End-Use Savings Shapes Measure Documentation:

Thermostat Control for Load Shedding in Large Offices

Jie Xiong and Janghyun Kim

National Renewable Energy Laboratory

NREL is a national laboratory of the U.S. Department of Energy
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Technical Report
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Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

List of Acronyms

DR	demand response
EUI	energy use intensity
GEB	grid-interactive efficient buildings
HVAC	heating, ventilating, and air conditioning
kW	kilowatt
NREL	National Renewable Energy Laboratory
TBtu	trillion British thermal units
TOU	time of use

Executive Summary

Building on the successfully completed effort to calibrate and validate the U.S. Department of Energy's ResStock™ and ComStock™ models over the past several years, the objective of this work is to produce national data sets that empower analysts working for federal, state, utility, city, and manufacturer stakeholders to answer a broad range of analysis questions.

The goal of this work is to develop energy efficiency, electrification, and demand flexibility end-use load shapes (electricity, gas, propane, or fuel oil) that cover a majority of the high-impact, market-ready (or nearly market-ready) measures. "Measures" refers to energy efficiency, electrification, and demand flexibility variables that can be applied to buildings during modeling.

An *end-use savings shape* is the difference in energy consumption between a baseline building and a building with an energy efficiency, electrification, or demand flexibility measure applied. It results in a time-series profile that is broken down by end use and fuel (electricity or on-site gas, propane, or fuel oil use) at each time step.

ComStock is a highly granular, bottom-up model that uses multiple data sources, statistical sampling methods, and advanced building energy simulations to estimate the annual subhourly energy consumption of the commercial building stock across the United States. The baseline model intends to represent the U.S. commercial building stock as it existed in 2018. The methodology and results of the baseline model are discussed in the final technical report of the End-Use Load Profiles project.

This documentation focuses on a single End-Use Savings Shape measure—thermostat control for load shedding.

The thermostat control for load shedding measure applies heating and cooling temperature setpoint offsets for reducing the heating and cooling load during the peak window. The measure takes daily peak load schedule inputs generated by the method "Dispatch Schedule Generation" described in the "Supplemental Documentation: Dispatch Schedule Generation for Demand Flexibility Measures" (on the ComStock webpage) to determine the start and end times of the peak window, and then adjusts the thermostat cooling and/or heating setpoints by an offset value from original schedules during the peak window to reduce the heating, ventilating, and air conditioning (HVAC) or whole-building daily peak load. The measure is flexible and allows users to adjust the heating and cooling offset values respectively, but for this study, the adjustments for heating and cooling setpoints are set to -2 °C and +2 °C by default. The measure provides the option of adding a rebound control period (default 2 hours) after peak windows for the setpoints to be ramped back to default values, to prevent the system from generating higher peak demand with step changes of setpoints in post-peak periods (depicted in Figure 4). This measure is currently applicable to large offices equipped with electric HVAC systems (either electric cooling only or both electric heating and cooling), which account for approximately 9.72% of the ComStock floor area.

The thermostat control for load shedding measure demonstrates 2%–5% median daily peak demand reduction (Figure 6) and 0.046% total site energy savings (2 trillion British thermal units

[TBtu]) for the U.S. commercial building stock modeled in ComStock (Figure 9). The savings are primarily attributed to:

- **0.023%** stock **natural gas heating** savings (0.2 TBtu)
- **0.34%** stock **heating electricity** savings (0.5 TBtu)
- **0.15%** stock **cooling electricity** savings (1.3 TBtu)
- **0.17%** stock **fan** savings (0.9 TBtu).

The objective of the measure is to provide demand flexibility by shaving load peaks on a daily basis instead of improving energy efficiency, so the energy savings and corresponding emission reduction are expected to be close to zero. On the other hand, the annual bill cost analysis demonstrates that, despite of negligible energy savings, the peak demand savings lead to 1%-2% annual bill cost savings (investment cost for making the building grid-interactive is not considered). The cost savings are mainly attributed to cost reduction from time-of-use rates or peak-demand-charge portion of utility rates, which are applicable to only small amount of buildings. Therefore, future analysis needs closer look by limiting to comparing buildings with peak-demand-charges/time-of-use rates to understand savings potentials for those impactful buildings.

In addition, providing the potential of switching to other objectives for the dispatch schedule, future work includes extending the scope of this measure to applying for carbon emission reduction, for more comprehensive analysis (refer to the “Supplemental Documentation: Dispatch Schedule Generation for Demand Flexibility Measures” for more details).

Acknowledgments

The authors would like to acknowledge the valuable guidance and input provided by Matt Leach and Chioke Harris at the National Renewable Energy Laboratory.

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Thermostat Control for Load Shedding

Accessing Results

This documentation covers "Thermostat Control for Load Shedding" upgrade methodology and briefly discusses key results. Results can be accessed on the ComStock™ data lake at "end-use-load-profiles-for-us-building-stock" or via the Data Viewer at comstock.nrel.gov.

Measure Summary

Measure Title	Thermostat Control for Load Shedding
Measure Definition	The thermostat control for load shedding measure applies heating and cooling temperature setpoint offsets for reducing the heating and cooling load during peak window. The measure takes daily peak load schedule inputs generated by the method "Dispatch Schedule Generation" described in the "Supplemental Documentation: Dispatch Schedule Generation for Demand Flexibility Measures" to determine the start and end times of the peak window, and then adjusts the thermostat cooling and/or heating setpoints by an offset value from original schedules during the peak window to reduce the HVAC or whole-building daily peak load. The measure is flexible and allows users to adjust the heating and cooling offset values respectively, but for this study, the adjustments for heating and cooling setpoints are set to -2 °C and +2 °C by default. The measure provides the option of adding a rebound period (default 2 hours) after peak hours for the setpoints to be ramped back to default values, to prevent the system from generating higher peak demand with step changes of setpoints in post-peak periods.
Applicability	Large offices with HVAC systems (either electric cooling only or both electric heating and cooling), accounting for about 9.72% of the floor area modeled in ComStock.
Not Applicable	Buildings that are not large offices or have no electric HVAC component.
Release	2024 Release 1: 2024/comstock_amy2018_release_1/

1 Technology Summary

1.1 Grid-Interactive Efficient Buildings with Demand Flexibility on HVAC

Electricity consumers across the residential, commercial, and industrial sectors are increasingly interested in opportunities to reduce their electricity bills and carbon footprint. Simultaneously, utilities, system operators, and state decision-makers are aiming to reduce costs, more effectively utilize existing grid assets, maintain power system reliability, and reach carbon reduction targets. At the intersection of the customer and utility perspectives, buildings and their associated loads offer opportunities to align the interests of consumers, system operators, and policy decision-makers. Interactivity between buildings and the broader electricity system expands these opportunities, and is enabled by advancements in building control technologies, data availability, advanced metering, new tariff designs, and improved analytics for energy management. Collectively these smart technologies for energy management are often referred to as grid-interactive efficient buildings (GEBs). GEBs utilize high-efficiency components to reduce electricity demand and increase the flexibility of specific building loads, responding to real-time signals or advanced calls for demand response (DR), or targeting bill savings associated demand regulations such as time-of-use (TOU) rates and rates with demand charges. By shedding and shifting building load, these GEBs can reduce electricity bills, the cost of operating the grid, and emissions, all while maintaining the comfort of building occupants.

Many studies have been devoted to building control for grid services during the past few years [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. There are five technical interventions or measures used in a building's demand profile modification in the literature [11], [12], [13], [14], [15], [16], [17]. The first, energy efficiency, refers to techniques that help reduce the net demand during both on-peak and off-peak periods. The second, peak shaving or load shedding, refers to reducing the on-peak demand, i.e., when the demand in the power grid is high. The third method is load shifting, which means altering the demand profile to meet certain performance criteria, usually involving a reduction in on-peak demand and an offset by a load increase at a different time. The fourth method is renewable energy, which utilizes distributed energy resources to coincidently reduce on-peak demand. The last is modulation, which provides rapid adjustments to regulate frequency and voltage and assure power quality. The existing methods that fall within these five categories can help reduce demand charges directly or indirectly.

Heating, ventilating, and air conditioning (HVAC) systems have an inherent ability to provide short-term energy flexibility without requiring massive changes and new investment. Temperature setbacks, precooling, and preheating are efficient methods to improve building energy flexibility. In addition to the temperature dead band (the range of temperatures centered around the setpoint at which the thermostat does not alter its operation status), other building characteristics such as thermal mass and internal load and climates are also significant. Meanwhile, flexibility approaches must balance the savings from peak load reduction (e.g., bill savings) and the risk of occupant discomfort. Temperature setbacks, precooling, and preheating are usually employed as the methods provide short-term peak load reduction, while thermal storage techniques (e.g., ice or water storage tanks) enable HVAC systems to serve as a longer-term temperature cushion.

1.2 Thermostat Control Strategies for Demand Flexibility

Zone temperature setpoint setback/setup and precooling/preheating, often using a "smart" internet-connected thermostat, are two common strategies used in HVAC systems to realize energy efficiency and demand flexibility strategies [18]. Chen [19] estimates that 28% of U.S. households will deploy smart thermostats by 2023. For temperature setpoint offset, peak period loads can be reduced if the thermal zone is a few degrees hotter in summer or cooler in winter than its normal thermostat setpoint. Precooling or preheating can help maintain comfortable conditions through the peak period when the setpoint is adjusted. The response time of electricity use reduction might not be consistently aligned with the setpoint change depending on the specific hardware logic of the HVAC equipment, but an ideal instant response is assumed in this study.

The Grid-interactive Efficient Buildings Technical Report Series [20] rated smart thermostat technologies as having high potential for GEBs, as they provide both load shedding and shifting capabilities, including management of complex scheduling and day-ahead service requests while optimizing operations to minimize impacts on customer comfort. The U.S. Department of Energy estimates about 10% utility bill savings with smart thermostats controlling most types of heating and cooling systems [21]. ENERGY STAR® smart thermostats save 8% of heating and cooling bills on average, accounting for both energy usage costs and demand charges [22], [23]. And applications of smart thermostats in low-income multifamily residential buildings have shown similar bill savings around 8% [24]. Various smart thermostat brands are available (Nest, Amazon, ecobee, etc.) for both commercial and residential customers, and ecobee reported up to 26% bill savings for their users in north America in 2021 [25].

HVAC control rules are specified in various standards, such as ASHRAE Standards 90.1, 189.1, and IECC Chapter 4. Advanced rule-based controllers that optimize energy efficiency have been described in ASHRAE Guideline 36 and ASHRAE RP-1455 [26]. Rule-based controllers are characterized by many tuning parameters that must be selected for each system and building and are often reset during seasonal transitions. More advanced controls, such as model-predictive control, for thermostats have shown 10% to 35% peak power reduction capability in commercial buildings [27]. Tests on model-predictive control chillers by Yang et al. [28] found energy savings of 2%, 17.1%, and 17.3% for cooling, heating, and transition seasons, respectively.

Most of the thermostat control strategies in studies and reports focus on energy efficiency performance analysis, but the nature of achieving demand flexibility requires similar thermostat control, but with more considerations on load shape.

Utility companies and grid services providers are more engaged with thermostat control for demand flexibility through DR programs. Smart thermostats are adopted as one of the major devices for direct-load controls, where utilities incentivize customers to yield control of their enrolled thermostats for notified peak periods predicted for the grid needs on a daily basis. There are various DR programs managed by different utility companies across the United States, but the programs share similar strategies such as taking control of the enrolled thermostats for setpoint setback by 4°F [29] during DR events (also suggested by ASHRAE GEB Guide [18]), which usually last from 2 to 4 hours per event per day, with a certain upper limit number for a month or a season.

Several case studies or program reports from the utility market were summarized in a report from the National Rural Electric Cooperative Association [30], which are mostly for the residential building market but still illustrative as a relevant reference for quantifying the potential for commercial buildings. For example, Midstate Electric has reported shedding 300 to 400 kilowatts of load per event on average in their pilot Peak Hour Rewards Program in 2017. There were 191 thermostats across Central Oregon enrolled in this program and it determined 3–5 peak events for each month with a 2-hour peak window in the morning. Kansas City Power & Light (currently Evergy) has partnered with Nest to start the Rush Hour Rewards program in 2016, which achieved 29 MW of deemed demand savings and 9.7 GWh of deemed energy savings over a three-year period via 23,000 Nest Learning Thermostats. The program allows a maximum of 1 event per day, 4 hours per event, 3 events per week, and 15 events throughout the summer season. Kansas City Power & Light estimates that customers participating in the program have attained 1.2 kW reduction on average per thermostat, which equates to 15% savings on cooling bills, 10%–12% savings on heating bills, and an average annual savings of $131 to $145 on their utility bill that is associated with a TOU rate.

In this measure, we do not limit the number of days (events) and fix the daily dispatch window for thermostat demand control, as we are targeting daily peak load reduction from the perspective of individual buildings, which are beneficial to building owners/managers/operators, and could provide insight of achievable demand flexibility in accordance with grid needs from the end-use (building) point of view.

1.3 Rebound Effect

Rebound effect, or snapback, is the increase in energy and demand in the hours immediately following a demand response event. This effect has been observed in HVAC and water heating control in both modeling and practical applications [31]. The reason for rebound effect is that the corresponding system usually runs at or close to its full capacity trying to bring the temperature back to its original setpoint after a DR event when the setpoint has been relaxed. For example, on a hot day, the room temperature could increase significantly with an increased setpoint during a DR event and the cooling demand will thus be high immediately after the event if the setpoint returns to its pre-event value, leading to higher total energy use than baseline. Pacific Gas and Electric conducted a modeling and field evaluation study [32] on their SmartAC thermostat DR program and quantified the snapback effect post-DR event at the program level and equipment (thermostat) level. They found most of the post-event periods experienced a snapback effect (13 out of 15) with up to 0.68 kW demand increase per air-conditioning unit, of which some matched or even exceeded the load reduction during the DR event. Although they concluded that snapback effect might introduce potential issues, they did not propose a solution to it as the program targets on-peak load reduction only. Michaels Energy [33], [34] also investigated the snapback effect from the two Minnesota utilities' (IOU and G&T) data and demonstrated it in models, with an average demand increase (post-event) of 0.34kW, 1.97kW, 2.71kW, and 2.03kW for air conditioner, electric heater, water heater summer, and water heater winter, respectively, in residential buildings in Minnesota. The study suggested the implementation of an electric thermal storage system (generate heat from electricity in off-peak periods and release the heat from thermal storage material in on-peak periods) to eliminate the snapback effect and improve demand flexibility. Typical demand flexibility control strategies designed for DR programs target only the load profile within peak window neglect rebound effect as it exists outside of the peak window, while DF measures concerning daily load shapes (peaks) must take into account the rebound effect to achieve overall demand flexibility or bill savings.

2 ComStock Baseline Approach

This measure modifies the existing model thermostat setpoint schedules during the daily peak demand windows (specifically on-peak and post-peak periods) only. For times outside of the event, the existing thermostat schedules in the model are unchanged. The details of the thermostat schedule in the existing ComStock models can be found in Section 4.2 "Hours of Operation and Occupancy," which determines building hours of operation, and Section 4.8.7 "Thermostat Set Points," which describes how thermostat setpoints/setbacks are applied to the schedule, in the ComStock Reference Documentation [35].

3 Modeling Approach

3.1 Applicability

This measure is likely applicable to most commercial building types as it targets thermostat (schedule) control regardless of the details of HVAC system operations. Although in this study we narrow down the applicability to large office buildings only, we will expand the applicability in the future.

There were two reasons behind the decision to make large office buildings the target building type. First was the initial feedback and decisions we got from the stakeholders in the early phase of the Energy Efficiency and Demand Flexibility State Level Potential project. An informal survey of a state-level working group and the initial engagement of stakeholders both found that large offices are a building type of interest to state-level energy policy and incentive program staff seeking to support the implementation of measures and enable GEBs in their jurisdictions. Second was to secure some time for correcting/improving the dispatch window generation method instead of planning time on testing/applying/debugging the measure on many more building types.

This measure is applicable to buildings with electric HVAC systems (either electric heating or electric cooling or both), as demand flexibility control is applicable to buildings and/or equipment associated with the electric grid. Correspondingly, this measure will only affect electric HVAC equipment present in a building, e.g., it will not apply changes to the heating setpoints of the thermostat if the building does not have electric heating equipment (e.g., if the building's heat is provided by natural gas furnace).

Figure 1 shows the area percentage of large office buildings among all the commercial building types in ComStock and the floor area percentage of applicable buildings with electric HVAC systems (cooling only or both heating and cooling) for each building type. All large office buildings are applicable to this measure; 33.3% of large office floor area has both electric heating and cooling systems, and the remaining 66.7% of the floor area only has electric cooling. In terms of building counts, this applicability corresponds to 3158 large office building model samples which then extend to 19212 large office buildings (with weighting factors applied) for representing the counts in national level.

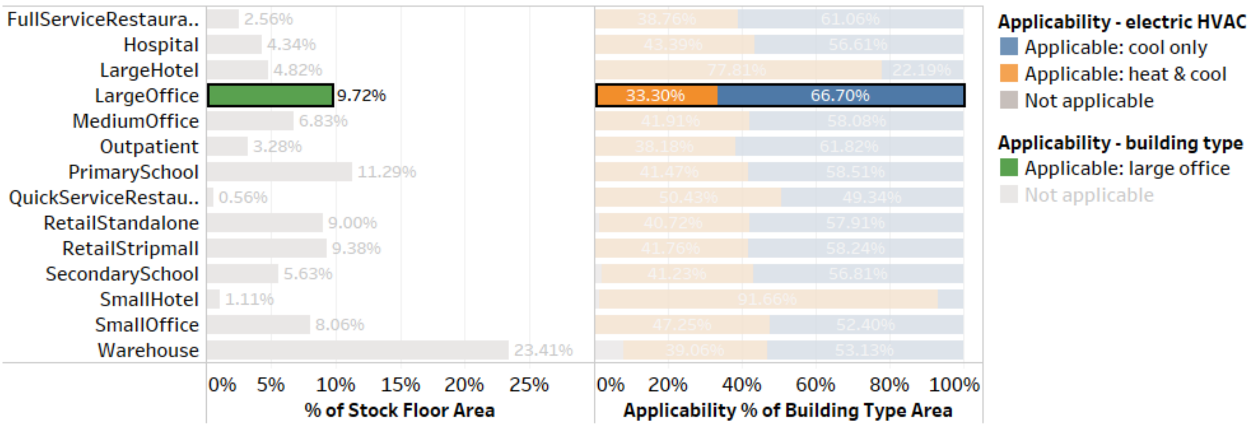

Figure 1. Prevalence of building types and applicability for each building type

3.2 Specifics of Thermostat Control for Load Shedding

3.2.1 Thermostat Setpoint Schedule Generation

By applying the method "Dispatch Schedule Generation" described in the "Supplemental Documentation: Dispatch Schedule Generation for Demand Flexibility Measures" on the ComStock webpage, a daily peak load schedule will be generated and used as the input of this measure. This measure will clone all the schedules that are used for cooling and heating (if applicable with electric heating) setpoints for thermal zones. Then the schedules are adjusted by the specified values during the peak window aligned with the input peak load schedule. The measure is flexible and allows users to adjust the heating and cooling offset values respectively, but for this study, the adjustment for heating and cooling setpoints are set to -2°C and +2°C by default according to the ASHRAE GEB Guide [18].

3.2.2 Thermostat Setpoint with Rebound Period

There are few solutions to address the rebound (snapback) effect proposed or demonstrated in current studies, mainly because snapback takes place in the post-DR event period—usually hours after peak window, which is not taken into consideration in most existing research that focus on demand control in peak window only, even if the effect generates higher peak load out of the window. Michaels Energy [34] proposed a solution of integrating electric thermal storage to mitigate snapback that requires the installation (and coordinated control) of a new system, and not all buildings are suitable for currently commercialized thermal storage (e.g., a large office building would require electric thermal storage with extreme high capacitance). A few companies [31] have applied gradual step changes rather than immediate restoration of setpoints on thermostats and water heaters to smooth the rebound effect and demonstrate the effectiveness. We adopt the stepped setpoint change method as it does not introduce new equipment and because this measure already applies peak period setpoint adjustments. The measure applies a rebound period of 2 hours for thermostat setpoints to ramp back to the original values after the peak period. The setpoint values in the rebound period are generated through linear interpolation from the setpoint value in peak period to the nominal setpoint value. This gradual restoration of the setpoint reduces the potential of creating a new peak load with immediate restoration, which was observed in simulation tests applying thermostat adjustment for peak demand periods.

Figure 2 shows an example where applying a gradual setpoint restoration period avoids creating a new peak demand event.

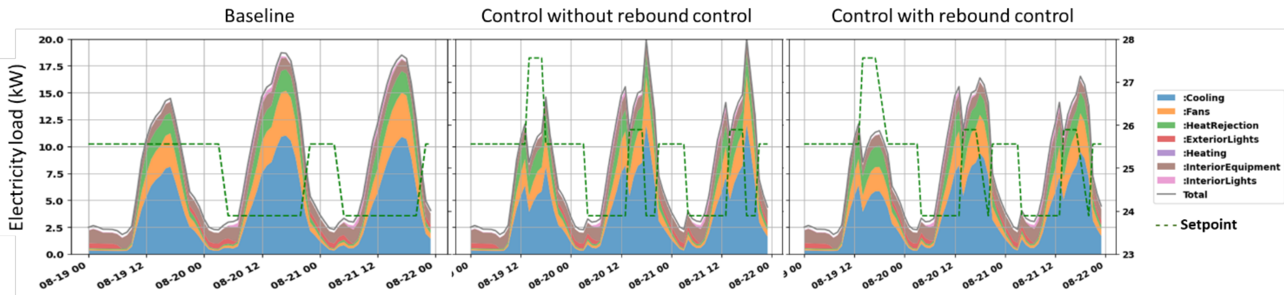

Figure 2. Example of applying rebound control (reset setpoint with ramp) after peak window

3.3 Greenhouse Gas Emissions

Three electricity grid scenarios are presented to compare the emissions of the ComStock baseline and the default thermostat control for load shifting scenario. The choice of grid scenario will impact the grid emissions factors used in the simulation, which determine the corresponding emissions produced per kilowatt-hour. Two scenarios—Long-Run Marginal Emissions Rate High Renewable Energy Cost 15-Year and Long-Run Marginal Emissions Rate Low Renewable Energy Cost 15-Year—use the Cambium data set, and the latter uses the eGrid data set [36], [37]. All three scenarios vary the emissions factors geospatially to reflect the variation in grid resources used to produce electricity across the United States. The Cambium data sets also vary emissions factors seasonally and by time of day. This study does not imply a preference for any particular grid emissions scenario, but additional analysis suggests that the choice of grid emissions scenario can impact results [38]. Emissions due to on-site combustion of fossil fuels use the emissions factors shown in Table 1, which are from Table 7.1.2(1) of draft American National Standards Institute/Residential Energy Services Network/International Code Council 301 [39]. To compare total emissions due to both on-site fossil fuel consumption and grid electricity generation, the emissions from a single electricity grid scenario should be combined with all three on-site fossil fuel emissions.

Table 1. On-Site Fossil Fuel Emissions Factors

Natural gas	147.3 lb/MMBtu (228.0 kg/MWh)[a]
Propane	177.8 lb/MMBtu (182.3 kg/MWh)
Fuel oil	195.9 lb/MMBtu (303.2 kg/MWh)

[a] lb = pound; MMBtu = million British thermal units; kg = kilogram; MWh = megawatt-hour

3.4 Limitations and Concerns

There are many limitations and concerns for this measure that have been identified to date.

- This measure is not similar to other upgrade measures where the upgrade implementation (i.e., hiring contractor, purchasing/installing equipment) is readily available in the market; our modeling is theoretical due to novelty in methodology rather than being grounded in a specific product type, although the barrier of implementation of the proposed method is low. In addition, the measure changes the operation of buildings but has limited impact on the hardware components or physical properties (assuming switching to smart thermostat has negligible impact on the existing HVAC system).

- This measure relies on the user-provided inputs of dispatch schedule, for which several options are developed and provided in the "Dispatch Schedule Generation" method. Different options yield distinctive dispatch time windows: perfect match to daily peak load (perfect prediction), a mimic of advanced application with uncertainty (bin-sampling), representative of simple logic (outdoor air temperature-based prediction), or fixed dispatch schedules by season and region (fixed schedule). The differences in performance of different options and the limitations and concerns of the dispatch window generation method described in the "Supplemental Documentation: Dispatch Schedule Generation for Demand Flexibility Measures" also apply to the implementation of this measure. For example, the objective function of generating daily dispatch window could vary depending on measure, such as emission reduction or utility cost savings, but it (currently) is peak demand reduction (peak load savings). The input parameters of a selected dispatch schedule generation methods also play a significant role in the performance, such as temperature offset value and length of peak window, and the impact may vary depending on building properties and weather conditions. We applied simple parametric analysis on the input parameters to justify the selection of default values, but detailed fine tuning is needed for determination of best parameter set(s).

- The current scope in terms of which building type we want to apply this measure to is limited to large offices, as discussed in Section 3.1. Different building types can have different operating hours, space temperature setpoints, and/or internal gains. We want to test and validate the new method rigorously before applying it to many other building types.

- In this measure, we do not limit the number of days (events) and fix the duration of daily dispatch window for thermostat demand control, as we are targeting daily peak load reduction from the prospective of individual building instead of the grid demand needs.

4 Output Variables

Table 2 includes a list of output variables that are calculated in ComStock. These variables are important in terms of understanding the differences between buildings with and without the thermostat control for load shedding measure applied.

Table 2. Output Variables Calculated from the Measure Application

Variable Name	Description
minimum_daily_peak_jan_kw	Minimum of daily electric peak loads (in kW) in January
minimum_daily_peak_feb_kw	Minimum of daily electric peak loads (in kW) in February
minimum_daily_peak_mar_kw	Minimum of daily electric peak loads (in kW) in March
minimum_daily_peak_apr_kw	Minimum of daily electric peak loads (in kW) in April
minimum_daily_peak_may_kw	Minimum of daily electric peak loads (in kW) in May
minimum_daily_peak_jun_kw	Minimum of daily electric peak loads (in kW) in June
minimum_daily_peak_jul_kw	Minimum of daily electric peak loads (in kW) in July
minimum_daily_peak_aug_kw	Minimum of daily electric peak loads (in kW) in August
minimum_daily_peak_sep_kw	Minimum of daily electric peak loads (in kW) in September
minimum_daily_peak_oct_kw	Minimum of daily electric peak loads (in kW) in October
minimum_daily_peak_nov_kw	Minimum of daily electric peak loads (in kW) in November
minimum_daily_peak_dec_kw	Minimum of daily electric peak loads (in kW) in December
maximum_daily_peak_jan_kw	Maximum of daily electric peak loads (in kW) in January
maximum_daily_peak_feb_kw	Maximum of daily electric peak loads (in kW) in February
maximum_daily_peak_mar_kw	Maximum of daily electric peak loads (in kW) in March
maximum_daily_peak_apr_kw	Maximum of daily electric peak loads (in kW) in April
maximum_daily_peak_may_kw	Maximum of daily electric peak loads (in kW) in May
maximum_daily_peak_jun_kw	Maximum of daily electric peak loads (in kW) in June
maximum_daily_peak_jul_kw	Maximum of daily electric peak loads (in kW) in July
maximum_daily_peak_aug_kw	Maximum of daily electric peak loads (in kW) in August
maximum_daily_peak_sep_kw	Maximum of daily electric peak loads (in kW) in September
maximum_daily_peak_oct_kw	Maximum of daily electric peak loads (in kW) in October
maximum_daily_peak_nov_kw	Maximum of daily electric peak loads (in kW) in November
maximum_daily_peak_dec_kw	Maximum of daily electric peak loads (in kW) in December
median_daily_peak_jan_kw	Median of daily electric peak loads (in kW) in January
median_daily_peak_feb_kw	Median of daily electric peak loads (in kW) in February
median_daily_peak_mar_kw	Median of daily electric peak loads (in kW) in March
median_daily_peak_apr_kw	Median of daily electric peak loads (in kW) in April
median_daily_peak_may_kw	Median of daily electric peak loads (in kW) in May
median_daily_peak_jun_kw	Median of daily electric peak loads (in kW) in June
median_daily_peak_jul_kw	Median of daily electric peak loads (in kW) in July
median_daily_peak_aug_kw	Median of daily electric peak loads (in kW) in August
median_daily_peak_sep_kw	Median of daily electric peak loads (in kW) in September
median_daily_peak_oct_kw	Median of daily electric peak loads (in kW) in October
median_daily_peak_nov_kw	Median of daily electric peak loads (in kW) in November

Variable Name	Description
median_daily_peak_dec_kw	Median of daily electric peak loads (in kW) in December
q_1_daily_peak_jan_kw	First quartile of daily electric peak loads (in kW) in January
q_1_daily_peak_feb_kw	First quartile of daily electric peak loads (in kW) in February
q_1_daily_peak_mar_kw	First quartile of daily electric peak loads (in kW) in March
q_1_daily_peak_apr_kw	First quartile of daily electric peak loads (in kW) in April
q_1_daily_peak_may_kw	First quartile of daily electric peak loads (in kW) in May
q_1_daily_peak_jun_kw	First quartile of daily electric peak loads (in kW) in June
q_1_daily_peak_jul_kw	First quartile of daily electric peak loads (in kW) in July
q_1_daily_peak_aug_kw	First quartile of daily electric peak loads (in kW) in August
q_1_daily_peak_sep_kw	First quartile of daily electric peak loads (in kW) in September
q_1_daily_peak_oct_kw	First quartile of daily electric peak loads (in kW) in October
q_1_daily_peak_nov_kw	First quartile of daily electric peak loads (in kW) in November
q_1_daily_peak_dec_kw	First quartile of daily electric peak loads (in kW) in December
q_3_daily_peak_jan_kw	Third quartile of daily electric peak loads (in kW) in January
q_3_daily_peak_feb_kw	Third quartile of daily electric peak loads (in kW) in February
q_3_daily_peak_mar_kw	Third quartile of daily electric peak loads (in kW) in March
q_3_daily_peak_apr_kw	Third quartile of daily electric peak loads (in kW) in April
q_3_daily_peak_may_kw	Third quartile of daily electric peak loads (in kW) in May
q_3_daily_peak_jun_kw	Third quartile of daily electric peak loads (in kW) in June
q_3_daily_peak_jul_kw	Third quartile of daily electric peak loads (in kW) in July
q_3_daily_peak_aug_kw	Third quartile of daily electric peak loads (in kW) in August
q_3_daily_peak_sep_kw	Third quartile of daily electric peak loads (in kW) in September
q_3_daily_peak_oct_kw	Third quartile of daily electric peak loads (in kW) in October
q_3_daily_peak_nov_kw	Third quartile of daily electric peak loads (in kW) in November
q_3_daily_peak_dec_kw	Third quartile of daily electric peak loads (in kW) in December
median_daily_peak_timing_jan_hour	Median hour of daily electric peak loads in January
median_daily_peak_timing_feb_hour	Median hour of daily electric peak loads in February
median_daily_peak_timing_mar_hour	Median hour of daily electric peak loads in March
median_daily_peak_timing_apr_hour	Median hour of daily electric peak loads in April
median_daily_peak_timing_may_hour	Median hour of daily electric peak loads in May
median_daily_peak_timing_jun_hour	Median hour of daily electric peak loads in June
median_daily_peak_timing_jul_hour	Median hour of daily electric peak loads in July
median_daily_peak_timing_aug_hour	Median hour of daily electric peak loads in August
median_daily_peak_timing_sep_hour	Median hour of daily electric peak loads in September
median_daily_peak_timing_oct_hour	Median hour of daily electric peak loads in October
median_daily_peak_timing_nov_hour	Median hour of daily electric peak loads in November
median_daily_peak_timing_dec_hour	Median hour of daily electric peak loads in December
total_electricity_use_jan_kwh	Total electricity energy consumption in January
total_electricity_use_feb_kwh	Total electricity energy consumption in February
total_electricity_use_mar_kwh	Total electricity energy consumption in March
total_electricity_use_apr_kwh	Total electricity energy consumption in April
total_electricity_use_may_kwh	Total electricity energy consumption in May

Variable Name	Description
total_electricity_use_jun_kwh	Total electricity energy consumption in June
total_electricity_use_jul_kwh	Total electricity energy consumption in July
total_electricity_use_aug_kwh	Total electricity energy consumption in August
total_electricity_use_sep_kwh	Total electricity energy consumption in September
total_electricity_use_oct_kwh	Total electricity energy consumption in October
total_electricity_use_nov_kwh	Total electricity energy consumption in November
total_electricity_use_dec_kwh	Total electricity energy consumption in December
average_of_top_ten_highest_peaks_timing_shoulder_hour	Average hour of top 10 highest daily electric peak loads during shoulder season
average_of_top_ten_highest_peaks_timing_summer_hour	Average hour of top 10 highest daily electric peak loads during summer season
average_of_top_ten_highest_peaks_timing_winter_hour	Average hour of top 10 highest daily electric peak loads during winter season
average_of_top_ten_highest_peaks_use_shoulder_kw	Average peak load of top 10 highest daily electric peak loads during shoulder season
average_of_top_ten_highest_peaks_use_summer_kw	Average peak load of top 10 highest daily electric peak loads during summer season
average_of_top_ten_highest_peaks_use_winter_kw	Average peak load of top 10 highest daily electric peak loads during winter season
annual_peak_electric_demand_kw	Building annual peak electric demand

5 Results

In this section, results are presented both at the stock level and for individual buildings through savings distributions. Stock-level results include the combined impact of all the analyzed buildings in ComStock, including buildings that are not applicable to this measure. Therefore, they do not necessarily represent the energy savings of a particular or average building. Stock-level results should not be interpreted as the savings that a building might realize by implementing the measure.

Total site energy savings are also presented in this section. Total site energy savings can be a useful metric, especially for quality assurance/quality control, but this metric on its own can have limitations for drawing conclusions. Further context should be considered, as site energy savings alone do not necessarily translate proportionally to savings for a particular fuel type (e.g., gas or electricity), source energy savings, cost savings, or greenhouse gas savings. This is especially important when a measure impacts multiple fuel types or causes decreased consumption of one fuel type and increased consumption of another. Many factors should be considered when analyzing the impact of an energy efficiency or electrification strategy, depending on the use case.

5.1 Single Building Measure Tests

Several single building measure tests are performed to demonstrate the implementation of the developed measure, as shown in the following sections. Specifically, a large office building model with both electric heating and cooling HVAC systems is applied as the baseline sample model, with multiple weather files that represent different climate characteristics to evaluate performance.

The default and alternative sets of input parameters are summarized in Table 3. Parametric analysis is performed using these input parameter sets (scenarios) to investigate the impact of thermostat setpoint adjustment magnitude, peak window length, and rebound control on peak load reduction.

Table 3. Default and Compared Options for Measure Parameters

Parameter	Default	More Aggressive Setback	Shorter Peak Window	No Rebound Control
Length of peak window	4 hours	Same as default	3 hours	Same as default
Length of rebound control	2 hours	Same as default	Same as default	0 hours
Thermostat setpoint adjustment (on peak)	2°C	3°C	Same as default	Same as default
Load prediction method	Perfect prediction (full baseline simulation)	Same as default	Same as default	Same as default

5.1.1 Daily Peak Window Variation

Figure 3 shows the load profiles for five consecutive days from several simulations corresponding to different buildings, weather locations, and scenarios (baseline or with default dispatch strategy) for comparison. Comparison between the baseline profile and the load shed events (appearing as valleys) in the default load shed profile illustrates the timing of the peak window each day. Figure 3 shows that peak windows are highly dependent on individual building characteristics and weather. Even identical buildings (Building 1) in slightly different climate zones (3A and 3B) result in different load profiles. Diversity in the stock models (e.g., location-based weather, internal heat gains, building operation hours, building envelope performance) results in different load profiles, and thus the peak windows each day for each building are also different.

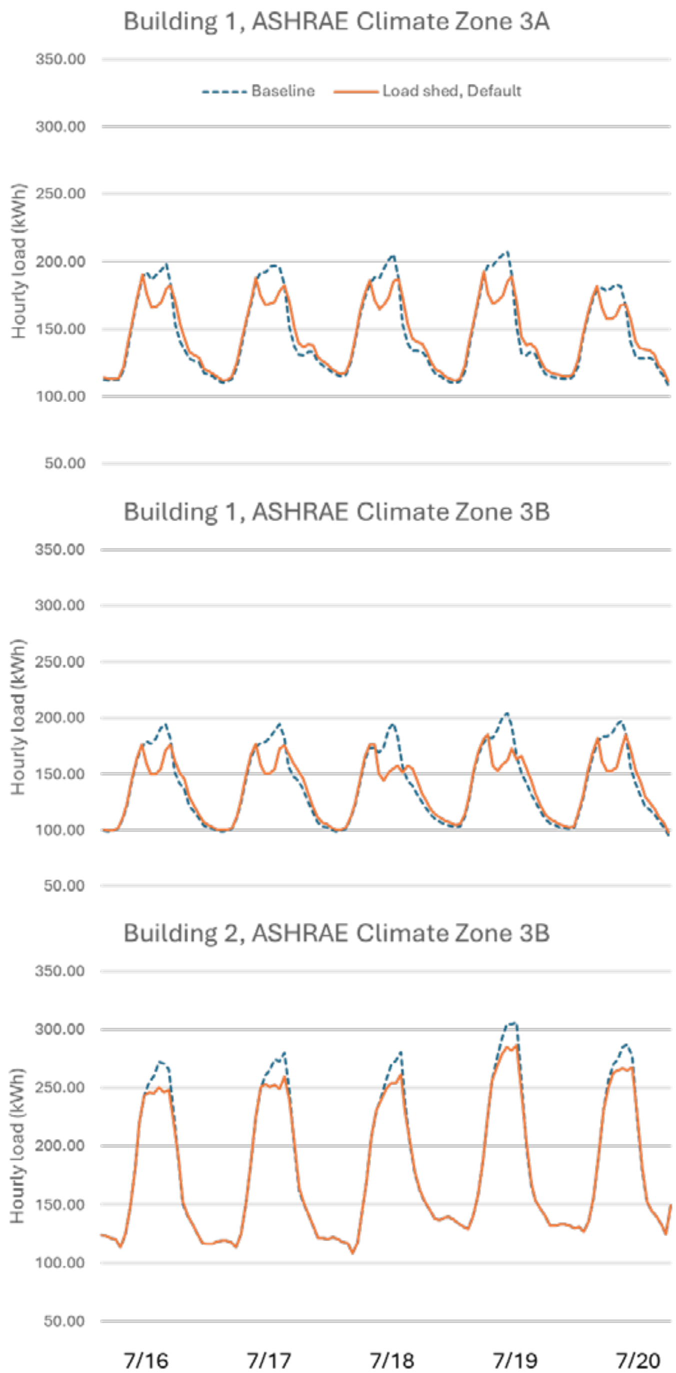

Figure 3. Daily load profile (baseline and load shed) comparison for two buildings with two climate zones

5.1.2 Rebound Effect

Figure 4 shows the daily load profile comparison of the same building in the baseline scenario, applying the "default" parameter set, and applying the "no rebound control" parameter set. As can be seen from the different post-peak load profiles, load shed strategy without addressing rebound effect would almost always generate new peak load higher than original baseline peak for the illustrated summer days, and this trend is maintained throughout the year among different building models. This reveals the natural drawback of rebound effect in load shed control for responsive systems that have ordinary differential equation component(s) such as HVAC systems. Therefore, rebound control is necessary in load shed strategy for thermostat control, and is included in the default scenario.

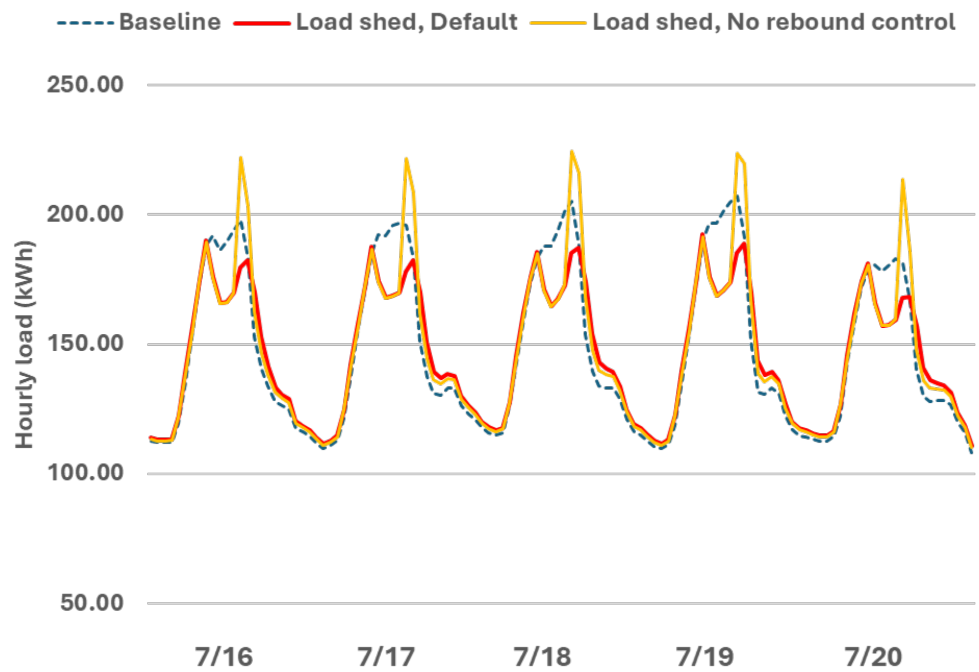

Figure 4. Daily load profile comparison for rebound control

5.2 Demand Flexibility Performance

This section includes additional and more detailed findings specific to the demand flexibility measure that are not covered in the previous sections. As the measure aims to reduce daily building peak load, we extract the daily peak load data from the simulation results. More specifically, 3158 large office building models (i.e., 19212 buildings with weighting factor applied) applicable to this measure record 365 daily peaks across the simulation year. For each month (e.g., January), there are certain number of daily peaks (e.g., 31 daily peak values) available to investigate. To balance the granularity of daily peak data and the visualization level of performance analysis, five quartile statistics (minimum, 25th percentile, median, 75th percentile, and maximum) of daily peak values in each month are calculated for all applicable models to represent the monthly performance of the applied upgrade. These statistics are further illustrated in a boxplot distribution for stock-level summary.

5.2.1 Justification of Default Parameters

Figure 5 shows the distribution of median daily peak load reduction percentages in each month compared to the baseline model for different scenarios (Table 3) to investigate the impact of shorter peak window length, no rebound control, and larger thermostat setpoint adjustment. The results are derived from a ComStock test run with 10,000 building model samples (among which

90 large offices are applicable), due to the limitation of computational resources for full sample run (350,000 samples). From the figure we can conclude that:

- Different scenarios outperform others for any given month, depending on the compatibility of weather characteristics and the parameter set.
- The larger setpoint adjustment scenario generally leads to larger variance in peak reduction performance with more load shed potential but also higher risk of increased daily peak load.
- The shorter peak window scenario has similar performance to the default scenario, but it has a lower potential (upper limit) of peak reduction for most months.
- The no rebound control scenario shows accorded performance with the single building test result (Figure 4) where the rebound effect results in increased daily peak load for many months (April to October).

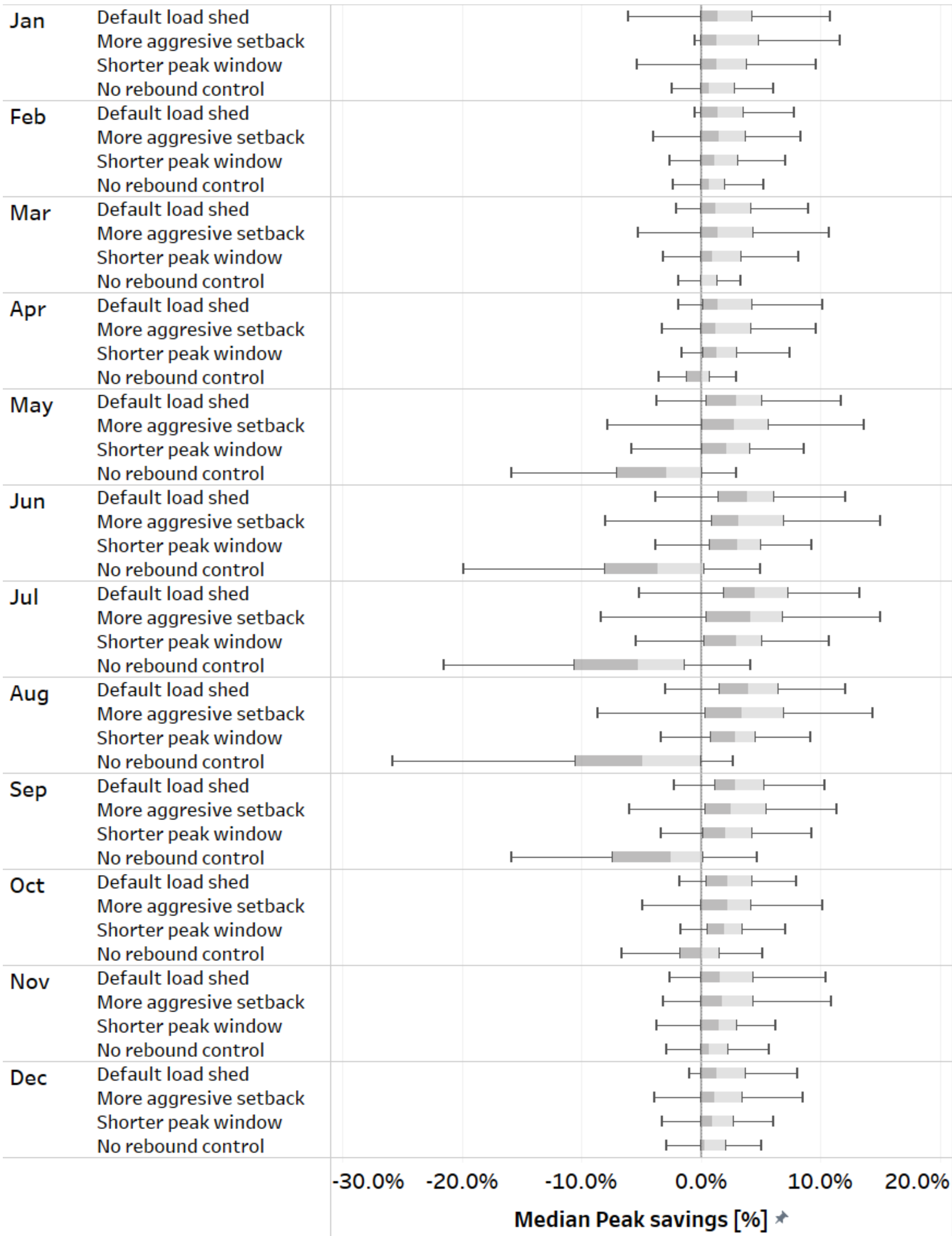

Figure 5. Distribution of reduction percentage of median daily peak load compared to the baseline model by month for measure with default and comparative scenarios

Based on the comparison, the performance of default setting of the measure is determined to be the overall best in terms of peak reduction potential and performance.

5.2.2 Monthly Quartile Statistics Distribution of Daily Peak Reduction

Figure 6 and Figure 7 show the percentage distributions of median and maximum daily peak load reductions, respectively, by month for the default scenario compared to the baseline model.

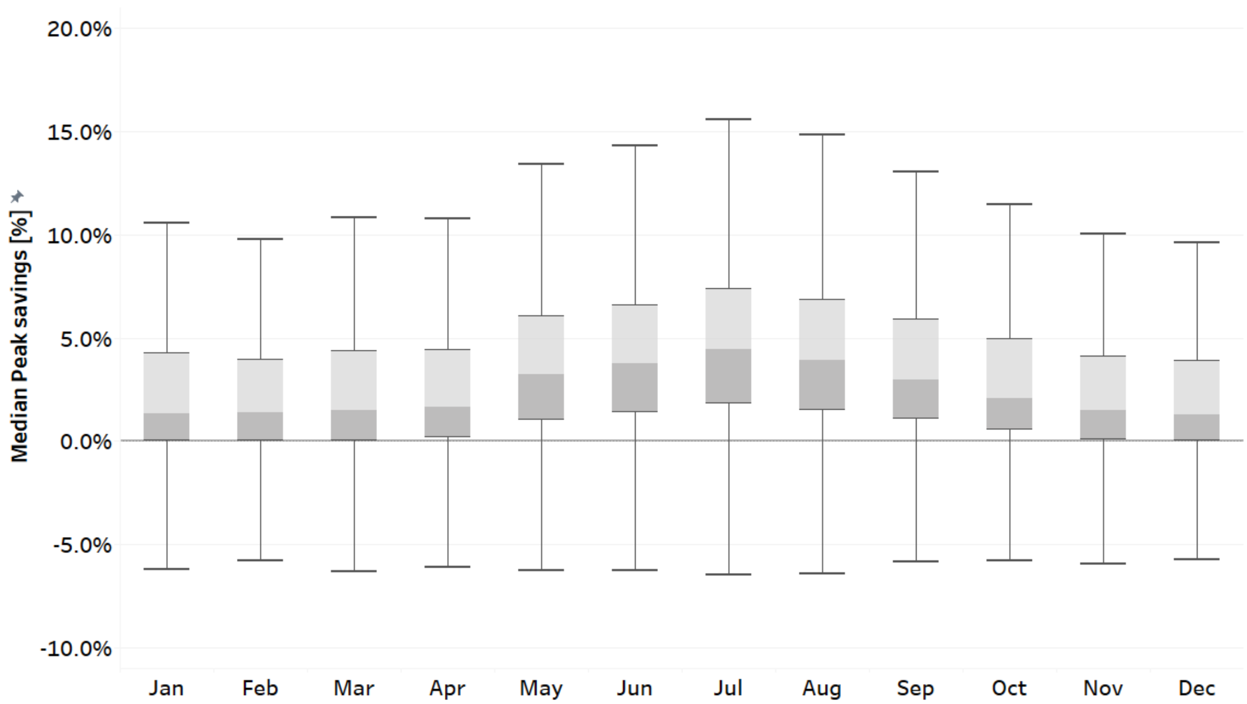

Figure 6. Distribution of the percentage of median daily peak load reduction by month compared to the baseline model for the default scenario

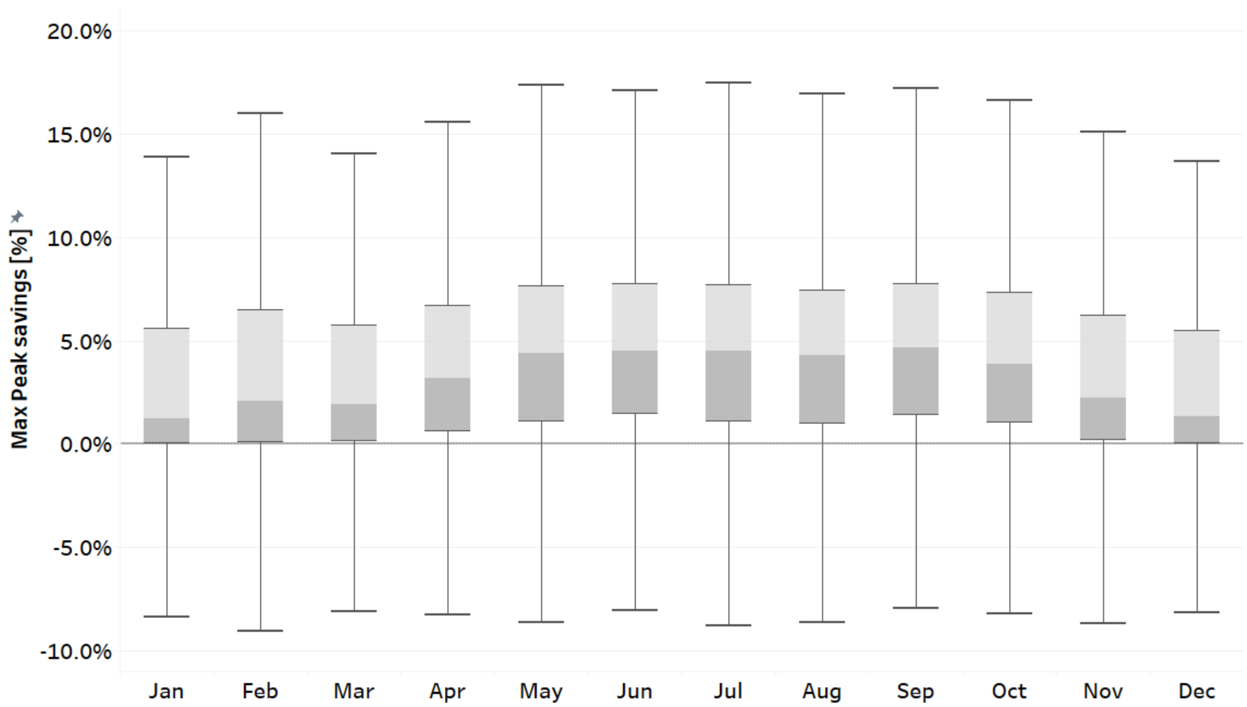

Figure 7. Distribution of the percentage of maximum daily peak load reduction by month compared to the baseline model for the default scenario

Both distributions of the statistics share a similar trend: a daily peak load reduction is not guaranteed with the upgrade, but there is an overall positive monthly reduction. The non-negligible portion of the stock with negative peak reductions is mainly due to the uncertainty in rebound effects with fixed rebound control length (2 hours) for all applicable buildings; some rebound effects are too strong to mitigate in 2 hours or the peak window ends too early for rebound control to take effect. Therefore, rebound control could and should be tuned for specific building models (in future work), as the impact of rebound effects is highly dependent on building properties and weather conditions. The larger variances for median statistics in summer and winter are contributed due to a similar reason, where rebound effects are typically stronger in summer and winter when the highest and lowest temperatures occur.

There is no obvious correlation between building size (floor area) and measure performance, or between heating system (fuel) type (electric or non-electric heating) and measure performance.

5.2.3 Annual Bill Savings

Figure 8 shows the distribution of annual bill savings for the default scenario with respect to the maximum, mean, and median bill costs among all considered utility rate structures (for more information related to utility bill costs, refer to the utility bills section in Section 5 of the ComStock Reference Documentation [40]). To provide high level context of the bill calculation, each building model with locational information is used to find all utility rate structures (from Utility Rate Database [41]) applicable/available for the building. After calculating annual utility bill costs for all applicable utility rates, we report statistics (mean, median, and max) of all utility bill costs for each of the building model. All the comparisons show positive bill savings of around 1%–3%, except for the no rebound control scenario. Savings corresponding to the max bill are generally smaller than the mean or median ones, indicating that the rate structure resulting in max bill typically benefits less in peak reduction or has no portion related to demand. When the building is equipped with an electric heating system, the savings would be increased around 1%, indicating that the savings potential from this load shedding strategy is lower for electric heating systems than for cooling systems. The bill savings are primarily from:

1) Net energy use reduction (major)
2) TOU rates that have matched time of peak prices with the peak windows on a monthly average (there could be negative savings for TOU rates that have peak prices outside of the daily peak window identified by this measure)
3) Applicable monthly or seasonal demand charge reduction.

These savings underestimate the benefits from a measure targeting daily peak load reduction, as most rate structures consider peak demand charge on a monthly or seasonal basis, while demand response programs or rate structures including DR incentives that favor daily demand flexibility control are currently not able to be directly integrated into ComStock analysis.

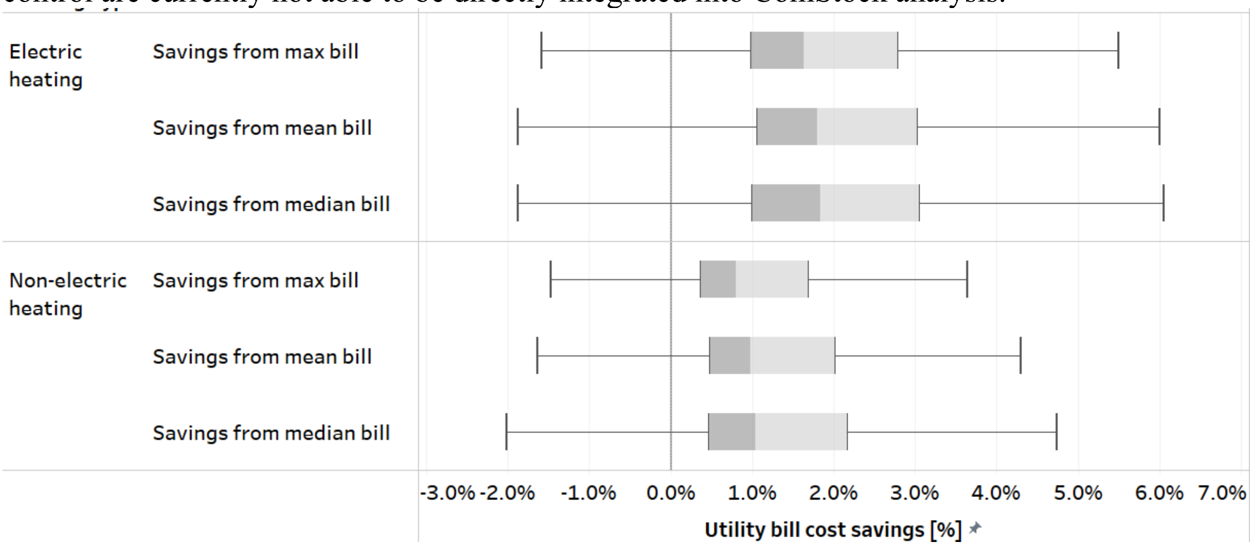

Figure 8. Distribution of annual bill savings compared to the baseline model for maximum, mean, and median bills, separated by buildings with electric and non-electric heating

5.3 Stock Energy Impacts

The thermostat control for load shedding measure with perfect load prediction method that is applicable to large office buildings—9.72% of the total building stock floor area—demonstrates 0.046% total site energy savings (2 trillion British thermal units [TBtu]) for the U.S. commercial building stock modeled in ComStock, as shown in Figure 9.

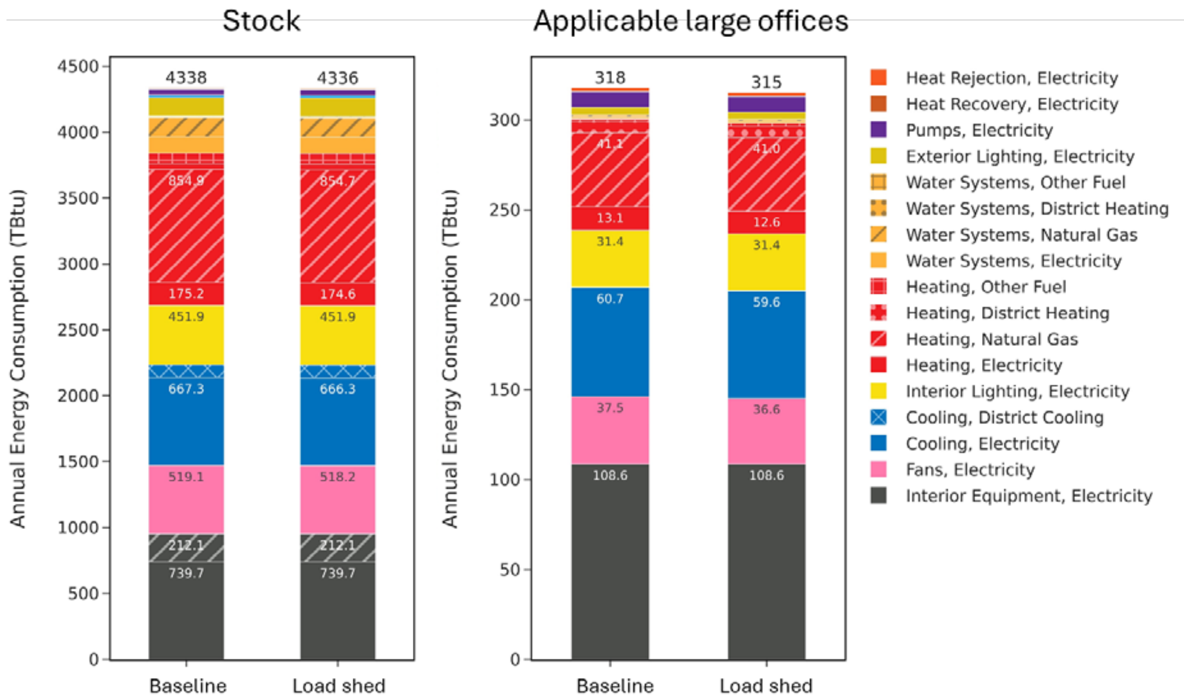

Figure 9. Comparison of annual site energy consumption between the ComStock baseline and the thermostat control for load shedding measure default scenario, for the whole stock (left) and applicable large offices only (right)

The savings are primarily attributed to:

- **0.023%** stock **natural gas heating** savings (0.2 TBtu)
- **0.34%** stock **heating electricity** savings (0.6 TBtu)
- **0.15%** stock **cooling electricity** savings (1.0 TBtu)
- **0.17%** stock **fan** savings (0.9 TBtu).

The measure focuses on load shed for electric HVAC systems in large offices only, so the energy savings are not prominent at the stock level, including various non-applicable building types, end uses, and fuel types. The natural gas savings are mainly attributed to the pre-heating effect indirectly caused by the cooling load shed during the shoulder season, when HVAC systems in some climate zones work in cooling and heating mode alternately. In addition, the HVAC electricity consumption reduction during peak windows is normally partly compromised by the increased HVAC electricity use (to recover the system to the original setpoint, even with rebound control) after the peak window, which diminishes the net savings. The objective of the measure is to provide demand flexibility by shaving load peaks on a daily basis instead of improving energy efficiency, so the minor energy savings are as expected. However, the developed load shed measure is not exclusive from other energy efficiency measures; it could be integrated with them to provide demand flexibility while saving energy.

5.4 Stock Greenhouse Gas Emissions Impact

Figure 10 shows the annual stock level impact of the measure on greenhouse gas emissions and presents approximately 0% emission reductions for all the three grid electricity scenarios. This is as expected due to the small energy savings. Future analysis will pursue the objective of saving carbon emission that will result in more impact on carbon emission savings.

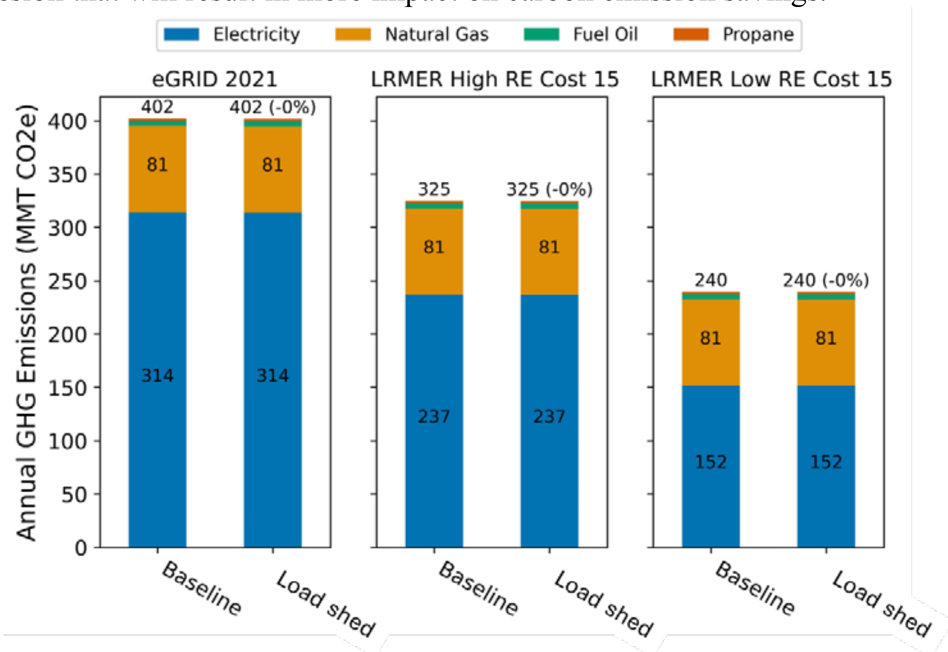

Figure 10. Greenhouse gas emissions comparison of the ComStock baseline and the thermostat control for load shedding measure default scenario

5.5 Site Energy Savings Distributions

Figure 11 through Figure 14 show the percent site energy and energy use intensity (EUI) savings distributions by end use and climate zones, respectively. Percent savings provide relative impact of the measure at the individual building level while site EUI savings provide absolute (or aggregated) scale of impact. Also, the data points that appear above some of the distributions indicate outliers in the distribution, meaning they fall outside 1.5 times the interquartile range. The value for n indicates the number of ComStock models that were applicable for energy savings for the fuel type category.

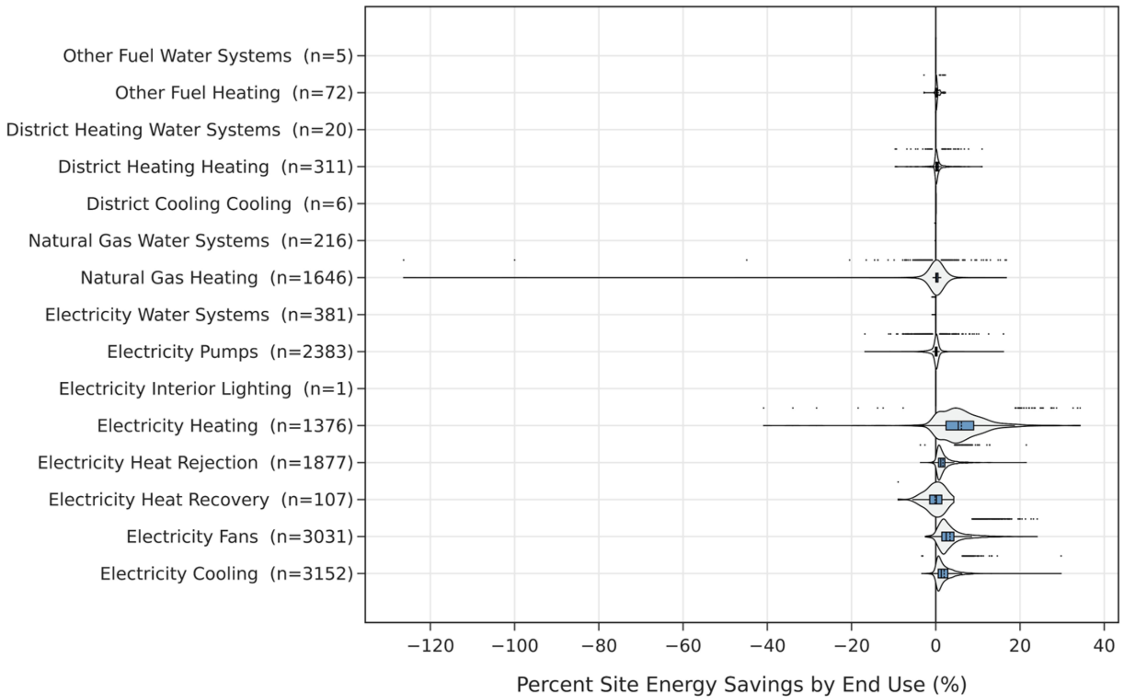

Figure 11. Percent site energy savings distribution for ComStock models with the thermostat control for load shedding upgrade by end use

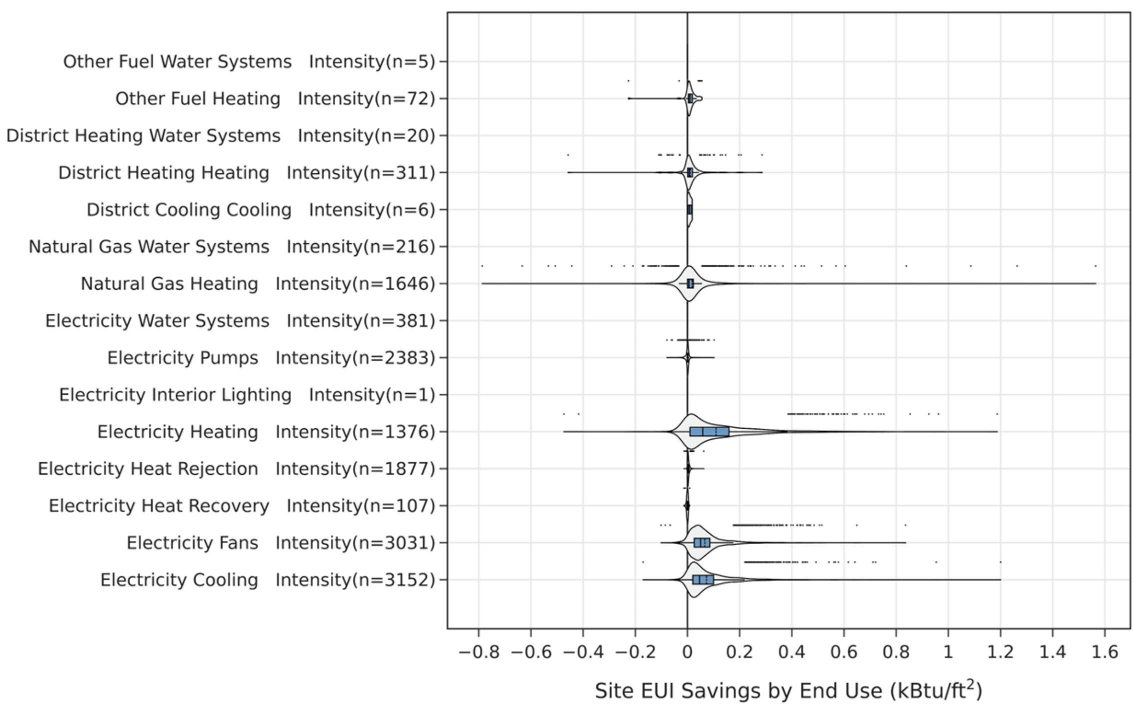

Figure 12. Percent site EUI savings distribution for ComStock models with the thermostat control for load shedding upgrade by end use

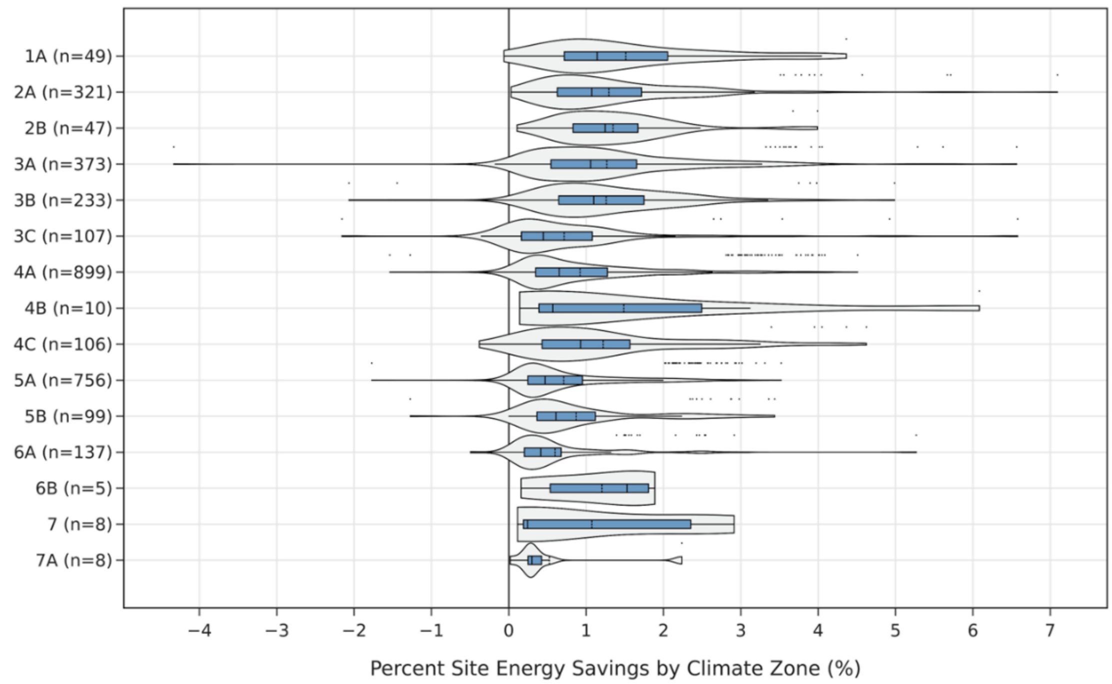

Figure 13. Percent site energy savings distribution for ComStock models with the thermostat control for load shedding upgrade by ASHRAE climate zone

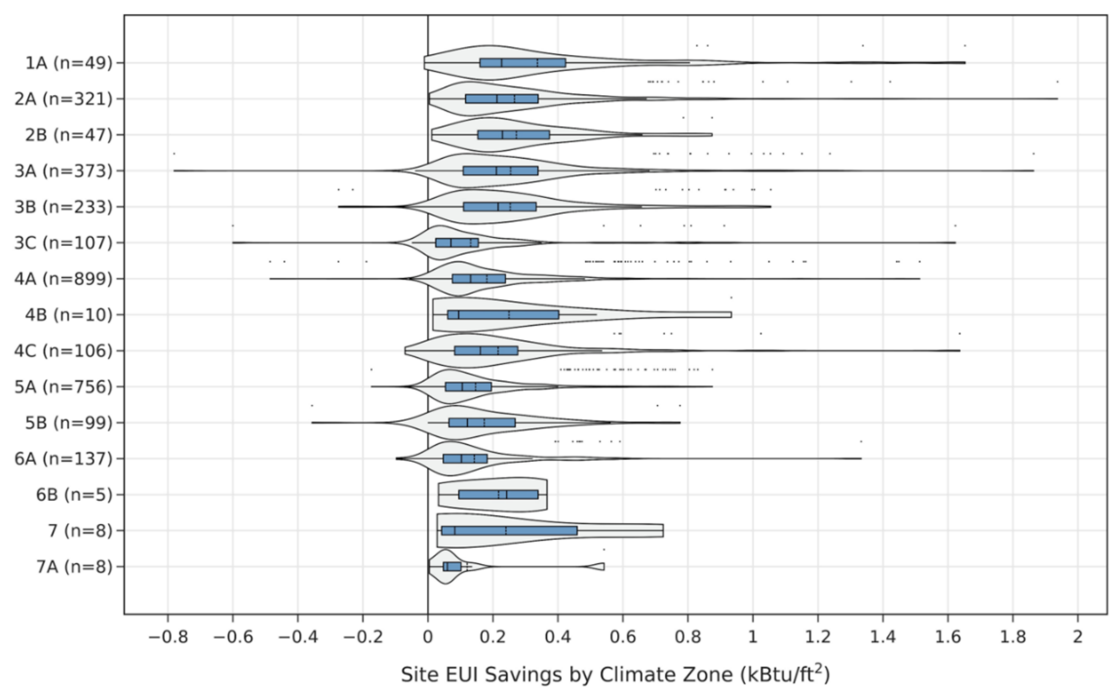

Figure 14. Percent site EUI savings distribution for ComStock models with the thermostat control for load shedding upgrade by ASHRAE climate zone

Both figures show a relatively larger energy impact compared to the EUI savings, indicating that the measure plays a more significant role in energy performance at the building level, but the savings are not significant once adjusted for building floor area. Highlights of savings presented in the figures include:

- 2%-10% savings on electric heating systems,
- Around 5% savings on fans, associated with reduced heating and/or cooling operations during the peak window,
- Around 3% savings on electric cooling systems.

The measure is effective for various weather zones, indicating that the demand flexibility opportunities are not weather-exclusive.

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Appendix A. Additional Figures

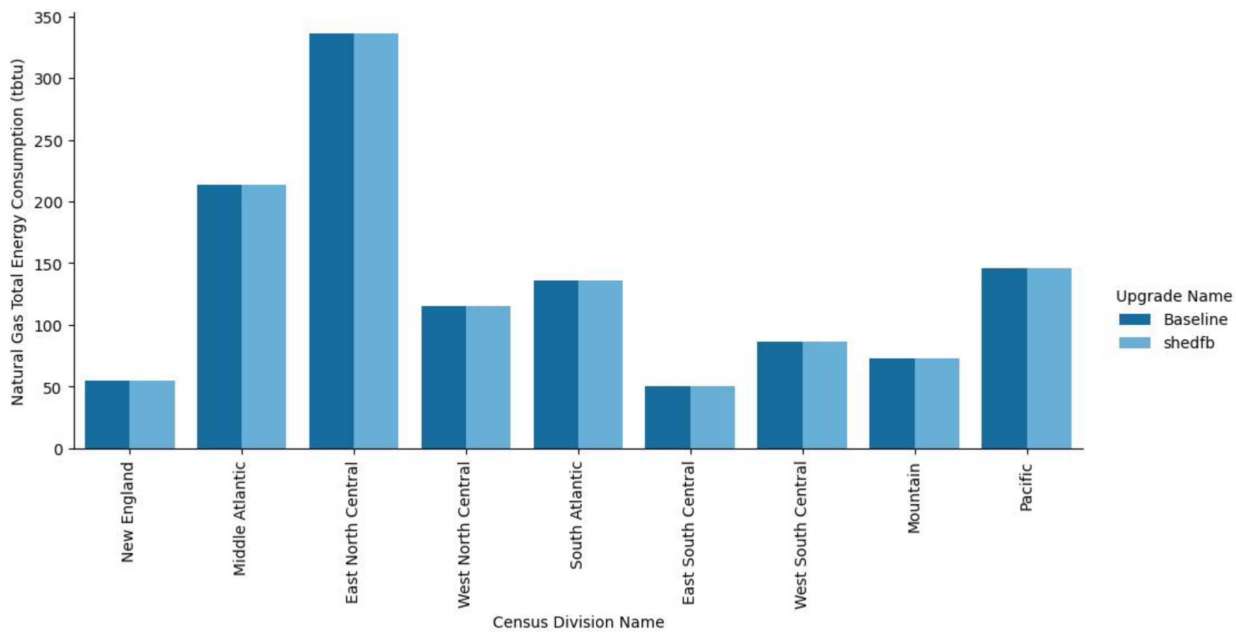

Figure A-1. Site annual natural gas consumption of the ComStock baseline and the measure scenario by census division

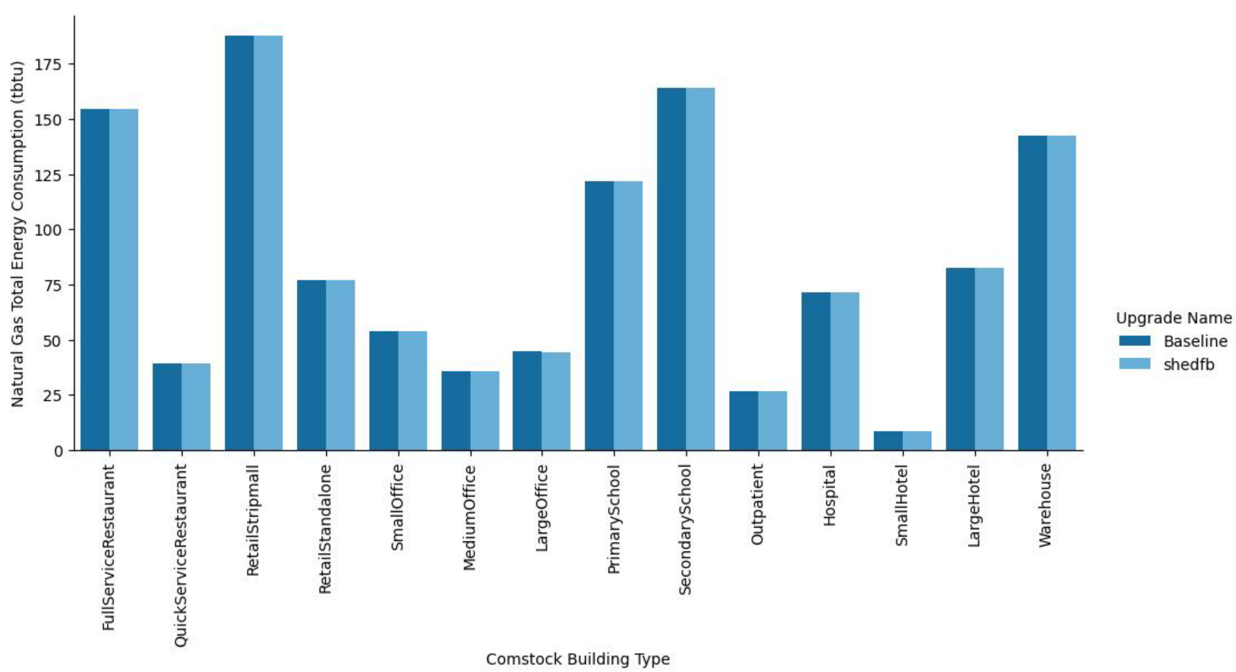

Figure A-2. Site annual natural gas consumption of the ComStock baseline and the measure scenario by building type

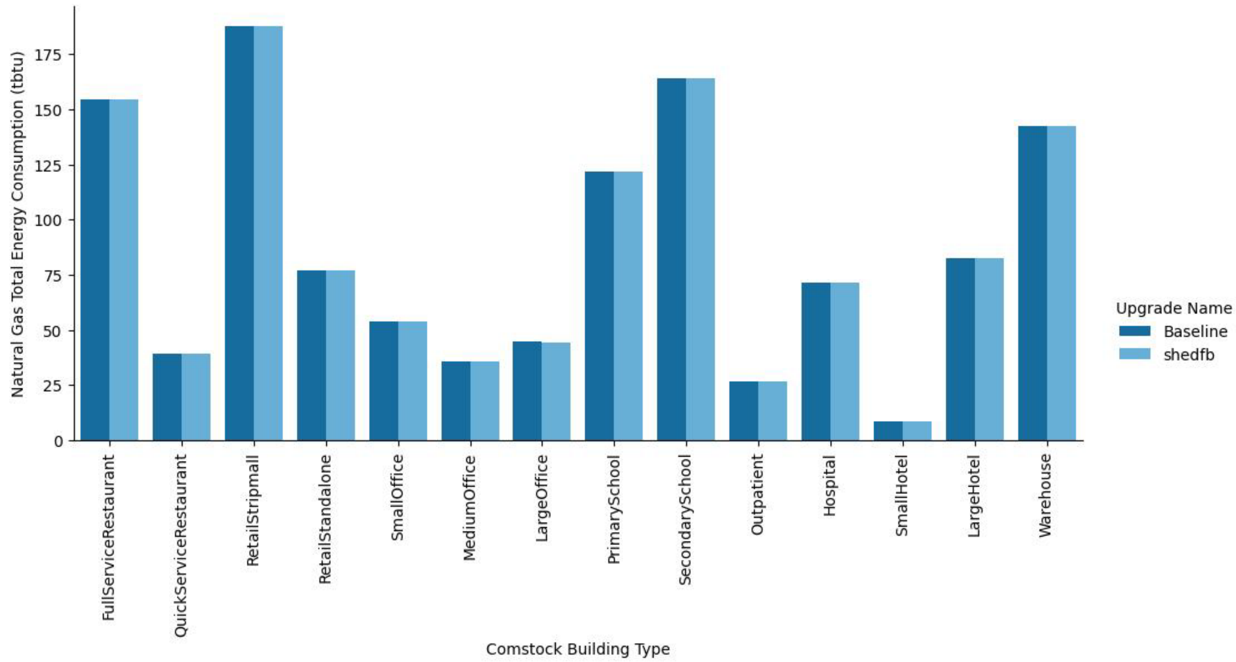

Figure A-3. Site annual electricity consumption of the ComStock baseline and the measure scenario by building type

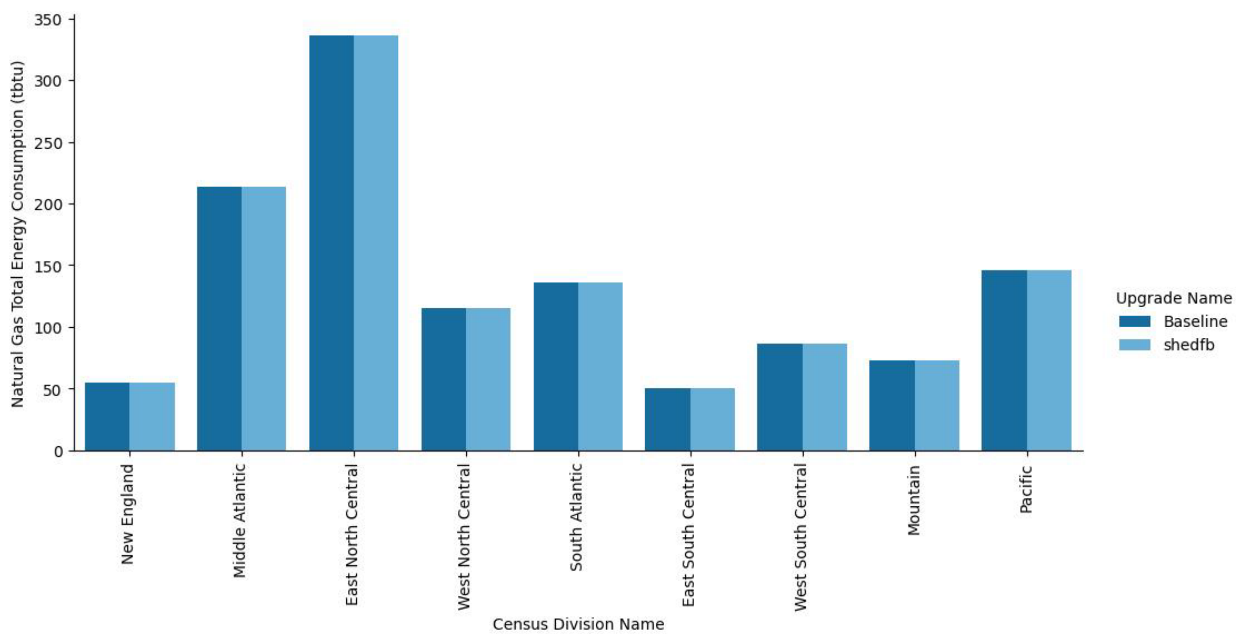

Figure A-4. Site annual electricity consumption of the ComStock baseline and the measure scenario by census division