A State-of-the-art Review of Multi-method Approaches for Building Energy Flexibility Evaluation

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Manuscript submitted June 26, 2026; accepted August 24, 2026; published September 23, 2026.
doi: 10.12720/sgce.15.2.79-91

Abstract: The increasing integration of renewable energy sources and the electrification of building sectors have created significant operational challenges for modern power systems, particularly at the distribution level. Buildings equipped with flexible assets, such as electric vehicles, heat pumps, smart appliances, HVAC and thermal mass, offer significant opportunities to enhance grid flexibility through demand response. This paper provides a comprehensive state-of-the-art review of multi-method approaches for quantifying and leveraging building energy flexibility, with a specific emphasis on optimization-based, simulation-based, data-driven/Artificial Intelligence (AI), and rule-based approaches. For each category, the characteristics, strengths, and limitations are summarised. The review highlights how each method can model or predict flexibility under varying conditions and underscores the necessity of tailoring choices to specific applications. An evaluation framework that integrates multiple methods and emphasises human-centric control is discussed. The findings reveal emerging trends, including the significance of explainable artificial intelligence and the real-world validation of flexibility schemes. Research gaps are identified, and future directions are suggested, such as integrating occupant behavior models and deploying hybrid methods in smart grids. These insights offer guidance for researchers and practitioners seeking to advance building energy flexibility.

Keywords: building energy flexibility, data-driven/Artificial Intelligence (AI) approaches, optimization-based methods, simulation-based methods, rule-based methods

1. Introduction

The global transition to low-carbon energy systems has resulted in a rapid increase in the integration of renewable energy sources, including solar photovoltaics and wind power [1, 2]. Although these resources are essential for reducing greenhouse gas emissions, their inherent intermittency and limited predictability present significant challenges for power system operation, particularly in maintaining real-time balance between electricity supply and demand [3, 4]. Simultaneously, the building sector is experiencing substantial electrification due to the widespread adoption of electric vehicles, HVAC systems, heat pumps, and smart home technologies [5–7]. Buildings, which have traditionally functioned as passive energy consumers, are now increasingly equipped with controllable loads and distributed energy resources, enabling active participation in grid operations [8, 9]. As a result, buildings have become both a major contributor to grid stress and a promising source of demand-side flexibility [3, 5]. In renewable-rich power systems, two critical challenges affect residential energy systems. First, the intermittency of renewable resources frequently causes mismatches between electricity generation and consumption, resulting in voltage and frequency deviations in distribution networks with high residential penetration [2, 10]. These imbalances increase reliance on reserve generation and elevate overall operational costs [1]. Second, peak demand, which typically occurs during morning and evening hours, imposes significant stress on grid infrastructure [11]. The concurrent operation of electric vehicle charging, heating systems, and household appliances often leads to transformer overloading, network congestion, and accelerated asset degradation [12]. Traditional grid reinforcement strategies are capital-intensive and slow to implement, rendering them insufficient as standalone solutions to these challenges [2]. Energy flexibility in the built environment is determined by five primary factors: occupant behavior, building characteristics, technology and HVAC systems, control and optimization mechanisms, and external conditions [13]. Occupancy and customer behavior introduce uncertainty due to unpredictable energy consumption patterns and limited data availability, significantly impacting the actual potential for energy flexibility [13]. Building characteristics, including thermal mass, insulation levels, material properties, and heat-loss rates, directly affect the potential for thermal storage and load shifting. Technology and HVAC systems provide the means to deliver flexibility through thermal and electrical storage, on-site generation, and rapid response capabilities. Control and optimization mechanisms, such as Building Energy Management Systems (BEMS) and associated algorithms, interpret grid signals and respond accordingly. The effectiveness of these tools depends on the quality of real-time data and the accuracy of forecasts. External factors, including weather variability, price fluctuations, and grid interactions, also play a critical role in determining the availability and economic viability of flexibility services.

Current demand response implementations predominantly utilize rule-based or static optimization strategies, which are often inadequate for addressing uncertainty, real-time grid conditions, and dynamic user behavior [14, 15]. Additionally, much of the existing literature assumes perfect forecasts, simplified occupant behavior, or centralized control architectures, thereby constraining scalability and limiting real-world applicability [16, 17]. These challenges underscore the necessity for intelligent, adaptive, and autonomous control mechanisms that can enhance building energy flexibility while maintaining user comfort and privacy [18]. In response to these challenges, this paper provides a comparative review of energy flexibility evaluation approaches in buildings. The review examines the role of buildings as flexibility providers within modern power systems and systematically compares rule-based, optimization-based, simulation-based, and AI-driven energy management methods [19]. Furthermore, it analyzes the application of machine learning, deep learning, and reinforcement learning techniques in building demand response. The paper also identifies key limitations, research gaps, and open challenges in current methodologies, and highlights emerging trends in edge AI and real-time smart building control to facilitate the translation of academic research into practical implementation.

2. Literature Review

The reviewed literature is organized around the sources of energy flexibility in buildings and the control and decision-making approaches used to exploit this flexibility, enabling systematic comparison across methodologies and applications. Buildings are widely recognized as significant contributors to demand-side energy flexibility due to the presence of controllable electrical and thermal loads [20]. Several studies define energy flexibility in buildings as the ability to modify electricity consumption in terms of timing, magnitude, or duration without violating comfort constraints [21]. Recent research has examined a range of methodological approaches, such as optimization-based frameworks, simulation-based analyses, data-driven artificial intelligence techniques, and rule-based control strategies. These methodologies vary in modelling complexity, computational requirements, adaptability, and potential for deployment. This section presents a critical review of five representative studies published between 2021 and 2025.

Pedram *et al.* [3] reviewed a wide array of methodologies for managing building energy flexibility resources, encompassing optimization-based, artificial intelligence-driven, and hybrid control approaches. The study offers a comprehensive overview of flexibility resources, control architectures, and implementation challenges in both residential and commercial buildings. However, the review mainly synthesizes existing knowledge and provides limited quantitative benchmarking across methodological categories. Fotouhi Ghazvini *et al.* [22] introduced a two-stage demand-side management framework that coordinates flexible energy resources using optimization techniques. This method efficiently schedules household loads, enhancing operational efficiency while adhering to system constraints. However, its effectiveness relies on accurate forecasting and centralized optimization assumptions, which may constrain practical scalability. Li *et al.* [20] examined the flexibility potential of building thermal inertia through a simulation-based robust optimization framework. The findings indicate that thermal energy storage within building structures can enable substantial load-shifting without reducing occupant comfort. Nevertheless, the results are highly dependent on simulation assumptions and the accuracy of the thermal building model. Petrucci *et al.* [23] developed a data-driven methodology to characterize energy flexibility by leveraging smart thermostat data, clustering techniques, and predictive control concepts. This framework facilitates large-scale flexibility assessment and supports aggregation strategies for demand response applications. However, the approach depends on extensive high-quality datasets and may encounter implementation challenges in data-limited environments. Li *et al.* [5] reviewed methods for characterizing energy flexibility and examined the role of rule-based control strategies in energy management systems. The study emphasizes the simplicity, transparency, and practical implementation benefits of rule-based approaches for flexibility activation. However, these methods typically demonstrate limited adaptability under dynamic operating conditions and when user behavior is uncertain.

3. Methodology

A systematic literature selection approach was employed to identify and analyze relevant studies on energy-flexibility-method-based evaluation in buildings. The paper selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency, reproducibility, and methodological rigor. Relevant studies were identified through major scientific databases, including IEEE Databases, Scopus, and Web of Science. The search strategy utilized combinations of keywords such as “energy flexibility”, “smart home energy management”, “building energy”, “demand response”, “optimization,” “simulation”, “data-driven”, “artificial intelligence”, and “rule-based control”, and “method-based energy flexibility evaluation”. The terms were combined using Boolean operators according to the search functionality of each database. A representative search structure was: (“energy flexibility” OR “building energy flexibility”) AND (“building” OR “smart home”) AND (“optimization” OR “simulation” OR “data-driven” OR “artificial intelligence” OR “rule-based”). Only peer-reviewed journal articles and conference papers published in English were considered. Duplicates were removed, and a total of 200 papers were screened. The review focused on the 2020–2026 reference interval; therefore, older records were excluded. A total of 120 reports could not be retrieved due to lack of access to full papers, such as paywalls, inaccessible links, conference abstracts, or missing documents. Exclusion criteria included non-original research (i.e., reviews), studies not pertaining to multi-method-based energy flexibility, and those not providing substantial application information. In total, 60 articles were analyzed in addition to papers describing the theoretical background.

The study selection process is depicted in the PRISMA flow diagram (Fig. 1), which outlines the sequential stages of identification, screening, eligibility assessment, and final inclusion of studies. Table 1 summarizes the inclusion and exclusion criteria used during the selection process, detailing the application domain, methodological content, reported outcomes, publication characteristics, and language.

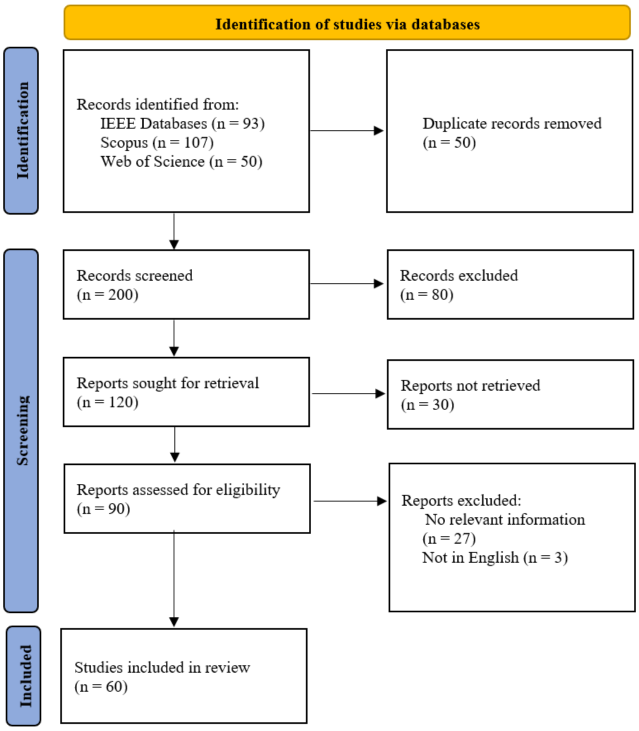

Fig. 1. PRISMA flow diagram of the review's identification, screening and inclusion process.

Table 1. Inclusion and Exclusion Criteria for Study Selection

Criteria	Inclusion	Exclusion
Application domain	Research that concentrates on energy flexibility, demand response, or the way that flexible energy resources are operated in buildings.	Topics unrelated to building energy flexibility.
Content	Studies that present, apply, or assess approaches to building energy flexibility based on optimization, simulation, data-driven or AI-based methods, rule-based methods, or a combination of these.	Research that lacks adequate methodological details or general energy management without evaluating the flexibility of building energy systems.
Outcomes	Studies that evaluate flexibility-related outcomes such as reductions in peak demand, costs, energy savings, flexibility potential, and control performance.	Studies that fail to report flexibility outcomes for methodological comparison.
Publication year	2020–2026	Outside the specified range
Language	English	Non-English

4. Quantification Method of Building Energy flexibility

The principal methodological approaches for quantifying and operationalizing energy flexibility in buildings can be grouped into four broad categories: optimization-based, simulation-based, data-driven or AI-based, and rule-based approaches. Fig. 2 illustrates the assessment, control, and translation of energy flexibility in buildings into demand response actions. Optimization-based methods utilize mathematical programming, such as linear programming, Mixed-integer Linear Programming (MILP), or Model Predictive Control (MPC), to schedule loads and resources for cost or peak-reduction objectives [19]. Simulation-based methods employ detailed physical or stochastic models, including EnergyPlus and TRNSYS, to quantify flexibility potential under various conditions. Data-driven or AI-based methods apply machine learning or statistical models, such as reinforcement learning and neural networks, to predict or control flexibility using historical data [24]. Rule-based methods use heuristic or expert rules, including if-then controllers and semantic rules, to implement flexibility strategies [25]. Each approach produces metrics such as peak reduction, load-shifted energy, ramp rates, or economic savings, and each possesses distinct strengths and limitations. Table 2 presents a comparison of the underlying techniques, required data, time horizons, and representative studies associated with each methodological approach.

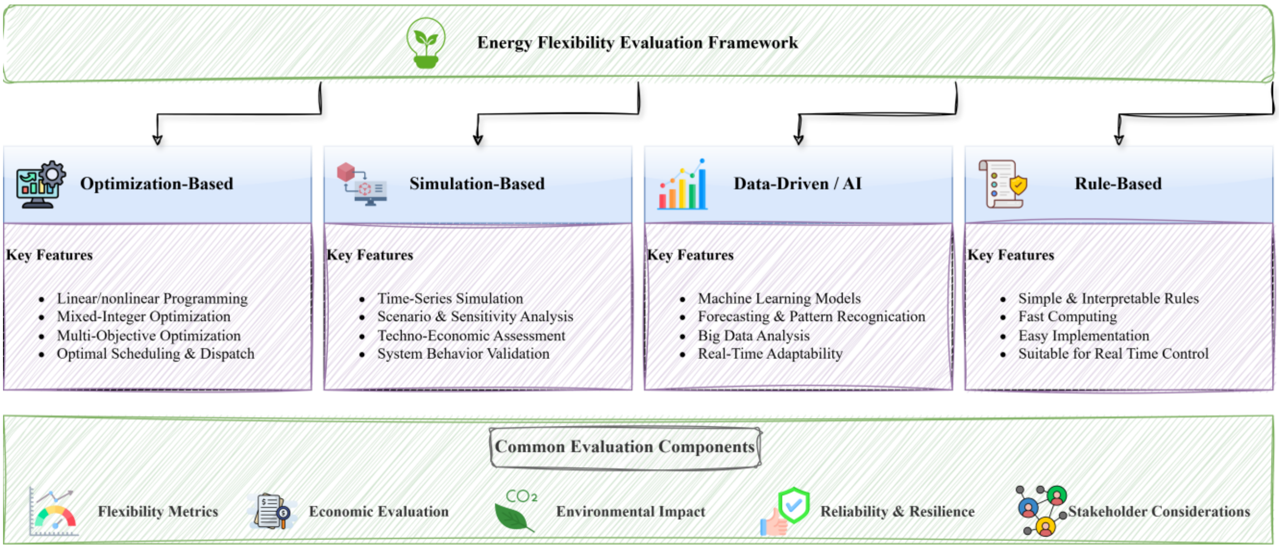

Fig. 2. Energy flexibility evaluation framework in buildings.

Table 2. Characteristics of Energy Flexibility Quantification Approaches

Method	Techniques	Data Requirements	Computational Complexity	Suitable Application Scale	Time Horizon	Reference
Optimization-based	MILP, MPC, dynamic programming	Detailed building model (thermal network, HVAC, occupant schedules), electricity prices, weather forecasts	High-Expands quickly with decision variables, binary states, constraints and number of buildings	Device, single building, cluster of buildings; large scale use generally requires decomposition	Typically, hourly to daily schedules	[15, 19, 26]
Simulation-based	Thermal modelling, scenario analysis, synthetic validation	Building geometry and materials, HVAC specs, weather data, occupancy patterns	Medium-High-according to model resolution, simulation period and number of scenarios	Single building to building clusters; district scale studies possible with simplified models	Sub-hourly to yearly	[20, 27]
Data-driven/ AI-based	Regression, ANN, SVM, clustering, RL, hybrid AI	Historical energy use, weather, price data; sensor and occupancy logs; training dataset	Low-Medium for inference, Medium-High for training	From single building to large building aggregators depending on data and architecture	Seconds/minutes to days	[23, 24, 28]
Rule-based	Fixed schedules, threshold rules	Current sensor readings, tariff signals, historical data	Low-Rules are assessed directly, without repeated optimization or model training	Device and single-building control	Real-time to hourly control	[25, 29, 30]

4.1. Optimization-Based

Optimization-based approaches are extensively utilized to quantify and leverage residential energy flexibility due to their capacity to explicitly represent objectives, constraints, and system dynamics. These methods frame flexibility as an objective-driven scheduling or control problem subject to constraints. Typically, mathematical programming or control theory techniques, such as linear programming, mixed-integer programming, and model predictive control, are employed to derive cost- or energy-optimal operating schedules [29]. Mixed-integer Linear Programming (MILP) is among the most widely adopted techniques for residential energy management and demand response [26]. MILP is frequently applied to schedule household appliances, electric vehicle charging, battery operation, and heating systems, with the aim of minimizing electricity costs or peak demand. MILP formulations facilitate precise modeling of binary on/off decisions, comfort constraints, and power limits. Nevertheless, several studies indicate that MILP-based approaches are characterized by high computational complexity and limited scalability when deployed across large numbers of households or in real-time control scenarios [15]. Model Predictive Control (MPC) represents another prominent optimization-based method in residential energy systems [22]. MPC utilizes rolling-horizon optimization, enabling control decisions to be updated as new information becomes available. This approach is particularly effective for managing thermal loads, such as heat pumps and space heating systems, as it can incorporate system dynamics and comfort constraints [12]. Despite these strengths, MPC-based methods are highly dependent on accurate system models and short-term forecasts, which constrains their robustness under uncertainty. Furthermore, centralized MPC architectures encounter scalability challenges in large residential networks. To address computational limitations, some studies implement heuristic or metaheuristic optimization methods, including genetic algorithms and particle swarm optimization, for energy scheduling [19]. These approaches can yield near-optimal solutions with reduced computational effort compared to exact optimization in certain cases. However, they do not guarantee optimality and often necessitate extensive parameter tuning, which can hinder reproducibility and robustness [17].

In summary, optimization-based methods are fundamental to quantifying energy flexibility in buildings, as they offer structured and interpretable decision-making frameworks. The literature indicates that optimization-based approaches, particularly linear and MPC formulations, are the most mature and widely implemented, making them suitable for safety- and comfort-critical applications. A field study of an all-electric school reported increases in energy flexibility of 36% during unoccupied periods and 61% during occupied periods while maintaining acceptable occupant-comfort conditions [31].

4.2. Simulation-Based

Simulation-based approaches are essential for assessing energy flexibility in buildings, as they enable the evaluation of flexible loads, building thermal behavior, and demand response strategies under controlled scenarios. These methods employ detailed physics-based building models and scenario analyses to quantify flexibility. Tools such as EnergyPlus, TRNSYS, Modelica, and co-simulation frameworks are used to simulate building dynamics under varying control or grid conditions [27]. Simulation-based methods can capture complex interactions, including multi-energy systems and storage, and generate energy profiles or flexibility metrics such as peak shaving and load-shifting potential. A substantial body of research quantifies flexibility through simulations of building thermal inertia, domestic hot water systems, and appliance scheduling under diverse operating conditions [5]. Thermal mass is frequently modeled as a flexibility resource, enabling preheating, delayed heating, or temporary load shifting without immediate occupant discomfort [10]. These simulation environments facilitate the assessment of flexibility potential across different weather conditions, occupancy patterns, and control horizons. Additionally, simulation-based studies are widely used to evaluate the performance of optimization-based and AI-based controllers prior to deployment. In many instances, reinforcement learning, Model Predictive Control (MPC), and scheduling algorithms are validated exclusively in synthetic or semi-synthetic residential settings, often with simplified assumptions regarding user behavior, renewable generation, and device availability [17]. Consequently, simulation-based analysis is valuable for benchmarking methods but is less reliable for demonstrating real-world robustness.

A primary advantage of simulation-based approaches is their capacity to facilitate detailed what-if analyses without incurring deployment costs or operational risks. However, a significant limitation is the strong dependence of results on modeling assumptions. Simplified representations of user behavior, idealized forecasts, and limited incorporation of real-world disturbances can result in overestimation of flexibility potential and overly optimistic control performance. EnergyPlus-based simulations reported peak-load shifting exceeding 80% in Atlanta, Buffalo, and New York City for control horizons of 9–12 h, and up to 70% in Tucson, while maintaining thermal comfort [32]. Therefore, while simulation-based quantification is valuable, it is insufficient as a standalone method. It should be regarded as a preliminary evaluation stage rather than a replacement for large-scale empirical validation.

4.3. Data-Driven/AI-Based

Data-driven and Artificial Intelligence (AI)-based methods are increasingly employed to quantify energy flexibility in buildings by extracting patterns directly from data, rather than relying solely on explicit physical models. These approaches utilize machine learning and statistical models, such as Regression, Neural Networks (including Long Short-Term Memory and Recurrent Neural Network), clustering, and reinforcement learning algorithms, to assess flexibility [24]. The primary objective is to leverage historical energy consumption, weather, and operational data to predict flexibility metrics or develop control policies. These methods are adaptive and capable of modeling non-linear or uncertain dynamics without explicit physical representations. RL-based techniques have been implemented for autonomous scheduling of Electric Vehicle (EV) charging, Heating, Ventilation, and Air Conditioning (HVAC) systems, and heat pump operations, while simultaneously balancing electricity costs, peak demand, and occupant comfort requirements [7]. Multi-agent reinforcement learning frameworks further enhance scalability by enabling decentralized coordination of multiple residential assets. Hybrid AI–optimization frameworks integrate machine learning for forecasting or flexibility estimation with optimization or Model Predictive Control (MPC) for constrained decision-making. While these approaches improve robustness and adaptability, they also introduce greater implementation complexity and integration challenges.

Overall, data-driven and AI-based methods offer considerable adaptability and reduce dependence on manually tuned physical models. However, these approaches require substantial amounts of high-quality data and remain vulnerable to overfitting and limited interpretability. Papias et al. developed a BiLSTM framework that achieved R^2 values above 0.85 for residential energy-consumption prediction [24]. Industry-focused research also identifies edge AI as a promising avenue for real-time residential energy control [33, 34]. By processing data locally, edge AI reduces latency, enhances privacy, and enables more resilient building-level control.

4.4. Rule-Based

Rule-based approaches constitute the simplest and earliest category of methods for quantifying and activating energy flexibility in buildings. These methods rely on predefined heuristics or expert rules to manage flexibility. Typical examples include thermostatic rules, setpoint adjustments in response to price signals, and semantic rule engines [25]. The fundamental principle is the use of “if-then” logic (for example, if price is high, then shed load), which requires minimal computational resources. Such strategies are transparent and straightforward to implement in building management systems or HVAC controllers, and their logic can be made interpretable [29]. Outputs are generally binary decisions or fixed control profiles, such as on/off schedules or cooldown thresholds, with performance assessed by achieved load shift or comfort metrics. However, rule-based approaches are not optimal; they provide limited flexibility and lack the capacity to adapt to complex, dynamic changes. Literature indicates that control- and rule-based strategies "offer robustness, transparency, and ease of implementation," but are constrained in adaptability under dynamic conditions. For instance, a semantic rule-based framework was recently introduced to automate HVAC control in buildings, enhancing decision-making transparency while managing resources as conditions evolve. Because rule-based systems do not learn from data or explicitly optimize decisions, their capacity to extract flexibility efficiently is limited. Nevertheless, rule-based methods remain relevant as baseline strategies and for low-complexity implementations. In comparative studies, they frequently serve as reference points for evaluating optimization-based and AI-based approaches.

5. Discussion

In summary, research on building energy flexibility demonstrates that several critical research gaps limit real-world deployment and large-scale impact. In multi-method studies, rule-based methods offer simplicity but exhibit limited adaptability. Optimization-based approaches provide strong performance under ideal conditions but encounter scalability and uncertainty challenges. Simulation-based methods are valuable for evaluating flexibility potential, yet they are highly dependent on modelling assumptions. Data-driven and AI-based methods demonstrate greater adaptability and predictive capability, although they continue to face challenges related to explainability, safety, and deployment maturity. Table 3 synthesizes the comparative characteristics of these approaches based on representative studies from the reviewed literature.

Table 3. Comparative Analysis of Multi Approaches Energy Flexibility Evaluation in Buildings

Method	Advantages	Limitations	Cost	Uses	Reference
Optimization-based	Strong constraint handling; Can generate optimal schedules; Suitable for multi-objective energy management	Accurate system models and forecasts are necessary; Centralized formulations may exhibit limited scalability; Performance may deteriorate in the presence of uncertainty	High	Cost minimization, peak shaving, thermal scheduling	[29, 30]
Simulation-based	Captures detailed thermal and energy-system dynamics, useful for flexibility assessment, benchmarking, and what-if analysis	The approach is highly dependent on model assumptions and calibration; Simulated performance may not accurately reflect occupant behavior or real-world disturbances	High	Flexibility estimation, controller evaluation, thermal behaviour assessment	[27, 35]
Data-driven/ AI-based	Strong predictive capability, adaptive decision support, data- driven modelling	Strongly assumption-Dependent; Models require sufficient representative data and are sensitive to data quality and distribution shifts	Medium to High	Load forecasting, flexibility estimation, EV/HVAC control	[28, 35]
Rule-based	Simple, transparent, and suitable for fast real-time decisions	performance depends on rule design and no inherent optimization mechanism	Low	Appliance shifting, thermostat control, basic EV charging	[25, 29]

While the reviewed studies collectively demonstrate significant technical progress in building energy flexibility, comparative analysis reveals several structural and methodological weaknesses that limit real-world applicability. The primary limitation across literature is the prevalent reliance on simulation-based validation. Most optimization-driven and AI-based frameworks are assessed using synthetic datasets, short time horizons, or idealized residential scenarios [6, 9, 26]. Empirical validation through long-term field experiments, large-scale pilot deployments, or integration with real utility systems is rare. As a result, many reported performance improvements cannot be confidently generalized to diverse, real-world residential environments. Additionally, idealized modeling assumptions are common throughout the reviewed works. Optimization-based studies often assume highly accurate forecasts of load demand, renewable generation, and Electric Vehicle (EV) availability [6, 7, 16], while AI-based approaches typically rely on stationary training distributions and simplified user models [3, 26]. These assumptions tend to inflate reported performance and obscure limitations in robustness under uncertainty. Real building systems are inherently stochastic due to weather variability, occupant behavior, and device-level unpredictability [11, 18]. The limited use of robust, stochastic, or uncertainty-aware formulations is a critical weakness in the current state of the art. Scalability also remains largely unresolved. Centralized Mixed-integer Linear Programming (MILP) and Model Predictive Control (MPC) frameworks exhibit rapidly increasing computational complexity as system size grows [6, 24]. Although reinforcement learning and decentralized strategies are proposed as scalable alternatives [26], most implementations are limited to small-scale simulations. Issues such as large-scale coordination, communication overhead, interoperability standards, and aggregator-based architectures are insufficiently addressed, raising concerns about practical deployment feasibility. Furthermore, the application of artificial intelligence remains fragmented and only partially mature. Machine learning techniques are primarily used for forecasting and classification tasks [3, 18], while control decisions are often handled by external optimization layers. Human-centric modeling is also underdeveloped. Although some studies incorporate comfort constraints [17, 18], aspects such as long-term behavioral adaptation, trust dynamics, rebound effects, and participation fatigue are rarely examined in depth [14, 18]. Finally, the lack of standardized benchmarking frameworks significantly limits objective comparison across studies. Differences in datasets, simulation platforms, time horizons, tariff structures, and performance metrics result in inconsistent cross-paper evaluation [12, 13, 26]. Without harmonized benchmarks and reproducible evaluation protocols, claims of methodological superiority remain difficult to validate.

From a critical comparative perspective, the literature demonstrates considerable methodological innovation but lacks sufficient system-level integration. Many studies focus on optimizing isolated subsystems, such as Electric Vehicle (EV) charging, heating, ventilation, and air conditioning (HVAC) control, or load forecasting, without fully addressing multi-layer coordination among grid signals, user behavior, artificial intelligence architectures, and deployment constraints. Addressing this integration gap is essential for advancing building energy flexibility research from controlled simulations to reliable, large-scale smart grid implementation.

5.1. Actionable Future Research Directions

Future research should prioritize the integration of multiple approaches and their validation in real-world building environments. Specifically, an open multi-climate benchmark should be established to compare rule-based control, model predictive control, robust optimization, and safe reinforcement learning based on at least one year of aligned load, weather, tariff, carbon-intensity, occupancy and comfort data. Performance should be quantified in terms of peak-load shifting, energy cost, carbon emissions, comfort violations, computation time and communication demand. Following that, matched field trials should be performed with these controllers in the same buildings for at least two seasons and quantify occupant overrides, user acceptance, rebound effects, operational reliability and seasonal performance. Furthermore, must benchmark privacy-preserving edge and federated-learning architectures against cloud-based control in terms of prediction error, inference latency, communication volume, measured privacy leakage or data-exposure risk and resilience to loss of connectivity. Fourth, ideally calibrated digital twins should account for uncertainties regarding weather, occupancy, energy prices, and equipment performance, and should provide confidence intervals of flexibility estimates, instead of a single deterministic value only. Lastly, building-to-aggregator demonstrations should coordinate multiple buildings under distribution-network congestion and carbon-intensity signals while assessing interoperability, cybersecurity, scalability, and fail-safe operation.

In summary, multi-method review demonstrates how various quantification techniques can complement one another and outlines specific directions for advancing energy flexibility in buildings. By implementing these recommendations, researchers and practitioners will be better equipped to leverage building flexibility in support of clean energy objectives.

6. Conclusion

This paper provides a comprehensive state-of-the-art review of building energy flexibility, quantified using multiple methodological approaches. Optimization-based methods, such as mixed-integer programming and model predictive control, are widely employed to quantify flexibility potential and inform scheduling decisions. These approaches can deliver optimal results under specified criteria but require accurate models and are often computationally intensive. Simulation-based approaches, including detailed building and grid simulations, are essential for evaluating flexibility under diverse scenarios. They effectively capture dynamic behaviors and enable scenario analyses, although their accuracy depends on model calibration and they can be time-consuming. Data-driven methods, particularly those utilizing artificial intelligence, are increasingly adopted to estimate flexibility by learning from historical data. These techniques can adapt to complex patterns without explicit physical models, but they require large datasets and may lack interpretability. Rule-based approaches, which use if-then logic to control flexibility resources, represent the simplest and earliest category. While easy to implement and understand, they generally yield suboptimal results and rely on expert-defined rules. Each method presents distinct trade-offs. In practice, hybrid approaches that combine multiple methods, such as integrating optimization with simulation or AI techniques, can balance accuracy and computational efficiency. Many studies primarily address technical potential, such as flexibility percentages or cost savings, whereas real-world constraints, including occupant comfort and user behavior, are less frequently considered. Published studies demonstrate substantial but context-dependent flexibility gains. However, direct comparison of results across studies remains challenging due to variations in methodologies and underlying assumptions.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Md Shamsul Arefin Tanim contributed to the conceptualization, methodology development, implementation, manuscript preparation, and writing. Md Asif Abbas contributed to the validation of the research outcomes, critical review, and supervision. All authors have read and approved the published version of the manuscript.

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