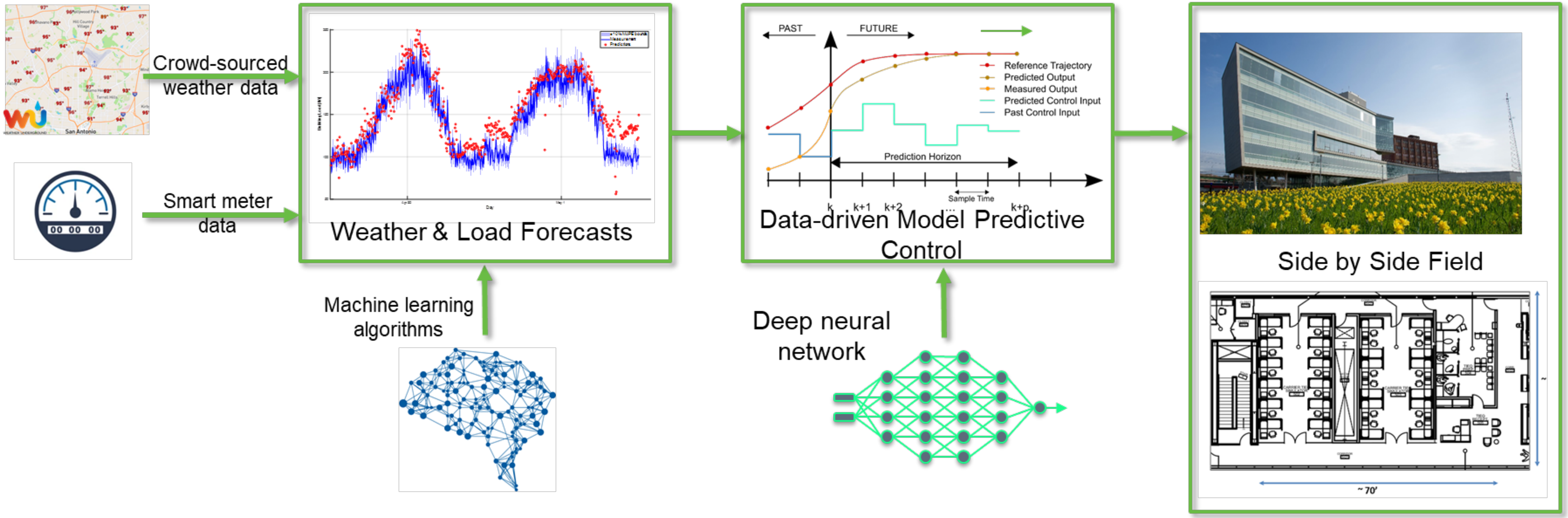
Spatial-Temporal Data-Driven Weather and Energy Forecasting for Improved Implementation of Advanced Building Controls



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Project Summary

Timeline:

Start date: 11/2018

Planned end date: 12/2021

Key Milestones

1. Data (setup and collect); 1/2019 – present)
2. Temperature forecasting method and study; 3/2020
3. Energy forecasting method and study: 9/2020
4. Energy saving analysis: 12/2021

Budget:

Total Project $ to Date:

- DOE: $750,000
- Cost Share: $0

Total Project $:

- DOE: $750,000
- Cost Share: $0

Key Partners:

Syracuse University
University of Texas at San Antonio

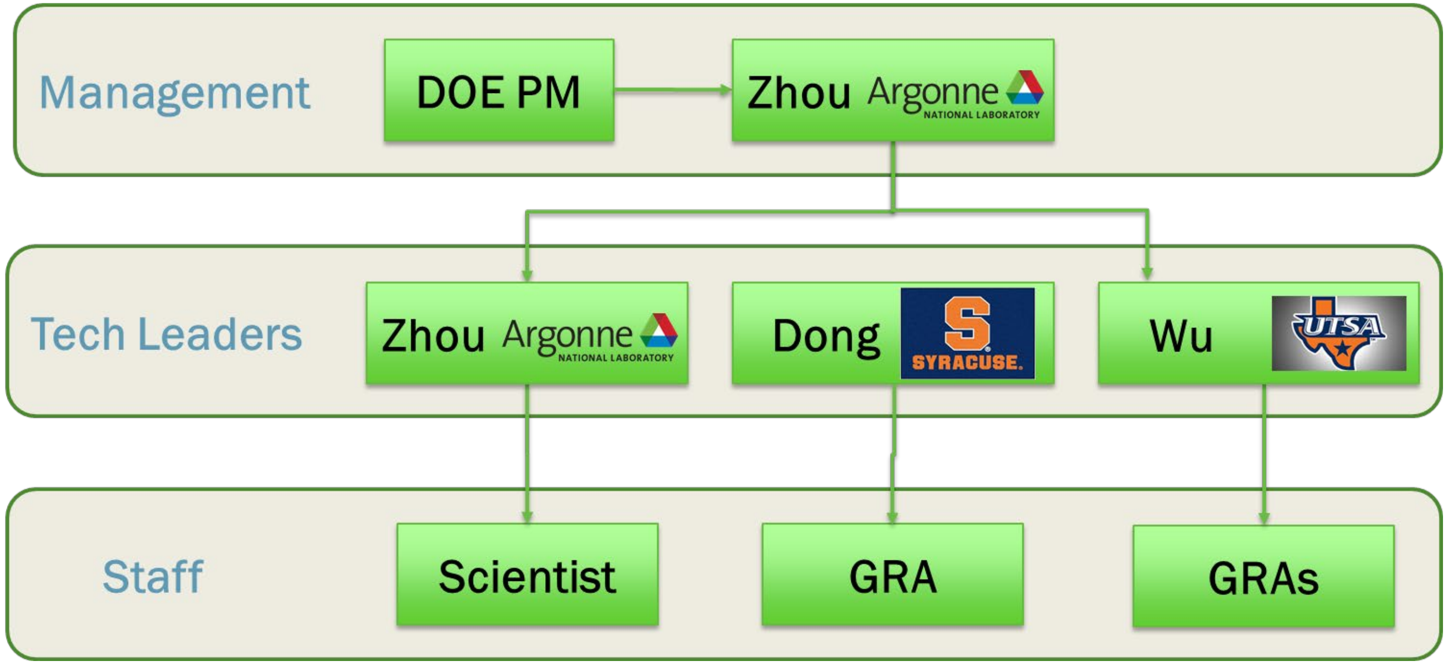
Project Outcome:

Data set, collected a weather data set from multiple private, public, and onsite sources over the whole project period.

Tools: developed a chain of models to provide accurate forecasts for onsite temperature and energy consumption by leveraging machine learning methods and spatial-temporal data in and around buildings.

Case study based analysis: Illustrate advanced forecasting tools can be leveraged as a supplement to improve building energy management in realistic application context. It will accelerate integration of renewable distributed energy resources and contribute to long-term de-carbonization goal.

Team



- **Zhi Zhou**: Principal computational scientist at Argonne National Laboratory, expert in energy forecasting[1][2], grid modeling[3][4], building grid integration[5].
- **Bing Dong**: Associate Professor of Mechanical and Aerospace Engineering at Syracuse University, expert in intelligent building controls [6][7].
- **Wenbo Wu**: Assistant Professor of Management Sciences and Statistics at University of Texas at San Antonio, expert in Statistical Inference [8][9], Machine Learning Theory and Application [10][11].

Challenge

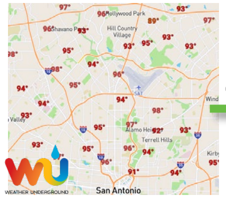
Problem Definition:

- Advanced building controls like MPC for buildings have been shown to achieve more than 30% energy savings in models and field tests. They also help accelerate de-carbonization in buildings with improved integration of distribution energy resources.
- But, MPC requires an accurate onsite short-term weather forecasting for future predictive control time horizon.
  - Most buildings lack onsite weather stations. Building operators largely rely on online/airport weather forecasting to operate building (e.g. set the chiller water temp set-point).
  - Micro-climates and urban heat island effects make local building weather very different from nearby airport
- Result: MPC is often fails to achieve predicted energy/carbon savings

Solutions:

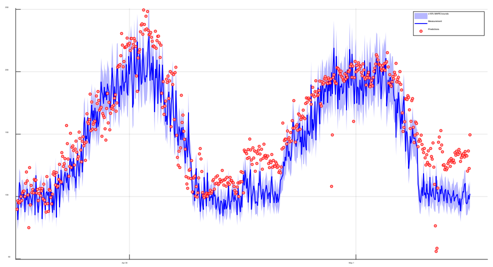
- Leverage data from multiple sources, especially **crowdsourcing data from private weather stations**;
- Develop advanced onsite weather forecasting algorithms for arbitrary locations within the regions covered by a PWS network
- Apply data-driven MPC for scalable building controls

Overall Project Approach



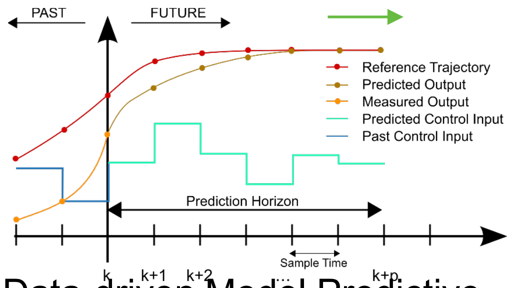
Crowd-sourced weather data

Smart meter data



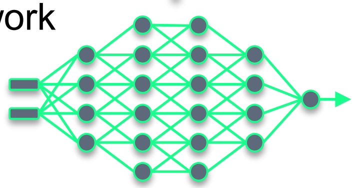
Weather & Load Forecasts

Machine learning algorithms

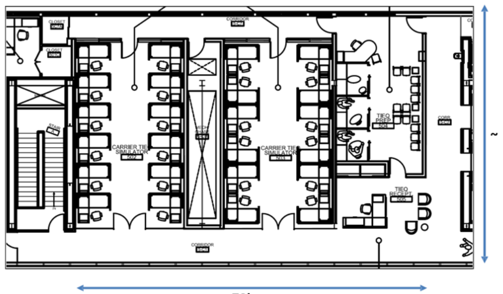


Data-driven Model Predictive Control

Deep neural network



Side by Side Field



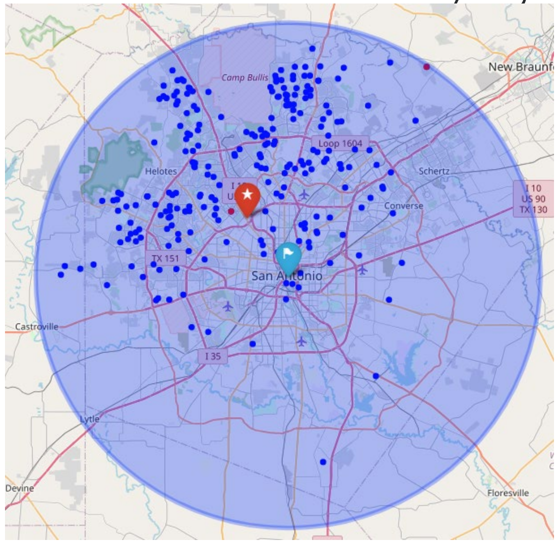
Using historical data from crowd-sourced personal weather stations as well as site-specific smart meters, advanced machine learning algorithms are trained to perform temperature and load forecasting. These algorithms are being validated using data from multiple buildings in different climate zones.

A deep neural network is developed, trained, and validated in order to predict building temperature response for control purposes. This data-driven building model replaces a traditional physics-based model in a model predictive control (MPC) scheme.

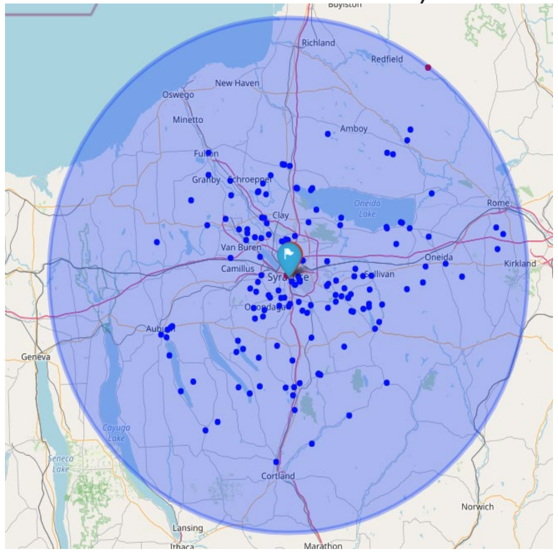
The forecasting algorithms and data-driven building MPC are implemented in a unique experimental facility. The facility features two identical spaces side-by-side, allowing direct evaluation of energy savings gained by this approach.

Approach: Data and sources

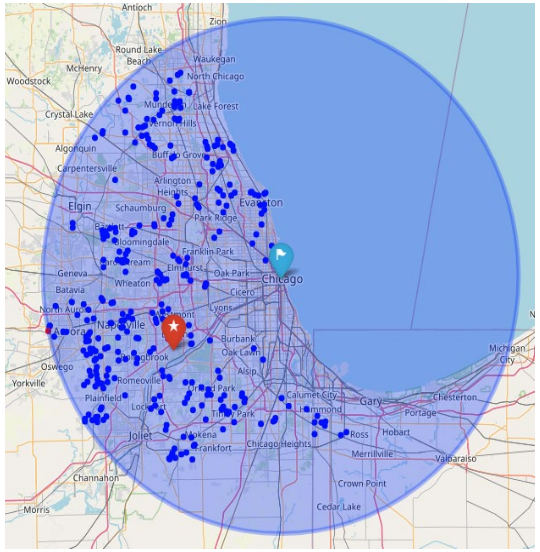
- **Weather data**
  - Sources:
    - Public weather stations (Airport)
    - Onsite weather sensors
    - Personal weather stations (Weather Underground)
      - Intra-hour resolution (5-min)
      - Comprehensive information: long/lat, temperature, humidity, solar irradiance, wind speed/direction, etc.
      - Data retrieved via API calls
      - Data reporting from PWSs is voluntary (no reporting/missing weather variables/missing data/asynchronization is more often)



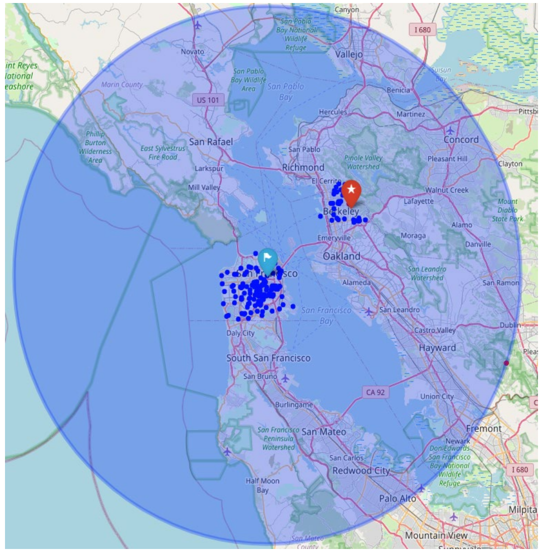
San Antonio, TX



Syracuse, NY



Chicago, IL



San Francisco, CA

Approach: Data and Sources

- **Building data**
  - Temperature and energy consumption

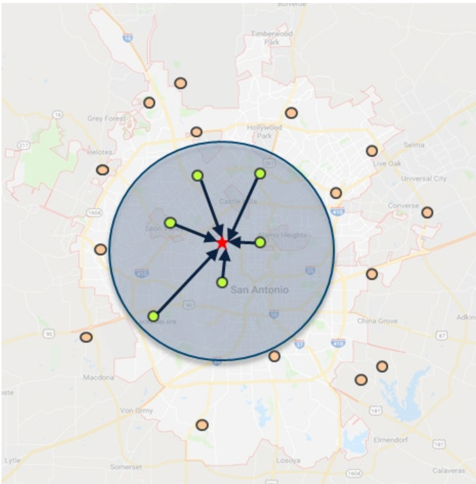
Building Name	City	Latitude	Longitude	Climate Zone	Building Type	Size (1000 ft^2)	Weather station #	Test Period	Terrain Characteristics
SATC	San Antonio, TX	29.5032	-98.5570	2A	Large office	78	344	March 2019 - Current	Relatively flat with rolling hills and wide river plains
COE	Syracuse, NY	43.0504	-76.1415	5A	Medium office/lab	12	208	March 2020 - Current	Rolling hills, flat plains, lakes and streams
ANL-201	Chicago, IL	41.7188	-87.9787	5A	Large office	203/176	521	March 2020 - Current	A relatively flat glacial plain
LBNL-59	San Francisco, CA	37.8764	-122.2527	3C	Large Office	112	235	Jan 2019 – Dec 2019	A hilly topography with the major elevations concentrating in the middle and a few hills on the peripheral

Approach: Temperature Forecasting

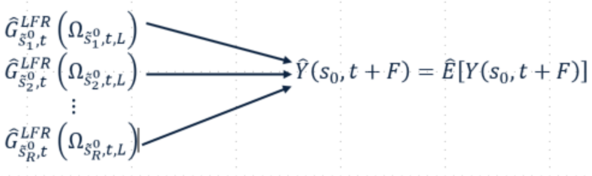
- Objective: design a two-stage modeling framework to enable onsite weather forecasting for arbitrary locations considering spatial temporal correlation

Stage 1: Local forecast model for target location S:

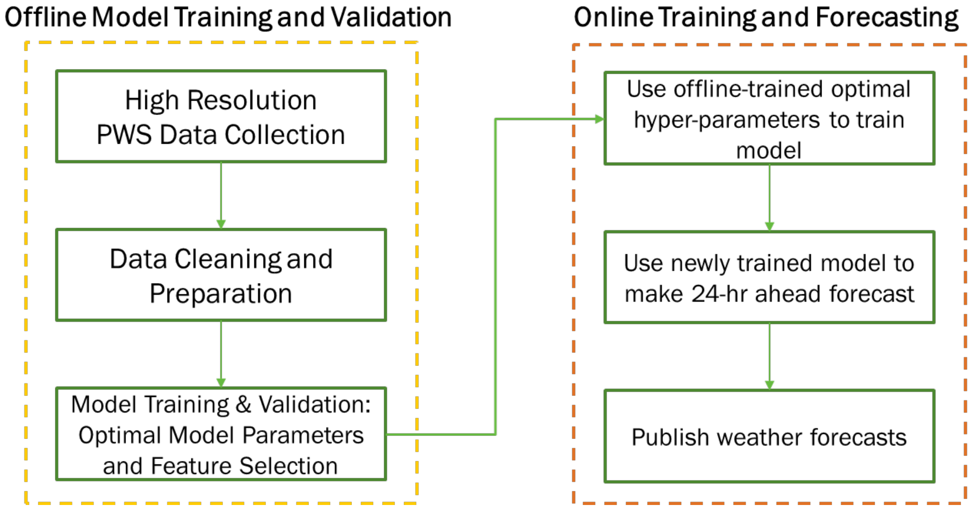
$$Y(s_0,t+F) = G^{LFR}_{s_i,t}\{\underbrace{Y(s_i,t),Y(s_i,t-1),\cdots,Y(s_i,t-L+1)}_{Endogenous\ \ Temporal},\underbrace{\mathbf{X}_{i,t},\mathbf{X}_{i,t-1},\cdots,\mathbf{X}_{i,t-L+1}}_{Exogenous\ \ Temporal},\underbrace{\delta^{\mathrm{lon}}(s_i,s_0),\delta^{\mathrm{lat}}(s_i,s_0)}_{Spatial}\} + \varepsilon_t$$



Stage 2: Integrated local forecast model for target location S.



- Advantages and characteristics:
  - Forecast at flexible temporal frequency
  - Non-parametric machine learning methods
  - Deliver forecast for arbitrary locations within the region covered by PWSs
  - Improved performance with explicit model on spatial-temporal correlation to take advantage of multiple sources of data



Approach: Load Forecasting

Objective: produce improved load forecasting with (1) advanced machine learning methods; (2) with improved temperature forecasts as input.

Preprocessing:
- Separate weekdays/weekends
- Split data into training/testing sets

Machine learning algorithms:
- Support vector regression
- Gaussian process regression
- Artificial neural network
- Gradient boosted regression
- Linear regression (baseline)

Hyperparameters tuned:
- Length of training period
- Data temporal resolution

Offline Training

Building historical data (weather, load)

Train machine learning algorithms

Pre-trained load forecasting algorithms

Online Prediction

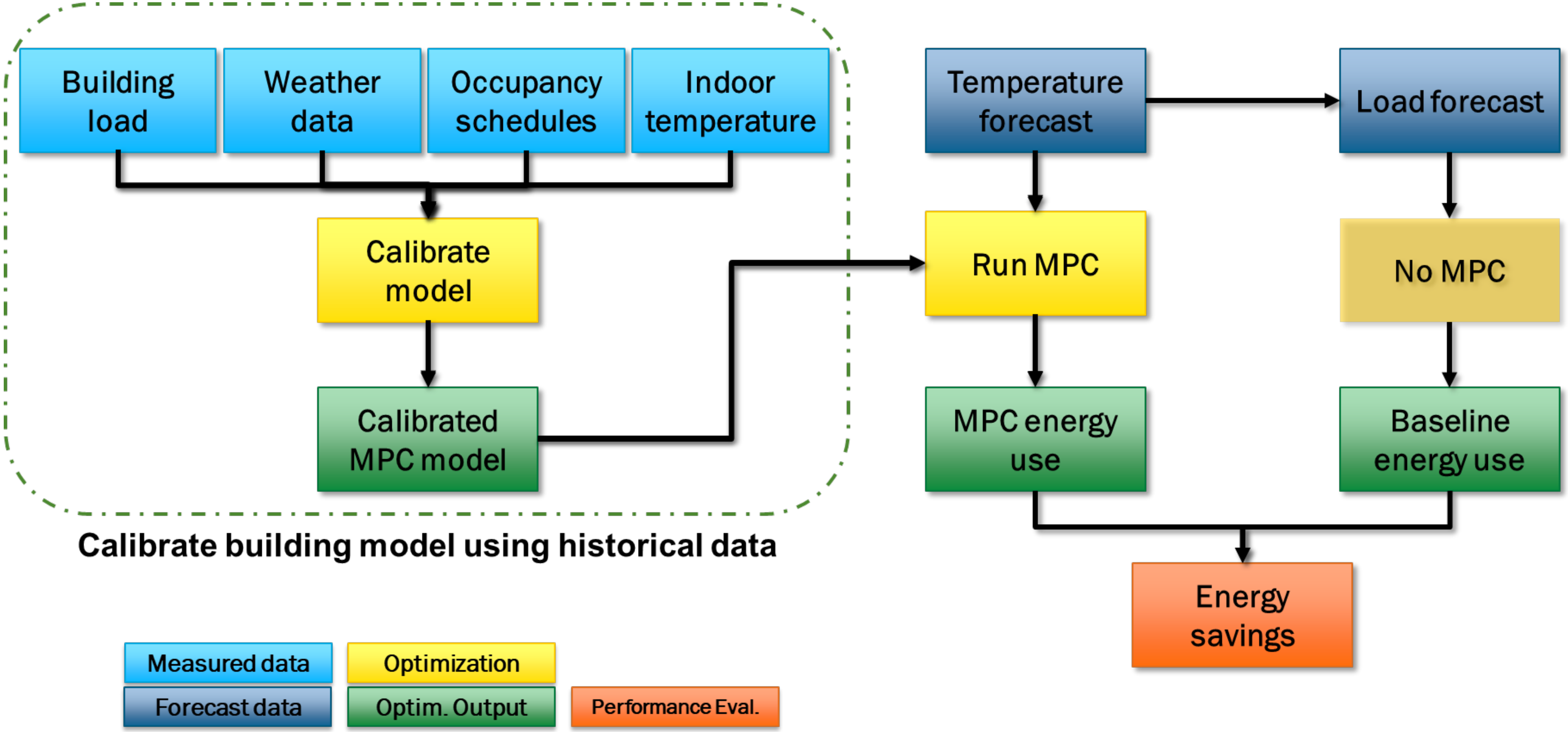
Local weather data

Pre-trained load forecasting algorithm

Building load prediction

Approach: MPC Energy Savings Evaluation

Objective: (1) Develop a data-driven building model to replace a traditional physics-based model in a model predictive control (MPC) scheme. (2) Evaluate impact of improved temperature and load forecasting on energy saving in a unique experimental facility. The facility features two identical spaces side-by-side, allowing direct evaluation of energy savings.



Impact

Societal impact:

At a target level of performance (5% saving in HVAC energy consumption by advanced MPC), a nationwide adoption of this tool will potentially reduce annual electricity usage by up to 250 billion kWh and save up to $25* billion.

Technology impact:

- Advance the knowledge of local building weather and load forecasting methodology and utilization of multiple data sources, including local private weather stations
- Improve the effectiveness of MPC with accurate and high-resolution local weather forecasts
- *Building operators* can better quantify the values that buildings flexible load, accelerate adoption of advanced building technologies and energy efficiency appliances, energy storage, and participate on grid ancillary services and realize the revenue in a full spectrum
- *Grid operators* have more accurate and finer resolution information about building loads to make smarter operational decision to improve grid economics and reliability to achieve its demand response program goals

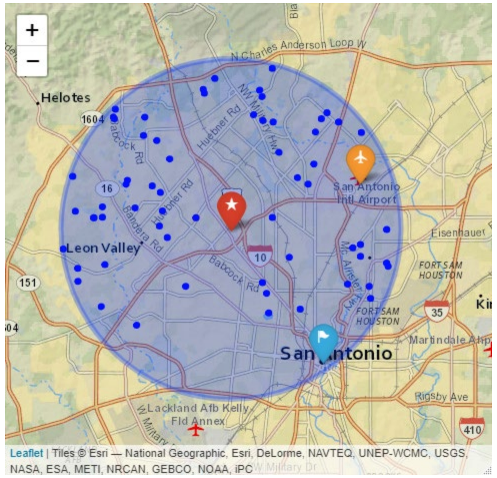
The impact can be achieved by making the model/tools publically available in the following ways:

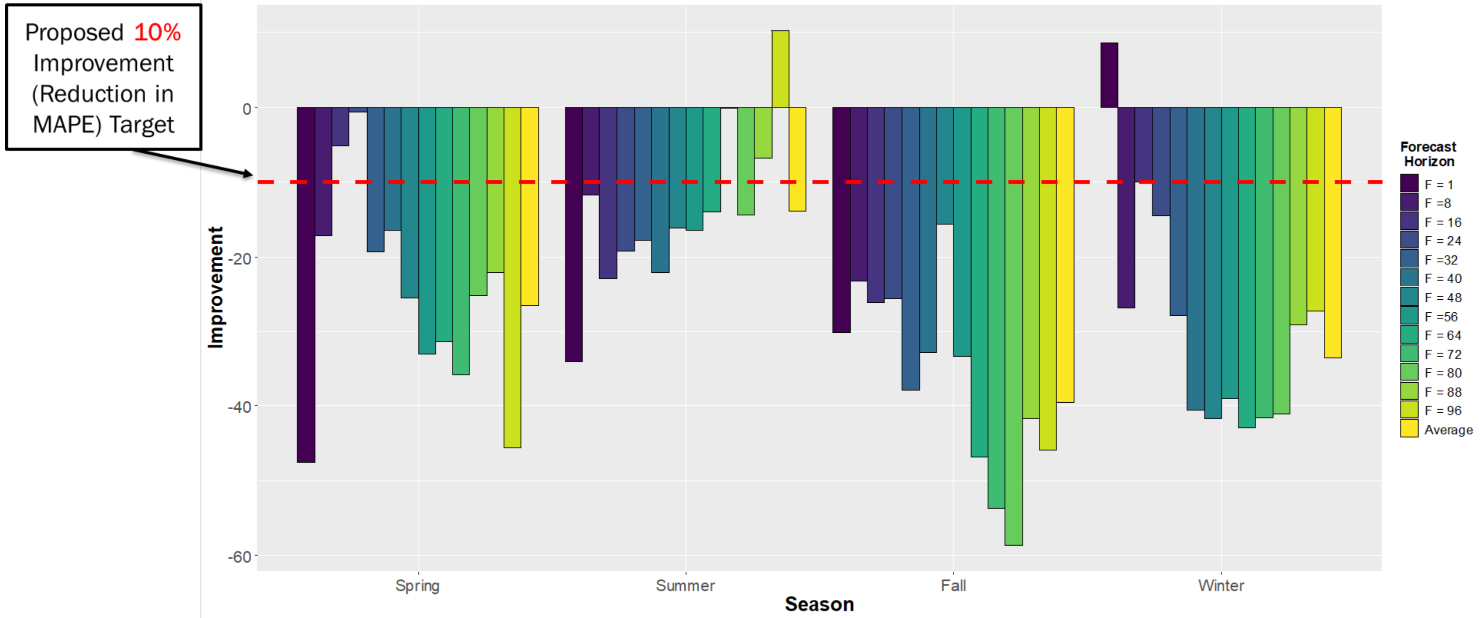
- The tools will be available for building managers, forecasting vendors, load aggregators, and utilities
- All codes will be uploaded into GitHub for future researchers
- Working with business through DOE commercialization program (e.g. SBIR)

* Assume an average electricity cost of 10c/kwh

Progress: Temp. Forecasting Model Development and Validation

- **Completed the temperature forecasting model development and validation**
- **Sample results and performance**
  - Target building and location: San Antonio Technology Center, San Antonio, TX

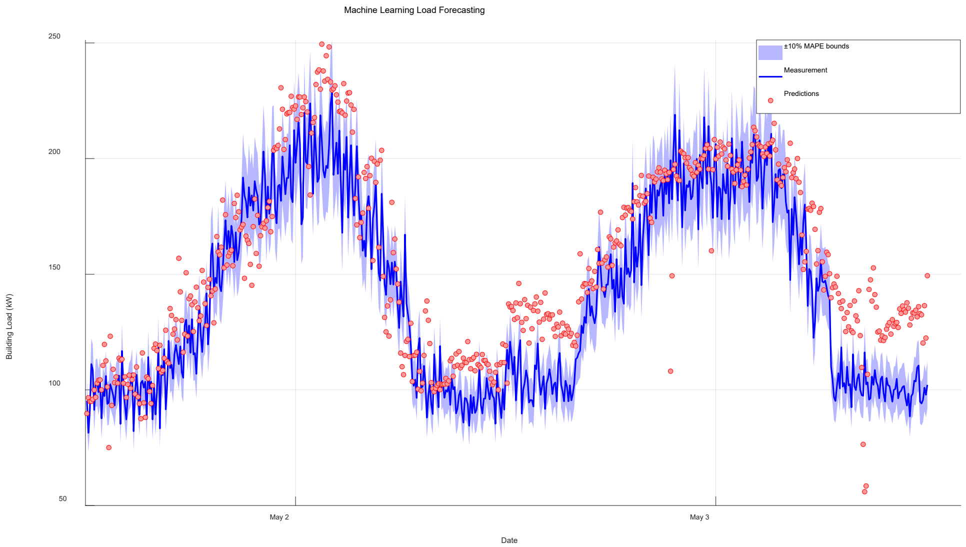


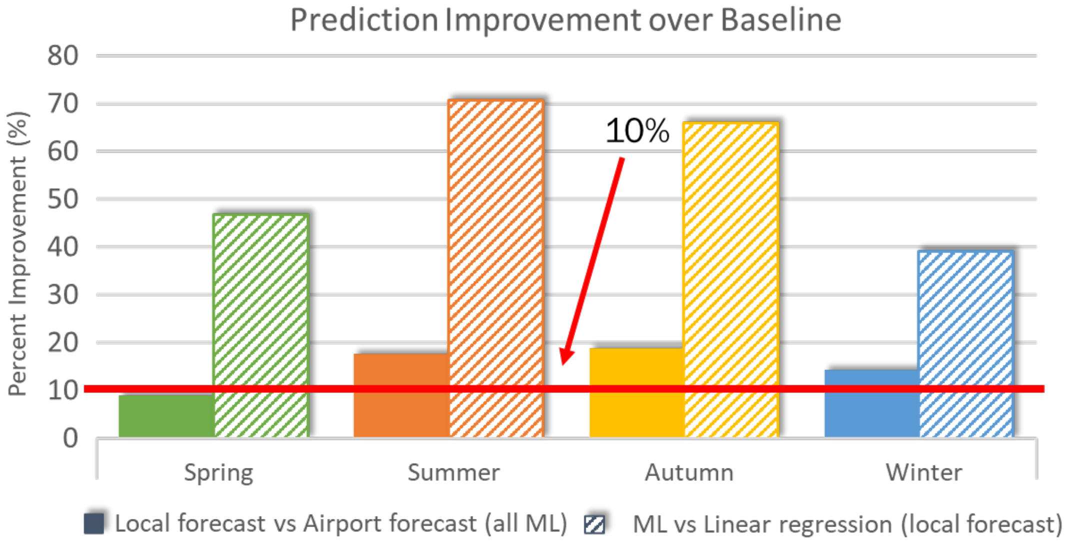


- **Lessons learned**
  - Advantage of local crowdsourcing data depends on (1) temperature distribution in the target area; (2) locations of PWSs in the target area
  - Correspondingly, forecasting performance improvement is impacted by: (1) data quality of crowdsourcing data; (2) temperature distribution in the area; (3) the number of PWSs and their relative positions to the target building
  - Temporal correlation is generally more dominant than spatial correlation, unless in a target area with significantly complicated temperature distribution, e.g. city heat island, high-rising building block

Progress: Load Forecasting Model Development and Validation

- **Completed the load forecasting model development and validation**
- **Sample results and performance**
  - Target building and location: San Antonio Technology Center, San Antonio, TX.
  - Sampled results:





- **Lessons learned**
  - Using machine learning (ML) methods to forecast building load significantly improves prediction performance compared to the industry standard baseline (linear regression)
  - Using temperature forecasts as input to load forecasts improves prediction performance compared to the baseline (airport temperature) – in most cases, the improvement is significant (>= 10%)
  - No method dominantly performs better than others in all application context (look-ahead time, seasons, etc.)

Progress: Data-driven MPC for Energy Saving Evaluation

- **Completed implementation of the data-driven MPC model, model tuning and validation is ongoing.**
- **Methodology and preliminary results**
  - Target building and location: COE building at Syracuse University, Syracuse, NY.
  - Critical components/procedures:

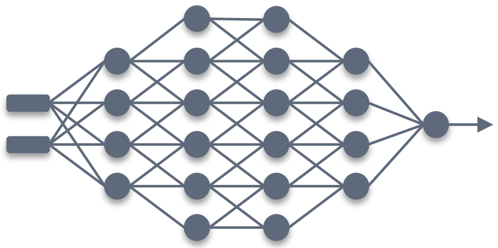
The trained DNN is inserted into an MPC control scheme as follows:

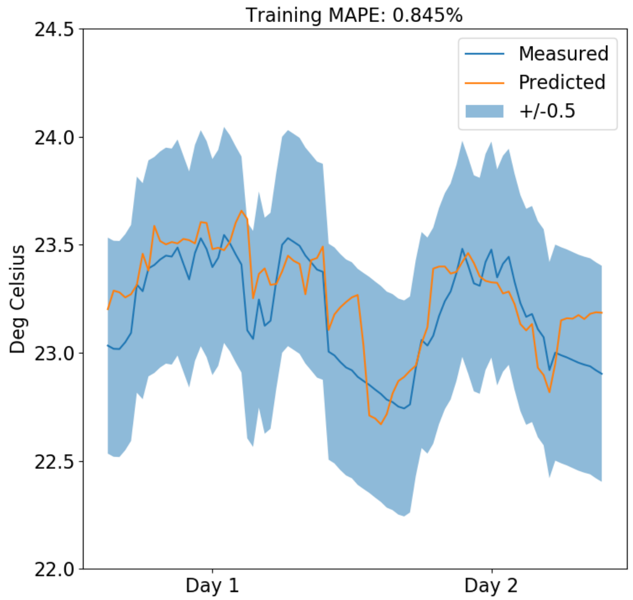
$$
\begin{aligned}
&\min_{x,u,\epsilon} && \sum_{k=1}^{N-1} J_k(x_{k+1}, u_k, \epsilon_k) = R u_k^2 + \lambda \epsilon_k^2 \\
&s.t. && x_{min} - \epsilon_k \leq \left(x_{k+1} = f_{DNN}(x_k, u_k, d_k)\right) \leq x_{max} + \epsilon_k \\
& && u_{min} \leq u_k \leq u_{max} \\
& && \epsilon_k \geq 0 \\
& && \forall k = 1, \ldots, N-1
\end{aligned}
$$

where N is the MPC prediction horizon and ϵ_k are slack variables to ensure feasibility at all times.

  - **Preliminary Results:** Validated room temperature profile resulting from data-driven control models by compared with measured room temperature profile
- **Lessons learned**
  - A relatively simple convex deep neural network ($\leq$ 6 hidden layers, $\leq$ 30 neurons per layer) can successfully predict indoor temperature to within 0.5 °C of the measured value

Data-driven building model: Convex Deep Neural Network





Stakeholder Engagement

- **The project is in its late stage (Year 3 of 3-year project)**
- **Stakeholder outreach**
  - Vendors: Outreached to commercial weather forecasting industry (e.g. IBM)
  - Building operators: Deployment and demonstration in the COE building at Syracuse University
  - Utilities: Outreached to local utilities (e.g. National grid)
  - Load aggregators/energy management solution providers: e.g. ConnectedSolutions
- **Other engagement**
  - Publications: one paper published [10], three in preparation.
  - Presentations:
    - Conference presentation: INFORMS 2020, 2021, IEA Annex 79 project on occupancy-centric building controls
    - Panel discussion: NSF Panel; 3rd Thermal and Fluids Engineering Conference (TFEC)

Remaining Project Work

- **Complete energy saving analysis**
  - Tune data-driven MPC (DDPC) model in further simulation studies
  - Implement DDPC in experimental setting

Phase	Room Type	Room 1	Room 2	Evaluation
1	Interior	No MPC	MPC, no forecast	Base savings from MPC vs scheduled control
2	Interior	MPC w/ forecast	MPC, no forecast	Savings from MPC with and without forecasting
3	Perimeter	MPC w/ forecast	MPC, no forecast	Savings from MPC with and without forecasting

  - Collect and analyze experimental results to evaluate energy saving potential.

- **Final project report**

- **Continuing dissemination and outreach**
  - Stakeholder outreach
  - Conference presentation
  - Open source release
  - Journal publications

Thank You

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Syracuse University
University of Texas at San Antonio

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References

1. Bessa, Ricardo J., V. Miranda, A. Botterud, Z. Zhou, and J. Wang. "Time-adaptive quantile-copula for wind power probabilistic forecasting." *Renewable Energy* 40, no. 1 (2012): 29-39.

2. Xie, Wei, Pu Zhang, Rong Chen, and Zhi Zhou. "A nonparametric Bayesian framework for short-term wind power probabilistic forecast." *IEEE Transactions on Power Systems* 34, no. 1 (2018): 371-379.

3. Park, Byungkwon, Zhi Zhou, Audun Botterud, and Prakash Thimmapuram. "Probabilistic zonal reserve requirements for improved energy management and deliverability with wind power uncertainty." *IEEE Transactions on Power Systems* 35, no. 6 (2020): 4324-4334.

4. Guo, Zhaomiao, Zhi Zhou, and Yan Zhou. "Impacts of integrating topology reconfiguration and vehicle-to-grid technologies on distribution system operation." *IEEE Transactions on Sustainable Energy* 11, no. 2 (2019): 1023-1032.

5. Zhou, Zhi, Fei Zhao, and Jianhui Wang. "Agent-based electricity market simulation with demand response from commercial buildings." *IEEE Transactions on Smart Grid* 2, no. 4 (2011): 580-588.

6. Pang, Z., Chen, Y., Zhang, J., O'Neill, Z., Cheng, H. and Dong, B., 2020. Nationwide HVAC energy-saving potential quantification for office buildings with occupant-centric controls in various climates. *Applied Energy*, 279, p.115727.

7. Dong, B. and Lam, K.P., 2014, February. *A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting*. In Building Simulation (Vol. 7, No. 1, pp. 89-106). Springer Berlin Heidelberg.

8. Wu, Wenbo, Bing Dong, Qi Ryan Wang, Meng Kong, Da Yan, Jingjing An, and Yapan Liu. "A novel mobility-based approach to derive urban-scale building occupant profiles and analyze impacts on building energy consumption." *Applied Energy* 278 (2020): 115656.

9. Luo, Wei, Wenbo Wu, and Yeying Zhu. "Learning heterogeneity in causal inference using sufficient dimension reduction." *Journal of Causal Inference* 7, no. 1 (2019).

10. Wu, Wenbo, Jiaqi Chen, Zhibin Yang, and Michael L. Tindall. "A cross-sectional machine learning approach for hedge fund return prediction and selection." *Management Science* (2020).

11. Dong, Bing, Reisa Widjaja, Wenbo Wu, and Zhi Zhou. "Review of onsite temperature and solar forecasting models to enable better building design and operations." In *Building Simulation*, pp. 1-23. Tsinghua University Press, 2021.

Project Budget

Project Budget: $750,000 (DOE) for three years

Variances: No cost extension to 12/31/2021 due to delay of funding at the beginning of fiscal year 2021.

Cost to Date: $600,000 spent by 6/30/2021
Additional Funding: N/A

Budget History					
11/2018 – FY 2019 (past)		FY 2020 (past)		FY 2021 – 12/2021 (planned)	
DOE	Cost-share	DOE	Cost-share	DOE	Cost-share
$250,000	0	$250,000	0	$250,000	0

Project Plan and Schedule

Project Schedule												
Project Start: 11/6/2018	Completed Work											
Projected End: 12/31/2021	Active Task (in progress work)											
	Milestone/Deliverable (Originally Planned)											
	Milestone/Deliverable (Actual)											
	FY2019				FY2020				FY2021			
Task	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Past Work												
Task 1: Complete data collection and cleaning for WU and airport weather data nearby the selected building												
Task 1: Complete literature review of current state-of-the art short-term weather forecasting methods												
Task 1: Complete development of machine learning methods on temperature forecasting												
Task 1: Complete development of new weather forecasts with uncertainties												
Task 1: Develop and implement the new uncertainty representation methods												
Task 2: Complete testing existing industry baseline/benchmark model for weather and energy forecasting												
Task 2: Complete testing and validation of new weather forecasting algorithms for buildings of selected cities across the U.S. and climate zones												
Task 2: Complete testing and validation of new energy forecasting algorithms for buildings of selected cities across the U.S. and climate zones												
Task 3: Complete required building level data collection for weather and energy forecasting and preparation for implementing MPC at the building level												
Current/Future Work												
Task 2: Prototype crowd source software to provide onsite weather and energy forecasting												
Task 3: Complete implementation of baseline case without new weather forecasting algorithm												
Task 3: Complete implementation and validation of new weather and energy forecasting methodologies for MPC in selected building												
Task 4: Final project report												

Delayed due to late FY2021 funding arrival