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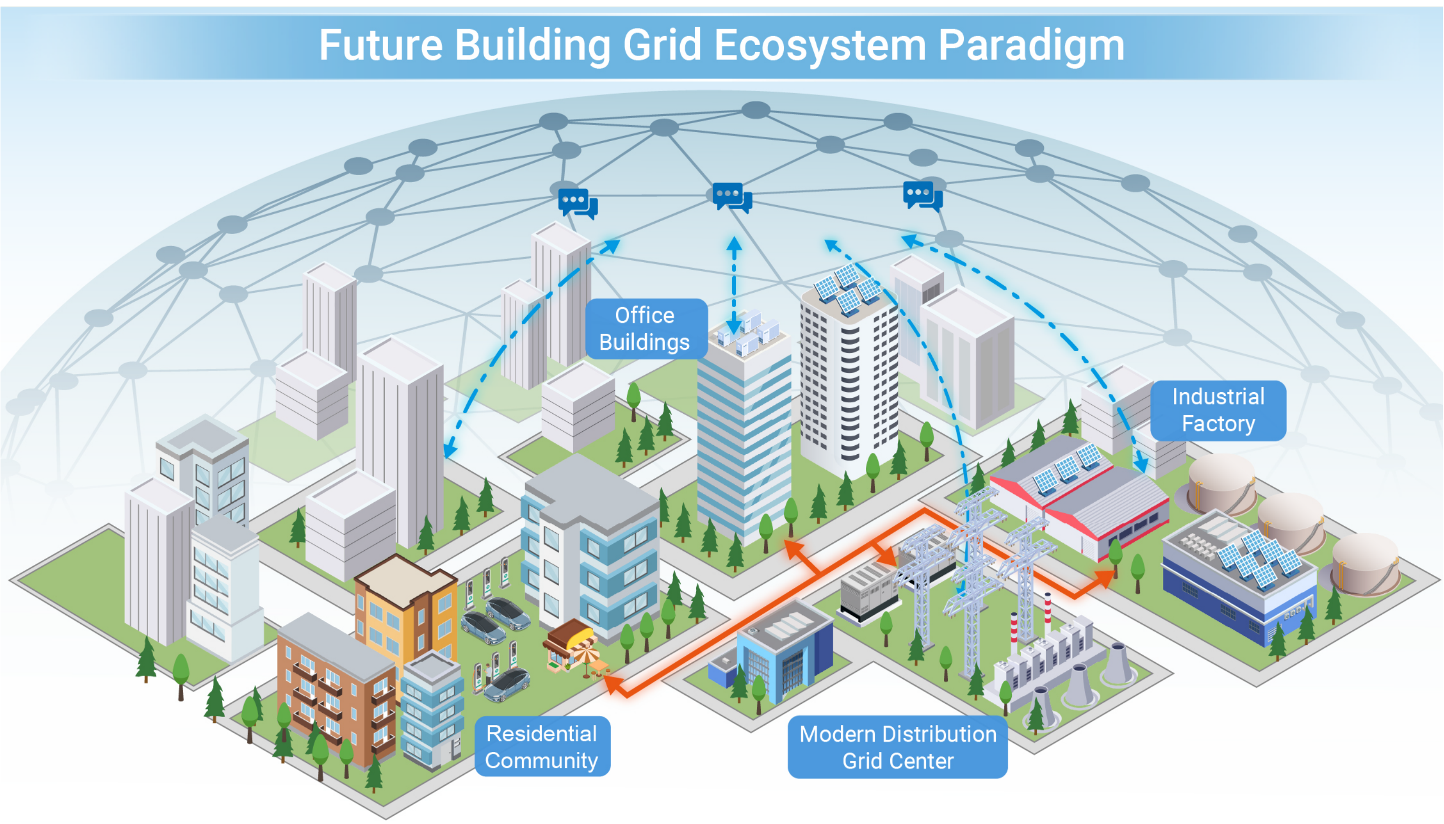
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Review formulates a framework for building-to-grid energy governance, turning buildings into active grid-interactive hubs.
- Explores how individual building flexibility can be quantified, aggregated, and coordinated to support grid operation across timescales.
- Analyzes the evolution of control strategies, shifting from standalone building optimization to multi-building hierarchical coordination.
- Examines the cyber-physical infrastructure needed for deployment, including communication protocols, data models, and hardware-in-the-loop validation.
- Discusses enabling conditions for large-scale adoption, emphasizing policy support, market mechanisms, and standardization frameworks.

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Rapid electrification and the rising penetration of variable renewable energy are fundamentally increasing the volatility of global power systems. In this context, activating demand-side flexibility has emerged as a critical strategy to maintain grid stability. Buildings, accounting for approximately 30% of global energy demand, offer a massive and controllable resource for such flexibility. By leveraging adjustable end-users, inherent thermal mass, and distributed energy resources, modern buildings can transform from passive consumers into active grid-interactive hubs. To navigate this paradigm shift, this review formulates a holistic framework for collaborative building-to-grid energy governance. It systematically examines how individual building flexibility can be quantified, aggregated, and coordinated into dispatchable resources to support grid operation across multiple timescales. The review further analyzes the evolution of control strategies, highlighting a clear shift from standalone building optimization toward multi-building hierarchical coordination. Recognizing that the practical implementation of these strategies depends on more than control algorithms alone, the review also examines the cyber-physical foundations required for deployment, including hardware infrastructure, communication protocols, semantic data models, and hardware-in-the-loop validation. In addition, it discusses the broader enabling conditions for large-scale adoption, with particular attention to policy support, market mechanisms, and standardization frameworks. By clarifying the technical, cyber-physical, and regulatory interdependencies of building-to-grid systems, this review provides an integrated reference for advancing flexible, resilient, and low-carbon energy systems.

INTRODUCTION

The rapid electrification of end-use sectors is fundamentally changing the relationship between global demand patterns and power systems. Global electricity consumption is projected to increase by 3.3% in 2025 and 3.7% in 2026, which is more than double the growth rate of total energy demand. This indicates a significant shift toward an electricity-centric energy model.[1] The historical connection between macroeconomic activity and electricity demand seems to be changing. In 2024, global electricity demand increased by 4.3%, surpassing the 3.2% growth in global GDP.[2] However, global grid investment has remained largely stagnant for over a decade. In this case, network expansion is struggling to keep pace with increasing dynamic demand, especially higher and more volatile peaks. Closing this infrastructure gap will require a step change in investment, with annual grid spending needing to nearly double to over USD 600 billion by 2030.[3]

System pressures are being amplified not only by faster demand growth but also by increasingly volatile load patterns. As the renewable share of global electricity generation rises from 32% in 2024 to 43% by 2030,[4] higher penetration of variable renewables increases residual-demand variability, steepens ramping requirements, and reduces system inertia. Meanwhile, climate change is reshaping load profiles, particularly through rising space cooling demand. Global electricity consumption for space cooling is projected to nearly triple by 2050 to around 6,200 TWh, contributing more than 20% of the total growth in global electricity demand.[5] Against this backdrop, these compounding trends further exacerbate reliability risks and increase the marginal costs of conventional capacity expansion.[6,7] Consequently, activating demand-side flexibility has emerged as a pivotal strategy to enable deep emission reductions while maintaining grid stability in a climate-stressed future.[8]

Among demand-side resources, buildings are especially compelling because of their scale and controllability. Buildings account for approximately 30% of global energy demand and have become a major driver of recent electricity growth. In 2024 alone, electricity use in buildings contributed nearly 60% of the total global growth in electricity consumption.[9] Beyond scale, buildings also offer substantial flexibility potential because they function as multi-resource coupled systems. They combine adjustable end users (e.g., HVAC, water heating, and plug loads), inherent thermal mass, dedicated thermal storage, and increasingly on-site distributed generation. This coupling enables multiple forms of flexibility, including efficiency improvement, load shedding, load shifting, fast modulation, and on-site generation, thereby supporting a range of grid services and market-oriented applications.[10,11] By transforming buildings from passive consumers into active grid-interactive resources, it is possible to provide a cost-effective pathway toward a resilient, zero-carbon energy future.[12]

To unlock building flexibility for grid support, building-to-grid (B2G) interaction has evolved through progressively deeper coupling between building

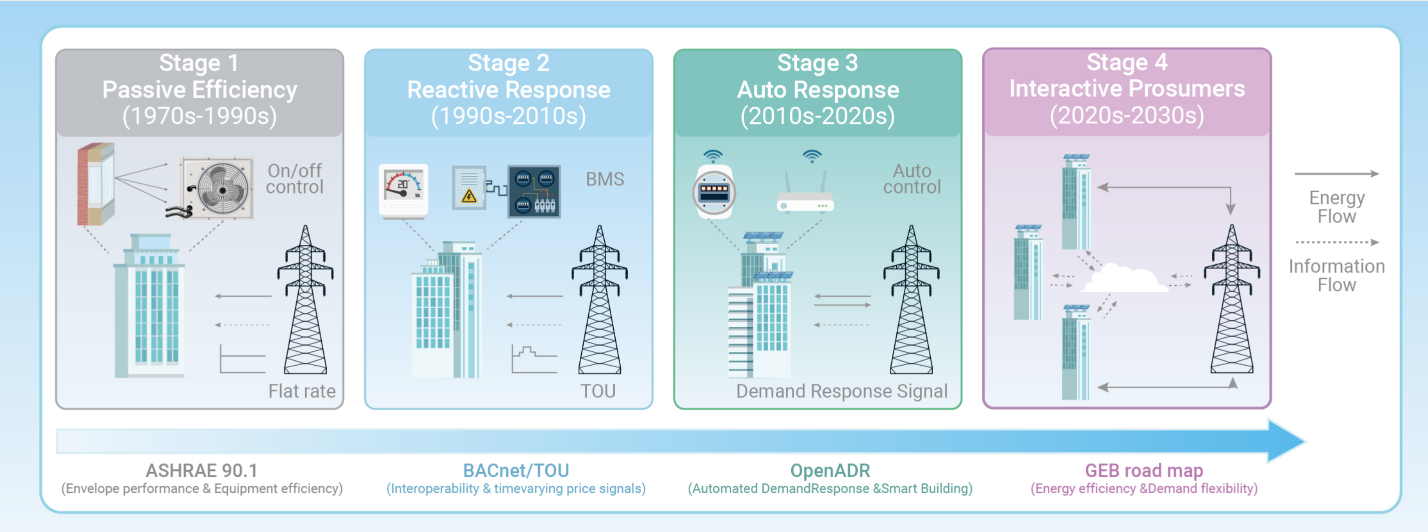

Figure 1. Evolution of Building-to-Grid Interaction

operation and grid requirements (Figure 1). This evolution is characterized by a shift from passive efficiency-oriented demand reduction toward increasingly responsive, automated, and coordinated flexibility provision, enabled by advances in sensing, communication, and control technologies. In Stage 1, buildings were treated as static demand nodes, with minimal operational coupling to grid conditions. Interaction was indirect and largely driven by compliance-oriented efficiency improvements, such as envelope and equipment performance requirements (e.g., ASHRAE 90.1[13]), with the primary objective of reducing energy use through improved components and conventional rule-based controls. In Stage 2, the rollout of building management systems (BMS) and time-varying tariffs enabled buildings to adjust their operation in response to price signals. Although interoperability advances such as BACnet improved coordination among internal subsystems, building-grid interaction remained largely one-way. In Stage 3, automated demand response and standardized communication protocols, such as OpenADR,[14] enabled faster, more reliable, and more scalable flexibility provision. The introduction of advanced sensing, metering, communication, and supervisory control improved buildings' ability to receive external grid signals, exchange operational information, and deliver timely and coordinated responses. At this stage, buildings primarily acted as responsive loads, and the main advance lay in shifting from occasional event-based curtailment to automated, schedulable, and verifiable flexibility provision. In Stage 4, buildings increasingly operate as interactive prosumers with bidirectional information exchange and diversified on-site resources, including photovoltaics, batteries, electric vehicles, and thermal storage. Beyond individual buildings, flexibility is increasingly aggregated across portfolios or districts, often through aggregators or virtual power plants (VPPs), to participate in demand response programs and electricity markets at scale. This expanded role of buildings has also been reflected in frameworks such as the DOE Grid-Interactive Efficient Buildings (GEB)[10] roadmap, which formalizes buildings as grid assets capable of delivering multiple services across timescales.

Looking ahead, building-to-grid development is likely to evolve beyond individual building optimization toward coordinated ecosystem-level governance (as shown in Figure 2). This future stage will be supported by semantic interoperability, trusted data exchange, and distributed decision-making across building clusters and distribution networks. Within a Building-Building-Grid paradigm, buildings will be able to share real-time operational states and network constraints through trusted data spaces, enabling constraint-aware coordination that goes beyond conventional price-only interaction. Through such mechanisms, distributed building resources can collectively manage congestion, support voltage stability, and improve resilience under distributed control. As a result, buildings may gradually shift from isolated prosumers to cooperative cyber-physical agents within a self-organizing energy ecosystem.

To provide a systematic and structured overview of the rapidly evolving B2G field, this review is based on a targeted literature survey of publications from Scopus and Web of Science covering the period 2010-2026. Relevant studies were identified using keywords related to building-to-grid interaction, demand response, flexibility quantification, aggregation, control, communication, and grid-interactive efficient buildings. After duplicate removal and relevance screening, approximately 208 papers were selected for detailed review. Based on this literature base, the B2G landscape is synthesized following the structure shown in Figure 3. Section 2 outlines grid-interactive services, with emphasis on grid-supportive services and their associated grid signals and response pathways. Section 3 characterizes building flexibility by clarifying key definitions, quantification approaches at the building level, and aggregation methods. Building on this, Section 4 reviews control and coordination strategies, including building-level control, multi-building coordination, and hierarchical control architectures. Section 5 discusses implementation and interoperability, focusing on hardware infrastructure, communication protocols, data models, and hardware-in-the-loop validation. Section 6 then reviews the policy, market, and standards frameworks that enable building–grid interaction across different countries. Finally, Section 7 summarizes the main findings and outlines future challenges and research directions.

GRID-INTERACTIVE SERVICES

In B2G systems, grid-interactive services represent the active engagement of buildings in power grid operations. To maintain system stability, buildings serve as controllable resources, leveraging their inherent energy flexibility to provide vital grid-support services. This section categorizes these services based on their required time scales and subsequently examines the corresponding grid signals and response mechanisms.

Gird-supportive services

Grid-supportive services integrate building flexibility into power grid operations to meet distinct operational objectives and dynamic performance requirements. Based on market hierarchies and required time scales, these services encompass fast dynamic services, operating reserves, peak shaving, and long-term capacity provision.

Fast dynamic services. At the seconds-to-minutes time scale, building flexibility primarily enables fast dynamic services, including frequency regulation, dynamic voltage support, and synthetic inertia. As renewable penetration increases, grid inertia decreases, and grid-interactive buildings can act as rapid-acting assets to counteract short-term transient fluctuations and meet the amplified demand for fast-response resources.

To deliver these high-speed services, buildings rely on several key fast-response resources. Some studies indicate that distributed energy storage systems can switch between charging and discharging within short time intervals and provide accurate power tracking, thereby meeting the basic requirements of frequency regulation.[15] Simulation and experimental results further show that coordinated operation of building-side storage and control-

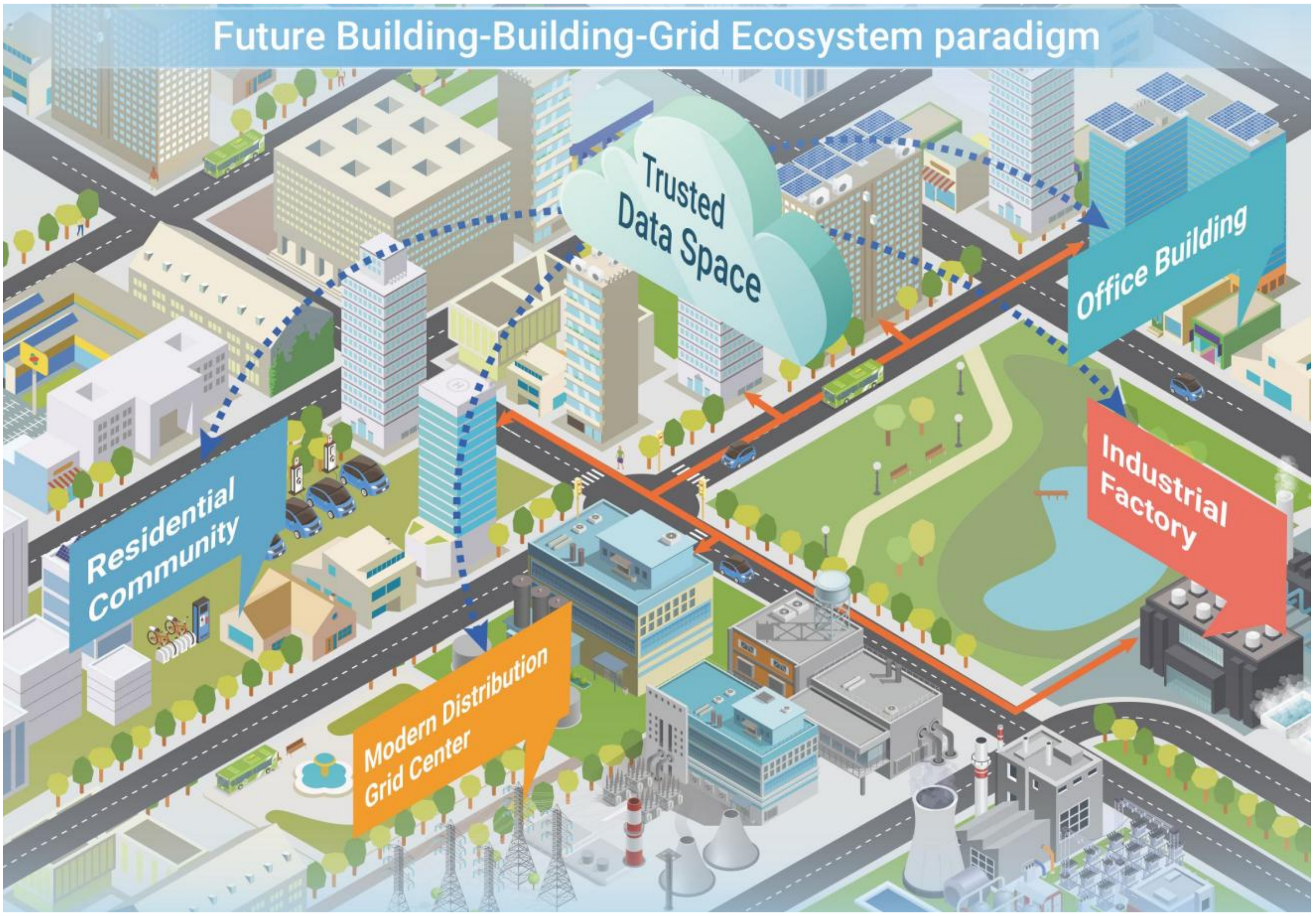

Figure 2. Future Building-Building-Grid Ecosystem paradigm

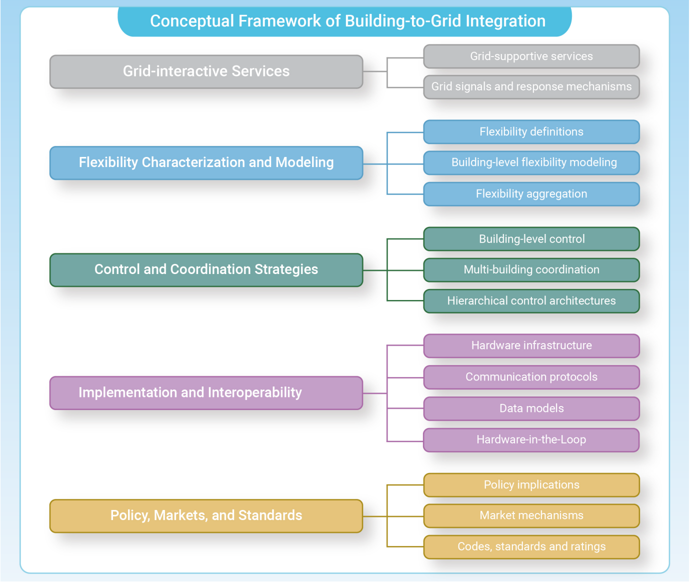

Figure 3. Conceptual Framework of Building-to-grid Integration

lable loads can deliver stable frequency support.[16–17] In addition to storage systems, variable-speed HVAC equipment and controllable electric vehicle charging facilities have demonstrated the potential to participate in fast regulation. When deployed at scale, building flexibility can have a measurable impact on system operation and mitigate renewable curtailment under high renewable penetration scenarios.[18]

In practical grid operation, these fast dynamic services are typically monetized and organized through ancillary service markets. From a system perspective, their effectiveness depends primarily on physical response capability. A key challenge is that individual buildings have limited capacity. Aggregation is therefore required to enable large-scale participation while maintaining response consistency and stability.

Operating Reserves and Ramping Support. At the minutes-to-hours time scale, building flexibility is mainly used for reserve provision and short-term power adjustment. These mid-term services are typically activated by grid operators to mitigate sudden systemic contingencies, such as unexpected generation outages or steep load surges.

To deliver these services, B2G systems leverage the coordinated operation of distributed demand response and energy storage.[19] Specifically, interruptible building loads have been incorporated into reserve arrangements or capacity assessment frameworks, serving as supplementary resources to conventional generation. Analyses indicate that coordinated operation of flexible loads and storage can reduce system stress during high-risk periods and partially decrease reliance on centralized reserve capacity.[20] Due to their wide geographical distribution, building resources can provide localized support and help alleviate power flow constraints in specific areas.

However, the reliable provision of these services heavily depends on robust coordination mechanisms.[21] A fundamental operational challenge is the high stochasticity of aggregated available capacity. Load profiles vary significantly across different building typologies, and during extreme weather conditions, elevated internal energy demands can severely diminish the building's available flexibility. Consequently, ensuring stable reserve regulation while safeguarding normal energy use and occupant comfort remains a critical research focus.

Peak Shaving and Load Shifting. At the hours-to-days (diurnal) time

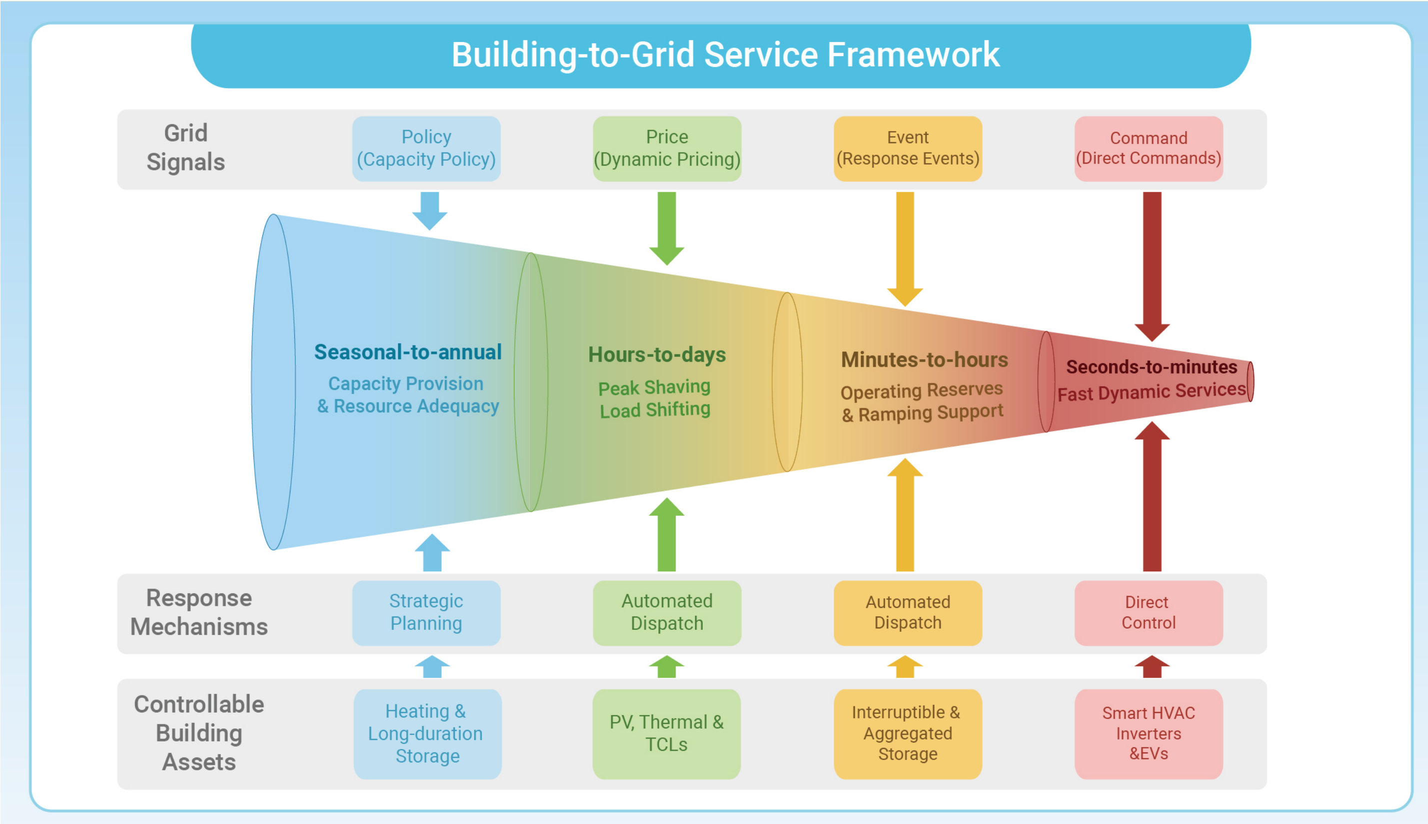

Figure 4. A framework for B2G grid services across market levels and time scales (Adapted from Ref. 15).

scale, building flexibility is harnessed to achieve systemic energy balancing, specifically through peak shaving and load shifting.[22] As the variability of renewable generation exacerbates intra-day net load fluctuations (e.g., the typical "duck curve"), proactive load shifting within buildings plays an indispensable role in smoothing the overarching grid demand profile.

Several studies have proposed scheduling frameworks based on real-time monitoring and optimal control to improve energy efficiency while maintaining occupant comfort. In some residential cases, energy savings of up to 11.4% have been reported.[23] Time-of-use and real-time pricing mechanisms have also been shown to effectively reduce peak demand.[24] Improved pricing strategies can mitigate rebound effects caused by synchronized load responses and reduce electricity expenditures for certain users.[25]

With the rapid development of distributed energy resources, coordinated scheduling of rooftop photovoltaics and storage enhances local energy self-balancing capability. In mixed community settings, multi-agent coordination mechanisms have been applied to improve overall performance.[26] Simulation results show that appropriate coordination strategies can significantly reduce local power fluctuations[27] and improve project feasibility through optimized benefit allocation.[28] However, large-scale distributed transactions may increase power exchange volatility with the main grid.[29]

Capacity Provision and Resource Adequacy. At the seasonal-to-annual time scale, building flexibility extends beyond operational dispatch to fundamentally influence grid capacity arrangements and long-term planning decisions. With the widespread deployment of demand response and energy storage technologies, studies indicate that large-scale integration of flexible resources can significantly reduce system stress during high-risk periods and optimize the overall cost structure of system operation.[20]

To formalize these long-term services, several countries have incorporated demand-side resources, such as building heating systems, into their capacity frameworks. Practical experience shows that, under high wind penetration scenarios, residential heating systems participating in capacity provision achieved approximately 7.36% reductions in electricity expenditures.[30] In contrast, systems that rely solely on extreme price signals without long-term coordination mechanisms exhibit higher operational risks under extreme conditions.[31]

From a planning perspective, incorporating building flexibility into long-term capacity assessment can alleviate the need for additional generation and network investments. However, the long-term availability of building flexibility is affected by technological upgrades and changes in energy-use behavior. It still lacks a standardized framework for evaluation and certification of B2G. Therefore, developing methods to quantify the contribution of building flexibility in planning processes remains an important research direction.

Grid signals and response mechanisms

Power grid operators drive building participation through different types of trigger signals. These mechanisms can be categorized as price-based signals, incentive- or event-based signals, and direct control or automated dispatch.

Price-based signals. Price-based signals refer to mechanisms in which electricity prices are more dynamic to influence user consumption decisions.[24] As price-responsive entities, buildings can autonomously optimize flexible loads such as HVAC systems and energy storage according to dynamic price variations. A study based on the California market showed that dynamic pricing can reduce peak net load by 5%-25% and lower electricity bills by 2.9%. As peak–valley price spreads widen, dynamic pricing further improves the economic feasibility of building-side energy scheduling.[32]

With increasing renewable penetration, negative electricity prices have become more frequent.[33] Empirical evidence indicates that building users exhibit higher elasticity under negative prices than under conventional positive prices.[34] Large-scale response of flexible loads to negative pricing not only generates financial returns but also facilitates the absorption of surplus renewable energy.

Incentive-based or event-based signals. Incentive-based or event-based signals are explicit response requests issued by grid operators or aggregators that specify target load reductions or capacity ranges. Upon receiving these signals, buildings adjust their operations to earn financial incentives as defined in their participation programs. In Singapore's commercial districts, demand-side bidding by air-conditioned buildings demonstrated that event-based participation better aligns with real market operations than traditional

Table 1. Summary of key flexibility metrics

Category	Sub-Category	Metric	Formula	Brief Description	Key References
Micro-level Indicators	Power & Capacity	Power change ($\triangle$P(t))		Instantaneous load deviation from baseline.	[50-53]
		Power capacity ($\triangle P_{max}$)		Maximum achievable power reduction/increase.	[51,54–55]
		Power ramp-rate capacity (R)		Speed of power output change.	[51,56]
		Average power change ($\triangle P_{ave}$)		Average load deviation during response.	[50]
	Time & Response	Response time ($\triangle t_{st}$)		Delay from signal receipt to response start.	[50–51,57]
		Flexibility duration ($\triangle t_{dur,fle}$)		Time load can sustain a modulated state.	[50–51,58]
		Rebound effect duration ($\triangle t_{dur,bou}$)		Time to return to baseline after response.	[50]
		Deferred operation time ($\triangle t_{defer}$)		Max postponement time for thermostatically controlled loads (TCLs) within comfort limits.	[51,59]
	Energy & Efficiency	Energy change during response ($E_{dif,fle}$)		Total energy adjusted during DR event.	[50]
		Peak reduction ratio (μ)		Ratio of energy reduction to reference consumption.	[50]
		Shedding/shifting efficiency (η)		Ratio of energy reduction to rebound increase.	[50]
Macro-level Indicators	Economic & Environmental	Total operating cost saving ($C_{op,tot}$)		Net change in electricity cost due to flexibility.	[50,60-63]
		Average peak/off-peak load impacts ($\triangle E^{flex,pk/opk}$)		Average demand change during system peak/off-peak hours.	[64]
		CO_2 emission change (E_m)		Net change in CO_2 emissions from flexibility.	[50]
	Self-Sufficiency	Self-sufficiency / Load covering factor (SS)		Degree of on-site renewable generation meeting load.	[50–51,65–66]
		Energy savings (η_{ES})		Reduction in final energy use from optimal control.	[51,67–68]

centralized dispatch.[35]

In practice, however, fragmented participant information and diverse optimization objectives make it difficult for aggregators to accurately estimate actual response capabilities. Game-theoretic models based on deep reinforcement learning can optimize incentive pricing under incomplete information and improve market efficiency.[36] Coordinated use of price-based and incentive-based signals can further reduce electricity costs and peak demand while respecting building operational constraints.[37]

Non-compliance and under-delivery remain key risks in event-based programs. To address performance uncertainty, Raman et al.[38] proposed a distributed event-stream monitoring framework. By triggering secondary incentives when under-performance is predicted, the framework can limit peak reduction gaps to within 1%. To mitigate financial uncertainty, Zhen et al.[39] developed a risk-averse bidding strategy that jointly optimizes declared capacity and operational schedules. This approach reduced subsidy loss rates from 37.16% to 17.75% and increased effective response duration from 18.68% to 65.93%.

Response mechanisms

Direct control. Under direct control mechanisms, power grid operators or aggregators send explicit power commands to building systems. Internal devices adjust their output in real time to track the requested power level.[40] This approach enables high-precision power tracking and fast response.

Accurate implementation requires reliable models of building thermal dynamics. These models capture the relationship between load adjustments and indoor environmental conditions.[41] Model-based control ensures that power tracking does not violate thermal comfort constraints. Reinforcement learning and multi-agent control methods have also been introduced to improve coordination among multiple buildings under centralized control frameworks.[42]

From a system perspective, integrating directly controllable resources into distribution network planning can reduce feeder reinforcement requirements and overall planning costs.[43] However, direct intervention raises concerns regarding occupant comfort and user acceptance. Therefore, control strategies must incorporate comfort constraints and fatigue mitigation mechanisms to ensure sustainable participation.[44]

Automated dispatch. Unlike direct control, where the grid takes full control of building devices, automated dispatch mechanisms enable intelligent grid interaction through the building's internal control systems.[45] Automated Demand Response (ADR) is the core mechanism. Its effective operation depends heavily on Demand Response Automation Servers, which act as intermediaries between the grid and facilities.[46] It also relies on standardized two-way communication protocols, such as OpenADR.

When the grid anticipates a capacity shortfall or peak demand, the building's automation system can execute pre-programmed response strategies upon receiving a warning signal. This process requires no manual intervention. Typical automated actions include dynamically adjusting HVAC setpoints, reducing non-essential lighting, and shutting down non-critical water pumps.[47] In modern microgrids that integrate distributed generation and energy storage, automated dispatch mechanisms can also control battery reverse discharge. Additionally, aggregated building resources can be converted into a Virtual Power Plant (VPP), allowing them to be dispatched by the grid like traditional power plants.[48]

From a macro power planning perspective, efficient automated dispatch mechanisms provide a green alternative to building new peaking plants to meet growing system capacity needs. By relying on advanced communication technologies and optimization models, large-scale building clusters can reliably support distribution grid peak shaving and supply-demand balancing.[49] This can be done while ensuring basic operations and accommodating user preferences.

FLEXIBILITY CHARACTERIZATION AND MODELING

The quantification of building energy flexibility relies on a set of metrics that capture different dimensions of demand response (DR) performance. These metrics are broadly classified into micro-level and macro-level indicators based on their scope and application.[50–51] This section provides a synthesized overview of commonly used flexibility metrics, highlighting their intended purpose and application context. A comprehensive summary is presented in Table 1.

Flexibility definitions

Micro-level indicators. Micro-level indicators directly characterize the tech-

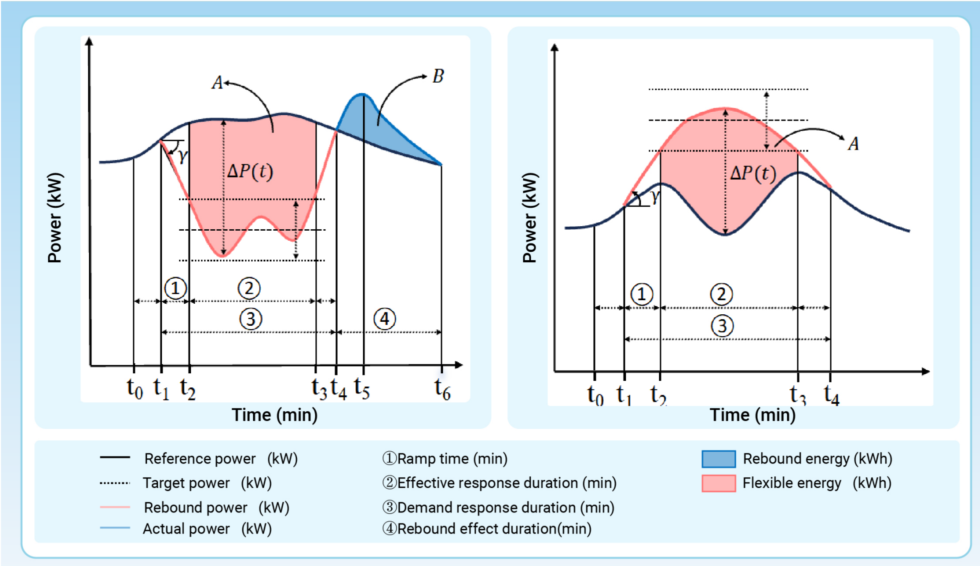

Figure 5. Micro-level indicators

nical performance of a building or its subsystems during a flexibility event. As indicated in Figure 5, these metrics are generally evaluated across three primary dimensions: power, time, and energy.

Power and time-related metrics capture the magnitude, speed, and duration of load adjustments, which are crucial for evaluating a building's capability to provide fast grid services (e.g., frequency regulation or peak shaving). Meanwhile, energy-related metrics assess the overall physical impact and efficiency of flexibility actions, such as the total energy shifted or the ratio of energy reduction to the subsequent rebound effect.

Macro-level indicators. Macro-level indicators translate micro-level technical flexibility into broader system-level or value-based outcomes. They are particularly useful for comparing different buildings, evaluating control strategies, or assessing policy scenarios. Rather than focusing solely on technical responses, these metrics quantify the tangible benefits of demand shaping, such as operating cost savings under dynamic pricing, contributions to system-wide peak reduction, and enhancements of renewable energy self-consumption and carbon emissions reductions.

Building-level flexibility modeling approach

A variety of modeling approaches have been developed to quantify building-level flexibility, differing in their representation of physical processes, data requirements, and model complexity. As illustrated in Figure 6, these approaches can be broadly grouped into three categories: white-box, grey-box, and black-box models.[69–70] Rather than reiterating their underlying mechanics, it is crucial to examine their operational trade-offs.

White-box models are physics-based models that explicitly represent the building thermal behavior and energy system operation through physically interpretable formulations, with detailed inputs on building characteristics, system parameters, and configurations.[50–51,71–73] This mechanistic representation offers strong interpretability and high accuracy, enabling detailed characterization of building thermal dynamics and flexibility under different operating conditions. However, their application is often challenged by intensive data input requirements, substantial modeling and calibration effort, and high computational cost.

To mitigate computational constraints, grey-box models simplified physical structures with data-driven parameter identification to represent building thermal dynamics and energy system behavior.[73-77] Typically based on reduced-order formulations such as resistance-capacitance (RC) networks, they retain partial physical interpretability while substantially reducing modeling complexity. This characteristic enables grey-box models to balance accuracy and computational efficiency, making them widely applicable to flexibility quantification, optimal control, and the analysis of thermostatically controlled loads at both building and district scales.[78–79] However, their generalizability may be constrained, since empirically identified parameters are often sensitive to variations in building structure, system configuration, and climate conditions.

Meanwhile, the increasing availability of smart meter data has accelerated the adoption of black-box models for behind-the-meter flexibility identification and large-scale aggregation.[51,64,80-82] These data-driven models are particularly effective at capturing complex and nonlinear dynamics without requiring explicit physical knowledge.[83] However, their application is often constrained by the need for extensive multi-source data to support accurate model training.

Flexibility aggregation

Individual buildings typically possess insufficient capacity to participate directly in wholesale electricity markets. Aggregation bridges this gap by clustering multiple buildings into a unified, dispatchable virtual resource. Existing studies generally classify flexibility aggregation methods into four main categories, each reflecting different trade-offs in accuracy, scalability, and uncertainty treatment. The following sections discuss these methods in turn.

Physics-based aggregation. Physics-based aggregation derives aggregate flexibility by preserving, to varying degrees, the physical dynamics of individual buildings or end uses. In this approach, the aggregate response is constructed from the combined behavior of multiple physically modeled units, typically using white-box models or simplified grey-box formulations such as RC or equivalent thermal parameter (ETP) networks.[50] By retaining the causal relationships among control actions, thermal states, and power responses, this method provides a physically interpretable, time-resolved representation of aggregated flexibility.

A typical application is the aggregation of thermostatically controlled loads, where simplified thermal models are combined with Monte Carlo simulation.[51] In this setting, each load is characterized by a small set of thermal and operational parameters, and population diversity is represented through parameter distributions from which aggregate power trajectories are estimated. The primary strength of physics-based aggregation lies in its high-fidelity tracking of dynamic responses and its explicit representation of physical constraints. However, its practical application is often challenged by the intensive need for detailed parameterization and the computational burden of simulating diverse, high-dimensional populations at scale.

Statistical aggregation. Statistical aggregation estimates aggregate flexibility directly from observed data, survey information, or population-level statistics, without explicitly modeling the physical dynamics of individual buildings. Rather than preserving the causal behavior of each building, it characterizes flexibility in terms of aggregate patterns, probability distributions, or representative load profiles.

A typical application is estimating shiftable load potential for deferrable appliances, where user preferences and usage patterns are represented statistically to estimate the amount and timing of flexible load.[58] Beyond flexibility potential assessment, statistical aggregation is also widely used in demand response evaluation, particularly for establishing aggregate baselines and quantifying net load reduction.[19,84] The main advantage of statistical aggregation lies in its strong scalability and its ability to incorporate real-world heterogeneity without requiring detailed physical models. However, because it lacks an explicit representation of the underlying physical processes, its ability to capture dynamic responses to control signals is limited.

Feasible region-based aggregation. Feasible region-based aggregation characterizes aggregated flexibility by the feasible set of collective power responses subject to device and comfort constraints. Instead of explicitly simulating individual responses or estimating aggregate behavior from statistical patterns, this approach represents the aggregated resource as a compact admissible region, such as a flexibility envelope or a time-coupled feasible set. In this way, aggregation is formulated as a mapping from

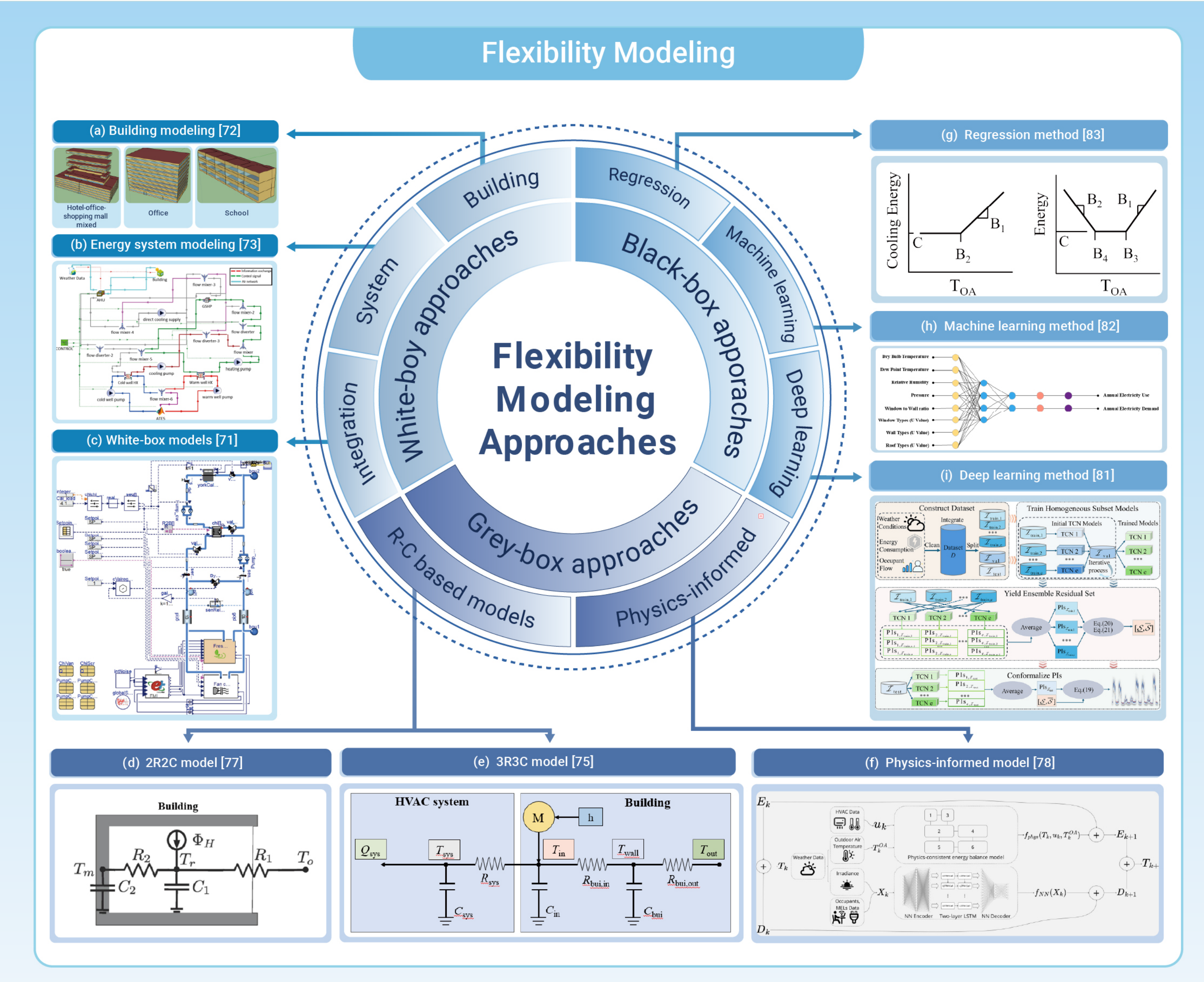

Figure 6. Building-level flexibility modeling approach

heterogeneous building-level constraints to a low-dimensional representation of collective flexibility that can be directly used in scheduling and control.

A key feature of this approach is that aggregate flexibility is represented not as a single scalar capacity, but as a bounded set of achievable responses over time. This allows the model to capture not only the magnitude of adjustable power, but also its temporal coupling, state dependence, and delivery limits within a scheduling horizon. Such representations are therefore particularly suitable for predictive control and dispatch-oriented applications.[85–86] For example, geometric and set-based methods have been used to characterize the aggregate flexibility of thermostatically controlled load populations under operational constraints.[87] More recent studies have further improved tractability by developing tighter inner approximations and structured set representations, such as generalized polymatroids or multi-battery models, thereby achieving a better balance between modeling fidelity and computational efficiency.[88–89]

Despite these advantages, a central challenge in feasible region-based aggregation is how to reduce the high-dimensional feasible set induced by individual-level constraints into a tractable low-dimensional representation while preserving the key temporal and operational characteristics of aggregate flexibility.[90]

Scalability of flexibility analysis

To support policy formulation and grid planning, building flexibility analysis must evolve beyond individual building assessments toward aggregated scales, including building stocks, districts, and national energy systems. At these broader scales, the primary objective shifts from characterizing the flexibility of a single unit to quantifying the collective potential that can be mobilized for system-level grid services. Existing studies have demonstrated the value of such scaling efforts. For example, bottom-up approaches have been used to estimate a nationwide space-heating load-shifting potential of 5.5 GW in Sweden,[91] while another study showed that aggregated non-residential HVAC fans in Hong Kong could provide up to half of the local grid's frequency regulation requirements.[92]

However, scaling flexibility analysis from individual buildings to large-scale systems introduces formidable challenges. Pronounced variations in building characteristics, system configurations, operational patterns, and occupant behavior introduce substantial uncertainty into aggregated estimates.[50] Consequently, probabilistic methods and representative building archetypes are increasingly employed to better capture this inherent heterogeneity and enhance the robustness of large-scale flexibility assessments. To address this, recent studies increasingly adopt representative building archetypes, probabilistic methods, and hybrid modeling frameworks that balance physical consistency with computational scalability. At the same time, improved treatment of uncertainty and the use of open-source benchmarking plat-

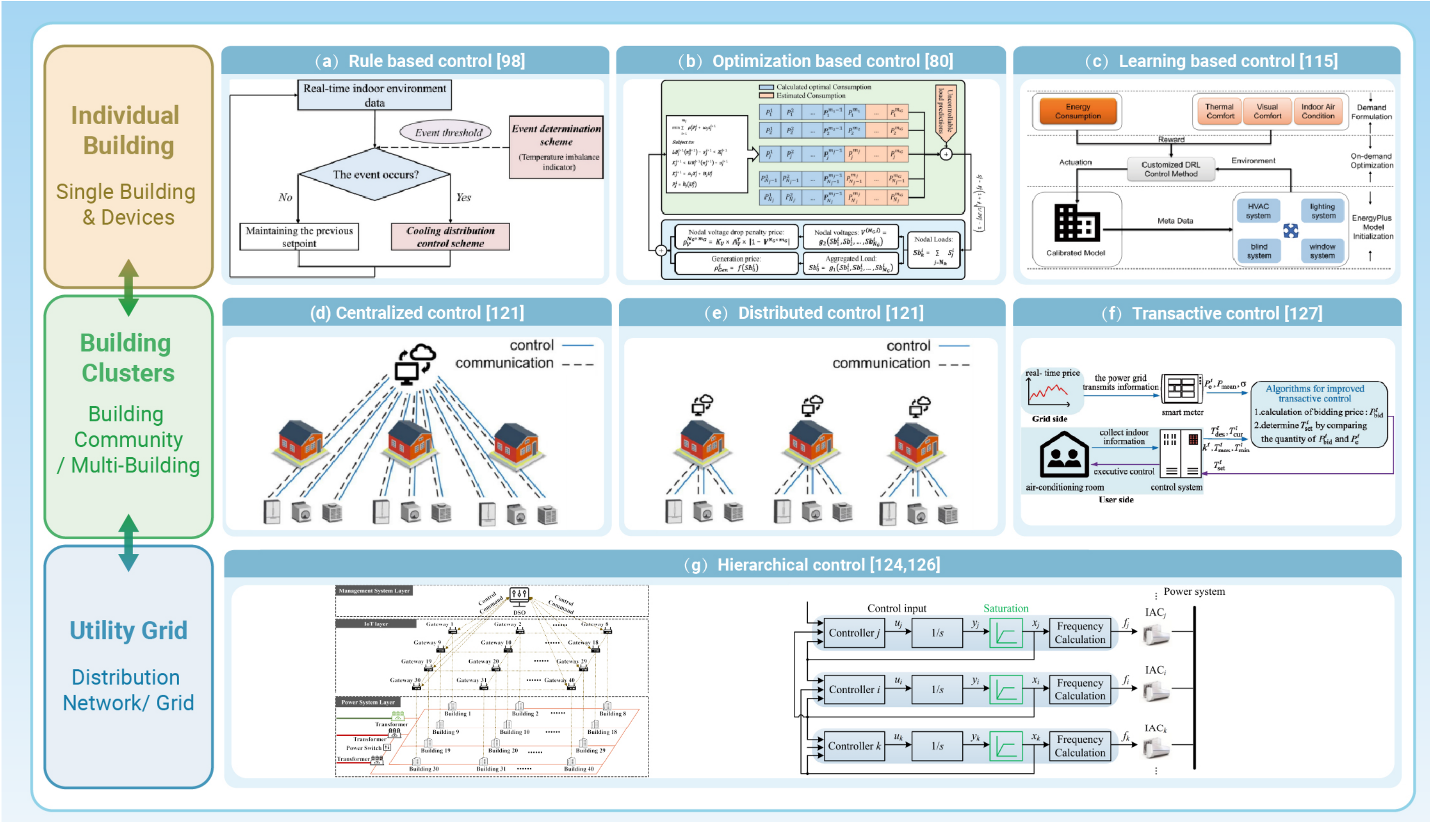

Figure 7. Typical applications of control and coordination strategies across building-level, multi-building, and hierarchical architectures

forms, such as CityLearn,[93] are helping to support more robust and comparable large-scale flexibility assessments.

CONTROL AND COORDINATION STRATEGIES

Effective control strategies are essential for unlocking B2G potential. By translating building flexibility into actionable operational responses, control algorithms allow buildings to respond to external signals while balancing economic performance, occupant comfort, and operational constraints.[94] This section reviews control strategies at three interconnected levels: building-level control, multi-building coordination, and hierarchical grid-interactive architectures. Typical applications across these levels are illustrated in Figure 7.

Building-level control

Building-level control strategies are essential for managing energy consumption and enhancing grid flexibility. This section reviews key control methods, including rule-based, optimization-based, and learning-based controls, highlighting their role in improving energy efficiency and supporting grid services.

Rule-based control. Rule-based control methods typically rely on predefined logic and threshold conditions to regulate loads.[95-97] This approach has a clear structure and low implementation cost, making it suitable for relatively simple scenarios. For example, in time-of-use scheduling, devices adjust their load based on price signals in different time periods, ensuring that high-energy-consuming equipment operates during off-peak hours when electricity prices are lower.[98–99] Predefined rule-based control automatically adjusts equipment load based on conditions set in advance to respond to changing grid demands.[100] Event-driven control, on the other hand, initiates response strategies based on specific events, such as system alarms or demand peaks, to achieve dynamic adjustments.[101] However, these methods often lack predictive capability and struggle to cope with complex pricing environments or multi-constraint optimization problems.[102]

With increasing load variability and the penetration of distributed resources, relying solely on rule-based control methods has become insufficient for refined management. In a more complex energy market, combining advanced optimization or learning algorithms with rule-based control has become a key path to enhancing demand response flexibility and efficiency.

Optimization-based control. Optimization-based control has become a mainstream approach for economic building operation. Model Predictive Control (MPC), due to its receding-horizon optimization framework, is widely applied to coordinate HVAC systems, energy storage, and renewable generation to reduce electricity costs.[103–104]

Studies show that optimization-based control not only reduces electricity expenditures but also supports load following and power regulation, thereby mitigating net load fluctuations.[105] In residential applications, exploiting building thermal inertia has achieved cost reductions exceeding 45% in some cases.[106] When combined with thermal storage technologies such as phase change materials, additional economic benefits can be realized.[107] In commercial and office buildings, more complex operational requirements must be considered, including thermal comfort, cold-chain safety, and equipment lifespan.[108] Existing studies demonstrate that MPC maintains strong adaptability under different climate conditions[109] and demand response scenarios.[110]

Beyond economic objectives, optimization-based control has been extended to support power quality. For voltage regulation, the focus has shifted from single active power adjustment to coordinated active and reactive power optimization.[111] For frequency response, buildings can modulate internal equipment in response to grid frequency signals and function as flexible frequency-responsive loads.[112]

Learning-based control. With improvements in data acquisition, learning-based control methods have gained increasing attention. These approaches train control policies using historical data and can operate without fully accurate physical models.[113–114] Reinforcement learning is widely applied to address dynamic pricing and uncertain operating conditions. Studies indicate that learning-based strategies can gradually improve operational performance and may outperform conventional optimization methods in certain scenarios.[115] Multi-agent learning frameworks have also been introduced to enhance adaptability to complex external signals.

However, learning-based control has limitations in handling physical constraints.[116] Unlike MPC, which enforces hard constraints, deep reinforcement learning typically represents comfort or operational limits as soft penalty terms.[117] In addition, these algorithms often exhibit black-box characteristics and limited interpretability. Their performance is sensitive to hyperparameter tuning and depends strongly on the availability of sufficient training data.

Multi-building coordination

As the scale of building participation increases, individual optimization cannot fully exploit collective flexibility. Coordinated control of multiple buildings has therefore become a key research focus.[104]

Centralized coordination. Centralized coordination relies on a unified scheduling platform that collects operational information from all buildings and performs global optimization. This approach enables system-level power allocation and load balancing. Under high renewable penetration, such approaches demonstrate favorable economic and operational performance. For example, centralized economic MPC applied to building clusters can significantly reduce peak demand and enhance the provision of aggregated flexibility.[118] Centralized deep learning approaches have also been explored to optimize multi-building energy management and achieve global performance improvement under multi-objective settings.[119]

The main advantage of centralized coordination lies in its strong global coordination capability and effective handling of inter-building coupling and uncertainty, which improves reliability in ancillary service provision.[102] However, it requires substantial communication and computational resources and introduces risks related to single-point failures and data privacy.[120]

Distributed coordination. Compared with centralized coordination, distributed coordination offers better scalability and robustness, though convergence speed and communication efficiency remain challenges. Distributed methods allow each building to perform local optimization while exchanging limited information to achieve coordinated decisions. The Alternating Direction Method of Multipliers (ADMM) has been applied to coordinate multi-energy systems in building clusters, reducing overall operating costs while preserving privacy.[121] To address uncertainty and price fluctuations, multi-agent reinforcement learning frameworks have been proposed to enhance system adaptability and achieve peak load reduction.[122] During multi-building dispatch, distribution network constraints such as voltage limits and harmonic requirements must also be satisfied.[123] Recent optimization frameworks incorporate these constraints into the coordination model, reducing system costs while maintaining compliance with technical standards.[124–125]

Transactive control. Transactive control coordinates power exchange among buildings through price signals or local market mechanisms to achieve supply–demand balance. It guides distributed decision-making using economic incentives while improving flexibility, utilization, and user benefits.[126] In multi-building environments, transactive mechanisms improve resource allocation efficiency. For example, peer-to-peer based transactive control enables decentralized energy management within building clusters, reduces operating costs, and enhances local self-sufficiency.[127] Studies show that price-based trading frameworks support demand response and flexibility aggregation in active distribution networks, improving the economic and operational performance of community microgrids.[128] In energy community scenarios, transactive storage coordination mechanisms with dynamic price updates have been shown to balance supply and demand among buildings and provide ancillary services.[129] Despite its potential under high distributed energy penetration, careful design of price update rules and information exchange is necessary to avoid synchronized responses and system instability.[130]

Hierarchical control architectures

Hierarchical grid-interactive architectures establish coordination across device, building, and system layers to reduce the complexity of large-scale scheduling.[125,131] At the device level, hierarchical predictive control has been applied to residential air-conditioning systems, achieving significant reductions in peak demand and electricity costs.[132] At the building level, integrating reserve scheduling, HVAC control, and fan regulation within a unified framework enables accurate frequency tracking while maintaining indoor comfort.[133] At the system level, hierarchical three-layer frameworks, comprising the building, microgrid, and distribution levels, have been developed to coordinate large-scale cluster interactions.[123,134]

Hierarchical structures help decompose complex problems, improve computational efficiency, and maintain overall coordination. A two-stage voltage regulation method coordinating photovoltaic capacity and air-conditioning inverter control has been proposed.[135] The first stage schedules photovoltaic capacity, while the second stage applies MPC to regulate air-conditioning inverters for additional voltage support, improving distribution voltage performance. To address performance degradation under frequent dispatch, response-state modeling has been introduced to limit power deviations and enhance the effectiveness of long-term demand response.[44] Such hierarchical approaches support robust operation under uncertainty and provide a technical foundation for large-scale B2G deployment.

IMPLEMENTATION AND INTEROPERABILITY

The theoretical control strategies discussed in Section 4 require physical and cyber infrastructures to be executed. This execution process relies on the implementation and interoperability of the B2G system. As shown in Figure 8, a comprehensive B2G implementation architecture is built upon a bottom-up framework: hardware infrastructure,[136] communication protocols,[137] and semantic data models.[138] To ensure these bottom-up components work safely together, they must be rigorously validated through hardware-in-the-loop (HIL) testing before real-world deployment.[139] Therefore, this section systematically reviews these four sequential elements to bridge the gap between theoretical algorithms and engineering practices.

Hardware infrastructure

B2G implementation begins with the deployment of physical hardware infrastructures in buildings.[140] These hardware infrastructures act as the fundamental cyber-physical interfaces between the power grid and building demand-side loads.[141] Based on their functionalities, these infrastructures are primarily divided into sensing devices and execution devices.[142] For the sensing devices, smart meters, and Advanced Metering Infrastructure (AMI), bidirectional power flows are measured at the grid connection point.[143] Simultaneously, distributed environmental sensors collect real-time data on indoor temperature, humidity, and occupancy states.[144] Once the comprehensive building states are collected, execution devices are required to physically adjust the electrical loads.[145] Typical execution devices include smart thermostats for HVAC systems, dimmable lighting, and controllable smart plugs.[146] Among them, smart thermostats are particularly important as they unlock the thermal inertia of buildings for demand response.[147] Beyond these traditional building demand-side loads, modern facilities increasingly integrate distributed energy resources.[148] This integration requires smart inverters to serve as advanced execution units. These smart inverters are critically needed in emerging hybrid AC/DC distribution networks to regulate bidirectional active and reactive power flows.[149] To safely coordinate all these diverse and heterogeneous execution units, a central hardware hub is necessary.[150] This central hub is typically the Building Energy Management System (BEMS), which is currently evolving into an edge computing gateway. By utilizing edge computing gateways, the BEMS provides the localized processing power required to run advanced, computationally intensive algorithms like MPC.[151] Ultimately, this localized edge computing capability closes the physical control loop and seamlessly transforms traditional passive buildings into active, flexible prosumers.[152]

Communication protocols

Hardware infrastructures establish the essential physical capability for regulation. However, to fully realize automated building operations, these devices must exchange information through communication networks.[153] These communication networks establish the cyber links necessary to coordinate distributed energy resources across different spatial scales.[154] Based on these spatial scales, B2G communication architectures are typically classified into local area networks within buildings and wide area networks connecting to the grid.[155] Within the building's local area network, traditional wired protocols such as BACnet and Modbus are predominantly utilized. These traditional wired protocols ensure reliable data transmission for centralized Building Energy Management Systems (BEMS). However, as

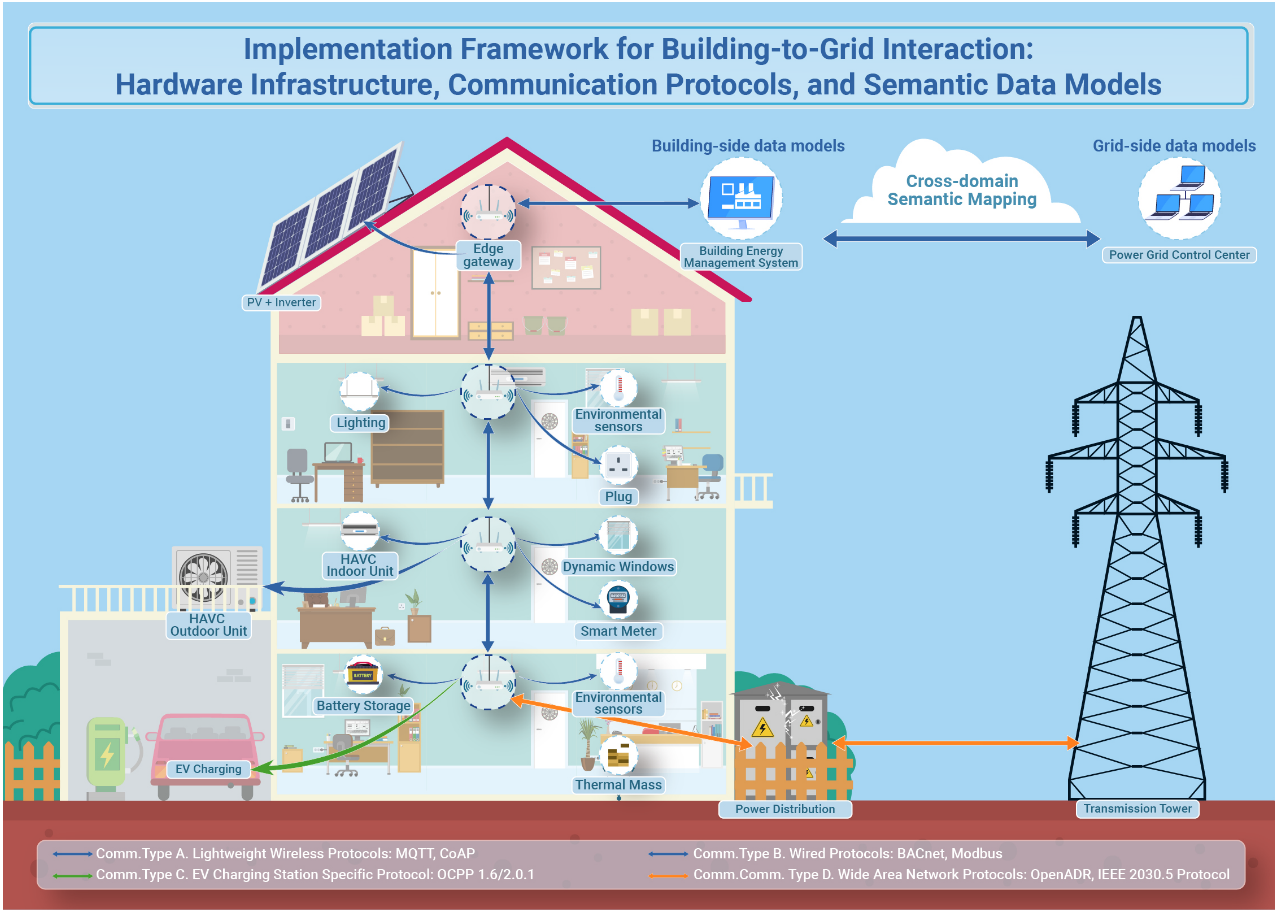

Figure 8. Implementation framework for building-to-grid interaction: hardware infrastructure, communication protocols, and semantic data models (Adapted from Ref.141).

BEMS evolve to manage massive numbers of decentralized IoT devices, traditional polling mechanisms suffer from high latency. To overcome this latency issue in dense IoT environments, lightweight wireless protocols like MQTT and CoAP have been widely adopted. These lightweight protocols facilitate efficient data aggregation at the building edge, paving the way for seamless interaction with the external power grid. For this external grid-to-building interaction, OpenADR and IEEE 2030.5 serve as the primary standardized wide-area protocols. These standardized protocols enable utility companies to securely dispatch pricing signals and demand response events to smart buildings. The successful execution of these dispatched events strictly depends on the real-time performance of the underlying communication channels. Specifically, performance degradation issues, such as time-varying communication delays, can severely undermine the stability of advanced distributed control algorithms.[156] Beyond stability concerns caused by communication delays, the open nature of these networks exposes the B2G system to significant cybersecurity threats.[157] These cybersecurity threats, particularly false data injection attacks (FDIAs), can manipulate control signals and disrupt the state estimation of the distribution network.[158] Therefore, implementing robust encryption and detection frameworks within the communication protocols is mandatory to ensure the secure operation of the entire cyber-physical system.[159]

Data models

The successful transmission of raw data via communication protocols is merely the foundational step. For effective interaction, this transmitted data must also be correctly interpreted by both building and grid systems. This correct interpretation relies on the establishment of semantic interoperability between the two domains. Currently, achieving semantic interoperability is hindered by the fundamentally different data structures used in buildings and power grids.[141] In the power grid sector, data structures are primarily standardized by the Common Information Model (CIM) and IEC 61850.[160] These grid-oriented standards strictly define electrical nodes, topological connections, and power flow properties.[161] Conversely, in the building sector, properties are traditionally organized around spatial layouts and thermal equipment.[162] To standardize these building-specific properties, ontology-based metadata schemas have been increasingly adopted.[163] The most prominent adopted schemas include the Brick Schema and Project Haystack.[164] These prominent schemas utilize the Resource Description Framework (RDF) and Web Ontology Language (OWL) to construct machine-readable knowledge graphs. Once constructed, these building knowledge graphs must be dynamically mapped to the grid-side CIM.[165] This cross-domain semantic mapping creates a unified cyber-physical data framework for the entire B2G architecture. A unified data framework enables buildings to automatically declare their flexibility capacities and operational constraints to utility operators. This automated declaration is a fundamental prerequisite for the scalable deployment of data-driven forecasting and advanced control algorithms. Without such standardized data inputs, migrating these algorithms across different buildings would require extensive manual reconfiguration.[145] Ultimately, these unified semantic data models form the core foundation of Digital Twins, which provide a comprehensive virtual environment for seamlessly managing and optimizing B2G interactions.

Hardware in the Loop

While unified semantic data models establish the structural foundation for virtual modeling, these virtual models must be rigorously validated against real-world physical dynamics.[166] This rigorous validation is traditionally performed using pure software simulations.[167] However, pure software simulations struggle to accurately capture the hardware latency and complex cyber-physical interdependencies inherent in modern power systems.[167] To comprehensively analyze these cyber-physical interdependencies and identify potential vulnerabilities, advanced analytical techniques such as Hardware-in-the-Loop (HIL) and co-simulation are essential.[168] HIL simulation effectively bridges the virtual and physical domains by interfacing real hardware components with a simulated grid environment.[169] Within this interfaced environment, Controller HIL (CHIL) is widely deployed to evaluate the execution logic and communication speed of physical building automation

Table 2. Representative cases under different market mechanisms for building flexibility

Market Type	Mechanism description	Representative application	Representative regions	Ref
Retail Market	Load and storage optimization under time-of-use or real-time pricing to reduce electricity costs	Building self-optimization or ESCO managed services	Global (common in CN, US, EU, AU , etc.)	[11]
Capacity Market	Compensation based on committed or available capacity; aggregators pool distributed resources for market bidding and revenue allocation	PJM/NYISO	United States	[186]
Ancillary services market	Performance-based compensation for grid support; aggregators manage dispatch, scheduling, and revenue allocation	CAISO/PJM/NYISO/ERCOT	United States	[184]
		Next Kraftwerke frequency regulation services	Belgium	[187]
		Enel X summer 7 GW demand response	Japan	[188]
Local / peer-to-peer trading	Buildings exchange electricity through local trading platforms to improve self-consumption and reduce network-related costs	Power Ledger	Australia	[188]
		Vandebron	Netherlands	
		Piclo	United Kingdom	

controllers.[170] Beyond testing controllers, Power HIL (PHIL) directly incorporates actual power devices, such as smart inverters and HVAC chillers, into the simulation loop.[171] Incorporating these actual power devices allows researchers to directly observe their transient electrical impacts on the distribution network.[172] To fully evaluate these electrical impacts alongside building thermal behaviors, HIL is increasingly integrated with cross-domain co-simulation platforms. These co-simulation platforms typically couple power system solvers, such as RTDS, with building thermodynamic engines, like EnergyPlus. Coupling these diverse solvers enables the panoramic reproduction of demand response events, from grid dispatch signals to indoor temperature variations. During these reproduced demand response events, customized IoT-based HIL architectures have proven particularly effective for validating fast ancillary services, such as frequency regulation.[173] Validating these fast services requires the HIL platform to accurately replicate the communication delays and vulnerabilities inherent in extensively interoperable grid infrastructures. Identifying these vulnerabilities through HIL stress testing is crucial for developing resilient B2G control strategies against extreme cyber-physical threats.[174] Ultimately, this comprehensive HIL validation is the final indispensable step in transitioning theoretical B2G algorithms from laboratory prototypes to safe engineering deployments.[175]

In summary, the successful deployment of B2G systems requires a comprehensive technical implementation across the cyber-physical domain. This comprehensive implementation is built upon four sequential pillars: physical hardware, communication networks, semantic data models, and hardware-in-the-loop (HIL) validation. Specifically, hardware provides the physical execution capacity, protocols and data models establish the semantic cyber links, and HIL validation ensures the operational safety of these integrated components. However, achieving operational safety through these technical solutions is not sufficient for the large-scale commercialization of B2G.[176] This large-scale commercialization is currently hindered by substantial non-technical barriers, such as the lack of economic incentives and regulatory frameworks. To overcome these non-technical barriers, the following section (Section 6) will shift to a macroscopic perspective. This macroscopic perspective will explore how to drive widespread adoption through rational market transaction mechanisms, comprehensive policy incentives, and mandatory industry codes.

POLICY, MARKET AND STANDARDS

Governments worldwide are increasingly introducing policies and regulatory measures to reduce institutional and technical barriers and to enable building flexibility resources to participate more actively in power systems. At the same time, market design and standardization are playing an increasingly important role in determining how such flexibility can be accessed, valued, and coordinated. This section reviews recent developments in policy, market mechanisms, and standards related to the integration of building flexibility.

Policy implications

Common policy instruments include financial incentives, electricity pricing reform, smart meter deployment, flexibility targets, building code revision, and market integration. Across different countries and regions, these measures are being translated into targeted initiatives to support building-grid integration.

In the United States, the Department of Energy has advanced the concept of grid-interactive efficient buildings through a series of technical reports, highlighting the role of buildings as flexible distributed energy resources for grid support.[177] In the European Union, recent electricity market reforms have strengthened policy support for demand-side flexibility,[178] with particular emphasis on dynamic pricing, digital infrastructure development, and broader market access. Under this policy framework, building demand response is expected to play a growing role in wholesale, capacity, and ancillary service markets by 2027. In China, policy support for building-grid interaction has emerged through both demand-side management and low-carbon building initiatives.[179–180] These efforts have focused on improving building flexibility and strengthening coordination between building energy systems and the grid. In Japan, ongoing policy reforms have emphasized smart meter deployment, time-varying pricing, and capacity compensation mechanisms to support demand response participation.[181] In South Korea, automatic demand response pilot programs have focused on digital infrastructure and incentives to enable automated building flexibility.[182]

Overall, these developments indicate a broader shift from exploratory policy support toward more structured and market-oriented approaches to building-grid integration. Nevertheless, unlocking the full potential of building flexibility will require stronger alignment among regulatory design, implementation mechanisms, and cross-sector coordination.

Market mechanisms

Building flexibility resources can derive economic value from four broad pathways: retail price arbitrage, capacity compensation, ancillary service provision, and local energy trading. These pathways differ in their compensation logic and revenue structure, while representative projects and countries are summarized in Table 2.

The most fundamental value stream comes from retail tariff structures. Under time-of-use or real-time pricing schemes, buildings can reduce electricity costs by optimizing on-site load operation or dispatching energy storage.[176] In practice, such projects may be implemented either by building owners themselves or by third-party service providers.

The capacity remuneration mechanism provides a more stable revenue option for building flexibility resources where demand-side participation is permitted. Compensation is typically linked to committed or available capacity, resulting in a more predictable and longer-term revenue structure. Aggregators can pool multiple building resources to participate in the market and distribute revenues among participants, thereby strengthening the investment case for storage and advanced control systems. Evidence from the United States and Europe suggests that aggregated demand-side resources are increasingly being incorporated into capacity-related mechanisms.[183] Ancillary service markets provide further revenue opportunities by compensating building flexibility resources for active grid support. Revenues in these markets depend more directly on service delivery performance, particularly response speed, accuracy, and reliability. Participation is commonly enabled

Table 3. Key Instruments for Building-to-Grid Integration

Functional Layer	Region/Country	Instrument / Standard	Key Function / Relevance to B2G
Foundational Efficiency Standards (Establish the low-energy baseline)	China	GB 50189-2015 (Public Building Efficiency)	Mandates minimum HVAC and lighting efficiency, creating a low-energy baseline.
		GB/T 50034-2024 (Lighting Design)	Recommend intelligent lighting controls, enabling lighting-based demand response.
		GB 50736-2012 (HVAC Design)	Mandates sub-metering and encourages variable frequency drives for precise load control.
		JGJ/T 334-2014 (Building Automation)	Provides framework for integrated control systems to receive and execute grid commands.
	United States	IECC (2024)	Legal baseline for minimum envelopes, HVAC, and lighting performance.
		ASHRAE Standard 90.1-2022	Mandates controls and monitoring infrastructure (lighting, HVAC, metering) essential for DR.
	European Union	EPBD Framework	Requires national methodologies that consider Building Automation and Control Systems (BACS).
	Japan	Building Energy Efficiency Act	Sets annual consumption limits, forcing integrated optimization across all systems.
	Australia	National Construction Code (2022)	Requires simulation-based verification that system combinations meet energy targets.
Grid-Interaction Codes & Standards (Govern connection, communication, and response)	China	GB 51368-2019 (Building PV Systems)	Mandates power quality monitoring, safety disconnection, and low-voltage ride-through for inverters.
		GB/T 51350-2019 (Nearly Zero-Energy Buildings)	First national standard to explicitly *encourage* grid interaction (peak load reduction/shifting).
		GB/T 44241-2024 (Virtual Power Plants)	Defines response, communication, and control requirements for buildings to participate in VPPs.
	United States	ASHRAE Standard 189.1-2020	Mandates whole-building metering and provides guidance on responding to grid signals.
		California Title 24 (2022)	Mandates PV systems and *automated* demand response (ADR) capable of receiving utility signals.
	European Union	EPBD 2024/1275	Most comprehensive framework: mandates zero-emission, grid-interactive buildings with solar deployment and the Smart Readiness Indicator (SRI).
	Germany	EnWG & EEG (2023)	Provides provisions for communication protocols and data exchange for flexible electricity trading.
	Japan	Next-Generation Housing Standard	Incentivizes HEMS and battery storage for grid coordination and resilience (islanding capability).
	UK	Building Regulations Part S (2022)	Mandates smart EV charging infrastructure, creating foundation for future V2G applications.
	Australia	AS/NZS 4777.2:2020	Grid-connection standard for inverters, focusing on anti-islanding, power factor, and voltage control.
	South Korea	KS F 1800 series (Building Energy Management System)	Foundational BEMS standards enabling core GEB functionality.
Rating Systems (Quantify and certify flexibility)	European Union	Smart R eadiness Indicator (SRI)	Measures and certifies (A-G rating) a building's capacity to adapt its operation to grid and occupant needs across nine technical domains. Makes flexibility measurable.
	United States	ASHRAE GEB Resource Guide (2023)	Technical guidance for designing grid-interactive buildings, establishing a foundation for future rating criteria.
	Japan	HEMS-oriented Certification	Tiered certification for homes based on demonstrated capability for automated optimization and grid coordination.

through aggregators, often in combination with fast-response storage and advanced control technologies. Relevant examples can be found in Europe, Japan, and the United States.[184]

At the local level, peer-to-peer trading and other community-based energy exchange arrangements provide additional revenue opportunities for building flexibility resources. By enabling local electricity exchange, these arrangements can improve self-consumption and create additional economic value for participating buildings. Their operation typically relies on platform-based matching and settlement, with revenues captured through transaction fees or revenue-sharing models. Pilot cases in Australia and several European countries highlight the potential of this approach.[185]

In sum, the market value of building flexibility is shifting from simple electricity cost savings to more diversified, stacked revenue streams. This trend improves economic potential but also raises new challenges related to revenue coordination, risk sharing, and fair market access across multiple participation pathways.

Codes, standards and ratings

B2G integration is supported by a layered ecosystem of codes, standards, and rating systems, which together provide the enabling conditions for buildings to act as grid resources. These frameworks define not only the minimum technical requirements for building performance, but also the broader conditions under which buildings can interact safely, responsively, and verifiably with power systems. Representative standards and their main roles are summarized in Table 3.

Building codes and minimum efficiency standards establish the low-energy and well-instrumented building stock that underpins flexibility provision, making flexibility both technically available and economically meaningful (e.g., GB 50189-2015;[189] GB 50736-2012;[190] IECC;[191] ASHRAE 90.1;[13] EPBD;[192] Japan's Building Energy Efficiency Act;[193] Australia's NCC[194]). Interconnection and power-quality standards define how on-site generation and storage systems can be safely integrated and remain supportive during disturbances (e.g., GB/T 51368-2019;[195] AS/NZS 4777[196]). Standards related to communication and automated response increasingly require advanced metering, controllability, and demand response capabilities, enabling buildings to receive signals and execute verifiable actions (e.g., ASHRAE Standard 135;[197] ASHRAE 189.1;[198] California Title 24;[199] EPBD;[192] Next-Generation Housing Standard[200]). At a higher level, aggregation and virtual power plant specifications define interface, control, and performance requirements for portfolios of distributed resources, enabling buildings to participate in grid services as aggregated assets (e.g., GB/T 44241-2024[201]). Meanwhile, emerging rating systems and certification frameworks are beginning to convert grid interactivity into measurable and comparable indicators, bridging technical readiness with compliance and potential market valuation (e.g., EPBD;[192] Next-Generation Housing Standard;[200] ASHRAE Grid-Interactive Buildings for Decarbonization: Design and Operation Resource Guide[202]).

Taken together, the global trend is shifting from prescriptive component compliance toward verifiable system-level capability. The scope of standardization is also expanding beyond the building boundary to include DERs, EV infrastructure, and grid communication, reflecting the inherently cross-sector nature of B2G.[192,201,203-205]

FUTURE CHALLENGES AND OUTLOOK

By systematically synthesizing the multi-dimensional landscape of Building-to-Grid (B2G) integration, this review formulates a holistic framework for collaborative energy governance. Fundamentally, the built environment is transitioning from a passive energy sink into an active, grid-interactive asset portfolio. However, transforming building flexibility into a reliably dispatchable and monetizable grid resource requires overcoming critical hurdles across several key dimensions:

- Flexibility Characterization and Grid-Service Alignment: While buildings can deliver supportive services across diverse temporal scales, mapping these capabilities to dynamic grid requirements remains challenging. Future efforts must prioritize standardizing flexibility metrics and advancing probabilistic quantification models that strictly adhere to occupant comfort and indoor air quality constraints.
- Control Paradigms and Cyber-Physical Resiliency: The field is definitively shifting from isolated, rule-based logic toward robust, hierarchical coordination. To scale these algorithms safely, operational frameworks must evolve beyond building-centric optimization to constraint-aware coordination that explicitly internalizes distribution network limits. Furthermore, this transition necessitates a seamless cyber-physical infrastructure, demanding universal semantic data models and rigorous hardware-in-the-loop (HIL) validation to mitigate vulnerabilities.
- Ecosystem Governance and Market Design: Macroscopic adoption requires transitioning from prescriptive component compliance to verifiable, performance-based capabilities. Unlocking sustained participation hinges on the implementation of mature market mechanisms that offer transparent baseline methodologies, performance-based compensation, and fair risk-sharing arrangements across aggregators, utilities, and prosumers.

B2G integration signifies a profound paradigm shift: replacing the historical rigidity of energy flows with the dynamic flexibility of information flows. The built environment is evolving from a collection of isolated demand nodes into a decentralized, self-organizing ecosystem of proactive cyber-physical agents. By harmonizing localized occupant needs with macroscopic systemic resilience, building flexibility serves as a critical buffer for the modern grid. This transformation offers a highly cost-effective, scalable pathway to stabilize power systems under high renewable penetration, fundamentally redefining the role of urban infrastructure in actualizing a resilient, zero-carbon global energy ecosystem.

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AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.