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Living Laboratories Can and Should Play a Greater Role to Unlock Flexibility in US Commercial Buildings

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Context & Scale

Demand flexibility will have tremendous value alongside efficiency in future energy systems and has a critical role to play in the ongoing transition. Commercial buildings could offer a large source of flexibility in consumption of electricity, gas, heating, and cooling. The decarbonization and electrification of our energy systems is an opportunity to invest in new demand management strategies and to update practices.

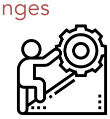
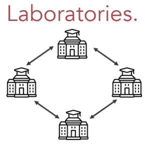
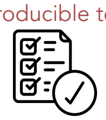
Beyond engineering calculations and simulations, energy system operators require measurement-based models to unlock efficiency and flexibility opportunities in building energy systems before they can fully integrate them into their decision-making. We provide an ambitious agenda for researchers to devote more resources to real-world experimentation as a much-needed complement to simulation and modeling efforts.

SUMMARY

Energy demand flexibility from commercial buildings can play a critical role in the ongoing energy transition. There is an urgent need to redirect more research and deployment effort towards real-world experimentation. Buildings-sector roadmaps overwhelmingly rely on simulations that imperfectly capture reality. We draw lessons from a review of two decades of literature on real-world flexibility and demand response experiments and from our "Living Laboratory" experiences at three major academic institutions in the United States. While the prevailing method is "model first, experiment second", there is also strong value in "experiment first, model second" and in improving our understanding of a system through experimentation while modeling it. Commercial building clusters on university and corporate campuses offer valuable and often untapped potential. They are both ideal testbeds for research on energy flexibility and a significant source of flexibility. Our research agenda provides practical recommendations for conducting and scaling experimentation in these testbeds, and leveraging experimental findings to improve modeling.

Demand-side Energy Flexibility, Demand Response, Commercial Buildings, Grid-Interactive Efficient Buildings

Summary Table. Challenges, opportunities, and our recommendations for expanding Living Laboratory efforts to accelerate the deployment of energy flexibility technologies in US commercial buildings**.**

	Commercial buildings are/have	Large, long-lived investments	Data-poor environments	Competing and evolving priorities
	Challenges 	• Dealing with legacy systems • Consumption patterns change • Interoperability and scalability	Data availability and quality remain low, integration is hard.	• Multiple uses, tangled incentive structures, and resource constraints • Socio-cultural barriers • Many different Distributed Energy Resources
	Opportunities 	• New methods for periodic and ongoing commissioning • Fewer control points and decision makers	Better harnessing modern data-driven methods, including Machine Learning and Artificial Intelligence.	• Momentum from decarbonization and electrification goals • Electric grid signals for flexibility
Recommendations for expanding Living Laboratory efforts	Encourage networks of Living Laboratories. 	Compare different vintages, control architectures, vendors. Network living labs to ensure broader applicability.	Pool data from different sources; Create more repositories for building datasets.	Share lessons learned, examples and case studies; Encourage positive emulation and example setting.
	Learn from building managers. 	Identify which legacy systems are most likely to remain, strengths and weaknesses of current practices, what is easy/hard to automate.	Identify actual data availability, bottlenecks, where new sensors would add real value, and where AI can augment building manager capabilities.	Identify stakeholder constraints and structure of cost functions. Align experimentation protocols with local incentives.
	Prefer less invasive control strategies. 	Discard non-scalable strategies. Focus on wrap-around software approaches that can adapt to pre-existing systems.	Develop less data- and parameter-hungry strategies than the equipment-level MPC strategies favored by researchers in the past.	Leverage hierarchical, decentralized, and distributed controls to delegate and coordinate while alleviating privacy concerns.
	Standardize rigorous, reproducible tests. 	Run tests periodically to update flexibility models; develop simple testing strategies that can be run in many different buildings.	Generate high quality datasets for research; encourage harmonization of data management practices.	Build trust by repeating tests to quantify uncertainty and resource reliability for electric grid and building operators.

Images from flaticon.com.

INTRODUCTION

Decarbonizing electricity and electrifying buildings and transportation will get us more than halfway toward achieving net zero greenhouse gas emissions in the United States[1]. Decarbonizing electricity involves injecting large shares of variable renewables at the transmission level and smaller local renewable generation at the distribution level. End-use electrification of heating and cooling is widely seen as a key step towards a low-carbon buildings sector but will further stress electric grids, even with transmission and distribution expansion. Demand flexibility will therefore have tremendous value alongside efficiency in future energy systems and has a critical role to play in the ongoing transition. We refer the reader to the US National Roadmap for Grid-interactive Efficient Buildings for definitions of demand flexibility and energy efficiency[2].

Commercial buildings could offer a large source of flexibility in consumption of electricity, gas, heating, and cooling. They include offices, schools, retail sites, hotels, supermarkets, warehouses, and healthcare facilities. Commercial buildings currently represent 35% of U.S. electricity sales[3], and electrification is likely to increase consumption. Natural gas still accounts for a third of the energy consumption of commercial buildings[4]. Medium to large commercial buildings (over 5,000 square feet) represent half the number of buildings but 91% of floorspace and consumed 92% of the sector's total energy in 2018[4]. We focus on medium to large commercial buildings with multi-zone central HVAC systems, which we will generically refer to as "commercial-scale buildings".

This Perspective identifies broad challenges for the deployment of energy demand flexibility technologies in commercial-scale buildings and opportunities for overcoming those challenges (Summary Table). We provide recommendations for future research to redirect efforts towards more real-world and at-scale experimentation. Those that are not immediately actionable will require coming together as a community to raise awareness, rethink incentive structures, and secure dedicated funding.

Commercial-scale buildings are 1) large, long-lived investments, 2) inherently data-poor environments, and 3) governed by competing priorities. We discuss pitfalls and best practices for experimenting with commercial buildings, drawing from academic literature and lessons learned in past and ongoing research projects at three different academic institutions in the United States. Partnering with different facilities teams to run experiments can be difficult due to conflicting priorities. We provide practical lessons learned from real-world experiences that we believe will be valuable to other researchers.

The technologies needed to implement the primary commercial demand flexibility measures include low cost, distributed, remotely accessible sensors and actuators, onsite generation, storage, automated feedback control systems, and dynamic optimization[2,5]. Many of these technologies have existed for several decades[5], but neither proactive nor reactive management of building energy demands have been widespread historically. There is still an important role for Research & Development (R&D) in better enabling the deployment of these technologies for at least two reasons. 1) Although there are mechanisms to monetize flexibility, energy market signals remain largely inadequate to bolster widespread adoption. Investing in flexible demand remains more often an R&D bet rather than an assured commercial venture. 2) Important practical challenges need to be solved before commercial buildings can truly become more active, including scalability, controls design and integration with legacy systems, data scarcity, the incorporation of occupant feedback, and developing reliable models that capture real building dynamics.

Researchers have a role to play. They should invest more of their efforts towards on-the-ground experiments and practical solutions to enable and spur real-world deployment. We make four main recommendations: 1) encourage (networks of) living laboratories; 2) learn from building managers to prioritize the real challenges they face; 3) abandon the quest for invasive, non-scalable, equipment-level Model Predictive Control (MPC) strategies and instead prioritize wrap-around control strategies, which could also leverage MPC; and 4) standardize more rigorous experiment procedures. We generically call "living laboratory" any building or group of buildings that can be experimented on but is being used by real people.

Beyond engineering calculations and simulations, energy system operators require measurement-based models to unlock efficiency and flexibility opportunities in building energy systems before they can fully integrate them into their decision-making. Experiments and simulations are synergistic, not exclusive. They can and should be used together. Experiments inform what to model, how to model it, and just as importantly what not to model, e.g., parameters that do not drive outcomes. Increasingly widespread adoption of distributed sensors and actuators coupled with recent advances in data-driven methods such as Machine Learning and Artificial Intelligence (ML/AI) also promise attractive new tools, options, and opportunities.

COURSE CORRECTION NEEDED: A HISTORIC BIAS TOWARDS SIMULATION

Simulations dominate research agendas

Current research and practice in building energy management overwhelmingly rely on synthetic simulations of reference buildings[6] to estimate the potential from different energy efficiency and flexibility options. These simulations most often use physics-based computational models, e.g., the US Department of Energy's (DOE) EnergyPlus software[7,8]. For example, the US National Roadmap for Grid-Interactive Efficient Buildings (GEBs) promise of 100-200 billion in electric system cost savings over the next two decades from adoption of GEBs is almost exclusively based on simulations[2]. This Perspective provides pragmatic pathways to implement Pillar 1, "Advancing GEBs Through Research, Development, and Data", and Pillar 3, "Empowering GEB users, installers, and operators", of that roadmap. We believe a much stronger emphasis on at-scale, real-world experimentation can help tackle several of the technical and market barriers identified by the report, such as interoperability, reliability, workforce training, technology cost, perceived risks, complexity, consumer awareness.

Simulations also promise that upgraded controls could improve building performance by 30%[9]; that aggressive efficiency measures, electrification, and high renewable energy penetration can reduce 2050 CO_2 emissions from buildings by 72%-78% relative to 2005 levels[10]; or that energy efficiency and flexibility measures can avoid 800 TWh of annual electricity use and 208 GW of daily peak load by 2050[11].

While valuable, the simulations behind these assessments can only offer an imperfect representation of reality. The actual impacts of retrofits or demand management strategies will likely vary significantly from building to building. Creating commercial building energy models is time-consuming and requires significant effort. Building energy models quickly become outdated as energy consumption patterns change and re-calibrating them also requires effort. Models are largely used during building design and construction, much less for operations[12]. State-of-the-art calibration methods typically rely on design parameters, and at best use data from whole building electricity meters rather than zone-level sensors and submeters[13,14]. Models cannot be reliably used to predict indoor air temperatures throughout the building during a flexibility event, for example, further reducing their on-the-ground usefulness for building managers and implementers. Even calibrated models do not always capture energy demands when compared to real-world operations[15], an issue which only grows with time as changes occur within the building. Comparisons of simulations to experiments also show that it is often difficult to fully capture the physical and operating characteristics of real-world commercial buildings with simulations only[16-18].

To realize the benefits promised by these simulation-based national assessments and spur real-world deployment and implementation, efforts now need to be redirected to empirical research agendas and the generation of data sets through on-the-ground testing and experimentation.

At-scale experiments and datasets remain rare but are sorely needed

In general, empirical and experimental research with commercial buildings have not received the same level of attention as modeling-based research. Real-world data from buildings remain scarce[19]. Initiatives like the Benchmark Datasets project[20] are the exception rather than the norm.

Real-world datasets that include flexibility events would be valuable to guide research but are even more rare than energy consumption datasets. Obtaining such data from utilities often involves signing non-disclosure agreements. A recent review identified only three flexibility datasets for commercial buildings[21]. Three more have been published since that review[18,22,23]. Much more is needed. The paucity of data makes it difficult to evaluate and to calibrate model predictions for how buildings behave during real-time demand response events.

Several reviews highlight that the buildings research community is still far from large-scale and widespread experimentation. In a 2023 review on building energy flexibility, only 26% of the 87 studies that were reviewed involved real measurements[21]. A third of those studies concerned the commercial sector. A 2019 review on field studies of occupant-centric controls similarly found very few implementations in real buildings relative to small-scale experiments, simulations, or concept papers[24]. Most of the 42 field studies in that review experimented in up to only ten zones during at most three months.

The experimental results that do exist often disagree and are difficult to compare[17]. Real building systems do not behave according to the assumptions used by building modelers[25]. Experiments in controlled environments and test chambers[26–28] are informative but cannot replace the value from at-scale experiments.

Finally, the geographical expanse of experimental studies in the United States is limited to a few regions in selected climate zones. Extrapolating across climates may be difficult. Humidity management is largely overlooked, unoptimized, and inflexible, for example[29].

The next three sections outline challenges and opportunities for Living Laboratory efforts to accelerate the deployment of energy flexibility technologies in US commercial buildings (Summary Table: Challenges and Opportunities). The last two sections discuss recommendations for expanding these efforts (Summary Table: Recommendations).

LARGE, LONG-LIVED INVESTMENTS

Dealing with legacy systems

Commercial building lifetimes are fifty years or longer. Stock turnover is correspondingly slow. In the US commercial sector, it is currently 1-2% per annum, and only 29% of the US commercial floorspace was built after 2000[4]. In fact, increasing lifetimes would reduce material use and the environmental burdens from construction, demolition, and waste management. As a result, researchers cannot afford to work on new buildings only. Tackling existing buildings is required for rapid decarbonization of current energy systems.

Working with existing buildings brings major technical constraints, however. Equipment does not always function as expected and control sequences can be out of date[25]. Reprogramming the core Building Automation System (BAS) can be expensive, so BAS wrap-around approaches that do not require such reprogramming are preferable. There is a lack of a guideline or standard to develop, commission, and validate demand control strategies when dealing with programming in existing BAS.

Significant research efforts in recent times have been devoted to advanced control strategies of commercial HVAC equipment using ML/AI[30-34]. While some of these methodologies may be adaptable to legacy control systems, those that do not account for the enormous effort it takes to update legacy building automation and sensing systems will almost certainly fail.

Consumption patterns change

The energy consumption patterns of a building change over time. In a commercial building, a tenant improvement or a retrofit of the building's HVAC system has the potential to dramatically change the building's energy profile. The same is true in a research facility, for instance, when new laboratory equipment is installed.

Adding to these constraints, significant change is expected to happen within the next decade with extreme weather events impacting the grid, such as cold storms in Texas[34] or wildfires and heat waves in California[36]. Electrification can also lead to seasonal peak demand shifts from the summer to the winter[37,38].

Interoperability and scalability

Largely because of their large size and long lifetimes, the information systems that serve commercial-scale buildings lack standardization[12], which makes the task of augmenting existing BAS non-trivial[39] and creates major interoperability and scalability challenges. Compounding these challenges is strong heterogeneity in BAS vendors (e.g., Siemens, Tridium, Schneider, Johnson Controls), communication protocols (LonWorks, BACnet, Modbus), network types (TCP/IP, Ethernet, Zigbee), and hardware devices for sensing and actuating. Experimental research will need to address how these challenges will be overcome as we scale demand flexibility. R&D and deployment effort is also needed in standardizing hardware devices to enable plug-and-play demand flexibility.

New methods for periodic and ongoing commissioning

Commissioning, the process of assuring efficient building operations, reliably provides 5-15% energy savings with payback times of 0.8-3.5 years[40]. Commissioning projects most often add value through changes to HVAC system controls, scheduling, setpoints and sequences of operations and are typically more valuable when augmented with monitoring and ongoing fault detection and diagnostics[41,42]. Labor costs are one of the main barriers today, but modern data management techniques and data-driven methods, including ML/AI, promise to make future commissioning processes cheaper, faster, and more automated. There is also an opportunity to expand existing commissioning procedures to include demand flexibility strategies.

Fewer control points and decision makers

The larger size of commercial-scale buildings and of building portfolios in the commercial sector is also an opportunity, because it implies fewer control points and decision makers. This is in strong contrast with the residential sector, where there is also more standardization. In 2018, large commercial buildings (over 100,000 square feet) accounted for 2% of all US commercial buildings and 34% of total US commercial floorspace. These buildings consumed 2,659 trillion Btu, which was 39% of total US commercial energy consumption[4]. A small number of decision makers also sometimes control a large portfolio of commercial buildings, as in the case of institutional or academic campuses. For example, the US government's General Services Administration owns and leases 8,600 buildings[43].

DATA-POOR ENVIRONMENTS

Data availability and quality remain low, integration is hard

Distributed sensors and actuators are increasingly widespread, but far from ubiquitous. According to the 2018 US Commercial Building Energy Consumption Survey[4], 40% of commercial floorspace had a BAS for heating or cooling, 22% had programmable thermostats, and 6% had internet-connected thermostats. Most BAS collect a subset of environmental and thermal system data (including water and air temperatures, air flow rates, carbon dioxide levels), more occasionally dynamic occupancy counts, and/or overall building energy consumption. Most do not include sub-metered electricity consumption data, which is challenging when using buildings for grid applications. To reduce data storage needs, BAS data are also often not collected at the highest temporal resolution available nor for extended periods of time. Increasing the rate of data collection can be invaluable in understanding the dynamics of building energy consumption and thermal behavior.

Where they do exist, building energy management system parameters are often not changed from their default values, so passive sensing only provides observations for a very limited range of possible controls, posing a major challenge for input/output calibration methods. By input/output calibration methods, we generically refer to methods to tune the parameters of models that relate observations of inputs (e.g., outside weather conditions or occupancy) to observations of outputs (e.g., building energy consumption or room temperatures).

Correspondingly, building information modeling (BIM) is currently seldom used for operations, in contrast with the design and construction phases[12]. The value proposition for analytics remains unclear to building managers[41], even though recent case studies show real value from sensor data with payback times of 2 years[42].

In many applications that have greatly benefited from recent advances in data-driven methods, such as online advertising, robotics, internet search, or ridesharing, data is abundant and experiments are low cost.

In comparison, the commercial buildings sector is and will remain a data-poor environment. Larger buildings are non-standardized, making knowledge transfer much more challenging (also related to the legacy challenge, see previous section). In smaller buildings, data tools are often more difficult and expensive to apply[41]. Almost all field studies we reviewed point out integration and data quality challenges. As for experiments, they are typically expensive, disruptive, and invasive, especially in comparison with the A/B testing routinely conducted in tech-heavy industries. A summer season contains 100-200 days of experiments, with strong heterogeneity within regions depending on the need for cooling in summer.

Better harnessing modern data-driven methods

Data-driven methods are promising but need to be better tailored to the built environment. Many ML/AI techniques that have been proposed require massive amounts of data or access to a reliable simulator that can act as the source of truth[31]. They also usually do not come with stability or performance guarantees which is problematic for physical systems, e.g., if they start to oscillate or violate physical constraints. Experimental research is needed to quantify data requirements, and to determine whether it would be feasible to obtain the required data in practice, to provide guidance on what types of techniques are suitable for building control. More research is also needed to explore methods to integrate building physics-based models into data-driven approaches, adding structure to the problem to reduce the need for massive amounts of data[30].

COMPETING AND EVOLVING PRIORITIES

Multiple uses, tangled incentive structures, and resource allocation constraints

While the commercial sector has fewer decision makers per unit energy and emissions than the residential sector, it serves many more stakeholders. Owners, designers, builders, operators, users of commercial buildings are often different groups of people[44]. Commercial buildings are mixed use. Requirements across groups of users can vary dramatically. Without distributed sensing and actuating, the tightest constraints are enforced throughout the entire building.

Resources and staffing are major constraints to pursuing energy efficiency opportunities and deploying flexibility technologies. The highest priorities for building owners and managers are typically the comfort of their occupants and the costs associated with building maintenance and operation, chief among which are labor costs. Mass adoption of data-driven methods could dramatically increase the productivity of maintenance and operations teams but has not happened yet[41,42].

When it comes to flexibility, incentive structures are also not clear. Demand response programs with unknowable baselines and reliability-based mechanisms such as capacity programs overlap with price-based mechanisms such as real-time or critical peak pricing[45]. This causes opacity and confusion at best, perverse incentives at worst, and ultimately economic inefficiency[46].

Socio-cultural and comfort barriers

Implementing change based on data insights and accessing best practices to do so is hard, because it requires diverging from existing business practices and norms[42]. In most buildings, equipment set points are very rarely changed[4]. Narrow temperature and humidity ranges are typically enforced even if occupants do not feel the difference[47], which leads to an estimated 8% extra costs from overcooling in the US[48]. By another estimate, relaxing temperature setpoints year-round while reducing minimum air flow rates would reduce heating and cooling needs by 30% without reducing satisfaction levels[49]. Field tests and thermal comfort studies help revisit implicit assumptions that have been made for decades[50]. For example, a study found potential for temporarily increasing the cooling temperature setpoint by at least 2°C across a campus in Georgia without impairing thermal comfort[51]. ASHRAE Standard 55 affords greater flexibility to the comfort zone and suggests comfort barriers may be perceived more than real. Soft flexibility operations, that very rarely violate comfort thresholds, may consequently be less of a burden than typically assumed to building occupants.

Many different Distributed Energy Resources

Commercial buildings need heating in the winter, cooling in the summer, and electric vehicle (EV) charging year-round. An estimated 2% of commercial buildings had EV charging stations in 2018[4], but rapid growth can be expected to follow exponential trends in EV sales[52]. Charging stations are arriving in large buildings first. In 2018, EV chargers were installed in 36% of buildings over 500,000 square feet, 20% of buildings from 200 to 500 thousand square feet and 10% of buildings from 100 to 200 thousand square feet[4]. Infrastructure interdependencies create barriers to greater efficiency and flexibility. Behind-the-meter batteries and onsite generation are additional "grid edge" infrastructure that is likely to expand in commercial buildings in the coming years and will create both challenges and opportunities for demand flexibility. Their operation will require coordination with building loads but will be easier in cases where load profiles are complementary. For example, mid-day EV charging with commercial air conditioning use can take advantage of high solar generation during the same hours.

Momentum from decarbonization and electrification goals

Major innovations in commercial buildings are needed to support the adoption of EVs and "grid-edge" infrastructure, meet public and private sector sustainability targets, and adapt to extreme weather events while maintaining the services they already provide to their occupants[53]. Decarbonization and electrification mandates especially will prompt significant changes to building operations and physical design[54]. Already, climate goals are increasingly reported as a driver for ongoing commissioning programs[40]. This context of rapid infrastructural change represents a huge opportunity to also invest in flexibility. Electrification could also mean more electric flexibility. Furthermore, as our energy systems electrify, they also become even more integrated, reinforcing the value in flexible uses of gas, hot water, and chilled water[55-57]. Flexible buildings can also potentially satisfy comfort constraints more effectively than static operational paradigms by more effectively tailoring to preferences and improving sensing and control systems.

Electric grid signals for flexibility

Economic incentives for demand flexibility are becoming increasingly important as energy system planning and operations adapt to account for decarbonization and electrification targets. The recent US DOE report on virtual power plants (VPPs) underscored the evolving grid's flexibility needs, recommending 80-160 GW of VPP deployment by 2030 to support electrification, mitigate capacity shortfalls from plant retirements, and decrease reliance on expensive peaking power plants[58].

Electric demand (peak) charge management and to a lesser extent time-of-use and peak pricing remains the main revenue stream for demand flexibility today, whether in small buildings[59] or building clusters[60]. These types of rates are used to approximate the time-varying value of consumption. New applications of demand flexibility have been receiving significant attention, including load shifting for managing renewable curtailment and faster timescale services like frequency regulation[61–64]. These applications often pay participants for flexible capacity, capturing the value of flexibility itself, rather than the time-varying value of consumption. Another source of value is in deferring expensive distribution system upgrades[2] through electrical system non-wires alternatives. Increased demand flexibility can also reduce the need for new generation and transmission capacity. Additionally, the need for long-duration grid storage[65] would be reduced if we had demand flexibility on longer timescales.

Though demand flexibility could be tremendously valuable in the near future, many customers are not exposed to time-varying electricity rates with a sufficient incentive to shift demand and most customers have little to no access to programs/markets that monetize demand flexibility. However, national/state goals and ensuing regulation have been forcing changes to the status quo. For example, recent U.S. Federal Energy Regulatory Commission (FERC) Order 2222 requires independent system operators to develop methods to integrate distributed energy resources (including distributed generation, storage, and flexible loads) in electricity markets, which, in time, will more fully enable flexible demand to participate in energy and ancillary services markets, and be rewarded for doing so. Given the massive changes underway in the electric power sector, there is opportunity right now for buildings researchers to work with system operators, regulators (e.g., public utility commissions), and utilities to inform the development of markets, programs, incentive/rate structures, and participation architectures (including communication network designs and mechanisms for grid signal/data exchange) for demand flexibility.

REDIRECTING RESEARCH EFFORTS TOWARD THE REAL WORLD

Living laboratories have a critical role to play in enabling flexibility technologies in commercial buildings but largely remain a pipe dream. There are some examples of successful living laboratories, in both the residential and commercial sectors[66-68], including a reconfigurable mixed residential-commercial building platform in Switzerland[69]. But their potential for research and development is currently massively under-utilized. Realizing that potential will require a structural shift in research activity towards more “in the wild” measurements of flexibility through real-world and at-scale experimentation. While the prevailing method is “model first, experiment second”, there is also strong value in “experiment first, model second” and in improving our understanding of a system through experimentation before modeling it.

In this section, we make four main recommendations for researchers looking to work in partnership with building managers and facilities teams (Summary Table: Recommendations). These recommendations are based on our collective experience working with our respective institutional campus facilities management staff to conduct flexibility experiments on different timescales[57,60,70–72].

Encourage networks of living laboratories

Clusters of institutional buildings can serve as test beds across the country for researching flexibility from commercial buildings. There is also great value in creating *networks of living laboratories*, as platforms to ensure broader applicability. Networking living laboratories will promote the production of common datasets, standards for tests and reporting, and platforms for discussion and sharing. They can be used to pool data from different sources, compare results across building vintages, control architectures and vendors, share lessons learned, examples and case studies, but also encourage positive emulation and example setting. A network also allows grid-scale experiments, where control of buildings is coordinated across an entire transmission network, e.g., for ancillary services.

While institutional buildings have their unique occupancy patterns, the hardware used by the central HVAC systems used for conditioning the air in buildings and the software that controls the operation of that hardware is often similar to other commercial building types. Additionally, promoting stronger partnerships with campus building managers in setting up the experiments and the aggregate response of campus building clusters will provide important insights on the scalability of commercial building flexibility technologies.

Research institutions, governments, and large corporations are uniquely positioned to start. Research institutions value the pursuit of new knowledge. Governments can help unlock future value and support public policy goals (decarbonization, cost reduction). Large corporations can demonstrate their commitment to grid modernization, while pursuing opportunities to reduce cost. Ultimately, however, a broad array of buildings, operational approaches and cost structures is needed to encompass the full spectrum of commercial buildings. The bigger the network, the more we will learn. With a broad enough collection of buildings, ambient conditions, and types of test signals, we can better generalize models and estimate the collective response across a fleet of buildings. Grid operators will also need to be involved to enable grid-scale experiments.

Learn from building managers

In a recent review on MPC in buildings[32], the authors argued that building managers need to be better educated in control technologies. We believe that having building managers educate researchers is much more pressing. They can help researchers better understand the strengths and weaknesses of legacy systems, data availability, where new sensors and data-driven methods can augment building manager capabilities (and where they do not add any value), and stakeholder constraints.

International meetings where both researchers and practitioners are invited already exist but can be reinforced. Research institutions also have a role to play. They can rethink incentive structures so that building managers find it in their interest to collaborate with researchers (e.g., get buy-in for time allocation) and explore how recognition can be expanded (e.g., seek to include such activities in job descriptions and performance reviews).

We also make the following more specific and practical recommendations for researchers experimenting in living laboratories.

1. *Adapt to data availability; identify submetering needs in collaboration with facilities staff.* Integrating new sensors can be expensive but also unlocks new experimentation opportunities.
2. *Start from real problems faced by building managers, don't create new problems for them.* Building HVAC systems are inherently complex. Their maintenance and robust operation present many challenges for building managers. Providing flexibility services requires accounting for pre-existing challenges and ensuring they are not exacerbated, nor new operational challenges created. Experiments that can help identify pre-existing errors in the control of buildings and ultimately result in improved overall efficiency will elicit stronger buy-in from operators.
3. *Demonstrate alignment with campus utility/facilities goals, campus sustainability goals, organizational goals, and/or student goals. Identify how facilities teams can be rewarded under existing incentive structures.* Experiments to study strategies for commercial building load control can be leveraged for many different purposes. Beyond problems, experiments can be designed to capture opportunities, such as reducing demand charges, exploring the value of participating in critical peak pricing programs or comfort management.
4. *Identify champions within facilities, involve them in research and ensure they are recognized for their efforts.* Researchers will need to collaborate

with staff who oversee the comfort and operation of several systems. Finding the right contacts is often difficult. In universities and large organizations, support from the administration helps. This is easier said than done. Our subjective experience is that valuing the expertise of building managers, listening, and showing respect, e.g., by including them on academic products, all help. Building sustainable collaborations and strong partnerships across research and operations teams is not without challenges but ultimately pays off.

Abandon the quest for equipment-level MPC, prefer less invasive control strategies

Despite decades of research, MPC approaches that rely on controlling equipment setpoints have not been widely adopted[31,32]. Instead, the de facto industry standard is Rule-Based Control (RBC).

Equipment-level MPC strategies require a full model for the building's actuators and sensors and extensive reprogramming of the core BAS[73–77]. The associated initial investment is too high to justify deployment, as highlighted by Sturzenneger et al.[74], who tested an equipment-level MPC strategy for seven months in a Swiss office building as the culminating effort of the multi-year predictive building control project OptiControl. What is more, while MPC approaches have been shown to dramatically outperform naive (fixed) control strategies, the performance gains are typically mild when compared to well-implemented RBC[78].

Our conclusion from this lack of adoption by industry is that a new research approach is needed. There is strong value in researching less invasive control strategies that do not seek to replace the industry-standard RBC but instead to augment it. A small number of measurement and control devices may be enough to mobilize most of the flexibility in demand[79]. Instead of developing ever more sophisticated control methods, researchers should re-prioritize those strategies that have the greatest chance of achieving significant market penetration in a short timeframe.

For example, strategies that rely on adjusting temperature controls are an attractive, less invasive, and naturally scalable option. While the design and implementation of commercial building HVAC control systems vary widely, their primary control objective is the same: maintaining thermal comfort, typically treated as equivalent to enforcing specified temperature boundaries throughout the building[80]. Initial research approaches to scalable demand flexibility strategies focused on these simple strategies[5].

These strategies can be implemented through a software overlay, providing remote visibility and automated control capabilities to a small team of human operators managing a large cluster of buildings, possibly in many different locations.

They are compatible with MPC technologies, but used for supervisory, hierarchical, or decentralized control. In this case, the optimizer sets higher-level targets, e.g., for energy consumption and indoor temperatures, but delegates equipment-level setpoints to lower-level controllers. This has obvious privacy and security advantages. It is more compatible with decades of industry practice. Simulation-based equipment-level MPC results can still be used as a best-case target to aim for.

To enable these strategies, models are needed for the full cyber-physical response of buildings, which the current state of the art in building energy modeling has difficulty with[15-17]. The full cyber-physical response of a building includes the impact of its physical characteristics, control systems, outside weather conditions and occupants.

Also, to be most effective, supervisory control methods require continuously re-learning models for the response of the building to the higher-level control inputs. Online and physics-informed data-driven methods hold promise for both problems[30,31].

Standardize more rigorous experiment procedures

In earlier applied demand response work, field demonstrations with small sample sizes in a few buildings were the norm rather than repeated experiments, which made it difficult to draw robust statistical conclusions[5]. Researchers now need to move beyond demonstrations and develop more rigorous experiment procedures and standardized reporting of test results, including more detail on building physical characteristics, controls, and weather data. In some cases, this means developing simpler testing strategies that can be run in many different buildings and over longer time periods.

Standardizing the testing and measurement of energy performance and flexibility from commercial buildings through real-world experiments will enable more reliable estimates throughout the U.S. commercial building stock[81]. This is needed to build confidence in the flexibility resource from building and electric grid operators. More regular testing of buildings will also lead to energy performance benefits by stress testing the response of a building's overall energy system to controlled perturbations, which will lead to benefits in the commissioning process.

Regular and repeated testing over long time periods will generate new understanding of building response, including across time scales, frequency of response, and time between events. This will be especially valuable so that tests can also be continuously adapted to the rapidly evolving context for electric grid signals and requirements for demand flexibility that was previously discussed.

Active and recurring stress testing of buildings will enable high accuracy assessments of baseline performance as well as improved forecasts for the impacts (i.e., benefits and costs) of demand management measures. Doing so will create high quality datasets for research and encourage the harmonization of data management practices. Standardized testing is especially important for providing fast timescale services like frequency regulation that need accurate tracking performance for service compensation[59–62].These standardized testing methods will also enable the development of online learning approaches to tune temperature control changes to achieve targets without needing to implement zone-level feedback control.

Dedicated funding from agencies like the US DOE will help, as will discussions involving both academics and practitioners to reach consensus.

MARRYING EXPERIMENTS AND MODELS

Experiments and models are both needed. Our call for a greater emphasis on experimentation should not be read as one to neglect modeling and digital twins, but rather to improve the ability of models to represent the real world.

Experiments are both a guide and a constraint to models. They tell us which building characteristics are most important to model and what aspects of the models affect or do not affect relevant outcomes. They allow us to explore how ambient conditions, the interaction of software and hardware systems, and human occupants all influence efficiency and flexibility options. They reduce the risk of researchers designing control methods that make unrealistic assumptions about implementation options.

Models inform experiment design. They are needed to extrapolate and generalize experimental findings. Simulation-based experiments are less expensive and quicker to deploy, allowing exploration of a much more exhaustive range of possibilities. They will continue to be highly influential for decision-making and planning purposes at scale, both for the electric grid and in the buildings sector as they become more tightly coupled.

Tight feedback loops between experiments and models will help ensure both types of research efforts are relevant and useful.

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AUTHOR CONTRIBUTIONS

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DECLARATION OF INTERESTS

J.C. declares an independent consulting relationship with TotalEnergies, SE.

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