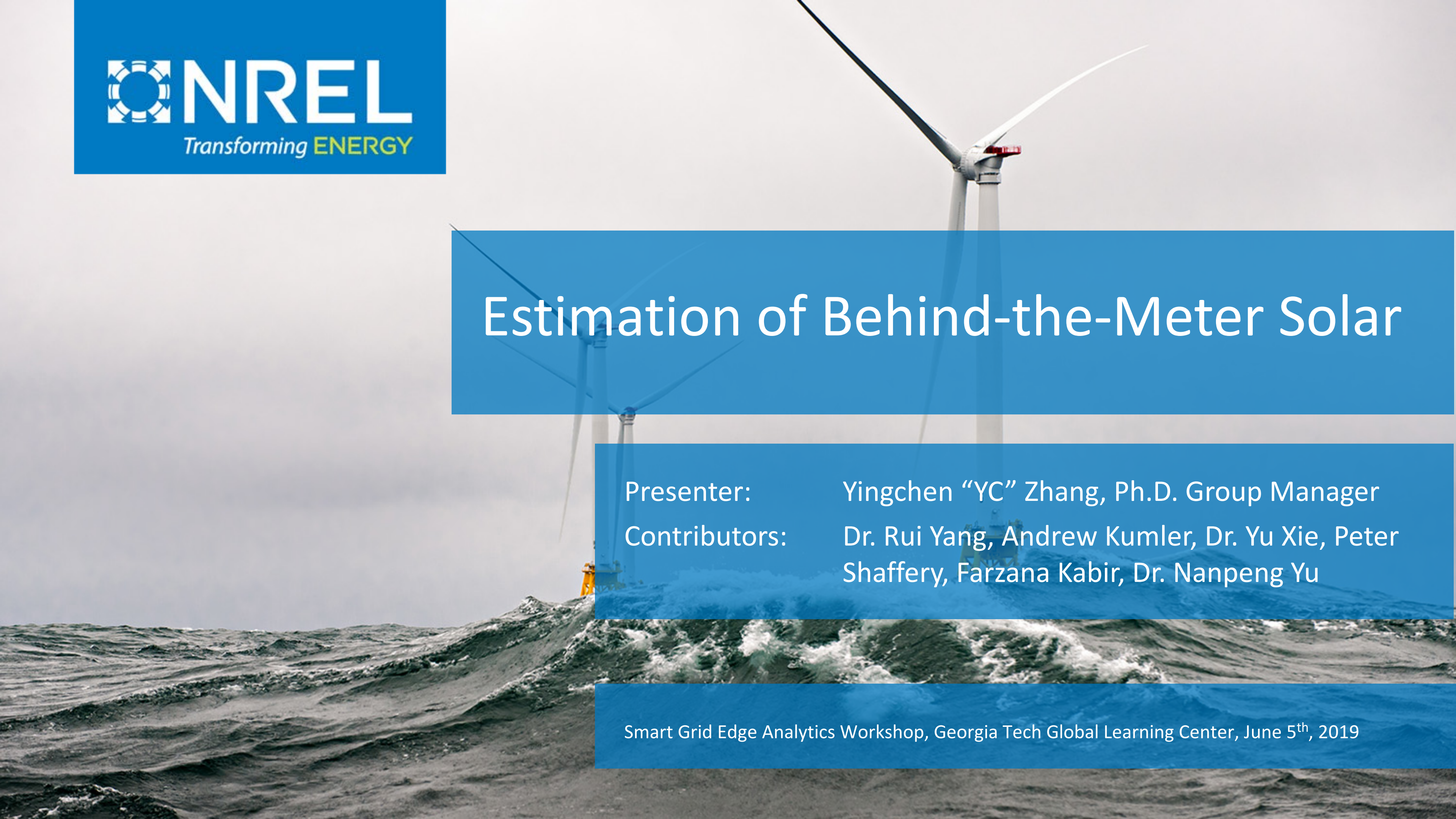

NREL
Transforming ENERGY

Estimation of Behind-the-Meter Solar

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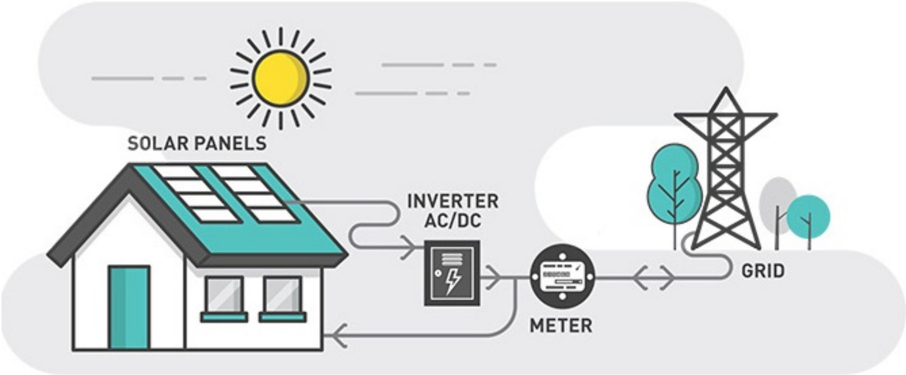
The Problem

- 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

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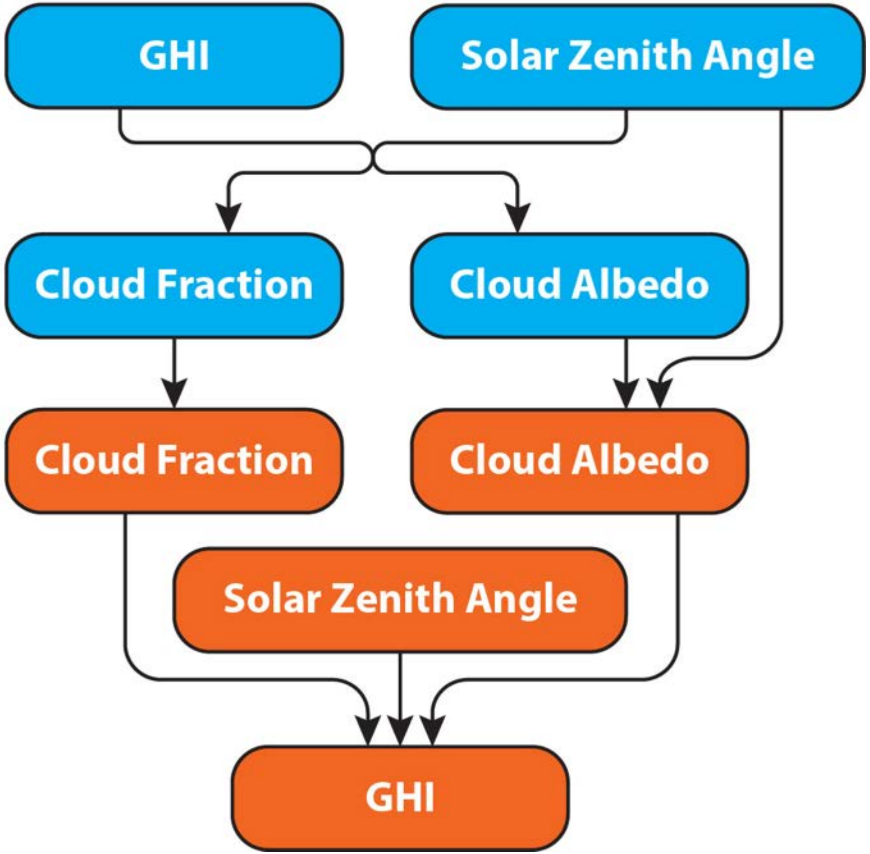
Problem(s) formulaiton

- 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?

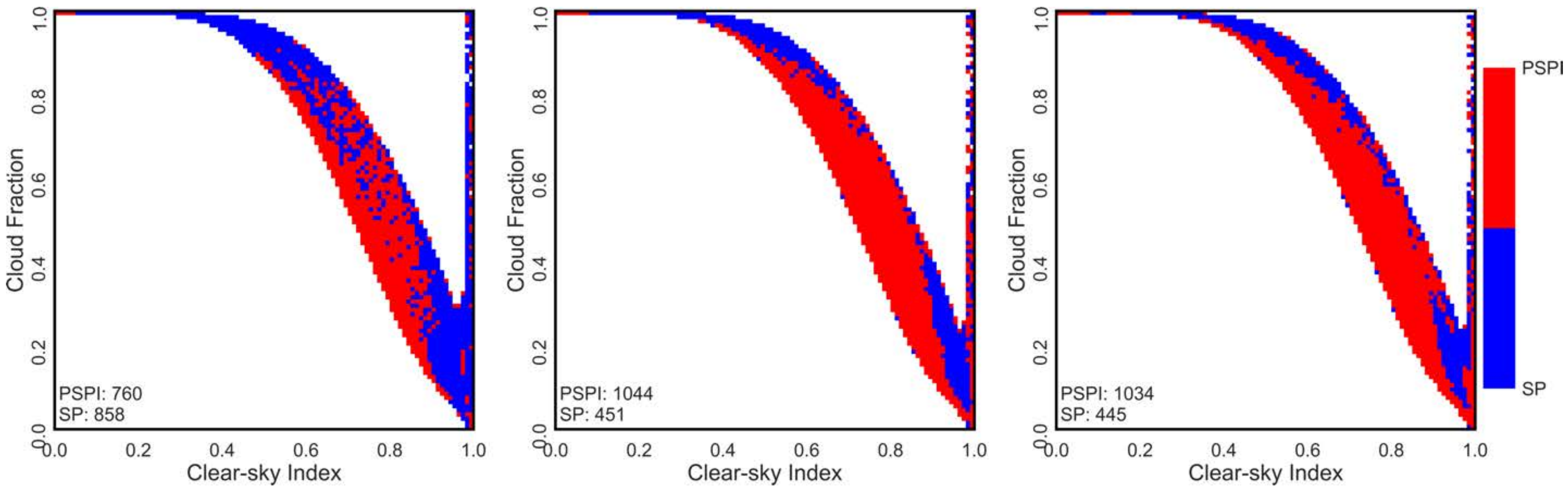
Flowchart for PSPI



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



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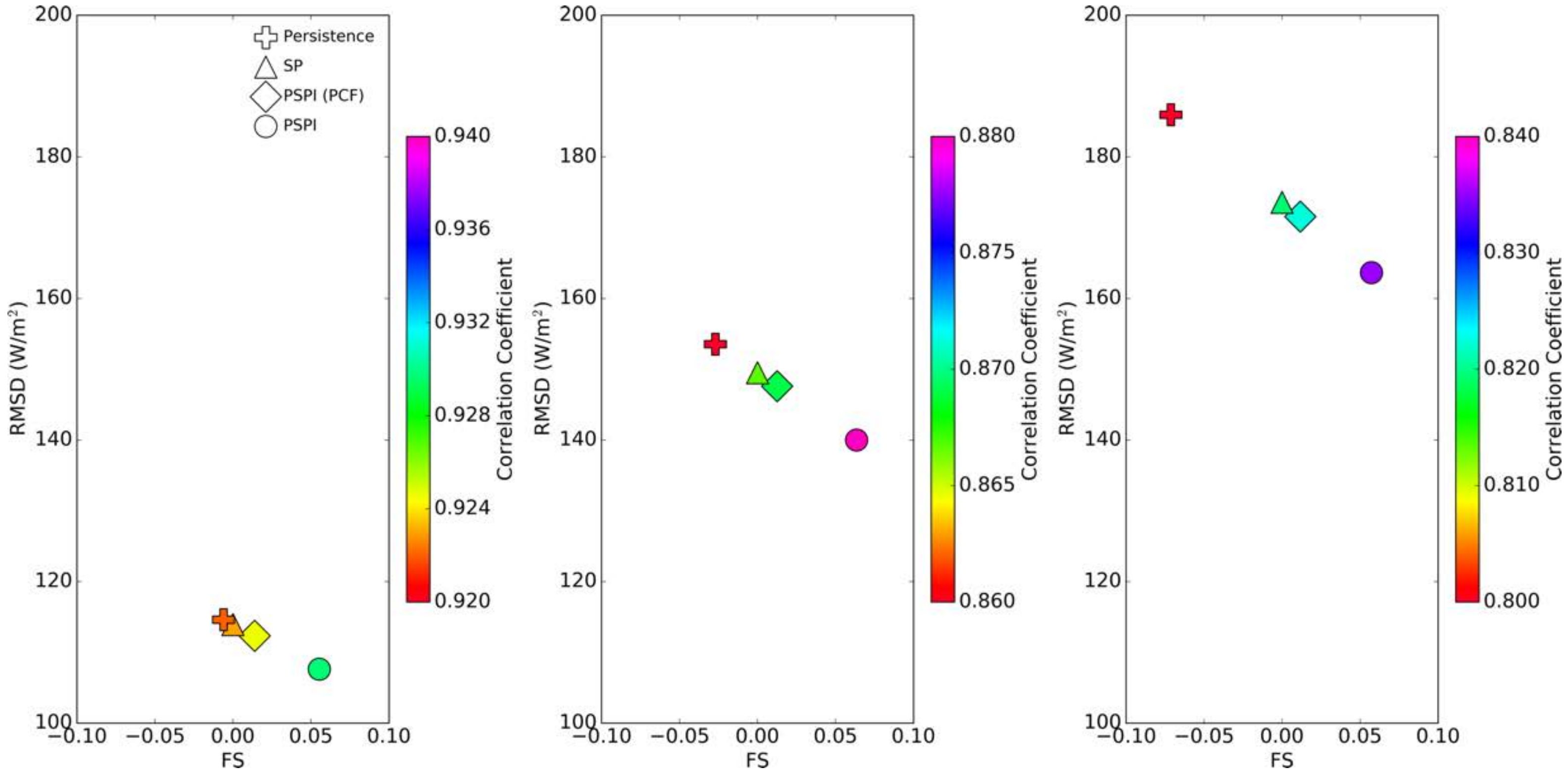
Results



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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

Data

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.

Data

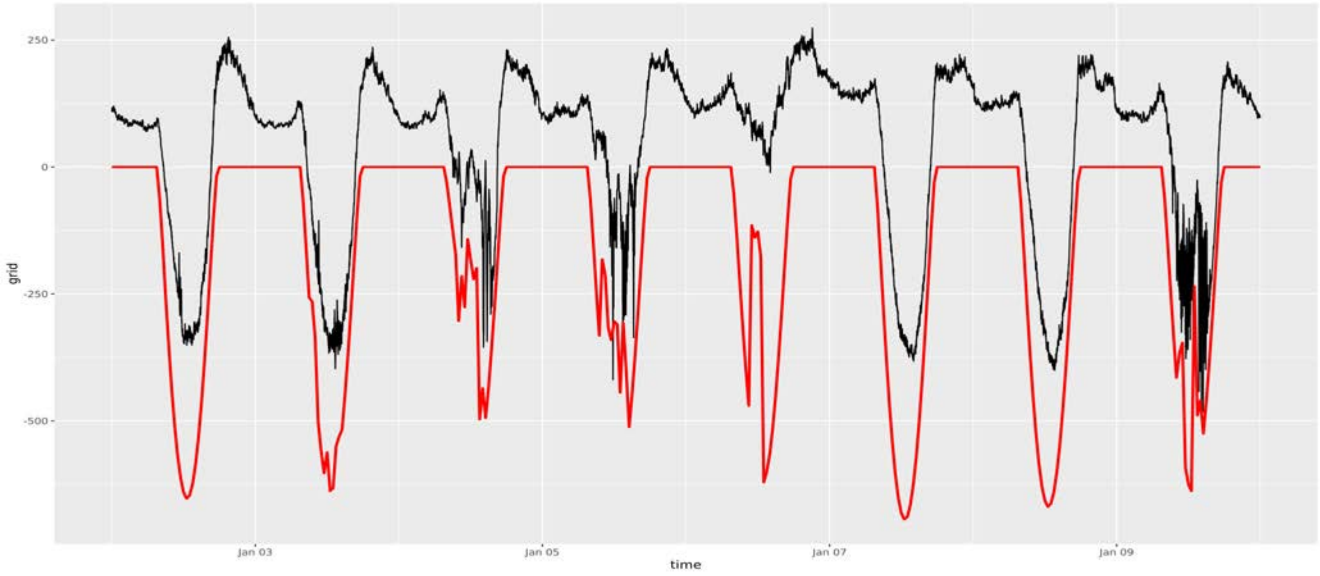

Figure 2: Synthetic feeder measurements of consumption data (summed AMI consumption) for the Pecan Street dataset. GHI again overlaid (flipped and scaled) in red.

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]

1. Scott and Varian. “Predicting the Present with Bayesian Structural Time Series,” June 28, 2013, 21.

Model

Definitions:

Symbol	Def
s_t	(Synthetic) feeder PV gen at time t
l_t	(Synthetic) feeder load at time t
y_t	(Synthetic) feeder measured load
ϕ_t	GHI
X_t	Piecewise-linear temperature covariates

Model

State space model evolves as:

$$s_{t+1} = \beta_{t+1}\phi_{t+1} + \epsilon_{t+1}^{(s)}$$

$$\beta_{t+1} = \beta_t + \epsilon_t^{(\beta)}$$

$$l_{t+1} = X_{t+1}^T\gamma + l_t + \delta_{t+1} + \eta_{t+1}^{(l)}$$

$$\delta_{t+1} = \delta_t + \eta_t^{(\delta)}$$

$$y_{t+1} = s_{t+1} + l_{t+1}$$

$$\text{Where } \epsilon_t^{(\cdot)} \sim N(0, \sigma_\cdot^2) \text{ and } \eta_t^{(\cdot)} \sim T_{\nu_\cdot}(0, \sigma_\cdot^2)$$

Model

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:

$$A^T = [1, 0, 1, 0, 0] \qquad Z_t(\gamma) = \begin{bmatrix} 0, \phi_t, 0, 0, 0 \\ 0, 1, 0, 0, 0 \\ 0, 0, X_t^T\gamma, 1, 1 \\ 0, 0, 0, 0, 1 \end{bmatrix}$$

BSTS Output

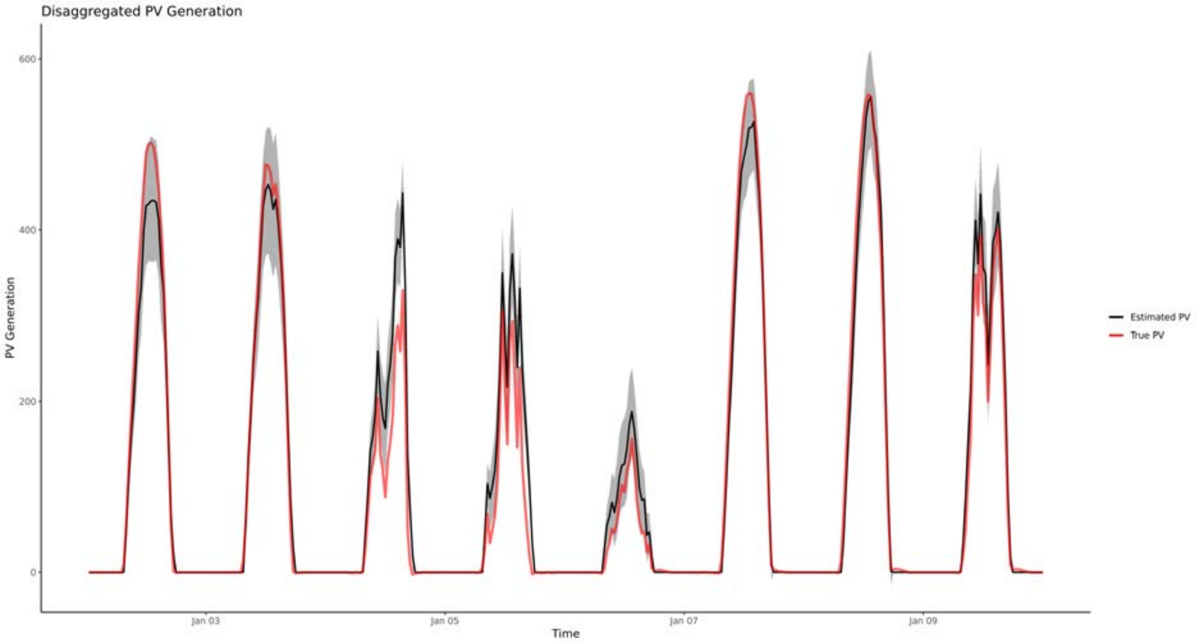

Figure 3: Estimated PV generation occurring over 7 days (black) with 95% credible intervals (gray) against true generation (red)

BSTS Output

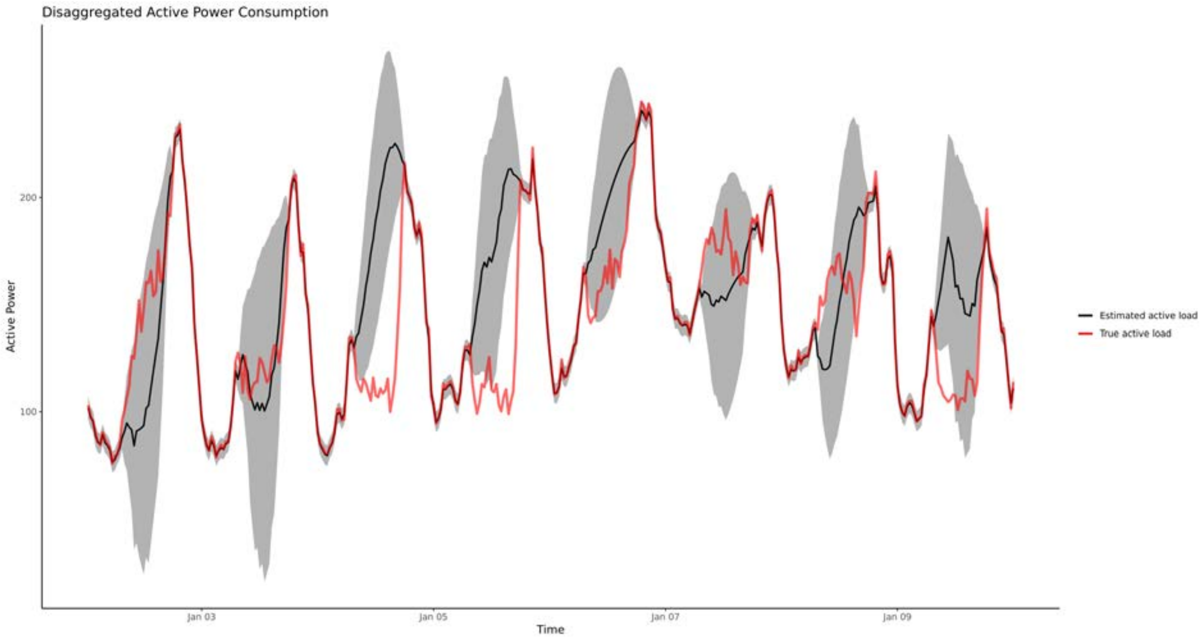

Figure 4: Estimated true load over 7 days (black) with 95% credible intervals (gray) against true generation (red)

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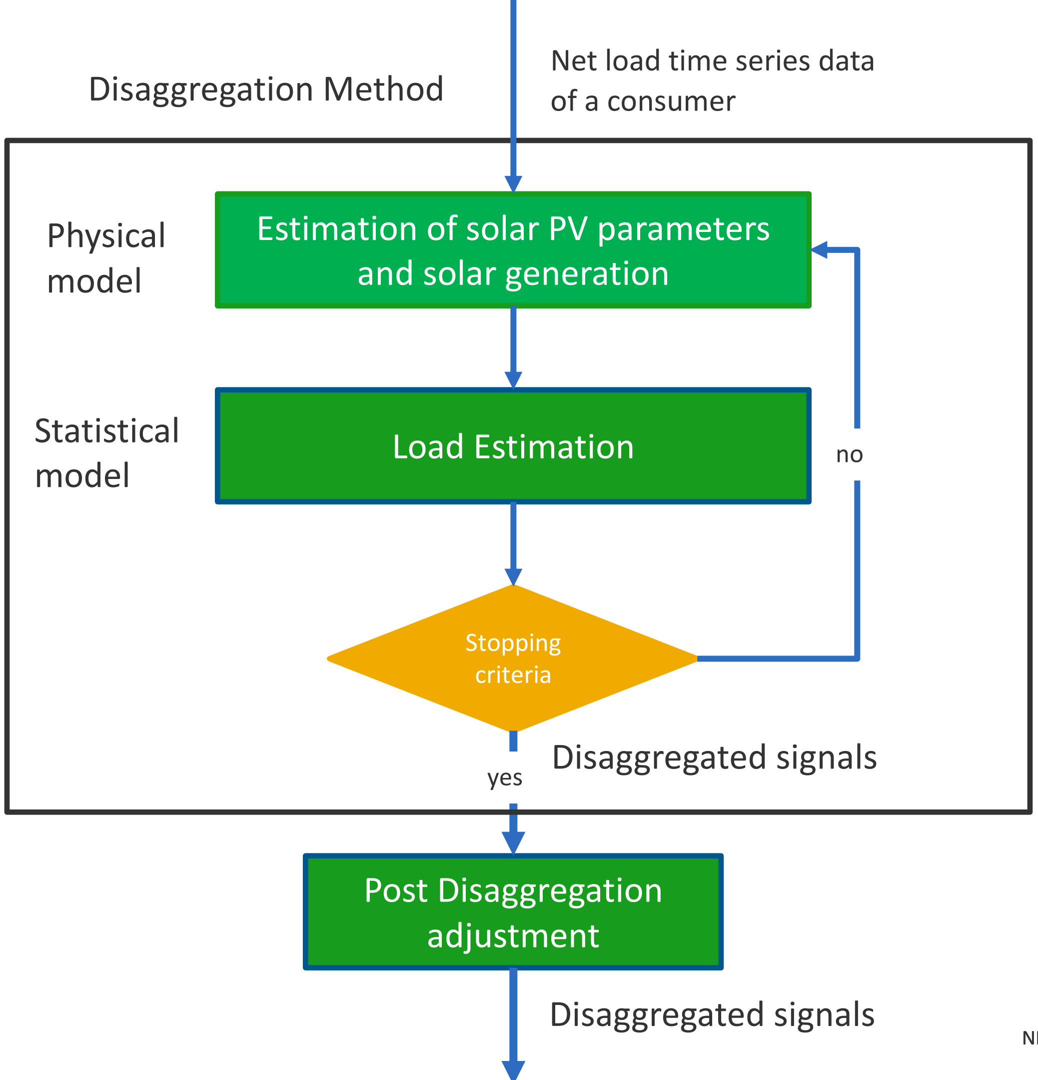
Objective

- From definition of net load

$$NL_t = L_t - S_t; \quad L_t \geq 0, \qquad S_t \geq 0, \forall t$$

- 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



Technical methods

Estimation of solar generation (S)

- Estimation of solar PV parameters θ_S
  - Perform a constrained numerical optimization
  - Solar PV parameters θ_S
    - DC size (P_{dc0})
    - Tilt (θ_t)
    - Azimuth (θ_{az})
    - Loss (l)
    - Nominal efficiency (η_{nom})
- Physical PV system performance model g
  - Estimate solar generation $S = g(\boldsymbol{\theta}_S)$

Estimation of Load (L)

- Statistical hidden Markov model regression

Estimation of Solar PV System Parameters

- 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

$$\underset{\theta_S}{\operatorname{argmin}} \sum_{t=1}^{T} \left(S_t - g_t(\boldsymbol{\theta}_S)\right)^2$$

$$\text{subject to } S_t \geq 0, \boldsymbol{\theta}_{S,min} \leq \boldsymbol{\theta}_S \leq \boldsymbol{\theta}_{S,max}$$

PV System Performance Model

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

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

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

- E_0, T_0, γ are known values

[4]Stein, J. S. (2012, June). The photovoltaic performance modeling collaborative (PVPMC). In 2012 38th IEEE Photovoltaic Specialists Conference (pp. 003048-003052). IEEE.
[5]Dobos, A. P. (2014). *PVWatts version 5 manual* (No. NREL/TP-6A20-62641). National Renewable Energy Lab.(NREL), Golden, CO (United States).

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:

Variables	Symbols
Temperature (3rd degree polynomial)	c, c^2, c^3
Hour of the day (3rd degree polynomial)	h, h^2, h^3
Weighted moving average of last 24 hours temperature	c_{wmv}
Day of the week	$d = \begin{cases} 1 & if\ weekend \\ 0 & if\ weekday \end{cases}$

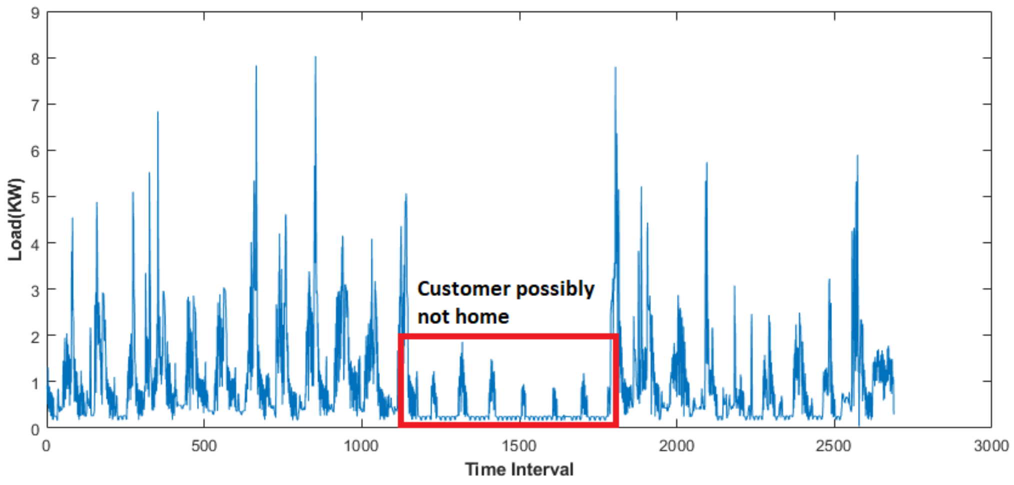


Figure 1: Load time series of a customer

Load Estimation

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

Hidden Markov Model Regression

- This change in behavior can be modeled by a hidden Markov model regression[6] (also called Markov switching regression model) given state s_t

$$L_t = \boldsymbol{X}_t^T \boldsymbol{\beta}_{s_t} + \varepsilon_{s_t} \quad \varepsilon_{s_t} \sim N\left(0, \sigma_{s_t}^2\right)$$

- $L_t \rightarrow$ 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

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

- Can be estimated by maximum likelihood (MS_Regress[7] package of MATLAB used)

[6] Fridman, M. (1994). Hidden markov model regression.
[7] Perlin, M. (2015). MS_Regress-the MATLAB package for Markov regime switching models. *Available at SSRN 1714016*.

Disaggregation Algorithm

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 $\hat{\mathbf{L}}$, solar generation $\hat{\mathbf{S}}$, and solar PV parameters $\boldsymbol{\theta}_S$

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

for each starting point $m \in M$ **do**
- Initialize solar generation, $\hat{\mathbf{S}}_m^{(0)} = g\left((\boldsymbol{\theta}_S)_m^{(0)}\right)$
- **for** j=1 to maxiter **do**
  - Estimate user consumption, $\hat{\mathbf{L}}_m^{(j)} = \mathbf{NL} + \hat{\mathbf{S}}_m^{(j-1)}$
  - Fit HMM regression model, denoted by $f(\boldsymbol{X}, \boldsymbol{\theta}_L)$, to $\hat{\mathbf{L}}_m^{(j)}$ and calculate parameters $(\boldsymbol{\theta}_L)_m^{(j)}$
  - Update user consumption, $\hat{\mathbf{L}}_m^{(j)} = f\left(\boldsymbol{X}, (\boldsymbol{\theta}_L)_m^{(j)}\right)$
  - Update solar generation, $\hat{\mathbf{S}}_m^{(j)} = \hat{\mathbf{L}}_m^{(j)} - \mathbf{NL}$
  - Determine $(\boldsymbol{\theta}_S)_m^{(j)}$ from Equation (2) using $(\boldsymbol{\theta}_S)_m^{(j-1)}$ as initial value
  - Update solar generation, $\hat{\mathbf{S}}_m^{(j)} = g\left((\boldsymbol{\theta}_S)_m^{(j)}\right)$
  - Estimate net load, $\hat{\mathbf{NL}}_m^{(j)} = \hat{\mathbf{L}}_m^{(j)} - \hat{\mathbf{S}}_m^{(j)}$
  - Calculate MSE of the net load, $E_m^{(j)}$
  - **if** $\left|(\boldsymbol{\theta}_S)_m^{(j)} - (\boldsymbol{\theta}_S)_m^{(j-1)}\right| \leq \varepsilon$ **then**
    - Break
  - **end if**
- **end for**

end for

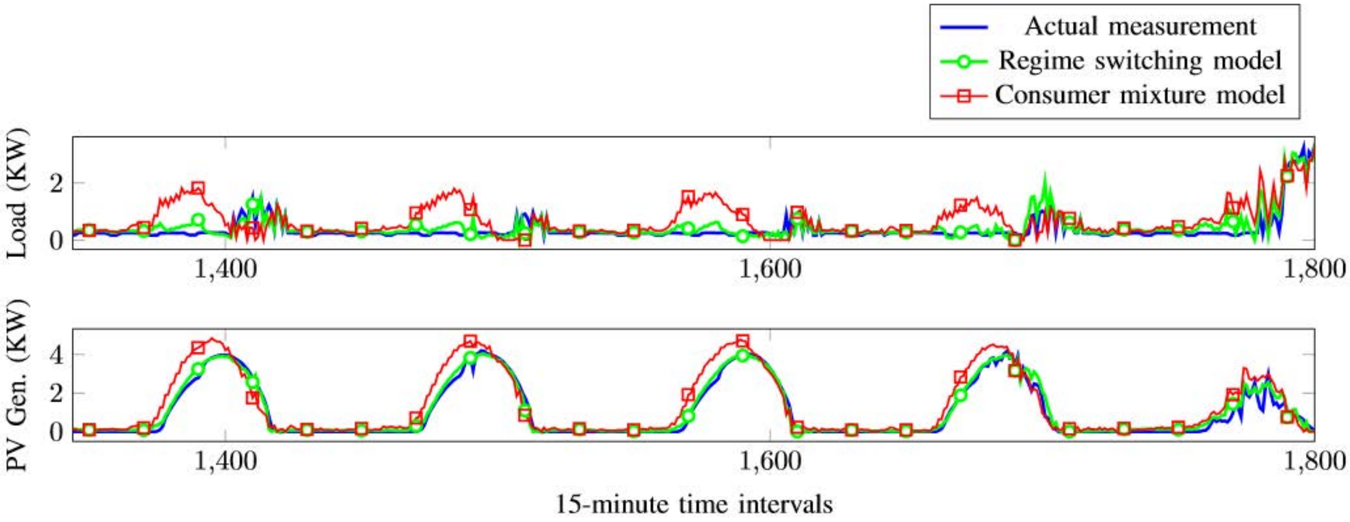
Determine $m^*, j^* = \underset{m,j}{argmin}\, E_m^{(j)}$

return $\hat{\mathbf{L}} = \hat{\mathbf{L}}_{m^*}^{(j^*)}$, $\hat{\mathbf{S}} = \hat{\mathbf{S}}_{m^*}^{(j^*)}$, and $\boldsymbol{\theta}_S = (\boldsymbol{\theta}_S)_{m^*}^{(j^*)}$

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 θ_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

[8]Holcomb, C. (2012). Pecan street INC.: A test-bed for NILM. In International Workshop on Non-Intrusive Load Monitoring, Pittsburgh, PA, USA.



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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A. Kumler, et. al. “A Physics-based Smart Persistent model for Intra-hour forecast of solar radiation (PSPI),” *Solar Energy*, 2018.

F. Kabir, et. al. “Estimation of Behind-the-Meter Solar Generation by Integrating Physical with Statistical Model,” IEEE SmartGridComm, 2019.

P. Shaffery, et. al. “Bayesian Structural Time Series for Distributed Photovoltaic Disaggregation,” in preparation

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