# **FlexAssist**: A risk-based framework for dynamic prioritization of flexible building loads

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BTO Peer Review, August 2021

# Project summary

- **Timeline:**
  - Start date: 10/01/2018; planned end date: 09/30/2021
  - Key milestones:
    - Initial surrogate modeling and discrete choice experiments complete (03/2020)
    - Initial demonstration of integrated recommender algorithm (07/2020)
    - Final testing and benchmarking of integrated recommender algorithm complete (09/2021)
- **Budget:**
  - Total project funds: $1.6M (DOE, FY19-21); no cost share
- **Key partners:** OvationMR
- **Project outcomes:**
  - Recommender engine (published as a Python module on GitHub) tested across several simulated commercial demand response (DR) scenarios
  - Suite of surrogate models for predicting likely changes in building demand and temperature under candidate DR strategies in multiple building contexts, developed based on synthetic data from large scale EnergyPlus simulations
  - Weightings of candidate load flexibility choices, developed based on large scale discrete choice experiments with people who operate and work in office and retail buildings

# Project team

## Overall project design and management

Jared Langevin (PI)
Research Scientist

## Technical advisors

Mary Ann Piette
Division Director

Tianzhen Hong
Staff Scientist, Deputy Head

## Surrogate modeling of building demand and services

## Testing/integration

Na Luo
Sc. Eng. Associate

Handi C. Putra
Postdoctoral Fellow

Sang Hoon Lee
Sc. Eng. Associate

## Discrete choice modeling and data collection

Margaret Taylor,
Research Scientist

Jeff Deason,
Program Manager

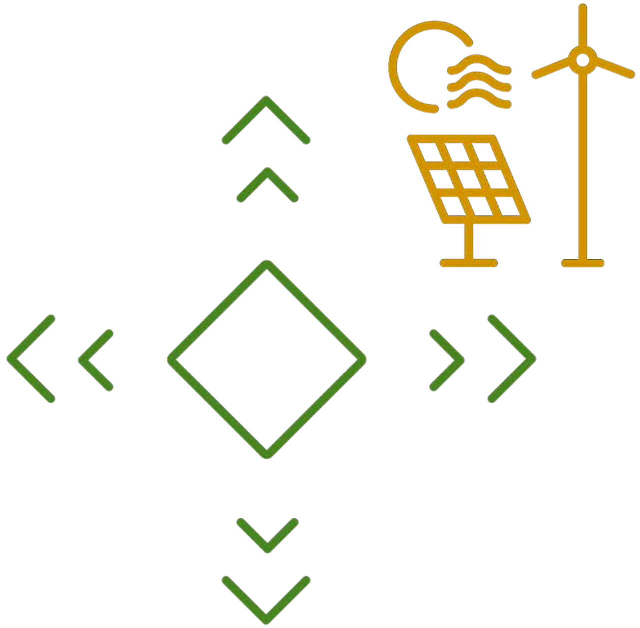
Jingjing Zhang,
Project Scientist

Hung-Chia Yang
Sc. Eng. Associate

Hassan Obeid
Ph.D. Candidate

Sarah Price
Research Associate

# **Challenge**: Commercial demand response (DR) cannot develop into a broad grid resource without building operator buy-in



Greater demand-side flexibility will aid the variable renewable energy transition, but will likely require more frequent and longer DR events in buildings

Building operators are concerned about service interruptions, loss of comfort, and employee impacts

Traditional DR programs do not address these operational risks, which would likely grow under future DR programs

# **Solution**: We develop a tool to inform next-gen DR response that is risk-aware, adaptive, and driven by operator preferences

**Status quo: Static, pre-defined response to infrequent DR calls from the grid**

Design/test pre-defined strategy for DR call response

Receive advance notification of DR event

Respond to DR call using pre-defined strategy

Receive payments for standby capacity and energy reductions

**Primary product:** Recommender engine (published as a Python module on GitHub) tested across several simulated commercial DR scenarios

**FlexAssist: Adaptive, risk-aware response to frequent DR calls**

Design/test pre-defined strategy for DR call response

Receive advance notification of DR event

FlexAssist recommends adjustment to default strategy (if warranted)

Respond to DR call using best available strategy

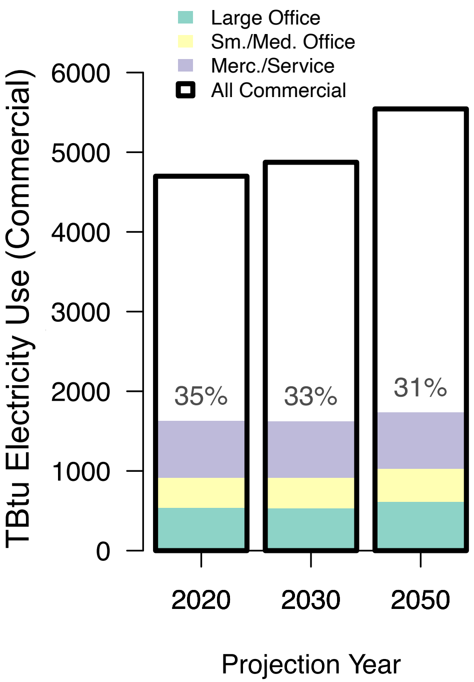
Receive payments for standby capacity and energy reductions

Adjust recommendation engine to reflect new event data

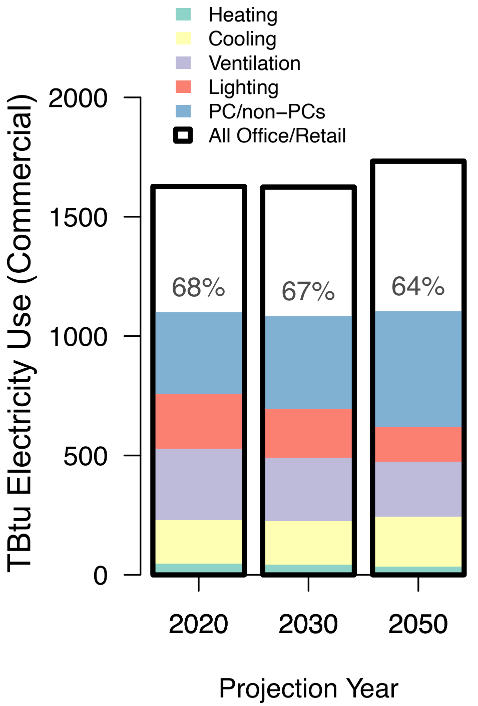
# **Impact**: Empowers end use customers in heavy-hitting segments of the building load flexibility market

- **Develops decision support tools to encourage flexible load adjustments with large energy/demand impacts:**
  - Focus on office/retail contexts, which comprise ~1/3 of all commercial electricity use
  - Focus on HVAC, lighting, and plug loads, which comprise ~2/3 of all office/retail electricity use
- **Directly addresses multiple key action items identified in BTO's National Roadmap for Grid-Interactive Efficient Buildings and goals for the Building Controls sub-program:**
  - Analyze user perceptions of demand flexibility value
  - Quantify user preferences for building service levels
  - Evaluate relationship between prices/load flexibility
  - Achieve economic worker comfort

**Office/retail portion of total commercial electricity**




**HVAC/lighting/plug loads portion of total office/retail electricity**




Source: EIA 2019 Annual Energy Outlook

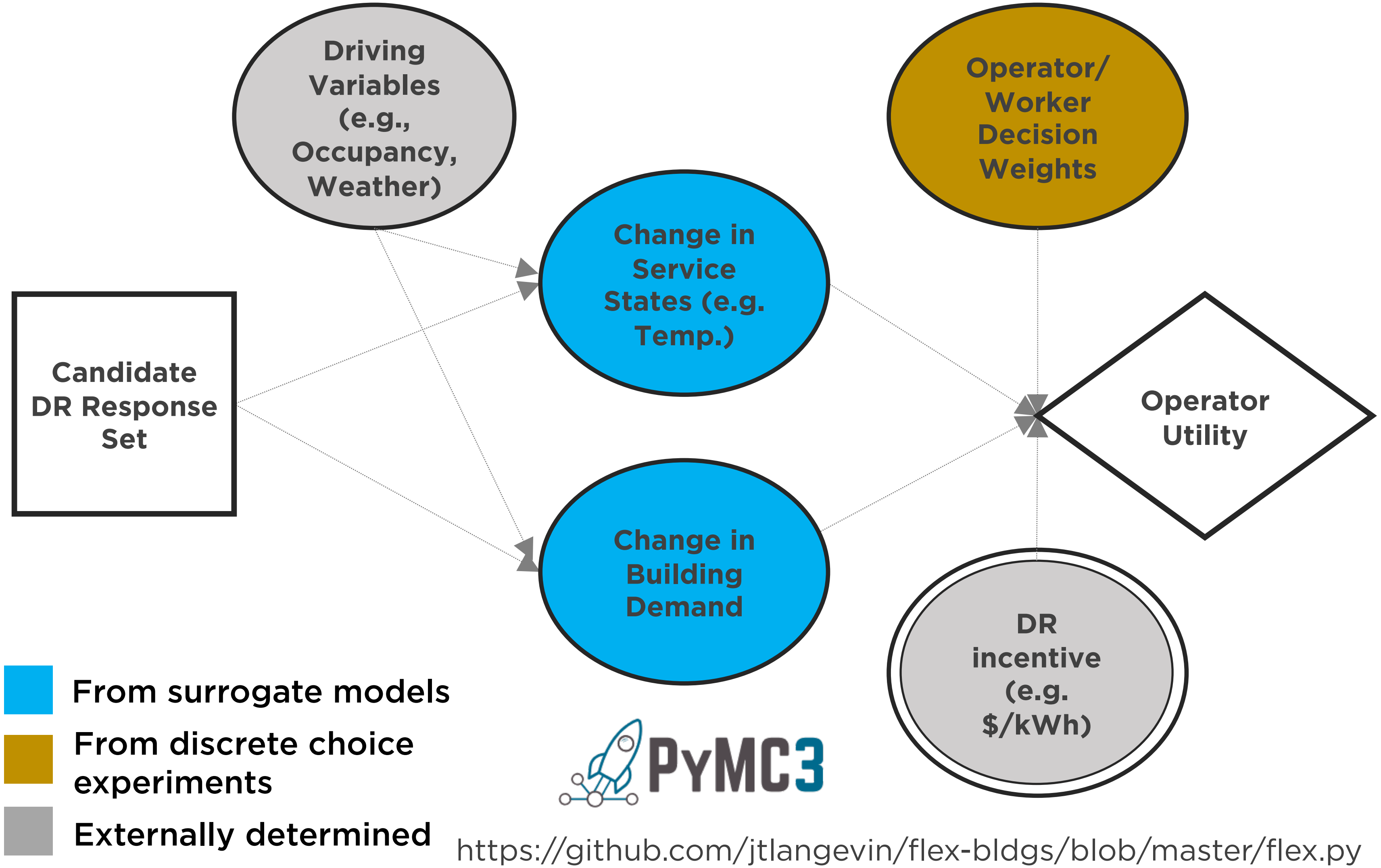
# **Approach:** FlexAssist leverages a probabilistic decision network that integrates a risk-benefit tradeoff with operator preferences

**The decision network is Bayesian, meaning it:**

- is probabilistic,
- incorporates prior expectations about model parameters, and
- enables parameter updating w/ new evidence

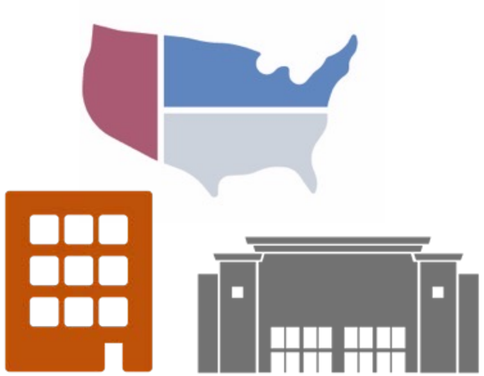
**Existing approaches to modeling demand flexibility strategies:**

- do not address risk/uncertainty,
- are not easily adaptable to real building settings, and
- only implicitly account for operator/occupant preferences (at best)

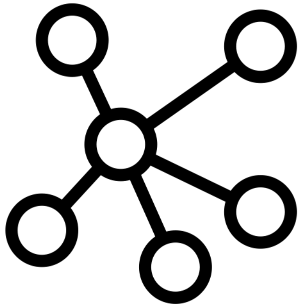



https://github.com/jtlangevin/flex-bldgs/blob/master/flex.py

# **Approach**: Surrogate models predict changes in core building services and electricity demand under dynamic conditions



$$y = XB + \epsilon$$



1. Define DR measures of HVAC, lighting, plug loads in EnergyPlus/OpenStudio

2. Simulate across all climates, building types, and vintages of interest

3. Compile results into synthetic database covering simulated energy and service outcomes

4. Use synthetic data to develop Bayesian surrogate models of building services and energy demand

5. Integrate surrogate models into operator decision network

# **Approach**: Discrete choice experiments elicit load adjustment valuations by building operators & workers

**Decision weights**

- Discrete choice experiments (DCEs) about the building condition outcomes of load adjustments during DR events provide the Bayesian priors for the decision weights in FlexAssist
- We implement DCEs with people who operate and work in office and retail buildings (“Operators” and “Workers,” respectively)

| DISCRETE CHOICE EXPERIMENT (DCE) | ALTERNATIVES A | ALTERNATIVES B |
|---|---|---|
| ATTRIBUTES: Economic benefit | $2,000 | $5,000 |
| ATTRIBUTES: Pre-cooling (2 hours) | 3°F colder | 2°F colder |
| ATTRIBUTES: Increased temperature | 2°F hotter | 1°F hotter |
| ATTRIBUTES: Reduced artificial lighting | 15% | 30% |

LEVELS

**RESPONDENT OCCUPATION**

OPERATORS:
- Role in building operations, demand response experience

WORKERS:
- Work schedule

**CHOOSE A BUILDING**

OPERATORS & WORKERS:
- Office or Retail building
- Special building loads
- Location
- Size
- Vintage

**INSIDE THE BUILDING**

OPERATORS:
- Technology details, presence of personal fans/space heaters, summer & winter bills

WORKERS:
- Workspace location, conditions, use of computers & control options, organization finance

**DCE 1 – CURRENT SUMMER**

Hot Afternoon

Choose A or B

8x

1/2 Sample

**DCE 2 – 2030 SUMMER**

Hot Afternoon

Choose A or B

8x

1/2 Sample

**DCE 2 – 2030 WINTER**

Cold @6-9 am - Office

Cold @ 5-8 pm - Retail

Choose A or B

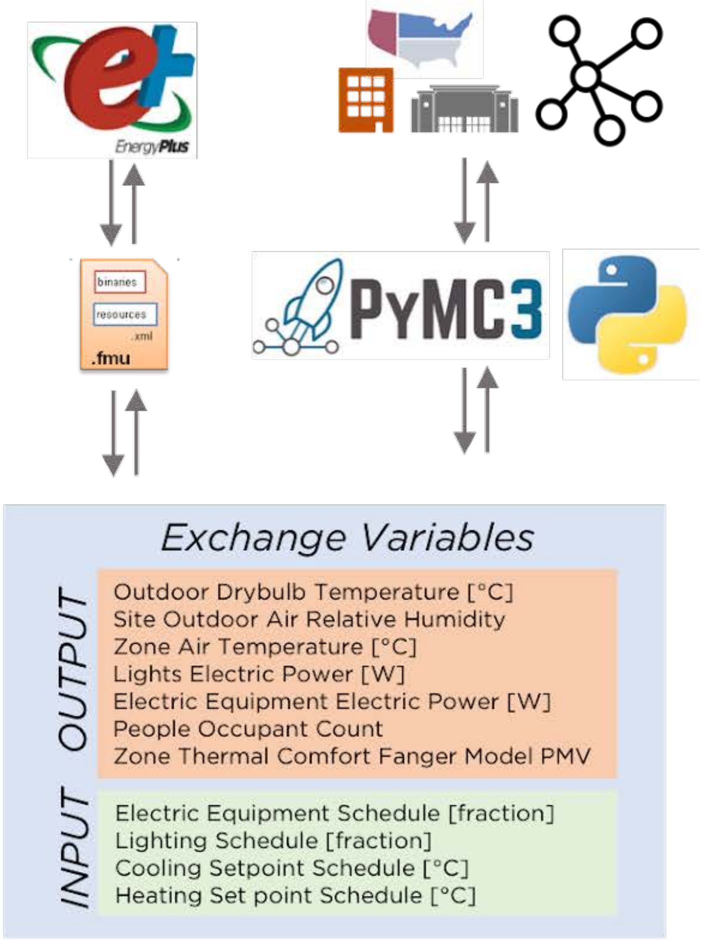
8x

**10 years from now, the building:**
- Is more controllable
- Has electric heat (winter DCE)

LEGEND

| | |
|---|---|
| Survey sections | Specific to office building |
| Specific to Operators | Specific to retail building |
| Specific to Workers | |

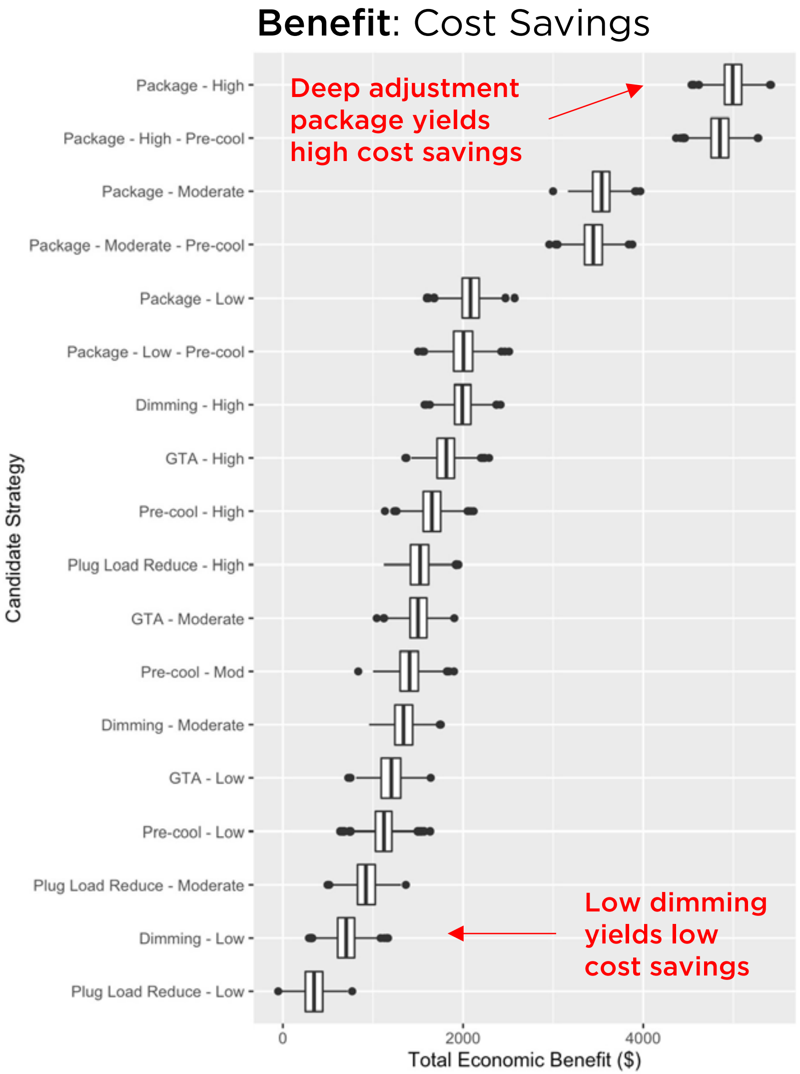
# **Approach:** EnergyPlus and Python are coupled to demonstrate the integrated tool's performance across several dimensions

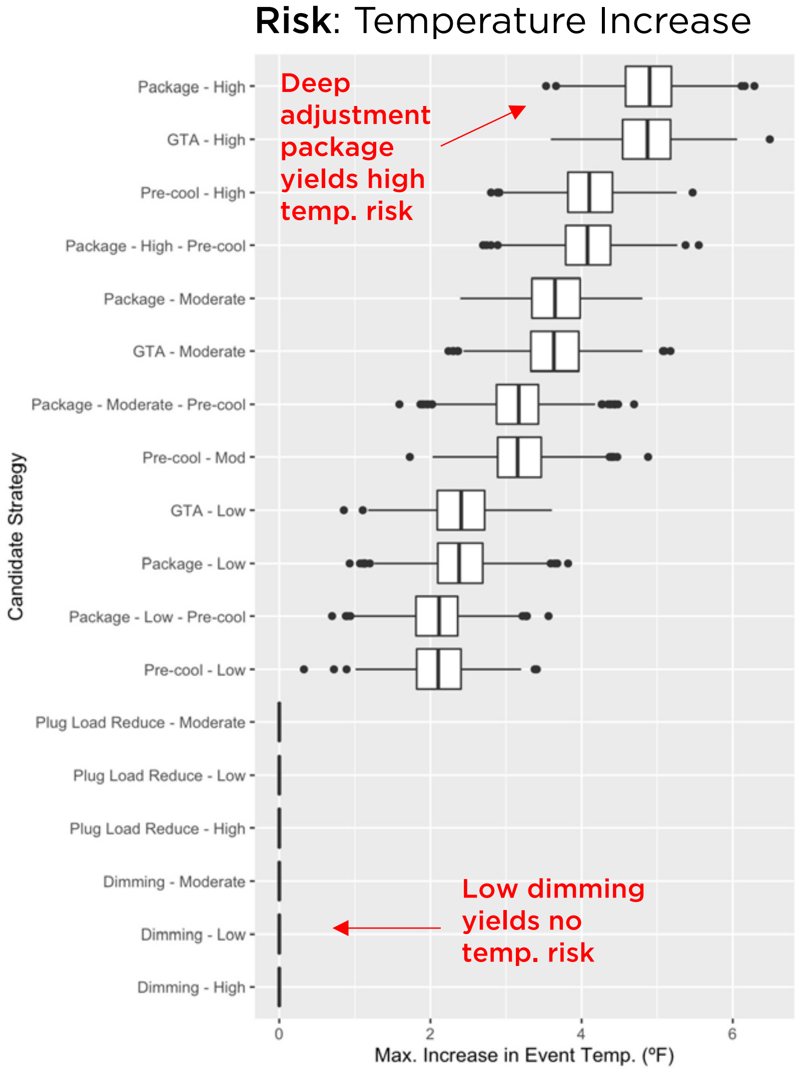


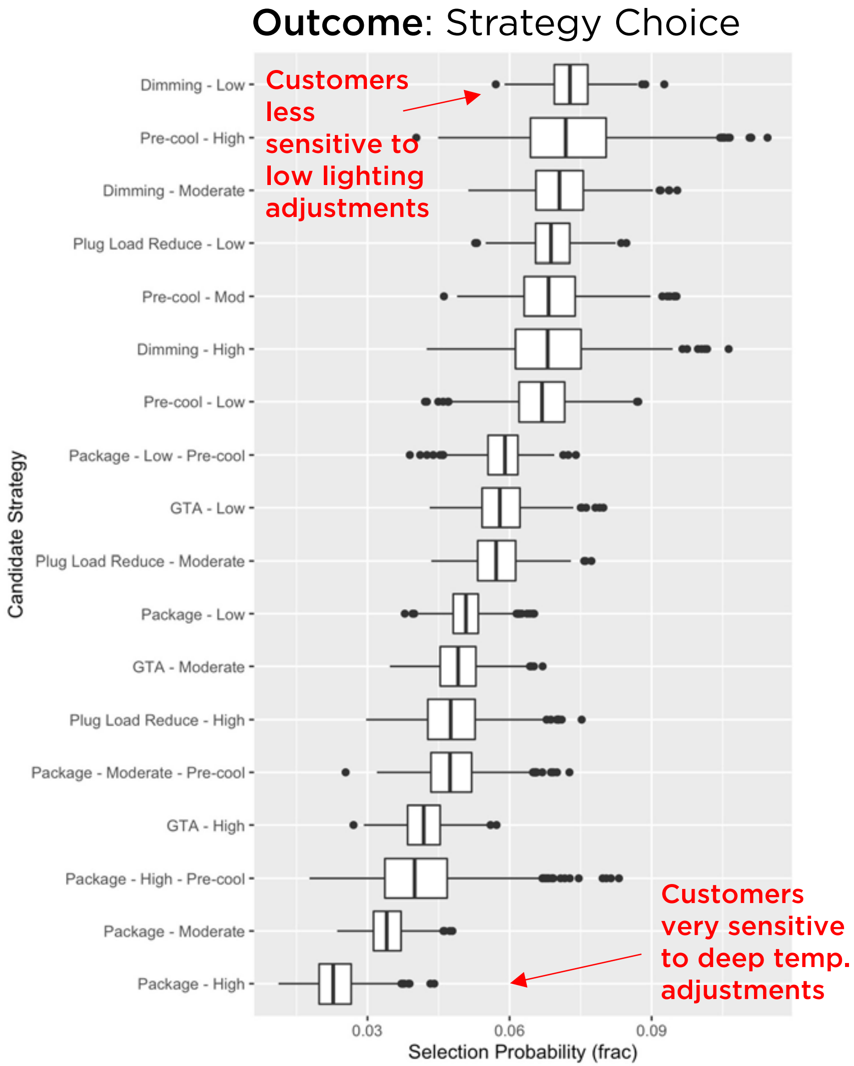

| | *Baseline* | *DR–Static* | *DR–Dynamic* |
|---|---|---|---|
| *Climate zones* | 2A (hot-humid), 3C (warm-marine), 6B (cold-dry) | | |
| *Building types* | Medium/Large Office prototypes (52K sf/500K sf), Big Box Retail (100K sf), Standalone Retail prototype (26K sf) | | |
| *Building vintages* | Newer (2010, 2004), older (1980-2004, pre-1980) | | |
| *Time horizon* | Summer (Jun-Sep) | | |
| *DR response* | N/A | Moderate temp. increase always | FlexAssist algorithm* |
| *DR event frequency/ duration* | N/A | 3-4/week; 1-6 hours/event (event days/durations are randomly drawn) | |
| *DR event reduction incentives* | N/A | \$0.6-\$1.5/kWh during event, \$0.1/kWh before/after event (incentives randomly drawn) | |
| *Demand reduction threshold*** | N/A | N/A | None, 25 kW, 100 kW (large offices only) |
| *Assessment metrics* | Energy savings % (daily, during event), operator utility, thermal comfort (Predicted Mean Vote or PMV) | | |

* Assumes that doing nothing is not a possible choice.
** When a reduction threshold is specified, the FlexAssist algorithm removes all strategies that are not predicted to meet the threshold from the choice set.

# **Progress**: FlexAssist predicts the probability of demand/service changes and choice probabilities under a given set of conditions

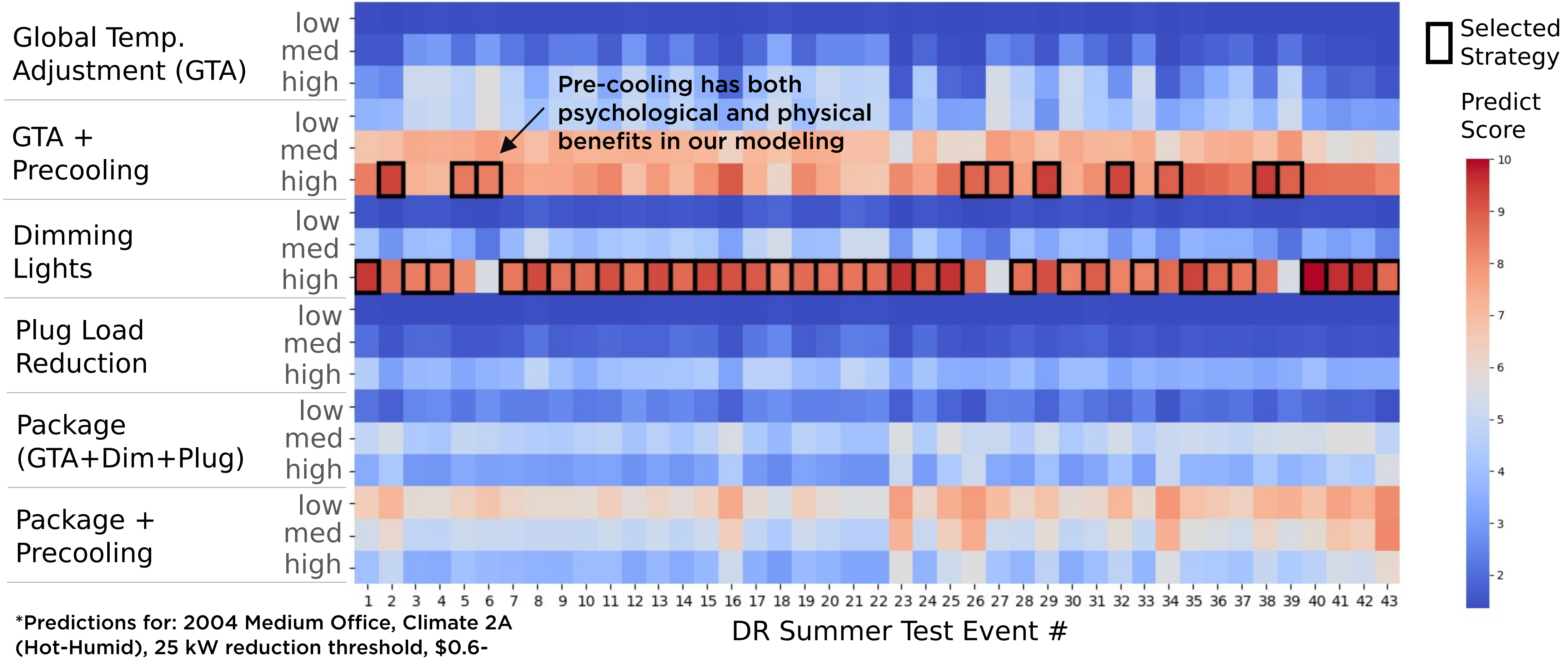



***Predictions for: 2010 Std. Large Office, Climate 2A, (Hot-Humid), NO demand reduction threshold, $3/kWh during event price signal, 3 hour event**

# **Progress:** The operation of the algorithm was tested across 43 hypothetical DR events in office and retail buildings



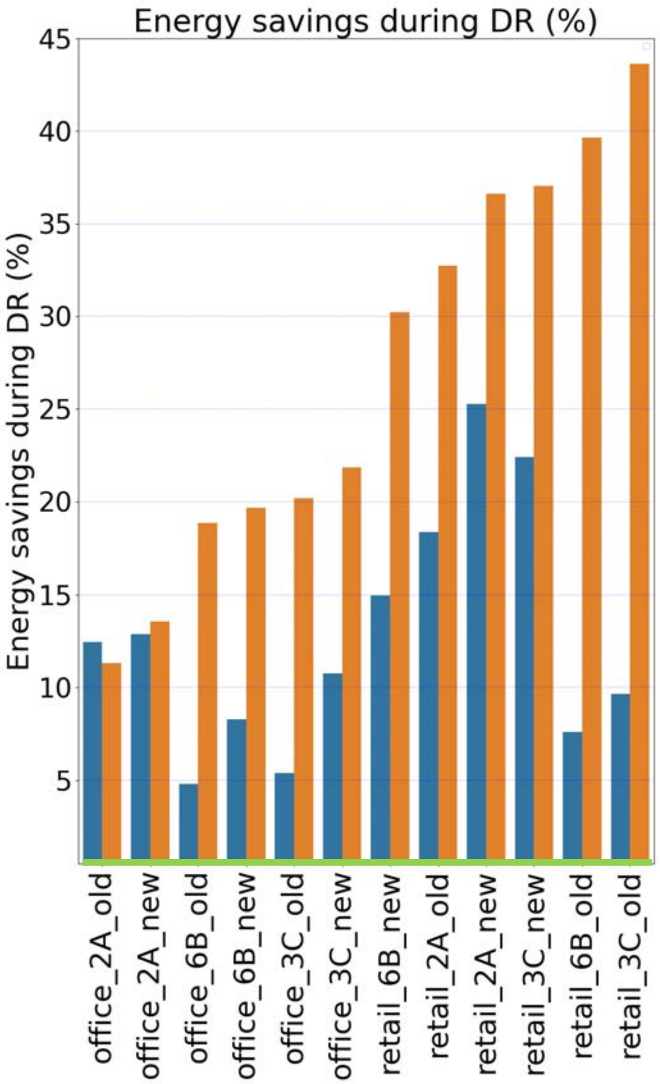

*Predictions for: 2004 Medium Office, Climate 2A (Hot-Humid), 25 kW reduction threshold, $0.6-$1.5/kWh during event price signal, 1-6 hour event

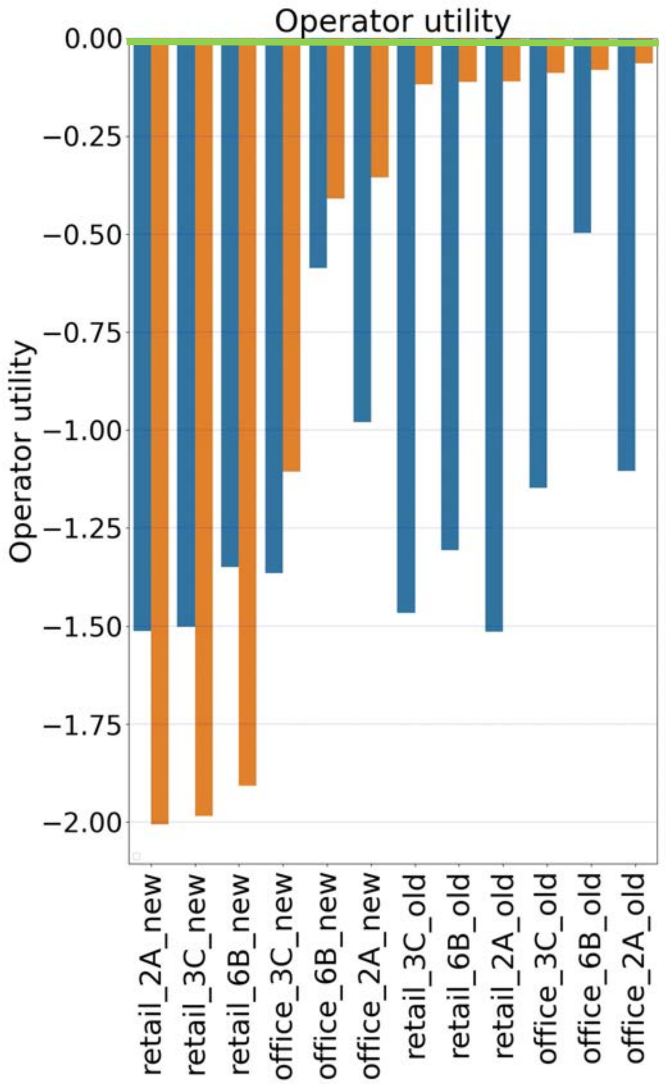
# **Progress:** With a kW reduction threshold, FlexAssist yields better energy savings and mostly better operator utility than static DR

Static response (always moderate temp. increase)

Response w/ FlexAssist

Baseline energy/utility




***Reflects application of 25 kW reduction threshold in medium office and standalone retail contexts (large office/big box retail forthcoming)**

# **Progress**: Surrogate models predict changes in demand and indoor temperature under DR with good accuracy

| | **Change in Whole Building Demand during DR Period (*thermally-driven*)** |
|---|---|
| **Output** | **Demand shed intensity (W/ft²)** |
| Input | Outdoor temperature (F) |
| | Outdoor humidity |
| | Occupancy fraction |
| | Cooling set pt. change (F) |
| | Lighting dimming (%) |
| | Plug loads reduction (%) |
| | Cooling set pt. lag (F) |
| | Hours since DR started |
| | Hours since DR ended |
| | *Cooling change * Outdoor temp.* |
| | *Cooling change * Occ. fraction* |
| | *Cooling change * Since DR started* |

| | **Demand changes during DR period** | **Demand changes during pre-cool period** | **Temperature changes during DR period** |
|---|---|---|---|
| R-square | > 0.88 | > 0.81 | > 0.76 |
| ARE* | > 83% | > 83% | > 81% |
| MADP** | < 16% | < 15% | < 17% |
| VIF*** | < 10 – No variable problematic collinearity among input variants | | |

*ARE: Absolute Relative Error (less than 20%)
**MADP: Mean Absolute Deviation Percentage Error
***VIF: Variance Inflation Factor

Reference: Luo, N., Langevin, J., and Chandra Putra, H. (2021). Quantifying the effect of multiple demand response actions on electricity demand and building services via surrogate modeling. Accepted: Building Simulation 2021, Bruges, Belgium, September 1-3.

# **Progress**: Choice experiments elicit adjustment preferences

| Attribute | Valuation | Comments |
|---|---|---|
| Economic benefits | Positive | • Respondents view this positively, with this attribute generally of the second-highest importance |
| Temperature increases in summer (or decreases in winter) during events | Negative | • Respondents view this negatively, with this attribute generally of the highest importance |
| Pre-cooling (or pre-heating in winter) just before events | Positive | • Respondents view this positively, with this attribute a way to mitigate during-event temperature change (but generally lesser importance) |
| Artificial lighting reduction | Unclear | • Additional responses will help clarify<br>• Preferences appear to be affected by building daylighting, with people in well-daylit buildings more accepting of artificial lighting reductions |

| Respondents (2020) | N |
|---|---|
| Office Operator | 138 |
| Retail Operator | 17 |
| **Total Responses** | **155** |

| Respondents (2021)* | N |
|---|---|
| Office Operator | 140 |
| Office Worker | 240 |
| Retail Operator | 199 |
| Retail Worker | 75 |
| **Total Responses** | **654** |

*Data collection ongoing

# **Stakeholder engagement**: Feedback on the tool's market potential is elicited from a diverse technical advisory group

- Technical advisory group includes aggregators, controls and equipment manufacturers, consultants/energy service providers, and facility managers
- Bi-annual TAG meetings to review progress and assess market relevance of key project outcomes
- Collected structured feedback organized by theme:
  - project concept and value proposition,
  - discrete choice analysis,
  - models of building demand and services under DR, and
  - testing and integration

Deloitte.

Danfoss

GSA

CPower

BuildingiQ

Johnson Controls

# **Remaining work**: Finish testing tool's application to new building types; complete integration and assessment of new choice data

- **Complete testing and integration of the tool for new building types and given updated operator/worker choice data (09/2021)**
  - Co-simulation testing reflects updated surrogate models and operator/worker load flexibility preferences, new building types (large office/big box retail)
  - Updated tool is published on GitHub with user documentation on ReadTheDocs
- **Complete processing and assessment of operator/worker choice data from new discrete choice experiments (09/2021)**
  - Analysis comparing/contrasting operator and worker preferences is complete
- **Finalize publications of key aspects of project work (09/2021)**
  - Surrogate modeling of building demand and services under DR (submitted)
  - Discrete choice modeling of operator and worker load flexibility preferences
- **Possible directions beyond FY21:**
  - Shorter-term (~6 mo.-1 yr.): develop and test simple web-based interface for tool
  - Longer-term (~1-2 years): field testing of FlexAssist in real buildings

# Thank you

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Code: https://github.com/jtlangevin/flex-bldgs
Docs: https://flexible-buildings.readthedocs.io/en/latest/

# REFERENCE SLIDES

# Project plan and schedule

| Project Schedule | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Project Start: 10/01/2018 | | Completed Work | | | | | | | | | | | |
| Projected End: 09/30/2021 | | Active Task (in progress work) | | | | | | | | | | | |
| | | Milestone/Deliverable (Planned) | | | | | | | | | | | |
| | | Milestone/Deliverable (Completed) | | | | | | | | | | | |
| | FY2019 | | | | FY2020 | | | | FY2021 | | | | |
| Task | Q1 (Oct-Dec) | Q2 (Jan-Mar) | Q3 (Apr-Jun) | Q4 (Jul-Sep) | Q1 (Oct-Dec) | Q2 (Jan-Mar) | Q3 (Apr-Jun) | Q4 (Jul-Sep) | Q1 (Oct-Dec) | Q2 (Jan-Mar) | Q3 (Apr-Jun) | Q4 (Jul-Sep) | |
| **Past Work** | | | | | | | | | | | | | |
| Overall decision network design and selection of load flexibility strategies to model complete | | | | | | | | | | | | | |
| Initial surrogate models for medium office/standalone retail complete | | | | | | | | | | | | | |
| Discrete choice experiment design for office/retail operators complete | | | | | | | | | | | | | |
| Discrete choice experiments on office/retail operators complete | | | | | | | | | | | | | |
| Validation of the tool's market potential and approach by technical advisory group | | | | | | | | | | | | | |
| Initial demonstration of integrated tool via case study co-simulations | | | | | | | | | | | | | |
| Initial benchmarking of integrated tool's performance | | | | | | | | | | | | | |
| Refinements to medium office/standalone retail surrogate models complete | | | | | | | | | | | | | |
| Expanded discrete choice experiment design for operators/workers complete | | | | | | | | | | | | | |
| New surrogate models for large office/big box retail complete | | | | | | | | | | | | | |
| Initial data from expanded discrete choice experiments integrated into decision tool | | | | | | | | | | | | | |
| **Current/Future Work** | | | | | | | | | | | | | |
| Revised discrete choice experiments and analysis comparing operator/worker prefs. complete | | | | | | | | | | | | | |
| Demonstration and benchmarking of expanded decision tool complete | | | | | | | | | | | | | |
| Journal manuscripts on surrogate modeling and discrete choice experiments complete | | | | | | | | | | | | | |

# Project budget

| Budget History | | | |
|---|---|---|---|
| **10/01/2018 – FY 2020 (past)** | | **FY 2021 (current) – 09/30/2021** | |
| DOE | Cost-share | DOE | Cost-share |
| \$1.2M<br>(\$238K carryover into FY21) | N/A | \$400K<br>(\$288K spent by July 2021) | N/A |

# FlexAssist makes a day-ahead recommendations of response strategy, implements/records the response, and updates models

**(1) Night before event:** receive event notification, forecast conditions, recommend response.

**(1a)** Forecast weather conditions, occupancy schedules for event day

**(1b)** Forecast event information (duration, incentive levels)

**(1c)** Prob(select strategy) = f(predicted $ benefit, reduction in services) given 1a-b

**(1d)** Recommend strategy with highest overall frequency of selection given 1c

**(2) During event and hours just before/after:** implement strategy, record demand/service impacts.

**(2a)** If pre-cooling strategy is implemented, record temperature/demand changes during the pre-cooling period

**(2b)** Record change in all demand/service variables during the event hours

**(2c)** Record change in all demand/service variables in the rebound hour after the event

**(3) Night after event:** update demand/service models based on recorded event data

**(3a)** Demand/service models updated based on observed change in demand/services /w DR strategy relative to base case (from 2a-2c)

**(3b)** Operator choice models can be updated based on whether or not recommended strategy was selected *(*currently testing)*

# The operator choice function translates the likelihood of benefits ($ savings) and risks (service losses) into a utility value

$$U_j = \beta_\$ x_{\$,j} + \beta_{t\_p} x_{t\_p,j} + \beta_t x_{t,j} + \beta_l x_{l,j} + \beta_e x_{e,j}$$

***Where:***

$\boldsymbol{U_j}$ = Operator utility, alternative j

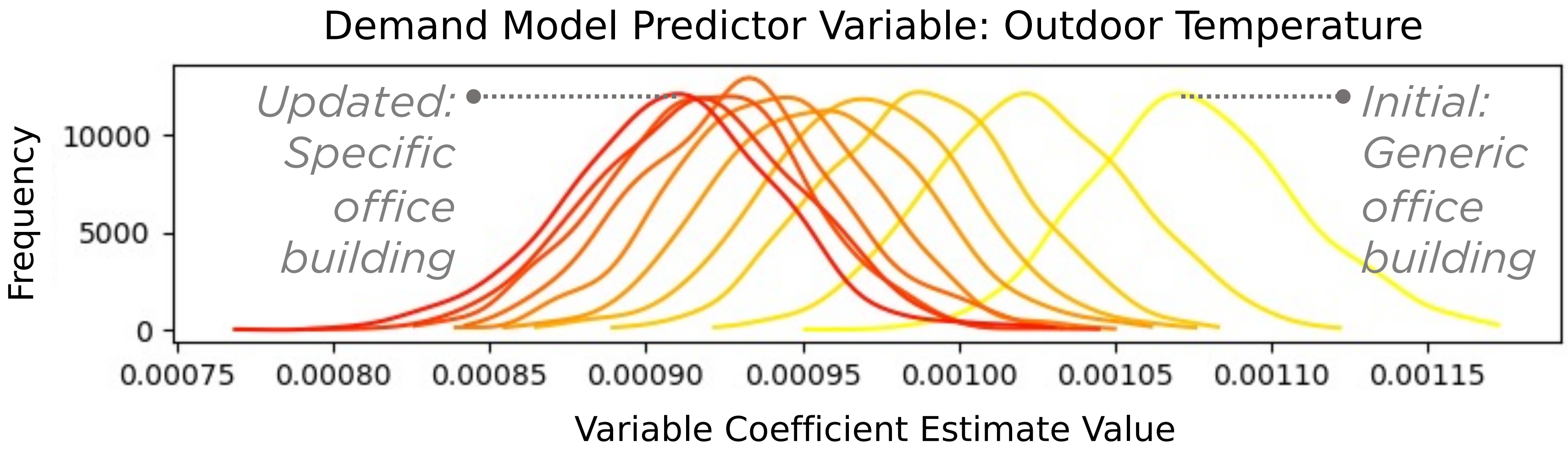
$\boldsymbol{x_{\$,j}, x_{t\_p,j}, x_{t,j}, x_{l,j}, x_{e,j}}$ = Predicted alternative j attributes (economic benefit, pre-cool temperature change, event temperature change, event lighting change, event plug power change)

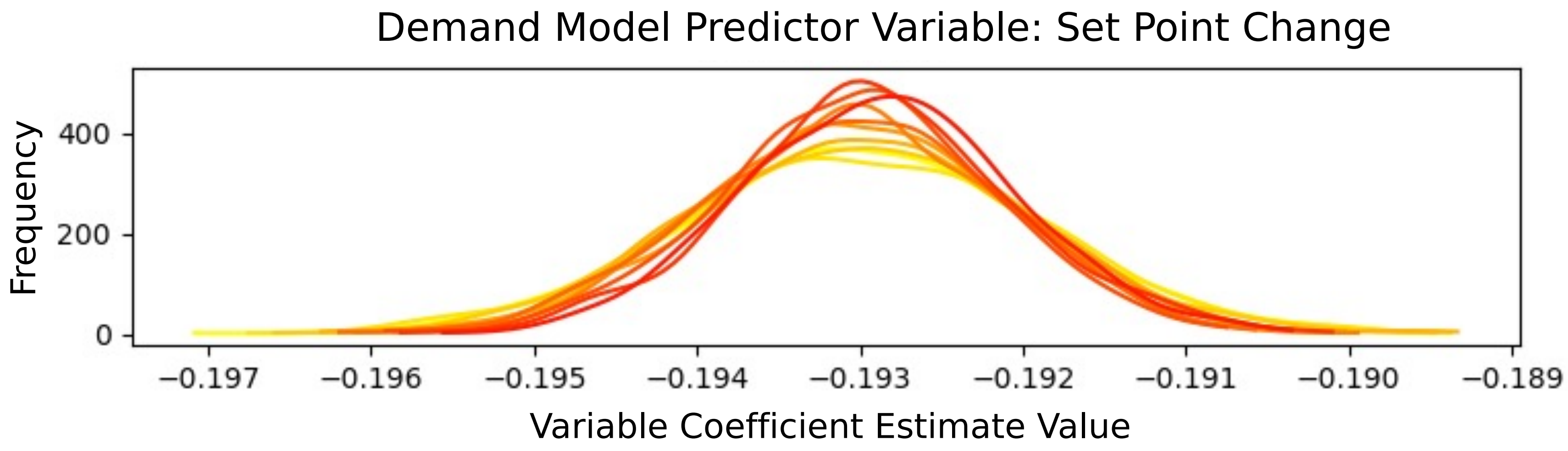
$\boldsymbol{\beta_\$, \beta_{t\_p}, \beta_t, \beta_l, \beta_e}$ = Choice attribute weights from discrete choice experiments (DCE)

# Tested DR strategies cover temperature, lighting, and plug load adjustments at low, medium and high levels

| *DR Strategy* | *Levels of Adjustment* |
|---|---|
| Global Temperature Adjustment (GTA) | +2ºF (low), +4ºF (med), +6ºF (high) during event |
| GTA + Precooling | +2ºF (low), +4ºF (med), +6ºF (high) during event; -2ºF 4 hours preceding event (all levels) |
| Dimming Lights | -20% (low), -40% (med), -60% (high) during event |
| Plug Load Reduction | -10% (low), -30% (med), -50% (high) during event |
| Package (GTA+Dim+Plug) | Low, medium, and high levels of GTA AND dimming AND plug load reduction during event |
| Package + Precooling | Package low, medium, and high settings during event; -2ºF 4 hours preceding event (all levels) |

# Updates to underlying models of change in building demand and services under DR recalibrate to building-specific dynamics




Original (prior) distribution **(2004 Med. Office, all climates)**

First update **(2004 Med. Office, climate 2A)**

Last update **(2004 Med. Office, climate 2A)**

*<u>Significance</u>: Merges prior expectations about changes in building demand/services under DR with new evidence collected during actual DR events*

# Summary of surrogate model inputs and outputs and synthetic data cleaning approach

| | **Whole Building Demand (DR, *Non-thermal related*)** | **Whole Building Demand (DR, *Thermal related*)** | **Whole Building Demand (Pre-cool)** | **Indoor Temperature (DR)** |
|---|---|---|---|---|
| **Output** | **Demand shed per sf. (W/sq.ft.)** | **Demand shed per sf. (W/sq.ft.)** | **Demand shed per sf. (W/sq.ft.)** | **Indoor temperature change (F)** |
| Input | Lighting dimming (%) | Outdoor temperature (F) | Outdoor temperature (F) | Outdoor temperature (F) |
| | Plug loads reduction (%) | Outdoor humidity | Outdoor humidity | Outdoor humidity |
| | | Occupancy fraction | Occupancy fraction | Occupancy fraction |
| | | Cooling set pt. change (F) | Cooling set pt. change (F) | Cooling set pt. change (F) |
| | | Lighting dimming (%) | Hours since pre-cool started | Cooling set pt. lag (F) |
| | | Plug loads reduction (%) | *Cooling change * Outdoor temp.* | Hours since DR started |
| | | Cooling set pt. lag (F) | *Cooling change * Occ. fraction* | Pre-cool set pt. change (F) |
| | | Hours since DR started | *Cooling change * Since Precool started* | Pre-cool duration |
| | | Hours since DR ended | | *Cooling change * Outdoor temp.* |
| | | *Cooling change * Outdoor temp.* | | *Cooling change * Occ. fraction* |
| | | *Cooling change * Occ. fraction* | | *Cooling change * Since DR started* |
| | | *Cooling change * Since DR started* | | *Pre-cool change * Pre-cool duration* |
| Data restrict | Weekday only | Weekday only | Weekday only | Weekday only |
| | 4-hour of DR | 4-hour of DR + 1-hour of rebound | Pre-cool hours (1 to 6 hours) | 4-hour of DR |
| | Across the whole year | Summer season only | Summer season only | Summer season only |
| | | Outdoor temperature > 70F | Outdoor temperature > 70F | Outdoor temperature > 70F |

# Dozens of DR measures are simulated across office/retail under a range of adjustment settings, yielding a synthetic database

| Category | Measure | Magnitude of adjustment: Low | *Uniformly distributed* | High | Duration of adjustment |
|---|---|---|---|---|---|
| HVAC | Global cooling temp. adjustment (GTA) | +1F | ~ | +6F | 3-7PM |
| | GTA | +1F | ~ | +6F | 3-7PM + 1 to 6-hour ahead *(Uniformly distributed)* |
| | + pre-cooling | -1F | ~ | -4F | |
| Lighting | Dimming | 0% | ~ | -100% | 3-7PM |
| Plug Loads (office only) | Low-priority device switching | | | | |

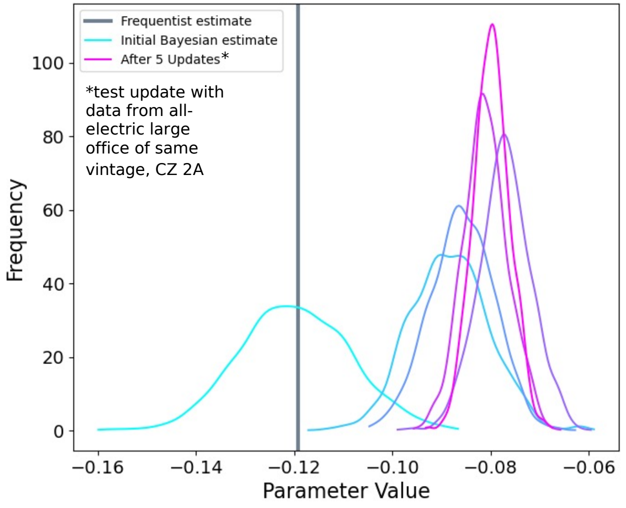
- Representative climate zones: 2A, 3C, 4A, 6B (covering hot to cold; moist, dry to marine regions)
- 5 Building types: medium office, large office, all electric large office, standalone retail, big box retail

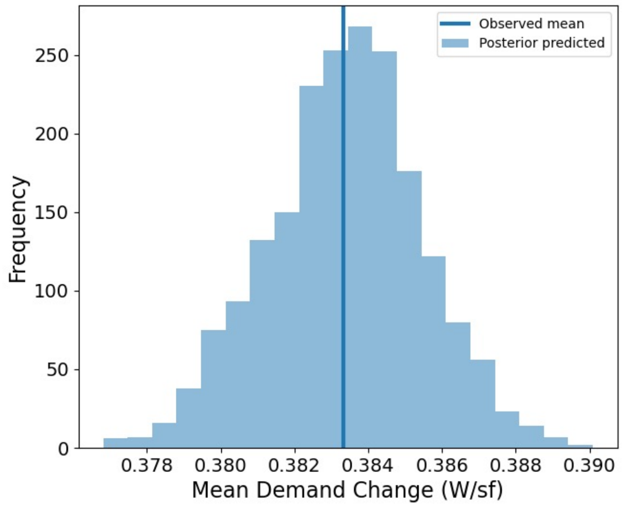
# Checks on the distribution of model input parameters and outputs demonstrate performance of Bayesian surrogate models

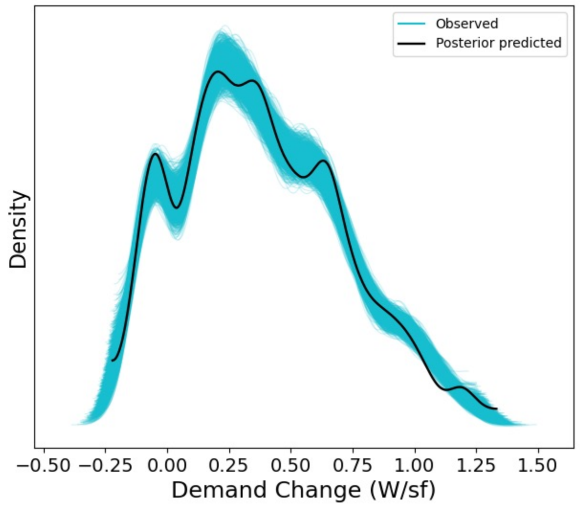
Set point chg. coef. distrib.

Posterior predictive checks, demand change output

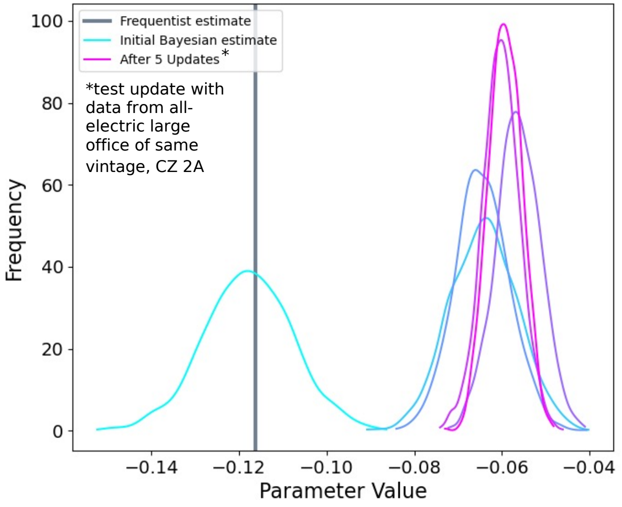
Thermally-driven demand model, std. large office, 2010 vintage

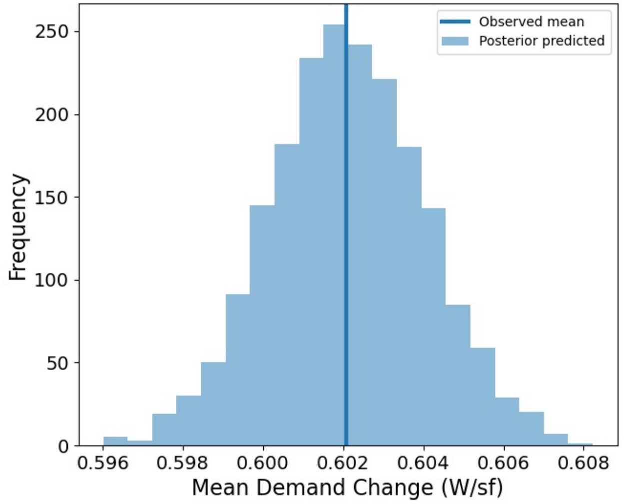


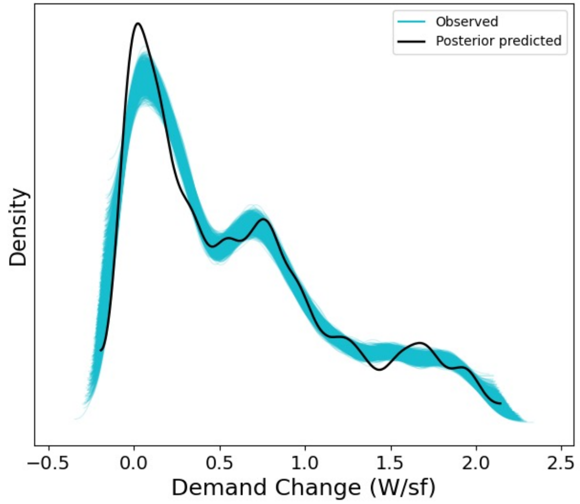




Thermally-driven demand model, std. large office, 1980-2004 vintage



# Office worker discrete choice experiment results to date

Model includes two interaction effects: (1) pre-cooling & during-event temp. change; (2) artificial lighting reduction with daylighting %

**Two preference variables are significant across all 3 scenarios:**

- During-event temperature change (*respondents disfavor, with average elasticity range -.15 to -.45*)
- Economic benefit (*respondents favor, with average elasticity range 0.17 to 0.21*)

**One preference variable is significant across 2 scenarios:**

- Pre-cooling if during event temp change >2°F (*respondents favor, with average elasticity range 0.05 to 0.06*)

**One preference variable is significant across 1 scenario:**

- Pre-cooling if during event temp change <=2°F (*respondents favor, with average elasticity 0.03*)

| | CS | FS | FW |
|---|---|---|---|
| Office Workers | 240 | 116 | 124 |
| Retail Workers | 75 | 34 | 41 |
| **Total workers** | **315** | **150** | **165** |

| Preference For: | Current Summer | | | Future Summer | | | Future Winter | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient estimate | Average elasticity | P-value | Coefficient estimate | Average elasticity | P-value | Coefficient estimate | Average elasticity | P-value |
| Economic benefit for organization | 0.000120 | 0.197770 | 0.0000 | 0.000125 | 0.208228 | 0.0000 | 0.000106 | 0.167713 | 0.0000 |
| Temperature decrease (increase*) before event if temperature increase (decrease*) during event <=2°F | 0.140768 | 0.033826 | 0.0027 | 0.046929 | 0.012084 | 0.4593 | 0.012712 | 0.002944 | 0.8415 |
| Temperature decrease (increase*) before event if temperature increase (decrease*) during event >2°F | 0.081117 | 0.048970 | 0.0193 | 0.104574 | 0.064740 | 0.0394 | -0.005410 | -0.002997 | 0.9124 |
| Temperature increase (decrease*) during event | -0.196725 | -0.445087 | 0.0000 | -0.197252 | -0.443165 | 0.0000 | -0.074237 | -0.151905 | 0.0088 |
| Artificial lighting reduction | -0.539548 | -0.103400 | 0.0512 | -0.556691 | -0.110051 | 0.1389 | -0.396805 | -0.067984 | 0.3320 |
| Artificial lighting reduction interacted with building daylighting % | 0.006384 | 0.063198 | 0.1585 | 0.002724 | 0.025803 | 0.6818 | 0.002768 | 0.025883 | 0.6672 |
| Plug-load reduction | N/A | N/A | N/A | -0.062000 | -0.008825 | 0.8259 | -0.378875 | -0.047676 | 0.1260 |
| Outdoor air flow reduction | N/A | N/A | N/A | 0.069400 | 0.008725 | 0.7949 | -0.069228 | -0.008063 | 0.7795 |

*** = For winter DCEs**

# Retail worker discrete choice experiment results to date

Model includes two interaction effects: (1) pre-cooling & during-event temperature change; (2) artificial lighting reduction with building daylighting %

**One preference variable is significant across all 3 scenarios:**

Economic benefit (*respondents favor, with average elasticity range 0.12 to 0.22*)

**One preference variable is significant across 2 scenarios:**

During-event temperature change (*respondents disfavor, with average elasticity range -.25 to -.47*)

| | CS | FS | FW |
|---|---|---|---|
| Office Workers | 240 | 116 | 124 |
| Retail Workers | 75 | 34 | 41 |
| **Total workers** | **315** | **150** | **165** |

| Preference For: | Current Summer | | | Future Summer | | | Future Winter | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient estimate | Average elasticity | P-value | Coefficient estimate | Average elasticity | P-value | Coefficient estimate | Average elasticity | P-value |
| Economic benefit for organization | 0.000111 | 0.180296 | 0.0000 | 0.000143 | 0.224549 | 0.0000 | 0.000100 | 0.128724 | 0.0000 |
| Temperature decrease (increase*) before event if temperature increase (decrease*) during event <=2°F | 0.065055 | 0.015033 | 0.4354 | 0.068029 | 0.013792 | 0.5961 | -0.070689 | -0.012986 | 0.5485 |
| Temperature decrease (increase*) before event if temperature increase (decrease*) during event >2°F | 0.088440 | 0.049984 | 0.1645 | 0.096688 | 0.051443 | 0.2937 | -0.016266 | -0.007498 | 0.8415 |
| Temperature increase (decrease*) during event | -0.217252 | -0.473580 | 0.0000 | -0.127418 | -0.252253 | 0.0271 | -0.055295 | -0.095464 | 0.2501 |
| Artificial lighting reduction | -0.113306 | -0.021117 | 0.8181 | -0.696280 | -0.125253 | 0.3472 | -0.546707 | -0.081859 | 0.3843 |
| Artificial lighting reduction interacted with building daylighting % | 0.009977 | 0.085461 | 0.2501 | 0.004831 | 0.039565 | 0.7114 | 0.016656 | 0.114778 | 0.1389 |
| Plug-load reduction | N/A | N/A | N/A | 0.159897 | 0.020576 | 0.7490 | 0.539617 | 0.057434 | 0.2041 |
| Outdoor air flow reduction | N/A | N/A | N/A | -0.078058 | -0.008522 | 0.8808 | -0.044358 | -0.003993 | 0.9203 |

* = For winter DCEs