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

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

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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

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• 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.
• **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
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)
## Approach: Data and Sources

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

<table>
<thead>
<tr>
<th>Building Name</th>
<th>City</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Climate Zone</th>
<th>Building Type</th>
<th>Size (1000 ft²)</th>
<th>Weather station #</th>
<th>Test Period</th>
<th>Terrain Characteristics</th>
</tr>
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<tbody>
<tr>
<td>SATC</td>
<td>San Antonio, TX</td>
<td>29.5032</td>
<td>-98.5570</td>
<td>2A</td>
<td>Large office</td>
<td>78</td>
<td>344</td>
<td>March 2019 - Current</td>
<td>Relatively flat with rolling hills and wide river plains</td>
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<tr>
<td>COE</td>
<td>Syracuse, NY</td>
<td>43.0504</td>
<td>-76.1415</td>
<td>5A</td>
<td>Medium office/lab</td>
<td>12</td>
<td>208</td>
<td>March 2020 - Current</td>
<td>Rolling hills, flat plains, lakes and streams</td>
</tr>
<tr>
<td>ANL-201</td>
<td>Chicago, IL</td>
<td>41.7188</td>
<td>-87.9787</td>
<td>5A</td>
<td>Large office</td>
<td>203/176</td>
<td>521</td>
<td>March 2020 - Current</td>
<td>A relatively flat glacial plain</td>
</tr>
<tr>
<td>LBNL-59</td>
<td>San Francisco, CA</td>
<td>37.8764</td>
<td>-122.2527</td>
<td>3C</td>
<td>Large Office</td>
<td>112</td>
<td>235</td>
<td>Jan 2019 – Dec 2019</td>
<td>A hilly topography with the major elevations concentrating in the middle and a few hills on the peripheral</td>
</tr>
</tbody>
</table>
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:

\[ Y(s_0, t + F) = G_{s,t}^{LFR}(Y(s_t, t), Y(s_t, t - 1), \ldots, Y(s_t, t - L + 1), X_{i,t}, X_{i,t-1}, \ldots, X_{i,t-L+1}, \delta^{lon}(s_t, s_0), \delta^{lat}(s_t, s_0)) + \varepsilon_t \]

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.
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:

    \[
    \min_{x,u,\epsilon} \sum_{k=1}^{N-1} J_k(x_{k+1}, u_k, \epsilon_k) = Ru_k^2 + \lambda \epsilon_k^2 \\
    \text{s.t.} \quad x_{\min} - \epsilon_k \leq (x_{k+1} = f_{DNN}(x_k, u_k, d_k)) \leq x_{\max} + \epsilon_k \\
    u_{\min} \leq u_k \leq u_{\max} \\
    \epsilon_k \geq 0 \\
    \forall k = 1, \ldots, N - 1
    \]

    where \( N \) is the MPC prediction horizon and \( \epsilon_k \) 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
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

- **Final project report**

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

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<thead>
<tr>
<th>Phase</th>
<th>Room Type</th>
<th>Room 1</th>
<th>Room 2</th>
<th>Evaluation</th>
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<tbody>
<tr>
<td>1</td>
<td>Interior</td>
<td>No MPC</td>
<td>MPC, no forecast</td>
<td>Base savings from MPC vs scheduled control</td>
</tr>
<tr>
<td>2</td>
<td>Interior</td>
<td>MPC w/ forecast</td>
<td>MPC, no forecast</td>
<td>Savings from MPC with and without forecasting</td>
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<tr>
<td>3</td>
<td>Perimeter</td>
<td>MPC w/ forecast</td>
<td>MPC, no forecast</td>
<td>Savings from MPC with and without forecasting</td>
</tr>
</tbody>
</table>

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

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University of Texas at San Antonio

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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

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<thead>
<tr>
<th>Budget History</th>
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<tbody>
<tr>
<td>DOE</td>
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<td>$250,000</td>
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# Project Plan and Schedule

## Project Schedule

**Project Start:** 11/6/2018  
**Projected End:** 12/31/2021

<table>
<thead>
<tr>
<th>Task</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q1</th>
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<th>Q4</th>
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<tbody>
<tr>
<td><strong>Past Work</strong></td>
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<td>Task 1: Complete data collection and cleaning for WU and airport weather data nearby the selected building</td>
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<td>Task 1: Complete literature review of current state-of-the art short-term weather forecasting methods</td>
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<td>Task 1: Complete development of machine learning methods on temperature forecasting</td>
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<td>Task 1: Complete development of new weather forecasts with uncertainties</td>
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<td>Task 1: Develop and implement the new uncertainty representation methods</td>
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<td>Task 2: Complete testing existing industry baseline/benchmark model for weather and energy forecasting</td>
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<td>Task 2: Complete testing and validation of new weather forecasting algorithms for buildings of selected cities across the U.S. and climate zones</td>
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<td>Task 3: Complete required building level data collection for weather and energy forecasting and preparation for implementing MPC at the building level</td>
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<td><strong>Current/Future Work</strong></td>
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<tr>
<td>Task 2: Prototype crowd source software to provide onsite weather and energy forecasting</td>
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<tr>
<td>Task 3: Complete implementation of baseline case without new weather forecasting algorithm</td>
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<tr>
<td>Task 3: Complete implementation and validation of new weather and energy forecasting methodologies for MPC in selected building</td>
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<td>Task 4: Final project report</td>
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### Delayed due to late FY2021 funding arrival