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Bridging Control and Deployment: A Cross-Layer Analysis of Scalable Building Cluster Control

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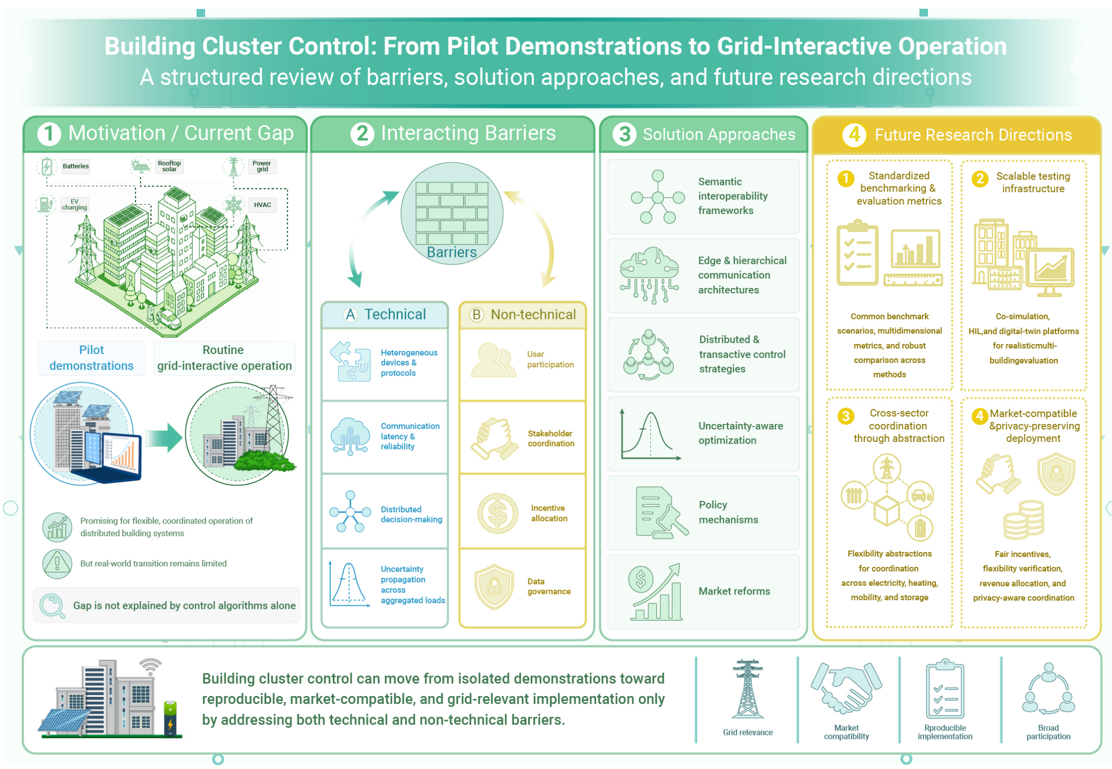
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Building cluster control faces slow large-scale rollout, and the issue is not merely limited to control algorithms.
- Barriers cover technical aspects like device heterogeneity and communication issues, plus non-technical ones such as stakeholder coordination and data governance.
- The paper summarizes existing solutions including interoperability frameworks, distributed control and policy reforms.
- Two core research directions are proposed: realistic test infrastructures and standardized flexibility abstraction methods.
- This review offers a systematic reference for scaling up grid-friendly building cluster control.

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Bridging Control and Deployment: A Cross-Layer Analysis of Scalable Building Cluster Control

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Building cluster control has emerged as a promising approach for enabling flexible and coordinated operation of distributed building systems, yet its transition from pilot demonstrations to routine grid-interactive operation remains limited. This paper argues that this gap cannot be explained by control algorithms alone. Instead, it arises from interacting barriers in communication infrastructure, data and semantic interoperability, uncertainty management, stakeholder participation, market design, and policy support. Accordingly, the paper reviews both technical and non-technical barriers to building cluster control. Technical challenges include heterogeneous devices and protocols, communication latency and reliability, distributed decision-making, and uncertainty propagation across aggregated loads. Non-technical barriers include user participation, stakeholder coordination, incentive allocation, and data governance. Existing solution approaches are synthesized, including semantic interoperability frameworks, edge and hierarchical communication architectures, distributed and transactive control strategies, uncertainty-aware optimization, policy mechanisms, and market reforms. Based on this analysis, two research directions are identified: testing infrastructures that can evaluate control performance under realistic multi-building conditions, and abstraction methods that allow building clusters to interact with other energy sectors through standardized flexibility representations. Overall, the paper provides a structured review of how building cluster control can move from isolated demonstrations toward reproducible, market-compatible, and grid-relevant implementation.

INTRODUCTION

Photovoltaic (PV) deployment has expanded rapidly, with installed capacity reaching 460GW globally in 2024, introducing significant variability and uncertainty into power generation.[1] This variability leads to operational challenges such as steep net-load ramps, renewable curtailment, and increased reliance on balancing resources.[2] Traditionally, these challenges are addressed using supply-side solutions such as battery storage; however, grid-scale battery systems remain capital intensive.[3] As a result, demand-side flexibility has emerged as a cost-effective complementary solution. Among available resources, buildings have been demonstrated to be a viable source of flexibility due to their large share of electricity consumption and inherent thermal storage capacity.[4] According to,[5] the power consumption of commercial buildings in the United States can be increased by up to 46 GW or reduced by up to 40 GW during peak summer days with only limited impacts on thermal comfort.

Existing research has predominantly focused on the characterization and control of flexibility at the individual building level. A wide range of methods have been developed to quantify building flexibility based on thermal dynamics and occupancy behavior, as well as to control flexible loads using strategies such as model predictive control and rule-based approaches.[5-7] These studies have established a solid theoretical foundation for understanding building-level flexibility and have demonstrated the potential of buildings to provide services such as load shifting and peak shaving.

Despite these advances, a fundamental limitation lies in the reliance on individual buildings, which restricts the full realization of demand-side flexibility. First, the flexibility of a single building is inherently limited in magnitude and often insufficient for grid services that require reliable capacity, sustained duration, or fast response.[8] Second, flexibility is temporally constrained by thermal states, occupancy patterns, and operational requirements.[9] Third, the stochastic nature of occupant behavior introduces significant uncertainty,[10] making it difficult to guarantee reliable flexibility delivery. These limitations highlight the need to move beyond individual buildings toward coordinated operation at larger scales.

Inspired by this, this paper presents a comprehensive review of demand-side flexibility in buildings, focusing on the transition from individual building control to coordinated operation across multiple buildings. It first examines the need for flexibility in modern power systems and the role of buildings as a viable resource and then synthesizes existing studies to identify key limitations at the individual-building level, including limited magnitude, temporal constraints, and uncertainty. Building on this, the paper discusses the benefits of aggregation, reviews real-world implementations, and analyzes how institutional and policy contexts shape their development, followed by an examination of key technical and non-technical challenges. It further reviews state-of-the-art methods for addressing these challenges, including standardization and semantic interoperability for control infrastructure, as well as transactive control and stochastic modeling for improving controllability. Finally, the paper discusses enabling policy and market mechanisms and provides insights into future research and development directions for building-based flexibility.

In this paper, the term "building cluster" refers primarily to a group of buildings whose controllable loads, such as heating, ventilation, and air conditioning (HVAC), lighting, water heating, and other building-side systems, are coordinated to provide demand-side flexibility. In real-world implementations, building clusters may also be coordinated with adjacent or co-located distributed energy resources, including photovoltaic (PV) systems, batteries, electric vehicles (EVs), telecom base stations, or industrial loads. These resources are considered associated flexibility resources within the broader implementation context, rather than buildings themselves. Accordingly, this review focuses on building-centered coordination while discussing non-building assets when they affect the control architecture, flexibility provision, or deployment pathway of building clusters.

This paper makes two primary contributions to the study of building cluster control. First, it shows that the limited expansion of building cluster control cannot be explained by algorithmic performance alone. Instead, the review links four technical barriers—interoperability, communication architecture, distributed control, and uncertainty propagation—with three deployment barriers: market design, institutional coordination, and user participation. This perspective addresses a key unresolved gap in literature, where existing studies typically examine these factors in isolation and therefore fail to explain the limited expansion beyond pilot and demonstration projects. Second, the paper provides a systematic synthesis of existing solution approaches by clarifying how different methods address specific barriers: semantic models reduce integration effort, edge architectures reduce communication burden, distributed control reduces centralized computation, and market mechanisms create incentives for participation. In doing so, it highlights an important unresolved issue: while system-level enablers such as market reforms create the conditions for participation, effective coordination and value allocation at the building cluster level remain insufficiently addressed. By identifying these gaps and organizing the solution space accordingly, the paper offers clearer guidance for advancing building cluster control toward scalable and practical implementation.

Previous reviews have examined building flexibility and demand response from several perspectives, including flexibility characterization, quantification methods, flexible load types, control strategies, occupant behavior, market participation, and building-to-grid applications. For example, Li et al.[11] systematically reviewed residential building energy flexibility with emphasis on characterization and quantification methods, modeling approaches, flexibility metrics, and applications. These studies provide important foundations for understanding the flexibility potential of individual buildings and building portfolios. However, less attention has been given to the implementation barriers that determine whether building cluster control can be replicated beyond pilot demonstrations. In particular, the practical deployment of building cluster control requires not only flexibility characterization, but also interoperable data models, communication architectures, distributed coordination mechanisms, uncertainty management, user participation, incentive allocation, data governance, and policy or market support. This review addresses this gap by organizing building cluster control around these technical and institutional conditions for implementation.

To clarify the scope of this review, targeted literature searches were conducted to identify studies relevant to building cluster control and demand-side flexibility. The searches were conducted in major scholarly databases, including Web of Science, Scopus, Google Scholar, and ScienceDirect. Keyword combinations included "building cluster control," "multi-building control," "building energy flexibility," "demand response," "building-to-grid integration," "distributed control," "multi-agent control," "transactive control," "semantic interoperability," "communication architecture," "uncertainty-aware optimization," "stochastic optimization," "robust optimization," "user participation," "incentive design," "data governance," and "privacy-preserving control."

Sources were selected based on their relevance to the analytical scope of this review. Peer-reviewed studies were prioritized when they met at least one of the following criteria: (i) they examined building energy flexibility, demand response, or building-to-grid interaction with relevance to aggregation or multi-building coordination; (ii) they addressed technical barriers or enabling methods for building cluster control, including interoperability, communication architecture, distributed or transactive control, and uncertainty-aware optimization; or (iii) they addressed non-technical factors that affect implementation, including user participation, incentive design, stakeholder coordination, data governance, or privacy-preserving control. Studies focused only on isolated single-building operation were used only when their methods or findings were directly transferable to aggregation or building-cluster control.

In addition to peer-reviewed literature, official project webpages, government or utility reports, and demonstration-related documents were used to characterize real-world implementation cases. These sources were used to document project scale, participating systems, funding support, and institutional context, rather than to provide peer-reviewed validation of technical performance.

BACKGROUND AND IMPLEMENTATION CONTEXT

Why building aggregation is needed

Coordinating multiple buildings as a unified system changes how demand-side flexibility behaves and how it can be utilized by the power grid. Rather than treating flexibility as isolated, site-specific adjustments, coordination enables it to be organized as a collective resource whose value emerges when many small load adjustments are combined into a dispatchable aggregate response. This shift is particularly important because many grid services require not only sufficient capacity but also consistency, responsiveness, and the ability to follow external signals—attributes that are difficult to achieve with independent operation.

One key advantage of coordination lies in the ability to consolidate dispersed and intermittent adjustments into a unified response. While individual buildings can only adjust their consumption within limited ranges and time windows, coordination allows these adjustments to be scheduled across multiple participants, effectively stacking their contributions. This makes it possible to form responses that are both large enough and sufficiently structured to interact with grid-level control signals, improving the practical usability of building-based flexibility.[12] For example, building clusters have been shown to provide shiftable capacities on the order of gigawatts at the national level and tens of gigawatt-hours of daily energy flexibility.[13]

Coordination also improves economic performance by enabling shared use of infrastructure and more efficient allocation of resources. Instead of equipping each building with fully independent sensing, communication, and control capabilities, coordinated systems can centralize or partially share these functions, reducing redundancy. In addition, flexibility can be dispatched where and when it is most effective, for example by shifting demand among buildings to better align with local generation or system conditions. This coordinated allocation reduces inefficiencies that arise when buildings operate independently under local objectives.[14] For example, coordinated control of building clusters has been shown to achieve up to 38.6% energy cost reduction compared to uncoordinated operation, demonstrating the value of collective scheduling over independent building operation.[15]

Another important effect is the reduction of variability in the aggregate load profile. Individual buildings exhibit fluctuations driven by occupant behavior, environmental conditions, and operational constraints, which can lead to unpredictable responses. When multiple buildings are aggregated, these fluctuations tend to offset each other due to asynchronous responses, leading to a smoother and more continuous aggregate flexibility profile. This effect is reflected in the expansion and regularization of feasible operating regions observed in aggregated building systems, where coordination enables the formation of continuous and dispatchable flexibility trajectories that are not achievable at the individual building level.[16] As a result, the collective response becomes more predictable and easier to manage, which is critical for applications that require reliable delivery of flexibility.[17]

Finally, coordination enables more effective use of diversity across buildings. Differences in building characteristics—such as usage patterns, equipment types, and current operating conditions—create opportunities to distribute adjustments in a way that avoids overburdening any single building. This allows the system to maintain performance while respecting local constraints, such as comfort or operational limits. For example, large-scale aggregation of over 2,000 residential buildings has been shown to increase load factor by up to 94% and reduce system ramping by approximately 20%, indicating a substantially smoother and more stable response profile.[18] By leveraging this diversity, coordinated control strategies can achieve outcomes that are not attainable through independent operation, improving both flexibility provision and overall system efficiency.[19]

Real-world implementation evidence

To complement the peer-reviewed literature on building cluster control methods and performance, this section summarizes representative real-world demonstration projects reported through official project webpages, government or utility documents, and demonstration-related sources. These sources are used to document implementation characteristics, including

Table 1. Representative implementation of Demand Responses with Building Clusters

Name	Location	Scale	Participating Systems	Funding Support
Spokane Community[20]	U.S.	50 residential homes and 25 commercial buildings	HVAC + Lighting + Battery + Electric Vehicle (EV)	U.S. Department of Energy(DOE), Connected Community Program
PacifiCorp Community[21]	U.S.	1 apartment and 1 office building	HVAC + Water Heater + PV + EV	DOE, Connected Community Program
ECOGrid Community[22]	Denmark	300 residential homes	HVAC	Danish Energy Agency, Energy Technology Development and Demonstration Program
Lisboa Social Community[23]	Portugal	9 apartment buildings	Unspecified building devices + PV	European Commission (EC), Horizon 2020 programme
Aardehuizen Community[24]	Netherlands	24 residential homes	HVAC + PV + Electric Boiler + EV	EC, Horizon 2020 programme
Lingang Special Area[25]	China	988 HVAC units	HVAC	Local government subsidy programs and utility company investments
Suzhou Industrial Park[26]	China	81 electricity end users	HVAC + PV + Energy Storage + EV + Industrial load + Telecom base stations	Local government subsidy programs and utility company investments
Guiyang National High-tech Industrial Development Zone[27]	China	Unspecified	HVAC + PV + Energy Storage + EV + Lighting	Ministry of Science and Technology of China's research programs and utility company investments

project scale, participating systems, funding support, and institutional context, rather than to provide peer-reviewed validation of technical performance.

As shown in Table 1, projects such as the Spokane Community and PacifiCorp Community in the United States are supported by the U.S. Department of Energy under the Connected Communities program, while European examples including the Lisboa Social Community and Aardehuizen Community are funded through the European Commission Horizon 2020 programme. These initiatives typically integrate multiple energy systems, such as Heating Ventilation, and Air Conditioning (HVAC), photovoltaics, electric vehicles, and storage, to demonstrate coordinated control and flexibility provision. In contrast, the Chinese cases summarized in Table 1 suggest a deployment pathway more closely linked to local government programs, utility-led platforms, and district- or industrial-park energy management. Rather than primarily operating as research-oriented pilots, these projects are often embedded within regional infrastructure development and grid operation practices, with a stronger emphasis on deployment through regional infrastructure projects and utility-led operation.

This divergence reflects two complementary development paradigms. The U.S. and European approach, largely driven by public research funding, provides a controlled environment for testing advanced control strategies, interoperability, and novel system configurations. Its advantages lie in methodological rigor, high-quality data collection, and systematic evaluation; however, it is often limited in scale and may lack direct alignment with real-world operational constraints and market conditions. In contrast, the China-oriented approach benefits from stronger top-down coordination, closer integration with utility operations, and larger implementation scale, which facilitates rapid deployment and validation under realistic conditions. Nevertheless, this approach may face challenges in terms of standardization, transparency, and the generalizability of results, as well as relatively less emphasis on systematic experimental design. These differences are not incidental, but arise from distinct institutional and policy contexts, which are further examined in the following section.

The strong reliance on public funding in Western projects highlights the early-stage nature of building cluster deployment, where technical uncertainty, system integration complexity, and the lack of clear business models continue to limit private-sector participation. Consequently, these projects primarily serve as pilot-scale testbeds for validating control strategies and establishing initial operational evidence. However, their scale remains relatively limited, typically involving tens of residential units or a small number of commercial buildings. This constraint is not only due to limited resources associated with non-commercial pilots, but also reflects deeper challenges in scaling, including increasing coordination complexity, uncertainty in aggregated response, and the absence of standardized frameworks for interoperability and replication.

In addition to their limited scale, existing demonstrations also exhibit important shortcomings in evaluation, temporal scope, and market integration. First, the lack of standardized performance metrics makes it difficult to compare results across projects. Second, most demonstrations are conducted over relatively short durations, limiting the assessment of long-term performance, seasonal variability, and operational robustness. Finally, many projects are not fully integrated into electricity market environments and therefore do not adequately validate the economic value of building-based flexibility under real market conditions.

Regional and institutional context

The different forms of building cluster control demonstrations are rooted in the historical evolution of electricity systems and policy ecosystems, rather than merely in technological preference. Across regions, the underlying motivation is broadly aligned: increasing shares of variable renewable energy, electrification of end uses, and the resulting need for flexible, grid-interactive demand. Buildings are therefore increasingly positioned as controllable resources capable of providing load shifting, peak reduction, and virtual storage. Policy frameworks in both the United States/Europe and China explicitly recognize this role, embedding building flexibility within broader agendas of grid modernization, decarbonization, and energy system transformation.

However, these shared motivations are institutionalized through fundamentally different policy ecosystems, which in turn shape how research problems are defined, funded, and translated into practice. In the United States and Europe, building cluster control has evolved within liberalized electricity markets,[28] where regulatory design, market rules, and technology development co-evolve. Policies such as enabling distributed energy resource participation, demand response programs, and aggregator-based market access are complemented by research funding structures that emphasize openness, competition, and cross-sector collaboration.[29] As a result, public programs, such as DOE Grid Modernization initiatives,[30] are designed not only to support technological development, but also to de-risk innovation, establish standards, and prepare technologies for market adoption.

This policy ecosystem has a direct and profound influence on research. Because building flexibility must ultimately function within decentralized, multi-actor systems, research questions are framed around interoperability, standardization, verification, and economic valuation. The need to align with regulatory requirements and market participation rules drives the development of common data models,[31] communication protocols,[32] and performance metrics.[33] At the same time, funding mechanisms that prioritize competitive proposals and multi-institutional collaboration encourage the formation of consortia involving national laboratories, universities, utilities, and technology providers, where knowledge production is oriented toward generalizability and transferability. Consequently, demonstrations are typically structured as research-intensive pilots at community scale, where controlled experimentation, high-resolution data collection, and rigorous evaluation can support the development of scalable, market-compatible solutions.[34]

In the representative Chinese cases summarized in Table 1, deployment is more closely associated with local government programs,[35] utility platforms,[36] and district- or industrial-park energy management.[37] For example, the Lingang Special Area case reports 988 controllable HVAC units, while the Suzhou Industrial Park case involves 81 electricity end users covering HVAC, PV, energy storage, EVs, industrial loads, and telecom base stations. These cases suggest that some Chinese deployments are embedded directly in operational grid or district-energy platforms. However, because the available evidence is mainly from project-level, government, or utility sources, this comparison should be interpreted as an observation from representative cases rather than a comprehensive regional classification.

Rather than focusing primarily on interoperability across independent actors, research is oriented toward utility-led aggregation, operational reliability, and direct integration with district- or park-level energy infrastructure.[38] The close coupling between research and deployment reduces the separation between experimental and operational environments, enabling large-scale demonstrations in districts or industrial parks that aggregate hundreds to thousands of controllable loads. At the same time, because research is often embedded within implementation programs, there is comparatively less emphasis on standardized evaluation frameworks, open benchmarking, or cross-context generalization. Knowledge is produced in a more application-driven and context-specific manner, with technology transfer occurring through replication within similar policy and operational settings.

A subtle but revealing distinction between these paradigms can be observed in how building flexibility is conceptually framed. In the United States and Europe, demand-side flexibility from buildings is often abstracted as a "virtual battery," where thermal inertia and controllable loads are represented using storage-like parameters such as state of charge, power limits, and energy capacity.[39] This abstraction reflects a system logic in which buildings are treated as modular, interoperable resources that can be integrated into optimization and market frameworks alongside conventional assets.

In contrast, in China, similar capabilities are more commonly framed under the concept of a "virtual power plant," where buildings are aggregated with other distributed resources into a coordinated entity that directly supports grid operation.[40] This distinction is not merely semantic: the "virtual battery" emphasizes standardization and compatibility with decentralized optimization and markets, whereas the "virtual power plant" emphasizes aggregation, coordination, and integration with grid dispatch, regional energy platforms, or utility operation. These conceptual differences further illustrate how policy and institutional context shape not only deployment pathways, but also the underlying representations through which building flexibility is understood and operationalized.

These differences in policy and institutional context have a direct impact on the achievable deployment scale of building cluster control. In market-oriented systems such as those in the United States and Europe, scaling is constrained by the need to coordinate across multiple independent actors, including building owners, utilities, aggregators, and market operators. Each layer introduces requirements for interoperability, contractual alignment, performance verification, and regulatory compliance, which increases transaction costs and slows expansion beyond pilot or community-scale deployments. As a result, most demonstrations remain at the level of 10s to 100s of buildings,[41] where coordination complexity is manageable and experimental control can be maintained.

In contrast, the centralized and policy-driven context allows aggregation to be organized through administrative planning and utility platforms. Because deployment can be coordinated through administrative mechanisms and utility-led platforms, building clusters can be integrated directly into district- or park-level energy systems, allowing aggregation at the scale of 100s to 1000s of controllable loads.[42] This reduces the need for market-based coordination in the early stages and facilitates rapid expansion under unified planning and investment frameworks.

CHALLENGES IN CONTROLLING BUILDING CLUSTERS

This section reviews the lessons learned from real-world implementations of building cluster control. Both technical and non-technical issues are considered. The discussion highlights the main challenges that must be addressed for broader deployment.

Technical challenges

Control Infrastructure. In practice, building cluster control systems are typically implemented through two main approaches, both of which introduce fundamental limitations to scalability. The first approach builds on existing building management systems,[43] which are often vendor-specific and designed as closed platforms. While these systems provide reliable local control, their limited interoperability and restricted access to internal data and control interfaces hinder integration across buildings, making large-scale coordination difficult. The second approach relies on ad hoc integration solutions that directly interface with heterogeneous devices and systems across buildings, offering greater flexibility but at the cost of increased system complexity.[44] These limitations stem from a fundamental interoperability challenge. Buildings typically comprise diverse equipment and vendor-specific platforms that rely on incompatible communication protocols and data structures, hindering seamless integration into unified control frameworks.[45] In addition, a significant portion of legacy equipment lacks native communication or control capabilities, requiring retrofitting or indirect estimation methods to be incorporated into coordinated control schemes.[46]

To overcome these barriers, demonstration projects often adopt custom integration solutions that translate between devices and systems. For example, in the Lisboa Social Community, smart plugs are deployed to monitor the power usage of legacy electrical devices lacking native communication capabilities.[47] While such instrumentation enables the inclusion of otherwise non-communicable loads, it introduces additional layers of sensing, communication, and data processing into the control architecture. These additional layers lead to several practical limitations. First, they increase system complexity and create new points of failure, as overall system performance becomes dependent on the reliability of auxiliary devices and data transmission pathways. Second, the reliance on external sensing and indirect data acquisition can introduce communication delays and measurement inconsistencies, which may degrade the timeliness and accuracy of control actions.[48] Finally, extending such ad hoc solutions to new buildings or applications often requires substantial manual engineering effort, including device mapping, protocol translation, and system reconfiguration, which limits scalability and replicability.[49]

Controllability. Controllability is limited by system scale and uncertainty. As building clusters grow, the control problem becomes increasingly high-dimensional, characterized by a rapid increase in decision variables and coupled constraints across buildings, which challenges real-time optimization and coordination.[50] The presence of coupled constraints across buildings also reduces problem decomposability, making centralized control approaches difficult to scale and coordination among distributed controllers more complex.[51] In addition, interactions among heterogeneous buildings introduce further complexity, as differences in system configurations and operating conditions lead to diverse and interacting responses, making overall system behavior sensitive to cluster composition and coordination strategies.[52] This heterogeneity increases the sensitivity of aggregate system behavior to cluster composition and coordination strategies, making system-level performance less predictable and further limiting controllability.[52]

In building clusters, controllability is further constrained by uncertainties arising from multiple sources, including occupant behavior, building characteristics, energy systems, and external conditions.[53] These uncertainties affect both individual buildings and their aggregated behavior, and can propagate through system dynamics and control processes, leading to discrepancies between predicted and realized flexibility at the cluster level.[54] While aggregation can partially mitigate aleatory uncertainty through diversity effects, this benefit is not guaranteed at small scales and typically requires sufficiently large building populations to become effective.[55] At the same time, clustering introduces additional epistemic uncertainties associated with system modeling, representation, and coordination, which limit the accuracy of flexibility estimation.[56] As a result, residual variability persists even in aggregated systems, constraining the predictability and controllability of building clusters in practice.

Non-technical challenges

Beyond technical challenges, non-technical factors play a critical role in limiting the deployment of building cluster control, particularly as system

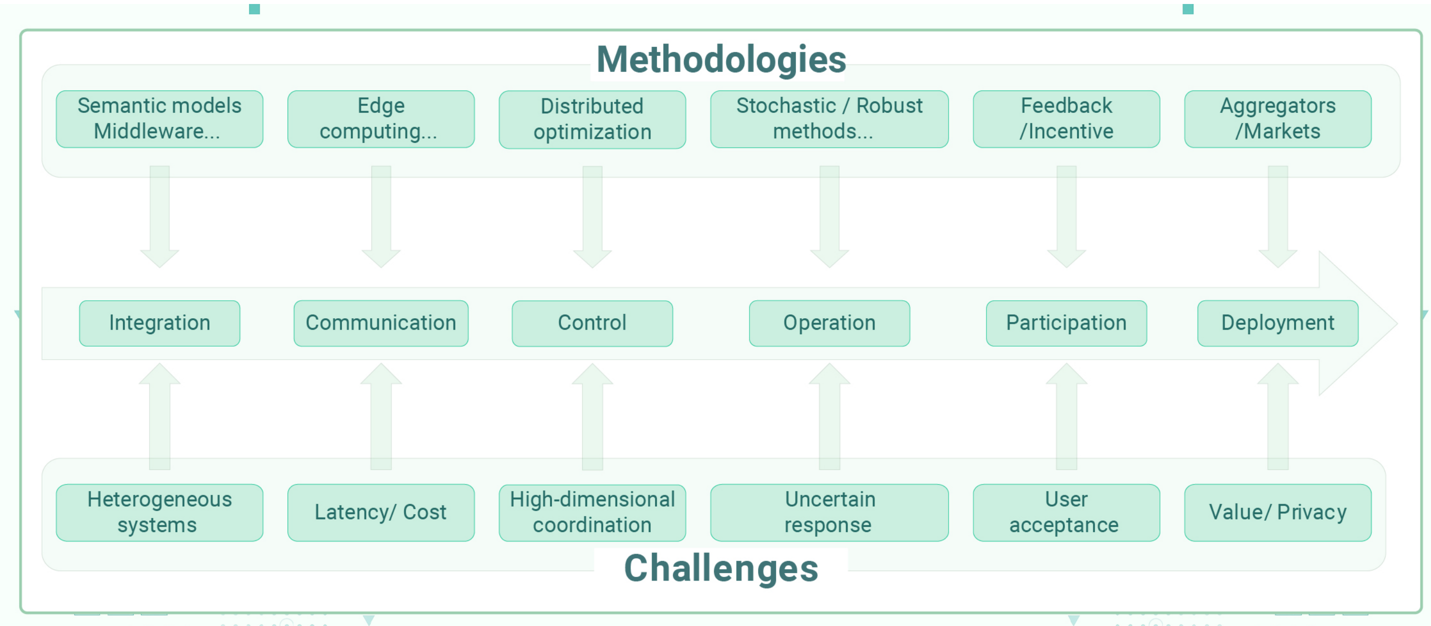

Figure 1. Challenge–method mapping along the development-to-deployment pathway of building cluster control.

scale increases. While many of these factors exist at the individual building level, they become more pronounced and structurally complex in clustered systems. User participation and acceptance, for example, shift from a local performance issue to a system-level coordination challenge, as inconsistent responses across buildings reduce the reliability of aggregated control actions.[57] Institutional fragmentation similarly evolves into a multi-stakeholder coordination problem, where building owners, operators, and tenants may have misaligned objectives and limited mechanisms for collaboration.[58] In addition, the absence of well-defined economic incentives becomes more critical at the cluster level, as the value of flexibility must be distributed across multiple participants, complicating investment and participation decisions.[59] Data governance and privacy concerns also intensify, as coordinated control requires cross-building data sharing, which is often constrained by regulatory requirements and stakeholder reluctance.[60] As a result, these non-technical factors not only persist but become amplified in building clusters, significantly limiting replication beyond individual pilot projects and increasing the transaction cost of multi-building participation.

To clarify how the identified barriers are connected to the solution approaches reviewed in the following sections, Figure 1 summarizes the challenge–method mapping along the development-to-deployment pathway of building cluster control.

METHODS FOR TECHNICAL CHALLENGES

Control infrastructure

Efforts to address interoperability challenges in building cluster control can be broadly categorized into two groups: (1) approaches that enhance and standardize existing protocol-based communication frameworks, and (2) approaches that restructure communication architectures to reduce device-by-device integration effort and limit dependence on tightly coupled communication links. The first category focuses on improving compatibility within current systems, while the second introduces alternative communication mechanisms better suited for large-scale and heterogeneous environments.

The first category focuses on improving interoperability within existing protocol-based communication frameworks by reducing integration effort and enabling more automated system configuration. For example, Lin et al.[61] implemented and tested an automated control hunting fault correction algorithm within a fault detection and diagnostics tool, demonstrating how analytics-based control correction can be integrated into operational building platforms.

Traditional building systems rely on protocols such as BACnet[62] and Modbus;[63] however, inconsistencies in implementation and data representation often require substantial manual engineering for integration. To address these limitations, initiatives such as the Electric Power Research Institute Distributed Energy Resources Interoperability Lab[64] provide standardized testing and validation environments for distributed energy resources, reducing the manual engineering required when new devices, buildings, or control platforms are added.

In parallel, middleware platforms such as VOLTTRON[65] extend protocol-based communication by introducing a message-bus architecture based on publish–subscribe communication. In this paradigm, as illustrated in Figure 2, devices and applications exchange data through a shared communication bus rather than direct point-to-point interactions, decoupling data producers and consumers. This reduces integration complexity, enables asynchronous communication, and allows new devices or applications to be added without redesigning the whole communication architecture. Complementing these efforts, semantic modeling frameworks such as Brick Consortium provide standardized representations of building systems.[66] By formalizing the relationships among equipment, sensors, and control points, semantic models enable automated configuration and reduce manual tasks such as device mapping and protocol translation.

The second category explores approaches that fundamentally restructure how communication is realized, moving beyond traditional protocol-centric integration. These methods aim to reduce communication burden and improve fault tolerance by reducing reliance on flat, tightly coupled communication structures. Edge computing[67] represents a key direction in this category. As shown in Figure 3, by distributing data processing and control execution to building-level nodes, edge architectures localize communication and reduce the need for continuous data exchange with centralized systems. This not only alleviates bandwidth and latency constraints but also limits cross-building communication to aggregate flexibility, status, or constraint information by limiting cross-building communication to higher-level aggregated information. In addition, edge devices can serve as local integration points for heterogeneous and legacy systems, encapsulating device-level complexity within each building and thereby simplifying coordination among buildings and cluster-level controllers.

Another important approach is the adoption of nested or hierarchical communication architectures,[68] in which communication is organized across multiple levels, such as device, building, and cluster. In this structure, lower-level interactions are handled locally within buildings, while higher-level coordination relies on aggregated signals exchanged between buildings and central controllers. This hierarchical organization reduces communication complexity, isolates heterogeneity within subsystems, and the number of direct communication links required as the number of buildings increases. A further development is the use of RESTful Application Programming Interface (API)-based communication frameworks,[69] which replace low-level protocol interactions with standardized service interfaces. In this approach,

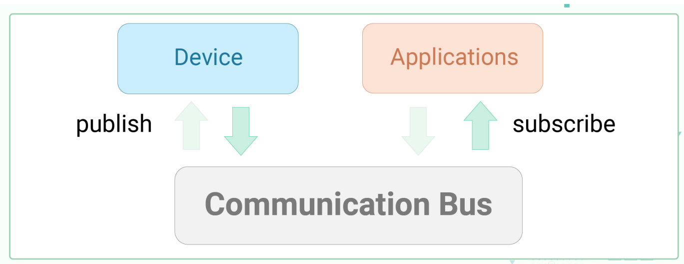

Figure 2. Publish–subscribe communication

building systems expose data and control functions through web-based APIs, allowing external applications to interact with them using uniform request–response mechanisms. This shifts communication from protocol-specific implementations to service-level interactions, improving interoperability and enabling more flexible integration across diverse systems.

Distributed coordination

As building cluster control scales to larger and more heterogeneous systems, centralized control architectures face increasing limitations in computational tractability, communication overhead, and system robustness. In conventional centralized approaches,[70] a single controller collects system-wide information and computes optimal control actions for all buildings. While this formulation can achieve globally optimal solutions under ideal conditions, it requires high-resolution data exchange and centralized computation, both of which become difficult to sustain as the number of buildings and controllable devices increases. In addition, centralized control introduces a single point of failure and relies on reliable, low-latency communication across all subsystems.[71] To address these limitations, distributed control[71] has been proposed as an alternative paradigm, where decision-making is decomposed across multiple agents—typically at the building or subsystem level—allowing coordination to be achieved through local computation and limited information exchange.

Distributed control frameworks for building clusters encompass a range of methodologies that differ in their coordination mechanisms, communication structures, and information exchange requirements, as illustrated in Figure 4. One important class of approaches is based on decomposition methods, such as dual decomposition or the alternating direction method of multipliers (ADMM),[72] where a global optimization problem is partitioned into multiple local subproblems coordinated through iterative information exchange with a supervisory coordinator. In these methods, coupling variables or dual information are exchanged iteratively to enforce system-level constraints while allowing local optimization to remain decentralized.

Another class includes consensus-based and multi-agent control strategies,[73] in which individual agents communicate directly with neighboring agents rather than relying on a centralized coordinator. Through iterative peer-to-peer information exchange, agents progressively update their local decisions and converge toward a coordinated operating condition. These approaches reduce centralized computational requirements and reduce centralized computation and avoid single-point failures, although they still depend on structured communication and synchronization among distributed agents.

More recently, hierarchical and market-based coordination approaches[72] have been explored to reduce the amount of information exchanged among heterogeneous buildings. As shown in Figure 4, hierarchical coordination organizes decision-making across multiple layers, where upper-level coordinators interact with intermediate aggregators or sub-clusters that subsequently coordinate lower-level subproblems. This layered structure reduces communication burden and computational complexity by limiting coordination within local groups. In market-based implementations, coordination can alternatively be achieved through economic signals such as prices or bids, enabling distributed agents to make autonomous decisions while indirectly satisfying system-level objectives. These approaches are particularly attractive for large-scale building-to-grid integration because they allow buildings to participate through modular control interfaces and price or bid signals across diverse building assets and operational conditions.

Although these distributed control paradigms share the common objective of reducing centralized computational burden and improving scalability, they differ substantially in coordination structure, communication requirements, convergence characteristics, privacy preservation, and implementation complexity, as summarized in Table 2. Decomposition-based methods generally provide strong theoretical convergence properties and enable rigorous handling of system-level constraints, but they often rely on iterative coordination with a central entity and may require substantial communication overhead as system size increases. Depending on the formulation, these methods may also require local agents to share operational states, flexibility boundaries, or dual variables with the coordinator, which can raise data privacy concerns for building operators. Consensus-based and multi-agent approaches offer greater decentralization and robustness by relying primarily on local neighbor-to-neighbor communication, making them well suited for geographically distributed systems with limited centralized infrastructure. Because information exchange is typically localized, these approaches can improve privacy preservation by reducing the need to disclose detailed building-level operational data to a central authority; however, their convergence speed and stability can become sensitive to communication topology, synchronization, and network delays. Hierarchical and market-based approaches further improve scalability by abstracting coordination across multiple layers or through economic signals, thereby reducing communication and computational requirements at the device level. In particular, market-based coordination can preserve privacy by allowing buildings to respond to price or incentive signals without directly exposing internal operational models or occupant information. Nevertheless, these approaches may sacrifice some degree of global optimality or require more sophisticated market design, incentive mechanisms, and interoperability standards to ensure stable and coordinated operation across heterogeneous building clusters. Note that the comparison in Table 2 is qualitative rather than quantitative because existing studies use different building models, cluster sizes, time resolutions, objective functions, comfort constraints, communication assumptions, and evaluation metrics, making direct numerical comparison across paradigms unreliable.

In the following, transactive control (TC)[74] is used as a representative distributed control approach to illustrate the key principles and implementation of distributed coordination. The following equations are provided as an illustrative formulation to clarify the basic coordination mechanism of transactive control, rather than as a new mathematical contribution of this review.

TC is a domain-free distributed control strategy that facilitates the optimal allocation of resources among entities, which is described below:

$$\underset{q_1,\ldots,q_n}{\text{maximize}} \quad J = \sum_{i=1}^{n} \vartheta_i, \tag{1}$$

$$s.t. q_i \in [q_i^{min}, q_i^{max}], i = 1, \ldots, n \tag{2}$$

$$\sum_{i=1}^{n} \sigma_i q_i = 0, \tag{3}$$

where q_i is the quantity of resources consumed or produced by entity i, ϑ_i describes the value from satisfaction of consuming or the cost of producing the resource q_i by entity i, σ is a constant with σ=1 if entity i consumes the resource (buyer) and σ=-1 if entity i produces the resource (seller). The q_i^{min} and q_i^{max} are the minimum and maximum amount of resource this participant can consume or produce, respectively.

TC solves this optimization problem in a distributed manner. Specifically, it establishes a transactive system. This transactive system consists of a coordinator, several buyers and sellers. The buyer or seller solves the following local optimization problem,

$$\underset{q_i}{\text{maximize}} \quad J = \sigma_i(\vartheta_i - q_i\lambda), \tag{4}$$

$$s.t. q \in [q_i^{min}, q_i^{max}], \tag{5}$$

$$\vartheta_i = f(q_i), \tag{6}$$

where λ is the price of the resource. $f()$ is a utility function to calculate ϑ_i.

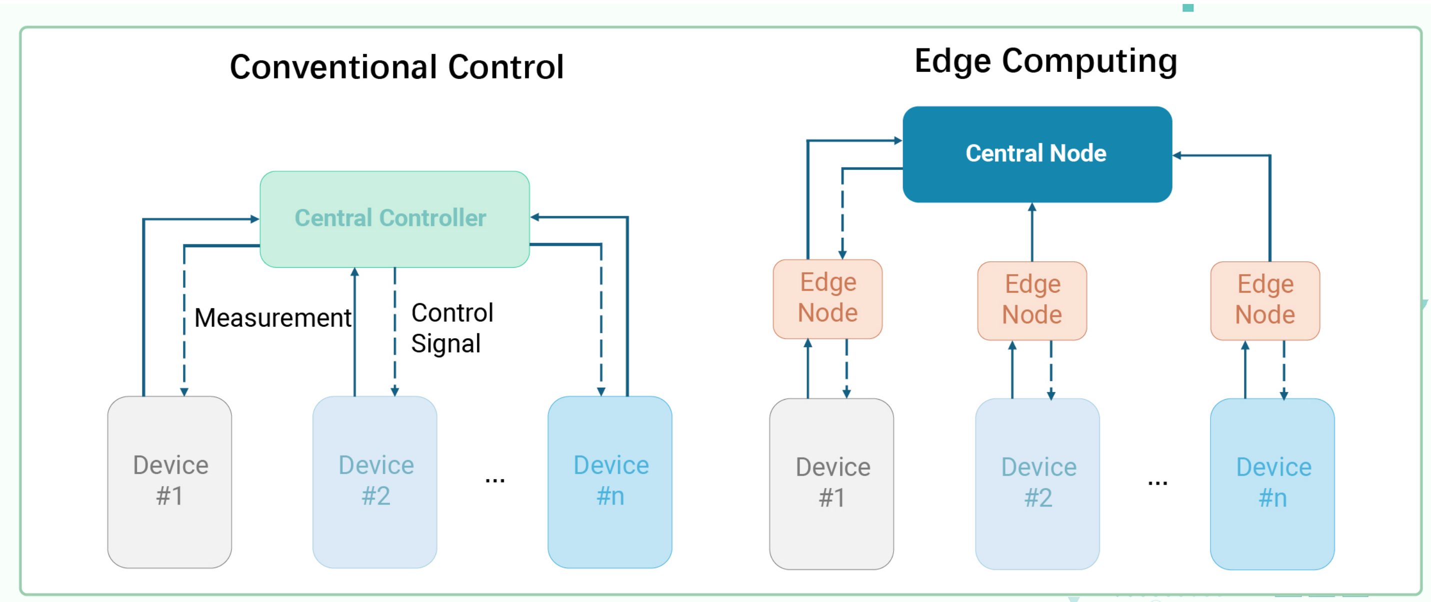

Figure 3. Edge architecture for reducing communication burden in building cluster control

The coordinator solves the following optimization problem:

$$\underset{\lambda}{\text{minimize}} \quad J = \left|\sum_{i=1}^{n} \sigma_i q_i\right|. \tag{7}$$

Equation (4) and Equation (7) are solved iteratively in a distributed manner, where the coordinator updates the price based on aggregate imbalance, and the agents update their quantities based on the price. Once the distributed optimization converges, the resulting equilibrium price is referred to as the *clearing price*. Compared with solving original optimization problem in Equation (1) centralized, TC offers two distinct advantages: (1) it is inherently scalable, as its distributed structure requires no reformulation when new participants are added, and (2) it preserves participant privacy by exchanging only price and quantity, keeping building-specific operational details and individual preferences confidential. Owing to these advantages, TC has been widely adopted for building cluster control, as demonstrated in numerous studies.[74-81] In addition, its potential has been further validated through both large-scale demonstrations and theoretical investigations.[82–83]

Stochastic and robust operation

To address the impact of uncertainty in building cluster control, a range of methods have been developed to explicitly account for variability in occupant behavior, environmental conditions, and system dynamics. One common approach is stochastic optimization,[84] where uncertain parameters are modeled as random variables with known or estimated probability distributions, enabling control decisions to be optimized in expectation or under probabilistic constraints. Alternatively, robust optimization methods[85] consider bounded uncertainty sets and seek solutions that remain feasible under worst-case realizations, thereby improving reliability at the expense of potential conservatism. More recently, data-driven uncertainty modelling approaches, including scenario-based optimization[86] and learning-based methods,[87] have been employed to capture complex and time-varying uncertainty patterns from historical data. Overall, these methods reflect a trade-off between performance, robustness, and data requirements: stochastic optimization emphasizes expected performance, robust optimization prioritizes reliability under uncertainty, and data-driven approaches aim to balance adaptability and modeling flexibility.

In the following, stochastic optimization is used as an illustrative example to demonstrate how various uncertainties can be explicitly incorporated into the control framework. Stochastic optimization aims to optimize the expected value of an objective function in the presence of uncertainty. Its foundational concept was introduced by George B. Dantzig in 1955.[88] Since then, advances in optimization theory and numerical methods have enabled its application across a wide range of domains, including the control of building energy systems. Stochastic optimization has been applied to handle various uncertainties, such as the prediction of future electricity price,[89–90] power demand,[91] weather conditions,[92] occupant behavior patterns,[93] renewable energy generation,[94] and their combinations.[95–96]

To illustrate its application, consider a load scheduling problem in which HVAC power demand is adjusted in response to time-varying electricity prices. The objective is to minimize total operating cost over a prediction horizon while maintaining indoor thermal comfort and satisfying operational constraints. In general form, the optimization problem can be expressed as:

$$\underset{P^1,\ldots,P^N}{\textit{minimize}} \quad \sum_{k=1}^{N} (\lambda^k P^k \Delta t), \tag{8}$$

where Δt, k, and N are the time step, the index of the time step, and the number of time steps within one optimization period, respectively. λ^k is the electricity price at time step k. P^k denotes the power of the studied system at time step k. The optimization is subject to building thermal dynamics, indoor temperature comfort constraints, and equipment operational limits. Building thermal behavior is represented through a dynamic model relating future zone temperatures to previous states, control actions, and exogenous disturbances such as weather conditions.

To account for uncertainty in temperature prediction, a stochastic load scheduling framework is formulated. Rather than optimizing system operation for a single predicted future, the controller considers multiple possible realizations (scenarios) of uncertainty and minimizes the expected operating cost across all scenarios. This can be generally written as:

$$\textit{minimize}\, \mathbb{E}[C(\xi)], \tag{9}$$

where $\mathbb{E}[C(\xi)]$ is the expectation of the electricity cost under the uncertainty in the temperature prediction, denoted by ξ. S is the number of the possible realizations of ξ. $\mathbb{P}\{\xi_r\}$ is the probability for one realization of ξ, denoted by ξ_r. ξ_r is defined as below.

Noted that $\mathbb{P}\{\xi_r\}$ is unknown in real practices. Thus, we use a sample of the possible realizations of ξ to approximate the true probability and change Equation (8) into:

$$\textit{minimize} \sum_{r=1}^{S^*} \frac{C(\xi_r)}{S^*}, \tag{10}$$

where $C(\xi_r)$ denotes the electricity cost under ξ_r and S^* is the size of the samples, also known as scenario number.

The stochastic optimization problem is typically implemented using a two-stage structure. In the planning stage, control decisions are optimized based on the expected performance across all uncertainty scenarios. In the operating stage, the system responds to the realized conditions while ensuring that indoor comfort constraints remain satisfied. Compared with deterministic

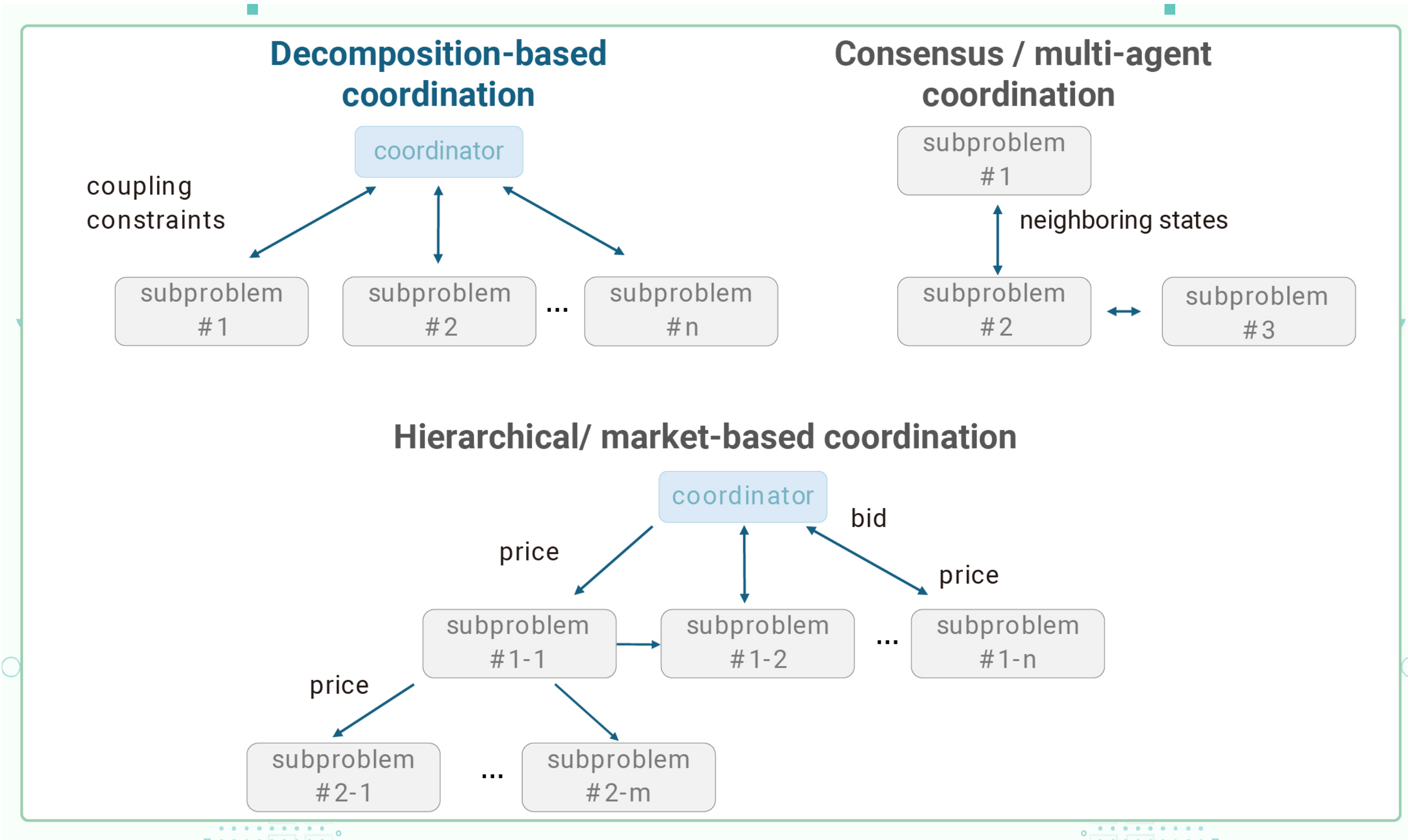

Figure 4. Distributed control frameworks

optimization, this framework explicitly considers uncertainty during decision making, thereby improving operational robustness and reducing the risk of comfort violations under inaccurate predictions. Prior studies have shown that stochastic optimization can mitigate the impacts of temperature prediction uncertainty on operating cost and thermal comfort, particularly under high-uncertainty conditions where prediction accuracy may lead to up to a 3.7-fold variation in daily cost savings.[97]

An important distinction should be noted regarding the nature of uncertainty considered in this formulation. Most existing studies focus on exogenous uncertainties, such as forecast errors in weather conditions or electricity prices, whose realizations are independent of the control decisions. In contrast, the temperature prediction error considered here represents an endogenous uncertainty because it is intrinsically coupled with building thermal dynamics and system operation. To address this issue, the expected value of the temperature prediction error is incorporated directly into the indoor temperature constraints, enabling the controller to maintain thermal comfort while accounting for uncertainty propagation within the building dynamics.

METHODS FOR NON-TECHNICAL CHALLENGES

To enable building cluster control beyond isolated demonstrations, a range of methods has been developed to address non-technical barriers related to user behavior, stakeholder coordination, economic incentives, and data governance. Among these, policy interventions and electricity market reforms play a central role, as they establish the institutional and economic conditions under which building-based flexibility can be effectively utilized. In particular, mechanisms such as demand response programs, dynamic pricing schemes, and flexibility markets are designed to translate grid needs, such as peak reduction, ramp mitigation, or flexibility procurement, into actionable signals for distributed participants. These efforts are complemented by coordination frameworks, incentive alignment strategies, and privacy-aware data governance models that facilitate participation and interaction across multiple stakeholders.

Institutional fragmentation and incentive misalignment

Policy interventions and electricity market reforms constitute the primary mechanism for addressing institutional fragmentation and incentive misalignment in building cluster control, as they redefine how distributed resources interact with the power system. In China, recent electricity market reforms provide a clear example of this transition. Since 2015, the power sector has progressively shifted from centrally administered dispatch toward a market-oriented framework, introducing competitive wholesale and retail markets, expanding cross-regional trading, and developing spot market mechanisms.[98] More importantly for building clusters, recent policies explicitly promote demand-side participation through price-based coordination, replacing administrative load control with market-driven signals such as time-varying electricity prices and demand response compensation.[99] These changes fundamentally alter the role of buildings—from passive consumers to active participants that can respond to economic signals—thereby creating the conditions for coordinating multiple buildings through shared incentives.

However, while these reforms establish the economic and institutional foundation for participation, they do not directly resolve how coordination is implemented across heterogeneous buildings. In particular, buildings remain owned and operated by different stakeholders with distinct objectives, and the value created through coordinated flexibility must still be allocated among participants. As a result, policy and market reforms enable building cluster control at the system level, but additional mechanisms are required to translate these market prices, demand response events, or grid-service requests into coordinated actions and equitable outcomes at the cluster level.

Specifically, institutional fragmentation can be addressed through structured coordination frameworks that facilitate interaction among multiple stakeholders. One effective approach is the use of hierarchical or aggregator-based models, in which an intermediary entity coordinates buildings on behalf of owners and operators, reducing the complexity of direct multi-party interactions. Within this context, transactive control, as introduced in Section 5.2, can be interpreted as a market-based coordination mechanism that complements such hierarchical structures by enabling decentralized decision-making through price or bid signals. This allows coordination to be achieved

Table 2. Comparison of distributed coordination paradigms for building cluster control

Paradigm	Communication	Convergence / optimality	Privacy	Implementation complexity
Decomposition-based methods	Medium–high	Strong	Moderate	High
Consensus-based /multi-agent approaches	Medium	Conditional	Moderate–high	Medium–high
Hierarchical coordination	Low–medium	Approximate	Moderate–high;	Medium–high
Market-based coordination	Low–medium	Approximate	High	Medium–high

without requiring centralized control over all participants, while still aligning their actions with system-level objectives. In addition, digital platforms[100] that integrate operational data and control interfaces can support collaboration by providing shared visibility and decision support. These mechanisms help align objectives across stakeholders and enable coordinated operation at the cluster level.

In parallel, cost-sharing and revenue allocation schemes are required to distribute the benefits of coordinated control among participating buildings. Methods based on cooperative game theory,[101] such as Shapley value or proportional allocation,[102] have been explored to ensure fairness and stability in multi-participant settings.[103] By establishing clear economic value and equitable distribution mechanisms, these approaches improve the attractiveness and feasibility of building cluster control.

User participation and privacy

Addressing user participation and acceptance requires mechanisms that align automated control with occupant preferences while maintaining the predictability of the aggregate load response. One common approach is the integration of human-in-the-loop control strategies,[104] where occupants are provided with adjustable comfort settings and bounded override options within predefined limits. This design preserves a degree of user autonomy and improves acceptability, but it also introduces variability into system response, as frequent or uncoordinated overrides can reduce the predictability of aggregate load behavior and weaken the effectiveness of coordinated control. To mitigate this issue, some implementations incorporate adaptive control logic that learns user preferences over time and anticipates override behavior, thereby reducing conflicts between automated decisions and occupant actions.

In addition, feedback mechanisms, such as real-time energy dashboards[105] and comfort indicators,[106] aim to enhance user awareness and trust by making system operations and their impacts more transparent. These tools can improve short-term engagement and encourage energy-conscious behavior; however, their long-term effectiveness is often limited by declining user attention and engagement fatigue. As a result, feedback mechanisms are typically most effective when combined with other strategies that reinforce participation. Behavioral incentive schemes,[107] including dynamic pricing and reward-based programs, provide a more direct means of influencing user decisions by linking actions to tangible economic benefits. Nevertheless, their effectiveness depends critically on incentive design, including the magnitude, timing, and interpretability of signals, and may vary significantly across different user groups due to differences in preferences, risk tolerance, and responsiveness to price signals.

Data governance and privacy concerns present another major barrier to scalable deployment, particularly as coordination across buildings requires the exchange of operational data. These concerns can be mitigated through architectural and algorithmic approaches that limit the need for raw data sharing. Privacy-preserving[108] methods, such as data aggregation,[109] anonymization,[110] and federated learning,[111] enable coordinated control while keeping sensitive information localized within individual buildings. For example, federated learning allows models to be trained across multiple buildings without transferring raw data, thereby reducing exposure to privacy risks while still learning common response patterns across buildings. However, these methods often introduce trade-offs between privacy protection and model accuracy or control performance,[112] as aggregated or anonymized data may omit fine-grained information needed for precise control.

In addition, access control mechanisms and standardized data governance frameworks define how data is shared, processed, and protected across stakeholders, providing a formal basis for trust and compliance with regulatory requirements. From a system design perspective, distributed and hierarchical architectures, such as those enabled by edge computing, further support privacy preservation by allowing coordination to be achieved using aggregated or abstracted information rather than detailed device-level data.[113] While these approaches reduce privacy risks and communication burdens, they may also limit global visibility and require controllers that can operate with aggregated or incomplete building-level information to compensate for reduced information granularity.[114] Overall, addressing user behavior and data governance requires a careful balance between autonomy, engagement, privacy, and system performance,[115] highlighting the need for integrated solutions that jointly consider human, institutional, and technical factors, as demonstrated in ref.[116]

FUTURE DEVELOPMENT

Despite rapid progress, the expansion of building cluster control beyond demonstrations remains constrained by the lack of comparable evaluation protocols and standardized interfaces with grid and energy-sector platforms. Future research should therefore focus on (i) establishing standardized benchmarking frameworks with consistent test scenarios, performance metrics, and evaluation procedures; (ii) developing scalable testing infrastructures that can evaluate diverse buildings, communication delays, uncertainty scenarios, and controller interactions under comparable and reproducible conditions; (iii) developing flexibility abstraction methods that allow building clusters to be coordinated with other energy sectors; and (iv) designing market-compatible and privacy-preserving deployment mechanisms that support participation, value allocation, and data governance in real-world implementation. These directions are essential for translating algorithmic advances into reliable control strategies that can be evaluated, replicated, and integrated with grid operation.

Standardized benchmarking and evaluation metrics

A fundamental limitation in current research is the absence of standardized and unbiased evaluation protocols, which hinders the comparability and reproducibility of reported results.[117] Existing studies typically rely on case-specific assumptions, customized datasets, and inconsistent performance metrics, making it difficult to assess the relative effectiveness of different control strategies. Beyond technical validation, standardized testing infrastructure plays a critical role in supporting evidence-based decision-making. Reliable and comparable evaluation results can inform the design of policy instruments and incentive mechanisms by quantifying the achievable flexibility and reliability of building clusters. They can also guide research directions by identifying performance limitations under realistic conditions, and support technology adoption decisions by clarifying trade-offs among cost, scalability, and performance. Therefore, developing robust and transparent testing methodologies is a prerequisite for bridging the gap between research and deployment.

Future work should establish formal benchmarking frameworks that define (i) standardized test scenarios, (ii) consistent performance metrics across multiple dimensions (e.g., cost, flexibility, comfort, emissions, communication overhead), and (iii) statistically robust evaluation procedures. Such frameworks would provide a common basis for evaluating control methods under comparable conditions. In addition, common benchmark scenarios for building cluster control should also be developed. These benchmarks should include representative building types, weather conditions, occupancy patterns, grid-service requirements, communication constraints, and uncertainty scenarios. Evaluation metrics should also extend beyond energy cost or peak reduction to include flexibility delivery accuracy, comfort impact, rebound effect, communication overhead, computational burden, privacy risk, user override frequency, and revenue allocation fairness. Such standardized benchmarks would make it possible to assess whether a method is not only effective in a single case study, but also transferable across different clusters and deployment contexts.

Scalable testing infrastructure

In addition to standardized metrics, building cluster control requires testing infrastructure that can evaluate control strategies under realistic multi-building conditions. Full field deployment is often costly, risky, and difficult to reproduce. Therefore, co-simulation, hardware-in-the-loop, and digital-twin-based platforms are important for testing the interaction among building dynamics, communication networks, controllers, occupants, and grid signals before field implementation.

A key research challenge is to design testing platforms that can represent large and heterogeneous building clusters while remaining computationally tractable. For distributed and multi-agent control methods, evaluation should also consider agent-level and interaction-level factors rather than only aggregated energy or cost outcomes. Recent work[118] on multi-agent reinforcement learning evaluation highlights the need to classify interaction structures, objectives, cooperation–competition relationships, and performance metrics when assessing multi-agent systems. This perspective is particularly relevant for building clusters, where controllers may operate under heterogeneous objectives, partial information, communication constraints, and coupled comfort or grid-service requirements.

In parallel, there is a need to develop testing platforms that can represent many heterogeneous buildings without requiring full physical deployment. Hardware-in-the-loop (HIL)[119] and co-simulation environments offer a promising approach by integrating physical controllers and communication devices with virtual building and grid models. These platforms enable the evaluation of control strategies under realistic operational conditions, including communication delays, device constraints, and uncertainty, without the cost and risk of full-scale deployment. A key research challenge is to design HIL frameworks that can represent large and heterogeneous building clusters while maintaining computational tractability, for example through representative building sampling,[120] model reduction,[121] and modular system design.[122]

Cross-sector coordination through abstraction

To provide grid services beyond building-only applications requires extending building cluster control beyond isolated applications to enable coordination with other energy assets, such as electric vehicles, charging infrastructure, and distributed storage. This necessitates the development of abstraction frameworks that allow heterogeneous systems to be represented and coordinated without relying on detailed device-level information. Such abstractions should capture the essential operational characteristics of building clusters, including flexibility limits, temporal dynamics, and uncertainty, while remaining computationally tractable for large-scale coordination.

One promising direction is the use of aggregated or reduced-order models to represent building clusters as flexibility resources with well-defined operational envelopes. For instance, the virtual battery model[123] abstracts the thermal and operational flexibility of buildings into an equivalent energy storage representation, characterized by parameters such as state of charge, power limits, and energy capacity. Such representations enable building clusters to participate in system-level optimization alongside other assets using standardized interfaces, thereby reducing integration complexity. However, the design of these abstractions involves a fundamental trade-off between model fidelity and scalability.[124] Overly simplified models may fail to capture important dynamics, such as nonlinear thermal behavior and rebound effects, while highly detailed representations may undermine computational efficiency and interoperability in large-scale coordination problems.

Future research should focus on developing adaptive and composable abstraction methods that can preserve critical system behavior while enabling coordination across buildings, electric vehicles, storage, and distributed generation without exposing detailed device-level models. In addition, these abstractions must be compatible with existing communication and control architectures, including hierarchical and distributed frameworks, and should support uncertainty representation and privacy constraints. Addressing these challenges is essential for enabling building clusters to function as integrated components of multi-sector energy systems, thereby unlocking their full potential in supporting grid flexibility, decarbonization, and system resilience.

Market-compatible and privacy-preserving deployment mechanisms

Technical control methods alone are insufficient to enable building cluster control in practice. Future research should also address how building clusters can participate in utility programs, flexibility markets, virtual power plants, and other grid-service mechanisms. This requires market-compatible coordination mechanisms that define how flexibility is requested, verified, compensated, and allocated among participating buildings.

Aggregator-based models, transactive control, dynamic pricing, flexibility markets, and cooperative revenue allocation methods provide possible pathways for aligning participant behavior with grid needs. However, several unresolved issues remain, including how to allocate value fairly among buildings, how to verify delivered flexibility, how to account for user overrides and comfort impacts, and how to design incentives that remain effective across different building types and occupant groups.

Privacy-preserving deployment is another important research direction. Coordinated control often requires operational data from multiple buildings, but owners and occupants may be reluctant to share detailed consumption, comfort, occupancy, or equipment information. Methods such as federated learning, anonymization, aggregation, access control, and edge-based data processing can reduce raw-data sharing while still enabling coordination. Future work should examine the trade-offs between privacy protection, model accuracy, control performance, and market verification requirements.

CONCLUSIONS

This paper has presented a comprehensive review of building cluster control, with a particular focus on its scalability challenges and enabling solutions. This review examined building cluster control as a pathway for converting dispersed building-side flexibility into a coordinated resource for grid operation. The reviewed literature shows that individual buildings are limited by small response magnitude, time-varying thermal states, occupancy-driven uncertainty, and local operational constraints. Aggregating buildings can partially address these limitations by increasing available flexibility, smoothing stochastic variations, and allowing load adjustments to be distributed across heterogeneous buildings. However, existing demonstrations indicate that this potential has not yet translated into routine deployment beyond pilot or project-specific settings.

A central finding of this review is that the main barrier is not the lack of control algorithms alone, but the difficulty of connecting algorithms with deployable infrastructure and institutional arrangements. At the technical level, building clusters remain difficult to implement because heterogeneous building management systems, legacy equipment, vendor-specific protocols, and inconsistent data models create substantial integration effort. As the number of buildings increases, centralized control also becomes less practical because of rising computational burden, communication requirements, privacy concerns, and uncertainty propagation across aggregated loads. At the implementation level, demonstrations remain difficult to compare because they differ in scale, duration, participating systems, evaluation metrics, and degree of market participation.

The reviewed solution approaches address different parts of this problem. Semantic modeling and standardized data representations reduce manual mapping between devices, systems, and control applications. Publish–subscribe middleware, edge computing, and hierarchical communication architectures reduce tightly coupled device-level interactions and limit the amount of information exchanged across buildings. Distributed and transactive control approaches reduce centralized computation and allow buildings to coordinate through limited information exchange, such as prices, bids, or aggregate constraints. Stochastic, robust, and data-driven optimization methods improve reliability by explicitly accounting for uncertainty in weather, occupancy, prices, and building response. Policy interventions, demand response programs, aggregator models, and revenue allocation mechanisms are also necessary because technical control strategies cannot by themselves resolve stakeholder misalignment, participation incentives, or data governance concerns.

The review also highlights two priorities for future research. First, building cluster control requires standardized testing infrastructure that can evaluate control performance across comparable scenarios, including different building types, communication conditions, uncertainty levels, comfort constraints, and market signals. Without such benchmarks, it will remain difficult to determine whether one control strategy is more reliable, transferable, or cost-effective than another. Second, building clusters need flexibility abstractions that can represent aggregated thermal and operational flexibility in forms usable by grid operators, aggregators, electric vehicles, storage systems, and other distributed energy resources. These abstractions must balance fidelity and simplicity: they should preserve key constraints such as power limits, duration, rebound effects, uncertainty, and comfort impacts, while remaining computationally tractable for coordination with other energy sectors.

Overall, building cluster control should be understood as a building-centered coordination problem that links device-level operation, building-level constraints, cluster-level aggregation, and grid-facing flexibility services. Progress will depend not only on improved control algorithms, but also on interoperable data models, modular communication architectures, uncertainty-aware evaluation methods, market-compatible participation mechanisms, and transparent evidence from real-world implementations. Addressing these issues together is essential for moving building cluster control from isolated demonstrations toward reliable use in future grid-interactive energy systems.

The review in this paper has several limitations. First, the real-world implementation cases summarized in Table 1 are primarily documented through official project webpages, government or utility reports, and demonstration-related sources. These sources are useful for identifying project scale, participating systems, funding mechanisms, and institutional context, but they should not be interpreted as peer-reviewed validation of technical performance. Accordingly, this review uses project-based sources mainly as implementation evidence, while relying on peer-reviewed studies to support technical findings, control methods, and performance-related claims.

Second, the reviewed demonstrations differ substantially in scale, duration, participating systems, evaluation metrics, and reporting detail. As a result, direct quantitative comparison across projects is limited. The purpose of the implementation review is therefore not to rank project performance, but to identify recurring deployment patterns, institutional differences, and unresolved barriers to broader adoption.

Third, the regional comparison among the United States, Europe, and China is based on representative policies and demonstration pathways rather than an exhaustive survey of all national or local initiatives. Other regions may follow different development trajectories depending on electricity market structure, regulatory design, building stock characteristics, and grid modernization priorities.

Finally, building cluster control is a rapidly evolving field. Communication standards, semantic modeling frameworks, electricity market rules, demand response programs, and virtual power plant practices continue to develop. Therefore, the barriers and solution pathways discussed in this review should be interpreted as a current synthesis of the field rather than a fixed or complete framework.

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AUTHOR CONTRIBUTIONS

All authors contributed to reviewing and editing the manuscript. All authors read and approved the final manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Readers may contact the corresponding authors for data upon reasonable request.