Making Buildings and the Electrical Grid Work Together

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IEEE Tech Conference Seattle
6/17/2022

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Overview

Edo offers a turn-key demand-side management platform for non-residential buildings that integrates building and grid operations.

Edo provides a customer-branded advanced energy efficiency and demand flexibility solution for utilities. This solution enables utilities to strengthen their customer relationships and engages hard-to reach customers such as schools. Edo's mission is to enable a faster, more reliable, and more equitable transition to zero-carbon energy.

Quick Stats

- Founded in 2020
- 1.8K+ buildings served
- 89M+ sq ft covered
- 119K+ Equipment
- 600K+ Mapped BAS Points
- 5K+ Utility meters

Main forces driving change in electric sector

Electrification

Carbon intensity of electricity supply is decreasing, electrification of energy sectors (heating/transportation/industrial).

EV adoption / large scale charging

Charging fundamentally changing the timing and location of load patterns.

Increased supply of variable RE generation

As RE increases on systems, increased need for grid flexibility at the generation/transmission & distribution level.

Increased frequency of extreme weather events

Decreased equator to pole temp gradient, reduced strength and stability of jet stream & polar vortex, increased frequency of extreme weather and duration of weather events.

What success looks like in a future energy sector

Climate Crisis

The first wave of consequences from climate change are here now. Without immediate action, these impacts will escalate to a point of no return by 2030.

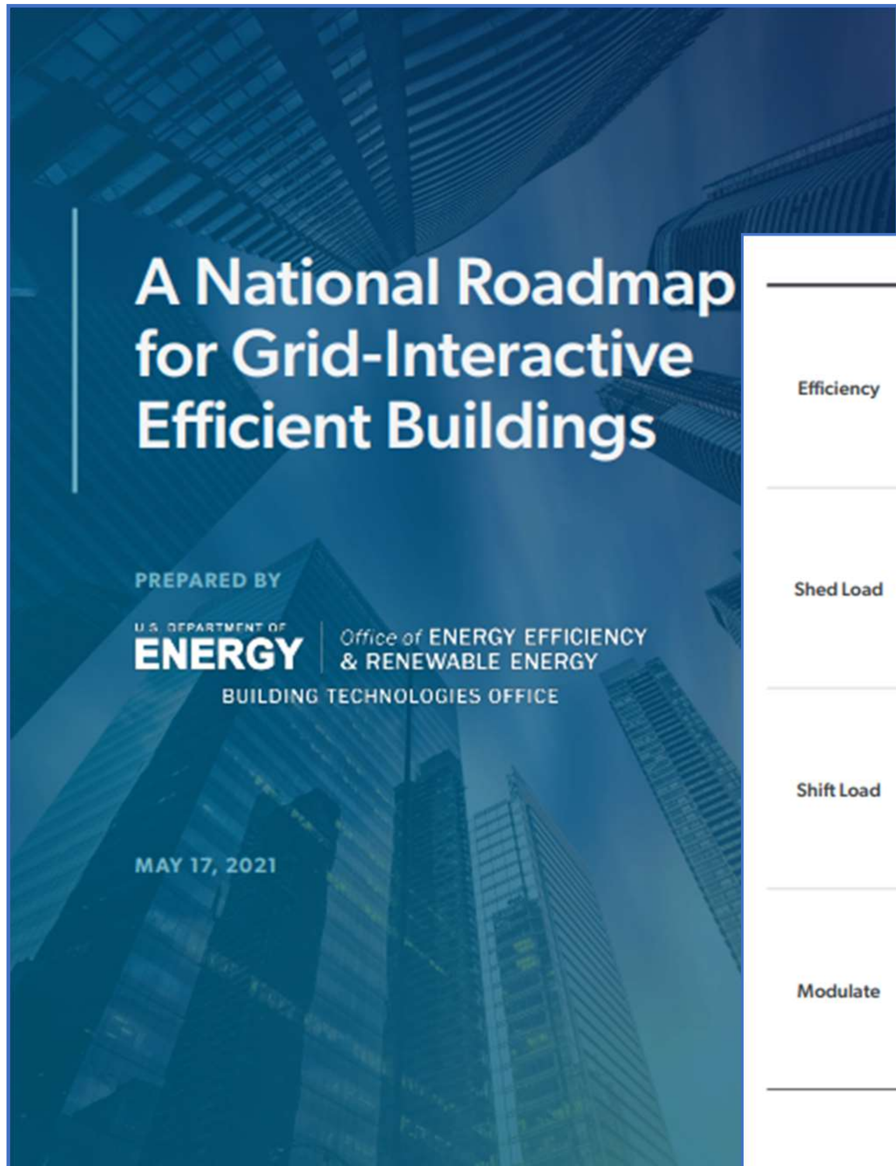
Affordability Crisis

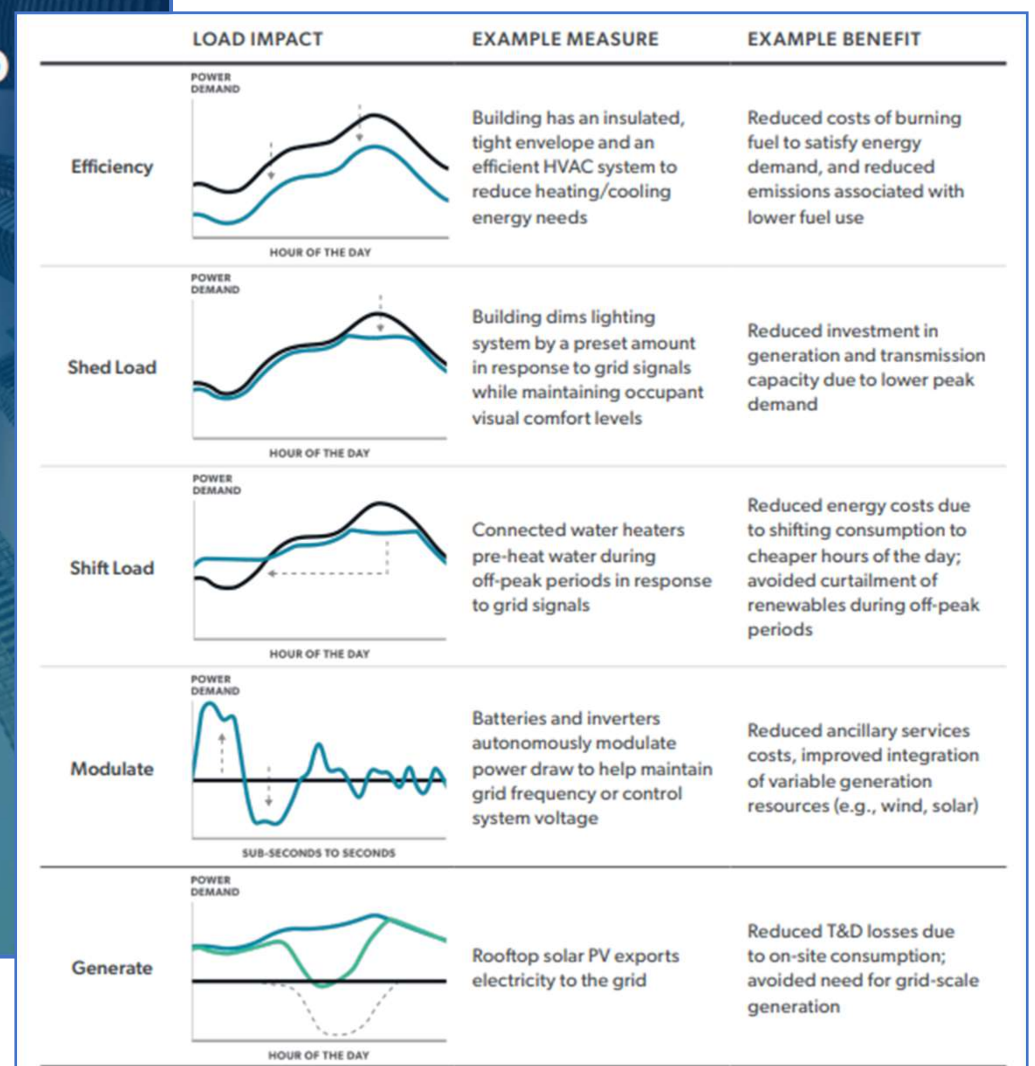
Rising costs are culminating in an affordability crisis that is unnecessary, unacceptable and limits the investment needed to balance the natural and built environment.

Equity Crisis

Systemic inequity and racism are embedded in nearly every aspect of our society, with those who have the least poised to suffer the most from the crises we face.

Impact of Grid-Integration of Buildings





	LOAD IMPACT	EXAMPLE MEASURE	EXAMPLE BENEFIT
Efficiency	POWER DEMAND / HOUR OF THE DAY	Building has an insulated, tight envelope and an efficient HVAC system to reduce heating/cooling energy needs	Reduced costs of burning fuel to satisfy energy demand, and reduced emissions associated with lower fuel use
Shed Load	POWER DEMAND / HOUR OF THE DAY	Building dims lighting system by a preset amount in response to grid signals while maintaining occupant visual comfort levels	Reduced investment in generation and transmission capacity due to lower peak demand
Shift Load	POWER DEMAND / HOUR OF THE DAY	Connected water heaters pre-heat water during off-peak periods in response to grid signals	Reduced energy costs due to shifting consumption to cheaper hours of the day; avoided curtailment of renewables during off-peak periods
Modulate	POWER DEMAND / SUB-SECONDS TO SECONDS	Batteries and inverters autonomously modulate power draw to help maintain grid frequency or control system voltage	Reduced ancillary services costs, improved integration of variable generation resources (e.g., wind, solar)
Generate	POWER DEMAND / HOUR OF THE DAY	Rooftop solar PV exports electricity to the grid	Reduced T&D losses due to on-site consumption; avoided need for grid-scale generation

US DOE National Roadmap for GEB[1]

- Potential \$100–200 billion annual energy cost savings.
- Potential 80 million metric tons of carbon emissions avoided by 2030 – or 6% of total power sector carbon emissions.
- A reduction of 9-15% in peak loads can reduce utility bills by 10-17%

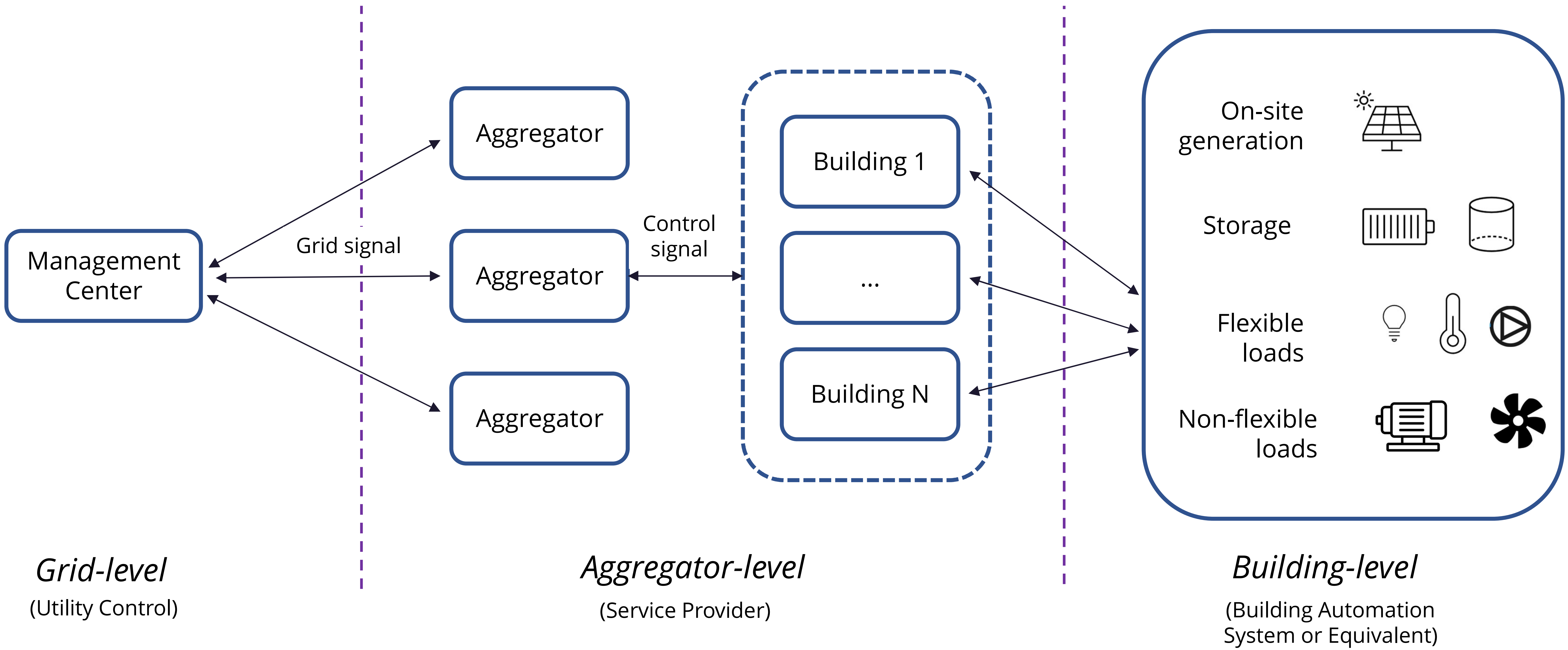
1. Satchwell, Andrew, Piette, Mary Ann, Khandekar, Aditya, Granderson, Jessica, Frick, Natalie Mims, Hledik, Ryan, Faruqui, Ahmad, Lam, Long, Ross, Stephanie, Cohen, Jesse, Wang, Kitty, Urigwe, Daniela, Delurey, Dan, Neukomm, Monica, and Nemtzow, David. 2021. "A National Roadmap for Grid-Interactive Efficient Buildings". United States. https://doi.org/10.2172/1784302. https://www.osti.gov/servlets/purl/1784302.

Demand Flexibility

"Building demand flexibility specifically represents the capability of controls and end-uses that can be used, typically in response to price changes or direct signals, to provide benefits to buildings' owners, occupants, and to the grid.[1]"

1. Satchwell, Andrew, Piette, Mary Ann, Khandekar, Aditya, Granderson, Jessica, Frick, Natalie Mims, Hledik, Ryan, Faruqui, Ahmad, Lam, Long, Ross, Stephanie, Cohen, Jesse, Wang, Kitty, Urigwe, Daniela, Delurey, Dan, Neukomm, Monica, and Nemtzow, David. 2021. "A National Roadmap for Grid-Interactive Efficient Buildings". United States. https://doi.org/10.2172/1784302. https://www.osti.gov/servlets/purl/1784302.

Grid-to-Building Control Topology



Demand Optimization Measures

Available Measures	Type	Response Time	Considerations
Dim lights	Shed	Seconds	Occupant comfort
Space temperature setpoint	Shift, Shed	Minutes	Occupant comfort, capacity based on current loads
Chilled water temperature setpoint	Shift, Shed, Efficiency	Minutes	May influence downstream systems (e.g., fan speeds)
Discharge Thermal Energy Storage (TES)	Shift, Shed, Efficiency	Minutes	Forecast load to determine optimal charge/discharge
Discharge Battery Energy Storage System (BESS)	Shift, Shed, Modulate	Seconds	Forecast load to determine optimal charge/discharge

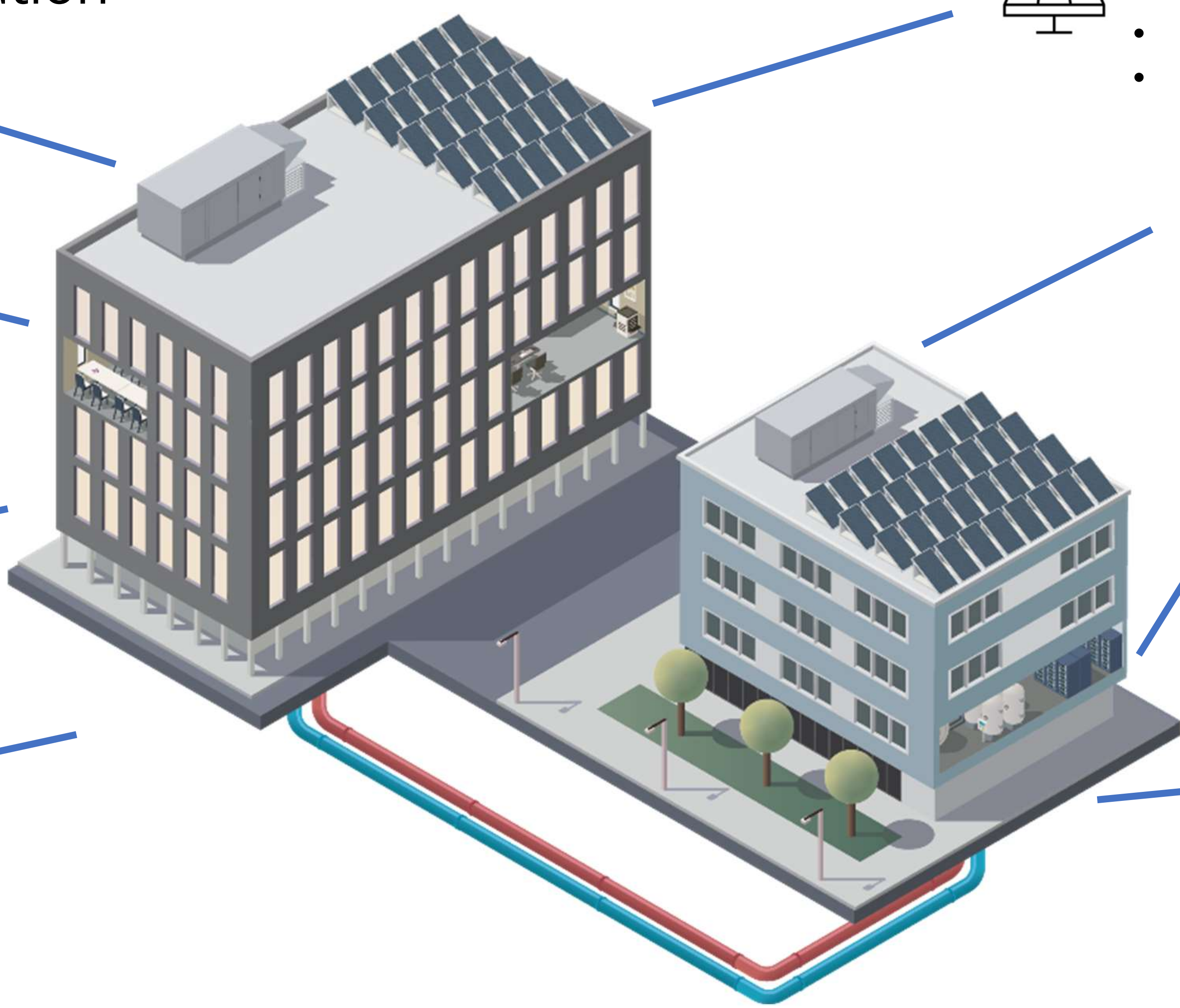
Spokane EcoDistrict – Living Lab for Building to Grid Integration

Occupancy-driven ventilation
- CO_2 sensors by zone

Networked Lighting
- Active dimming & schedules

CLT Construction
- Net-zero carbon building
- Less thermal inertia

EV charging
- Coordinated charge/discharge



Rooftop PV
- 259kW DC-tied to BESS
- Optimized for energy & capacity

Battery Storage
- 660kW / 1320kWh
- 1MW inverter

Thermal Storage
- Three 8,000 gal water tanks
  - 187 ton-hrs
- Five 626 gal phase change tanks
  - 200-225 ton-hrs
- 1400 kWh thermal storage

All-Electric Central Plant
- Air-source heat pump
- Water-source heat recovery chiller
- Electric boiler

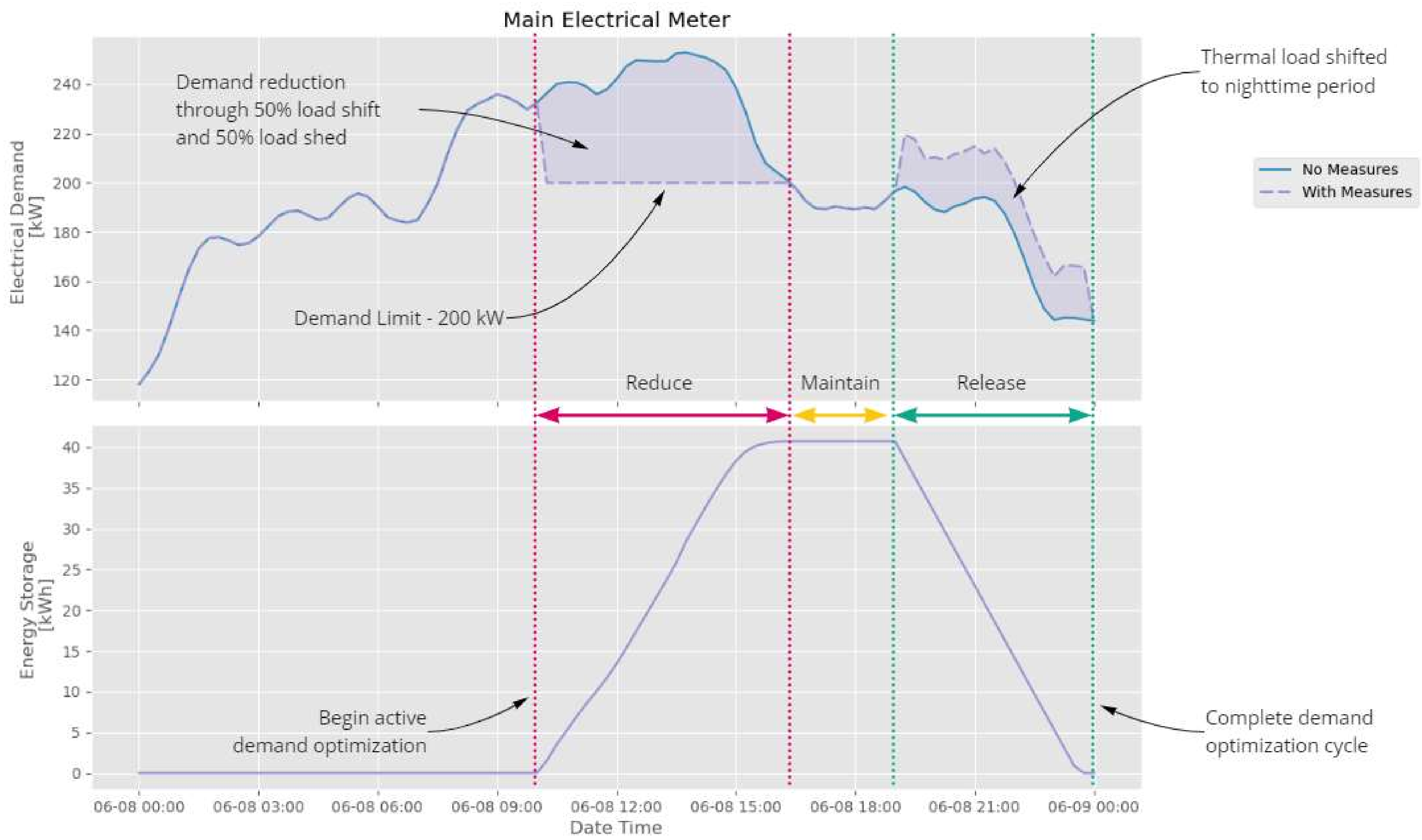
Demand Optimization as a Time Series Problem

<u>Types of Forecasts Needed</u>

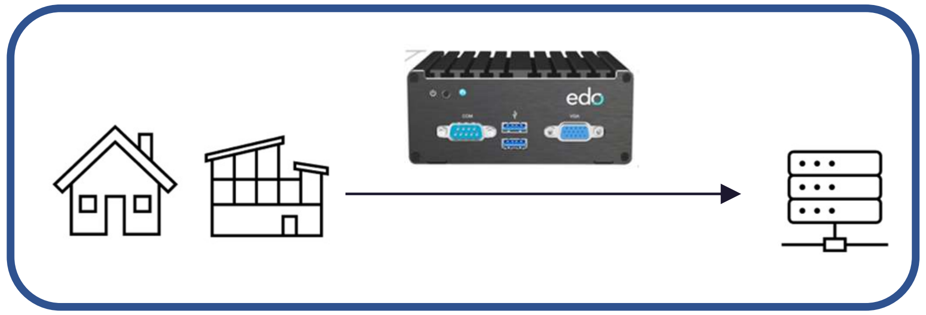
- Weather
- Building Level
  - ***Electricity demand***
  - Available demand flexibility
- Equipment Level
  - DF measure impact
  - Thermal response of space

<u>Other Models</u>

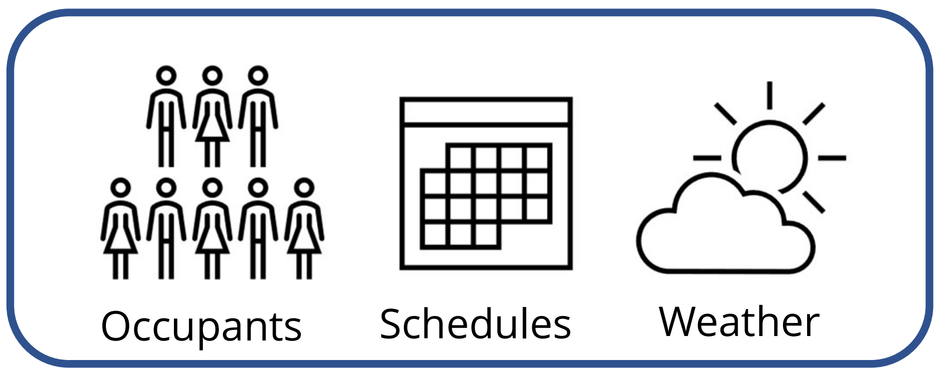
- Equipment performance
- Control response



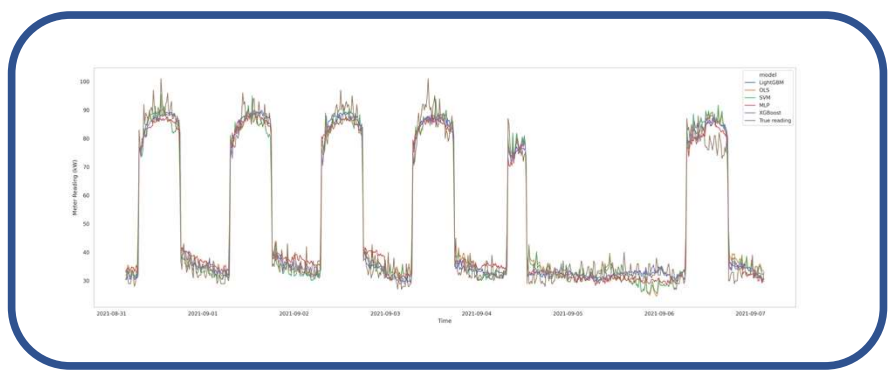
ML Model Development Workflow



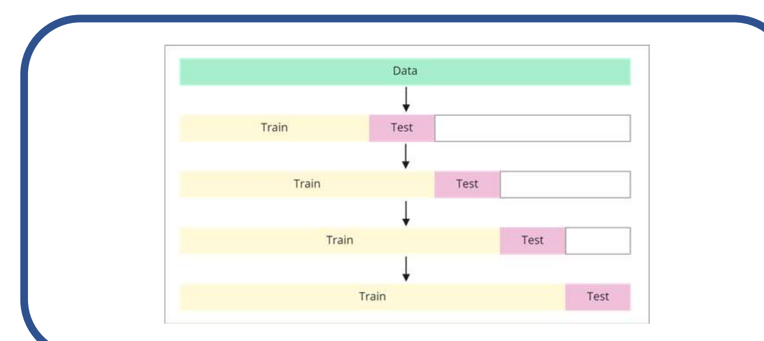
Data Collection



Feature Engineering



Model Selection



Validation

Getting Data from Buildings

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- Commonly access Building Automation System (BAS) using BACnet protocol or other common IoT protocols
- May have 1,000+ equipment reporting 10,000+ data points.
- Device and point names are often not descriptive, so use ML classification to group into device and point classes
- Lacks description of system topology, which may limit purely data-driven approach
- Points are polled at differing times, so need to align data on uniform time stamps

ID	PointName	PointDisplayName	EquipID
8712341	230800:pCOWeb230800/1078:M2_CIR_A_EEV_STEPS	230800:pCOWeb230800/1078:M2_CIR_A_EEV_STEPS	345235
8712342	230800:pCOWeb230800/1082:M2_COMP_A_HRS	230800:pCOWeb230800/1082:M2_COMP_A_HRS	345235
8712343	230800:pCOWeb230800/1063:M1_COMP_B_ZONE	230800:pCOWeb230800/1063:M1_COMP_B_ZONE	345235
8712344	230800:pCOWeb230800/1050:M1_CIR_A_LP	230800:pCOWeb230800/1050:M1_CIR_A_LP	345235
8712345	230800:pCOWeb230800/1089:M2_COMP_B_RPM	230800:pCOWeb230800/1089:M2_COMP_B_RPM	345235
8712346	230800:pCOWeb230800/1087:M2_CIR_B_EEV_STEPS	230800:pCOWeb230800/1087:M2_CIR_B_EEV_STEPS	345235
8712347	230800:pCOWeb230800/1083:M2_CIR_B_EEV_REG	230800:pCOWeb230800/1083:M2_CIR_B_EEV_REG	345235
8712348	230800:pCOWeb230800/1060:M1_CIR_B_EEV_STEPS	230800:pCOWeb230800/1060:M1_CIR_B_EEV_STEPS	345235
8712349	230800:pCOWeb230800/1049:M1_CIR_A_HP	230800:pCOWeb230800/1049:M1_CIR_A_HP	345235
8712350	230800:pCOWeb230800/1061:M1_COMP_B_REQ_RPM	230800:pCOWeb230800/1061:M1_COMP_B_REQ_RPM	345235
8712351	230800:pCOWeb230800/1004:LEAD_COMP	230800:pCOWeb230800/1004:LEAD_COMP	345235
8712352	230800:pCOWeb230800/1073:M2_MODE	230800:pCOWeb230800/1073:M2_MODE	345235
8712353	230800:pCOWeb230800/1066:M1_COMP_B_WARN	230800:pCOWeb230800/1066:M1_COMP_B_WARN	345235
8712354	230800:pCOWeb230800/1016:COOL_TDIFF	230800:pCOWeb230800/1016:COOL_TDIFF	345235
8712355	230800:pCOWeb230800/1017:COOL_STAGE_OFF_DELAY	230800:pCOWeb230800/1017:COOL_STAGE_OFF_DELAY	345235
[illegible]	[illegible]	[illegible]	[illegible]
8712357	320532:CHW_EV/27:DeltaT_F	320532:CHW_EV/27:DeltaT_F	345236
8712358	230800:pCOWeb230800/1014:LEAD_COMP_DISPLAY	230800:pCOWeb230800/1014:LEAD_COMP_DISPLAY	345237
[illegible]	[illegible]	[illegible]	[illegible]
8712360	320532:CHW_EV/26:T2_F	320532:CHW_EV/26:T2_F	345236
[illegible]	[illegible]	[illegible]	[illegible]
8712362	320532:CHW_EV/13:AbsFlow_gpm	320532:CHW_EV/13:AbsFlow_gpm	345241
8712363	230800:pCOWeb230800/1090:M2_COMP_B_ZONE	230800:pCOWeb230800/1090:M2_COMP_B_ZONE	345242
8712364	230800:pCOWeb230800/1001:COMPS_ONLINE	230800:pCOWeb230800/1001:COMPS_ONLINE	345243
8712365	230800:pCOWeb230800/1020:CONTROL_MODE	230800:pCOWeb230800/1020:CONTROL_MODE	345244
8712366	230800:pCOWeb230800/1019:SYSTEM_FAULT	230800:pCOWeb230800/1019:SYSTEM_FAULT	345245
8712367	320532:CHW_EV/25:T1_F	320532:CHW_EV/25:T1_F	345236
8712368	230800:pCOWeb230800/1008:SYSTEM_STATUS	230800:pCOWeb230800/1008:SYSTEM_STATUS	345247
8712369	230800:pCOWeb230800/1018:HEAT_TDIFF	230800:pCOWeb230800/1018:HEAT_TDIFF	345248
8712370	230800:pCOWeb230800/1019:HEAT_STAGE_OFF_DELAY	230800:pCOWeb230800/1019:HEAT_STAGE_OFF_DELAY	345249
8712371	230800:pCOWeb230800/1094:M2_FAULT_A	230800:pCOWeb230800/1094:M2_FAULT_A	345250

Equip to Points to Trends

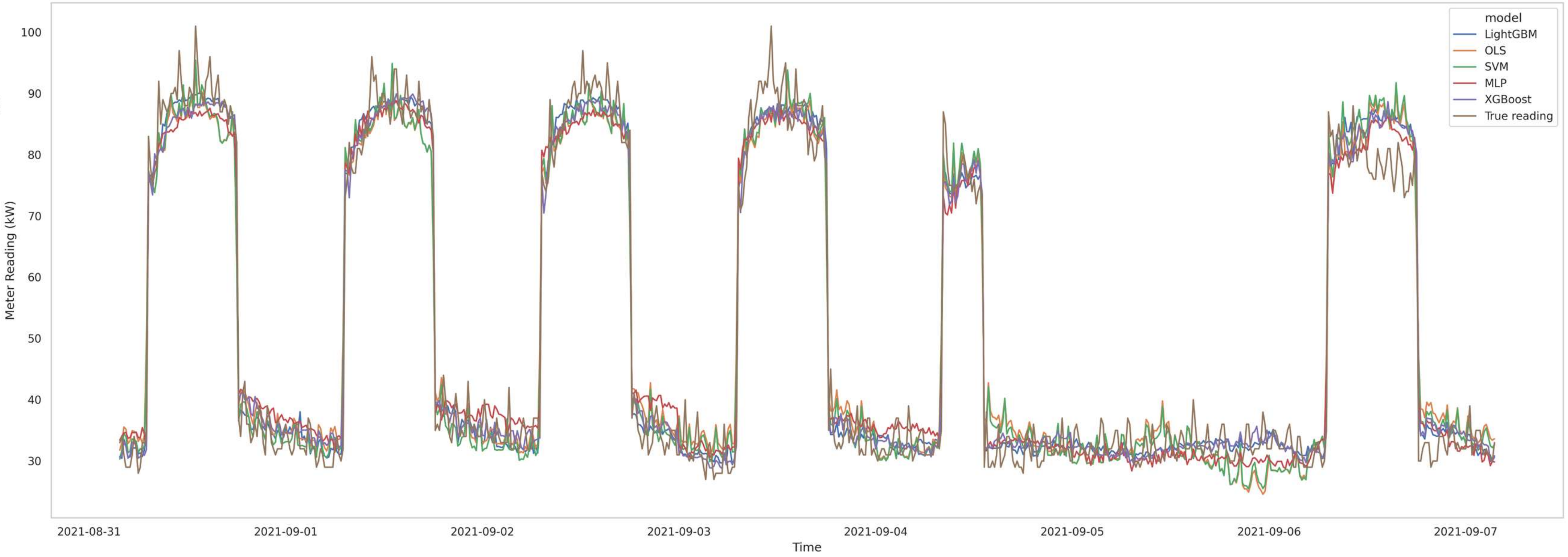
DateTime	320532:CHW_EV/13:AbsFlow_gpm	320532:CHW_EV/25:T1_F	320532:CHW_EV/26:T2_F	320532:CHW_EV/27:DeltaT_F
4/30/2022 19:48				
4/30/2022 19:48	120.6295	53.86308	54.06015	0.197077
4/30/2022 19:49	120.6295	53.97846	54.15708	0.178615
4/30/2022 19:49	140.3241	53.92308	54.14323	0.210923
4/30/2022 19:50	147.7096	53.51231	53.88939	0.377077
4/30/2022 19:50	146.4787	52.71846	53.22477	0.506308
4/30/2022 19:51	146.4787	52.24308	52.52785	0.284769
4/30/2022 19:51	146.4787	52.55692	52.66169	0.104769
4/30/2022 19:52	145.2477	53.00462	53.10939	0.104769
4/30/2022 19:52	148.325	53.31385	53.44169	0.127846
4/30/2022 19:53	137.2468	53.44308	53.63554	0.192462
4/30/2022 19:53	136.6313	53.51231	53.68631	0.174
4/30/2022 19:54	140.9395	53.68769	53.87554	0.187846
4/30/2022 19:54	148.9405	53.87692	54.05554	0.178615
4/30/2022 19:55	148.325	53.98769	54.16169	0.174
4/30/2022 19:55	147.7096	54.08923	54.29554	0.206308
4/30/2022 19:56	139.7086	53.62769	54.05554	0.427846
4/30/2022 19:56	129.8613	52.95846	53.40939	0.450923
4/30/2022 19:57	126.1686	52.53385	52.92939	0.395538
4/30/2022 19:57	118.1676	52.13231	52.54631	0.414
4/30/2022 19:58	117.5522	51.65692	52.14938	0.492462
4/30/2022 19:58	126.784	51.25077	51.59092	0.340154
4/30/2022 19:59	126.1686	51.72615	51.77092	0.044769
4/30/2022 19:59	124.9377	52.37692	52.37554	0.001385
4/30/2022 20:00	125.5531	52.88923	52.97554	0.086308
4/30/2022 20:00	125.5531	53.12461	53.31246	0.187846
4/30/2022 20:01	129.2459	53.24	53.43246	0.192462
4/30/2022 20:01	126.784	53.43385	53.61708	0.183231
4/30/2022 20:02	136.6313	53.66462	53.85246	0.187846

Model Selection

- Compare commonly used models for time series forecasting
  - Ordinary Least Squares (OLS)
  - Gradient Boosting Decision Trees (GBDT)
    - LightGBM
    - XGBoost
  - Support Vector Machines (SVM)
  - Multi-layer Perceptron (MLP)
- Others
  - Deep Learning
  - Temporal Fusion Transformers
  - ARIMA
  - Ensemble
- Hyperparameter tuning

- Mean Average Error (MAE) is primary metric

	MAE (KW)
OLS	4.85 ± 0.79
LightGBM	3.78 ± 0.78
SVM	4.66 ± 0.73
MLP	4.3 ± 0.89
XGBoost	3.82 ± 0.61
Naïve Baseline	5.51 ± 0.62
Ensemble	3.69 ± 0.67



Issues with Data

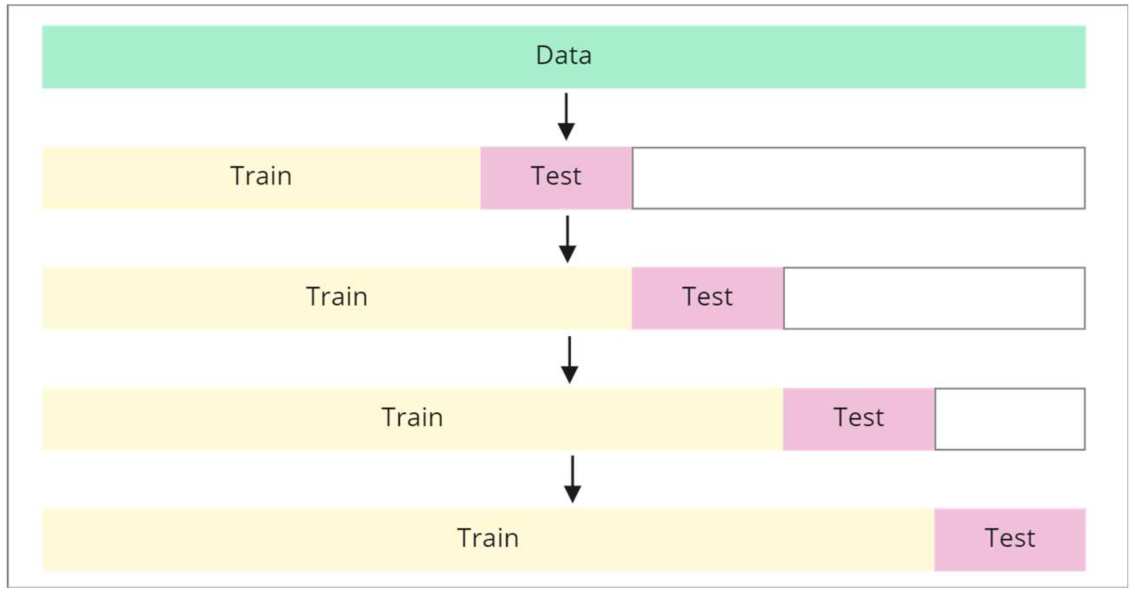
Spikes in MAE in particular training data are related to

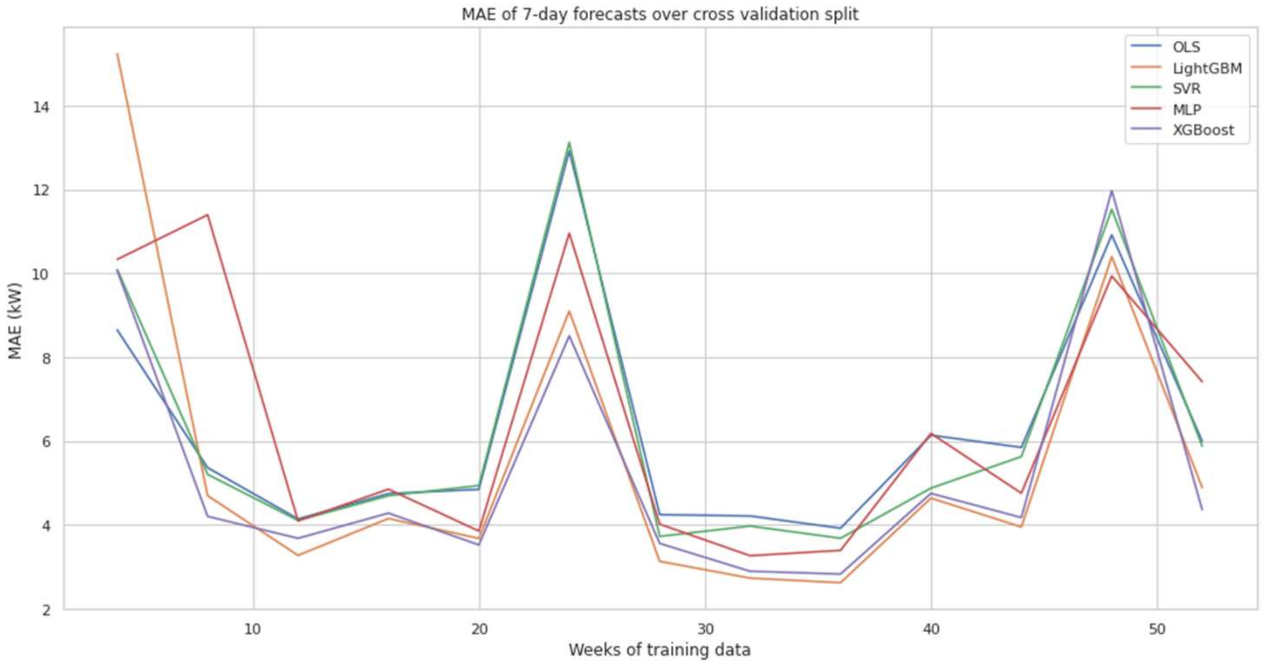
- 24 weeks: Electrical meter reading errors
- 40 weeks: Student returning to educational classes
- 48 weeks: Model is first seeing a holiday period

Solutions:

- Limit the use of prior electrical meter data as a feature
- Human-in-the-loop to update models when irregularities may occur

Modified cross validation split

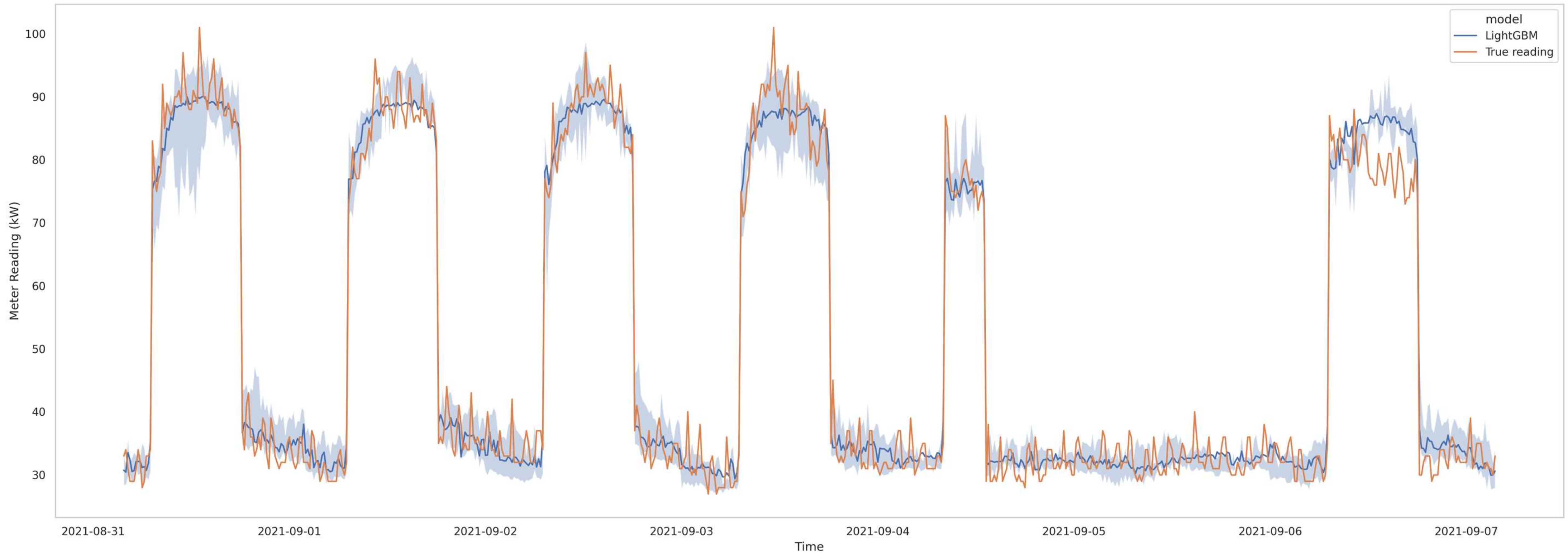




Predictions

- GBDT and pre-processing of data appear to perform well compared to other methods.
- Requires hyper-parameter tuning for best results.
- Similar findings by Miller et al.[2].

Example of prediction for unseen data



2. Miller, Clayton and Hao, Liu and Fu, Chun. 2022. "Gradient Boosting Machines and Careful Pre-Processing Work Best: ASHRAE Great Energy Predictor III Lessons Learned. https://doi.org/10.48550/arxiv.2202.02898. https://arxiv.org/abs/2202.02898.

General Lessons Learned

Data and Features

- Building operation and data quality is constantly changing. Need human-in-the-loop to ensure quality.
- The ability to estimate the impact of occupancy on building operation is key for building energy.
- Each building type may have different set of features, so need flexibility in approach and domain knowledge to facilitate feature reduction.

Modeling

- Evaluate the prediction accuracy requirements vs training efficiency for large-scale deployments.
- Combination of physics-based simulation and ML when domain knowledge is necessary or limited training data is available.
- Ensemble models may improve performance over single models.
- Consider switching between models as length of training data or prediction time horizon changes.

Questions?