Application of Advanced Data Analytics in Distribution Grid Operation and Planning

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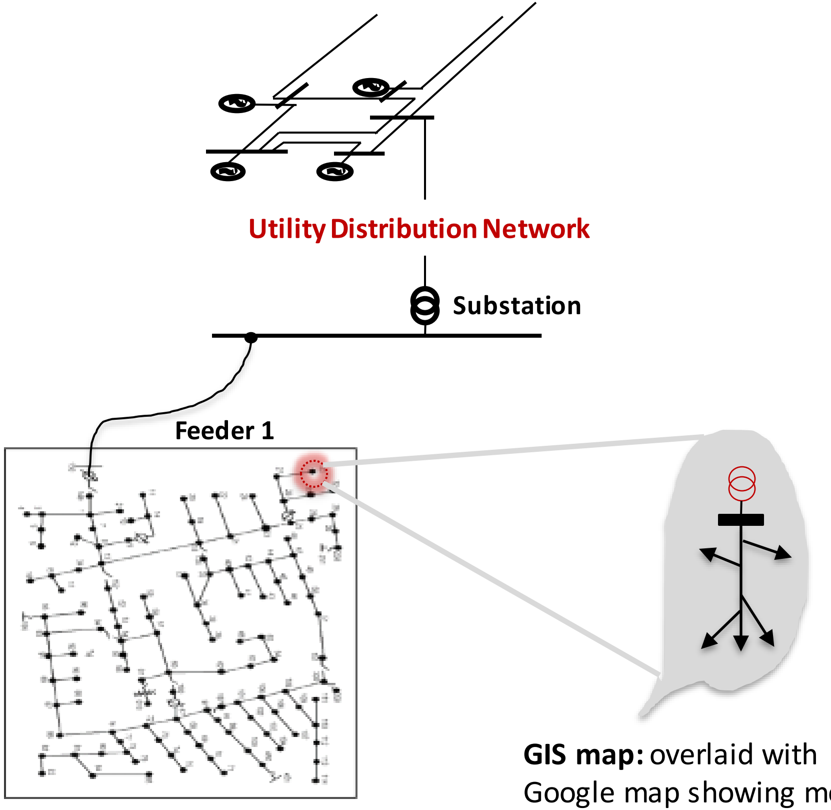
Outline

- Advanced Data Analytics
  - Sponsored by **ElectriCities** and collaborated with **New River**, **Wilson Power, Fayetteville PWC**
  - Characteristics of utility data sets

- Use Cases
  - Use Case 1: Mislabeled meter phase
  - Use Case 2: Mislabeled transformer-Meter pairing
  - Use Case 3: Load disaggregation
  - Use Case 4: Impact of PV and EV integration
  - Use Case 5: Baseline estimation

Utility Data Used in Our Study

- Smart Meter Data
  - Real and reactive power or power factors
  - Voltage
- SCADA Data
  - Feeder level data (Voltage, Current, Real and Reactive Power)
  - Demand Response and CVR events
- Customer Information System Data
  - Network connections (i.e., meter-transformer-substation connections)
  - Load types

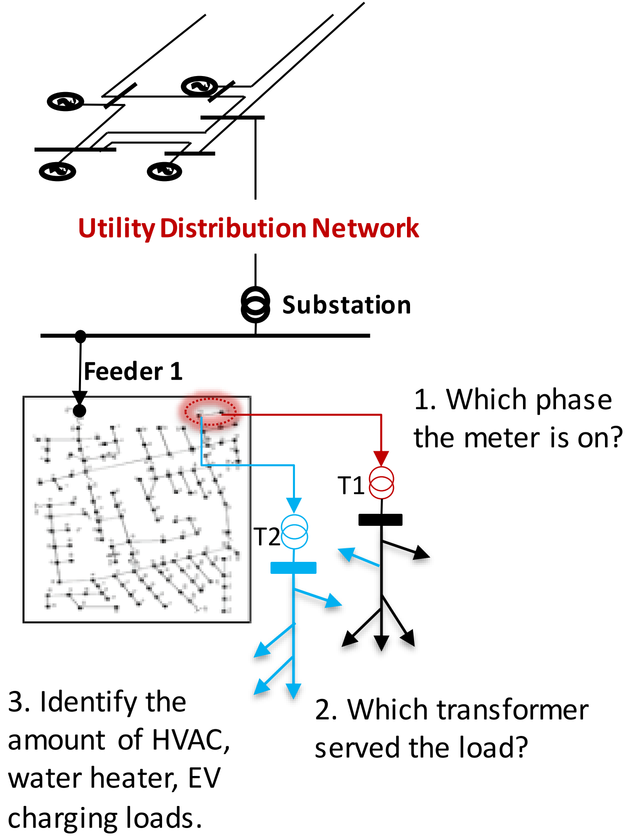


Feeder models: showing only distribution transformer locations

GIS map: overlaid with Google map showing meter to transformer connections

Main Data Analytic Applications

- **Use Case 1: Mislabeled meter phase**
- **Use Case 2: Mislabeled transformer-Meter pairing**
- Causes
  - Erroneous entries
  - Feeder reconfiguration
  - Transformers and meters can be moved to another location
  - Labor intensive to maintain the information up-to-date
- **Use Case 3: Load disaggregation**
- **Use Case 4: EV and PV Integration Analysis**
- **Use Case 4: Baseline estimation**
- Needs
  - Identify high-quality demand response resources
  - Understand DER impacts on load curves
  - Quantify load reductions by CVR and DR



Use Case 1: Meter Phase Identification

Study conducted by: Hanpyo Lee (hlee39@ncsu.edu)

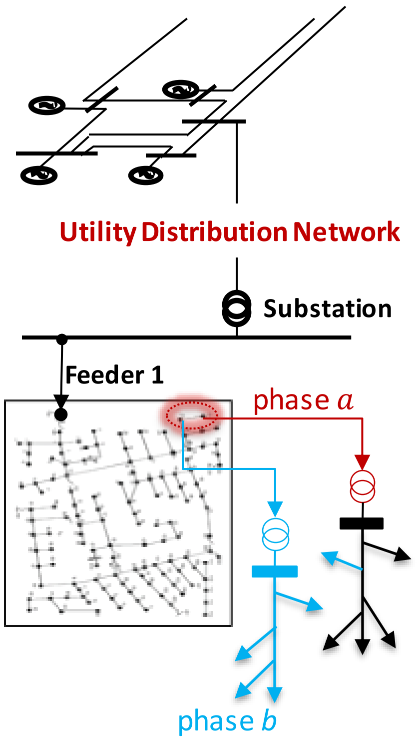
Industrial Advisors:

ElectriCities: PJ Rehm

New River Light and Power: Matthew Makdad, Edmond Miller

Problem Description

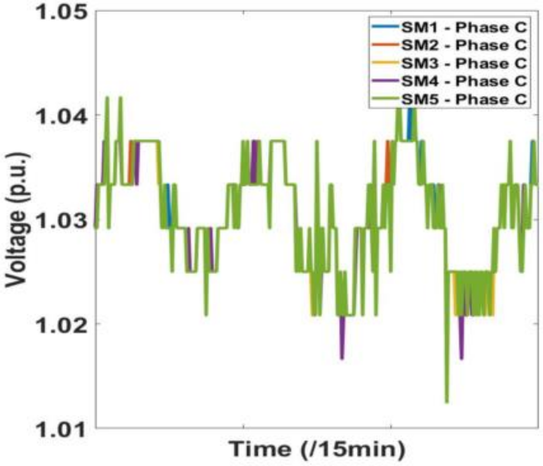
- Needs
  - Input errors are inevitable
  - Approximately 6% mislabeled meters
  - Manual checking is labor intensive
  - Need to automate the process
- Approach: basically a classification problem
  - Group meters together by the similarity of their voltage profiles
- Two Scenarios
  - Known meter-phase-label:
    - Label is right or wrong?
  - Unknown meter-phase-label
    - Which phase is the meter connected to?



Why comparing voltage profiles?

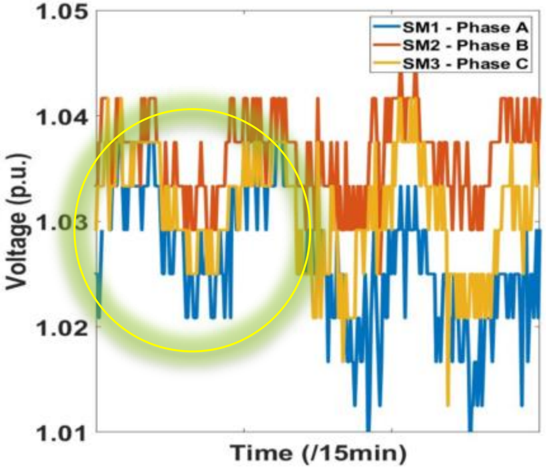
- Meters on the same phase and close to each other tend to see similar voltage profiles. The similarity can be estimated by **correlations**.

For five meters supplied by the same transformer on phase c



Voltage profiles are similar as they go up and down almost in sync with each other

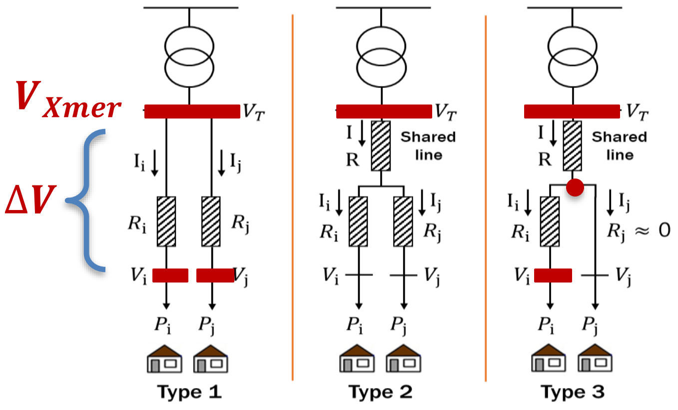
For three meters supplied by different transformers and on different phases

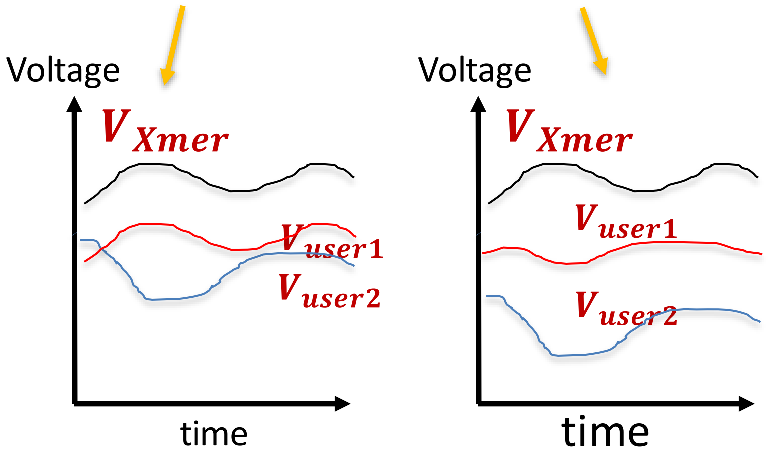


Voltage profiles differ from each other and out of sync

Correlation Deterioration Phenomenon

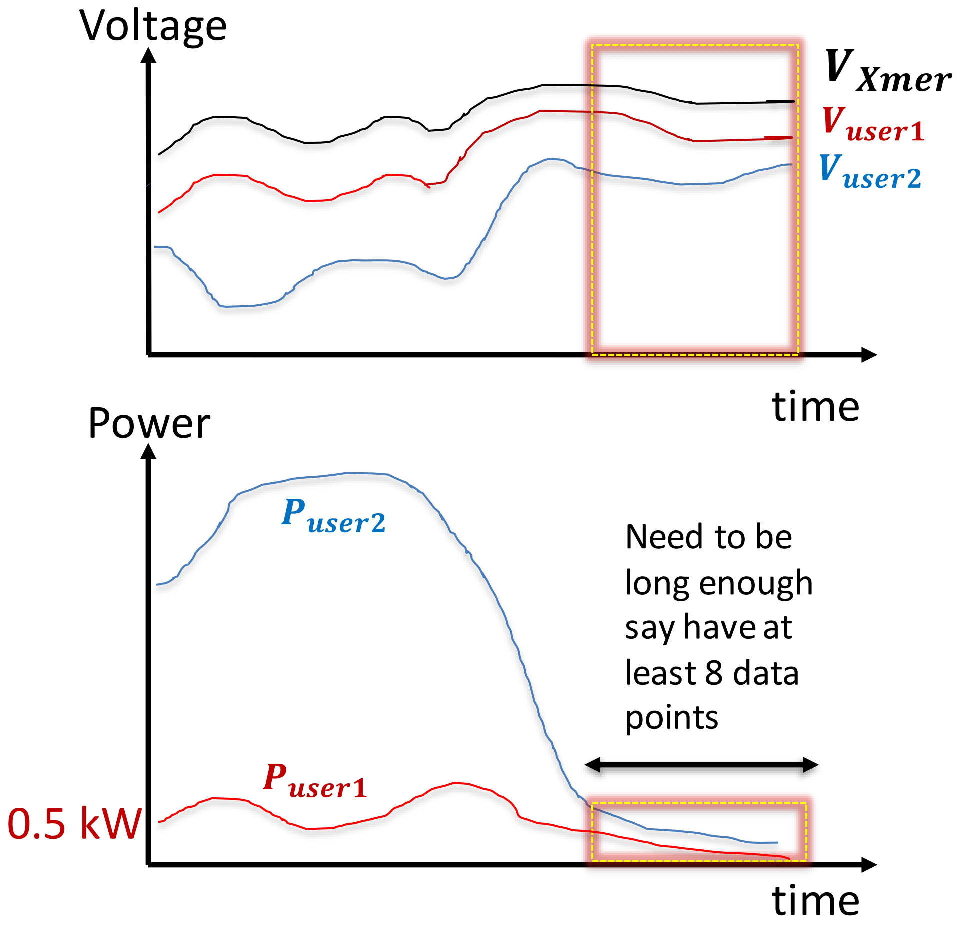
- Impact of circuit topology
  - Meters **in series** tend to have stronger correlation
  - Meters **in parallel** tend to have weaker correlations
- Causes
  - In a parallel circuit, voltage change at the end can change in differently ways
  - Especially when one user has high consumption and the other has low consumption

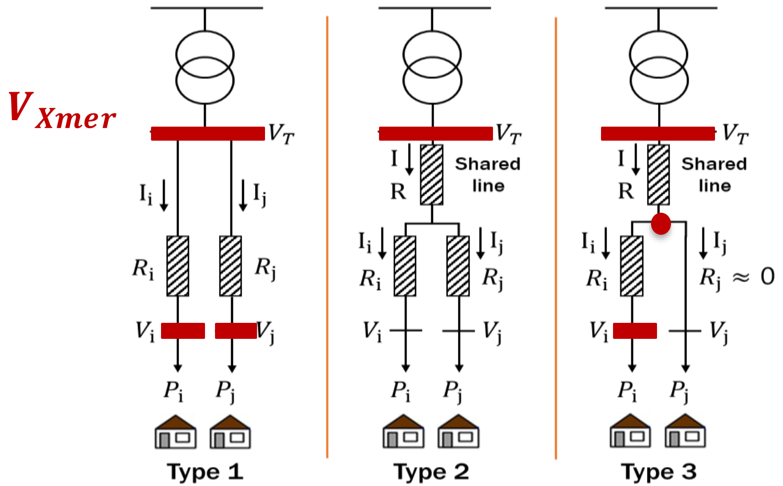




Han Pyo Lee, Mingzhi Zhang, Mesut Baran, PJ Rehm, Edmond Miller, Matthew Makdad, and Ning Lu, "A Novel Data Segmentation Method for Data-driven Phase Identification," 22PESGM0071, *Proc. of 2022 PES General Meeting*. Available online at: http://arxiv.org/abs/2111.10500.

Select Low Consumption Periods

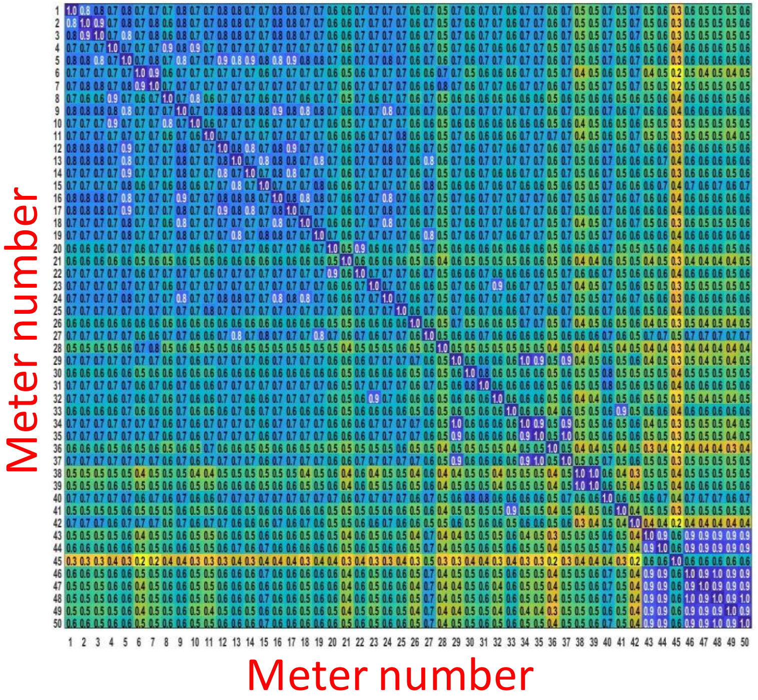




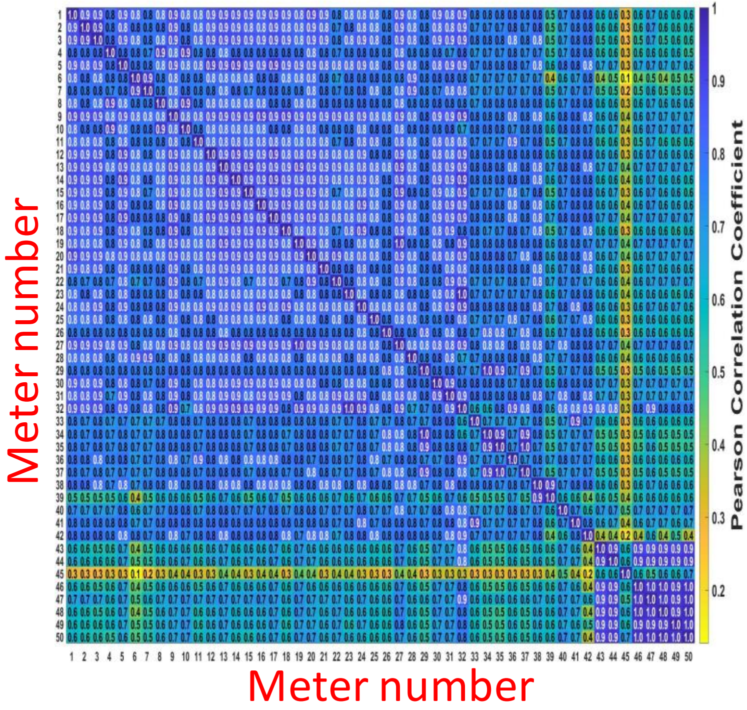
When the consumption is low, say P<0.5 kW, meter side voltages are very close to the transformer voltage as the secondary circuit voltage drop is negligible.

Performance Improvements

Using all voltage data



Use voltage segments from low-power periods



The figure shows the correlation of meters with each other

The right correlation map shows much clear boundary between meter groups

Input Data and Parameter Settings

- Testing on 1 synthetic and 13 real feeders
- Real data: 3 groups (small, medium, and large)
- Parameters: P_{th}, T_{dur}, and number of clusters

Data type	Group	Feeder No.	Optimal parameter values		
			P_{th} [kw] [0.5 2.0]	T_{dur} [h] [1.0 3.0]	$3 \times n$ [3 36]
Synthetic			[0.8 1.2]	1.0, 1.5	12
Real	Small	1, 3, 11	[0.8 1.2]	1.0, 1.5	6
	Medium	8, 10, 12, 13	[1.3 1.7]	2.5, 3.0	18
	Large	2, 4, 5, 6, 7, 9	[1.3 1.7]	1.0, 1.5	36

Han Pyo Lee, Mingzhi Zhang, Mesut Baran, PJ Rehm, Edmond Miller, Matthew Makdad, and Ning Lu, "A Novel Data Segmentation Method for Data-driven Phase Identification," 22PESGM0071, *Proc. of 2022 PES General Meeting*. Available online at: http://arxiv.org/abs/2111.10500.

Results of Known Meter-Phase-Labels

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Feeder No.	Phases in the utility records				Phases predicted by the algorithm				Detected as correct (N_C1)	Detected as incorrect (N_RT-N_C1)	Validated 1 (N_V1)	Accuracy1 ((N_C1+N_V1)/N_RT)	Detected as correct (N_C2)	Detected as incorrect (N_RT-N_C2)	Validated 2 (N_V2)	Accuracy2 ((N_C2+N_V2)/N_RT)
	A	B	C	A+B+C (N_RT)	A	B	C	A+B+C (N_PT)								
Proposed																
Synthetic	436	293	371	1,100	436	293	371	1,100	1,100	-	-	100.0%	1,100	-	-	100.0%
1	7	24	2	33	5	25	3	33	31	2	-	93.9%	31	2	-	93.9%
2	146	159	145	450	139	152	159	450	415	35	35	100.0%	447	3	-	99.3%
3	11	26	36	73	11	26	36	73	73	-	-	100.0%	73	-	-	100.0%
4	147	91	178	416	144	94	178	416	399	17	10	98.3%	411	5	-	98.8%
5	192	214	231	637	210	218	209	637	605	32	24	98.7%	629	8	-	98.7%
6	344	249	306	899	363	262	274	899	803	96	80	98.2%	898	1	-	99.9%
7	113	102	109	324	115	104	105	324	313	11	5	98.1%	318	6	-	98.1%
8	51	51	71	173	49	53	71	173	169	4	2	98.8%	171	2	-	98.8%
9	62	193	301	556	57	194	305	556	505	51	35	97.1%	543	13		97.7%
10	22	42	67	131	22	42	67	131	131	-	-	100.0%	131	-	-	100.0%
11	3	10	11	24	3	10	11	24	24	-	-	100.0%	24	-	-	100.0%
12	39	37	32	108	39	37	32	108	108	-	-	100.0%	108	-	-	100.0%
13	55	56	26	137	55	56	26	137	137	-	-	100.0%	137	-	-	100.0%
Total	1,192	1,254	1,515	3,961	1,212	1,273	1,476	3,961	3,713	248	191	98.6%	3,921	40	-	99.0%
SC [3]																
Synthetic	436	293	371	1,100	424	276	400	1,100	1,063	37	-	96.6%	1,063	37	-	96.6%
1	7	24	2	33	9	24	-	33	29	4	1	90.9%	30	3	-	90.9%
2	146	159	145	450	158	155	137	450	435	15	8	98.4%	441	9	-	98.0%
3	11	26	36	73	11	24	38	73	70	3	-	95.9%	70	3	-	95.9%
4	147	91	178	416	164	80	172	416	397	19	12	98.3%	408	8	-	98.1%
5	192	214	231	637	204	221	212	637	606	31	16	97.6%	619	18	-	97.2%
6	344	249	306	899	347	250	302	899	831	68	60	99.1%	893	6	1	99.4%
7	113	102	109	324	115	103	106	324	312	12	5	97.8%	318	6	-	98.1%
8	51	51	71	173	49	50	74	173	167	6	-	96.5%	167	6	-	96.5%
9	62	193	301	556	50	183	323	556	527	29	14	97.3%	532	24	2	96.0%
10	22	42	67	131	21	42	68	131	130	1	-	99.2%	130	1	-	99.2%
11	3	10	11	24	4	10	10	24	23	1	-	95.8%	23	1	-	95.8%
12	39	37	32	108	39	37	32	108	108	-	-	100.0%	108	-	-	100.0%
13	55	56	26	137	55	56	26	137	135	2	-	98.5%	135	2	-	98.5%
Total	1,192	1,254	1,515	3,961	1,226	1,235	1,500	3,961	3,770	191	116	98.1%	3,874	87	3	97.9%

[3] Blakely, Logan, Matthew J. Reno, and Wu-chi Feng. "Spectral clustering for customer phase identification using AMI voltage timeseries." *2019 IEEE Power and Energy Conference at Illinois (PECI)*. IEEE, 2019.

Results of Unknown Meter-Phase-Labels

Feeder No.	Phases in the utility records				Phases predicted by the algorithm				Detected as correct (N_C1)	Detected as incorrect (N_RT-N_C1)	Validated 1 (N_V1)	Accuracy1 ((N_C1+N_V1)/N_RT)	Detected as correct (N_C2)	Detected as incorrect (N_RT-N_C2)	Validated 2 (N_V2)	Accuracy2 ((N_C2+N_V2)/N_RT)
	A	B	C	A+B+C (N_RT)	A	B	C	A+B+C (N_PT)								
Proposed																
Synthetic	436	293	371	1,100	436	293	371	1,100	1,100	-	-	100.0%	1,100	-	-	100.0%
1	7	24	2	33	7	25	1	33	31	2	-	93.9%	31	2	-	93.9%
2	146	159	145	450	133	153	164	450	412	38	37	99.8%	444	6	4	99.6%
3	11	26	36	73	11	26	36	73	73	-	-	100.0%	73	-	-	100.0%
4	147	91	178	416	152	90	174	416	407	9	6	99.3%	402	14	4	97.6%
5	192	214	231	637	213	218	206	637	606	31	25	99.1%	630	7	-	98.9%
6	344	249	306	899	330	253	316	899	796	103	103	100.0%	898	1	-	99.9%
7	113	102	109	324	114	104	106	324	314	10	4	98.1%	315	9	1	97.5%
8	51	51	71	173	49	54	70	173	170	3	-	98.3%	170	3	-	98.3%
9	62	193	301	556	36	174	346	556	505	51	40	98.0%	548	8	-	98.6%
10	22	42	67	131	22	42	67	131	131	-	-	100.0%	131	-	-	100.0%
11	3	10	11	24	3	10	11	24	24	-	-	100.0%	24	-	-	100.0%
12	39	37	32	108	39	37	32	108	108	-	-	100.0%	108	-	-	100.0%
13	55	56	26	137	55	56	26	137	137	-	-	100.0%	137	-	-	100.0%
Total	1,192	1,254	1,515	3,961	1,164	1,242	1,555	3,961	3,714	247	215	99.2%	3,911	50	9	99.0%
CAM-EC [4]																
Synthetic	436	293	371	1,100	406	276	418	1,100	1,053	47	0	95.7%	1,053	47	-	95.7%
1	7	24	2	33	6	24	3	33	27	6	1	84.8%	28	5	-	84.8%
2	146	159	145	450	155	159	136	450	435	15	8	98.4%	441	9	-	98.0%
3	11	26	36	73	18	20	35	73	65	8	-	89.0%	65	8	-	89.0%
4	147	91	178	416	165	77	174	416	394	22	12	97.6%	400	16	-	96.2%
5	192	214	231	637	205	218	214	637	606	31	16	97.6%	619	18	-	97.2%
6	344	249	306	899	322	248	329	899	803	96	88	99.1%	895	4	-	99.6%
7	113	102	109	324	115	104	105	324	313	11	5	98.1%	318	6	-	98.1%
8	51	51	71	173	49	46	78	173	165	8	-	95.4%	165	8	-	95.4%
9	62	193	301	556	58	182	316	556	526	30	16	97.5%	521	35	-	93.7%
10	22	42	67	131	21	42	68	131	130	1	-	99.2%	130	1	-	99.2%
11	3	10	11	24	4	10	10	24	23	1	-	95.8%	23	1	-	95.8%
12	39	37	32	108	37	39	32	108	106	2	-	98.1%	106	2	-	98.1%
13	55	56	26	137	55	56	26	137	135	2	-	98.5%	135	2	-	98.5%
Total	1,192	1,254	1,515	3,961	1,210	1,225	1,526	3,961	3,728	233	146	97.8%	3,846	115	-	97.1%

[4] Blakely, Logan, and Matthew J. Reno. "Phase identification using co-association matrix ensemble clustering." IET Smart Grid 3.4 (2020):

Summary

- Data segmentation methods can significantly improve the accuracy of correlation-based identification algorithms
- For meter phase identification algorithms, the proposed algorithm outperforms the state-of-art methods in both accuracy and robustness
  - Known meter-phase-label: 99.0%
  - Unknown meter-phase-label: 99.0%
- Advantages of using machine-learning based approach
  - Automated the previously manual process
  - Make it a cheaper approach with higher efficiency and accuracy
  - Can be run periodically to identify changes
  - This will stream-line the maintenance of an accurate customer information system

Scan to access paper

Use Case 2: Meter –Transformer Pairing Identification

Study conducted by: Hanpyo Lee (hlee39@ncsu.edu)

Industrial Advisors:

ElectriCities: PJ Rehm

New River Light and Power: Matthew Makdad, Edmond Miller

Use Case 3: Load Disaggregation

Studies conducted by PhD students:

Kai Ye

Hyeonjin Kim

Industrial Advisors:

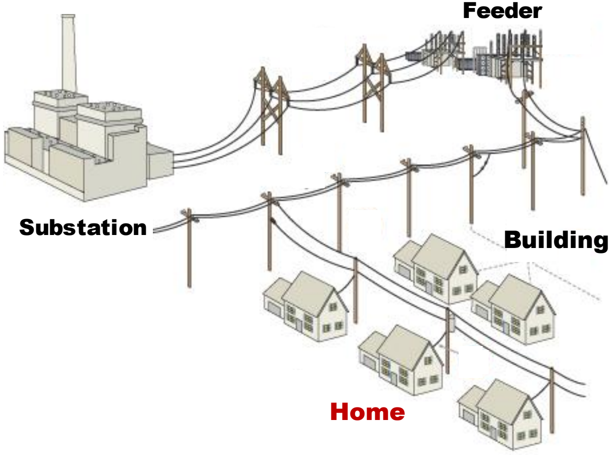
ElectriCities: PJ Rehm

New River Light and Power: Matthew Makdad, Edmond Miller

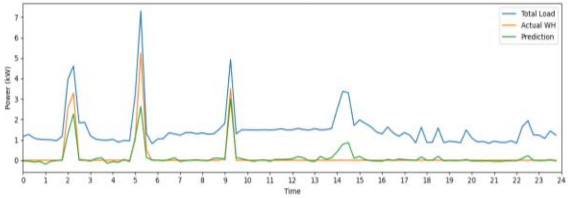
Fayetteville PWC: Timothy Stankiewicz

Motivation

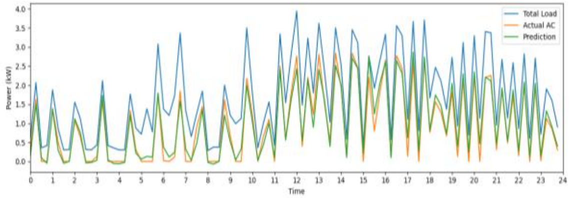
- Automated processing of smart meter data
- Identify behind-the-meter Distributed Energy Resources
- HVAC disaggregation
  - **DR** resource identification
  - Individual household → Different aggregation levels
  - Residential → Different user types



Water Heater



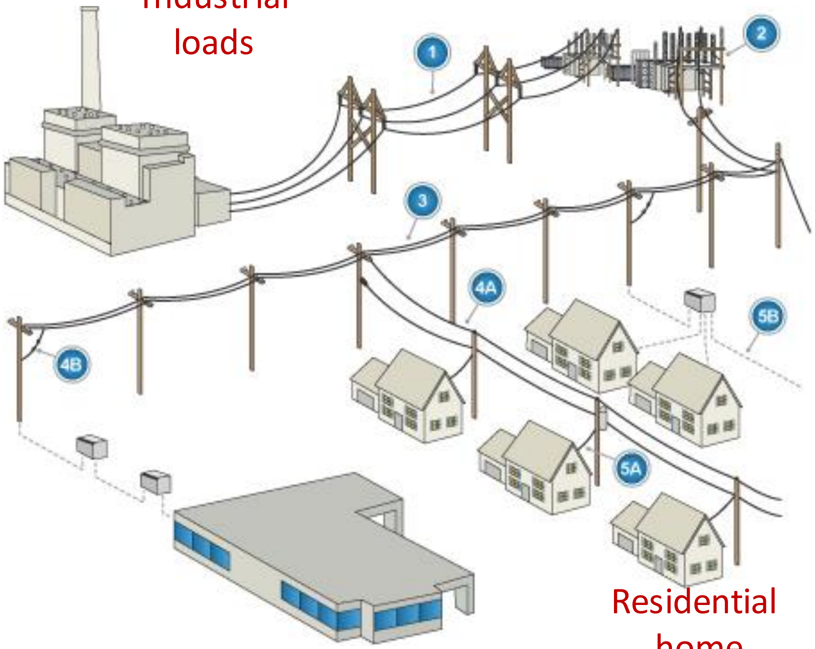
HVAC



K. Ye, H. Kim, Y. Hu, N. Lu, D. Wu, PJ Rehm, " A Modified Sequence-to-point HVAC Load Disaggregation Algorithm", 2023 IEEE PES General Meeting. Available online at: http://arxiv.org/abs/2212.04886

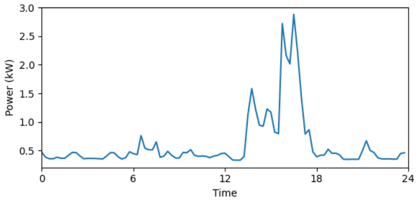
Motivation

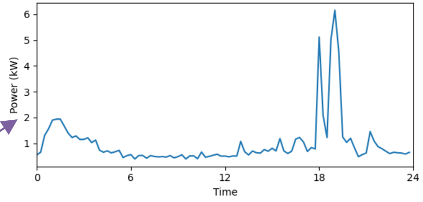
- Data sources:
  - smart meter data
  - Sub-meter data
  - Weather data
- Identify behind-the-meter resources
  - Water heater
  - HVAC
  - EV
  - PV
- Demand response quantification
  - Individual loads (residential, commercial, industrial)
  - Transformer and feeder loads

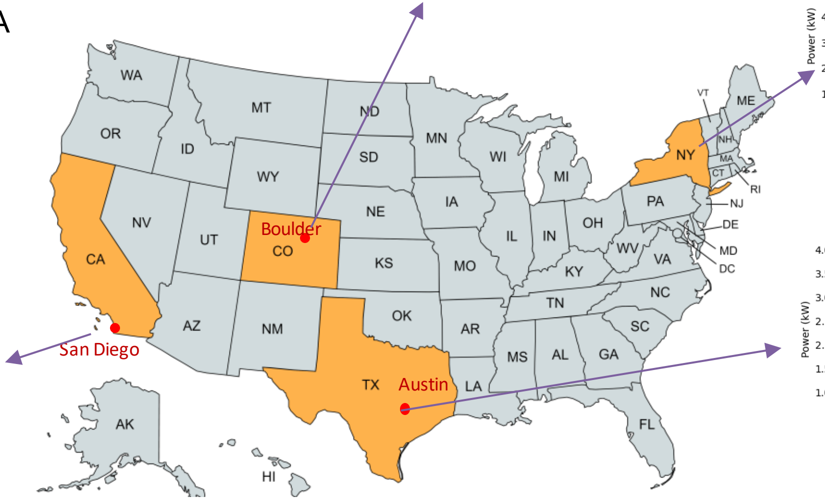


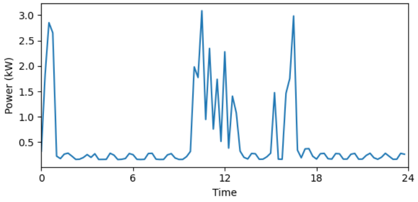
Data Set Overview

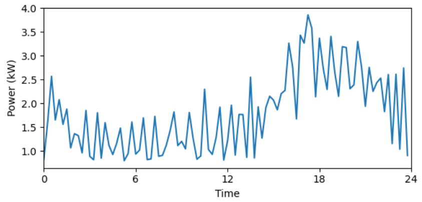
- Pecan Street Data: 1-min smart meter data of 1070 users with sub-metering
  - Down-sampled to 15-min
  - 90 days in summer of 2015
  - 230 customers
    - 200 in Austin, TX
    - 20 in Boulder, CO
    - 10 in San Diego, CA





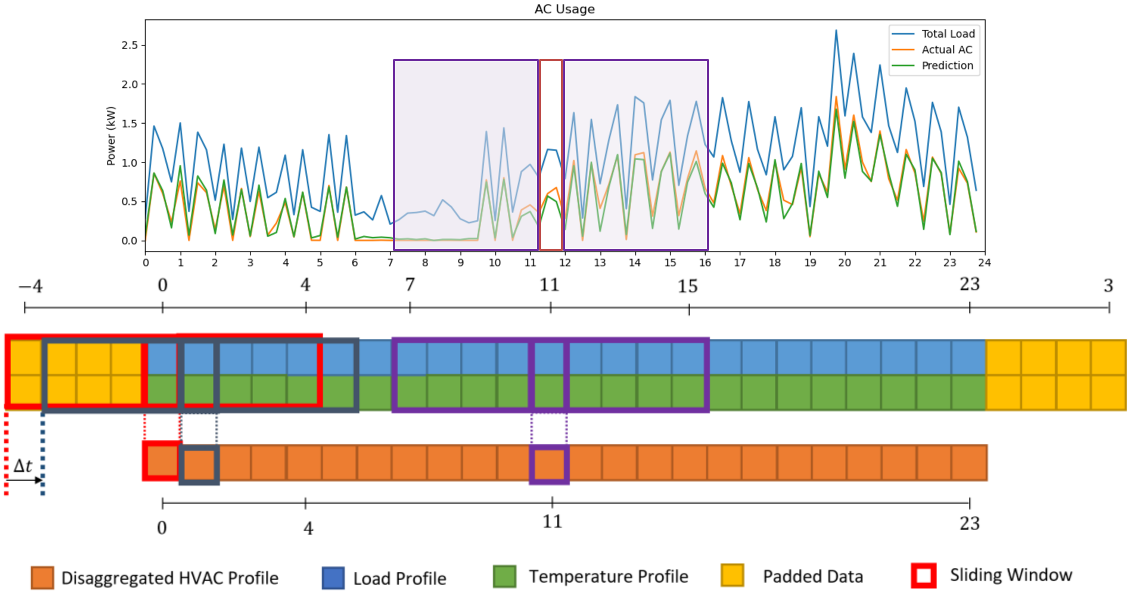






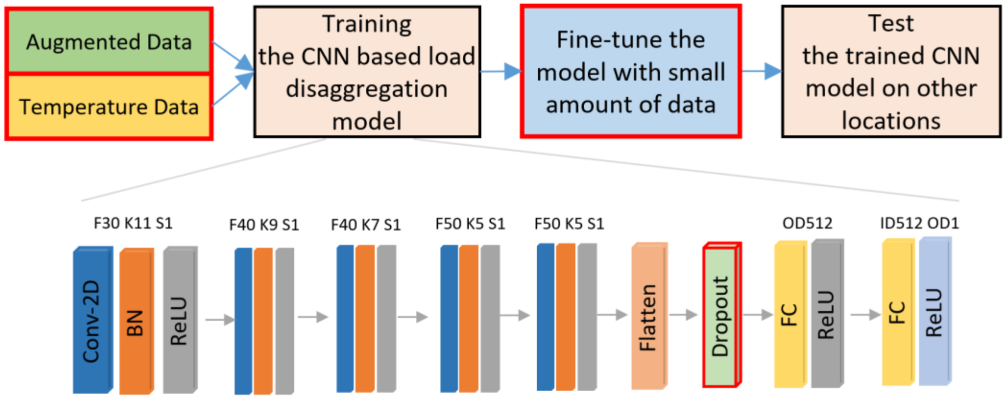
Method 1: Sequence-to-Point CNN

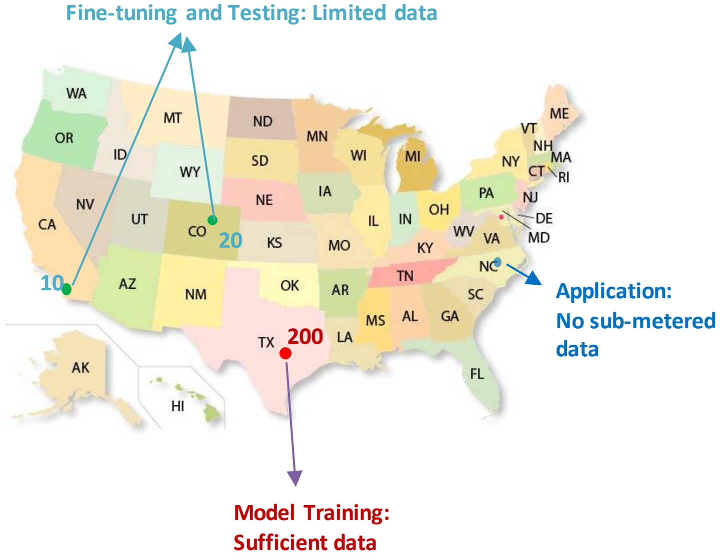
- CNN stands for Convolution Neural Network. It is a machine-learning based method.
- Input: **K** data points before and after time **t** from the power profile and the corresponding temperature profile
- Output: The HVAC load at time **t**



Algorithm Overview

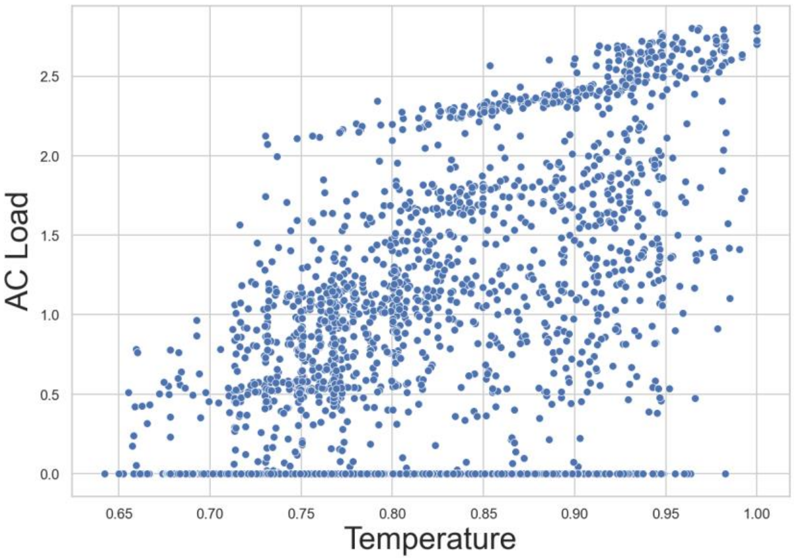
- Data augmentation
- Training and testing the model on one location
- Transfer learning (port the pre-trained model to other locations) with fine-tuning



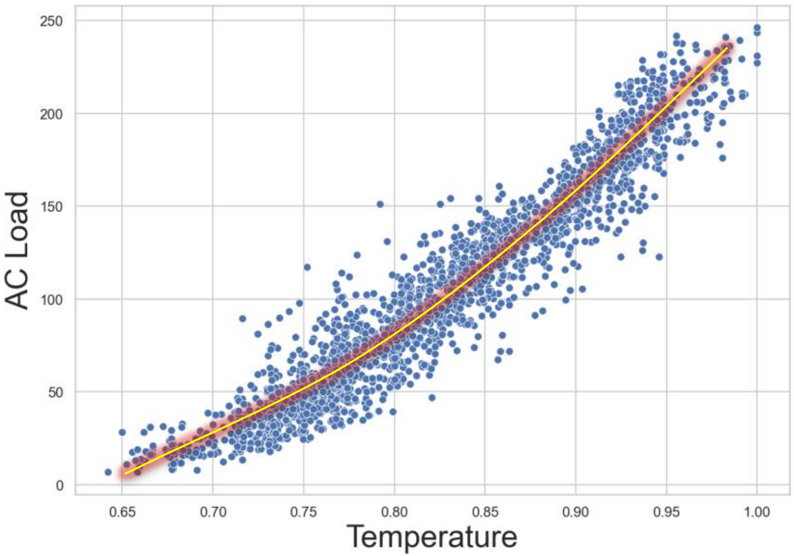


Method 2: Mutual Information Estimation

- One customer case



- 100 Aggregated customer case



- Relationship between outdoor temperature and HVAC load are clear in aggregated case
- HVAC load can be modeled with temperature parameterized by 1**) Rating (k), 2) Convexity (a)**

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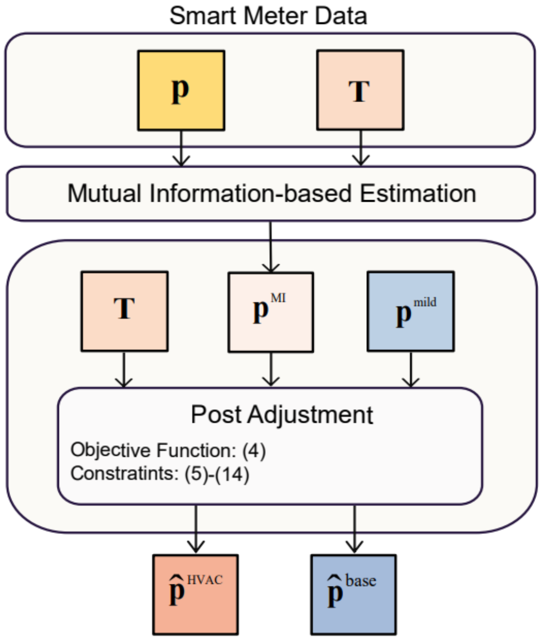
Algorithm Overview



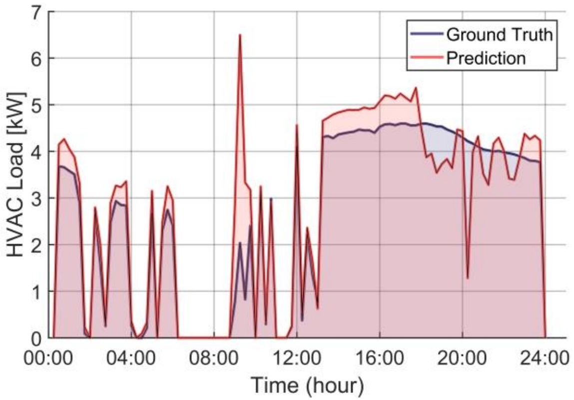
Input data: 15-min granularity of smart meter data (**target day**, **mild days, temperature**)

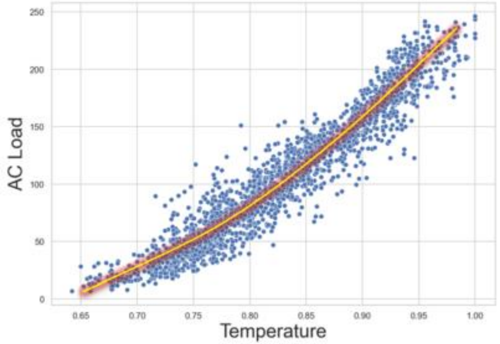
Step 1: Mutual information based estimation

Find the best linear form that maps temperature to AC usage

Step 2: Optimization-base post-adjustment

(Input: **Step 1 outputs**, **mild days load**)





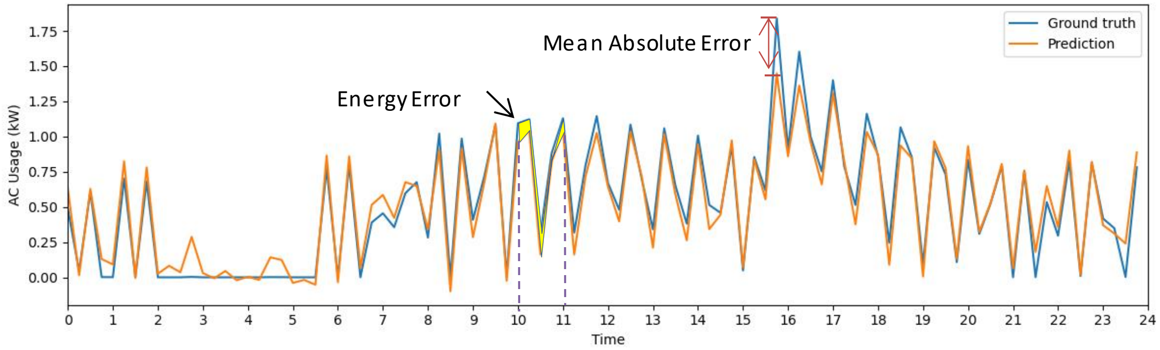
Performance Evaluation Metrics

- Performance evaluation:
  - nMAE (normalized Mean absolute error): Point-to-point difference measurement

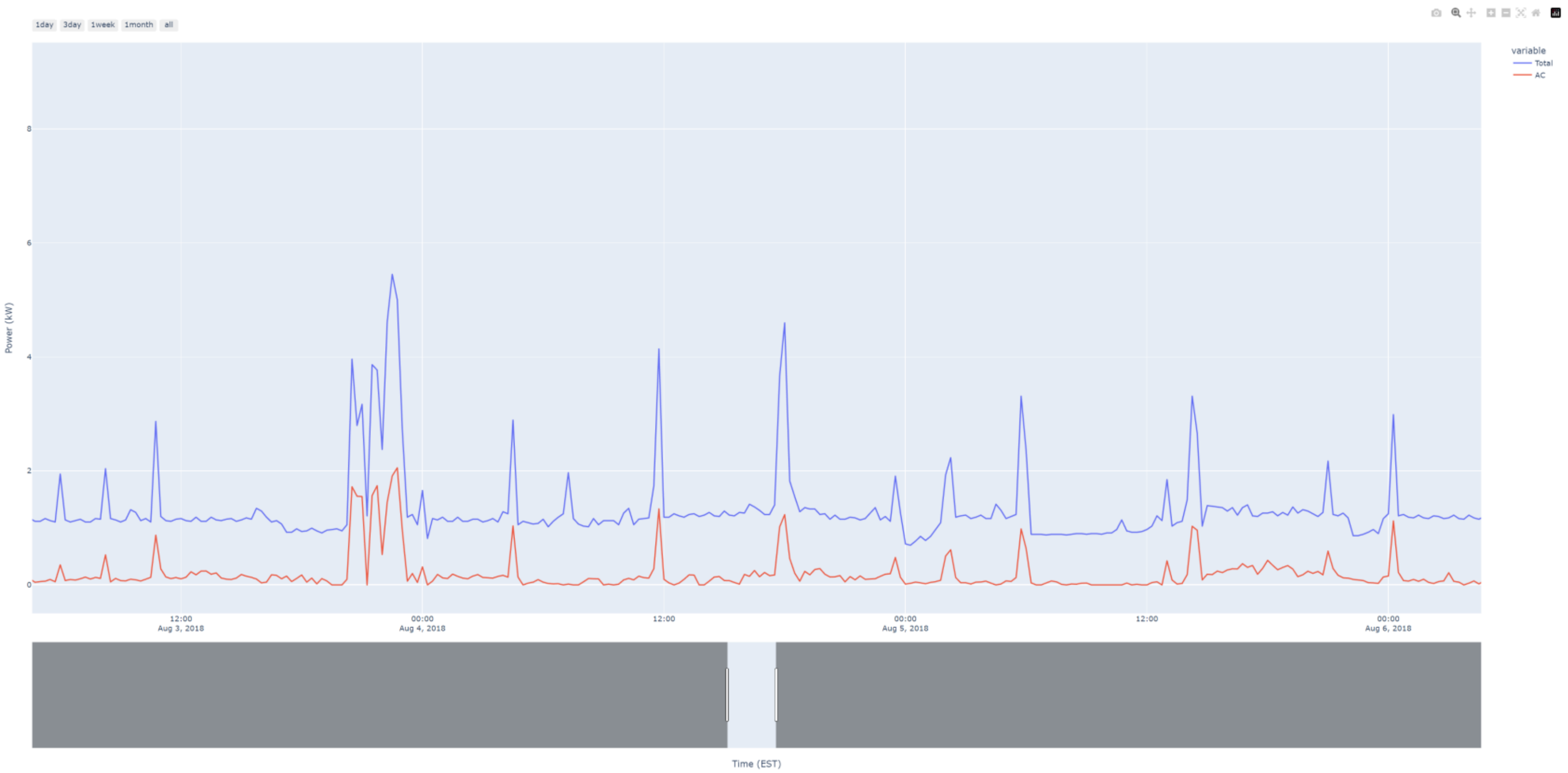
$$n\mathbf{MAE} = \frac{1}{N} \cdot \sum_{t=1}^{N} \frac{\left|\tilde{P}_t^{\mathrm{HVAC}} - P_t^{\mathrm{HVAC}}\right|}{P_t^{\mathrm{rated}}}$$

  - nEE (normalized Energy error): Energy amount difference measurement

$$n\mathbf{EE} = \frac{\left|\sum_{t=1}^{N_{\mathrm{hour}}} \tilde{P}_t^{\mathrm{HVAC}} - \sum_{t=1}^{N_{\mathrm{hour}}} P_t^{\mathrm{HVAC}}\right|}{\sum_{t=1}^{N_{\mathrm{hour}}} P_t^{\mathrm{rated}}}$$



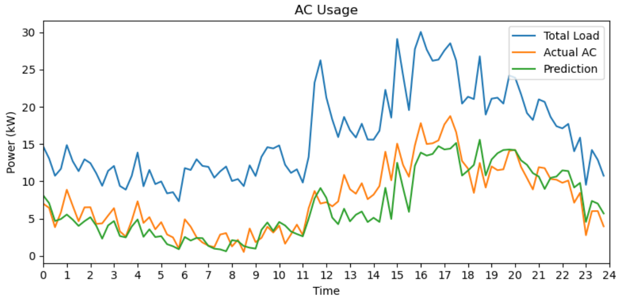
Simulation Results



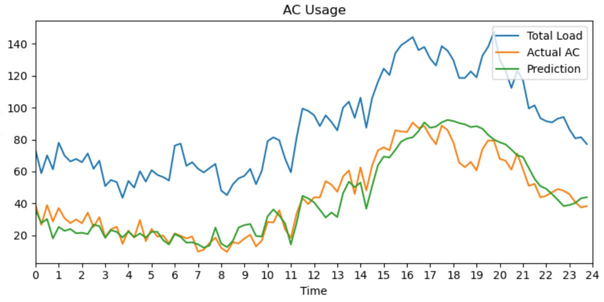
Simulation Results

- The algorithm has similar satisfactory results on different aggregation levels at all locations.

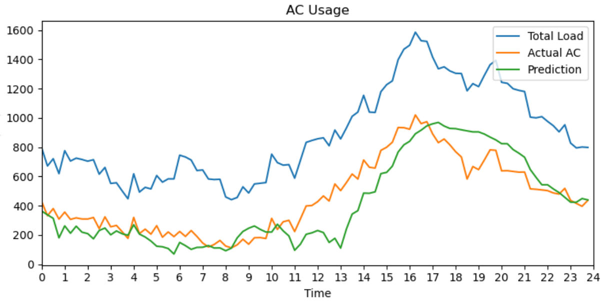
Aggregation level	1	10	50	500
nMAE (%)	7.17	8.47	8.15	8.02
nEE (%)	3.51	6.42	5.35	4.19
std(nMAE) (%)	2.85	1.16	0.39	0.11
std(nEE) (%)	1.86	1.86	0.81	0.23



10-user



50-user

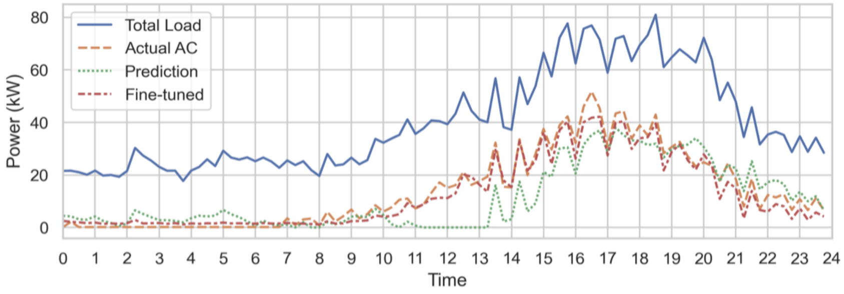


500-user

At Different Aggregation Level

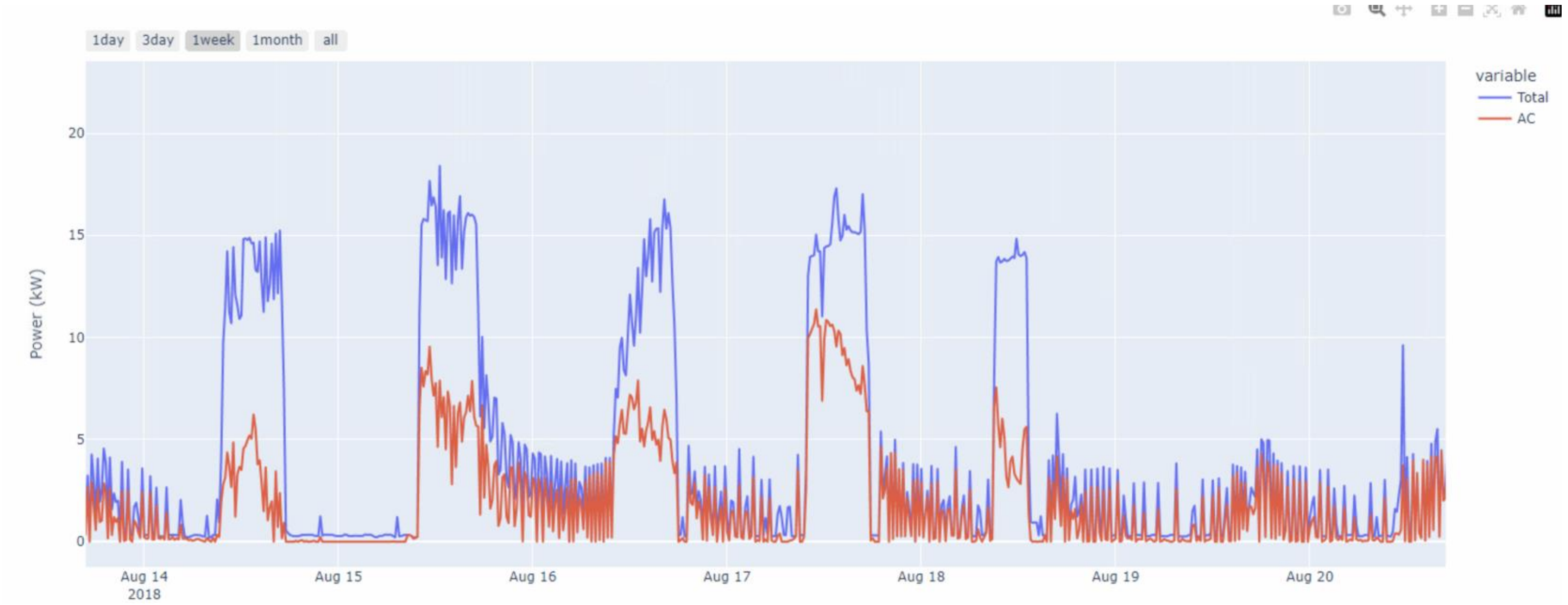
- Fine-tuning has been proved to be effective at different aggregation level..

Area	Metrics	No Fine-tuning		With Fine-tuning	
	Aggregation Level	10	50	10	50
CO	nMAE (%)	7.73	8.80	4.54	3.92
	nEE (%)	4.84	4.93	2.18	1.65
CA	nMAE (%)	4.12	3.77	3.53	3.10
	nEE (%)	2.19	2.11	1.83	1.75

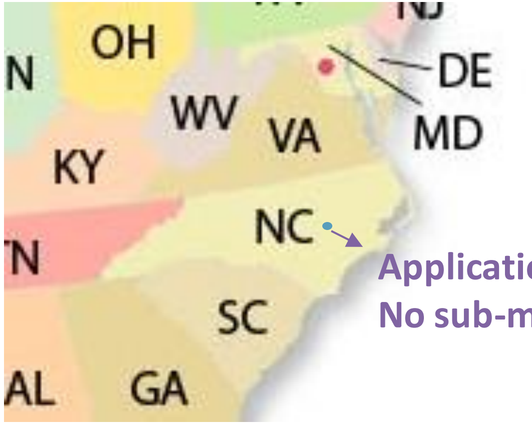


Simulation Results on Wilson Data

- The algorithm has been tested on residential and commercial users in Wilson, NC.
- The algorithm achieves reasonable results without sub-metered data.



Application and Future Work



Application:
No sub-metered data

- Automated processing of smart meter data
- DR resource identification
- Cold load pickup impact analysis
- Next step: Port the model to disaggregate other behind-the-meter DERs for energy management study

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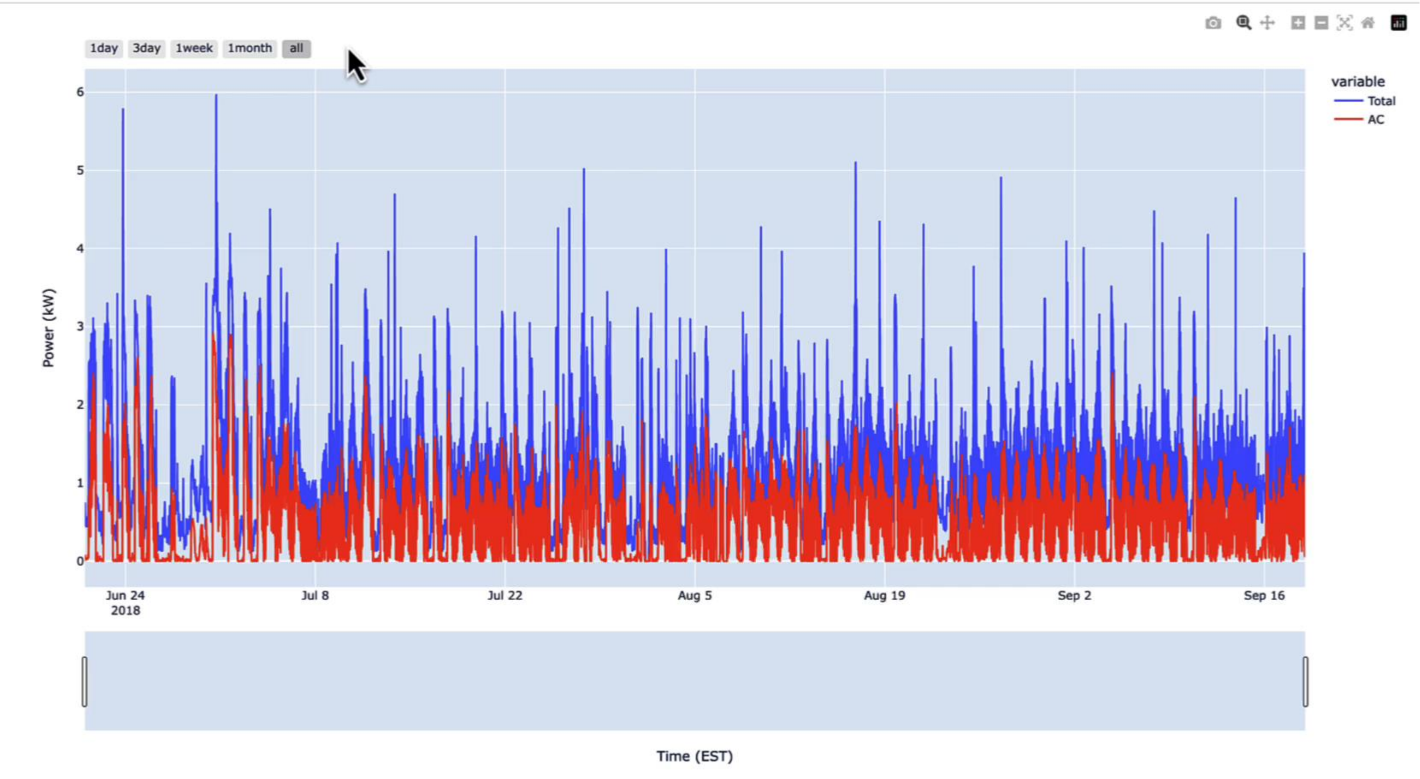
Demo of the Load Disaggregation Results



Use Case 4: Impact of PV and EV Integration on Load Shapes (Gismo EV Charger study)

Studies conducted by PhD students:

Industrial Advisors:

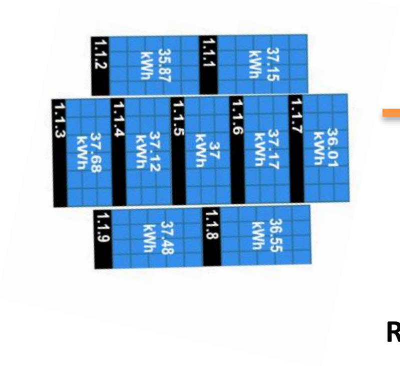
- **Gismopower:** Achim Ginsberg-Klemmt
- **ElectriCities:** PJ Rehm
- **New River Light and Power:** Matthew Makdad, Edmond Miller
- **Fayetteville PWC:** Timothy Stankiewicz

Kai Ye

Hyeonjin Kim

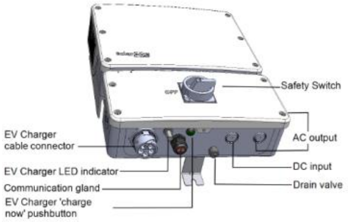
System Overview

9 PV panels with 0 tilt angle 4.14kW peak



DC

SolarEdge EV Charging Single Phase Inverter 7.6kW

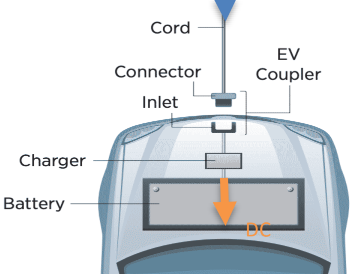


AC

Grid

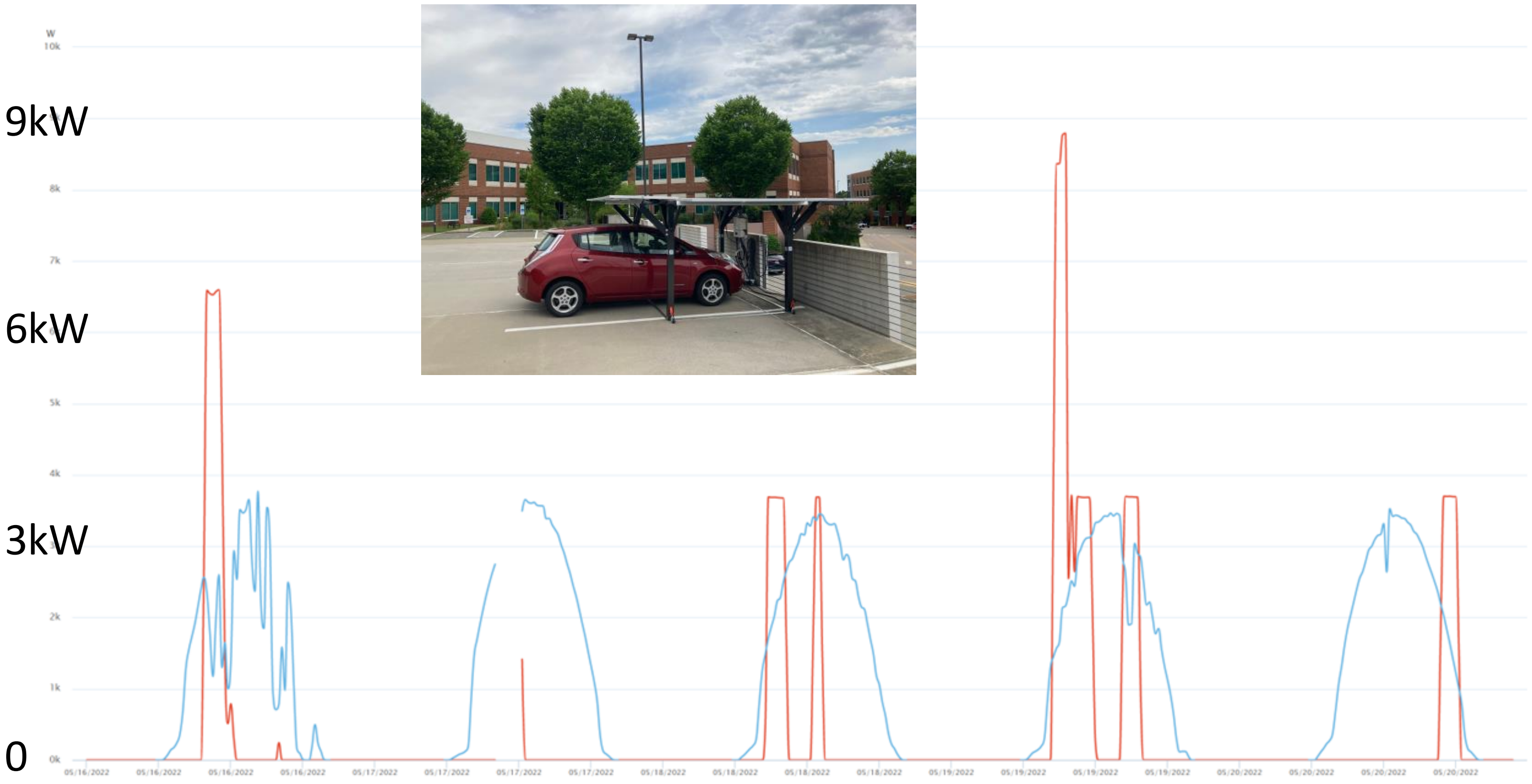
Level 2 EV Charger
Rated AC Output (Grid & PV) 9.6kW

AC



A solar panel powered charger

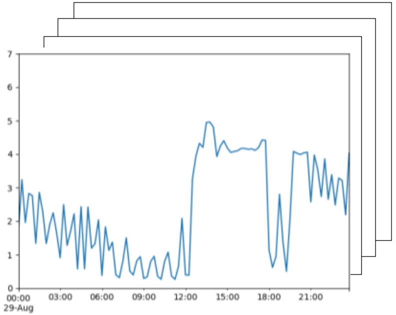
PV-powered Charger



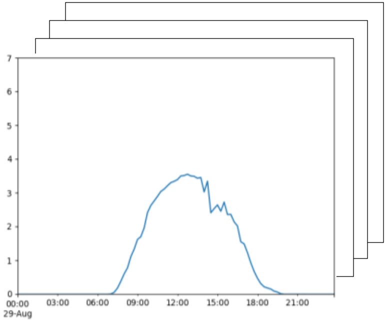
PV and EV integration studies

1. Base Case: Smart meter data (No EV, No PV)
2. Add PV and EV charging curves onto the base case
3. Study impacts of EV charging on transformer loading

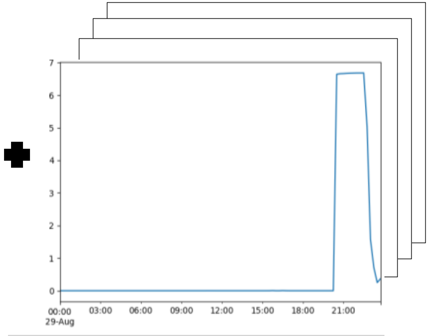
Load profiles w/o PV & EV



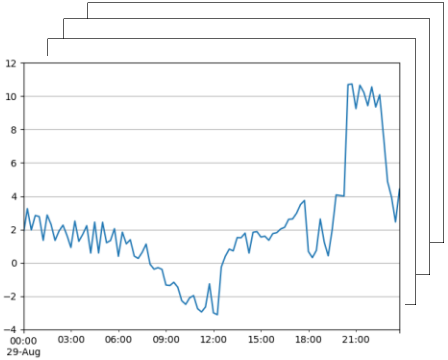
Normalized PV profiles



(Modified) EV profiles

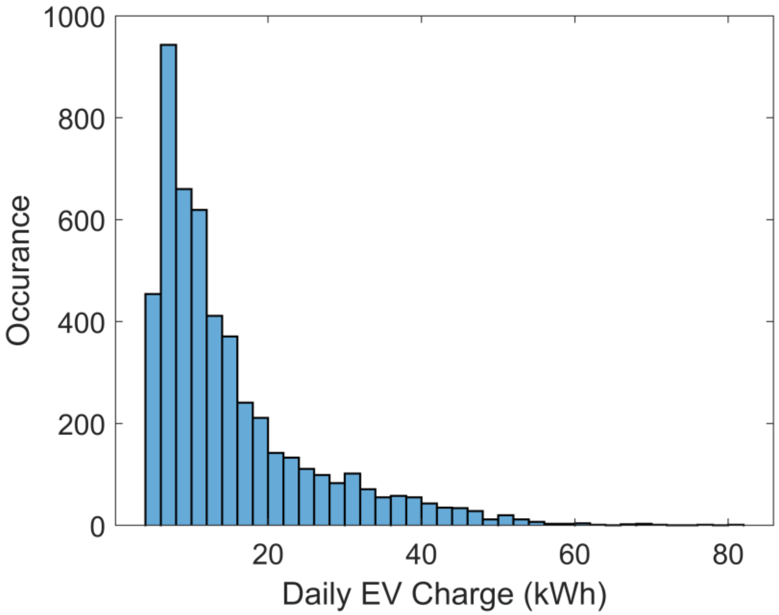


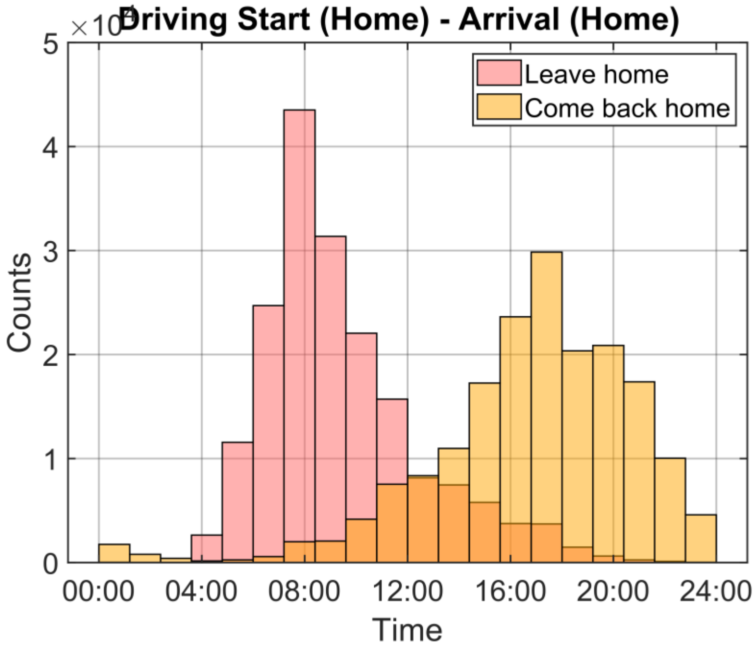
Augmented profiles for impact analysis



Data Description

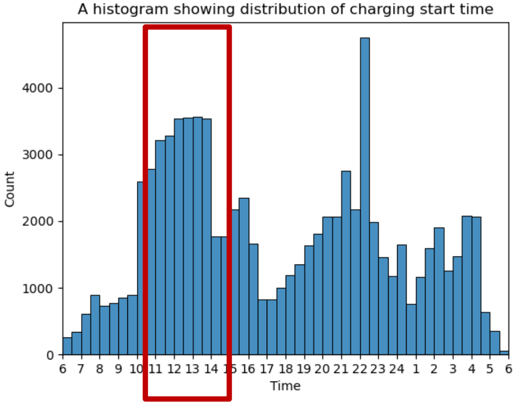
- **Daily Charging Energy** (we have obtained sub-metered data from Pecan Street)
- **EV leaving / Arrival time** (using the NHTS Data)
- **EV types** (using the 2022 EV market Share)



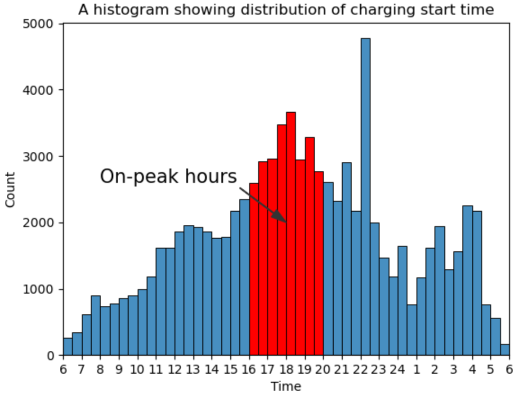


Scheduled EV Charging

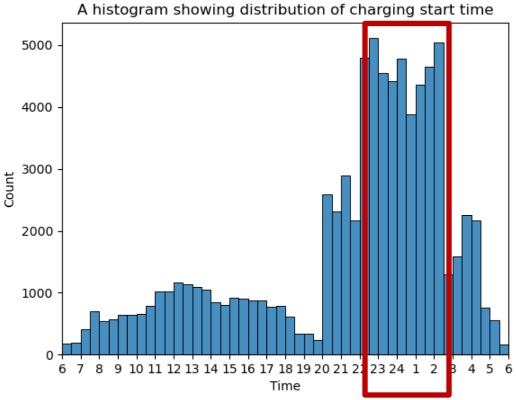
Rescheduled to 10:00 – 14:00



No EV control



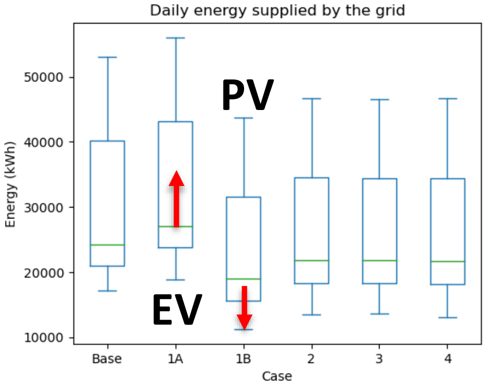
Rescheduled to 22:30 - 2:30



Aggregated Impact of 1000 Users

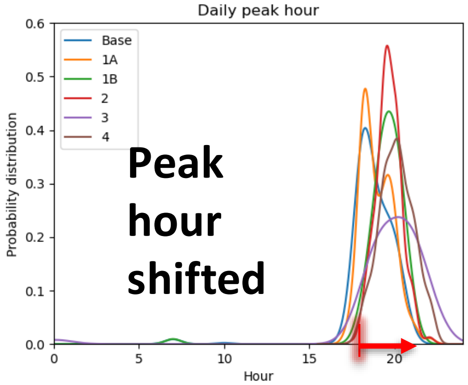
	Set-up
Base	No PV or EV
1A	Base + **EV**
1B	Base + **PV**
2	Base + PV + EV **No Control**
3	Base + PV + **day time charging**
4	Base + PV + **night time Charging**

Daily Energy

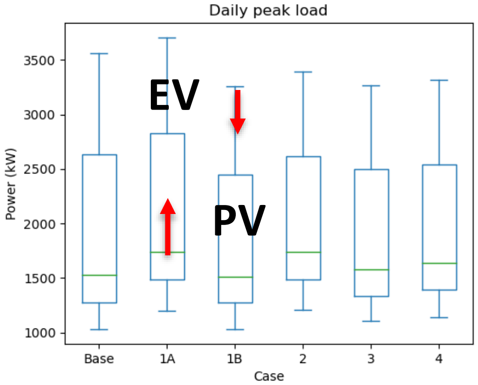


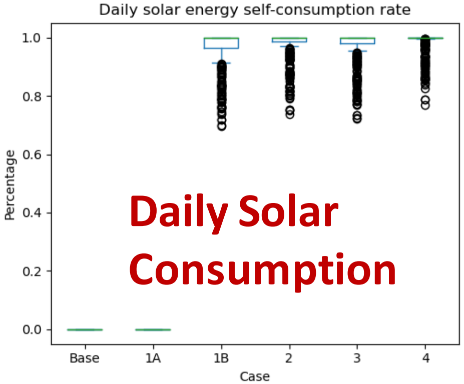
Daily Peak hour

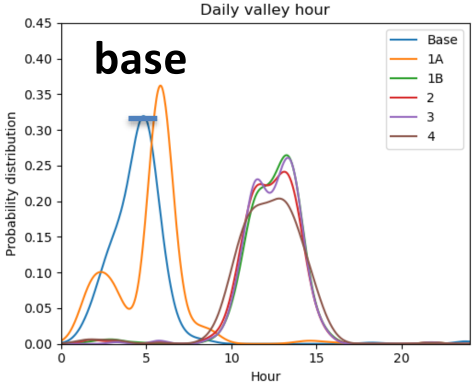
Impact for 1000-user case at 50% penetration



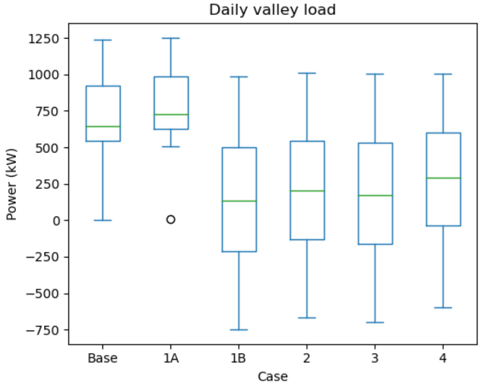
Peak load







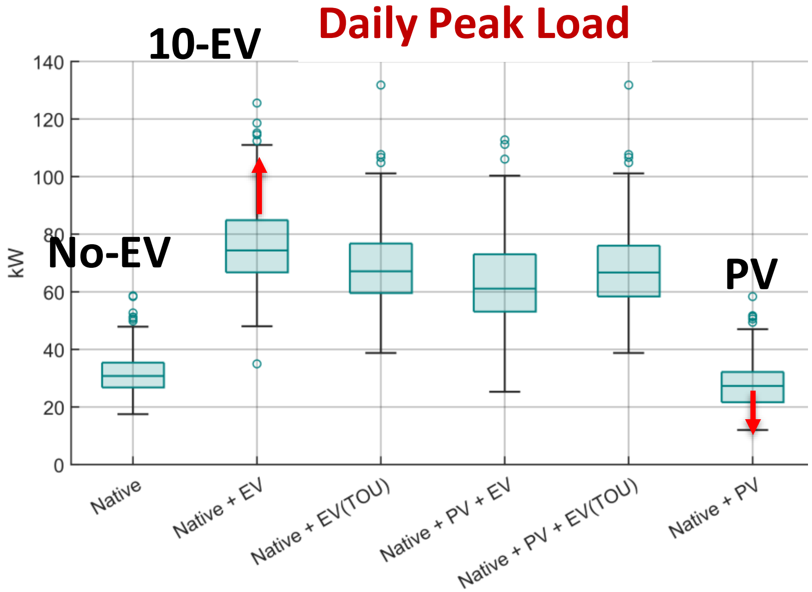
Daily Valley hour



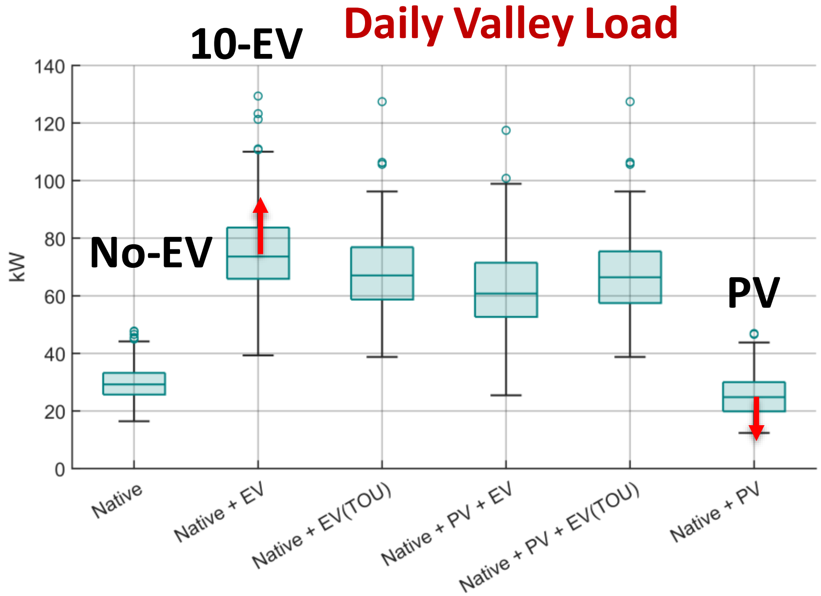
Valley load

An Apartment Complex in New River

- 44 Customers
- 10 EVs
- PV Capacity: 41.4 [kW]

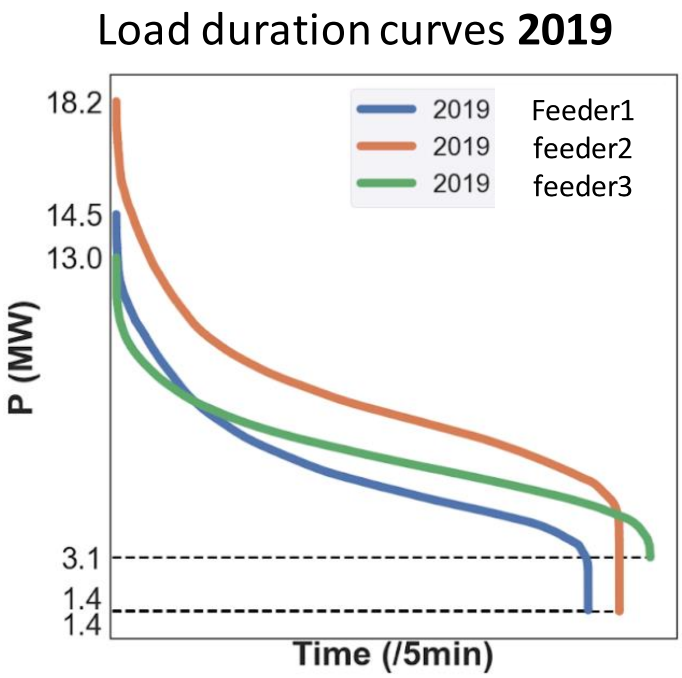


2019



2020

Normal Load Growth: 2019 → 2021



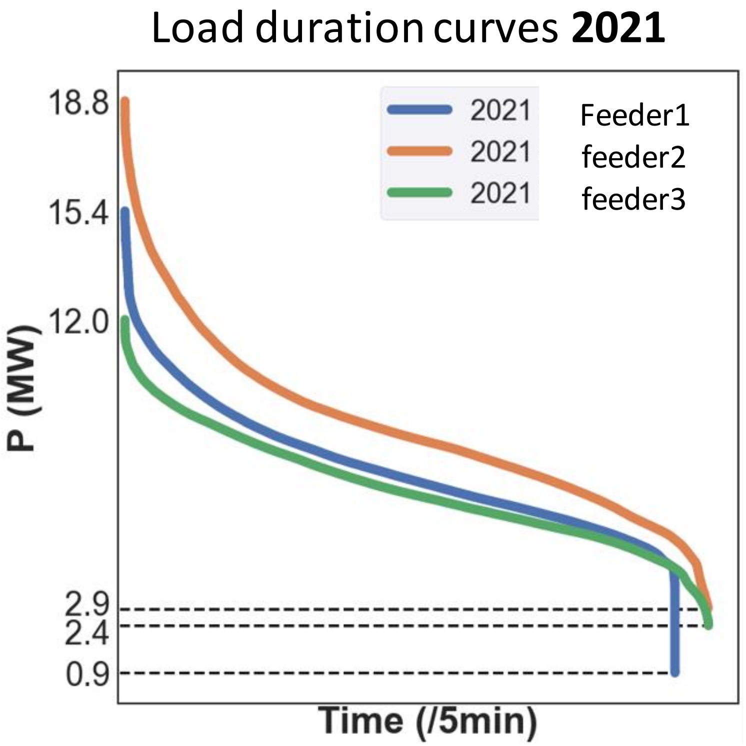
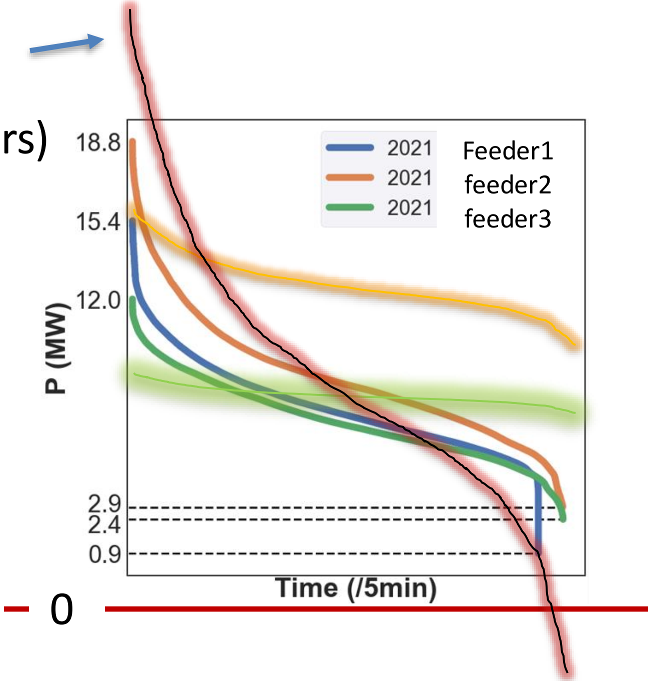


Figure produced by Hanpyo lee using **Fayetteville data**

Expected Changes: 2021→2030?

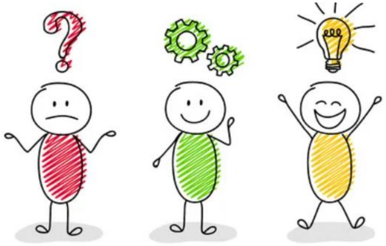
New Electrification Loads (e.g., EVs and electric water heaters)



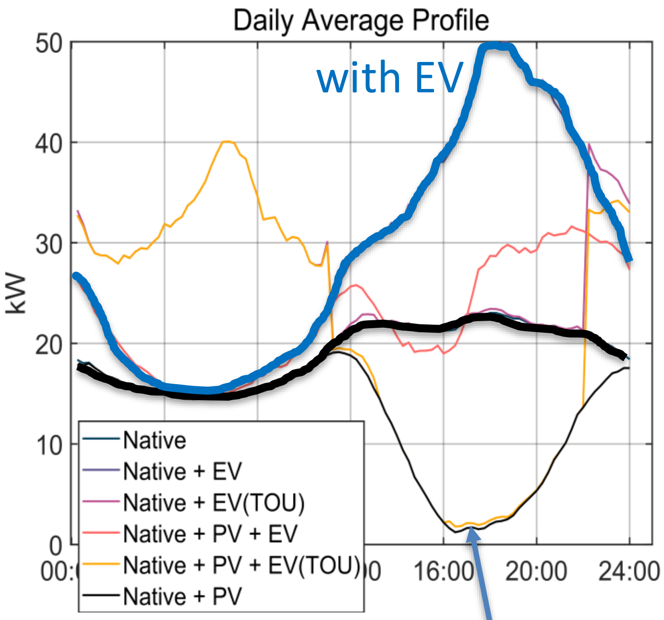
Roof-top PV

Project Fayetteville data into the future?

Can we guess what the load duration curves in **2030** will look like**?**



Expected Changes: 2021→2030?

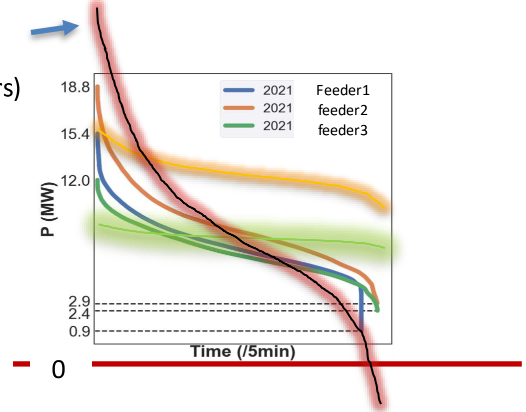


Base case

with PV

Then, what the load profile in **2030** will look like**?**

New Electrification Loads (e.g., EVs and electric water heaters)



Roof-top PV

Use Case 5: Baseline Identification

Study conducted by: Hanpyo Lee (hlee39@ncsu.edu)

Industrial Advisors:

ElectriCities: PJ Rehm

New River Light and Power: Matthew Makdad, Edmond Miller

Fayetteville PWC: Timothy Stankiewicz

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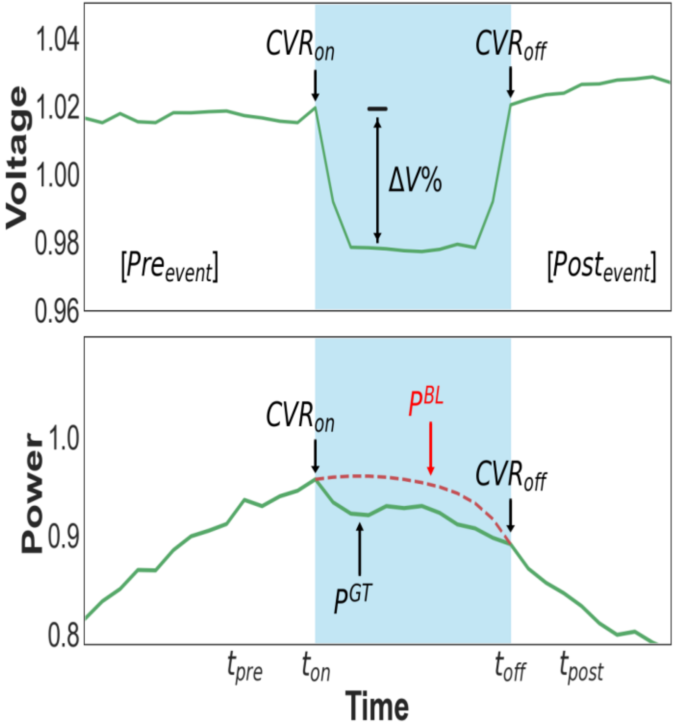
Baseline Identification

- Conservation Voltage Reduction (CVR)
  - Peak demand reduction and energy savings
  - Easiest DR option in a grid with high penetration
- DR Baseline Identification
  - Quantifying the DR effect
  - Crucial for executing DR in MG operation
- Baseline (P^{BL})
  - Load profile during the CVR event if the voltage is not reduced

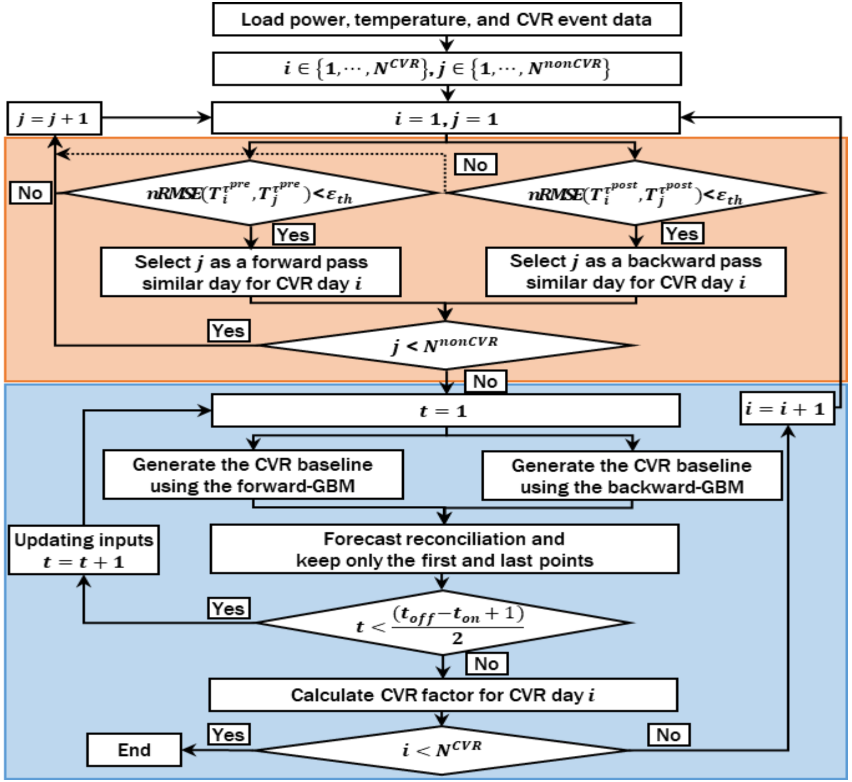


H.P. Lee, L. Song, Y. Li, N. Lu, D. Wu, PJ Rehm, M. Makdad, E. Miller, "An Iterative Bidirectional Gradient Boosting Algorithm for CVR Baseline Estimation", Available online at: http://arxiv.org/abs/2211.03733

Flowchart

Stage 1) Similar day selection algorithm

Stage 2) Iterative bi-directional GB-based algorithm with reconciliation



H.P. Lee, L. Song, Y. Li, N. Lu, D. Wu, PJ Rehm, M. Makdad, E. Miller, "An Iterative Bidirectional Gradient Boosting Algorithm for CVR Baseline Estimation", Available online at: http://arxiv.org/abs/2211.03733

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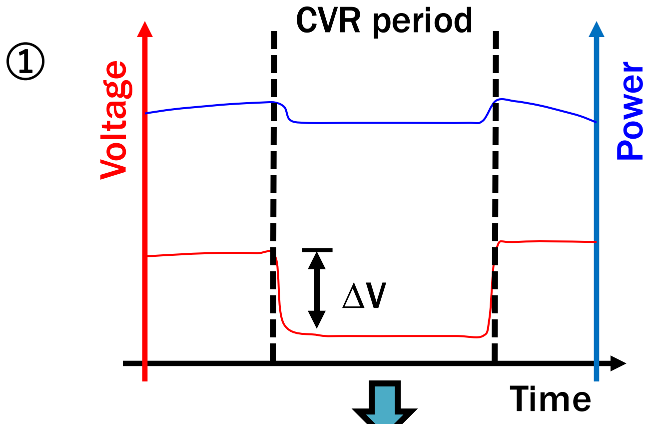
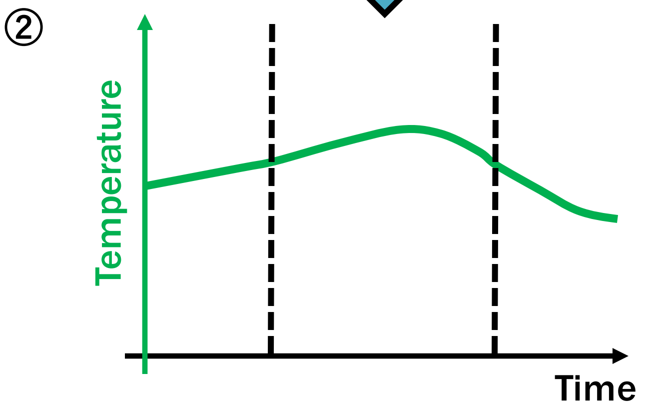
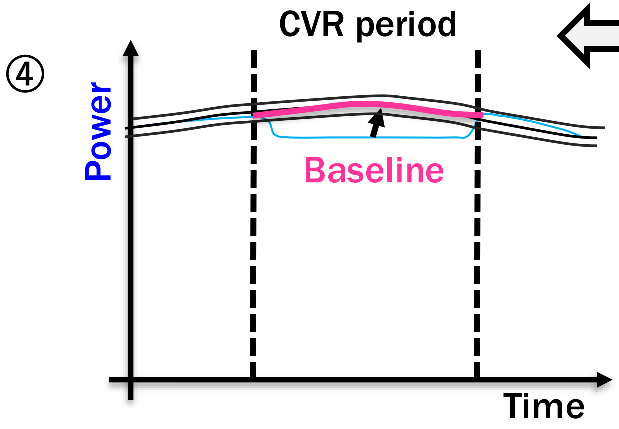
Similar Day Selection Algorithm

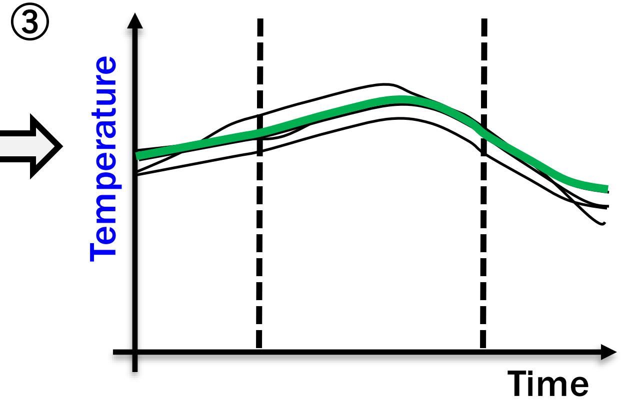




Step 1.
Find the CVR day
Voltage and
temperature profiles

Step 2.
Use the CVR day
temperature profiles
to find similar days



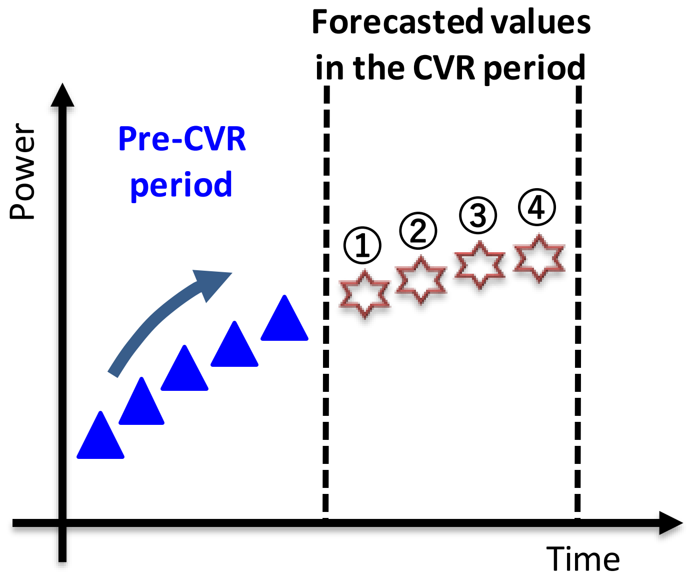


Step 3.
From power
profiles of
similar days,
we can
estimate the
CVR baseline.

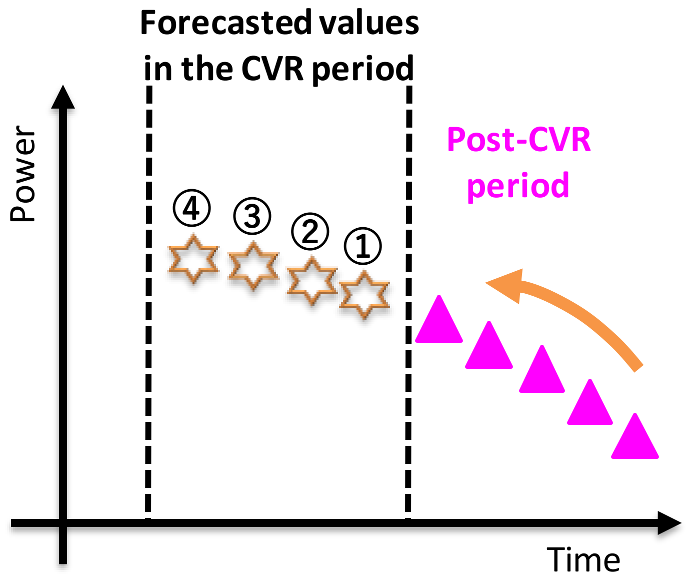
H.P. Lee, L. Song, Y. Li, N. Lu, D. Wu, PJ Rehm, M. Makdad, E. Miller, "An Iterative Bidirectional Gradient Boosting Algorithm for CVR Baseline Estimation", Available online at: http://arxiv.org/abs/2211.03733

Bidirectional Estimation

Step 1: Run the forward pass

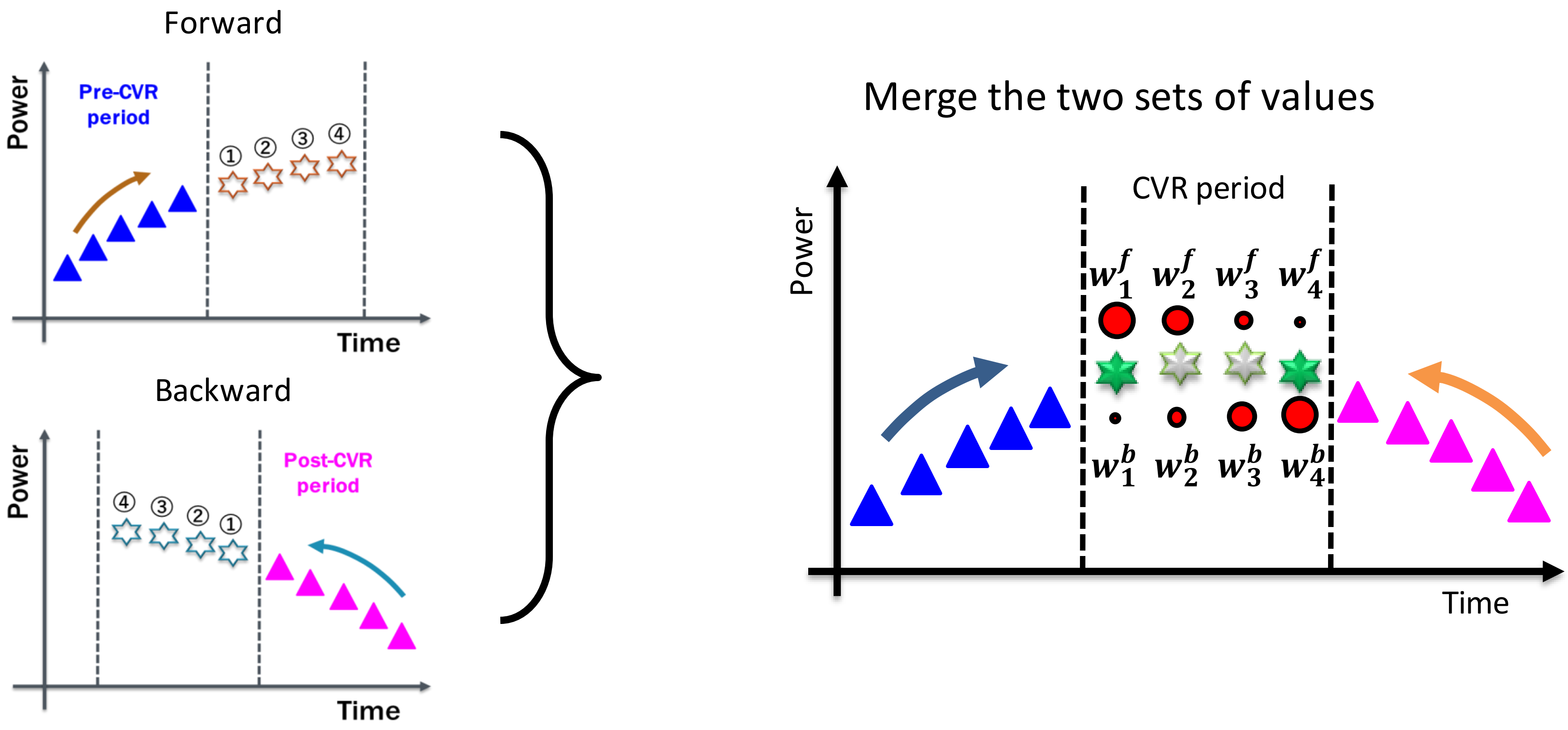


Step 2: Run the backward pass



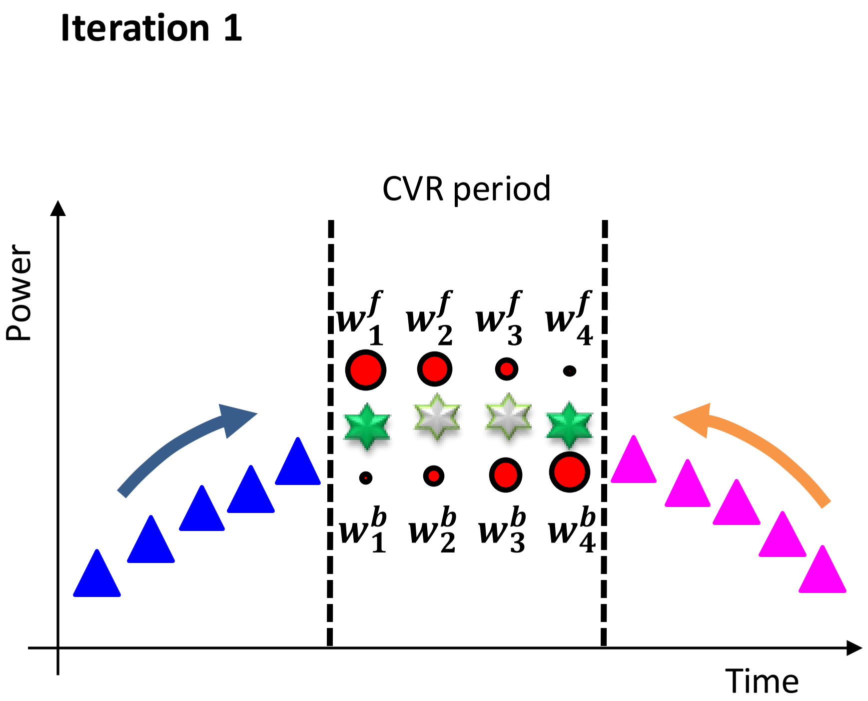
H.P. Lee, L. Song, Y. Li, N. Lu, D. Wu, PJ Rehm, M. Makdad, E. Miller, "An Iterative Bidirectional Gradient Boosting Algorithm for CVR Baseline Estimation", Available online at: http://arxiv.org/abs/2211.03733

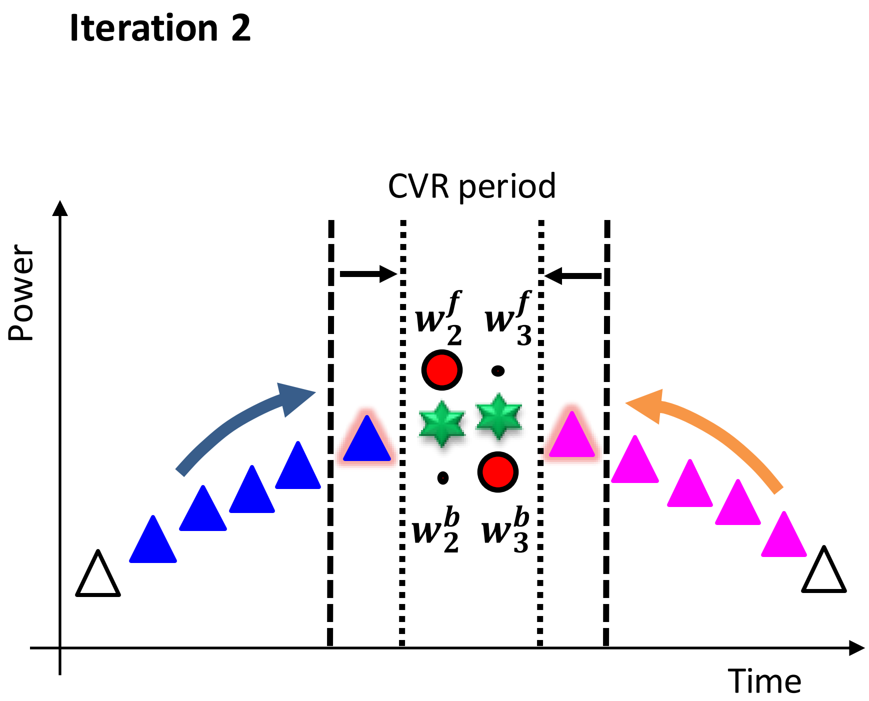
Reconciliation



H.P. Lee, L. Song, Y. Li, N. Lu, D. Wu, PJ Rehm, M. Makdad, E. Miller, "An Iterative Bidirectional Gradient Boosting Algorithm for CVR Baseline Estimation", Available online at: http://arxiv.org/abs/2211.03733

Iterate until the last value is estimated





H.P. Lee, L. Song, Y. Li, N. Lu, D. Wu, PJ Rehm, M. Makdad, E. Miller, "An Iterative Bidirectional Gradient Boosting Algorithm for CVR Baseline Estimation", Available online at: http://arxiv.org/abs/2211.03733

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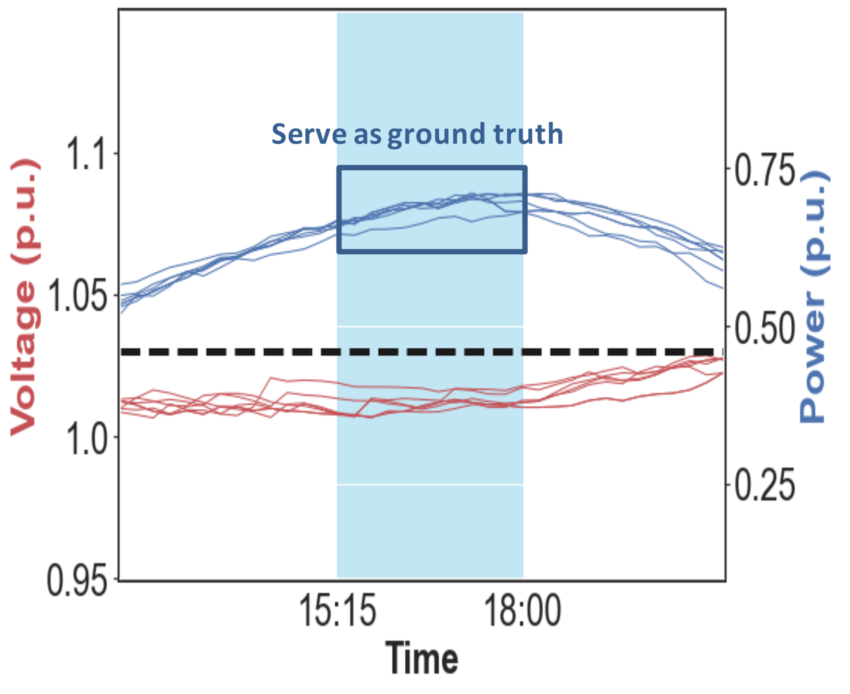
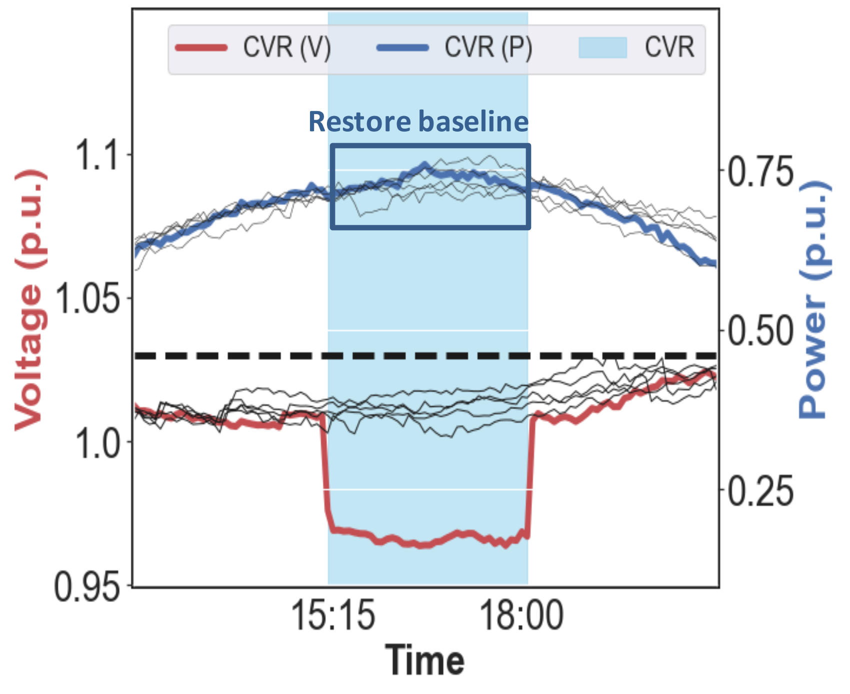
Data Preparation

Non-CVR day $\{1, \cdots, N_{non-CVR}\}$	CVR day $\{1, \cdots, N_{CVR}\}$
	

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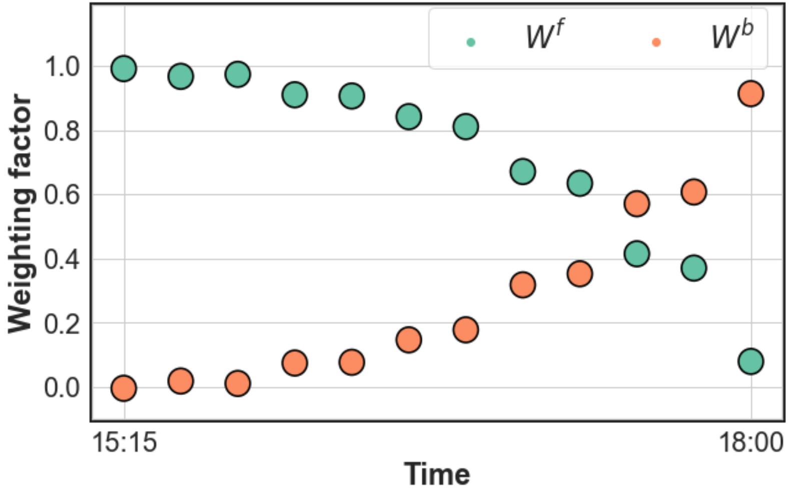
Reconciliation Weight Selection

- Reconciled the forward and backward pass estimations
  - Linear reconciliation $\hat{P}_t^R = w_t^f \times \hat{P}_t^f + w_t^b \times \hat{P}_t^b$ (1)
  - Linear regression $P_{j,t}^{GT} = \hat{P}_{j,t}^f \times w_t^f + \hat{P}_{j,t}^b \times w_t^b$ (2)



Reconciliation weights

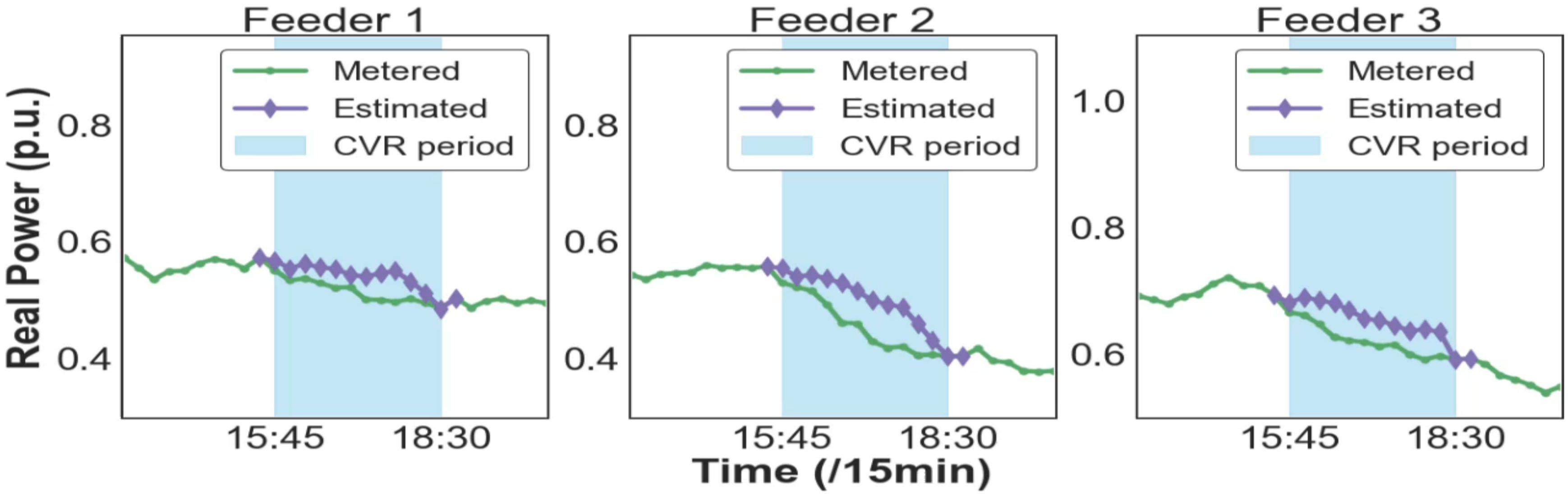
Datasets

- Collected by a utility on 3 distribution feeders in NC in 2019 and 2020
- Aggregated from meters belonging to the same feeder (15-min rez.)

Feeder No.	CVR	non-CVR	Missing	Total	CVR duration
1	24	677	30	731	3 h
2	24	679	28	731	3 h
3	24	679	28	731	3 h

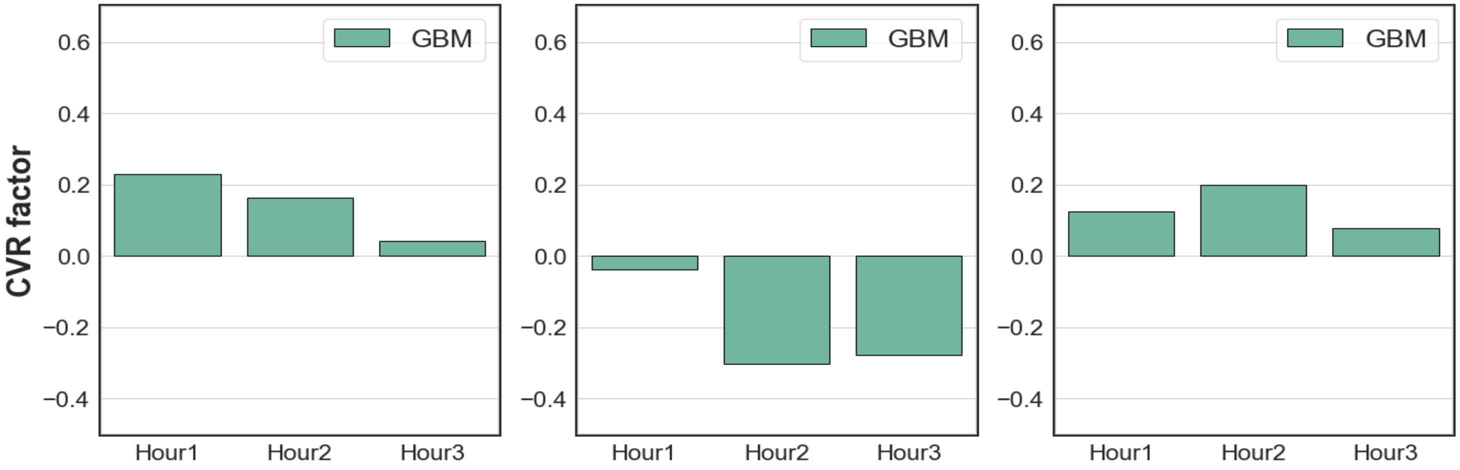
Simulation Results of Actual CVR Days

- Test on the actual 24 CVR days
- CVR performance varies:
  - Time-of-the-day, load composition, and weather variations



Hourly Average CVR Factor

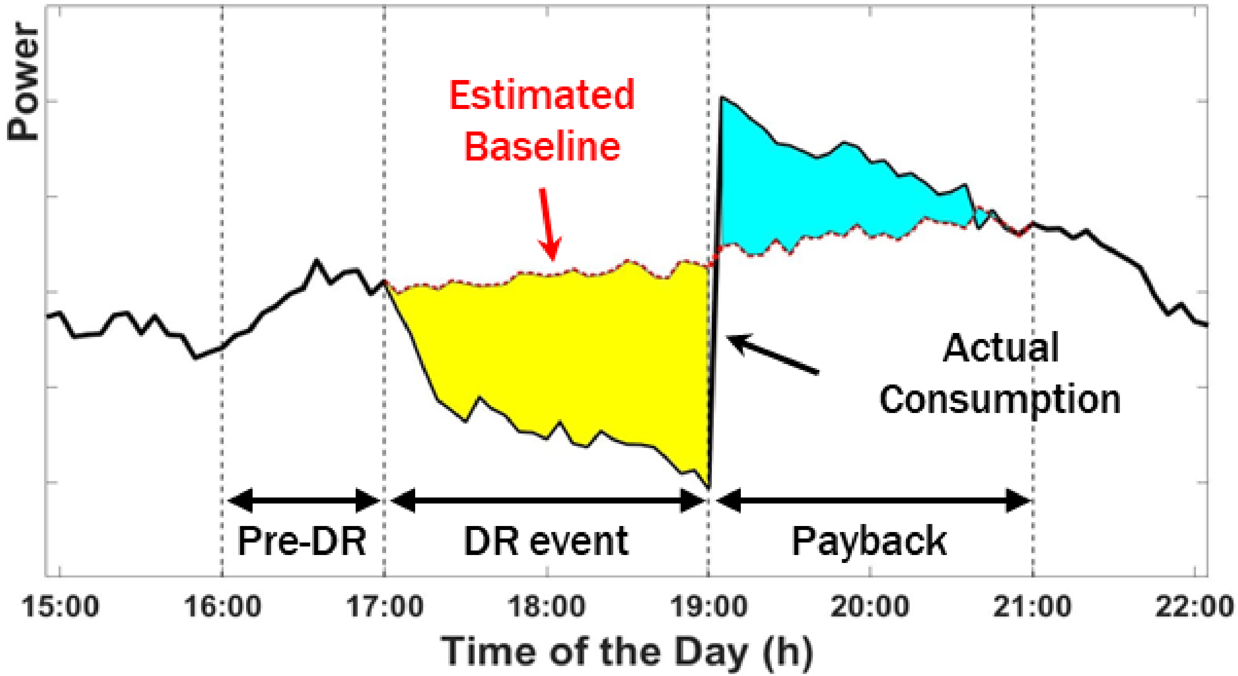
- Observations from Hourly Average CVR factor
  - Lower than literature reported $\mathrm{CVR_f}$ (from 0.3 to 1) due to different load compositions
  - Initial load drops due to the CVR, and then bounce back



(a) Feeder 1 (b) Feeder 2 (c) Feeder 3

Next Step

- Expanded application to DR baseline estimation



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Connections Summit Breakout
Session #2 Feedback

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