Improving satellite-derived irradiance estimates using sparse rooftop solar data and optimal interpolation

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Summary

- **Idea:** Combine satellite derived irradiance estimates with sparse ground irradiance measurements through optimal interpolation.
- **Motivation:** Accurate irradiance estimates are needed for resource assessment, realtime estimates of PV power generation, and forecasts of PV power generation.
- **Results:** Optimal interpolation reduces root mean square error (RMSE) by ~20% and mean bias error (MBE) by ~85% for cloudy images.

Essentials of optimal interpolation

Suppose you estimate that irradiance outside is ~900 W/m² and a sensor measures the irradiance to be ~850 W/m². How can you optimally combine these two pieces of information?

- Call your estimated value \( x_b \) and the measurement \( y \).
- The error variances, \( \sigma_y^2 \) and \( \sigma_b^2 \), measure how large of an error you expect from each estimate.
- Optimal interpolation (equivalent to least squares) is the best, linear, unbiased estimate of the true value:

\[
x = x_b + w(y - x_b)
\]

where

\[
w = \sigma_y^2(\sigma_y^2 + \sigma_b^2)^{-1}
\]

Optimal Interpolation

Better Estimate

Ground Measurement

Satellite and ground data

- Data are derived from two sources, geostationary satellite images and ground irradiance measurements from sensors and PV cells.
- Optimal interpolation enables sparse ground data to improve the irradiance estimate over a large area.

Visibility satellite image

Visible satellite images are converted to a surface irradiance estimate using a radiative transfer model. The background, \( x_b \), is this surface irradiance divided by the clear sky expectation. Optimal interpolation combines measurements, \( y \), with this background to form the analysis, \( x \).

Visible satellite image

\[
P = D^{1/2}CD^{1/2}
\]

\[
W = PH^T(R + HPH^T)^{-1}
\]

\[
x = x_b + W(y - Hx_b)
\]

C is the satellite correlation matrix. Points in the background are more correlated if they have similar cloud cover. For example, if two points in Arizona have a similar pixel value in the visible satellite image the clouds over the two points will likely have similar properties.

D is the background error variance. It describes how far from the truth one can expect the background irradiance estimate to stray.

P and R are the satellite and sensor error covariance matrices. If we know the error at one location this will tell us what to expect at others.

R is a diagonal matrix because we expect the error correlation between sensors to be negligible.

H maps points in the satellite image to sensors on the ground.

W is the weight matrix. The larger the weight the more we trust our ground observations.

Results

For the example shown in the center column, optimal interpolation reduces the error 54%. This is only for one image and others may have a lower or higher reduction. Errors are calculated using 5 test sensors which were not used for the interpolation process.

Future work

- Improve process by optimizing over parameters within satellite correlation matrix \( P \).
- Optimaly combine correlation methods based on spatial distance and a cloudiness index.
- Combine 15 minute satellite images with a numerical cloud advection model and ground irradiance measurements using a Kalman filter in order to create forecasts.

References