Estimation of Behind-the-Meter Solar

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The Problem

- Managing grids with distributed generation (DG) components requires real-time state information
- DG frequently “behind-the-meter”
- Observed net load reflects sum of DG and true, consumption load
- Can we use heterogenous data source (eg. GHI measurements, AMI, SCADA) to estimate behind-meter?
1 A Physics-based Smart Persistence Model
2 Probabilistic Disaggregation at Feeder Level
3 Estimation by Integrating Physical with Statistical Models
A Physics-based Smart Persistence Model

Probabilistic Disaggregation at Feeder Level

Estimation by Integrating Physical with Statistical Models
Problem(s) formulation

• For solar forecasting, clouds are the most difficult problem
  – Type of cloud, duration of cover, etc.
• What type of data can be used
  – Local weather stations
• Computation time
  – Is computation time > forecast horizon?
Flowchart for PSPI

GHI

Solar Zenith Angle

Cloud Fraction

Cloud Albedo

Cloud Fraction

Cloud Albedo

Solar Zenith Angle

GHI
Reconstruction of GHI

• Before testing the forecasting capabilities of PSPI, PSPI must be able to reconstruct current GHI
• Reconstruction (and thus, forecast) uses simplified atmospheric radiation physics (Xie and Liu (2013))
  – Combines GHI observations, modeled clear-sky variables, and general assumptions about the atmosphere
• Algorithm allows a physics-based representation of GHI without the need to run a entire NWP model
Performance in all-sky conditions

Kumler et al. 2019
Results

Kumler et al. 2019
1. A Physics-based Smart Persistence Model
2. Probabilistic Disaggregation at Feeder Level
3. Estimation by Integrating Physical with Statistical Models
Problem(s) formulation

Normally the data available are at the feeder head

Apply “Bayesian Structural Time Series” to disaggregation problem:

- Perform disaggregation probabilistically
- Enables reasoning about uncertainty
- Straightforward, yet flexible, model class
Data

• Pecan Street Austin dataset contains household-level power usage and PV generation data (1-min time resolution, 7 days in both Aug and Jan 2017)
• NSRDB contains GHI and temperature data (30-min time resolution, 1 year total)
• Sum household data to create synthetic feeder data, downsample to 30-min and match to NSRDB
Figure 1: AMI power consumption data for 5 houses in the Pecan Street dataset (January). Global Horizontal Incidence (GHI) overlaid (flipped and scaled) in red.
Figure 2: Synthetic feeder measurements of consumption data (summed AMI consumption) for the Pecan Street dataset. GHI again overlaid (flipped and scaled) in red.
Bayesian Structural Time Series

• Formulate a synthetic state space model
• Model structure mimics classic time series model
• Fitting is performed by combining Kalman Filtering and Markov Chain Monte Carlo\(^1\)

# Model

## Definitions:

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Def</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_t$</td>
<td>(Synthetic) feeder PV gen at time $t$</td>
</tr>
<tr>
<td>$l_t$</td>
<td>(Synthetic) feeder load at time $t$</td>
</tr>
<tr>
<td>$y_t$</td>
<td>(Synthetic) feeder measured load</td>
</tr>
<tr>
<td>$\phi_t$</td>
<td>GHI</td>
</tr>
<tr>
<td>$X_t$</td>
<td>Piecewise-linear temperature covariates</td>
</tr>
</tbody>
</table>
State space model evolves as:

\[ s_{t+1} = \beta_{t+1} \phi_{t+1} + \epsilon_{t+1}^{(s)} \]
\[ \beta_{t+1} = \beta_t + \epsilon_t^{(\beta)} \]
\[ l_{t+1} = X_{t+1}^T \gamma + l_t + \delta_{t+1} + \eta_{t+1}^{(l)} \]
\[ \delta_{t+1} = \delta_t + \eta_t^{(\delta)} \]
\[ y_{t+1} = s_{t+1} + l_{t+1} \]

Where \( \epsilon_t^{(\cdot)} \sim N(0, \sigma^2) \) and \( \eta_t^{(\cdot)} \sim T_v(0, \sigma^2) \).
Can be brought into conventional Kalman Filtering format by setting:

\[ \chi_t = [s_t, \beta_t, 1, l_t, \delta_t]^T \]

Then the state space evolution can be rewritten:

\[ \chi_{t+1} = Z_t(\gamma) \chi_t + \omega_t \]
\[ y_{t+1} = A \chi_{t+1} \]

Where:

\[ A^T = [1, 0, 1, 0, 0] \quad Z_t(\gamma) = \begin{bmatrix} 0, \phi_t, 0, 0, 0 \\ 0, 1, 0, 0, 0 \\ 0, 0, X_t^T \gamma, 1, 1 \\ 0, 0, 0, 0, 1 \end{bmatrix} \]
Figure 3: Estimated PV generation occurring over 7 days (black) with 95% credible intervals (gray) against true generation (red)
Figure 4: Estimated true load over 7 days (black) with 95% credible intervals (gray) against true generation (red)
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Objective

• From definition of net load
  \[ NL_t = L_t - S_t; \quad L_t \geq 0, \quad S_t \geq 0, \forall t \]

• For each residential customer with solar PV installation- disaggregate net load measurement \( NL_t \) at each time \( t \) into-
  – Load \( (L_t) \)
  – Solar generation \( (S_t) \)

• Integrate a physical PV system performance model and a statistical load estimation model

• Following information are not available-
  – Historical load and PV generation data
  – Solar panel configuration and parameters (DC size, tilt, azimuth, loss of the PV array and nominal efficiency of the inverter)
  – Exact location of each customer (city’s approximate longitude and latitude work as proxy)
Overall Framework

Disaggregation Method

Net load time series data of a consumer

Physical model

Estimation of solar PV parameters and solar generation

Statistical model

Load Estimation

Yes

Stopping criteria

Post Disaggregation adjustment

Disaggregated signals

Disaggregated signals

No
Technical methods

Estimation of solar generation ($S$)

- Estimation of solar PV parameters $\theta_S$
  - Perform a constrained numerical optimization
  - Solar PV parameters $\theta_S$
    - DC size ($P_{dco}$)
    - Tilt ($\theta_t$)
    - Azimuth ($\theta_{az}$)
    - Loss ($l$)
    - Nominal efficiency ($\eta_{nom}$)
- Physical PV system performance model $g$
  - Estimate solar generation $S = g(\theta_S)$

Estimation of Load ($L$)

- Statistical hidden Markov model regression
Assume the following are available-

- an estimate of solar generation, $S$
- PV system performance model, $g$

Solve the constrained nonlinear numerical optimization problem for each customer

$$\arg\min_{\theta_S} \sum_{t=1}^{T} (S_t - g_t(\theta_S))^2$$

subject to $S_t \geq 0$, $\theta_{S,\text{min}} \leq \theta_S \leq \theta_{S,\text{max}}$
PV System Performance Model

- Computes AC output power $P_{ac}$ (solar generation $S$) of the PV array when $\theta_S$ is known
- Based on PV system performance collaborative (SANDIA)$^4$ and PVWatts$^5$ (NREL)
- Calculation:
  $P_{ac} = g(\theta_S) = \eta(\eta_{nom}, P_{dc})P_{dc}$

- $\eta \rightarrow$ Efficiency of inverter, $P_{dc} \rightarrow$ DC output power of the PV array

$$P_{dc} = g'(P_{dc0}, \theta_t, \theta_{az}, l) = (1 - l) \times \frac{E_{tr}(\theta_t, \theta_{az})}{E_0} P_{dc0}[1 + \gamma(T_c(\theta_t, \theta_{az}) - T_0)]$$

- $E_0, T_0, \gamma$ are known values

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PV System Performance Model

- Calculate operating Cell Temperature $T_c$ from Sandia cell temperature model using
  \[ T_c = T_m + \frac{E_{POA}}{E_0} \Delta T \]

- Sadia module temperature model
  \[ T_m = E_{POA} \times e^{a+b\times WS} + T_a \]

- Calculate plane of array and transmitted irradiance ($E_{POA}$ and $E_{tr}$)
  - Solar irradiance data ($DNI$, $DHI$ and $GHI$)
  - Solar PV installation geometry (PV array tilt and azimuth angle)
  - Solar position data (Solar zenith and azimuth angle → can be calculated from solar position algorithms)
Load Estimation

- No historical load data → Time series models not applicable
- Linear regression models are common
- Explanatory variables:

<table>
<thead>
<tr>
<th>Variables</th>
<th>Symbols</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature (3\textsuperscript{rd} degree polynomial)</td>
<td>$c, c^2, c^3$</td>
</tr>
<tr>
<td>Hour of the day (3\textsuperscript{rd} degree polynomial)</td>
<td>$h, h^2, h^3$</td>
</tr>
<tr>
<td>Weighted moving average of last 24 hours temperature</td>
<td>$c_{wmv}$</td>
</tr>
<tr>
<td>Day of the week</td>
<td>$d = \begin{cases} 1 &amp; \text{if weekend} \ 0 &amp; \text{if weekday} \end{cases}$</td>
</tr>
</tbody>
</table>
Load Estimation

Load time series can exhibit quite different patterns depending on whether the consumer(s) is present at home or not.

Figure 1: Load time series of a customer
Hidden Markov Model Regression

- This change in behavior can be modeled by a hidden Markov model regression (also called Markov switching regression model) given state $s_t$

$$L_t = X_t^T \beta_{s_t} + \varepsilon_{s_t} \quad \varepsilon_{s_t} \sim N(0, \sigma_{s_t}^2)$$

- $L_t \rightarrow$ load of a consumer at time $t$
- $X_t \rightarrow$ explanatory variables at time $t$
- $s_t = \{s_1, s_2\}$ indicates latent state at time $t$
- Probability of a change in regime is modeled by a first-order time-invariant two-state Markov chain

$$P(s_t = j \mid s_{t-1} = i, s_{t-2} = q, \ldots) = P(s_t = j \mid s_{t-1} = i) = p_{ij}, \quad \sum_{j=1}^{2} p_{ij} = 1$$

- Can be estimated by maximum likelihood (MS_Regress package of MATLAB used)

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Algorithm 1 Algorithm for the disaggregation of net load of each customer and estimation of solar PV parameters

**Input:** Net load of a customer from AMI measurement, $NL$

**Output:** User consumption $\hat{L}$, solar generation $\hat{S}$, and solar PV parameters $\theta_S$

**Initialization:** Determine $M$ initial solar PV system technical parameters $(\theta_S)_1^{(0)}, \ldots, (\theta_S)_M^{(0)}$

1: for each starting point $m \in M$ do
2: Initialize solar generation, $\hat{S}_m^{(0)} = g \left( (\theta_S)_m^{(0)} \right)$
3: for $j = 1$ to maxiter do
4: Estimate user consumption, $\hat{L}_m^{(j)} = NL + \hat{S}_m^{(j-1)}$
5: Fit HMM regression model, denoted by $f(X, \theta_L)$, to $\hat{L}_m^{(j)}$ and calculate parameters $(\theta_L)_m^{(j)}$
6: Update user consumption, $\hat{L}_m^{(j)} = f \left( X, (\theta_L)_m^{(j)} \right)$
7: Update solar generation, $S_m^{(j)} = \hat{L}_m^{(j)} - NL$
8: Determine $(\theta_S)_m^{(j)}$ from Equation (2) using $(\theta_S)_m^{(j-1)}$ as initial value
9: Update solar generation, $\hat{S}_m^{(j)} = g \left( (\theta_S)_m^{(j)} \right)$
10: Estimate net load, $\hat{NL}_m^{(j)} = \hat{L}_m^{(j)} - \hat{S}_m^{(j)}$
11: Calculate MSE of the net load, $E_m^{(j)}$
12: if $\left| (\theta_S)_m^{(j)} - (\theta_S)_m^{(j-1)} \right| \leq \varepsilon$ then
13: Break
14: end if
15: end for
16: end for
17: Determine $m^*, j^* = \argmin\limits_{m, j} E_m^{(j)}$
18: return $\hat{L} = \hat{L}_{m^*}^{(j^*)}$, $\hat{S} = \hat{S}_{m^*}^{(j^*)}$, and $\theta_S = (\theta_S)_{m^*}^{(j^*)}$

Disaggregation Algorithm
Numerical Study

- 15-minute interval data from Pecan Street Dataset$^8$
  - Has net load, load, and solar PV generation data
- Customers located in Austin, Texas
- Study period: 10/03/2015-10/30/2015 (28 days)
- 197 consumers with PV installation available
- Solar irradiance and temperature data obtained from National Solar Radiation Database
- Feasible ranges of solar PV system parameters $\theta_S$ specified
- 8 initial solar PV system technical sets selected
  - Gradually increase $P_{dc0}$ from 1KW to 8 KW
  - $[\theta_T, \theta_{AZ}, \eta_{nom}, l]$ set at their most common values
- Compared result with consumer mixture model and SunDance model

Result

Comparison of disaggregated load and solar PV generation with actual values for a customer for 5 days from 10/14/2015-10/19/2015
Thank you

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