Predictive Analytics for Behind-the-Meter Resources

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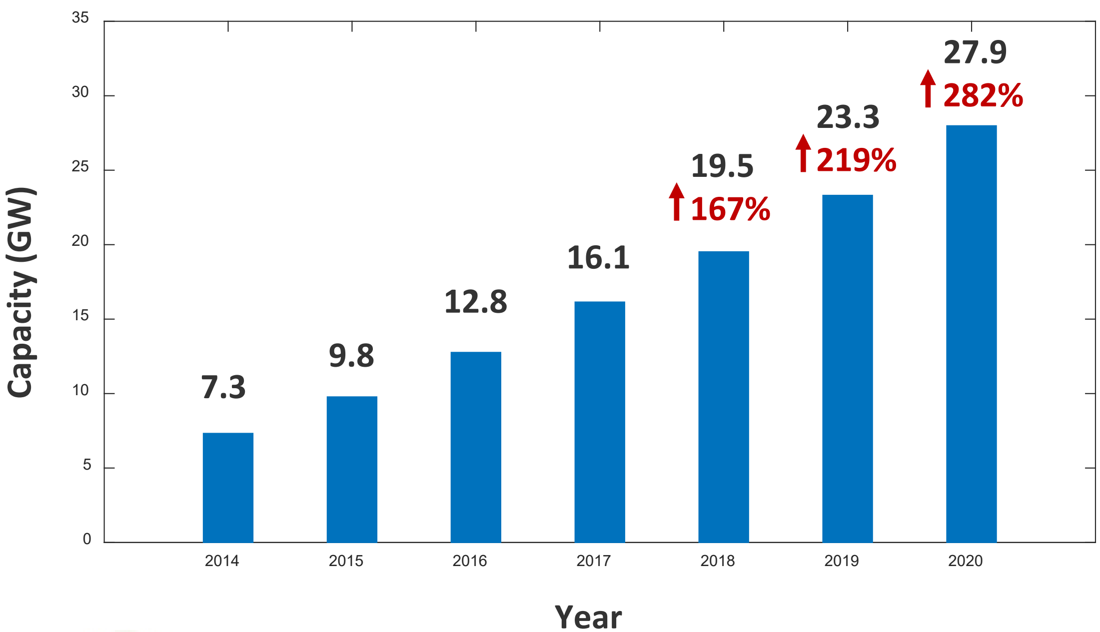
Rapid Growth of Behind-the-Meter Resources

- Increasing penetrations of distributed energy resources

Total Installed Capacity of Small-Scale PV in the U.S.

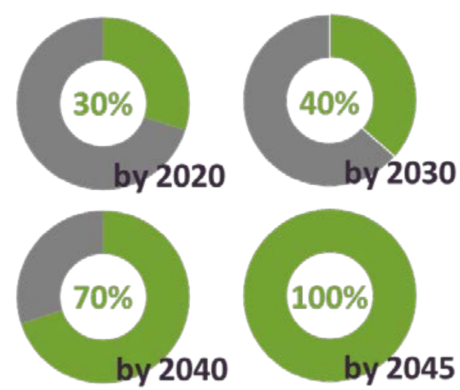


Data source: U.S. Energy Information Administration

California

Requires solar panels on all new homes

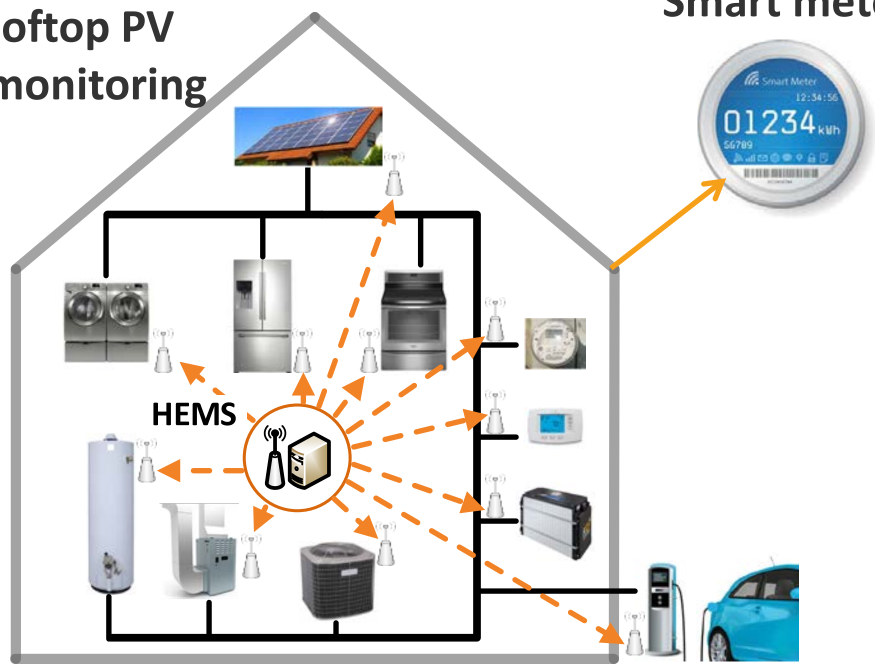
Hawaii



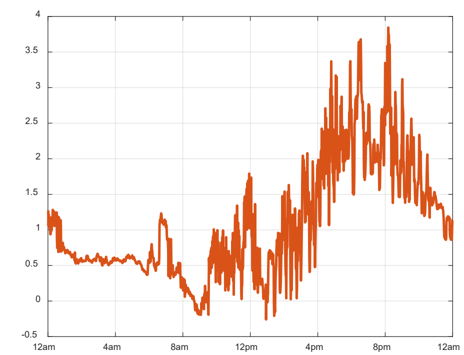
326 MW rooftop PV by 2021

Lack of Visibility of Behind-the-Meter Resources

Rooftop PV
No monitoring



Whole-House Power Consumption



PV Generation

No real-time monitoring of behind-the-meter (BTM) photovoltaic (PV) generation

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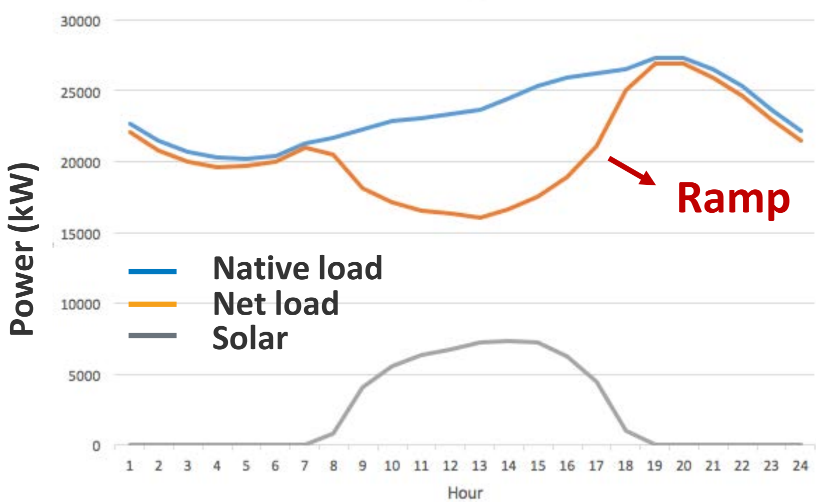
Behind-the-Meter Visibility

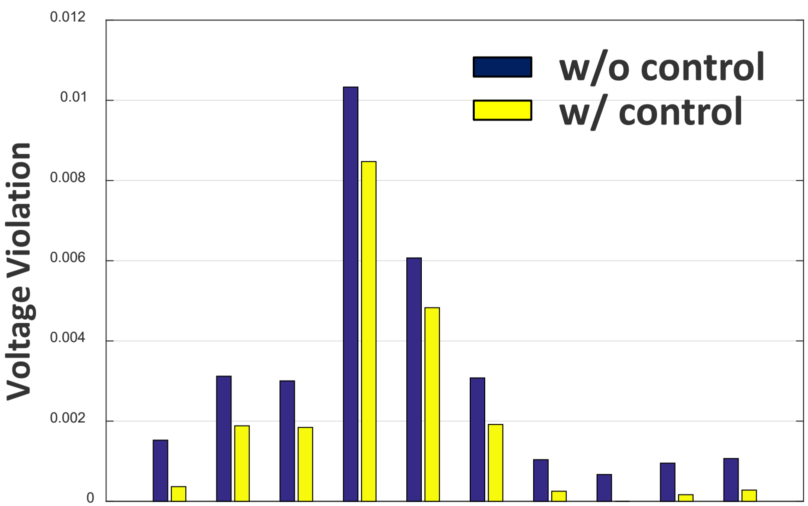
Forecasting



Reduce operation costs

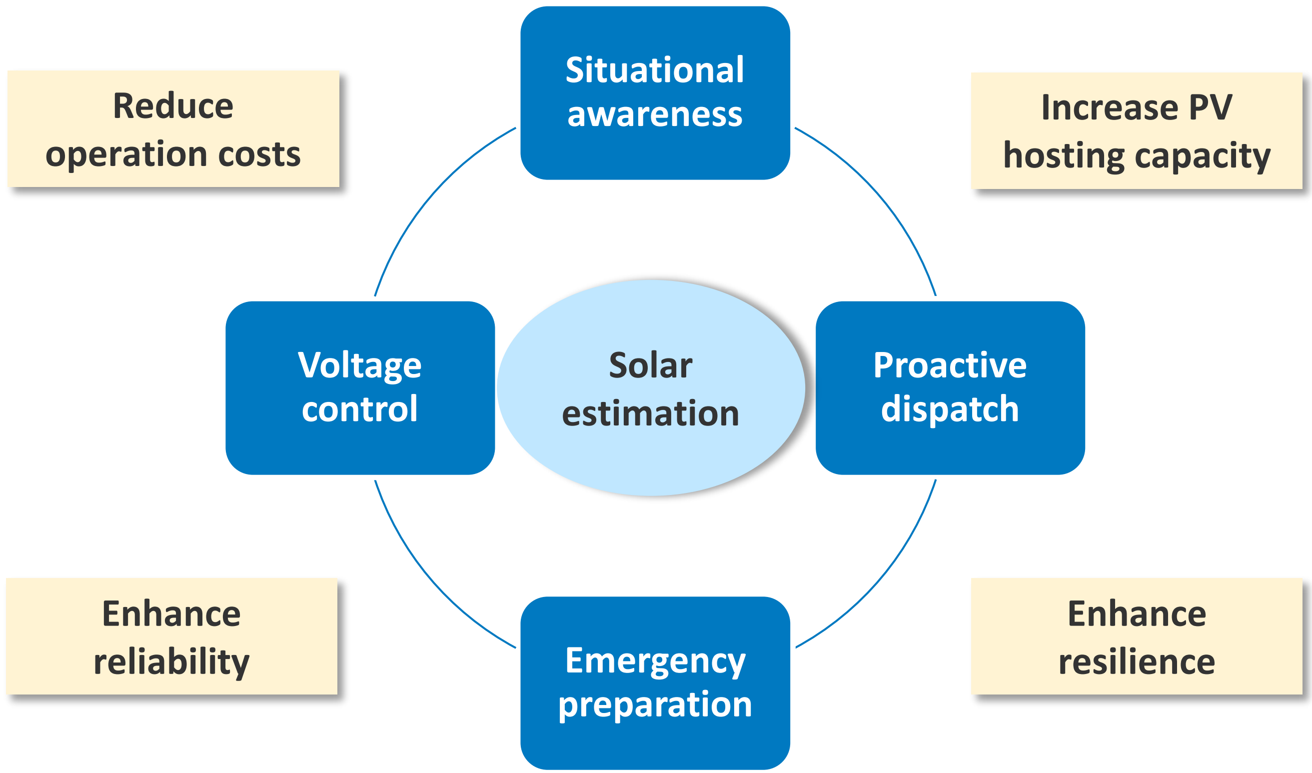
Reduce reserve margins

Voltage Regulation



Optimize voltage profile

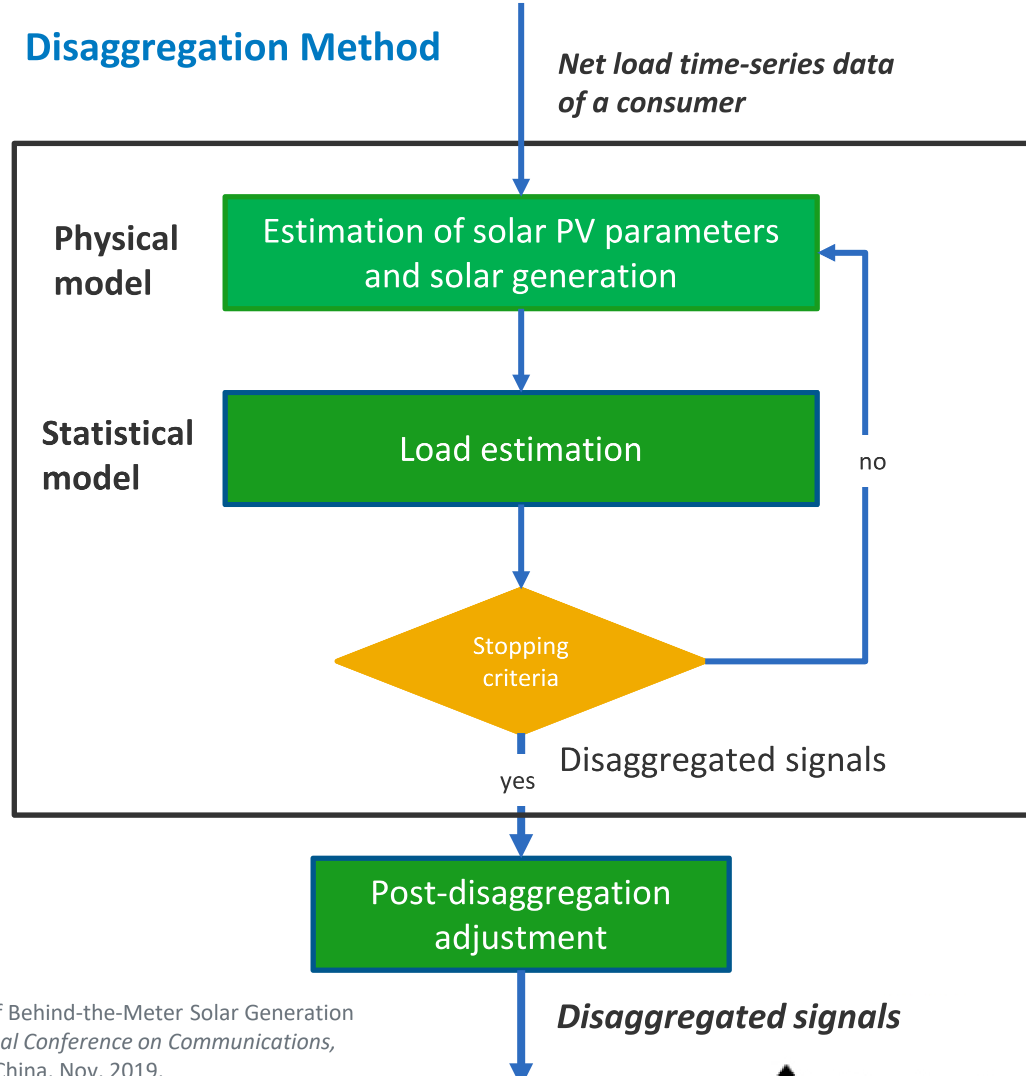
Why Is it Important?



Challenge: Estimating and forecasting BTM PV generation using heterogenous data, e.g., GHI, AMI, SCADA

Estimation of BTM PV

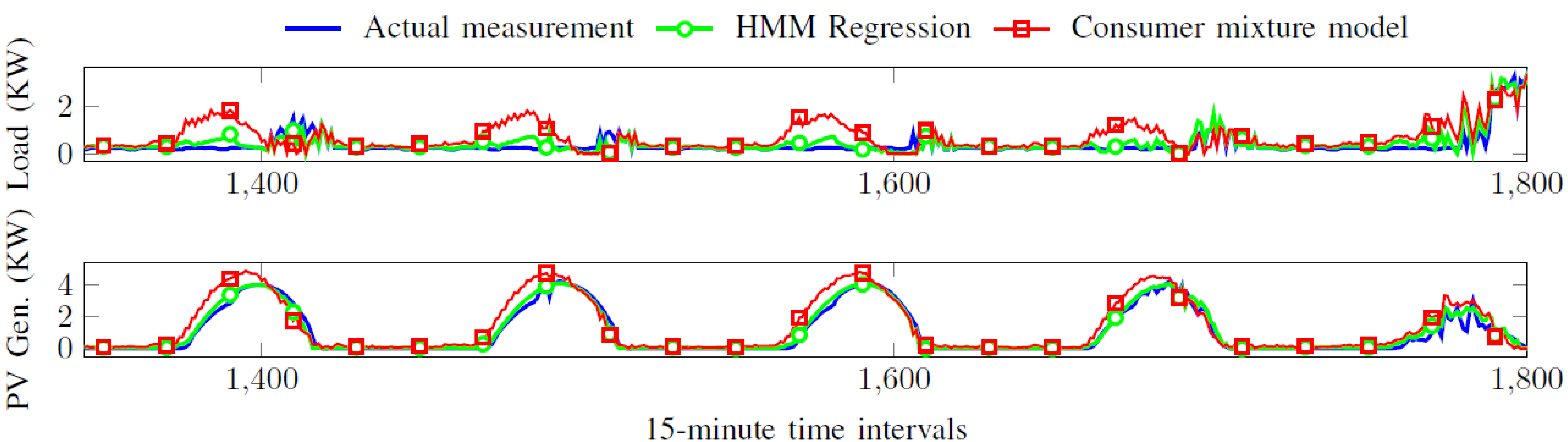
- **Key innovation: Physical + statistical models**
- Estimation of solar generation (S)
  - Estimation of solar PV parameters θ_S
  - Physical PV system performance model g
- Estimation of load (L)
  - Statistical hidden Markov model regression
- Iterative method [1]



[1] F. Kabir, N. Yu, W. Yao, R. Yang, and Y. Zhang, "Estimation of Behind-the-Meter Solar Generation by Integrating Physical with Statistical Model," *IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids*, Beijing, China, Nov. 2019.

Representative Results

- Validation
  - 28 days: 10/03/2015 – 10/30/2015
  - 197 consumers with PV installation



44% reduction in mean squared error compare to state-of-the-art methods

Probabilistic Estimation of BTM PV

- **Key innovation: Probabilistic estimation with uncertainty quantification**
- Method: Bayesian structural time series (BSTS) model [2]
- Model:

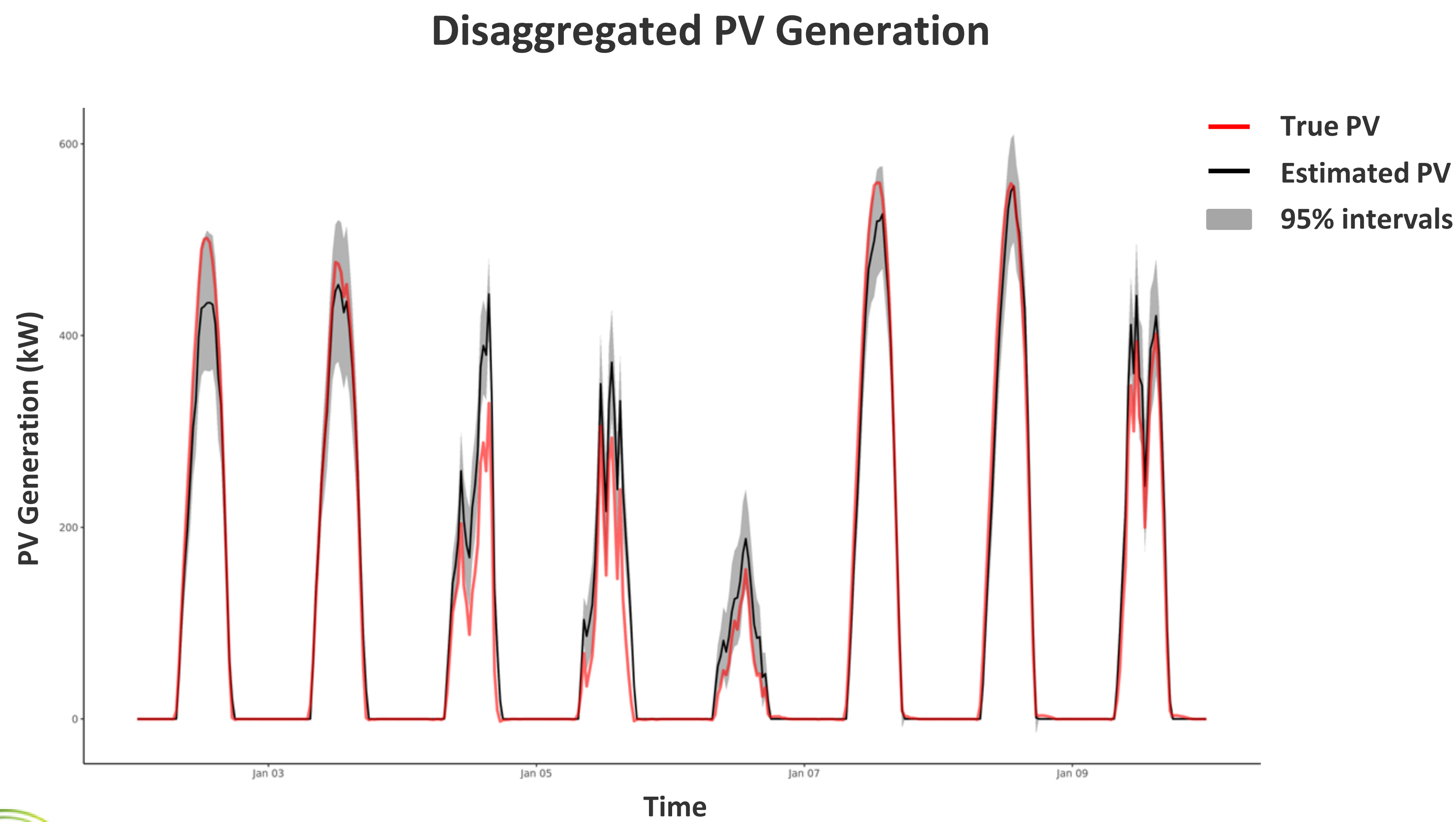
$$
\begin{aligned}
S_t &= \beta_t \phi_t + \epsilon_t^{(s)} \\
\beta_t &= \beta_{t-1} + \epsilon_t^{(\beta)} \\
L_t &= \boldsymbol{X}_t \gamma + L_{t-1} + \epsilon_t^{(l)} \\
P_t &= S_t + L_t
\end{aligned}
\quad \Rightarrow \quad
\begin{aligned}
\boldsymbol{y}_t &= \boldsymbol{Z}_t(\gamma) \boldsymbol{y}_{t-1} + \omega_t \\
P_t &= \boldsymbol{A} \boldsymbol{y}_t
\end{aligned}
$$

Synthetic state space model

- Fitting is performed by combining Kalman Filtering and Markov Chain Monte Carlo.

[2] S. Shaffery, R. Yang, and Y. Zhang, "Bayesian Structural Time Series for Behind-the-Meter Photovoltaic Disaggregation," The Eleventh Conference on Innovative Smart Grid Technologies, Washington D.C., Feb. 2020.

Representative Results



Conclusion

Key takeaways:

- Visibility of BTM resources is **crucial**
- Physics + data-driven methods

Challenges:

- Heterogenous data
- Scalability
- Use cases

Thank you!

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