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An open control specification to scale building demand flexibility via analytics software

Abstract

For over two decades, researchers and practitioners have showcased the ability of large commercial buildings to provide grid services by shedding or shifting load. Various utility demand response (DR) and virtual power plant (VPP) programs throughout the United States are presently utilizing these demand-side resources. However, growth of these programs have been limited, in part due to the high cost necessary to integrate the DR control strategies into the building automation system (BAS). Implementing these strategies involves adjusting control sequences, necessitating dozens of hours of customized programming per building, limiting their adoption to large organizations and progressive owners.

Recent efforts by researchers and industry have demonstrated the capability of energy management and information systems (EMIS), originally designed for fault detection and diagnostics, to interface with existing BAS and perform supervisory control to optimize building operations. While these approaches are quickly being adopted by industry, demand flexibility (DF) control strategies remain limited in product offerings. One of the challenges is the lack of documented best-practice DF sequences, despite the rich literature on field implementations.

This paper develops a new open-specification for a zone-based temperature adjustment shed strategy for commercial building HVAC systems, describing the specification's implementation in two EMIS tools in both experimental and field settings. Both implementations successfully reduced electric load by at least 40% on average during the called event, while maintaining temperature limits. This study's detailed process from specification to deployment shows the potential for scalability as well as highlights challenges related to integration with heterogeneous BAS products.

1. Introduction/ Background

As researchers and practitioners in the building industry shift their focus from energy efficiency to decarbonization, new questions are being asked about how to drive an affordable, reliable energy transition. It is now well-documented and commonly recognized that achieving a net-zero emissions buildings sector will require deep efficiency, electrification of fossil-powered loads, and a low-carbon electricity supply (Langevin et al, 2021). In addition, new research and current trends in energy use and generation, are establishing the critical role of demand-side load flexibility in a net-zero future. Demand flexibility (DF) can enable customers to use less

power during times of day when electricity is more expensive. It can also provide critical reliability services such as reducing the peak when loads are at their highest, and can enable increased use of renewable power by adjusting use to times of day when clean energy is most abundant. These benefits are becoming more important as increased electrification changes the magnitude and timing of peak loads (Muratori and Mai, 2021) (Gerke et al., 2020 & 2024), and as curtailment of renewables due to oversupply becomes more common (EIA 2024). In fact, it has been documented that, in an aggressive scenario of building efficiency and flexibility measures, over \$100B in bulk power system investments could be avoided by 2050 (Langevin et al. 2023). California, recognizing the value of demand-side flexibility, recently set a state-wide goal of 7 GW of DF by 2030, a portion of which is expected to come from buildings (Neumann and Lyon 2023).

The term demand flexibility, or demand response (DR) may be used differently in various contexts. For example, the California public utility commission uses a broad definition of *“reductions, increases, or shifts in electricity consumption by customers in response to their economic signals or reliability signals”* (CPUC 2024). The International Energy Agency characterizes DR as *“providing incentives to shift or shed electricity demand in wholesale and ancillary power markets to help balance the grid”* (IEA 2024). The US Department of Energy characterized load shift and load shed demand-side management strategies according to the grid services they can support, e.g., generation energy and capacity, non-wires solutions, contingency reserves (Neukkom and Nubbe 2019). This characterization also describes the associated duration, response time and frequency of the service.

In the US, demand response has historically been most commonly implemented as short term reductions, i.e., ‘sheds’, in load to alleviate grid stress. However, the dynamics of the energy transition are expected to make load shifting, and even load increases more valuable. In the literature, there is extensive documentation of the ability to implement demand response using common building automation infrastructure, with most of these implementations running in a manual or semi-automated fashion. Various field studies have demonstrated successful demand response strategies targeting HVAC systems in the field (Yin, Piette and Kiliccote, 2010) (Afroz et al, 2023)(de Chalendar et al., 2023) through rule-based controls. However, as described by Kiliccote et al 2019, implementations are site or BAS specific, require expensive skilled labor, and vary across building configurations and flexibility objectives. Moreover a literature review of industry-accepted controls used for demand response finds that despite these strategies having been employed and documented since the early 2000’s, there is yet to exist a single body of work or specification that comprehensively combines these strategies into a replicable, scalable manner.

Traditionally, demand responsive load reductions are implemented by either directly modulating the equipment during the event (Chen, 2018) (Jensen et al 2019), or modifying setpoints in a control loop to disable equipment to indirectly reduce its electricity consumption (Kiliccote and Piette, 2006). These sequences may be summarized through 3 different levels of control: plant level, air-handler level, and zone (room) level control. (Motegei et al, 2007). In commercial buildings, demand response strategies have historically targeted thermostats or variable-air

volume (VAV) systems via a zone temperature setpoint, supply fan operation through static pressure setpoint adjustments (Waston et al 2006) (Blum and Norford 2014), or chiller operation via a chilled water temperature reset (Li, Yang and Ning, 2019) (Ran et al 2020). As suggested in the literature (Motegi et al 2007), in order to minimize occupant discomfort, zone-level control should be prioritized, followed by air-handler control and plant control as a last resort. Although larger equipment could provide more meaningful load shed during a demand response event, occupant comfort has been shown to be preserved during zone-level DF control (Keskar et al 2022) and as such, we prioritized the development of zone-level specifications. Future work will focus on AHU fan speed limiting and chilled water reset DF algorithm specifications. Table 1 summarizes various demand flexibility control strategies found in the literature, aimed at the zone, air distribution and plant level.

Table 1: Summary of published plant, air-distribution and zone level DF control strategies for HVAC systems in commercial buildings.

System controlled	Strategy name	Strategy Description	References
Thermostat, zone-controller	Global temperature adjustment , pre-cooling	Adjust thermostat setpoint by predetermined interval (e.g. 2-4 degF) to modulate zone-level demand	(Piette et al 2005) (Killicotte and Piette, 2006) (Cai and Braun, 2019)
Air distribution	Fan limiting	Adjust static pressure setpoint to reduce fan speed	(Piette et al 2005) (Waston et al 2006) (Blum and Norford 2014)
	Chilled-water valve limiting	Set high-limit for CHW position	(Energy Solutions 2014) (Motegi et al 2007)
	SAT Reset	Increase supply temperature by predetermined interval (e.g. 2-4 degF) to modulate AHU-level demand	(Piette et al 2005) (Olivieri et al 2013)
Chiller	Direct chiller capacity limiting	VFD limiting	(Piette et al 2005) (Shan, Wang and Tang, 2018)
	Chilled water temperature reset	Adjust chilled water temperature to reduce compressor speed	(Li, Yang and Ning, 2019) (Ran et al 2020)

Demand flexibility strategies implementing zone-level controls have proposed zone qualification checks to ensure that algorithms can target zones with flexibility capacity for shed or shift and prioritize those with most potential to achieve a given reduction target (Kundu et al 2021). These analytical methods may also be employed to exclude zones that have comfort issues or faulted equipment that lead to suboptimal results, as described in ASHRAE's Guideline 36 (Pritoni et al 2022). As proposed in several studies, prioritization of qualified zones during qualification checks can focus on those that are more comfortable or are associated with larger pieces of equipment and therefore require the most electrical demand (Lu, 2012)(Mathieu, Kick and Callaway, 2013) (Hao et al., 2015) (Kim and Katipamula, 2016). This primarily ensures that flexibility is first delivered by zones where it is less likely to impact comfort, thereby reducing potential issues due to the control adjustments.

Once qualified and prioritized, zone-level control strategies can be implemented by sequentially adjusting temperature setpoints for every participating zone or unit. Global temperature adjustments have been one of the more common zone level strategies, with a 2006 study surveying field-tested DR strategies, found global temperature adjustment in 21 of 35 total sites, recommending a global 1-2 °C change in setpoint across conditioned zones (Watson et al 2006). Another study focusing on demand peaks resulting from DR strategies for precooling and global temperature adjustment found that demand shed profiles were flatter using a step function that incrementally raises the cooling setpoint during the event (Yin, Piette and Kiliccote, 2010)).

Several studies have discussed closed-loop demand response strategies that take into account the real time demand reduction relative to a target in order to achieve more reliable flexibility from controlled systems (Hu et al., 2015). Moreover, demand rebound following an event is a phenomenon that, if left unmanaged, can result in a new demand peak for an electric customer. Studies surrounding mitigation of this rebound effect (Watson et al 2006) (Meng et al 2023) have also been taken into consideration for cases in which setting new building demand peaks can lead to significant costs. Another common theme from the literature is that the DF control algorithms define required variables to enact the sequence while also defining parameters or settings that tune the aggressiveness of the demand flexibility strategy, such as upper and lower zone temperature limits based on occupant comfort guidelines, the frequency of which the algorithm reads and writes data, and in the cases of real-time demand feedback, the target demand reduction.

Reflective of the industry's acquired understanding of the methods and potential benefits of providing grid services via buildings and their HVAC systems, demand response has found its way to mainstream implementation, with incentive programs offered nationwide in the US, for both residential and commercial building demand response. The EIA reports that in 2022, demand response programs implemented upwards of 30 GW of peak load reduction nationwide (EIA 2022). Despite this success, the US Department of Energy has established the goal to triple building demand flexibility by 2030, relative to a 2020 baseline (Satchwell et al. 2021).

Barriers and enablers to more pervasive utilization of building demand flexibility are well documented in the literature, for example by Bogdanova et al. 2023, Good et al. 2017, Satchwell et al. 2021, Saele et al. 2023, Mlecknick et al. 2020, Brown and Chapman 2021, Parrish et al. 2020. They span several overlapping dimensions of utility regulation and planning, customer awareness, market and incentive structures, as well as technology capability and availability. Technology enablers that are particularly relevant to commercial buildings include control automation, optimized DR algorithms, modern IT and communications, smart meter systems, and integrated interoperable systems. With these enablers in mind, we introduce a body of research that explores the use of energy management and information systems (EMIS) and open specifications of best practice control sequences as a vehicle to significantly scale the delivery of demand flexibility in commercial buildings.

EMIS are a diverse family of software products that are used to monitor, analyze, and control building energy use and system performance. Characterized in (LBNL 2015) and (LBNL 2021), these products are constantly evolving. They typically integrate data from heterogeneous sources, including energy meters, rooftop unit (RTU) controllers or building automation systems that control HVAC, and sometimes lighting and security systems, internet of things devices, and distributed energy resources. EMIS are typically offered as cloud-based software-as-a-service products, and due to their cost-effective savings potential, they are seeing rapid uptake in larger commercial buildings, campuses, and portfolios in North America. For example, portfolio users of EMIS with HVAC fault detection and diagnostics (FDD) capabilities have reported average savings of 9% in whole building energy use, with two-year payback (Kramer et al. 2020, Lin et al. 2022).

Recent work has documented research to innovate EMIS technology in partnership with EMIS product providers, by enhancing FDD software to integrate supervisory control capability (LBNL 2023). This enables the ability to not only automatically identify equipment and control faults, but now also the ability to automate fault corrections, commissioning, and the implementation of advanced control sequences upon operator approval (Pritoni et al. 2022, Lin et al. 2023). This is accomplished by adding ‘write’ capability to the FDD platform to supplement the traditional ‘read’ capability, and by complementing the FDD logic with additional control logic. In this prior work, an EMIS-based implementation of the advanced trim and respond air-handling unit reset strategies was proposed based on the openly specified ASHRAE Guideline 36 (ASHRAE 2021).

By utilizing the EMIS infrastructure it is possible to avoid extensive involvement of a controls contractor, which often comes with significant costs, additional hardware/software upgrades, and lead time to schedule the work. The EMIS *already* interfaces with a variety of RTU controllers and BAS providing rapid ROI and value proposition for users (Kramer et al. 2020, Lin et al. 2022). Given that EMIS are built upon modern software infrastructure (cloud implementations, and common programming languages), they can implement a “push” paradigm to significantly simplify advanced supervisory control upgrades, as documented in (Pritoni et al. 2022). Moreover, EMIS technologies utilize semantic data modeling, which promises to further scale application configuration and provisioning (Bergmann et al., 2020). As such, the technology is well primed to deploy DF at scale.

Building upon this value proposition, and the prior work in advanced reset implementation, we pursue an analogous approach for demand flexibility. As established by our literature review, the principal gap this study is addressing is the lack of a single body of work or specification that comprehensively combines best practice demand flexibility strategies in a replicable, scalable manner. In addressing that gap, we aim to answer two primary research questions:

1. Can we translate the demand flexibility approaches that are loosely described in the implementation literature (field studies and utility programs) into generalized well-articulated control sequence specifications?
2. Can these specifications be successfully implemented in EMIS to provide grid flexibility in existing buildings?

In answering these questions we provide the following contributions to extend the state of knowledge in commercial building demand flexibility: 1) Open specifications for demand-flexible control algorithms that are applicable to the most common types of HVAC systems in the US; 2) field-validation of these specifications as deployed in commercially available EMIS products, including proprietary and open-source software code; 3) an understanding of practical implementation considerations for further deployment.

2. Method

2.1 Design of the DF algorithm specifications

The DF algorithms developed in this work are based upon the published literature documenting industry-accepted controls used for demand response since the early 2000's. To inform our articulation of the algorithms in the format of a control sequence specification, we drew upon the conventions used in specifications from engineering societies such as ASHRAE, in particular ASHRAE Standard 90.1 and ASHRAE Guideline 36 (ASHRAE 2021 & 2022). We also reviewed visual aids for logical flow, and pseudocode of control sequences from academic papers such as (Shan, Wan & Tang, 2018; Winstead et al, 2020; Pereira et al, 2024).

Consistent with these analogous works, the open specification presented in this paper is documented using three elements: 1) a logical flow diagram of that depicts the sequence as a series of functions that are executed at specified time frequencies; 2) an english language description of the sequence, and; 3) a pseudocode description for those interested in translating the sequence into programmable execution environments.

Fully detailed in Section 3.1 the specified control sequence comprises 4 main components : 1) zone qualification, 2) execution of the strategy, 3) a ratcheting operation , and 4) a post-event rebound management sequence. Additionally, the specification provides a set of user-defined

parameters and required variables, either monitored from the BAS point list or calculated as part of the strategy are also provided. The strategy is meant to target zone-level controllers, either complex multi-zone AHU-VAV or single-zone RTU systems. The specification is written for demand flexibility of HVAC system operation in cooling mode, the heating mode analogue would be largely the same with some variations. For example, the strategy would reset the zone heating temperature setpoint down to a user-set minimum and the directionality of setpoint changes and conditional comparisons would be reversed.

2.2 Software Implementation, Lab and Field Test design

The demand flexibility control strategies specified in Section 3 were instantiated in two different EMIS products as part of a 2-step process. The first being a preliminary Lab test, which served as an intermediate proof of concept, qualitatively verifying that the sequence was able to trigger demand shed below a certain target while running through the specified functions. The lessons learned from this initial test were collected and used to refine the specification, improving the resulting instantiated algorithm used during scaled field testing with the second EMIS product. This process of development, deployment and refinement of our specification is illustrated in Figure 1 below.

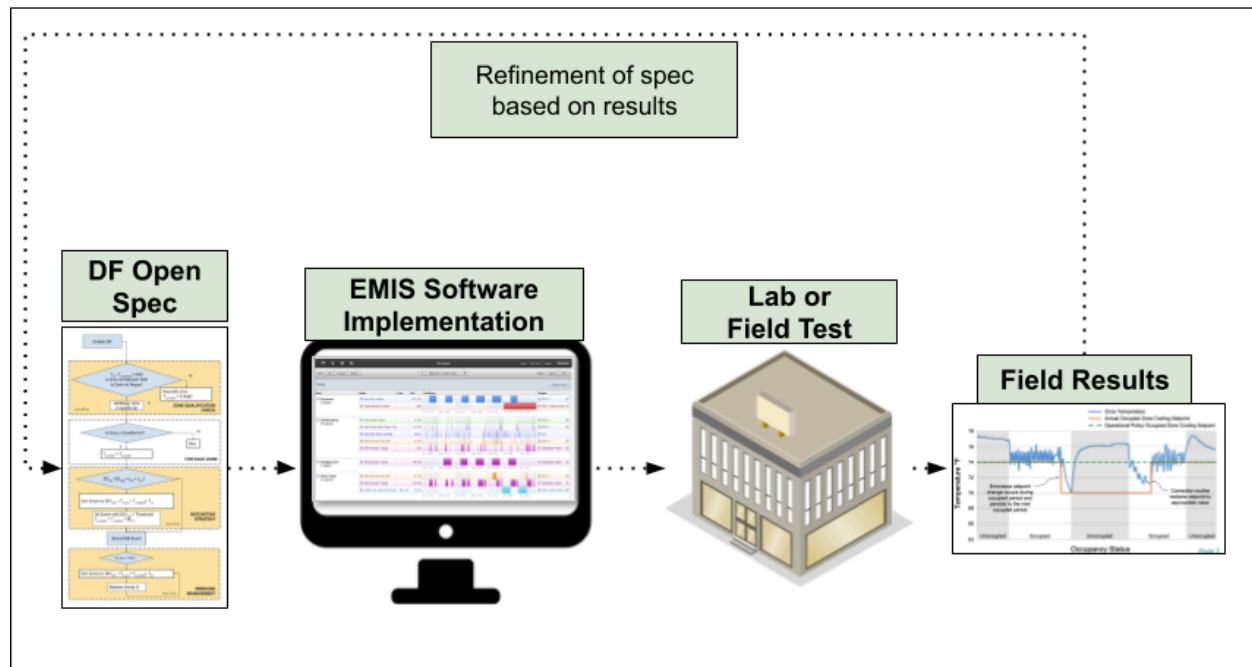


Figure 1: DF Open spec process of development, testing, refinement and deployment

In both cases, EMIS provided a straightforward way to translate the developed specification into instantiations in both software environments. Unlike traditional BAS controllers, the logic in the EMIS is being represented in programming text-based language that is accessible and replicable across multiple instances of the same EMIS, which made EMIS implementation favorable for our study's objectives. The first EMIS product is a platform offering that is programmed by analytics distribution service providers (or end-users), using the Haxall

framework and Axon language (Vitti and Weyandt, 2023). This platform can be implemented in cloud-based, on-premise, edge, or desktop architectures. In this case, the authors programmed a variant of the specified demand flexibility strategies into their licensed platform offering. This implementation is available as an open-source reference (LBNL, 2023) for the ecosystem of distribution service providers to draw into their offerings. The second EMIS product is a cloud-based software-as-a-service offering. In this case, the EMIS provider programmed the desired demand flexibility variant into their development environment (as described in Section 3, the specification contains four variants). This implementation will be made available as an additional feature to the existing commercial EMIS product.

In the EMIS-1 implementation, Lab testing was conducted in an existing 140 square meter (1500 square feet) office space in Berkeley, CA served by 2 Bard-type heat pump units. This office space contains five rooms and an open working area. The EMIS was integrated with two connected thermostats from Pelican, using a 3rd party open source plugin, which polls the Pelican OpenAPI to monitor and control the HVAC state, room temperature and room setpoints for heating and cooling at regular intervals. The open specification was translated into the EMIS platform's proprietary Axon code language, and configured to control the two (thermally coupled) zones in the space as seen in Figure 2. After initial functional testing, the field test was implemented for a 3-hrs load-shed period on an afternoon in September 2023.

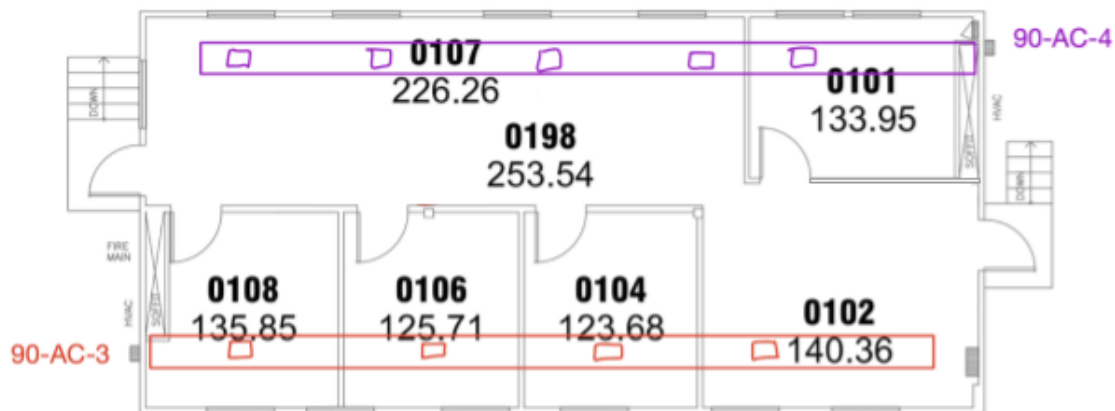


Figure 2. Top view of test building for EMIS-1 implementation

In the EMIS-2 implementation, field testing was conducted in an existing 223,000 square meter (2.4 million square feet) retail facility in Tysons, VA served by 22 single-zone rooftop units (RTUs) 18 of which participated in the field test. Each zone is served by its individual RTU and thermally independent from the other zones. Figure 3 displays the thermal zoning of the space along with their corresponding equipment. The labels of all HVAC systems have been redacted, however the 18 RTUs that participated in the DF test are outlined in red. The EMIS was integrated through the BACnet protocol with the help of an on-premise gateway tied to the site's existing Niagara platform. All points were brought into the EMIS and tagged using the Haystack tagging convention, while each RTU was assigned a capacity value based on nameplate

capacities. The open specification was translated and adapted to align with an existing demand limiting algorithm offered by the EMIS company. The field test was implemented for a 5-hr load shed period on an afternoon in June 2024.

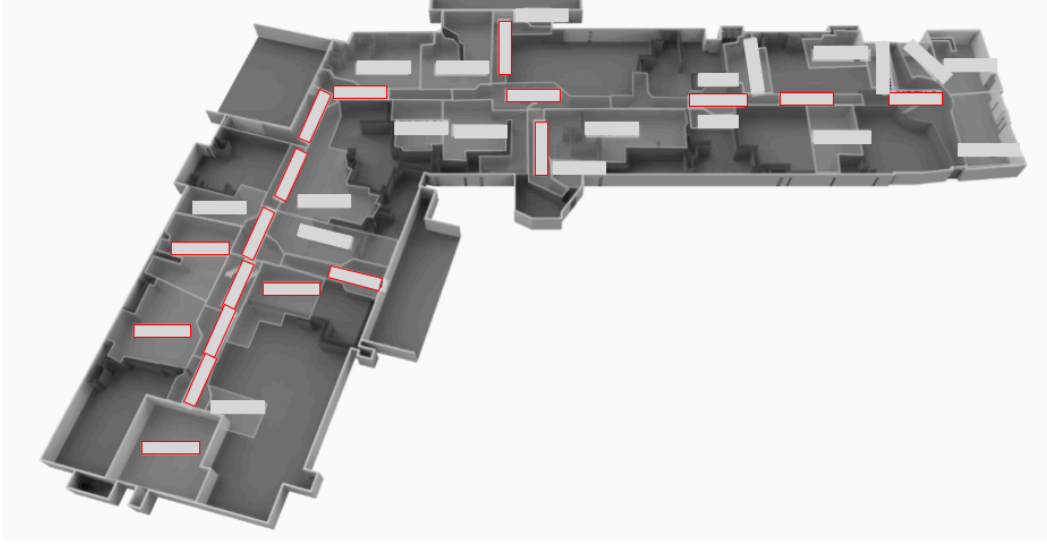


Figure 3. Top view of test building for EMIS-2 implementation, all participating RTUs and zones are outlined in red

These implementation cases illustrate not only different EMIS products, but also different climate zones, HVAC systems and control integration architectures, complexity in space type and size, controlled loads, and variants of the specified demand flexibility strategies. To characterize the changes in building demand that were achieved from implementing the specified control strategies, common methods and metrics from the literature were used in both field tests. We quantified the magnitude of the change in load that was achieved relative to baseline operation, and the adherence to maximum zone temperature comfort constraints.

The average demand decrease percentage for the controlled HVAC systems was defined consistent with Liu et al. 2022, in Equation 1.

$$\sum_{i=1}^n \left(\frac{\hat{P}_i - P_i}{P_i} \right) * 100 \quad (1)$$

Where $\hat{P}_i$ is the baseline demand at time i , P_i is the actual demand at time i , and n is the number of demand measurements across the time period of interest.

The baseline demand was calculated using an industry-standard adjusted day matching approach as defined and accuracy tested in prior work (Bode and Ciccone 2017, Granderson et

al. 2021). In the day matching algorithm, the baseline comprises the ten working days that preceded the day of interest. For each hour of the day of interest, the corresponding hours from the baseline data are averaged to calculate hourly predictions. As detailed in the prior work, an adjustment ratio, capped at +/- 20% was applied to account for weather impacts to load on the day of interest.

The demand flexibility strategies that were tested include a user-defined maximum zone temperature, and in the case of precooling, a minimum zone temperature (see Section 3). Therefore, it was also important to assess the extent to which these limits were met during operation.

The average departure from the zone temperature limits across all zones, summed across the event duration is defined in Equations 2a and 2b.

$$\frac{\sum_{Zone_1}^{Zone_n} (\max(0, T_{za} - T_{za,set,max}))}{n} \quad (2a)$$

$$\frac{\sum_{Zone_1}^{Zone_n} (\max(0, T_{za,set,min} - T_{za}))}{n} \quad (2b)$$

Where $Zone_1$ through $Zone_n$ denote the number of zones participating in the event, T_{za} denotes the zone temperature associated with each participating zone, $T_{za,set,min}$ and $T_{za,set,max}$ denote the minimum and maximum temperature bands set by the operating parameters for the implementation, and n denotes the number of participating zones.

3. Results

3.1 DF Specification

The literature indicates that zone temperature setpoint adjustment is one of the most dependable ways to shed and shift load in commercial building HVAC systems while minimizing the risk of adverse impacts on system control or behavior. Correspondingly, this work presents a fully articulated specification of zone temperature setpoint adjustment. Derived from a synthesis of the literature that drove utility demand response programs, this specification includes four variants of zone temperature-based strategies, depicted in Figure 4 and requires a set of variables and user defined-parameters as summarized in Table 2.

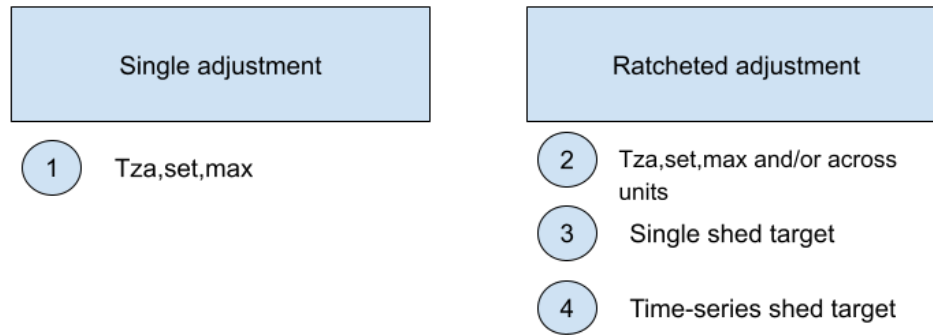


Figure 4. Illustration of the four variants of zone temperature adjustment strategies that are included in the demand flexibility specification.

In all variants a zone temperature setpoint limit (maximum and/or minimum) is a parameter defined by the user. In Variant-1, the zone temperature setpoints are adjusted in a single step. Variant-2 uses a ratchet across HVAC units, or temperature setpoints. That is, either all qualified zone temperature setpoints are adjusted over incremental steps (up to but not exceeding the maximum temperature limit), or HVAC units themselves are incrementally adjusted to the setpoint limit (up to but not exceeding the total number of qualified units). Variants 3 and 4 introduce a performance-based load target, in which temperature setpoints or number of zones/units are ratcheted until the target change in load is met. For Variant-3, the target may be a single absolute load (kW) for the duration of the flexibility period, or in Variant-4, the target may be a time series of different load values (for example, if the site is tracking performance relative to a historic baseline).

These variants accommodate a wide set of use cases that span the most common HVAC system configurations, diverse grid service program designs, site demand flexibility goals, and operational practices and preferences. For example, a setpoint-based ratchet on a collection of staged-RTU systems will eventually result in a plateaued load reduction, while a ratchet based on the number of adjusted units is more appropriate for continuous load reduction. Considering operational practices and preferences, a single-step adjustment may be useful for an owner who prioritizes simplicity. For sites that seek to participate in demand flexibility programs that involve bidding or penalties, or that prioritize achieved load reductions for other reasons, a target-based ratchet may be ideal - it allows the site to deepen and extend a load shed across longer time durations. In general, zone temperature setpoint adjustment can be implemented to pre-cool zones prior to the response period, in order to deepen the achieved load reduction, or it can be used exclusively during the response period.

Table 2: Inventory of parameters and variables:

Abbreviation	Data point	Data type	Unit	Requirements (Defined/Calculated/ Read/Write)
$T_{za,set,min}$	Minimum allowable zone air temperature setpoint	User-defined parameter	°C	Defined
$T_{za,set,max}$	Maximum allowable zone air temperature setpoint	User-defined parameter	°C	Defined
n	# of zones on qualified list	Algorithm variable	-	Defined
Zone _{#_max}	Maximum # of zones allowed on qualified list	User-defined parameter, Algorithm variable	-	Defined
DD _{cap}	objective electrical demand decrease	User-defined parameter	kW	Defined
ϵ_{min}	Minimum allowable difference between DD _{cap} and DD _{bldg}	User-defined parameter	kW	Defined
t _{wait}	Wait time to determine conditions for ratcheting	User-defined parameter	seconds	Defined
ϵ_{DEV}	Threshold to trigger temperature ratcheting to maintain shed	User-defined parameter	°C	Defined
$T_{za,set, def}$	Default zone air temperature setpoint for all zones	User-defined parameter	°C	Defined
$T_{za,ztadel}$	Adjustment factor for ZTA strategy	User-defined parameter	°C	Defined/Write
$\delta_{ratchet, i}$	Zone-specific incremental delta for ratcheting zone temperature setpoint	User-defined parameter	°C	Defined/Write
DD _{bldg}	Building demand decrease	Time-series sensor reading from BAS/meter	kW	Calculated
ϵ_{DD}	Calculated difference between DD _{cap} and DD _{bldg}	Algorithm variable	kW	Calculated

DEV_{tspt}	Zone temperature deviation from effective setpoint	Algorithm variable	°C	Calculated
T_{za}	Zone air temperature	Time-series sensor reading from BAS	°C	Read
P_{bldg}	Electric demand from building meter	Time-series sensor reading from BAS	kW	Read
$T_{za,set}$	Effective zone air temperature setpoint for all zones	Time-series sensor reading from BAS	°C	Read/Write
$T_{za,set,i}$	Effective zone air temperature setpoint for each zone ($Zone_i$), which is equal to $T_{za,set}$ during regular hours, and is equal to a different value during shed and precool periods	Time-series sensor reading from BAS	°C	Read/Write

The open specification spans all 4 variants and multiple system configurations, including AHU-VAV and single zone RTU systems. This paper will cover a generalized sequence capturing both cases as fully summarized in Figure 4. The control case assumes the HVAC system is serving a thermally independent zone, with discrete staged control via a thermostat. We define a set of user-definable parameters based on the constraints set by the use-case or the controlled building. These parameters include the minimum and maximum temperatures, $T_{za,set,min}$ and $T_{za,set,max}$ that are allowed by the DF zone control (set to 15.6°C/60°F and 26.7°C/80°F in our case study), the step change for each ratchet, $\delta_{ratchet,i}$ (set to 0.5°C/1°F), and wait time before each logical cycle, t_{wait} , (set to 300 seconds).

Once the DF event has started, the sequence starts in Function 1 as shown in Figure 5 the units should be prioritized by one of or a combination of relevant characteristics such as cooling capacity, current deviation from setpoint (DEV_{tspt}) or current state (off, stage 1 or stage 2) in order to ensure the most comfortable zones or largest capacity units are called upon first in the event. The units that are prioritized are then sequentially qualified to make sure that the units or zones are not above the $T_{za,set,max}$ threshold or faulted in any way. The qualified units will only be added to the active list if the max number of zones called upon has not been reached. Once $Zone_i$ is in the active list, the setpoint is adjusted to shut the compressor off in Function 2 as shown in Figure 5.

Function 3 as shown in Figure 5 is initiated once all of the zones in the active list have their setpoints adjusted and only applies to variants 2,3, and 4. For variants 3 and 4, assuming there is a live demand measurement at intervals at the building or HVAC level, the algorithm may compare the current level of reduction of electric demand relative to a baseline or immediately prior to the event. The error between the target reduction and current building electric demand is calculated at regular intervals. The algorithm in Function 3 increases the number of participating zones until the error falls below the minimum error, $\epsilon_{\min}$. The event strategy will also concurrently monitor the zone air temperature T_{za} at regular intervals in order to determine whether or not the zone can be further adjusted to maintain shed or if conditions in each zone have reached unmanageable conditions that could lead to thermal comfort issues. Given the discrete nature of staged systems like RTU's, the unit associated with each included zone will need to remain off when called upon until the end of the event, unless the unit has reached the maximum allowable setpoint. In cases in which Variant-2 is being activated. If a qualified zone's temperature deviation falls below the set deviation threshold, the setpoint is slowly adjusted to maintain the shed.

These logical processes cycle at a frequency defined by t_{wait} until the DF event has concluded. After the DF event has concluded, a rebound management function, Function 4 in Figure 5 is triggered. This function releases all participating zones sequentially in an order defined by the DEV_{tspt} . As zones are released, the setpoints are gradually returned back to their default value, $T_{\text{za,set, def}}$ by an interval defined by $\delta_{\text{ratchet, i}}$ at the logical cycle frequency, t_{wait} .

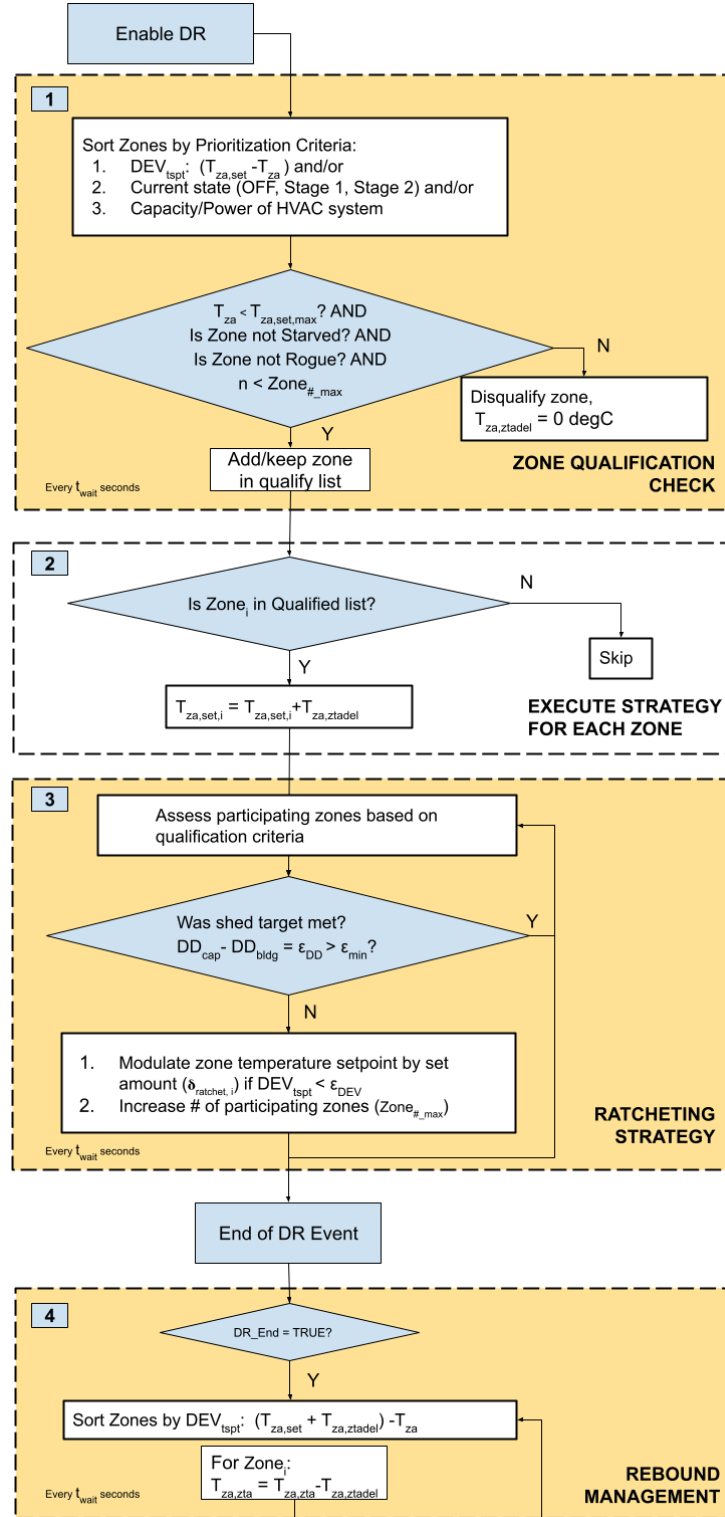


Figure 5: Open specification of generalized demand flexibility strategy for zone temperature adjustment

3.2 Algorithm Instantiation, Lab and Field Test

The 2 EMIS implementations described in section 2.2 were tested using two different Variants of the zone temperature adjustment sequence specification. This was due to varying availability of reliable real time demand data for each site. Table 3 summarizes the details of each site, including values of a subset of user-defined parameters listed in Table 2.

Table 3: Summary of both tests performed in EMIS implementations

Test	EMIS-1	EMIS-2
HVAC type	Staged Bard System	Staged RTU
Building Type	Temporary building trailer	Light commercial retail
Event time and duration	14:00, 3 hours	15:00, 5 hours
# of zones included	2	18
Variant	3: Reduction to single load value	2: Ratcheted adjustment
Prioritization method	Zone temperature	Zone temperature, zone capacity
Rebound mitigation included?	Yes	Yes
t_{wait}	300 sec	300 sec
$T_{\text{za,set,max}}$	26.7°C/80°F	25.6°C/78°F

The EMIS-1 test was conducted on September 10, 2023 for a span of 4 hours, including 3 hours of shed and 1 hour of rebound. The specific variant of the demand flexibility sequence was aligned with Variant 3, in which the algorithm sequentially adds HVAC systems until a single load reduction value is met. The maximum temperature setpoint limit was set to 26.7°C (80°F). On the test day, the building cooling load was low due to temperate weather conditions. In order to demonstrate the functions resulted in an active demand reduction in the building, the thermostat temperature setpoint was reduced to 20.5°C (69°F) in the moments leading up the scheduled event. The demand target for this test was 2 kW, meaning the system will qualify and shed units until the building load is below 2 kW. This reduction target was based on knowledge of observations of demand with both units on rather than a historical baseline, as would be used in a real world implementation of Variant 3 & 4. Furthermore, the 2 kW target is set with the intention of turning all units off sequentially, in order to test the gradual activation of each HVAC system to fall below the target as described in Function 3 of the specification.

The results show that the test successfully ran through Function 1 without adverse effects, qualifying both HVAC units, and prioritizing them by their deviation from their current setpoint. As expected, the algorithm prioritized the colder zone and reset its setpoint, successfully running through Function 2. After the given wait time of 300 seconds the sequence, the algorithm successfully runs the logic in Function 3, making a determination that the reduction target (2kW) had not been met, activating the second zone's setpoint reset. In order to maintain the shed, the activated HVAC system setpoints are slowly ramped up as the rising zone temperature setpoints approach within 0.5°C (1°F) of the current setpoint as described in Function 3. During the time between 13:45 and 16:45, the electric demand of the building is maintained below the target of 2 kW as the HVAC systems remain off. At 16:45 the event ends, which activates the rebound mitigation sequence found in Function 4 which includes incrementally reducing the temperature setpoint of each system incrementally to its default temperature setpoint starting with the hottest zone first. The zone setpoint is reset until the setpoint is restored to a default setpoint of 22.2 °C (72° F), however the setpoints were reduced to their default value faster than the temperatures could decrease. This resulted in a demand spike, which can be improved by dynamically changing the rate of decrease of each unit based on a demand limit. The results of this test are shown in Figure 6.

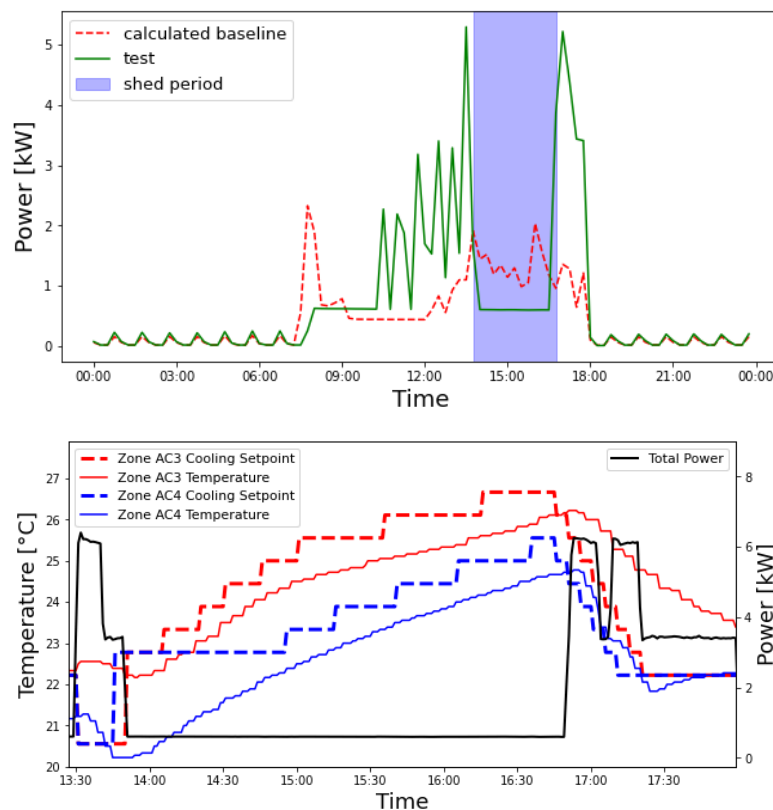


Figure 6: EMIS-1 field test results: (top) baseline demand is shown in the dashed line, metered demand is indicated in the solid line, and the shed period is highlighted in the vertical shaded bar; (bottom) zone

setpoints before, during, and after the event are shown in dashed lines, measured zone temperatures and metered power are depicted in solid lines, with power plotted on the secondary axis.

During the EMIS-2 test, the demand flexibility algorithm slowly ramps up to sequentially include zones and ratchet their temperatures as defined by Variant 2. Due to the lack of reliable meter data, the algorithm bases the demand reduction on a predefined number of units, which is later verified by a virtual meter calculated with predefined capacities of each unit. The top half of Figure 7 shows the gradual HVAC electric demand reduction relative to a baseline as RTUs are activated as part of the strategy. The bottom half of the figure shows the gradual addition of zones into the strategy throughout the duration of the event which coincides with the average zone temperature setpoint profiles. The max temperature plot shows that all zones stayed under the 25.6 °C (78°F) maximum limit set for the strategy. The event lasted around 4 hours and resulted in minimal demand rebound due to the end of the test coinciding with the end of the occupancy period. Therefore, the rebound function resulted in a gradual deactivation of the RTUs that avoided a demand peak. Unlike the EMIS-1 test, this test did not include real time demand feedback, which meant that the reduction was estimated before the event. The metrics results for both the lab and field tests are summarized in Table 4.

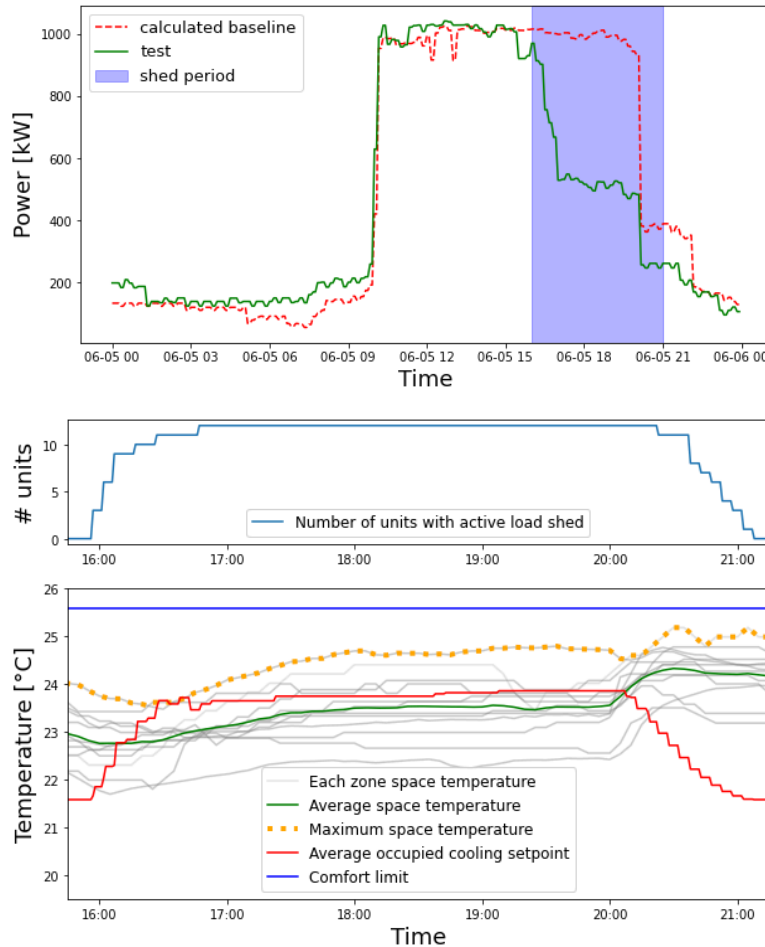


Figure 7: EMIS-2 field test results: (top) baseline demand is shown in the dashed line, virtual metered demand is indicated in the solid line, and the shed period is highlighted in the vertical shaded bar; (middle) cumulative number of units activated as part of the DF strategy during the course of the event; (bottom) average zone setpoint in the red line compared to the average zone temperature in the green line, the temperatures never exceeded the set temperature limit in the blue line as shown by the maximum participating zone's temperature in the yellow dotted line

Table 4: Demand shed and temperature departure metric results from the lab and field tests.

Metric	EMIS-1 test	EMIS-2 test
Shed period demand reduction vs. Baseline (kW, % reduction)	0.70 kW, 50.4%	358.1 kW, 40.2%
Total departure from the zone temperature limits across all zones	0.0 °C-h	0.0 °C-h

4. Discussion

4.1 Development of a Generalizable Specification

The results of this work demonstrate a successful translation of best practice demand flexibility approaches from the literature into a fully articulated control sequence specification. Moreover, the specification that was developed offers a level of specificity that is sufficient to prescribe effective supervisory control sequences. This marks a major contribution in that the body of literature that documents the performance of demand flexible controls does not typically provide details on the control algorithms deployed. The specification also proved sufficiently flexible to generalize across diverse HVAC system types, configurations, and topologies, and real-world data availability. The sequences defined in the specification were successfully applied to a small office building served by 2 heat pumps, and to a large retail site served by 22 RTUs, while maintaining the core components of the strategy.

When instantiating this specification for future buildings, the user-defined parameter definitions must be defined to align with achievable targets, owners' operational policies and the capabilities of the BAS/EMIS to pull data and push control values. For example $T_{za, set, def}$ will typically be found to be between 23.3 and 24.4 °C for cooling. The range for $T_{za, set, min}$ and $T_{za, set, max}$ could be anywhere from 18.3 °C to 26.7 °C respectively in more general cases, whereas policies for sensitive zones may only allow for a 1 to 2°C delta between these values. $Zone_{\#_{max}}$ should be determined prior to a live flexibility event either through a preliminary test (as the minimum number of units or zones that can be set back while meeting the demand reduction objective, DD_{cap}) or by simply setting $Zone_{\#_{max}}$ to the number of zones in the building. DD_{cap} is a value that should be set to match the estimated reduction potential of all participating HVAC

systems, this value is usually 20-30% of peak electric demand but can be further estimated based on nameplate capacities or through electricity meter data analysis. The minimum allowable difference between real time measurement and the load shed target, $\epsilon_{\min}$ should be determined based on the resolution, accuracy, and magnitude of the electrical meter reading, and could range from 1kW for small systems to 100kW for large buildings. The execution frequency of each function, defined by t_{wait} should be aligned with the BAS-to-EMIS read/write frequency which is typically 5-15 minutes or 300 to 9000 seconds. Implementations with t_{wait} times of 15 minutes should use higher values for $T_{\text{za,ztadel}}$ and $\delta_{\text{ratchet, i}}$ (0.5 to 1°C) so that participating systems, especially those with higher thermal loads, are not triggered between cycles. Users should consider that some sites in humid climate zones may want to add a relative humidity component to their thermal comfort determination; the provided specification only employs dry bulb temperature as a marker for acceptable conditions during flexibility events. In more advanced cases, EMIS platforms with integrated occupancy data could leverage the unoccupied zones for additional flexibility via a wider range of acceptable temperature conditions during an event.

It is important to note the limitations of the initial tests conducted as part of this study. One limitation was the need to activate the systems prior to the shed event in the lab test, this was done by artificially lowering the cooling setpoint to turn on the systems. This was due to the cooling load being too low when the DF event started. This caused a demand spike prior to the event start which would not be typical of a shed strategy in the field. Furthermore, the rebound management function during the lab test was unsuccessful in avoiding a demand spike, due to the temperature setpoints resetting faster than the system could respond. The strategy would ideally be tuned to match the rate of decrease of the setpoints to the system capacity to avoid this scenario. The field test also did not thoroughly test the effectiveness of its rebound management function, given the sequence was initiated after occupancy hours, which avoided any possibility of a demand peak.

The results presented here are not broadly indicative of what one would expect to achieve in the field, although the reduction values seen in our study align with what has been reported in other field implementations of shed strategies cited in our literature review. However, as described by (Liu et al 2022), the DF potential of a specific implementation and benchmarking of performance relative to other implementations, is highly dependent on building and HVAC system characteristics and the resulting thermal load of a system.

The zone temperature control principles that are employed can be applied to all building types and HVAC configurations, and as reported in the literature, zone temperature-based demand flexibility approaches are least likely to cause system instabilities and occupant discomfort. As such, the specified sequences are likely robust to built-up HVAC system configurations, however additional testing will be required to demonstrate the full potential for generalizability, as well as the spectrum of flexibility performance.

4.2 Implementation in Existing Buildings Via EMIS

The lab and field implementations showed that the control sequences from the specification could be integrated into contemporary EMIS software architectures. This was demonstrated with two products that are representative of the EMIS product landscape. One is a software as a service product, and the other is a user-configurable platform as a service product. The HVAC systems in this study adequately represent demand flexibility control of staged, direct-expansion systems, however there is still future work needed to demonstrate the performance of this strategy with VAV-based systems that can more continuously modulate their thermal capacity and electrical demand. The field implementations in occupied existing buildings showed that the specified sequences delivered average HVAC load reductions of at least 40% on average, while satisfying temperature constraints.

The EMIS-based deployment path offers several advantages over today's common practices that solely utilize the capabilities of the building automation system (BAS). First, it obviates the need to custom program the demand flexibility sequences into the BAS, which usually requires a BAS contractor increasing time and cost burdens as well as a 'hassle factor'. In addition, the sequences can be more easily modified and updated over time, given the push-based software implementation. Second, the EMIS offers native analytics that are not possible in the BAS environments, and can be leveraged to improve the robustness of the flexibility strategies. For example, capabilities such as zone qualification, and ratcheting to achieve a target can improve performance and reliability of the load flexibility. Finally, EMIS technology enables automated initiation, execution, and release of the demand flexibility control sequences, with modern user interfaces that are straightforward for facility managers and operators to engage with. The lack of automated flexibility in the commercial sector is frequently cited as a barrier to more pervasive use of demand side resources for the grid, such as in virtual power plant (VPP) programs.

Beyond traditional rule-based controls, which has been shown to integrate and perform well in EMIS software, there are emerging methods of actuating demand flexibility through optimized control strategies such as model predictive control (Zhang et al., 2022) (Ham et al., 2023) (Urrutia et al, 2025), reinforcement learning (Touzani et al, 2021) and priority stack based controls (Winstead et al, 2020) (Wang et al, 2024 & 2025). Unlike traditional rule-based control, these algorithms are predictive, and can perform multi-objective optimization to yield performance that exceeds that of our specified rule-based control algorithm. While not yet widely adopted in commercial buildings, these algorithms promise to extend performance even further as shown in the literature. Future work should address methods of better integrating these with industry-available solutions and gain wider acceptance among practitioners.

4.3 Scalability

Open, standardized control sequences that are implemented in supervisory architectures using analytics software in concert with the BAS offer a compelling solution for robust, scalable

demand flexibility. However there are aspects of scalability that were not addressed in this work, that are being addressed in concurrent work.

For instance, there exists a pervasive difficulty in accessing data consistently across BAS and equipment instances; difficulty reusing control code across different buildings due to lack of semantic interoperability (Bergmann, 2020). ASHRAE Standard 223p and other semantic schemas (i.e., Project-Haystack, Brick) can be leveraged to improve interoperability and portability of programmed sequences across buildings. Lastly, as demonstrated in this paper, there is not currently an ability to validate sequences before deployment. Virtual controls evaluation testbeds such as those found in DFLEXLIBS which utilizes the BOPTEST framework (Blum et al., 2021) to test the performance of newly developed sequences under a variety of conditions prior to field implementation. Semantically informed configurations of DF controls applications are also being studied (de Andrade Pereira et al., 2024) to streamline the deployment of DF controls across multiple system designs.

Lastly, there is currently a lack of interoperable and machine-readable code to describe control sequences (Wetter et al., 2022) such as those described in this study. This gap is currently being addressed by ASHRAE standard 231p, which aims to introduce a vendor-neutral and machine-readable control description language (CDL) (Wetter et al., 2018). Theoretically, CDL could be leveraged to further codify the existing open-source library of DF sequences.

5. Conclusions

In this study, we proposed an open specification for a generalized, zone-level demand flexibility control sequence with four variants. The open specification incorporates principles of thermal comfort, closed-loop control and demand management, in the context of a digitized building system with access to real-time data. The results of the study showed the ability for this sequence to scale across buildings with different HVAC systems, software environments and demand reduction goals. Both the lab and field tests showed each EMIS implementation of our openly specified demand flexibility sequence was successful in running through each logical function while actively reducing electric load by at least 40% on average during the called event, while maintaining temperature limits. This study also highlights the potential to deploy demand flexibility through EMIS platforms, an untapped pathway for scaled DR and VPP programs nationwide. As section 4.3 states, there is still more work needed in enhancing the scalability of these sequences through semantic interoperability, software environments for testing and prototyping, and ensuring success and persistence of these methods by ensuring buy-in of facilities operators and managers.

In terms of broad application and attractiveness, future work should focus on an expanded set of implementations across more buildings accompanied with quantification of reduced time and effort (compared to traditional DF methods). This is needed to establish a compelling value proposition to building owners or technology adopters searching for scalable solutions to commercial VPP program participation and revenue.

Lastly, future work should focus on further development in the integration of the DF applications in other software environments including programming these sequences in standardized control languages such as CDL as defined by ASHRAE 231p, and establish interoperability through semantically informed validation and configuration processes. Expansions of the open specification are planned to include upstream systems such as fan VFD limiting at the air distribution level and chilled water reset strategies at the plant level.

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