Assessing the performance of global thermostat adjustment in commercial buildings for load shifting demand response

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Abstract
Efficiently leveraging new sources of flexibility is critical to mitigating load balancing challenges posed by variable renewable resources. The thermal inertia of commercial buildings allows us to shift their power consumption on minute to hourly timescales to provide demand response (DR) to the grid while maintaining occupant comfort. Global thermostat adjustment (GTA) provides a readily available and scalable approach for implementing load shifting DR using commercial heating, ventilation, and air conditioning (HVAC) systems, since it leverages the inherent sophistication of modern building automation systems. However, there is an incomplete understanding of GTA’s performance for this purpose and its impact on building systems and occupant comfort. In this paper, we explore the performance of GTA by analyzing results from nearly nine hundred experiments on eight university campus buildings in Michigan and North Carolina. Using GTA, we manipulate each building’s thermostat setpoints causing the building to shift its power consumption with respect to its baseline. We quantify the magnitude of HVAC power response, energy use of HVAC subsystems, and impact on occupant comfort. Finally, we connect our experimental results with power system operation using an optimization model that coordinates GTA actions across a large collection of grid-interactive efficient buildings to reduce high ramp rates on the grid and mitigate renewable energy curtailment. Overall, our work finds that the impacts on HVAC subsystems are often complex, and may result in additional energy being consumed by fans and terminal reheat. These effects must be considered when using GTA for load shifting. Additionally, we demonstrate that occupant comfort, as assessed by indoor temperature and humidity, can be maintained during GTA events. From a societal perspective, our modeling work finds that the additional renewable energy that can be integrated through the use of GTA strategies eclipses any additional energy consumed by buildings.

List of abbreviations
ACC Additional chiller consumption
AEC Additional energy consumption
AHU Air handling unit
ARC Additional reheat consumption
ASHRAE American Society of Heating, Refrigerating, and Air-conditioning Engineers
BAS Building automation system
BBB Bob and Betty Beyster building
DR Demand response
EB2 Engineering building 2
EB3 Engineering building 3
GEB Grid-interactive efficient building

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1. Introduction

Critical challenges remain along the path to a decarbonized electricity system. One such challenge, that of balancing supply and demand over multiple time-scales, is addressed in this paper. As the penetration of renewable resources on the grid increases, achieving this balance will require greater responsiveness of both generation and demand. The challenge of ensuring sufficient grid flexibility is further exacerbated as fossil-fuel based resources that previously provided such flexibility, e.g., existing thermal generators with high rotational inertia and load-following governor systems, are increasingly displaced [1]. Efficiently leveraging new sources of flexibility to ensure reliable and economic power grid operation is a critical step in achieving deep decarbonization of our energy system [2, 3].

In recent years, considerable research effort has been devoted to investigating the potential of commercial building heating, ventilation, and air conditioning (HVAC) systems for providing flexibility in the form of a variety of grid services [4–10]. The United States Department of Energy Building Technologies Office released a series of reports in 2019–2021 [11–16] on the development of grid-interactive efficient buildings (GEBs), laying a roadmap for improving connectivity and communication capabilities of buildings to better manage building comfort, while simultaneously providing grid services. Commercial buildings consume nearly 37% of electricity generated in the United States [17] and, while traditionally passive consumers of energy, they offer great potential to provide flexibility to the power grid through demand response (DR), which is defined as a change in electricity consumption by the consumer in response to a price signal or a command by the grid operator [11]. A 2018 survey of 190 US utilities found that among the 20.8 GW of enrolled DR capacity, 13.4 GW of capacity was provided by commercial and industrial customers [18].

DR from commercial buildings can be achieved through load shedding or load shifting. Traditionally, both have been used to reduce the system load at times when the grid is operating near its peak (typically on hot summer days) or during contingency events [19]. Typically load is shed or shifted for long time periods, e.g., 2–6 h. However, commercial buildings can also load shift over faster timescales, including those of frequency regulation (seconds) [20–24] and real-time energy markets (sub-hourly) [25–27]. Reference [11] details the many benefits of load shifting DR. DR can be achieved through load control or by eliciting changes in consumption due to price signals (e.g., time of use pricing or critical peak pricing), although the latter approach has limited applicability for fast timescale applications.

Global thermostat adjustment (GTA) is one of the most readily available strategies to shift HVAC power consumption using existing building automation systems (BAS). This is because GTA only involves manipulating temperature setpoints of building thermostats by broadcasting a signal to them through the BAS. The signal causes the HVAC system to increase or decrease its power consumption, depending on the direction of the temperature setpoint change. The building-agnostic nature of GTA makes it an attractive strategy for providing a range of grid services. Given the timescales over which GTA best operates, it could be an especially effective strategy for addressing emerging challenges caused by high renewable penetration, including increased power system ramping and renewable energy curtailment.

The performance of GTA in providing load shifting on sub-hourly to hourly timescales has not been fully studied. Specifically, there has not been a comprehensive examination of the ability of GTA to elicit desired responses, its impact on occupant comfort, and its impact on energy used by HVAC subsystems. Perry et al [19] note that a potential technological barrier to the deployment of GEBs is the complexity of interconnected building systems within commercial buildings, meaning that a change made to one building system can affect others in complex ways. In particular, GTA can impact the electricity and gas consumption of multiple HVAC subsystems.

In this paper, we conduct an in-depth experimental and modeling investigation into the performance of GTA-based load shifting DR on hourly and sub-hourly timescales, offering new insights on: (1) the factors influencing the magnitude of fan power and chilled water system response, for a range of commercial-scale
buildings, (2) the net impact on building energy consumption, (3) the impact on occupant comfort and cooling service provided, and (4) the implications of scaling up load shifting DR to mitigate power system ramping and renewable energy curtailment. Expanding on prior work [27], we conducted nearly 900 experiments on eight campus buildings at the University of Michigan (UM) and North Carolina State University (NCSU), and provide detailed analysis of the impacts of GTA-based load shifting DR at subhourly timescales.

Some prior work has investigated how DR affects building energy consumption and occupant comfort. Previous experimental work [25–27] found that HVAC fans can consume significantly more energy when providing GTA-based load shifting DR than under normal operation. However, previous modeling work provided contradictory results, finding that energy use could increase or decrease [28], or would increase but by only a small amount [29, 30]. MacDonald et al [31] provide a comprehensive review of prior literature in this domain and hypothesize that the asymmetry of fan power response (i.e., poor tracking response of the reference signal) and baseline error could be dominant contributing factors to the significant increase in energy reported in the experimental work, and emphasized the need for further experimental work. They also highlighted the need for a deeper understanding of the comfort implications of DR. The impact on occupant comfort is critical for building owners who wish to participate in DR but want to ensure there are no adverse impacts on employees or residents. Poor indoor comfort has significant cost implications for building owners compared to additional utility costs and is cited as a high source of dissatisfaction for building occupants [33].

Previous research quantifies the impact of temperature setpoint changes on occupant comfort, though this has largely been conducted for traditional DR shed events and not load shifting DR [34].

Our study makes several novel contributions. We provide an empirical assessment of building response to GTA-based load shifting DR experiments on a wide variety of commercial buildings. Furthermore, our analysis at the HVAC subsystem level is more comprehensive than prior studies in this domain. We develop metrics to quantify impacts on comfort and unmet cooling service, providing new ways to verify that occupant comfort is maintained—a critical attribute of GEBs. Finally, we explore the use of load shifting DR with GEBs to provide services, beyond traditional peak load management, that mitigate grid challenges posed by high renewable penetration.

The paper is organized as follows: section 2 describes the building-level methods used to assess the performance of GTA for load shifting DR. We first pose three building-level research questions (RQs), describe the characteristics of typical commercial HVAC systems, detail our experimental design, and describe the processes of building selection and data collection. We then detail the metrics that we use to quantify the magnitude and efficiency of building response, and occupant comfort. Section 3 describes the results from the building-level

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4 The 3-30-300 rule of thumb is often use to estimate (in $ per square foot per year) the utility, rent, and employee salary costs respectively for a typical commercial building [32].
methods using experimental data from eight campus buildings. In section 4, we pose a grid-level RQ and present an optimization model that investigates the power system implications of our experimental results. We conclude by providing our key findings and an in-depth discussion of the key gaps that require further research.

2. Experimental methods

We address the following building-level RQs to investigate the performance of GTA in providing load shifting DR in commercial buildings.

RQ1. What factors influence the magnitudes of the HVAC fan and chilled water system responses to GTA setpoint changes?

RQ2. How much additional energy do building HVAC subsystems (fan, chilled water, and terminal reheat) consume when they provide load shifting DR using GTA?

RQ3. What are the impacts on occupants in terms of the temperature, comfort, and overall cooling service when buildings provide GTA-based load shifting DR?

Section 2.1 provides a brief overview of the architecture of a single duct variable air volume (VAV) HVAC system. Section 2.2 then describes the GTA setpoint signals that were designed to address the above RQs. In section 2.3, we describe the buildings included in this study and detail our data collection methods. Finally, we define the metrics used to quantify the performance of GTA to provide load shifting DR in section 2.4. We connect each metric detailed in section 2.4 to the research question (RQ1, RQ2 or RQ3) that it addresses.

2.1. HVAC architecture

Commercial HVAC systems are composed of multiple subsystems that can exhibit complex interactions. Figure 1 shows a typical layout of a single duct VAV HVAC system with terminal reheat. The chilled water loop, hot water loop, and air distribution loop work cooperatively to regulate the temperature of the conditioned spaces of the building. In responding to room temperature setpoint changes, components within the loops exhibit response times that span multiple time-scales. First, the change in temperature setpoints (referred to as VAV setpoints) triggers VAVs to adjust damper positions to control the amount of supply air entering a thermal zone to achieve and maintain the newly commanded setpoint. The supply air provided by air handling units (AHUs) to VAV units is at a constant temperature (usually set between 55–60°F, depending on the sensible and latent cooling demand of the building). Modulation of the dampers causes changes in the static duct pressure. To return the static duct pressure to its constant setpoint, variable speed drive fans respond. The response of VAV dampers to room temperature setpoint changes and the resulting increase or decrease in fan power consumption occur on a minute timescale [35]. The terminal reheat coils operate as a corrective measure when the adjustment of dampers alone cannot maintain the setpoint, in particular when a damper, despite operating at its minimum opening, is still overcooling a space. Terminal reheat systems also respond on a minute timescale [35]. While some HVAC systems have a reheat coil at the output of the AHU, all of the buildings in this study have terminal reheat systems which are served by hot water loops fed by natural gas-fired boilers. The chilled water system is generally the largest consumer of electricity in the HVAC system. To avoid mechanical wear and tear, its response to changes in cooling demand is slower than that of the fans.

2.2. Experimental design

We implemented GTA by adjusting VAV setpoints through the BAS. In our experiments, we controlled a majority of the VAV setpoints, only omitting building zones with sensitive loads, such as lab equipment, which require tight temperature control. Different approaches were used to implement GTA across the two universities, as shown in figure 2. At NCSU, a Python program running on a cloud-hosted virtual server was used to change VAV temperature setpoints in all the buildings, with each building receiving the same command for changing setpoints. At UM, the tests were coded into the BAS on field panel(s) of each building to control VAV setpoints of that building. Appendix A describes the relative advantages and disadvantages of the two GTA approaches.

We conducted experiments using three types of setpoint signals, as shown in figures 3(a)–(c). The setpoint adjustments were broadcast to building thermostats within the test window $t_w$. We also analyzed the response of the building after the test, over an assumed settling window $t_s$, during which the building returned to its

5 The term zone refers to a collection of conditioned spaces with similar conditioning requirements and the same heating and cooling VAV setpoint.

6 Terminal reheat systems can also be electric, in keeping with the trend to electrify space heating in an effort to decarbonize buildings [36].
Figure 2. The GTA approaches implemented at the two campuses.

Figure 3. Thermostat setpoint shapes implemented using GTA on the eight buildings and the resulting aggregate fan power response relative to the baseline. A down setpoint change leads to increased fan power consumption, and vice versa. We expect the chiller to respond similarly, but on a slower timescale. Opposite polarity tests were also conducted.

baseline (setpoints unperturbed) operation. The total window of analysis \( t_t \) is the sum of the test and settling windows \( (t_t = t_w + t_s) \).

The symmetrical setpoint signal, shown in figure 3(a), is the same as the signal used in previous experimental work [26], which was based on experimental work conducted at Los Alamos National Laboratory [25]. Provided symmetric setpoint changes elicit approximately symmetric power responses\(^7\), this signal achieves load shifting DR. References [25, 26] found that the increase in overall fan energy usage was less when the fan power was increased and then decreased with respect to its baseline (i.e., up-down power), than when the

\(^7\) This assumption is discussed in detail later in this section.
power was first decreased and then increased (i.e., down–up power). We refer to the direction and sequence of a power deviation pattern as its polarity. The results of the symmetrical setpoint signal tests were used to address RQ2 and RQ3.

The second type of setpoint signal, shown in figure 3(b), is the unipolar setpoint signal (i.e., setpoint changes in a single direction, either up or down). These signals do not achieve load shifting DR, but rather result in a load shed or load increase. They were used to investigate the change in fan power and chilled water system response as a function of the magnitude of the setpoint change and as a function of the outdoor air temperature. Unipolar tests were also used to determine whether the building responded more in the up direction or the down direction. The results of the unipolar setpoint signal tests were used to address RQ1.

The third type of setpoint signal, shown in figure 3(c), is the successive setpoint signal inspired by the modeling work of [29, 30]. The successive setpoint signal replicates the symmetric setpoint signal multiple times, and therefore also achieves load shifting DR. The energy use impacts of successive GTA-based load shifting DR have received little prior experimental investigation [27]. The results of the successive setpoint signal tests were used to address RQ2 and RQ3.

Table 1 summarizes the experimental test parameters, including the signal type, polarity, duration of the test and settling windows, and full magnitude (FM, see figure 3) of the setpoint change. Different FMs were used at UM and NCSU because initial experiments found different setpoint perturbations were required to elicit responses that were clearly visible in the BAS data.

The assumption that symmetric setpoint changes in figure 3(a) elicit approximately symmetric power responses was justified by Bell et al. [25] on the basis of empirical data from one building that showed approximately equal down and up fan power responses to equal up and down setpoint changes [35]. However, we would not expect this to be true for all buildings, and so we explore the validity of this assumption in section 3.1.1. If symmetrical setpoint changes do lead to symmetric power responses, load shifting within the test window \( t_w \) is energy neutral with respect to the baseline. Here we use the term neutral to describe situations where the changes in the up and down directions, with respect to an estimated baseline, balance, i.e., the integral of the changes over the time period is zero. If load shifting within \( t_w \) is approximately energy neutral, then the energy-use impacts of GTA-based load shifting DR can be estimated from the additional energy consumed over the total window \( t_s \), which is approximately equal to the additional energy consumed in the settling window \( t_i \).

All experiments were open-loop, i.e., the GTA setpoint was adjusted by a predetermined amount and the HVAC system responded accordingly. There was no feedback mechanism. This experimental approach allowed us to observe the inherent (natural) response of the HVAC system. It also had the advantage of simple implementation as no BAS modifications were required. This provided a good representation of operations that could be practically implemented for wide-scale deployment on commercial buildings.

### 2.3. Building selection and data collection

We selected buildings which had a large number of VAVs with controllable temperature setpoints. We also chose diverse buildings of different sizes, types, HVAC system layouts, and number of fans, as shown in Table 2. This diversity is important since we expect different buildings to have different responses to the experiments. Seven of the eight buildings have multi-zone single duct VAV systems with terminal reheat. Their chilled water is supplied by chilled water plants, each serving multiple buildings, and air is cooled using air-to-water heat exchangers. The DNA building also has chilled water beams that provide radiant cooling for some conditioned spaces. The remaining building (SS at NCSU) has a direct expansion system in which the refrigerant cools the air directly. In the United States, direct expansion systems (or packaged air conditioning units) condition 52% of commercial building floorspace [37]. Five of the buildings have floorspace more than 100,000 ft\(^2\), while buildings of this size account for less than 3% of commercial buildings, they represent 34% of commercial building floorspace [38]. The NCSU buildings are located in Raleigh, North Carolina (mixed-humid, IECC.

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**Table 1.** Experimental test parameters.

| Signal type | Polarity (power) | Test window \( t_w \) | Settling window \( t_i \) | Full magnitude (FM) |
|-------------|-----------------|----------------------|-------------------------|---------------------|
| Symmetrical | Up--down         | 1 h                  | 1 h                     | 4°F at UM           |
|             | Down--up        |                      |                         | 6°F at NCSU         |
| Unipolar    | Up              | 30 min               | 1 h                     | 1,1,5,2°F at UM     |
|             | Down            |                      |                         | 1,2,3°F at NCSU     |
| Successive  | Up--down--down  | 1 h                  | 1 h                     | 4°F at UM           |
|             | Down--up--up    | or 2 h               |                         | 6°F at NCSU         |

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8 The median size of commercial buildings in the US is 5400 ft\(^2\) [38].
Table 2. Characteristics of the buildings included in the study\textsuperscript{a}.

| Building name | EB2 | EB3 | PS | SS | BBB | THY | NQ | DNA |
|---------------|-----|-----|----|----|-----|-----|----|-----|
| Location      | NC  | NC  | NC | NC | MI  | MI  | MI | MI  |
| Year built    | 2005| 2010| 1914| 2011| 2005| 2006| MI | MI  |
| Building type | Classroom/office/lab | Classroom/office/lab | Office | Office | Classroom/office | Office | Classroom/office | Classroom/office |
| Area (ft\textsuperscript{2}) | 202 400 | 175 000 | 50 000 | 13 500 | Unavailable | 3160 | 508 | 117 100 |
| Annual energy consumption (MWh) | 4284 | 4649 | 761 | Unavailable | 3160 | 3979 | 288 400 | 1595 |
| HVAC system type | Chilled water | Chilled water | Chilled water | Direct expansion | Chilled water | Chilled water | Chilled water | Chilled water |
| #Temperature setpoints controlled | 265 | 335 | 85 | 15 | 193 | 94 | 124 | 162 |
| BAS manufacturer | Metasys | Metasys | Metasys | Metasys | Siemens | Siemens | Siemens | Siemens |
| BAS installation year | 2006 | 2008 | 2009 | 2010 | 2006 | 2006 | 2010 | 2002 |
| #Air handling units | 6 | 10 | 2 | 1 | 3 | 2 | 16 | 3 |
| Fans instrumented (#Supply fans) | 16(10) | 14(7) | 4(2) | 1(1) | 7(3) | 2(1) | 4(2) | 3(2) |
| Test periods | April–October 2019 | April–October 2019 | May–October 2019 | June–October 2019 | June–September 2019 | August–September 2019 | August–September 2019 | July–September 2019 |
| Test times | 9 am–12:30 pm | 9 am–12:30 pm | 9 am–12:30 pm | 9 am–12:30 pm | 9–11 am | 9–11 am | 9–11 am | 9–11 am |
| #Total tests conducted | 166 | 147 | 132 | 116 | 98 | 77 | 79 | 83 |

\textsuperscript{a} EB2: engineering building 2; EB3: engineering building 3; PS: park shops building; SS: Sullivan shops building; BBB: Bob and Betty Beyster building; THY: Thayer building; NQ: north quadrangle complex; DNA: Dana building; NC: Raleigh, North Carolina, United States; MI: Ann Arbor, Michigan, United States.
2.4. Metrics for quantifying GTA performance

This section describes the metrics used to quantify the performance of GTA in providing load shifting DR. The metrics quantify the response magnitudes, impact on energy use of HVAC subsystems, and impact on occupants. In order to compute some of the metrics, we need to establish baseline values (i.e., the power consumption minus the baseline consumption, averaged over the test window)

Load shifting DR using GTA is scalable to a wide swath of the US commercial building stock, as it only involves the manipulation of temperature setpoints of building thermostats. The only requirements are (a) the building has a way to automatically adjust thermostat setpoints through a BAS and (b) the building has VAV boxes (as opposed to constant air volume boxes) that allow fans to respond to any changes in static duct pressure. However, this approach does not generally scale to residential buildings. In the US residential air conditioning systems typically cycle (on/off) to maintain the temperature within a small range of the setpoint. Therefore, GTA cannot elicit the desired sub-hourly to hourly load shifting DR from individual buildings. However, the responses of individual residential air conditioners can be aggregated and coordinated to provide load shifting.

Figure 1 illustrates the HVAC data collection points and methods. We submetered the supply and return air distribution fans to estimate their three-phase power consumption. Specifically, we installed current sensors (Onset CTV-D 20-200A) on a single phase of each of the supply fans and return fans associated with the AHUs serving conditioned spaces included in our experiments. The current sensor probes were attached to data loggers (Onset HOB0 4 Channel U120-006) that stored the collected data. Using constant voltage and power factor assumptions (480 V, and a power factor for the supply and return fans of 0.95 and 0.99 lagging, respectively), we estimated per-minute three-phase fan power consumption. Installing three-phase power meters on each of the fans was impractical due to the large number of fans and associated high cost. Even though voltage and power factor varied throughout the day, data collected from one building at NCSU indicated such variation was minimal (±1% for voltage and ±1% for power factor). BAS data collected from each building included: zone temperature setpoints, room temperatures and humidity; VAV damper positions; reheat valve positions; supply fan airflow rates; return fan airflow rates; chilled water flow rate; chilled water supply temperature; chilled water return temperature; building steam flow; outside air temperature and humidity; return air humidity; and some electrical load data. Chilled water system data for PS was unavailable on the BAS. Additionally, we collected the rated valve capacity (in gallons) of the terminal reheat valves from the mechanical schedules of each building, along with the entering and leaving hot water temperatures.

2.4. Metrics for quantifying GTA performance

This section describes the metrics used to quantify the performance of GTA in providing load shifting DR. The metrics quantify the response magnitudes, impact on energy use of HVAC subsystems, and impact on occupants. In order to compute some of the metrics, we need to establish baseline values (i.e., the power consumption that would have occurred without the experiment), and so we first describe our baseline estimation method. Then, we describe our outlier filtering criteria. Finally, we define each metric.

Estimating a counterfactual baseline is necessary to assess the impact of GTA. We estimated the fan power baseline by first computing the aggregate fan power consumption from all fans submetered in the building, and then using least squares to fit a linear baseline to the fan power data collected over the 5 min period just before and the 5 min period immediately after the total window \( t_t \), as proposed in \[25\]. References \[40, 41\] provide a comprehensive overview of a variety of methods commonly used for DR baselining. Those studies show that this linear baseline method performs well in baselining fan power.

We use the same method to compute baseline chiller power, but we use data from the 15- or 20 min period just before and after the total window \( t_t \) because the time constant of the chilled water system is around 15 min \[35\].

The choice of time period (15 or 20 min) was made based on the coefficient of variation (CV, quantifying the accuracy) and normalized mean bias error (NMBE, quantifying the bias), computed by applying the method to baseline days. The time period yielding lower CV and NMBE values was chosen. We present the results of our chiller baseline error analysis in appendix C. We also baseline the terminal reheat energy consumption, average zone temperature, and cooling service using the same method, with data from the 5 min period just before and immediately after the total window \( t_t \). The errors associated with this method for baselining the zone temperature and reheat energy consumption were detailed in \[27\].

We next describe the process for filtering outliers. We filtered unipolar tests in which the building showed unusually small or large responses, possibly due to atypical events not captured by the baseline model, e.g., shutting down of an AHU during the test window to replace the air filter. Responses are computed as the actual power consumption minus the baseline consumption, averaged over the test window \( t_t \). We used Tukey’s method \[42\], where responses outside minimum and maximum thresholds (selected as the 25th and 75th
percentiles respectively) were classified as outliers. A test was removed if classified as an outlier based on either its fan response or its chiller response. We present the results of the non-outlier tests in section 3.1.1.

We also filtered symmetrical and successive tests that were, (1) without an observable response, or (2) without an approximately symmetrical fan power response during the test window, as in [26]. For this, we first computed the up and down energy responses over \( t_w \), i.e., the integrals of the positive and of the negative fan power responses over \( t_w \), respectively (both responses are defined as positive). The first criterion is evaluated by calculating the magnitude of the response as the sum of up and down energy responses, and comparing it to a magnitude tolerance \( \epsilon_m \), which was determined per building by inspecting the time-series data. (Values of \( \epsilon_m \) are provided in Table E.6 in appendix E.) The second criterion is evaluated by computing the response symmetry. If the up energy response is smaller than the down energy response, then the response symmetry is the up energy response divided by the down energy response, and vice versa. This value is compared to a symmetry tolerance \( \epsilon_s = 20\% \), and the test is classified as an outlier if the response symmetry is below that tolerance. We further defined \( \zeta \) as the ratio of the non-outlier tests to total tests of a specific type for a specific building. Thus, \( \zeta \) reflects the ability of each building to provide desired responses to each test type.

2.4.1. Magnitude of fan power response

To address RQ1, we quantified the magnitude of the fan power response to temperature setpoint changes using unipolar tests, computed as the average fan power (kW) change (relative to the baseline) over \( t_w \). To compare the fan power response magnitudes across all buildings, we normalized each building’s fan power response by the maximum absolute value of the responses of all unipolar tests conducted on that building, which allowed a comparison of the responses as a function of outside temperature.

2.4.2. Magnitude of chilled water system response

To further address RQ1, we quantified the magnitude of the chilled water system response. We first estimated the electric power consumed by the chilled water system. For this estimation, we determined the cooling load tonnage of a building by multiplying the difference between chilled water return temperature and supply temperature, the chilled water flow rate, and a constant that accounts for the specific heat capacity. At NCSU, we also collected the electric power (kW) consumed per ton of cooling load supplied by the central utility plant serving EB2 and EB3. The product of the tonnage and the electric power consumed per ton of cooling load results in the electric power consumed by the chilled water system. The central utility plant data included the power consumption of the chiller compressor (the plant has a 10 000 ton chiller system), as well as the primary and secondary pump systems. Since equivalent central plant data was unavailable at UM, we assumed 0.8 kW/ton (the average of the NCSU central plant data) for the buildings at UM.

We then quantified the magnitude of the chilled water system response to temperature setpoint changes and outdoor temperature for unipolar tests. Similar to quantifying the fan power response magnitude, the chilled water system response is computed as the average chiller power (kW) change over \( t_w \) compared with the baseline.

2.4.3. Impact on fan energy use

To address RQ2, we quantified the additional energy consumption (AEC) in kWh of HVAC fan(s) during symmetrical and successive tests. The AEC was defined as the extra energy consumed by the fan(s) compared with the baseline [26, 43]. We separately assessed the AEC over the test window \( t_w \), the settling window \( t_s \), and the total window \( t_t \). Higher AEC values indicate more energy consumed by fans over the test cycle, and thus an overall increase in fan energy use [26]. If the tests were to achieve energy-neutral load shifting, then the AEC over \( t_w \) would be zero (though the AEC over the settling window \( t_s \) and hence over the total window \( t_t \) may be non-zero). However, due to asymmetrical response in the up and down directions, the AEC over \( t_w \) is generally non-zero. Note that we used AEC instead of round-trip efficiency (RTE, a standard metric for quantifying the efficiency of an energy storage system) because previous work demonstrated limitations of this metric in building applications [26].

2.4.4. Impact on chilled water system energy use

To assess the impact on energy used by the chilled water system (see RQ2), we compute the additional chiller consumption (ACC) in kWh over \( t_t \) with respect to the estimated chiller baseline. A higher ACC indicates more energy consumed by the chilled water system.
2.4.5. Impact on terminal reheat system energy use

Additionally, we addressed RQ2 by quantifying the impact on energy used by terminal reheat systems. Time series data of the supply and return water temperatures and flow rate of the hot water loop, or the entering and leaving air temperatures and airflow rate going through each VAV terminal reheat coil, are needed to precisely calculate the reheat system energy consumption. However, data on the hot water loop and HVAC terminal reheat systems were not broadly available from the BAS.

Consequently, to compute the impact on terminal reheat energy consumption, we used the rated valve capacity (in gallons) and Btu ratings of terminal reheat systems obtained from building mechanical schedules. We also collected the time-series reheat valve position data from the BAS for a subset of valves in the building. Using these parameters and data, we first calculated the sum of all reheat valve capacity ratings. We then computed the weighted average reheat valve position (using the available valve position data) for the building, where the weighting was given by each valve’s capacity rating. This enabled the flow rate (gallons per minute) of the building’s hot water loop to be estimated. That was then used to assess the total reheat energy consumed in therms per hour based on the Btu ratings. Finally, we computed the additional reheat consumption (ARC) in therms over $t_t$ with respect to the baseline. A higher ARC indicates more energy consumed by terminal reheat systems. Further description of this approach and associated equations are provided in appendix D.

2.4.6. Effective temperature deviation

We addressed RQ3 by quantifying the impact on occupant comfort. For each building, we averaged a subset of zonal temperature trends to quantify the effective temperature deviation across the conditioned spaces. This deviation was calculated as the temperature difference with respect to the estimated baseline. Specifically, we subtracted the mean room temperature time-series from its baseline estimate and then averaged those temperature differences over time $t_t$ to obtain the effective temperature deviation in degrees. A higher value of the effective temperature deviation indicates warmer conditioned spaces.
2.4.7. Occupant comfort analysis

To further address RQ3, we used psychrometric charts to analyze the impact on occupant comfort for a subset of buildings where relative humidity data were available. We plotted the baseline building operational data on the psychrometric chart to indicate the region in which the building operates under normal (non-testing) conditions. We then plotted measured data from symmetrical and successive load shifting DR events. The ideal comfort zone differs for each building based on factors such as clothing level, occupant activity, and ventilation, (see [44]). This complicates assessment of individual building comfort zone boundaries that are compliant with the ASHRAE Standard 55 (a standard specifying conditions for an acceptable thermal environment in buildings). Consequently, we plot the same comfort zone for all buildings on the psychrometric charts, approximating ASHRAE 55 compliance. A significant deviation from baseline operating conditions, due to load shifting DR events, would indicate a large deviation from normal occupant comfort.

2.4.8. Unmet cooling service

We propose a new method of assessing occupant comfort that quantifies unmet cooling service using psychrometric principles (addressing RQ3). The cooling service is a function of the temperature, humidity, and air flowing into the conditioned spaces. Quantifying the cooling service gives us another way to investigate the relationship between the quality of service (occupant comfort) and the cost of service (additional energy consumed by HVAC subsystems).

We first compute the enthalpy of the air in conditioned spaces using the mean room temperature and mean relative humidity of a subset of conditioned spaces within the building. We then compute the product of the air enthalpy and the supply fan air mass flow rate to quantify the cooling service provided to the building in MMBtu per hour. The unmet cooling service (MMBtu) over \( t \) is calculated by integrating the difference between the computed cooling service and its estimated baseline. A higher unmet cooling service implies that load shifting DR has increased the cooling required by the building to return to baseline levels of service. (Equations for enthalpy calculations are presented in appendix F.) Due to the limited availability of BAS data for this method, we present these results for only one of the eight buildings.

3. Building-level results

Here we present the results from nearly 900 GTA-based load shifting DR experiments, conducted on eight buildings at UM and NCSU. To provide an initial overview of HVAC behavior, figure 4 shows the responses of
the HVAC subsystems when thermostat setpoints are shifted using GTA. The figure shows time series plots for three types of GTA experiments at EB2 at NCSU: up–down symmetrical (left column), up unipolar (center column), and up–down successive (right column). We see that the change in setpoints (row one in figure 4) causes the dampers (row five) to adjust, which causes the aggregate fan power consumption (row two) to vary to maintain the desired static duct pressure. Static duct pressure values in this building ranged from 0.8 to 1.2 inches of water column depending on the AHU size. Furthermore, the change in zone temperature (row one) and reheat energy consumption (row four) show that their shifts with respect to their estimated baselines follow the polarity of the setpoint signal, as expected. Hence, the terminal reheat typically responds with the opposite polarity to the fans. We also see the response of the chilled water system (row 3) to the three different GTA test types. Appendix G provides the time series plots for both polarities of setpoint signals across all eight buildings. Those time series plots show that fan power response times vary from within a few minutes (e.g., BBB) to over 30 min (e.g., EB2, EB3). While some buildings exhibit near classical first-order step response (e.g., DNA), other buildings display more complex behavior (e.g., NQ).

The following three subsections report results, organized by the RQ they address.

3.1. Factors influencing response magnitude (RQ1)
3.1.1. Magnitude of fan power response
To address RQ1, we first quantified the magnitude of the fan power response for each building in both the up and down directions using unipolar tests. Figure 5 shows the change in the magnitude of the fan power as a function of these unipolar GTA setpoint changes. As observed from the fitted lines’ slopes (shown in red), we found that increasing the magnitude of the GTA signal leads to a larger fan power response. In a majority of our buildings, we also found that fans responded more in the up direction (caused by a temperature setpoint decrease) than in the down direction (caused by a temperature setpoint increase of the same magnitude), indicating an asymmetry in fan response to the polarity of the setpoint signals. The BBB building had approximately equal magnitudes of fan response in the up and down directions. The response asymmetry for the majority of the buildings, however, suggests the assumption that setpoint signal neutrality leads to energy-neutral fan power response does not necessarily hold true across commercial buildings.

When comparing the responses of larger buildings to the smaller buildings, we found heterogeneity in building responses. The fans in EB2 and EB3, two of the largest buildings, consumed around 200 kW and
300 kW, respectively, during baseline operation, but typically responded to the tests with less than 5 kW change in fan power. Conversely, the smallest building we tested (SS, which has a direct expansion system with a single 5.6 kW rated supply fan), responded with 50% of its baseline fan power. However, when we consider both the UM and NCSU buildings we find no clear trend between building size and the magnitude of the response. The heterogeneity in building responses can at least partially be explained by the lack of a universal relationship between a building’s inherent energy consumption/efficiency level and its ability to provide DR. This lack of a universal relationship was one of the key findings of Satchwell et al [45], which detailed the complex interactions between energy efficiency investments by building owners and the building’s capability to provide DR. The lack of a relationship was further corroborated by Andrews et al [46], who found, using empirical building-level DR event data, that efficiency, as measured by traditional metrics like energy use intensity, does not correlate with DR capabilities, though buildings with more operational flexibility (such as being able to reduce more load during the night or weekends) can provide more DR.

We also examined the variation in the magnitude of the fan power response with the outdoor temperature, as shown in figure 6. We found that the fan response from some, but not all, buildings varied with the outdoor temperature and signal polarity. For example, in the BBB and SS buildings (figure 6, left panels), we found that the amount of down response provided by the buildings (due to a GTA setpoint rise) increased with the outdoor temperature, i.e., for the same setpoint increase, the fans decreased their power consumption more on hotter days. Additionally, in EB2, EB3, NQ, and DNA buildings, we detected an increase in the amount of up fan power response (due to a GTA setpoint decrease) at higher outdoor air temperatures. The increase in response (both up and down) on hotter days, for some buildings, can be explained by the higher heat transfer between the outdoor and indoor spaces, which requires more fan energy to condition the space. In [31], MacDonald et al detail this as one potential mechanism impacting the overall energy consumed by fans during DR events.
3.1.2. Magnitude of chilled water system response

To further address RQ1, we quantified the magnitude of the chilled water system power response for six out of the eight buildings, in both up and down directions using unipolar tests, as shown in figure 7. For all buildings except BBB, we found no significant changes in chiller response with increasing setpoint changes. As indicated by the slopes of the fitted lines in figure 7, for BBB, we see that increasing the GTA signal magnitude does result in more pronounced chiller power response.

We also examined the variation in the magnitude of the chilled water system power response against the outdoor temperature, as shown in figure 8. We found that the up response of the chilled water systems at BBB and THY and the down response of the chilled water system at BBB increased with higher outdoor temperature conditions. Other buildings did not show clear trends.

3.2. Impact on energy used by HVAC subsystems (RQ2)

3.2.1. Impact on fan energy use

To address RQ2, we used symmetrical and successive load shifting events to quantify the impact of DR on fan energy use. Only those tests which were not deemed outliers (i.e., showed meaningful response) were considered. Recall that $\zeta$ provides the ratio of non-outlier tests to total tests. Table 3 provides the $\zeta$ values for the four types of load shifting DR tests. We found for PS, EB3, and SS that a large number of tests were removed...

Table 3. Values of $\zeta$ for symmetrical and successive tests of each building.

| Building | $\zeta_{UD}$ | $\zeta_{DU}$ | $\zeta_{UDUD}$ | $\zeta_{DUDU}$ |
|----------|--------------|--------------|----------------|----------------|
| EB2      | 35/39        | 28/41        | 10/11          | 9/11           |
| EB3      | 18/32        | 11/29        | 9/11           | 4/11           |
| PS       | 9/21         | 13/24        | 3/11           | 4/11           |
| SS       | 8/14         | 7/17         | 7/9            | 2/9            |
| BBB      | 16/16        | 16/16        | 7/8            | 8/8            |
| THY      | 5/8          | 8/8          | 6/6            | 6/6            |
| DNA      | 11/12        | 14/16        | 3/6            | 3/6            |
| NQ       | 5/5          | 5/5          | 9/9            | 8/9            |
Figure 9. HVAC AEC of fans over $t_t$ for symmetrical and successive load shifting events for the eight buildings. Each dot represents the metric value of each event. (UD: up–down; DU: down–up; SUD: successive up–down; SDU: successive down–up.)

Figure 10. HVAC ACC over $t_t$ for symmetrical and successive load shifting events for six of the eight buildings. Each dot represents the metric value of each event. (UD: up–down; DU: down–up; SUD: successive up–down; SDU: successive down–up.)

by the outlier filtering criteria, as indicated by the low $\zeta$ values, whereas nearly every test was deemed viable for BBB, THY, and NQ.
Figure 9 shows the AEC values, computed over \( t \), for symmetrical and successive load shifting DR experiments for the eight buildings. These results show that the change in fan energy use can differ greatly across buildings and for different types of tests.

As shown in the first two boxplots in every panel of figure 9, down–up symmetrical events have higher AEC values than up–down events on average, for six of the eight buildings, the exceptions being NQ and SS. This trend is consistent with prior experimental results [26, 27, 43]. The SS building (which has a direct expansion system) fan responded with nearly zero AEC, on average, for both symmetrical and successive events, indicating a minimal net impact on the fan energy use of that building. Similarly, we found that NQ showed negligible AEC values, on average, and PS had negative AEC, on average, for all types of tests.

We also observed that the successive down–up experiments, on average, had higher AEC values compared to successive up–down events. However, when comparing the AEC values for symmetrical events with those of successive events, no consistent trends were found; the results varied across buildings. This suggests that successive events need not necessarily lead to more efficient fan power response, in contrast to the results obtained in [29, 30].

Overall, we found the polarity of the GTA signal (up–down or down–up) to be a significant factor impacting the change in energy consumption of fans over the sub-hourly to hourly time-frame of interest. The positive fan AEC can also be explained by the asymmetry in the response to up and down GTA setpoint changes, as shown in section 3.1.1. Since a majority of buildings responded more in the up than the down direction for the same magnitude of GTA setpoint change, a setpoint neutral test can cause more response in the up direction and increase the overall fan energy consumption with respect to the baseline.

3.2.2. Impact on chilled water system energy use
The impact of symmetrical and successive load shifting DR experiments on the energy used by the chilled water system is presented in figure 10, for six of the eight buildings. The BBB, DNA and THY buildings show a generally small impact of GTA-based load shifting DR on the electricity consumed by their chilled water systems. Likewise, the NQ building’s chilled water system varied very little, though on average consumed slightly less energy compared with the baseline. However, EB2 and EB3 were more responsive and on average incurred an increase in the electricity consumed by their chilled water systems. In particular, the symmetrical down–up experiments at EB2, on average, had much higher ACC values compared to the symmetrical up–down events.
Figure 12. Effective temperature deviation over $t_i$ for symmetrical and successive load shifting events for the eight buildings. Each dot represents the metric value of each event. (UD: up–down; DU: down–up; SUD: successive up–down; SDU: successive down–up.)

Figure 13. Psychrometric charts for four buildings showing the impact of load shifting DR events on occupant comfort. The experiments did not cause the buildings to operate outside of the comfort bounds. Each dot represents a data point from the time-series of an event.

In this case, the chiller ACC dominates the fan AEC (e.g., for symmetrical down–up events, the median chiller ACC was 32.6 kWh while the median fan AEC was only 4.9 kWh).
3.2.3. Impact on terminal reheat system energy use

In further consideration of RQ2, we quantified the impact on terminal reheat energy consumption using symmetrical and successive load shifting DR experiments. Figure 11 presents the change in the energy used by the terminal reheat system, for seven of the eight buildings. Note that the upper row in figure 11 shows results for UM buildings, whereas the lower row shows results for NCSU buildings, where humidity is much higher.

As shown in figure 11, there was minimal impact on the energy use for the NQ, THY and SS buildings. Moreover, BBB exhibited a decrease in terminal reheat energy use. However, figure 11 shows on average a sizable increase in the terminal reheat energy use of EB2, EB3, and to a lesser extent PS. This can be attributed to the larger latent cooling load for NCSU buildings due to the higher need for dehumidification. The higher latent cooling load requires the discharge AHU air temperature setpoint to be lower (for NCSU buildings this setpoint was 53–55°F; for UM buildings it was 57–60°F). Therefore, more reheat energy was needed for NCSU buildings to bring their conditioned spaces to the desired setpoint. This greater requirement for reheat energy is amplified when the GTA-based load shift tests are implemented. This finding is important since terminal reheat systems typically respond with the same polarity as the setpoint signal, i.e., the opposite direction to the fan power response. For such buildings where the electric terminal reheat systems are quite responsive to load shifting GTA signals, there can be an unintended impact on the ability of the building to follow the desired power signal. Furthermore, the results also suggest that climate zone conditions affect the extent to which GTA-based load shifting impacts terminal reheat energy usage.

3.3. Impact on building occupants (RQ3)

3.3.1. Impact on zone temperature
To address RQ3, we first quantified the impact of symmetrical and successive load shifting DR experiments on building zone temperatures. In figure 12, we show the effective temperature deviation caused by symmetrical and successive load shifting DR tests. As seen by the small effective temperature deviation values in a majority of the buildings, we did not find a significant change in zone temperatures over \( t_r \) for our buildings, indicating that the high thermal inertia of the buildings prevented significant deviations of zone temperatures from their baseline conditions during our experiments. In SS, PS, and EB3, we observed that successive DR events led to larger effective temperature deviations, indicating warmer conditioned spaces of these buildings during our experiments. Section 3.3.3 explores the reasons behind this warming during successive tests at EB3.

3.3.2. Impact on comfort
We further address RQ3 using psychrometric chart analysis. As shown in figure 13, we found that our tests did not cause the buildings to deviate from their baseline operating conditions (baseline operation is indicated by dark gray dots in the figure) and generally maintained the occupant comfort within ASHRAE Standard 55 thermal comfort bounds. The similarity to baseline operation on the psychrometric chart shows that load shifting DR using GTA generally has minimal impact on occupant comfort, assessed from temperature and humidity, which is a vital requirement for wide-scale deployment of grid-interactive buildings. In addition,
none of our experiments resulted in a rate of indoor temperature change that would violate section 5.4.3.2 of ASHRAE Standard 55. It is important to note that full consideration of occupant comfort may include factors beyond temperature and humidity, such as ventilation, lighting, noise level, and air quality. Alternative methods can more fully reflect occupant comfort across a range of building designs (e.g., adaptive thermal comfort models for naturally ventilated buildings).

3.3.3. Impact on cooling service provided

We also address RQ3 by quantifying the impact of the symmetrical and successive tests on the cooling service provided to the building. Figure 14 shows the unmet cooling service values for the symmetrical and successive texts at EB3. The successive events have positive unmet cooling service compared to the symmetrical events, which have negative unmet cooling service. Note that successive events at EB3 also have higher fan AEC, higher additional terminal reheat energy consumption, and higher effective temperature deviation, on average (as shown in figures 9, 11 and 12, respectively), compared with symmetrical events.

The higher unmet cooling service observed for successive events may be explained by its complex relationship with AEC consumed by the fans and ARC of the terminal reheat. The higher fan AEC corresponds to more air flowing into the conditioned spaces to provide cooling. However, the higher ARC indicates that the terminal reheat system responds to counter the increased air flow. The net result is an increase in the effective temperature deviation of the space. This leads to an overall increase in the unmet cooling service for successive events, compared to symmetrical events.

4. Power system implications

This section considers the implications of our building-level experimental results at the power system level. Specifically, we evaluate the capability of GTA-based load shifting DR, applied across a large number of commercial buildings, to assist in achieving supply-demand balance on the grid. The following RQ is addressed:

RQ4. Is it technically plausible, in terms of the required number of buildings and cost-benefit trade-off, to use GTA-based load shifting DR to improve renewable energy integration?

In the following, we first explain the motivation for the study and the approach taken. Results are then presented.

4.1. Motivation and approach

The response of building HVAC systems to GTA fundamentally impacts their ability to provide DR that can assist in grid operations. The form of their response must be taken into account in strategies that coordinate the participation of the large number of buildings that are required for HVAC-based DR to play a meaningful role in power system operation.

Moreover, it is necessary to understand the impact of building response and AEC on the cost-benefit trade-off of HVAC-based load shifting. Accordingly, this section connects our building-level experimental results with power system operations.
Of particular interest is the use of GTA-based load shifting DR for mitigating high ramp rates, i.e., extended periods of rapid change, in the grid’s net demand. Ramp rate issues are becoming increasingly common across power systems with high renewable generation. Specifically, we consider the ‘duck curve’ challenge being faced by the California Independent System Operator (CAISO) [47]. As shown in figure 15, the net demand has large ramps during the early morning and the evening, mainly due to timing mismatches between peak demand and high solar energy production. Large ramps are difficult for grid operation. They require fast power output adjustments which are onerous for traditional power plants due to their limited ramp-up and ramp-down capabilities. Ramping can also require quick start-up of off-line generating units (during evening ramps) or short-term shut-down of operating units (during morning ramps). We investigate the use of HVAC-based load shifting to assist in reducing such ramping. Mitigating this issue enables greater integration of renewable generation.

To assess the ability of GTA to reduce ramping, we developed an optimization formulation that was informed by our HVAC DR experiments and designed to mitigate the rapid changes in demand shown in figure 15. Let \( P_{t,d}^{ud}, P_{t,d}^{du}, \) and \( P_{t,d}^{set} \), be the average load change (in kW) of a building actuated by an up–down power event in the first half of the event window, the second half of the event window, and the settling window, respectively. The equivalent load changes induced by a down–up power event are given by \( P_{t,d}^{du}, P_{t,u}^{du}, \) and \( P_{t,u}^{set} \). We divide a day into a set of time-steps \( T = \{1, 2, \ldots, |T|\} \), and let \( t \in T \) index those time-steps. Let \( \Delta t \) be the time-step interval, with \( \Delta t = 0.5 \) h used throughout our study. The optimization formulation determines the number of buildings actuated by up–down and down–up events, \( N_{t,d}^{ud} \) and \( N_{t,d}^{du} \) respectively, at time \( t \). Let \( P_{t,d}^{ind,0} \) be the system’s uncontrolled (baseline) net demand at \( t \), and \( P_{t,d}^{ind} \) be the net demand adjusted by HVAC-based DR. Let \( R^n \) and \( R^d \) be the system’s ramp-up and ramp-down rate limits (in MW h\(^{-1}\)), respectively.

Minimizing the DR required to achieve the specified ramp rates can be achieved through the formulation:

\[
\min_{N_{t,d}^{ud}, N_{t,d}^{du}, t \in T} \sum_{t \in T} (P_{t,d}^{ind} - P_{t,d}^{ind,0}) \Delta t
\]

subject to,

\[
P_{t,d}^{ud} = P_{t,d}^{ind,0} + N_{t,d}^{ud} P_{U}^{ud} + N_{t,d}^{du} P_{D}^{ud} \tag{2}
\]

\[
P_{t,d}^{du} = P_{t,d}^{ind,0} + N_{t,d}^{ud} P_{U}^{du} + N_{t,d}^{du} P_{D}^{du} + N_{t,d}^{ud} P_{U}^{du} + N_{t,d}^{du} P_{D}^{du} \tag{3}
\]

\[
P_{t,d}^{set} = P_{t,d}^{ind,0} + N_{t,d}^{ud} P_{U}^{set} + N_{t,d}^{du} P_{D}^{set} + N_{t,d}^{ud} P_{U}^{set} + N_{t,d}^{du} P_{D}^{set} + N_{t,d}^{ud} P_{U}^{set} + N_{t,d}^{du} P_{D}^{set} \quad \text{for } 3 \leq t \leq |T| \tag{4}
\]

\[
- R^d \leq \frac{P_{t,d}^{ind} - P_{t,d-1}^{ind}}{\Delta t} \leq R^n, \quad 2 \leq t \leq |T| \tag{5}
\]

\[
\max\{P_{t,d}^{ind} : t \in T\} \leq \max\{P_{t,d}^{ind,0} : t \in T\} \tag{6}
\]

\[
\min\{P_{t,d}^{ind} : t \in T\} \geq \min\{P_{t,d}^{ind,0} : t \in T\} \tag{7}
\]

where (1) is the objective function minimizing the additional energy consumed by HVAC systems when providing load shifting DR and (2)–(4) give the modified net demand (adjusted by building DR) over the time horizon. Note that (4) implicitly assumes that HVAC power consumption settles back to its baseline within the settling window \( \Delta t \).

The ramp rate limits are enforced by (5), while (6) and (7) ensure the DR actions do not induce a higher load peak or a lower load valley. Once a building is actuated, it follows a full cycle, including the settling period. When a building has completed its cycle, it can again be actuated. However, we assume that the building is actuated only once so we can evaluate the upper bound on the number of buildings required (to address RQ4). We refer to this optimization formulation as the load shifting model.

By solving this optimization problem, using parameters appropriately set from our building experimental results and the duck curve scenario depicted in figure 15, we obtain the optimal schedule for up–down and down–up events across a large number of buildings. This schedule bounds the net demand ramp rate within the specified limits and minimizes the additional energy consumed due to inefficiency in building HVAC load shifting. Thus, energy efficiency, along with cost-benefit trade-offs, can be analyzed accordingly.

Limiting the net demand ramp rate can also be accomplished by curtailing renewable generation. Hence, we also built another optimization formulation to compute the minimum renewable energy curtailment required in order to satisfy the specified ramp rate limits. This allows us to compare the cost-benefit trade-offs of the two approaches—building HVAC load shifting and renewable energy curtailment—to mitigating large ramps in the net demand.

---

9 Net demand is defined as the total electrical demand minus variable renewable generation.
Table 4. Optimization parameters of the base case.

| Parameter | Value  |
|-----------|--------|
| $p_{ud}^u$, $p_{du}^u$ | 15 kW |
| $p_{ud}^d$, $p_{du}^d$ | −15 kW |
| $p_{ud}^{sett}$ | 2 kW |
| $p_{du}^{sett}$ | 4 kW |
| $R^−$, $R^+$ | 4000 MW h $^\text{−1}$ |

Let $P^d_t$ be the system’s gross demand at time $t$, $P_{rg,0}^t$ be the system’s available renewable generation at $t$, and $P^R_t$ be the system’s post-curtailment renewable generation at $t$. The following optimization problem can be used to compute the minimum renewable energy curtailment required to satisfy the ramp rate limits:

$$\min \sum_{t \in |T|} (P_{rg,0}^t - P^R_t) \Delta t$$  \hspace{1cm} (8)

subject to,

$$P_{nd}^t = P^d_t - P^R_t, \quad t \in |T|$$  \hspace{1cm} (9)

$$-R^− \leq \frac{P_{nd}^t - P_{nd}^{t-1}}{\Delta t} \leq R^+, \quad 2 \leq t \leq |T|,$$  \hspace{1cm} (10)

where (8) is the objective function minimizing the system’s renewable generation curtailment, (9) gives the net demand at each time-step, and (10) enforces the net demand ramp rate limits. We refer to this formulation as the renewable curtailment model.

The load shifting model does not curtail any renewable generation but results in additional energy consumed system-wide. The renewable curtailment model does not result in any additional energy being consumed, but does result in curtailment of renewable energy. With the same values of $R^+$ and $R^−$ in the two models, the objective value of the load shifting model can be seen as the cost (in energy units) of using GTA-based load shifting DR to enforce the ramp rate, while the objective value of the renewable curtailment model can be seen as the benefit (in energy units) of avoiding renewable curtailment by using GTA-based load shifting DR to limit the ramp rate.

4.2. Results

4.2.1. Base case

We first show the results of a base case, which uses the parameters listed in table 4. The time-step $\Delta t = 0.5$ h, and the data is obtained from CAISO [48] and depicted in figure 15.

Figure 16 shows the number of buildings actuated up–down or down–up at each time-step. Figure 17 compares the net demand and ramp rates of the system with and without DR from buildings. By using GTA-based load shifting DR to slightly adjust the system’s net demand in the early morning and the evening, the ramp rate is effectively bounded within both ramp-up and ramp-down limits. Considering the vast footprint of commercial buildings [37], along with their DR potential and availability profiles [49, 50], figure 16 indicates that the approach is technically plausible in the sense that the order of magnitude of buildings needed is achievable.

For some time-steps in which the net demand increased due to DR (e.g., see 17:00–18:30 in figure 17), the renewable production is high. Without DR from buildings, renewable curtailment might be necessary to mitigate the high ramp rate during those periods. Hence, using GTA-based load shifting DR to reduce ramp rates may improve renewable energy integration.

Using the renewable curtailment model, we estimate that the base-case system would require 2810 MWh of renewable energy curtailment (on that one day) to satisfy the same ramp rate limits. It is clear that the HVAC load shifting strategy avoids significant renewable curtailment. Doing so incurs a cost though, as the DR strategy induces system-wide AEC of 325 MWh. However, that cost is small relative to the avoided renewable energy curtailment. Dividing the above two numbers by the total number of buildings that were utilized, the per-building contribution to the avoided renewable energy curtailment and the average AEC were 9.2 kWh and 1.1 kWh, respectively. Hence, a building may consume a little more energy in GTA-based load shifting DR but on average helps integrate a much larger amount of renewable energy.

4.2.2. Impact of building HVAC response magnitude

The load shifting model and the renewable curtailment model can be used to explore the sensitivity of the results to variations in the magnitude of the building HVAC response. In the base case, the response magnitude (i.e., the absolute value of parameters $p_{ud}^d$, $p_{ud}^u$, $p_{du}^d$ and $p_{du}^u$) was set to 15 kW. We varied this value, while
adjusting the settling power parameters $p_{	ext{ud}}^{\text{sett}}$ and $p_{	ext{du}}^{\text{sett}}$ proportionally, i.e., the settling parameters were changed by the same percentage as the response magnitude. However, due to the structure of the optimization formulations, such parameter adjustments change the values of the optimal $N_t^{\text{ud}}$ and $N_t^{\text{du}}$ but make no difference to the renewable energy curtailment nor the AEC.

4.2.3. Impact of ramp rate limit
We also conducted a sensitivity analysis with respect to the ramp rate limit. Recall parameters $R^+$ and $R^-$ were set to 4.0 GW h$^{-1}$ in the base case. This value was varied to investigate the impact of the ramp rate limit on the number of participating buildings and the cost-benefit trade-off.

As shown in figure 18, although the ramp rate limits can be satisfied over a wide range using GTA-based load shifting DR, tight ramp rate limits cause the total number of actuated buildings to increase significantly. Satisfying stringent ramp rate limits would rely on participation and coordination of a large number of commercial customers.

Figure 19(a) shows the variation of system-wide AEC and avoided renewable curtailment for a range of ramp rate limits. It can be seen that even with stringent limits on the ramp rate, the GTA-based DR strategy remains effective and avoids an increasing amount of renewable energy curtailment. The system-wide additional energy use also increases, but both its magnitude and rate of increase are smaller than those of the avoided renewable curtailment.
5. Conclusions and future work

This work investigated the performance of GTA for load shifting DR by conducting nearly 900 experiments across eight buildings at North Carolina State University and the University of Michigan. Our experiments and analyses, based on a wide range of metrics, identified a variety of factors that impact building HVAC subsystems and their energy use. These factors include the asymmetric nature of fan power response and additional energy consumed by fans and terminal reheat systems. These effects demonstrate that the complex and interdependent operation of subsystems within commercial HVAC must be carefully considered when assessing the performance of GTA for providing load shifting DR. Importantly, we found that load shifting DR using GTA can be deployed in a manner that maintains indoor temperature and humidity within bounds suitable for occupant comfort. Achieving load shifting capability while maintaining comfortable conditions for building occupants is essential for the wide-scale deployment of GEBs.
Our study of power system applications of GTA-based HVAC load shifting DR showed that high ramp rates, caused by high renewable penetration on the grid, can be mitigated using a practical number of buildings. More importantly, it showed that any additional energy consumed by the buildings in providing load shifting DR is much smaller than the renewable energy that would otherwise be curtailed. Overall, our work shows promising results for using load shifting DR from commercial building HVAC systems for grid services. If implemented correctly, we find that the service can lead to clear benefits for participating building owners and the grid. However, we note that our quantitative results are specific to solar curtailment used to satisfy ramping limits in California. Possible reductions of renewable energy curtailment will differ from grid to grid depending upon the mix of renewable resources and the nature of the critical grid constraints. For example in some regions, wind is curtailed more than solar, and wind curtailment is driven by transmission constraints not ramping limits. Buildings still have a role to play in mitigating this situation, but the costs/benefits would be different.

This study has broad implications for key stakeholders. Our results offer new insights into the additional building energy consumption that could occur due to participation in load shifting DR, providing guidance on compensation for building operators to cover the associated energy costs. As full electrification of building HVAC systems gains impetus, the interplay between subsystems will become increasingly important. Our investigation has, for example, identified mechanisms whereby the reheat subsystem may have a detrimental effect on the building’s ability to track the DR reference signal. In this regard, this research is of significance to third party DR aggregators for designing control strategies that enable buildings to efficiently track grid operational requirements. Furthermore, our demonstration of load shifting DR across a wide range of commercial buildings has identified key challenges that must be addressed before system operators can fully access this largely untapped source of grid flexibility. This demonstration may also be helpful to state and local regulators to bolster participation of demand-side resources by encouraging utilities to include pilot load shifting DR programs in their grid planning.

Work remains to fully understand the physics of load shifting DR, its potential applications, and its energy-use implications. Our recommendations for future research include: (a) modeling building HVAC systems in appropriate simulation software to investigate the dynamic interactions that underpin GTA-based load shifting DR and address seemingly contradictory results obtained from the experimental and modeling work conducted so far; (b) designing and deploying load shifting DR schemes that more closely track energy neutral power trajectories, including closed loop feedback strategies that modulate the GTA signal to achieve improved performance across the metrics developed in this paper; and (c) conducting experiments in other climate zones and on other commercial building types; (d) investigating the impact of advanced energy efficiency measures such as demand control ventilation and economizers on the performance of GTA-based load shifting demand response.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Appendix A. Implementing GTA on campus buildings

GTA was implemented using two different approaches at UM and NCSU. At UM, the tests were coded into the BAS on the field panels of each individual building to control the VAV setpoints of that building. At NCSU, a Python program running on a cloud-hosted virtual server was used to change the VAV temperature setpoints in the buildings (i.e., each building receives the same change in setpoint command). A significant advantage of the approach at NCSU is scalability, as adding buildings is as simple as including the VAV network numbers.
of the new buildings (which can be easily obtained through the BAS) in the central Python program. The program relies on an open-source library called Bacpypes [51], which enables the Python code to communicate using the BACnet/IP protocol (a communication protocol developed by ASHRAE for BASs). A disadvantage of this method, especially on a campus network, is that significant coordination with information technology organizations is required to ensure network firewall settings do not block the BACnet traffic from reaching the buildings. Another disadvantage of the approach at NCSU is that the slower communication rate capability of the field devices compared to the virtual server that communicates the setpoint signals to them. This difference can overload field controllers with BACnet traffic and result in decreased controller performance. To overcome this challenge, we implemented a parameter in the Python program which limits the rate of communication to field devices compared to the virtual server that communicates the setpoint signals to them. This difference is generally between 20–40 US gallons per minute. At UM, only the VAV cooling setpoints were simultaneous control was done to follow campus energy conservation protocols of maintaining the deadband was much higher (0.49% for 20 min compared to 0.10% for 15 min) so the duration of 15 min was chosen.

At NCSU, the GTA setpoint signal altered both the heating and cooling VAV setpoints of the building. The slower communication rate capability of the field devices compared to the virtual server that communicates the setpoint signals to them. This difference is generally between 20–40 US gallons per minute. At UM, only the VAV cooling setpoints were simultaneous control was done to follow campus energy conservation protocols of maintaining the deadband was much higher (0.49% for 20 min compared to 0.10% for 15 min) so the duration of 15 min was chosen.

Appendix B. Equation to calculate chiller tonnage and equivalent electricity consumed

Let $T_{s}^{\text{cool}}$ be the chilled water supply temperature ($^\circ$F) and $T_{i}^{\text{cool}}$ the chilled water return temperature ($^\circ$F). Let $f_{\text{cool}}$ be the chilled water flow rate (US gallons per minute). The specific heat capacity of water is 1 Btu/lb-$^\circ$F, and 1 US gallon of chilled water (at $T_{s}^{\text{cool}} \sim T_{i}^{\text{cool}}$ $^\circ$F) weighs approximately 8.34 lbs. Let $L_{\text{cool}}$ be the chiller cooling load tonnage (tons). Note that 1 cooling ton equals 200 Btu/min, and $L_{\text{cool}}$ can be obtained by:

$$L_{\text{cool}} \ [\text{tons}] = f_{\text{cool}} \ \text{gal} \ \text{min}^{-1} \ \times (T_{s}^{\text{cool}} - T_{i}^{\text{cool}}) \ \times 1 \ \text{min} \ \times 200 \ \text{Btu} \ \text{min}^{-1} \ \times 8.34 \ \text{lbs} \ \text{gal}^{-1}.$$

We multiply the tons of cooling by the kW of electricity consumed per ton of chilled water produced by the central chiller plant to quantify the electricity consumed by the chilled water system.

Appendix C. Chiller baseline

The methods to compute the CV and NMBE can be found in [41] (table C.5).

At EB3, the CV for 20 min was lower (6.11% compared to 6.16% for 15 min) but the difference in NMBE was much higher (0.49% for 20 min compared to 0.10% for 15 min) so the duration of 15 min was chosen.

Appendix D. Equation to calculate additional reheat consumption

Let $T_{s}^{\text{heat}}$ be the hot water supply temperature ($^\circ$F) and $T_{i}^{\text{heat}}$ the hot water return temperature ($^\circ$F). (Their difference is generally between 20–40$^\circ$F.) Let $f_{\text{heat}}$ be the hot water loop’s flow rate (US gallons per minute). Let $L_{\text{heat}}$ be the estimated terminal reheat energy consumption rate (therms/hr), which can be obtained by:

$$L_{\text{heat}} \ [\text{therms} \ \text{hr}^{-1}] = 0.5 \ \left( \frac{\text{min}}{\text{hr}} \times \left( T_{s}^{\text{heat}} - T_{i}^{\text{heat}} \right) f_{\text{heat}} \ [\text{gal} \ \text{min}^{-1}] \times \left( \frac{1}{100} \right) \ \frac{\text{therms}}{\text{kBtu}} \right).$$

Table C.5. Chiller baseline error analysis.

| Building | Time period chosen for baseline estimation (minutes) | Time period for baseline estimation (minutes) | Number of baseline windows $n$ | $\langle \text{CV} \rangle$ $\langle \sigma \rangle$ % | $\langle \text{NMBE} \rangle$ $\langle \sigma \rangle$ % |
|----------|------------------------------------------------------|---------------------------------------------|---------------------------------|---------------------------------|---------------------------------|
| EB2      | 15                                                   | 20                                          | 37                              | 7.53 (9.53)                     | 2.57 (9.74)                     |
|          | 15                                                   | 15                                          | 37                              | 7.31 (8.97)                     | 2.46 (9.04)                     |
|          | 20                                                   | 37                                          | 6.11 (5.39)                     | 0.49 (4.93)                     |                                 |
| EB3      | 15                                                   | 20                                          | 37                              | 6.16 (5.37)                     | 0.10 (5.01)                     |
|          | 20                                                   | 20                                          | 94                              | 9.24 (12.91)                    | 0.03 (12.39)                    |
| THY      | 20                                                   | 15                                          | 94                              | 9.24 (12.32)                    | -0.08 (12.94)                   |
| NQ       | 20                                                   | 20                                          | 222                             | 29.80 (30.94)                   | 0.78 (22.65)                    |
|          | 15                                                   | 15                                          | 30.50 (33.68)                   | 0.78 (25.92)                    |                                 |
| DNA      | 15                                                   | 20                                          | 242                             | 17.61 (12.83)                   | 1.92 (12.18)                    |
|          | 15                                                   | 15                                          | 242                             | 17.53 (12.83)                   | 1.91 (11.96)                    |
| BB 5     | 15                                                   | 20                                          | 240                             | 10.51 (6.55)                    | 0.16 (6.00)                     |
|          | 15                                                   | 15                                          | 240                             | 10.47 (6.46)                    | -0.11 (5.84)                    |
The hot water loop’s flow rate $f_{\text{heat}}$ is obtained by taking the product of the sum of gallon ratings of all building reheat valves and the weighted average of the reheat valve positions using the time-series valve position data obtained from the BAS. The gallon ratings of the subset of valves are used as weights for computing the average.

**Appendix E. Magnitude tolerances for filtering**

See table E.6.

**Appendix F. Unmet cooling service equations**

Let $T_{\text{air}}$ denote the average zone temperature (°F), obtained by taking the mean of a subset of zone temperatures from the building. Let $h_{\text{air}}$ be the computed enthalpy (Btu/lb). Let $f_{\text{air}}$ be the air flow rate (ft³ min⁻¹). Let $m_{\text{air}}$ be the computed mass air flow rate (lb/hr). Let $S_{\text{cool}}$ be the computed cooling service provided to the conditioned spaces (MMBtu/hr).

The specific heat of air 0.24 Btu/lb-°F. The evaporation heat of water vapor is 1061 Btu/lb. The specific heat of water vapor is 0.4 Btu/lb-°F.

We use the following assumptions for this calculation: the specific volume of the supply air is 13.8 ft³/lb and the humidity ratio is 0.008.

We first calculate $h_{\text{air}}$ by:

$$h_{\text{air}} \left( \frac{\text{Btu}}{\text{lb}} \right) = 0.24 \left( \frac{\text{Btu}}{\text{lb} \cdot \text{°F}} \right) \times T_{\text{air}} \, \text{[°F]} + 0.008 \times \left( 0.4 \left( \frac{\text{Btu}}{\text{lb} \cdot \text{°F}} \right) \times T_{\text{air}} \, \text{[°F]} + 1061 \left( \frac{\text{Btu}}{\text{lb}} \right) \right).$$ (F.1)
We then calculate $m_{air}$ using $f_{air}$:

$$m_{air} \text{ [lb/hr]} = \frac{f_{air} \text{ [ft}^3\text{/min]}}{13.8 \text{ [ft}^3\text{/hr]}} \times 60 \text{ [min/hr]}.$$  \tag{F.2}

And $S_{cool}$ is computed as:

$$S_{cool} \text{ [MMBtu/hr]} = h_{air} \text{ [Btu/lb]} \times m_{air} \text{ [lb/hr]} \times 10^{-6} \text{ [MMBtu/Btu]}.$$  \tag{F.3}

**Appendix G. Results from other buildings**

See figures G.1–G.8.
Figure G.2. Results from EB3 for symmetrical, unipolar, and successive events. The five rows (top to bottom) show the setpoint signals (and corresponding changes in zone temperature), aggregate fan power consumption, chiller flow from campus chiller loop, average reheat natural gas therms consumed, and average VAV damper positions, respectively. The darkened lines show the average response of each subsystem.
Figure G.3. Results from BBB for symmetrical, unipolar, and successive events. The five rows (top to bottom) show the setpoint signals (and corresponding changes in zone temperature), aggregate fan power consumption, chiller flow from campus chiller loop, average reheat natural gas therms consumed, and average VAV damper positions, respectively. The darkened lines show the average response of each subsystem.
**Figure G.4.** Results from NQ for symmetrical, unipolar, and successive events. The five rows (top to bottom) show the setpoint signals (and corresponding changes in zone temperature), aggregate fan power consumption, chiller flow from campus chiller loop, average reheat natural gas therms consumed, and average VAV damper positions, respectively. The darkened lines show the average response of each subsystem.
Figure G.5. Results from THY for symmetrical, unipolar, and successive events. The five rows (top to bottom) show the setpoint signals (and corresponding changes in zone temperature), aggregate fan power consumption, chiller flow from campus chiller loop, average reheat natural gas therms consumed, and average VAV damper positions, respectively. The darkened lines show the average response of each subsystem.
Figure G.6. Results from PS for symmetrical, unipolar, and successive events. The five rows (top to bottom) show the setpoint signals (and corresponding changes in zone temperature), aggregate fan power consumption, average reheat natural gas therms consumed, and average VAV damper positions, respectively. The darkened lines show the average response of each subsystem.
Figure G.7. Results from SS for symmetrical, unipolar, and successive events. The five rows (top to bottom) show the setpoint signals (and corresponding changes in zone temperature), aggregate fan power consumption, average reheat natural gas therms consumed, and average VAV damper positions, respectively. The darkened lines show the average response of each subsystem.

Figure G.8. Results from DNA for symmetrical, unipolar, and successive events. The five rows (top to bottom) show the setpoint signals (and corresponding changes in zone temperature), aggregate fan power consumption, chiller flow from campus chiller loop, average reheat natural gas therms consumed, and average VAV damper positions, respectively. The darkened lines show the average response of each subsystem.
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