Technical Working Group:
Meeting 9

August 1, 2023

Agenda: 8/1/23 Technical Working Group

- Wrapping up CalTRACK 2.1
- Moving on to Hourly Methods
  - Where is CalTRACK 2.0 Hourly limited?
  - What are the opportunities for a refreshed model framework?
- Academic literature review

Wrapping up CalTRACK 2.1

What to Expect

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CalTRACK 2.0 Hourly: A Brief Background

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CalTRACK 2.0 Hourly: Broad Strokes

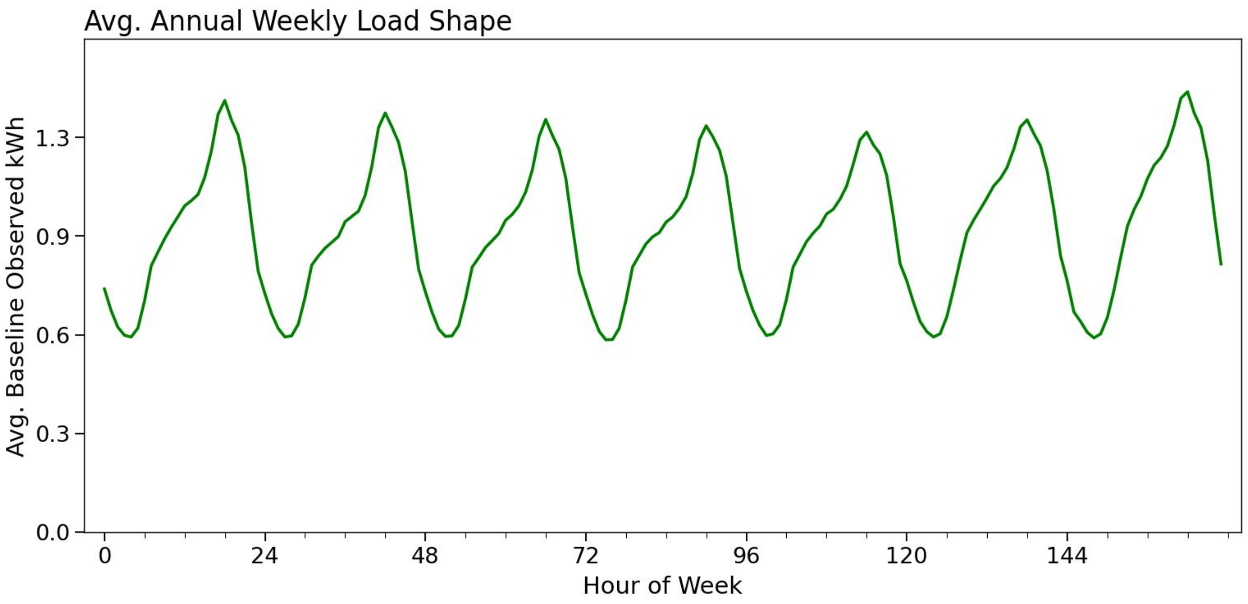
Version of a Time-Of-Week-and-Temperature (TOWT) model

Variables

- Hour of Week
- Temperature

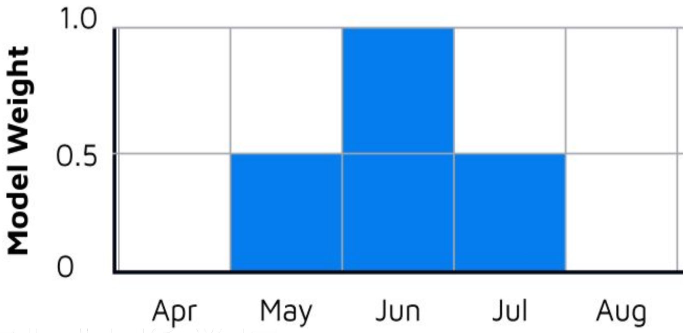
Unique prediction for

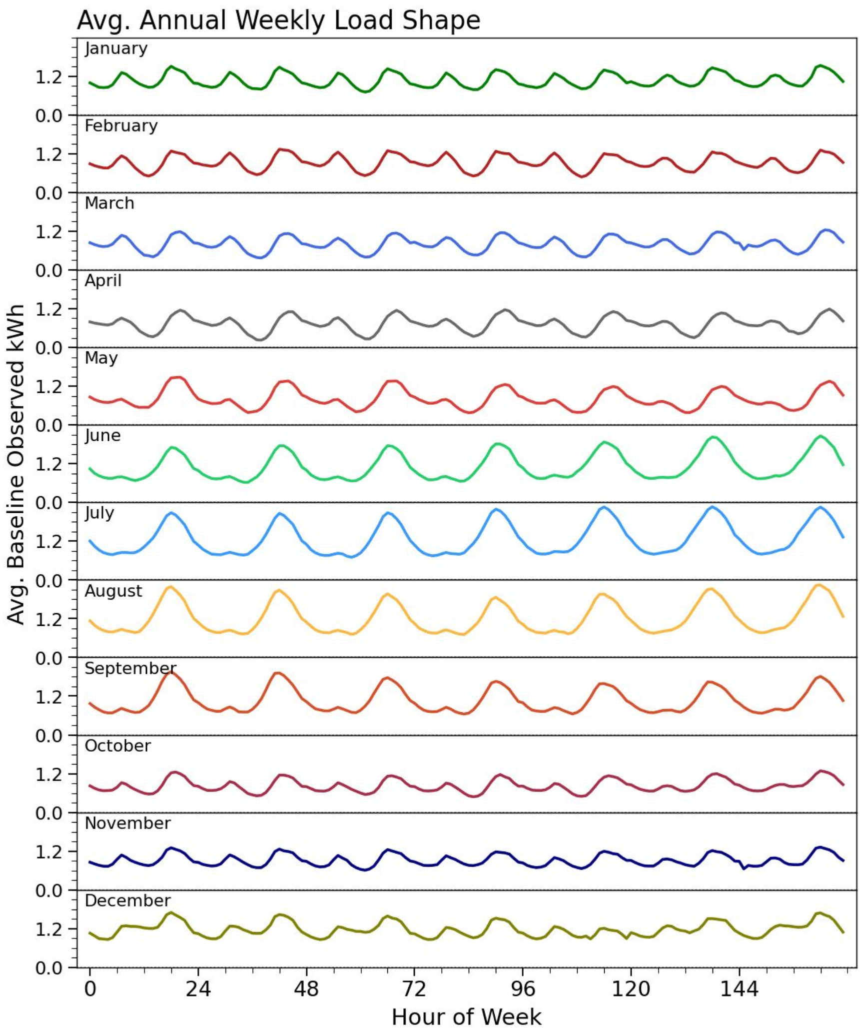
- Tuesday, 7 pm
- Sunday, 3 am
- ...



But…Energy consumption changes throughout the year

Therefore, a unique CalTRACK 2.0 model is produced for every month





Temperature Binning

Example temps and corresponding parameter multipliers

Bin:	<30	30-45	45-55	55-65	65-75	75-90	>90
T_p	$T_{1,p}$	$T_{2,p}$	$T_{3,p}$	$T_{4,p}$	$T_{5,p}$	$T_{6,p}$	$T_{7,p}$
20	20	0	0	0	0	0	0
40	30	10	0	0	0	0	0
50	30	15	5	0	0	0	0
60	30	15	10	5	0	0	0
70	30	15	10	10	5	0	0
80	30	15	10	10	10	5	0
100	30	15	10	10	10	15	10

Model includes up to 7 coefficients depending on the presence of a threshold number of data points at preset temperature ranges

Occupancy

Initial fixed balance point regression conducted to determine an occupancy flag.

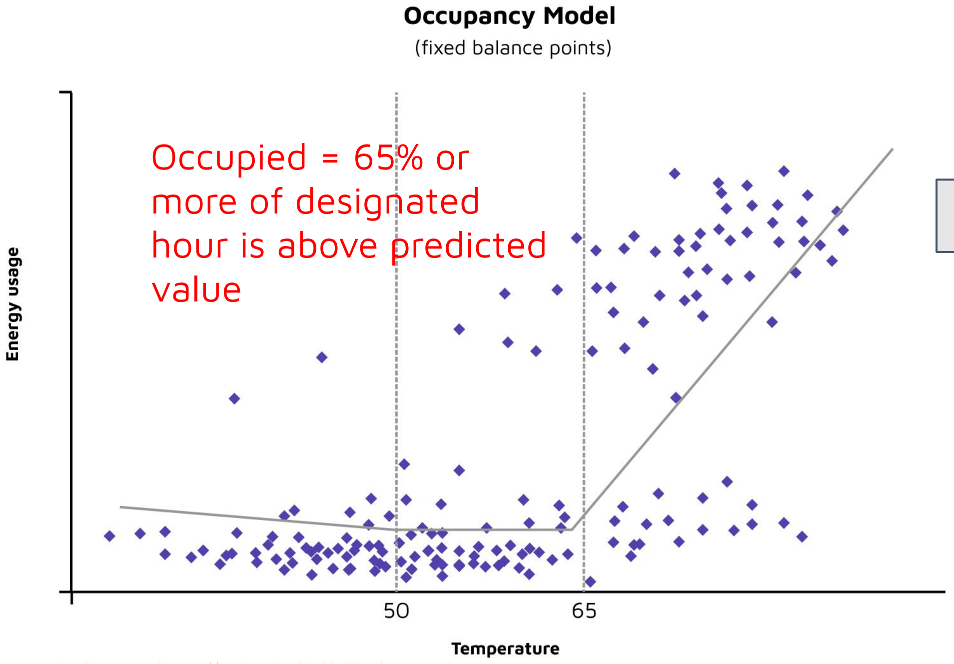
- Regression on all 8760 hours
- CalTRACK Daily-style model (Cooling, Heating, Temp-Independent regions)
- Fixed heating and cooling balance points of 50 and 65 F

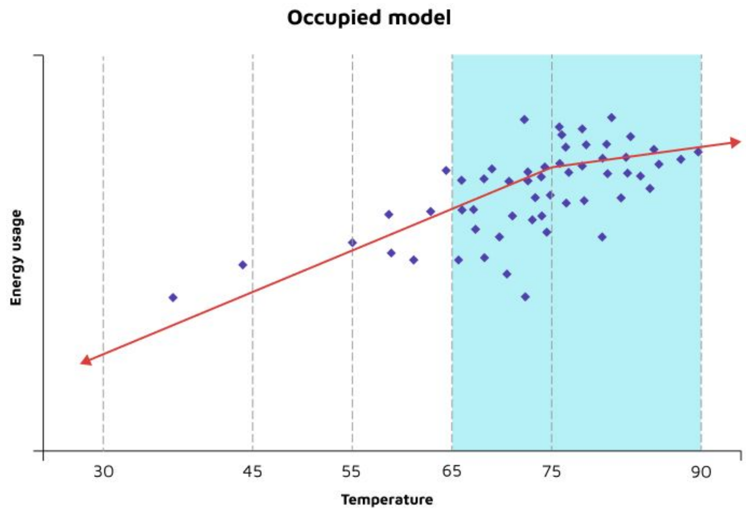
$$UPH_{pi} = \mu_i + \beta_{Hi} HDH50_p + \beta_{Ci} CDH65_p + \epsilon_{pi}$$

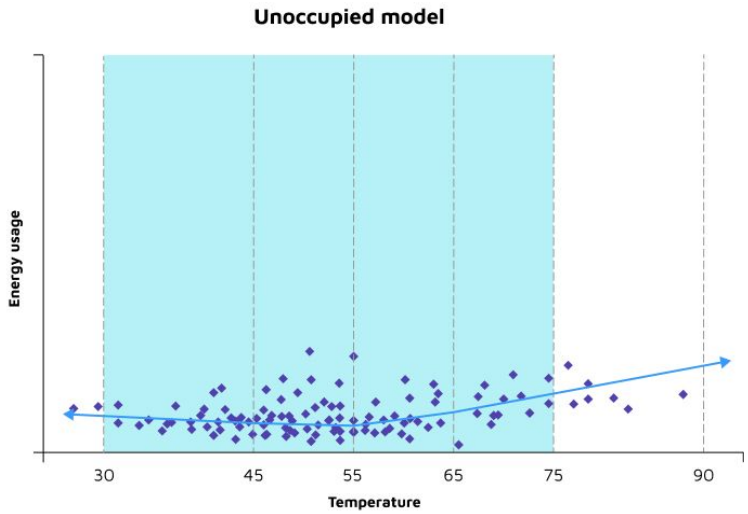
- Results grouped by hour of week
- If residuals are positive for > 65% of points for any given hour then that hour is determined to be “occupied” otherwise the hour is “unoccupied”

2-Models From Occupancy

Model includes up to 7 coefficients depending on the presence of a threshold number of data points at preset temperature ranges







CalTRACK 2.0 Final Model

$$UPH_{pi} = \sum \alpha_t TOWp + \sum \beta_{T,n} Tc_{n,p} + \sum occupied\alpha_t TOWp + \sum occupied\beta_{T,n} Tc_{n,p} + \epsilon_{pi}$$

Non-temp dependent term that varies by hour of week	**Temp dependent term applied to all hours**	**Non-temp dependent term that varies by hour of week applied to only "occupied" hours**	**Temp dependent term applied to only "occupied" hours**

These terms alone comprise the "unoccupied" model

CalTRACK 2.0 Hourly: Model Components

Each model component attempts to capture a distinct "bucket" of energy consumption.

Reminder: annual model stitched together from monthly models

$$\sum occupied \beta_{T,n} Tc_{n,p}$$

Additional temp-dependent usage during "occupied" hours

$$\sum occupied \alpha_t TOWp$$

Additional temp-independent usage during "occupied" hours

$$\sum \beta_{T,n} Tc_{n,p}$$

Temp-dependent usage during "unoccupied" hours

$$\sum \alpha_t TOWp$$

Building baseload (always-on) consumption

CalTRACK 2.0

Primary Issues

- Model is likely prone to overfitting
- DR baselines remain undefined
- Model is incomplete for solar PV customers
- Unclear how readily model is extensible to other technologies/programs beyond energy efficiency

Potential for Overfitting

Take an "occupied" hour...

- Model determined from:
  - A baseload term
  - An additional non-temp dependent term
  - From *effectively* 2 months* of data (~9 data points for each hour of week)
  - Up to 14 temperature parameters (7 "unoccupied, 7 "occupied")

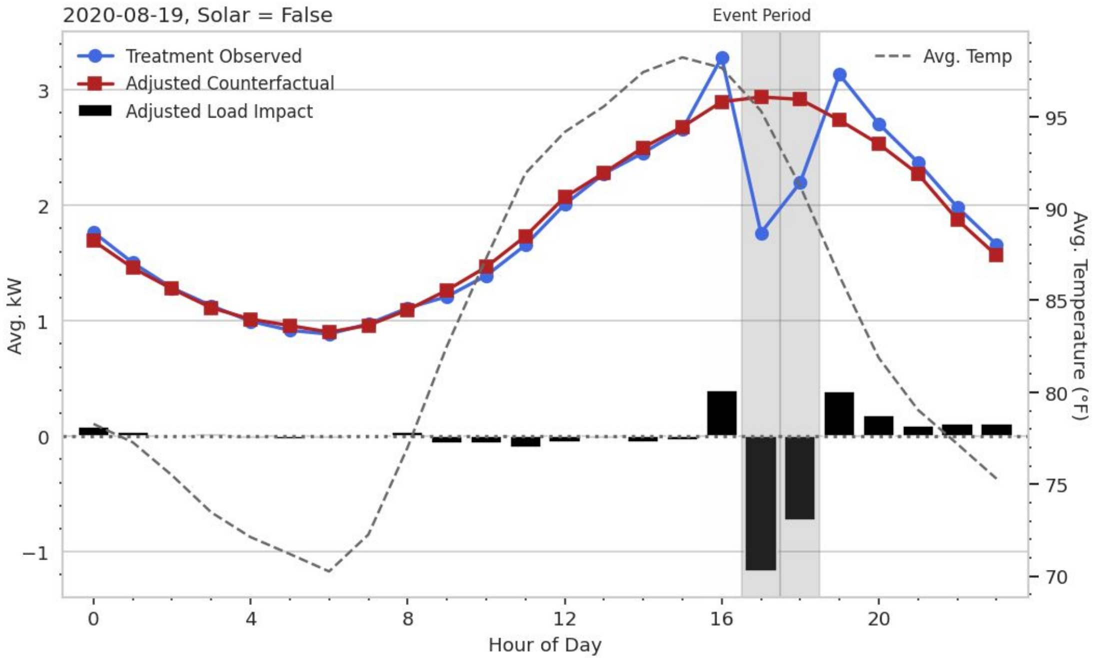
*4 x full weight + 8 x half weight points

Opportunity for the Demand Response use case

“Long-term” baseline not needed/appropriate for DR

CalTRACK 2.0 Occupancy flag not formulated for DR and may cause problems

Example from Recurve’s CAISO DR study



J. Glass, S.Suffian, C. Best, A. Scheer, Recurve, *Demand-Response_Advanced_Measurement_Methodology*, February 2022

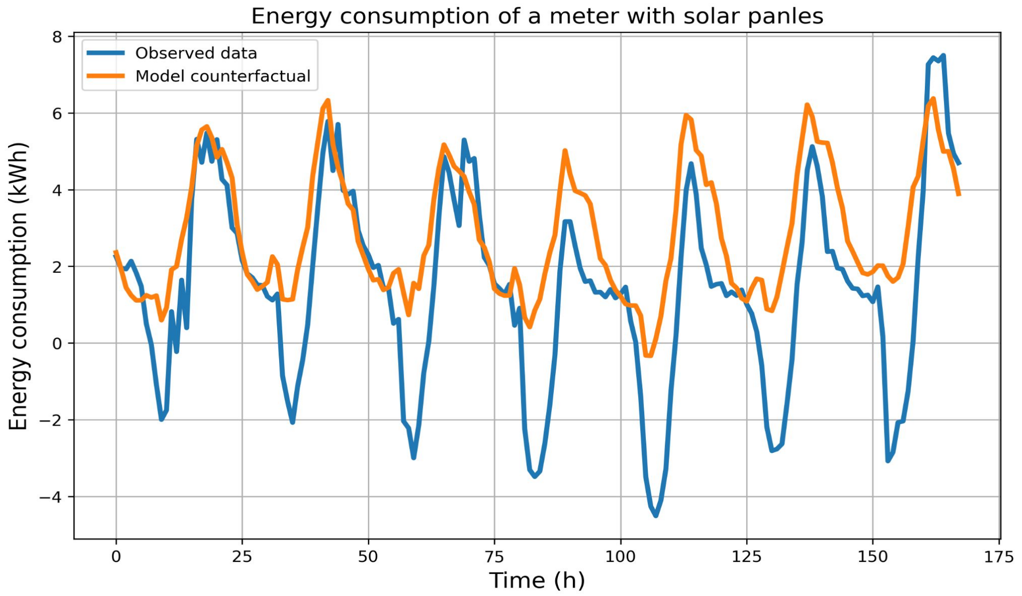
Yet..The model is still unaware of *critical* variables

Huge Risk For Solar PV Customers

- October, 2022 = Cloudy

  October, 2023 = Sunny

  → Huge false savings



Median Hourly Error from 1000 meter Res sample

- Non-solar = 0.41 kWh
- Solar = 0.98 kWh

Solar PV Still Growing Fast

CBS NEWS

Number of Americans using solar power expected to more than triple by 2030

Los Angeles Times

Starting in 2020, all new homes in California must come with solar panels. Builders are getting ready

iea

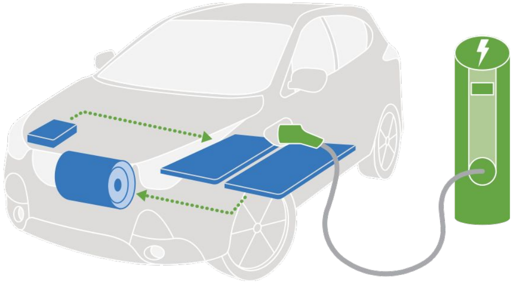
Approximately 100 million households rely on rooftop solar PV by 2030

Pew Research Center

OCTOBER 14, 2022

Home solar panel adoption continues to rise in the U.S.

Modern Demand Side Programs



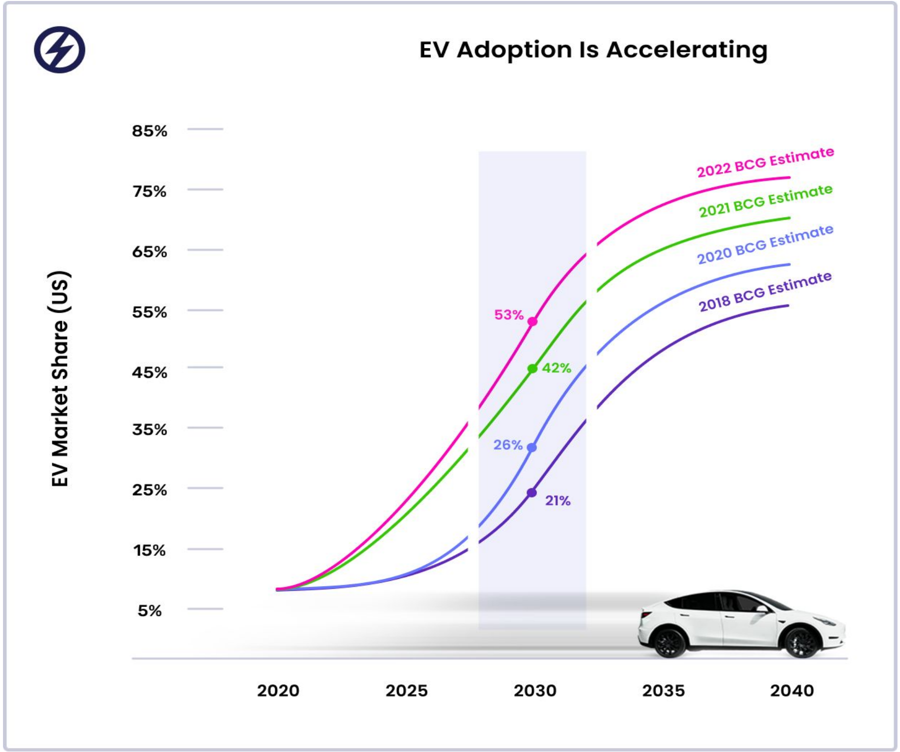
- EVs
- Heat Pumps
- Solar+Storage
- Load Shifting

We need more adaptable modeling approaches given the new mix of technologies and programs

Electric Vehicle Adoption

EEI Projects 26.4 Million Electric Vehicles Will Be on U.S. Roads in 2030

- 30% increase in res electricity
- New peaks, unknown peak demand impacts
- Do utilities know who has an EV?
- How to connect customers to EV programs?



Hourly Methods: Literature Review

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Outline

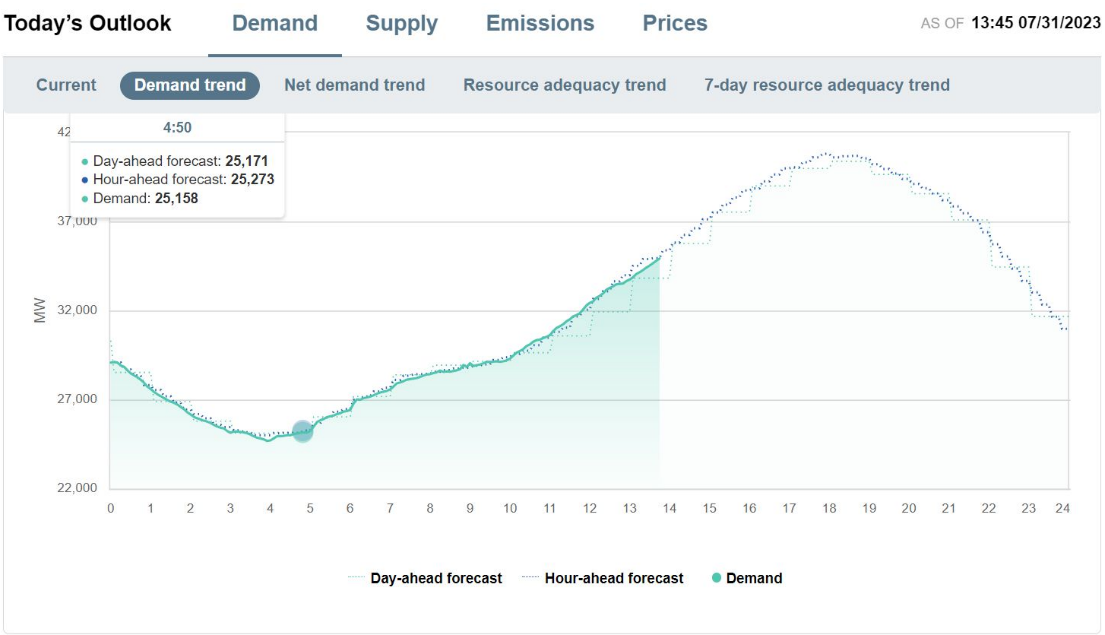
Literature review for CalTRACK 3.0 Hourly

- Measurement and Evaluation (M&V) → AMI counterfactual
- Solar disaggregation

M&V

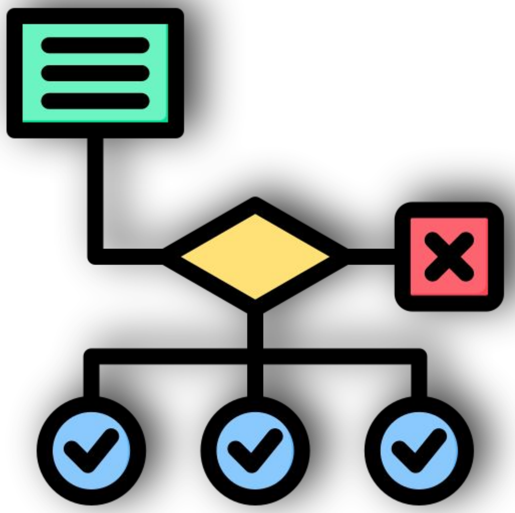
Before We jump into the literature review:

- Load prediction
  - Primary variable
  - Covariates
- M&V
  - Covariates



M&V Literature review

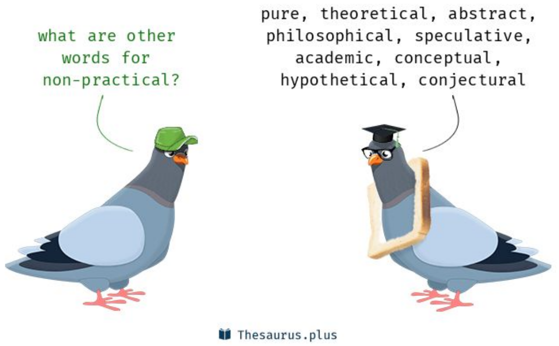
- Methodology (Main focus)



- Tools review and industry application: [1]

M&V methodology literature review

- Building load simulation software like EnergyPlus
  - Theoretical savings
- Consumption driven model using AMI data
  - Statistical learning
  - Machine learning
  - Bayesian methods



M&V methodology literature review

- Consumption driven model using AMI data [2]

❖ Statistical learning	❖ Linear regression → CalTRACK hourly ❖ Kernel regression ❖ Transfer functions
● Machine learning	● Neural Nets ● Support Vector Machine (SVM) ● Random forest
★ Bayesian methods	★ Bayesian inference ★ Gaussian process ★ Gaussian mixture regression

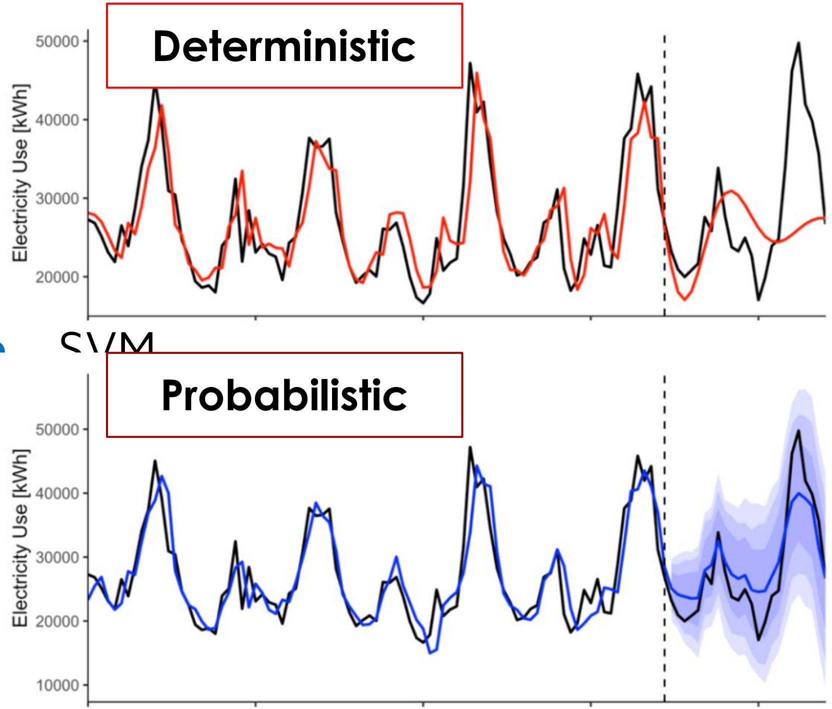
M&V methodology literature review

- Consumption driven model using AMI data [2]

  ❖ Statistical learning

  ● Machine learning

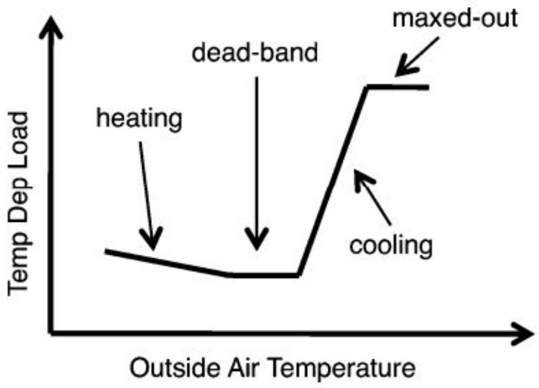
  ★ Bayesian methods

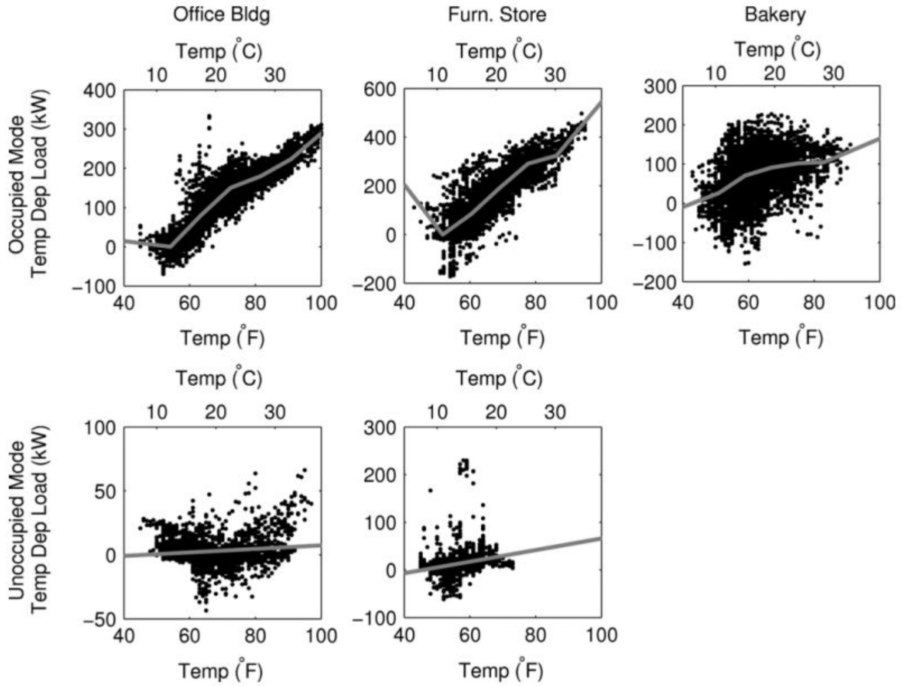


M&V methodology literature review

Statistical learning [2],[4-7]

[4] Linear regression +
time-of-week +
outdoor air-temperature





M&V methodology literature review

Machine learning [8-10]

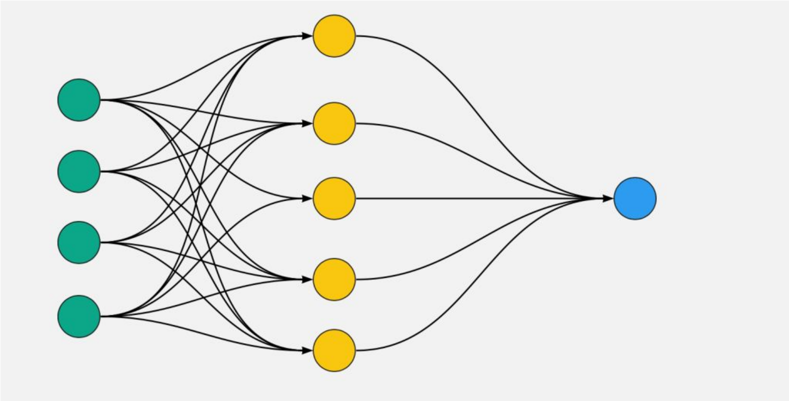
[8] Neural net +

Contextual features +

Temperature +

previous load

DR baseline estimation for an aggregated load including solar customers.



M&V methodology literature review

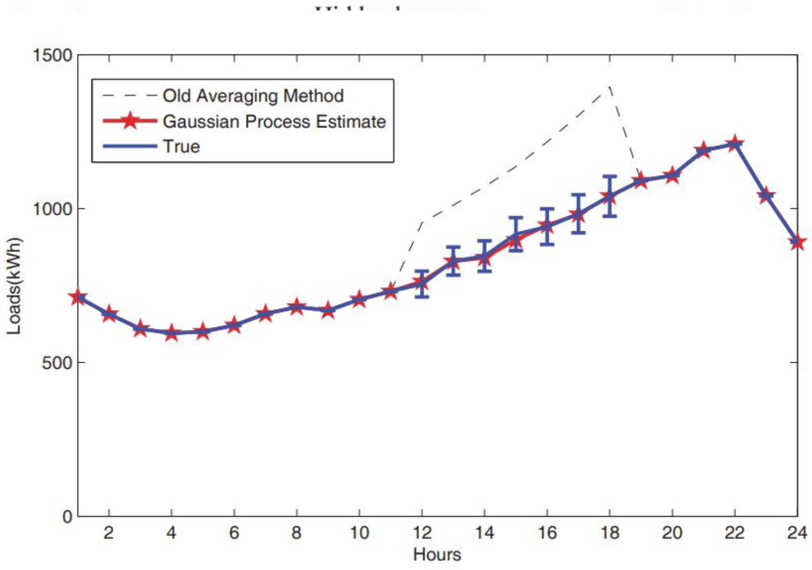
Bayesian methods [3,11,12]

[11] Prior knowledge
using Bayes rule
update posterior

Contextual features +

Temperature

$$P(y(\boldsymbol{x})|X,\boldsymbol{y}) = \frac{P(\boldsymbol{y}|y(\boldsymbol{x}),X)P(y(\boldsymbol{x}))}{P(\boldsymbol{y}|X)}$$



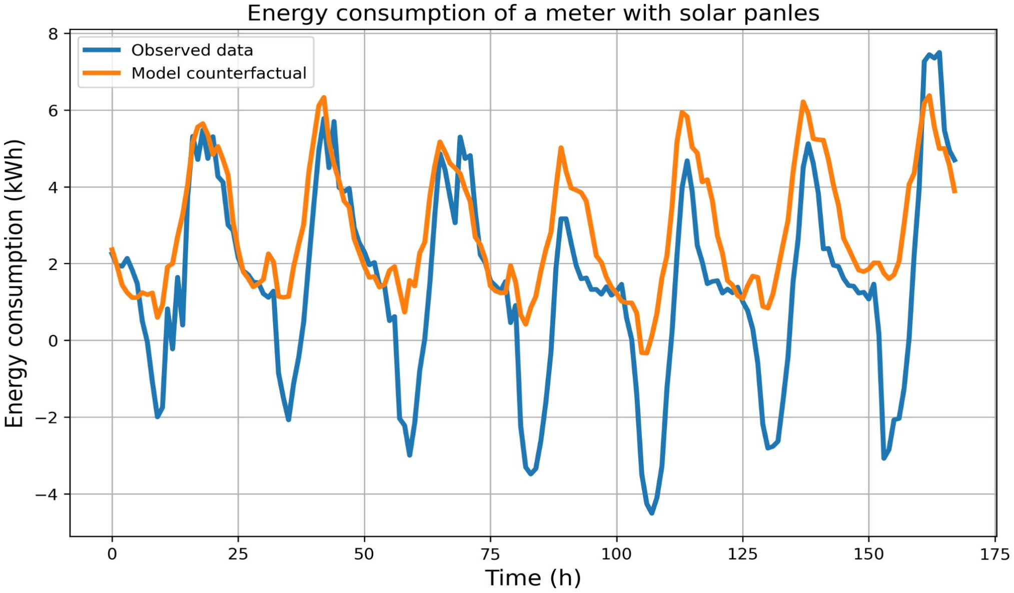
(c) Aggregation of 1000 users

Yet..These models are still unaware of *critical* variables

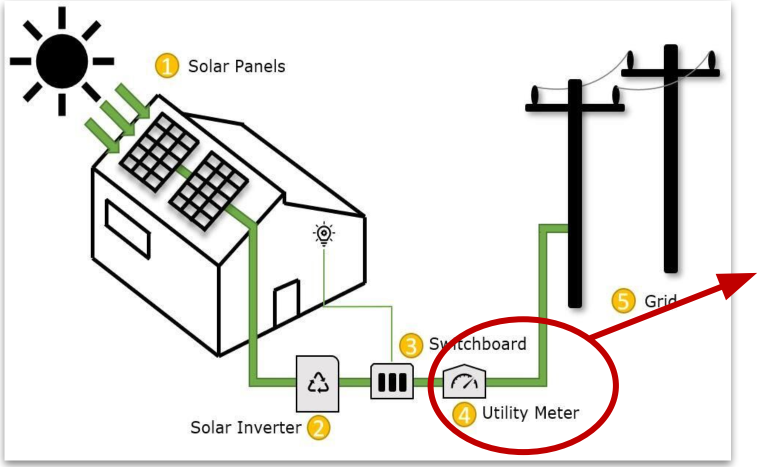
Two main solutions:

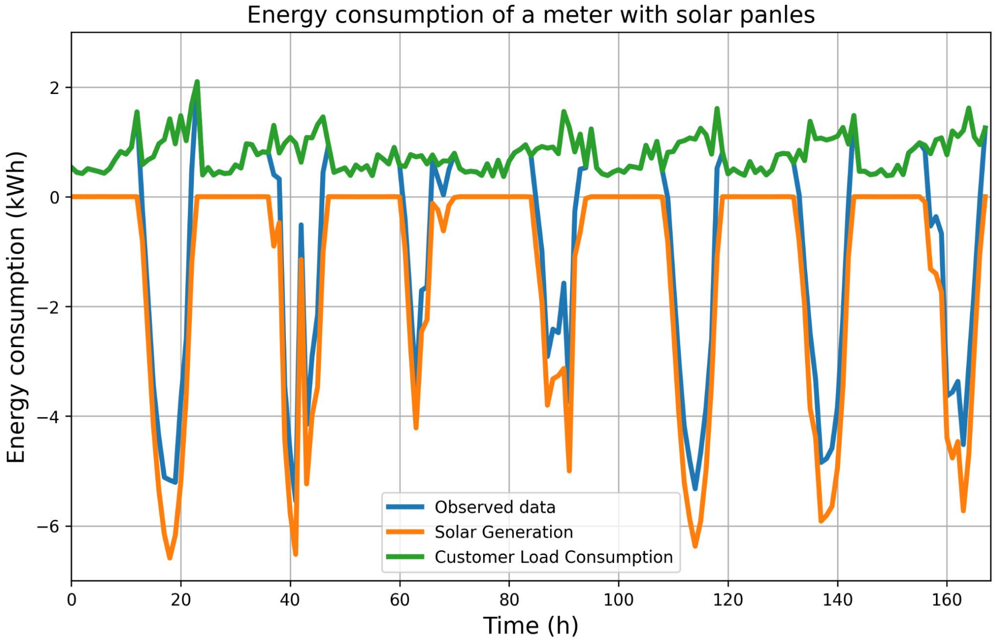
1. Use solar data for more accurate AMI prediction

2. Disaggregate solar generation and use for actual load



What do we mean by solar modeling?





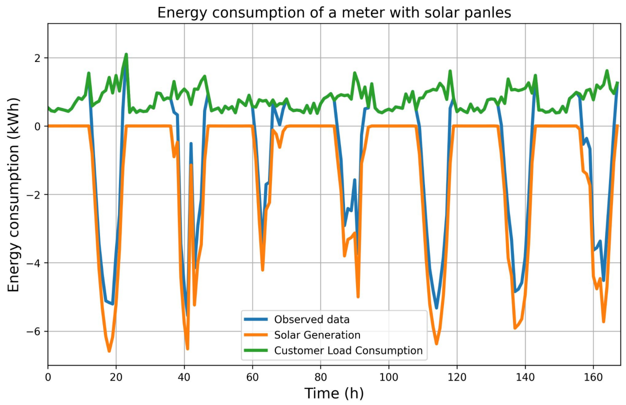
AMI = Load - Solar

- To do that we need to use solar/weather data as proxy

Solar disaggregation literature review

Different point of views: [13-19]

- Deterministic or probabilistic
- Optimization or machine learning
- Using other smart meters data as proxy
  - Smart meters without solar PV
  - Smart meters with solar PV and sub-meter data
- Using solar data as proxy or using physical model
- Individual smart meter or aggregation



Solar disaggregation literature review

Ref [13]:

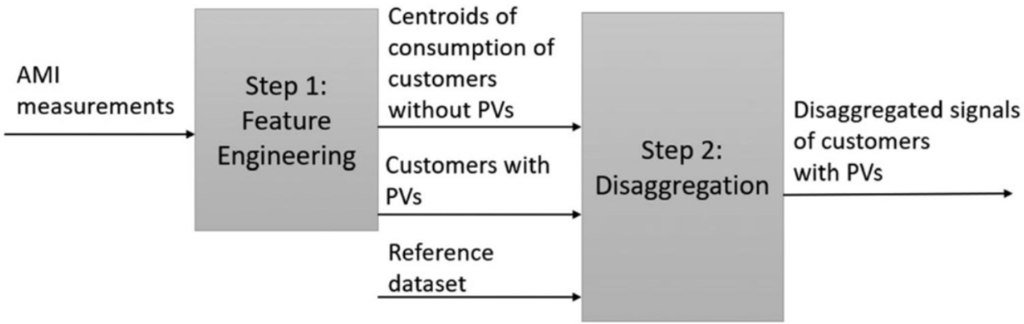
Deterministic +

Convex optimization +

smart meters without solar +

solar data +

Different level of aggregation



Solar disaggregation literature review

Ref [14]:

Probabilistic +

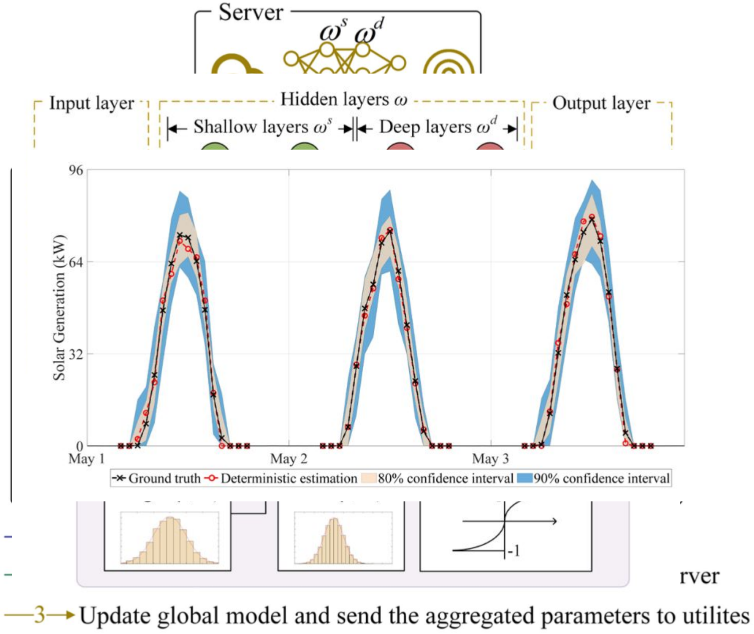
Deep learning +

smart meters without solar +

smart meters with solar and

submeter data +

Community level



Solar disaggregation literature review

Ref [15]:

Deterministic +

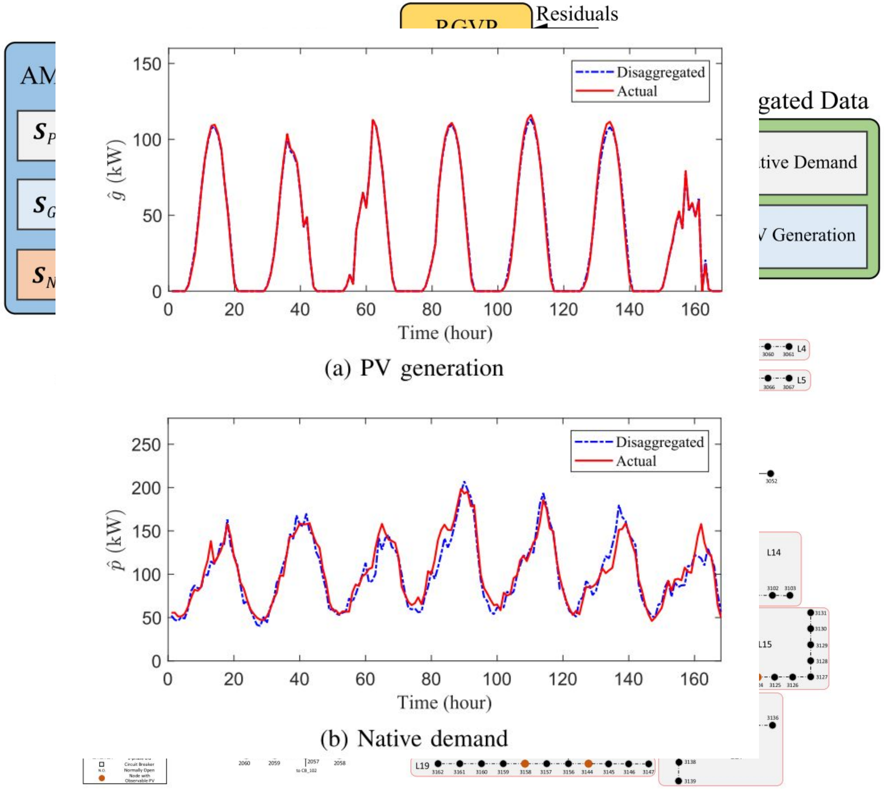
Optimization + Game theory

smart meters without solar +

smart meters with solar and

submeter data +

Feeder and lateral level



(a) PV generation

(b) Native demand

Next steps

- Focus on low bias model for AMI baseline prediction
- Models should be implementable at scale
- Explore and implement optimization and machine learning models
- Explore and implement probabilistic models
- Explore and implement solar weather data
- Combine solar disaggregation with AMI modeling
- Focus on individual level solar disaggregation
- Explore and implement solar PV physical model

References

1. Granderson, Jessica, and Samuel Fernandes. "The state of advanced measurement and verification technology and industry application." The Electricity Journal 30.8 (2017): 8-16.
2. Severinsen, Alexander, and Øystein Myrland. "Statistical learning to estimate energy savings from retrofitting in the Norwegian food retail market." *Renewable and Sustainable Energy Reviews* 167 (2022): 112691.
3. Roth, Jonathan, et al. "Uncertainty matters: Bayesian probabilistic forecasting for residential smart meter prediction, segmentation, and behavioral measurement and verification." *Energies* 14.5 (2021): 1481.
4. Mathieu, Johanna L., et al. "Quantifying changes in building electricity use, with application to demand response." *IEEE Transactions on Smart Grid* 2.3 (2011): 507-518.
5. Díaz, Julián Arco, et al. "A daily baseline model based on transfer functions for the verification of energy saving. A case study of the administration room at the Palacio de la Madraza, Granada." *Applied Energy* 224 (2018): 538-549.
6. Brown, Matthew, Chris Barrington-Leigh, and Zosia Brown. "Kernel regression for real-time building energy analysis." *Journal of Building Performance Simulation* 5.4 (2012): 263-276.
7. Grillone, Benedetto, et al. "A review of deterministic and data-driven methods to quantify energy efficiency savings and to predict retrofitting scenarios in buildings." *Renewable and Sustainable Energy Reviews* 131 (2020): 110027.

References

8. Jazaeri, Javad, et al. "Baseline methodologies for small scale residential demand response." *2016 IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia)*. IEEE, 2016.
9. Oyedokun, James, et al. "Customer baseline load estimation for incentive-based demand response using long short-term memory recurrent neural network." *2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*. IEEE, 2019.
10. Yalcintas, Melek. "Energy-savings predictions for building-equipment retrofits." *Energy and Buildings* 40.12 (2008): 2111-2120.
11. Weng, Yang, and Ram Rajagopal. "Probabilistic baseline estimation via gaussian process." *2015 IEEE Power & Energy Society General Meeting*. IEEE, 2015.
12. Tehrani, Nima H., Usman T. Khan, and Curran Crawford. "Baseline load forecasting using a Bayesian approach." *2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)*. IEEE, 2016.
13. Cheung, Chung Ming, et al. "Behind-the-Meter Solar Generation Disaggregation at Varying Aggregation Levels Using Consumer Mixture Models." *IEEE Transactions on Sustainable Computing* 8.1 (2022): 43-55.
14. Lin, Jun, Jin Ma, and Jianguo Zhu. "A privacy-preserving federated learning method for probabilistic community-level behind-the-meter solar generation disaggregation." *IEEE Transactions on Smart Grid* 13.1 (2021): 268-279.
15. Bu, Fankun, et al. "A data-driven game-theoretic approach for behind-the-meter PV generation disaggregation." *IEEE Transactions on Power Systems* 35.4 (2020): 3133-3144.

References

16. Saffari, Mohsen, et al. "Behind-the-Meter Load and PV Disaggregation via Deep Spatiotemporal Graph Generative Sparse Coding With Capsule Network." *IEEE Transactions on Neural Networks and Learning Systems* (2023).
17. Chen, Xinlei, Moosa Moghimi Haji, and Omid Ardakanian. "A data-efficient approach to behind-the-meter solar generation disaggregation." *arXiv preprint arXiv:2105.08122* (2021).
18. Bu, Fankun, et al. "Disaggregating customer-level behind-the-meter PV generation using smart meter data and solar exemplars." *IEEE Transactions on Power Systems* 36.6 (2021): 5417-5427.
19. Brown, Joe, Alessandro Abate, and Alex Rogers. "Disaggregation of household solar energy generation using censored smart meter data." *Energy and Buildings* 231 (2021): 110617.