduced due to geographic diversity?

Ota City, Japan

- Unique case where PV production is often much greater than load, creating a net load flow back into the substation.
- PV variability dominates net load variability.



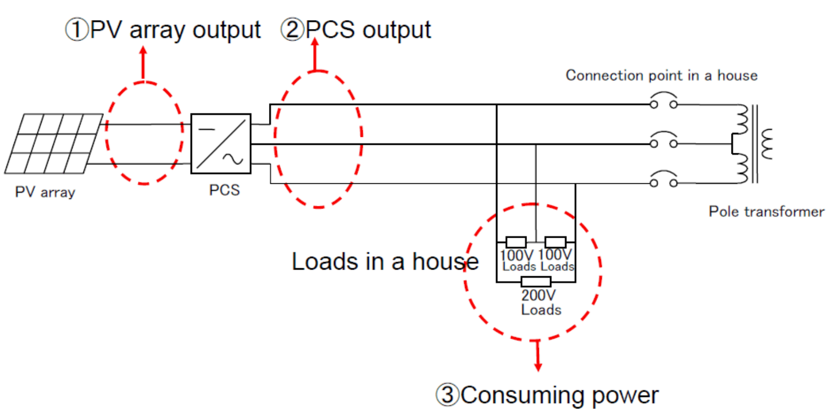
Ota City Data Set

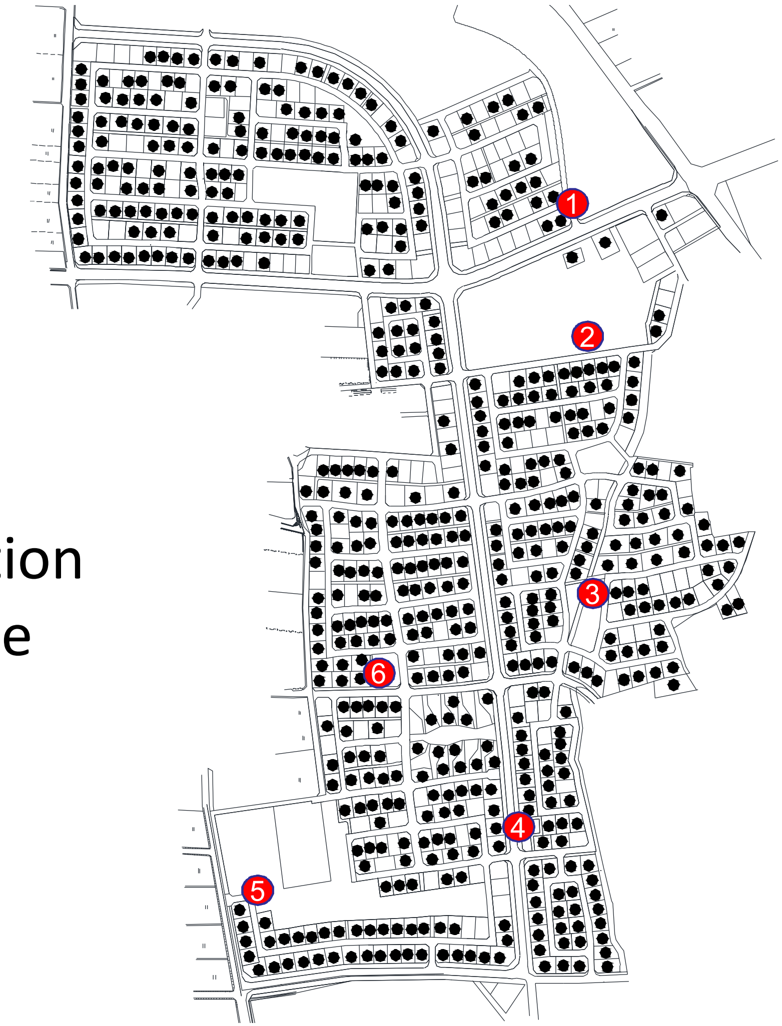
Ota City PV System

- 553 homes with PV (~4kW each)
- Single feeder (6.6kV, 3.26km)

Data available to Sandia

- 2/1/06 to 12/31/07, 1-sec resolution
- PV output and load for each house
- Irradiance at 6 locations





Pictures courtesy of Kandenko

Overview of Analysis

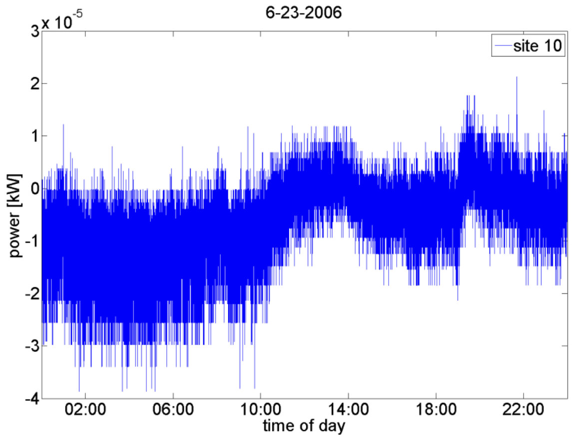
Showed the reduction in variability through 2 different methods:

- Compared Ramp rates (RRs) of varying numbers of houses (1-500) at timescales of 1-sec to 10-min

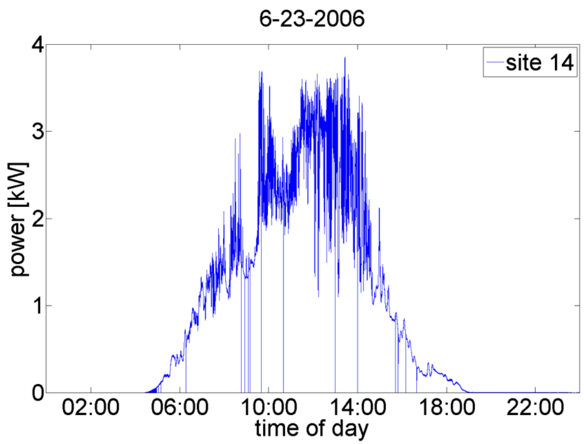
- Used a wavelet decomposition to show the reduction in variability at various timescales
  - Separates fluctuations by time scale, isolating cloud effects
  - Can determine variability reduction as a function of timescale

Data Quality Control

Lots needed!

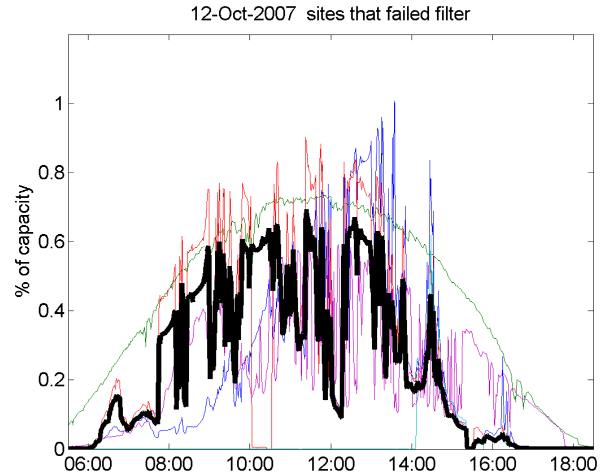


72 houses eliminated

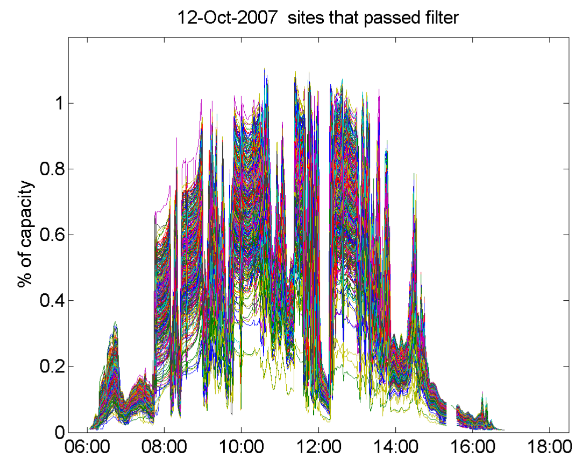


missing data times eliminated

Some sites reported essentially zero all day (top), or had “outages” where missing data was recorded as zero (bottom).



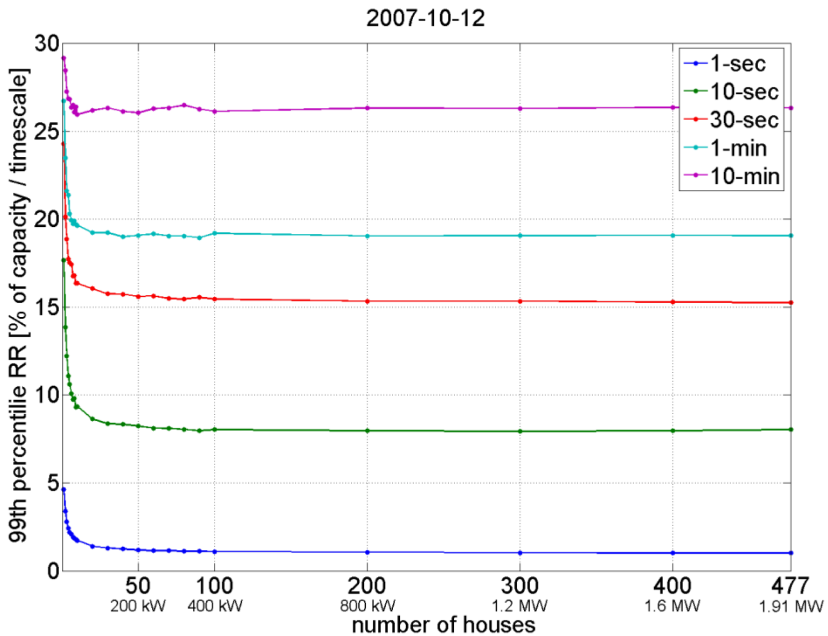
4 houses eliminated



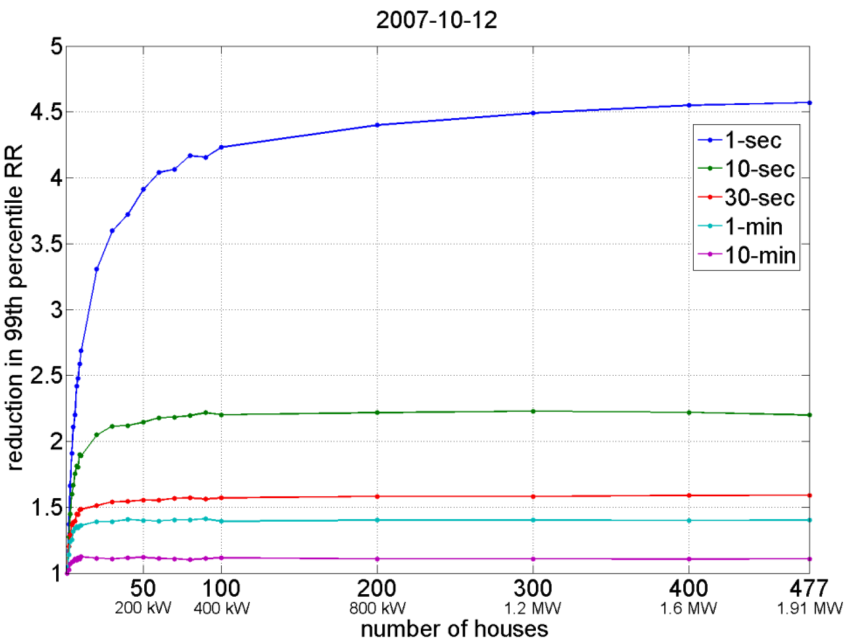
477 houses kept

Aggressive correlation filter applied to eliminate unreasonable sites (i.e., green line in top figure).

Ramp Rates Method



RRs decrease with increasing number of houses.

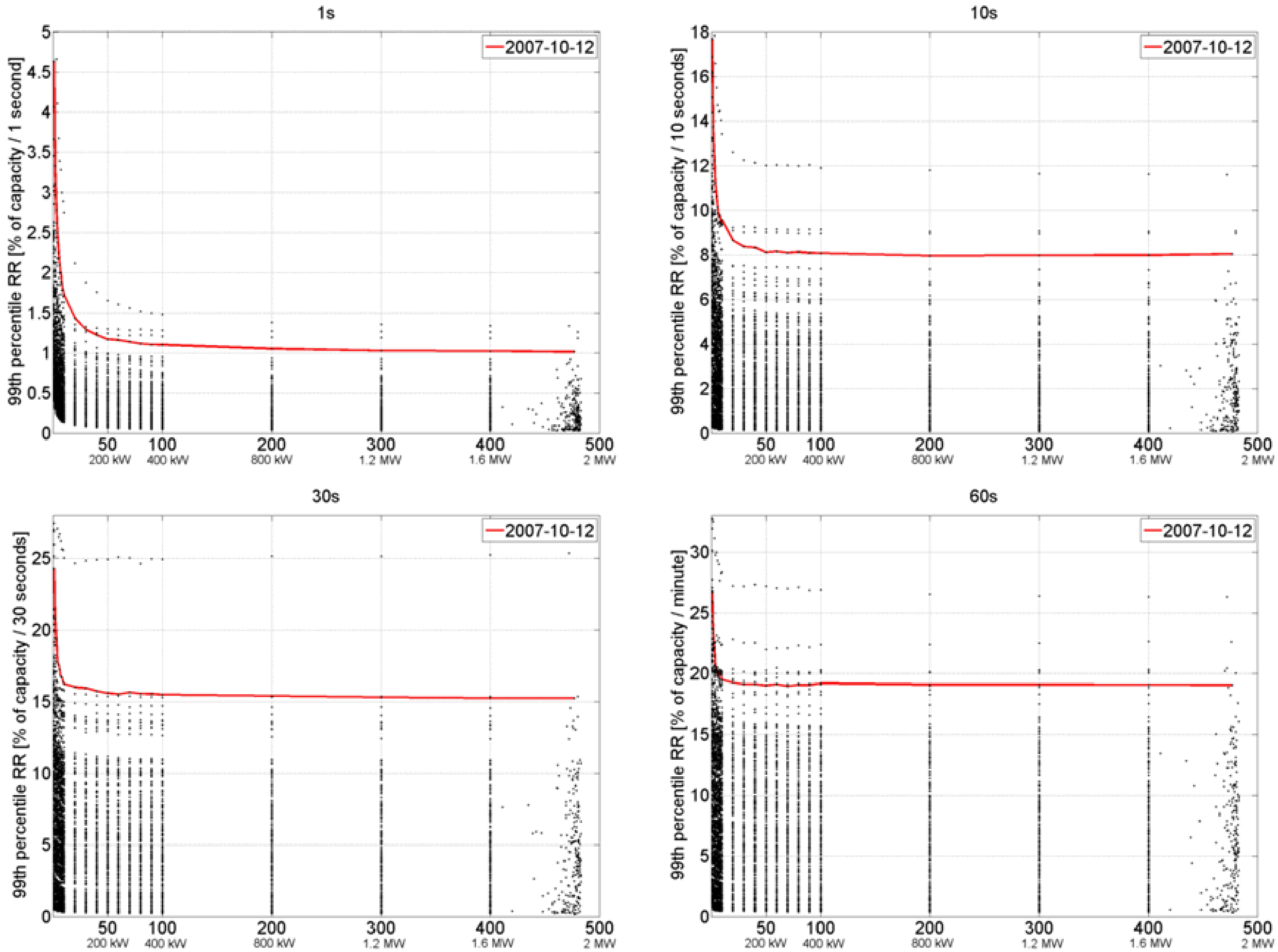


Reduction in RR = RR(1 house) / RR(many houses)
Large numbers mean large reductions in variability.

Note: when normalized to %/sec, long-timescale RRs are always smaller than short-timescale RRs

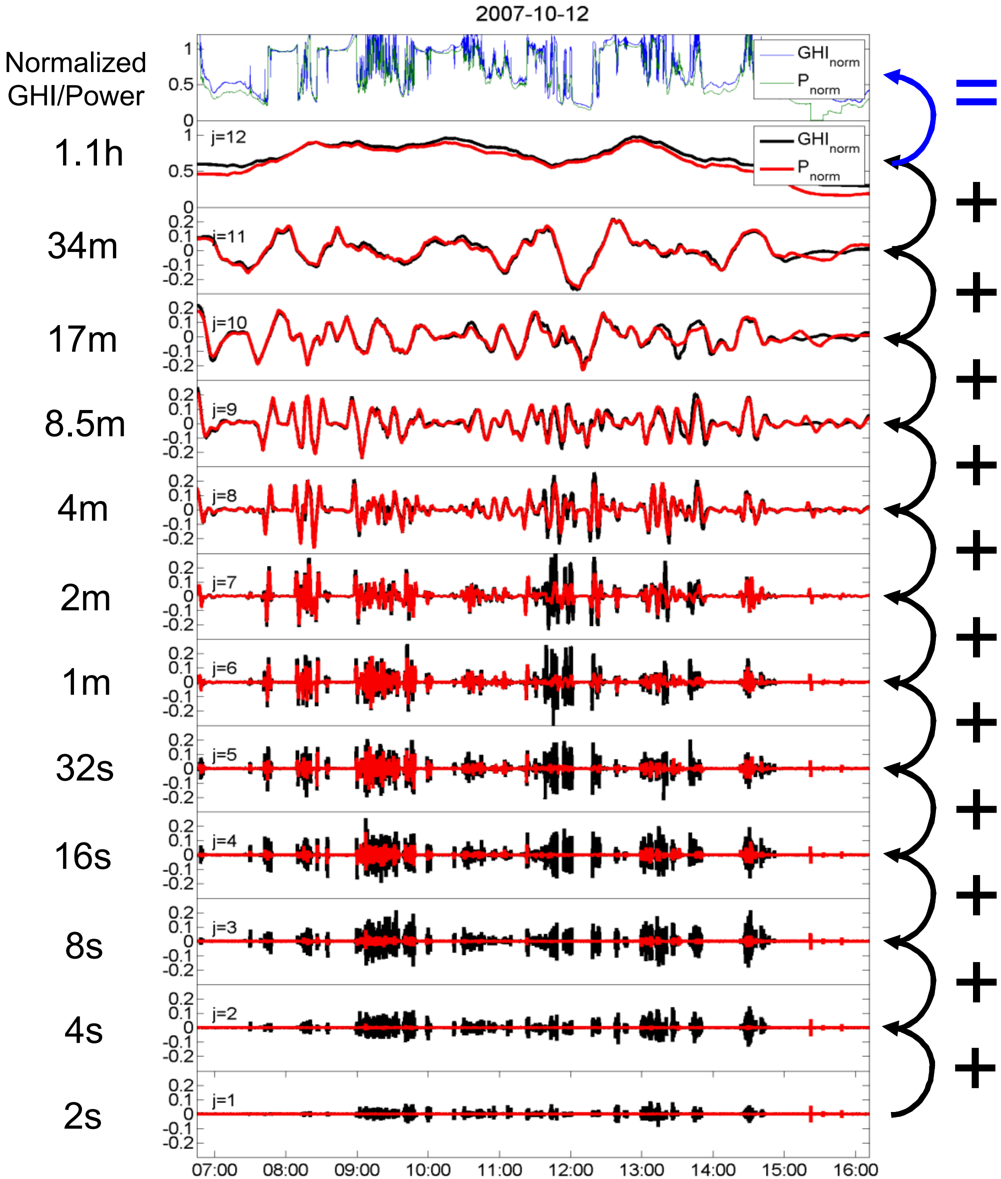
1-sec RRs are always reduced as more houses are added, but longer timescale RRs reach a limit at ~100 houses.

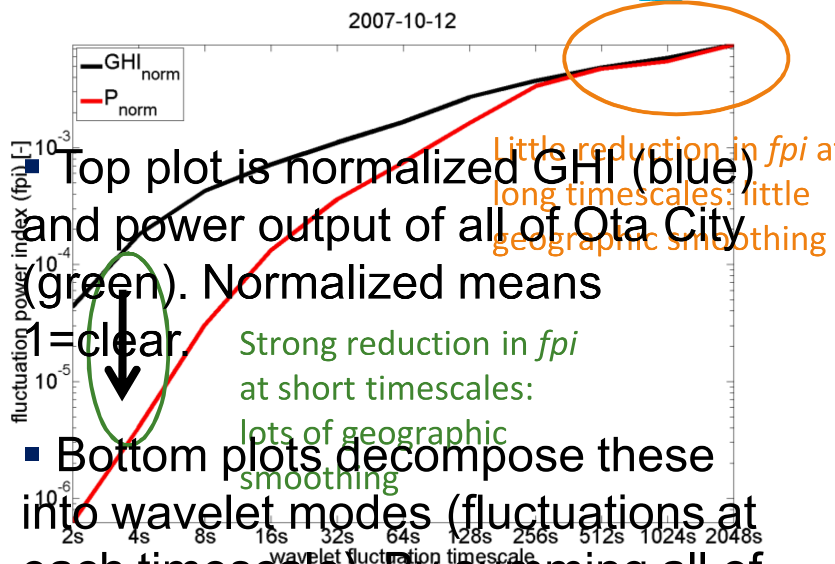
Ramp Rates Method



RRs for every day of the year. The same trend of decaying extreme RRs with increasing number of houses appears on all days. October 12th, 2007 was one of the most variable days all year.

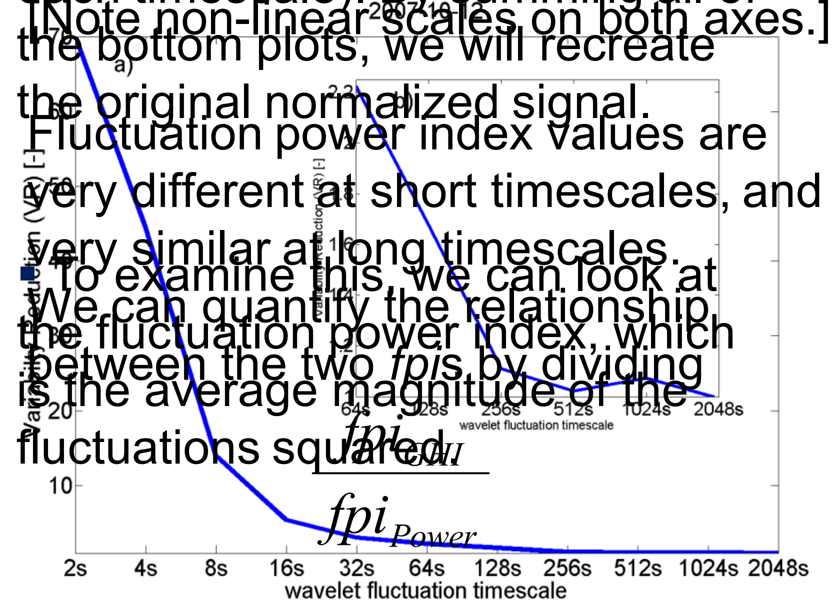
Wavelet Decomposition





- Top plot is normalized GHI (blue) and power output of all of Ota City (green). Normalized means 1=clear.
- Bottom plots decompose these into wavelet modes (fluctuations at each timescale). By summing all of the bottom plots, we will recreate the original normalized signal.
- To examine this, we can look at the fluctuation power index, which is the average magnitude of the fluctuations squared.

[Note non-linear scales on both axes.]



Fluctuation power index values are very different at short timescales, and very similar at long timescales.

We can quantify the relationship between the two *fpis* by dividing

$$\frac{fpi_{GHI}}{fpi_{Power}}$$

Conclusions from Ota City

- Extreme RRs tend to decrease with increasing levels of installed PV due to geographic smoothing

- The incremental benefit of adding more houses with PV on reducing extreme RRs gets exponentially smaller as more houses are already in the system

- Short timescales show a larger reduction in extreme RRs and wavelet fluctuation power content when going from 1 to 500 houses than longer timescales.

- Wavelet fluctuations are reduced at timescales shorter than 4-min, meaning clouds corresponding to timescales >4-min are highly correlated in Ota City.

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?

- Ota City is 2MW: what happens for larger plants?
- 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.

Variability Model

- Method to estimate aggregated PV plant output variability given only a single point sensor measurement (additional sensors can be added to improve accuracy)

- Universal: works for plants at any location, with any arrangement of PV panels

- Accounts for different variability reduction (VR) at different timescales

- Can adjust PV density to simulate a distributed plant, a central plant, or combinations of both

Variability Model

Model Inputs

PV Footprint

Point Sensor Timeseries

PV Plant Capacity or Density

Model Outputs

Variability Reduction at Each Timescale

Plant Areal Average Irradiance*

*can convert to power using the Sandia Photovoltaic Array Performance Model, or a simple linear multiplier if not all inputs are to the Performance Model are known.

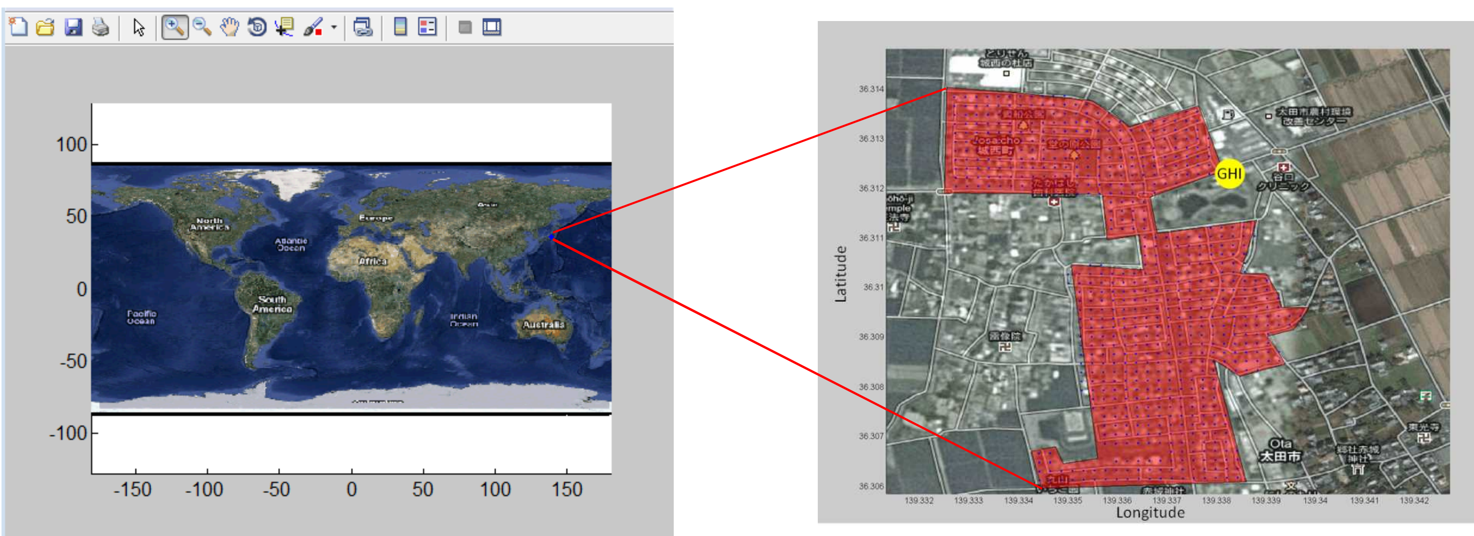
Use Ota City To Test Variability Model

- Since we have GHI point sensors and total power output at Ota City, we can use it to test the variability model

Model Inputs: PV Footprint

- Input area of interest by drawing one or many polygons on a Google Map

- Intuitive controls: start with map of world and then zoom in to area of interest (i.e., Ota City)



Red shaded area shows example drawn polygon (Ota City, Japan).

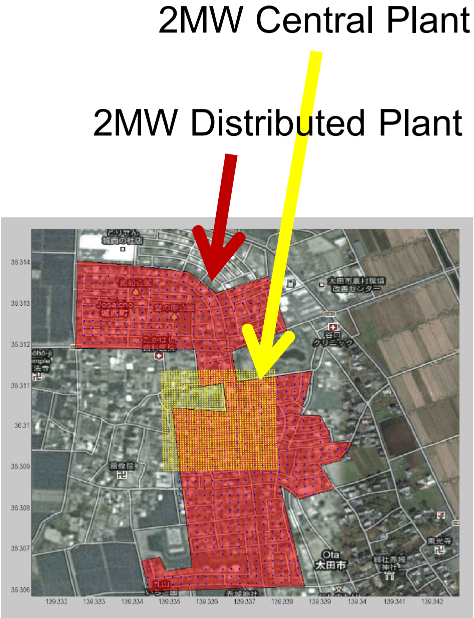
Model Inputs: Timeseries and PV Density

Timeseries

- Input point sensor timeseries from *.csv file or pick from library of already saved timeseries
- Timeseries resolution determines simulation resolution: 1-sec data in -> 1-sec data out

PV Density

- If plant size (MW) is known, simply enter it and program will calculate PV density
- Otherwise, estimate density of PV in W/m^2 : central PV plant ~25 W/m^2, Ota City ~7 W/m^2



Turning the Crank: Correlations

Variability model is based around a correlation equation between PV sites (i.e., between individual houses)

- Correlation equation is of the form:

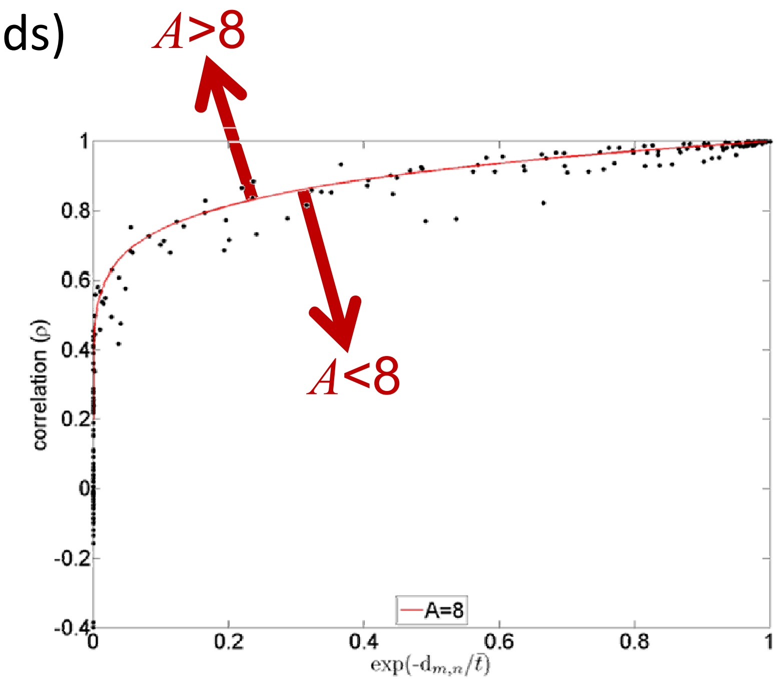
$$\rho(d_{m,n}, \bar{t}) = \exp(-\frac{d_{m,n}}{A\bar{t}})$$

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

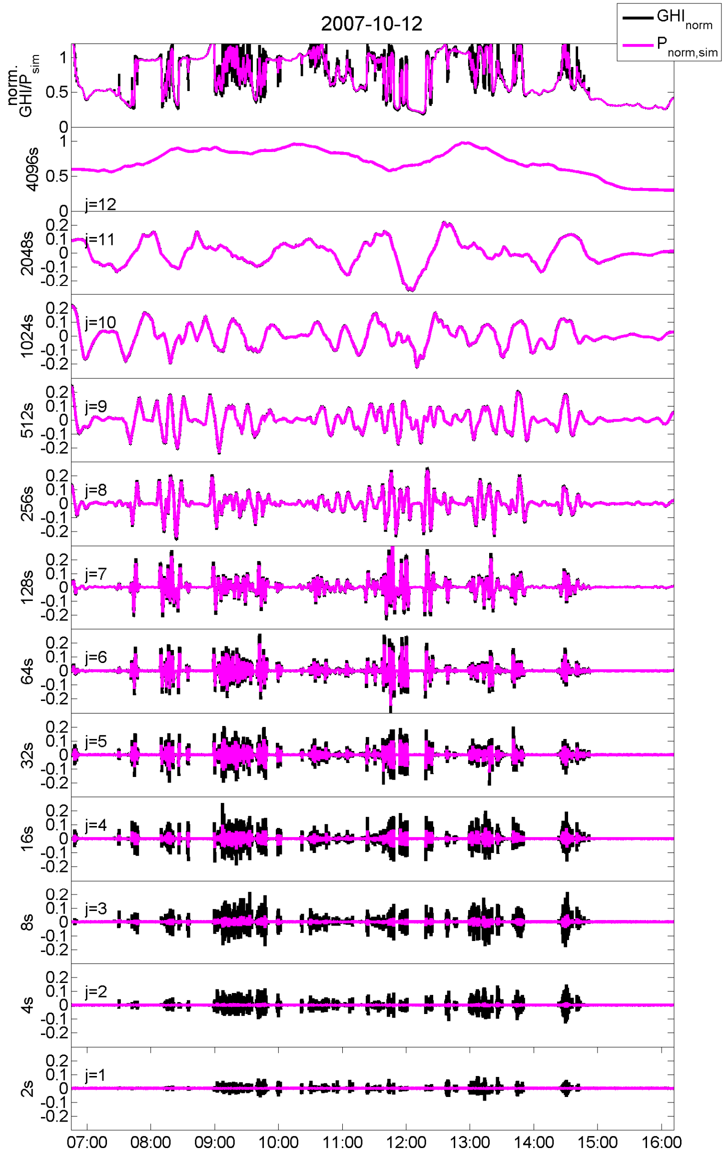
- A value depends mostly on geographic location, but also varies from day to day

Determining A Value

- A value describes how well sites are correlated:
  - Large A: sites correlated even at long distances (expected at inland sites with large clouds)
  - Small A: weak correlation at long distances (expected at coastal sites with small clouds)
- Ota City on October 12th, 2007: A=8
- Ota City on variable days:
  - $A \approx 5$ to 12
- Lanai, HI (every day is variable!)
  - $A \approx 1$ to 3
- UC San Diego:
  - $A \approx 1$
- Alamosa, CO on variable days (limited data available):
  - $A \approx 13$ to 55?

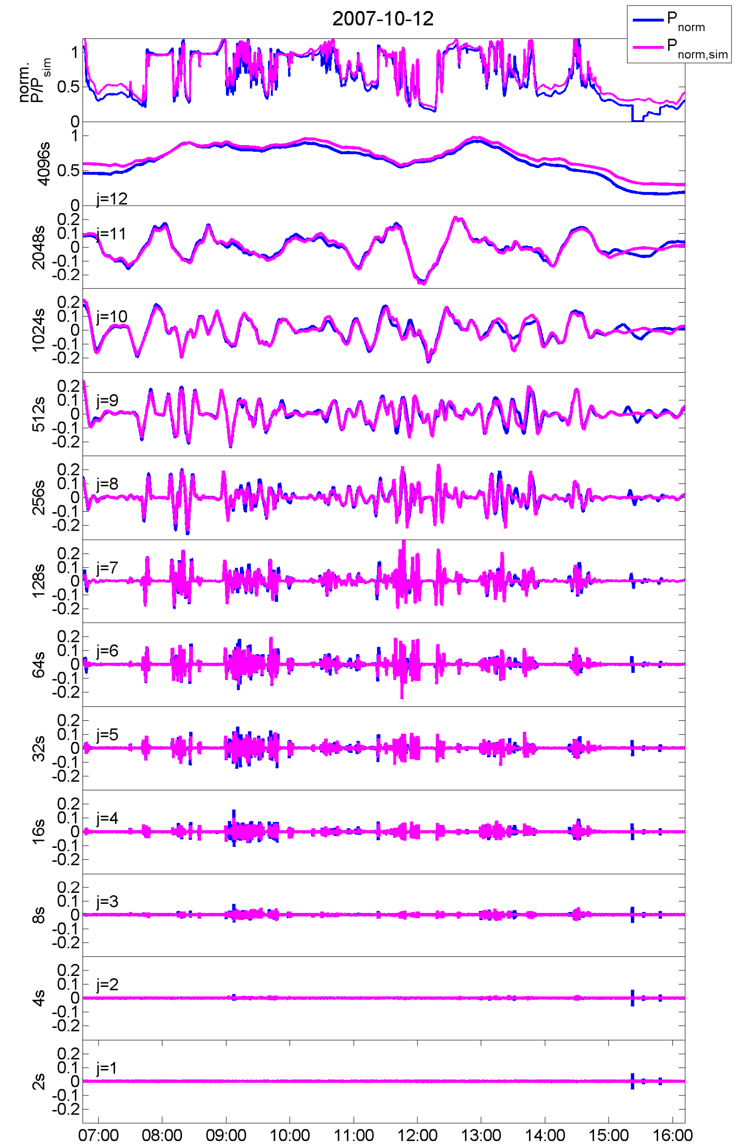


Wavelet Modes



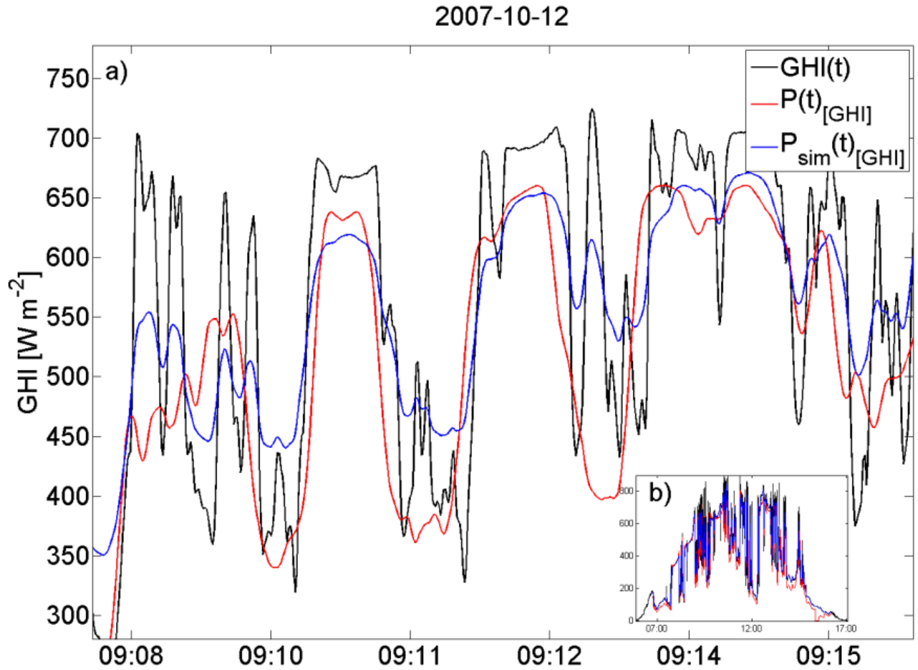
Simulated wavelet modes derived from GHI wavelet modes by scaling based on simulated VR.

Compare well with wavelet modes of the actual power output of all of Ota City.



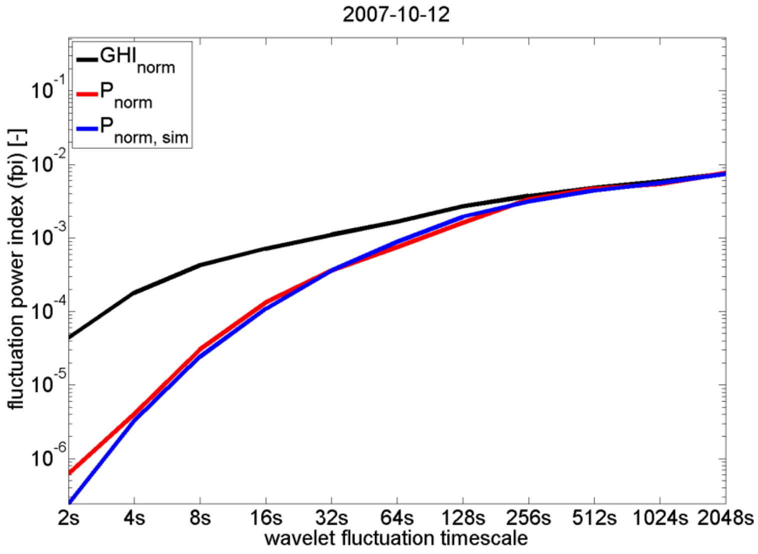
Compare output profile and *fpi*

Areal Averaged GHI



Simulated timeseries not an exact match but appears visually realistic.

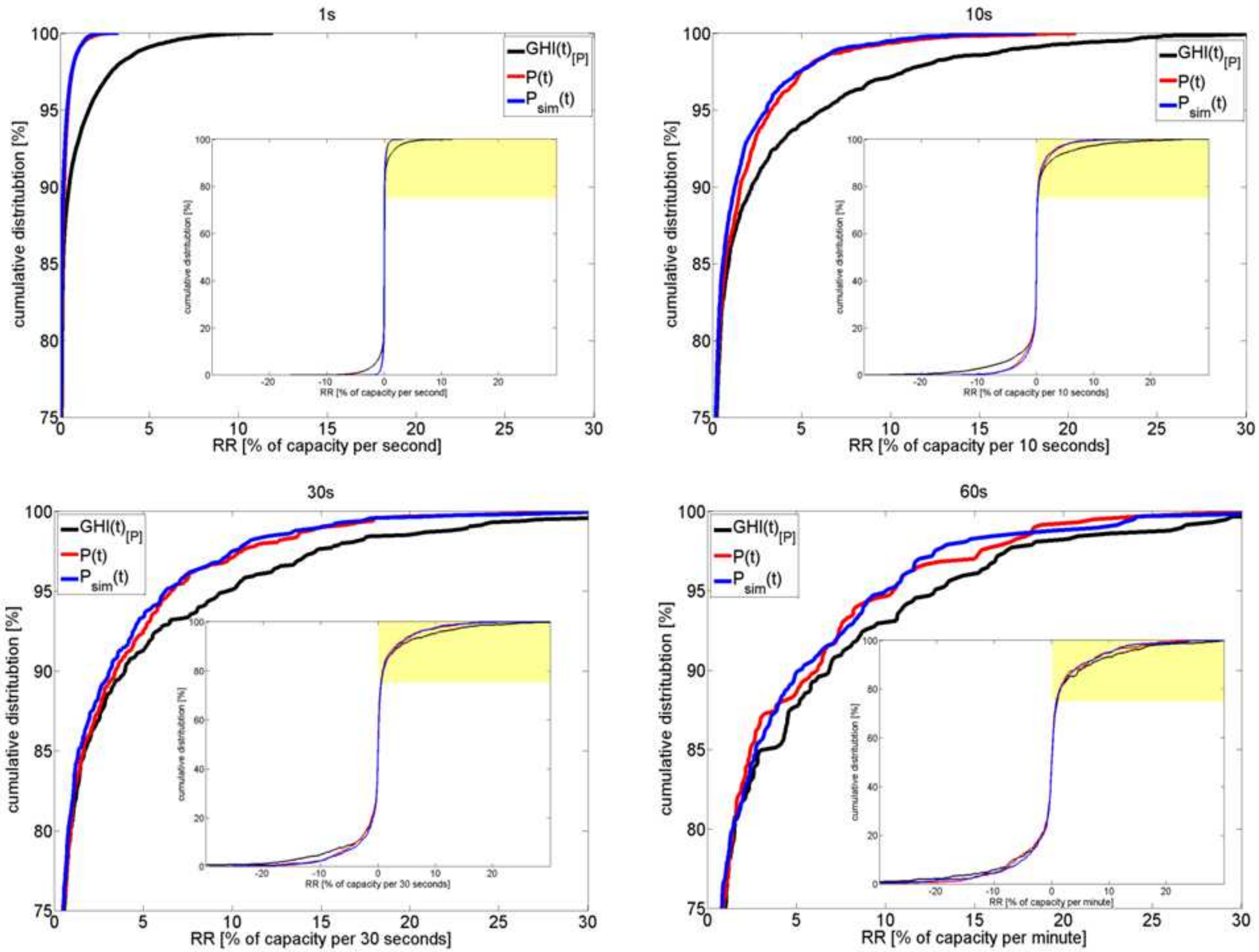
fluctuation power index



Goal of simulation is to reproduce power content of fluctuations, so *fpi* is the real test.

Compare Ramp Rates

Although matching fpi is the test for a successful wavelet simulation, most utilities and power plant operators are more interested in RRs.

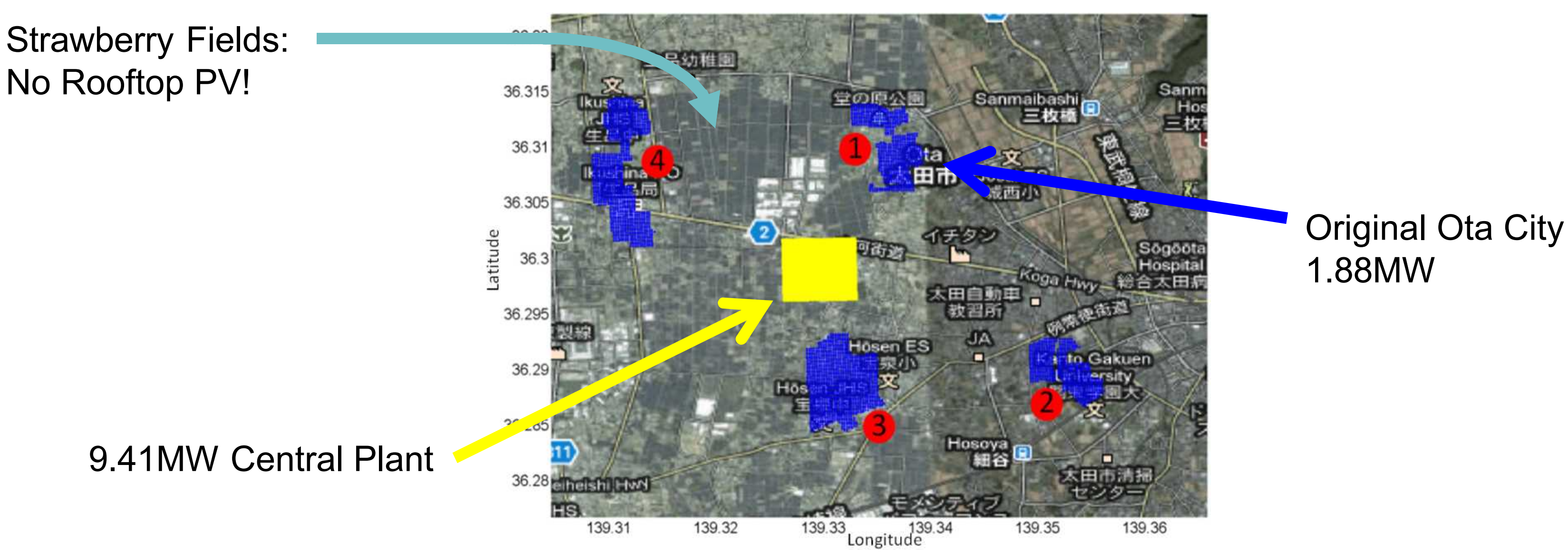


sim RRs compare well to actual power RRs at all timescales.

sim is much better at matching RRs than GHI at short timescales.

Extension: Add More PV

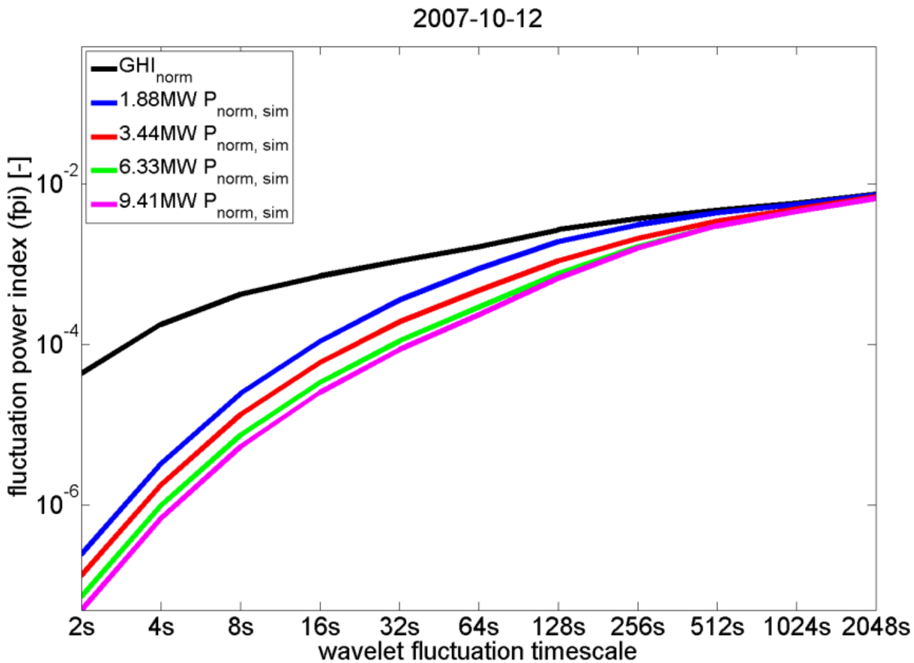
- Neighborhoods with a similar density of houses such that they could accommodate the same PV density as Ota City were added sequentially to create 4 scenarios:
  - 1.88MW (1, Original Ota City)
  - 3.44MW (1+2)
  - 6.33 MW (1+2+3)
  - 9.41MW (1+2+3+4)
- For all scenarios, both a central and a distributed plant were simulated.



Extension: Add More PV

- While a timeseries is produced for each scenario, comparing them would be difficult and arbitrary
- Instead, we can look at the *fpi*s

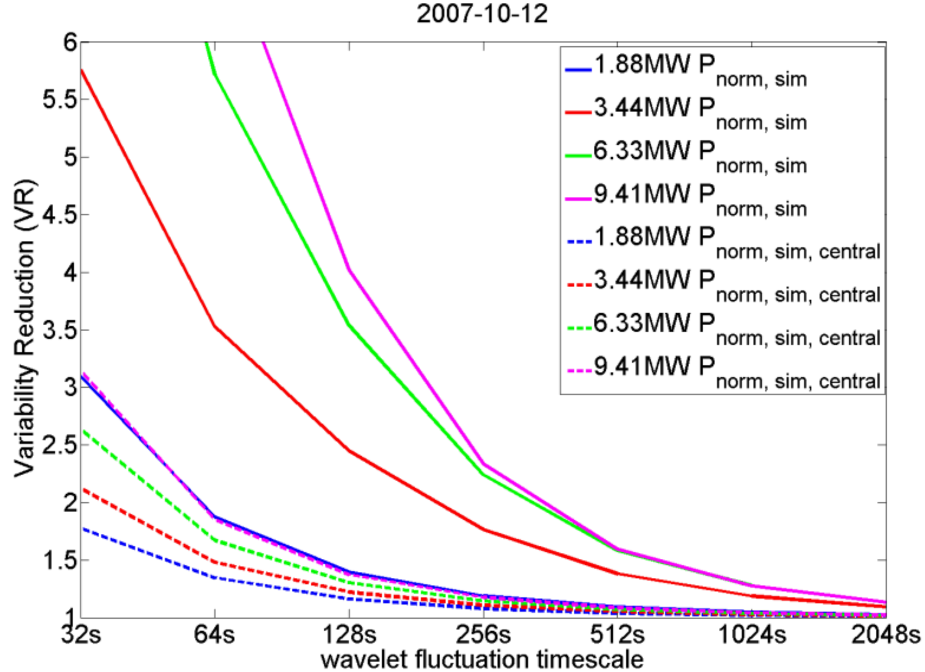
Distributed PV plants



- *fpi* is always reduced with increasing MW capacity, even at long timescales due to the relatively long distances (2-5km) between added neighborhoods.

Extension: Add More PV

- Can also look at VR for an understanding of the reduction in variability at each timescale.



- VR always higher for larger plants, but much higher for distributed vs. central plants.
- VR approximately equal for 9.41MW central plant and 1.88MW distributed plant: strong case for distributed generation!

Next Steps

- Submit papers on Ota City variability analysis (joint with Kandenko) and on variability model (joint with UCSD) for publication to journals

- Test model on Copper Mountain (Boulder City, NV), Alamosa, and other actual PV plant datasets.

- Collaborate with EPRI to give realistic PV plant inputs to OpenDSS feeder simulations

- Collaborate with SunPower to test variability model against more data sets and determine how the A value changes geographically and based on other factors such as cloud type, wind speed, etc.

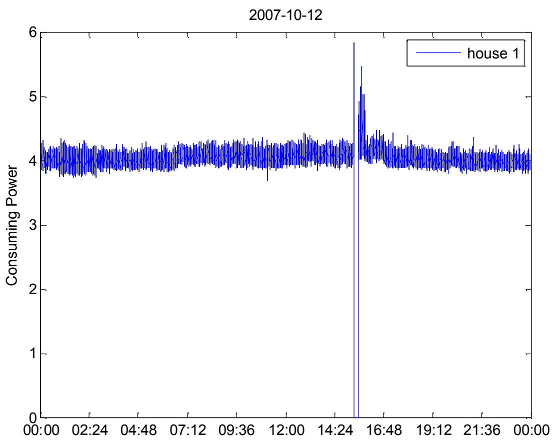
Thank You!

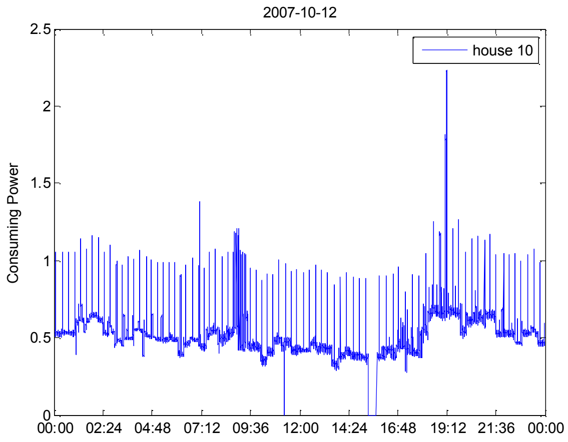
Special thanks to Josh Stein, Abraham Ellis, and Cliff Hansen for all their help, support, and for all the opportunities they have provided to me.

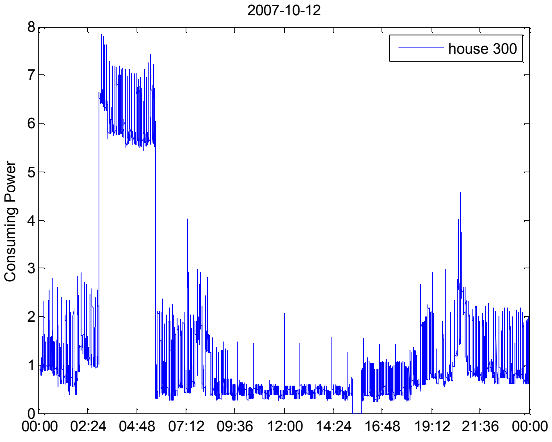

Questions/Comments?

Example of Ota City Load Data

- One House







- Total for all houses