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IoT-Enabled Demand Response Frameworks for Integrated Energy Management in Smart Buildings: A Systematic Review

Omofuma, Osamonyi Ighodalo[1]; Nwaogu, Julia Obianujunwa[2]; & Akinrogunde, Oluwatoyin Olawoye[3]

[1]Department of Electrical/Electronics Engineering, Ogun State Institute of Technology, Igbesa, Nigeria. osas@ogitech.edu.ng [2]Department of Computer Engineering, Ogun State Institute of Technology, Igbesa, Nigeria. nwaogu.julia@ogitech.edu.ng [3]Department of Urban and Regional Planning, Ogun State Institute of Technology, Igbesa, Nigeria. akinrogunde.oluwatoyin@ogitech.edu.ng

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Abstract

This study conducted a systematic review of IoT-enabled demand-response frameworks for integrated energy management in smart buildings. Adhering to PRISMA 2020 guidelines, the review synthesises 51 peer-reviewed studies published between 2011 and 2026. The study examined IoT-driven improvements in demand-response efficiency, evaluated solar-aligned HVAC and EV scheduling to reduce fossil-fuel use, identified adoption barriers to IoT demand-response technologies, and compared dynamic IoT controls with static scheduling for peak loads. The literature indicates that automated, artificial intelligence- and machine learning-driven control strategies achieve total energy consumption reductions of 13–30%, peak-load reductions of 10–55%, and operational cost savings of up to 58%. These intelligent systems replace slow, manual interventions with closed-loop controls, significantly enhancing energy efficiency and grid stability. However, scaling these technologies faces critical barriers, including high upfront capital costs, infrastructure heterogeneity, cybersecurity vulnerabilities, and resistance to user behaviour. Furthermore, the review exposes a pronounced methodological gap: roughly two-thirds of the existing research corpus relies on theoretical models and simulations rather than large-scale, real-world empirical validation. To bridge the divide between simulated potential and field-proven performance, future investigations must prioritise an integrated research agenda encompassing multi-building district coordination, edge intelligence, digital twins, blockchain-enabled energy trading, and harmonised regulatory frameworks. Therefore, optimised IoT architectures are vital for advancing sustainable smart buildings, mitigating grid congestion, and achieving resilient, net-zero urban futures.

Keywords: Internet of Things; demand response; building energy management; smart buildings; systematic review

Introduction

The accelerating pace of urbanisation and economic growth has catalysed a paradigm shift in global energy management, placing unprecedented demands on modern building infrastructure (Moghimi, Gulliver & Chelvan, 2024). As urban buildings account for a substantial share of global energy consumption, researchers emphasise that traditional energy models are insufficient and that advanced digital tools, machine learning, and IoT-driven strategies are needed to manage surging urban energy loads (Moghimi et al., 2024; de Oliveira & Pimenta, 2023). The building sector remains a primary driver of global energy consumption and greenhouse gas emissions, underscoring the urgent need to transition from traditional fossil-fuel-reliant architectures towards sustainable, green infrastructure and renewable energy systems (Barwińska-Małajowicz, Banaś, Piecuch, Pyrek, Szczotka, & Szymiczek, 2024). Recent studies highlight the importance of developing effective, grid-connected schemes and deploying advanced renewable energy sources to achieve decarbonisation objectives in modern infrastructure (Barwińska-Małajowicz et al., 2024; Bayasgalan, Park, Koh & Son, 2024). Smart buildings are now perceived as flexible loads that can be optimised for energy consumption through advanced energy management and microgrid systems integrated within the buildings (Mannini, Darure, Eynard & Grieu, 2024). Given that the HVAC system accounts for 30% to 60% of the building's overall energy consumption, microgrid coordination becomes essential (Mannini et al., 2024; Hernández, de Miguel, Vélez, & Vasallo, 2024).

As a result, IoT-based demand response models have emerged, employing sensing, automation, and optimisation techniques to align building loads with grid signals, renewable energy generation schedules, and electric vehicle operations (Yusoffdeen, 2025; Toderean et al., 2024; Pan et al., 2015). The use of IoT-based demand response models results in reductions in operational costs and carbon dioxide emissions, and an increase in grid flexibility for residential and commercial buildings (Fei et al., 2022; Poyyamozhi et al., 2024; Kamal et al., 2023). As a result of the integration of IoT in buildings, there will be reductions in energy use and operational costs of up to 30% and 20%, respectively (Poyyamozhi et al., 2024), but challenges such as the high costs of IoT integration and its complexity have prevented its adoption.

Other classifications of these programmes include price-based and incentive-based approaches (Javed et al., 2023; Fei et al., 2022). Price-based programmes include ToU, CPP, and RTP, which offer different rates to influence behaviour (Udayakumar et al., 2023). By contrast, incentive-based programmes include reward schemes that use virtual energy currency (Marinakis & Doukas, 2018; Fei et al., 2022). RTP can reduce costs by up to 58%, but this depends on customers' behaviour (Hafeez et al., 2020). At the same time, CPP can reduce costs by up to 55%. The main disadvantage of CPP is the lack of automation characteristic of the traditional approach (Toderean et al., 2024). This problem can be solved using IoT.

Beyond device automation, the use of renewable energy sources such as solar photovoltaics (PVs) and energy storage in microgrids, enabled by Internet of Things (IoT) technology, will reduce operational costs (Fei et al., 2022; Kanakadhurga & Prabaharan, 2024). The integration of electric

vehicles, along with V2G and V2H operations, enables energy exchange and reduces dependence on the utility grid (Fei et al., 2022; Kanakadhurga & Prabaharan, 2024; Marinakis & Doukas, 2018). Machine-learning-based forecasting helps predict energy production and consumption, thereby informing pricing and scheduling (Alijoyo, 2024; Yusoffdeen, 2025). Hybrid methods that include genetic algorithms, particle swarm optimisation, and wind-driven optimisation algorithms address multiple objectives (Hafeez et al., 2020; Kanakadhurga & Prabaharan).

Despite these innovations, a research gap remains in integrating smart buildings, renewable energy sources, and electric vehicles into the IoT-based demand response system (Fei et al., 2022; Javed et al., 2023). In this regard, the existing academic literature on the issue mainly examines the problem in isolation within each field, and proprietary technology does not allow open access (Javed et al., 2023). Market participation is constrained by several factors, including regulatory challenges, incompatible grid-BMS systems, data security risks, insufficient financial incentives (Toderean et al., 2024; Teixeira et al., 2022), and a lack of empirical studies (Yusoffdeen, 2025). To address the gap between theory and practice in demand response modelling, the paper examines IoT-driven improvements in demand response efficiency, evaluates solar-aligned HVAC and EV scheduling for fossil fuel reduction, identifies adoption barriers for IoT demand response technologies, and compares dynamic IoT controls with static scheduling for peak loads. The paper consists of six main parts: introduction (Part 1), literature review (Part 2), methodology (Part 3), results (Part 4), discussion (Part 5), and conclusion (Part 6).

Statement of Problem

Although the emergence of IoT technology offers tremendous prospects for implementing dynamic demand response (DR) to achieve intelligent energy management in smart buildings, many issues remain that hinder the development of a DR scheme using IoT technology (Toderean et al., 2025). Conventional building energy management systems depend on manual interventions, fail to monitor energy usage in real time, and are inefficient in load management, leading to inadequate reductions in peak demand, excessive energy consumption, and reduced grid flexibility, especially with the expansion of renewable energy systems (Khan et al., 2024; Toderean et al., 2025).

The major challenges in this area include achieving interoperability among heterogeneous IoT-enabled devices and sensors that use different communication protocols and data formats, making scalable, coordinated control of HVAC, lighting, storage and other flexible loads difficult; security and data privacy issues arising from continuous sensing and cloud-edge data transfer, which leave the system vulnerable to attacks such as false data injection and unauthorised access (Das, 2025; Khan et al., 2024; Teixeira et al., 2022); high costs, limited scalability and a lack of return on investment, which hinder large-scale deployment, especially retrofits of existing buildings; and an inadequate regulatory framework, protocols and financial incentive mechanism, which make it difficult for automated buildings to participate in DR programmes and optimise energy efficiency, thermal comfort and grid stability amid uncertain occupancy patterns, variable weather and renewable energy production (Das, 2025; Toderean et al., 2025).

However, there remains a need to develop reliable, privacy-conscious, and interoperable IoT-based DR systems that utilise sophisticated sensing and intelligent control to implement an integrated and adaptive energy management system in smart buildings, thereby increasing the resilience of the grid, reducing costs and the carbon footprint, and fostering sustainable energy systems in cities. To bridge the gap between theoretical models and practical implementation, this research paper provides a comprehensive

review of the literature on implementation issues, IoT-DR integration methods, and interactions among renewable energy sources, electric vehicles, and urban environments.

Research Questions

Based on the above, the following research questions were posed:

i. How do IoT-driven enhancements improve the efficiency of Demand Response?
ii. To what extent does solar-aligned HVAC and EV scheduling reduce dependence on fossil fuels?
iii. What are the main barriers to adoption of IoT Demand Response technologies?
iv. How do dynamic IoT controls compare with static scheduling in managing peak loads?

Research Aim and Objectives

The aim of this study is to conduct a systematic review of IoT-enabled demand-response frameworks for integrated energy management in smart buildings, with the view to optimising building energy efficiency through the synchronised integration of renewable energy sources and electric vehicles. Therefore, the following objectives are to be pursued in order to achieve the above-stated aim. These objectives are to:

i. examine IoT-driven improvements in Demand Response efficiency;
ii. evaluate solar-aligned HVAC and EV scheduling for fossil-fuel reduction;
iii. identify adoption barriers for IoT Demand Response technologies, and
iv. compare dynamic IoT controls with static scheduling for peak loads.

Architecture, Technologies, and Regulatory Frameworks of Smart-Building Energy Management Systems

The transition from mechanical control systems to a fully digital BEMS is central to reducing global energy consumption. Buildings contribute significantly to energy consumption and carbon emissions, so deploying advanced BEMS is crucial for achieving environmental goals (Shaqour & Hagishima, 2022; Hannan et al., 2018; Manic et al., 2016). Advances in IoT, artificial intelligence, and cloud computing have enabled conventional systems to evolve into dynamic systems capable of managing HVAC performance and occupant comfort (Sayed & Gabbar, 2018; Digitemie & Ekemezie, 2024; Halim et al., 2026).

Sittón-Candanedo et al. (2019) present a multi-layer IoT framework in which smart meters and voltage sensors collect telemetry data in the perception layer (Liu et al., 2022; Nguyen et al., 2022); terminal devices support continuous environmental monitoring (Ben Dhaou et al., 2022); a network/middleware layer provides data transmission, edge computing, and standardisation; and an application layer uses artificial intelligence to enable energy automation processes (Ben Dhaou et al., 2022). This hierarchical structure links environmental data acquisition to intelligent automation processes.

Operational efficiency requires hardware, communication, and software enablers to transform sensor data into actions, such as HVAC valve and circuit-switch adjustments (Sittón-Candanedo et al., 2019; Liu et al., 2022). Edge computing helps minimise latency by processing data at the edge, whereas cloud computing provides the computing capabilities needed to optimise all buildings (Minh et al., 2022; Sittón-Candanedo et al., 2019). Communication enablers enable hardware to communicate over distances by utilising MQTT for cloud communication, Zigbee for short-range automation, LoRaWAN for long-range metering, and 5G for faster connections (Ben Dhaou et al., 2022; Minh et al., 2022; Spanoudakis et al., 2023). In combination with BIM and AI control systems, these technologies have

reduced HVAC energy consumption by 37% in commercial buildings (Halim et al., 2026; Hannan et al., 2018; Ali et al., 2024). Full-scale deployment, however, is hindered by high installation costs, limited interoperability with legacy systems, and heightened cybersecurity risks (Mustapha et al., 2025; Akbulut et al., 2025; Digitemie & Ekemezie, 2024).

Combined demand-response methods, along with RES and V2G, make smart buildings flexible energy generators rather than mere consumers. Unlike earlier demand response based on time-based rates and manually set restrictions, today's systems are automated, using digital feedback control and real-time prices (Ben Dhaou et al., 2022; Nguyen et al., 2022; Minh et al., 2022). EVs serve as decentralised storage via V2G, with power electronics and IoT integration enabling batteries to absorb additional renewable power and feed it back into the system when demand is high (Spanoudakis et al., 2023; Ben Dhaou et al., 2022; Liu et al., 2022). Standardised approaches, i.e., the NIST and ETSI reference model frameworks, along with IEEE and IEC interoperability standards, provide structural governance for these systems (Ben Dhaou et al., 2022; Minh et al., 2022). Open standards such as OpenADR and supportive policies are considered necessary to overcome implementation challenges and create transparency in energy markets (Liu et al., 2022; Spanoudakis et al., 2023; Khan et al., 2022; Halim et al., 2026; Phan et al., 2025).

Conceptual Framework

Conceptual frameworks are a crucial methodology for transforming complex domains characterised by many variables into structured constructs that can be analysed effectively (Munck et al., 2013). In line with this, the synthesised conceptual framework for IoT-based building energy management integrates key energy management processes with a multi-layered Internet of Things framework, as illustrated in Fig. 1. Energy management is realised as a repetitive plan-do-check-act (PDCA) cycle that encompasses characterisation, monitoring, indicator assessment, and planning.

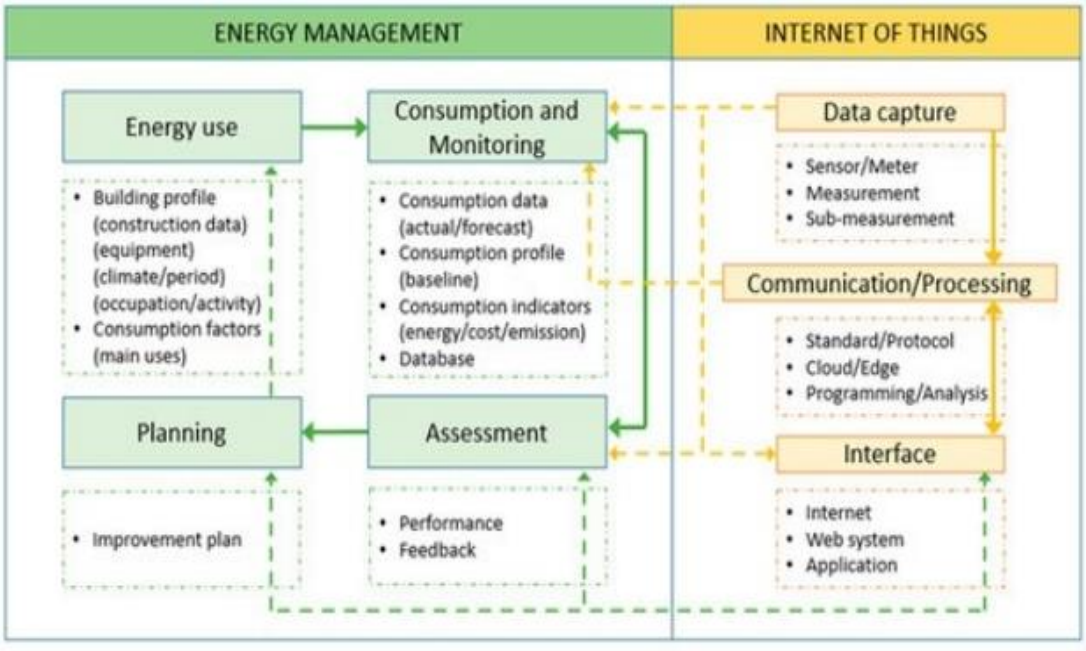


Figure 1: Conceptual framework of electrical energy management in buildings based on the IoT
Source: de Oliveira Cavalcanti & Pimenta, 2023

Systematic Review Methodology (PRISMA-Compliant)

This systematic review follows the PRISMA framework (as presented in Fig. 2), ensuring a structured, evidence-based approach. A staged methodology, in which records are identified, screened, assessed for eligibility, and included in the analysis, reduces potential bias. The PRISMA statement provides guidelines for reporting the study.

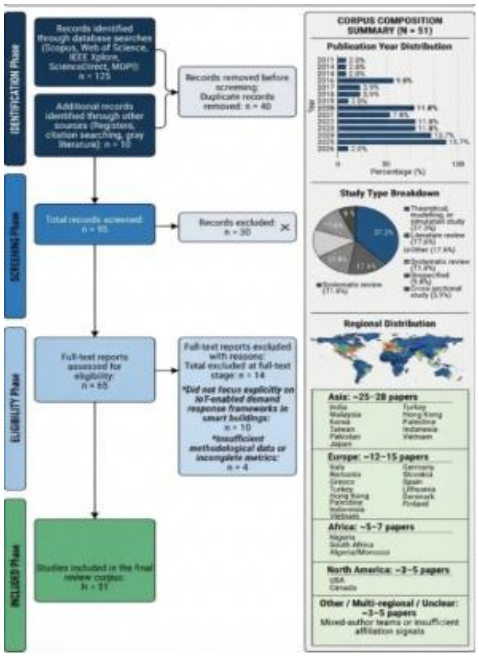


Figure 2: PRISMA 2020 flow diagram
Source: Author's Compilations, 2026

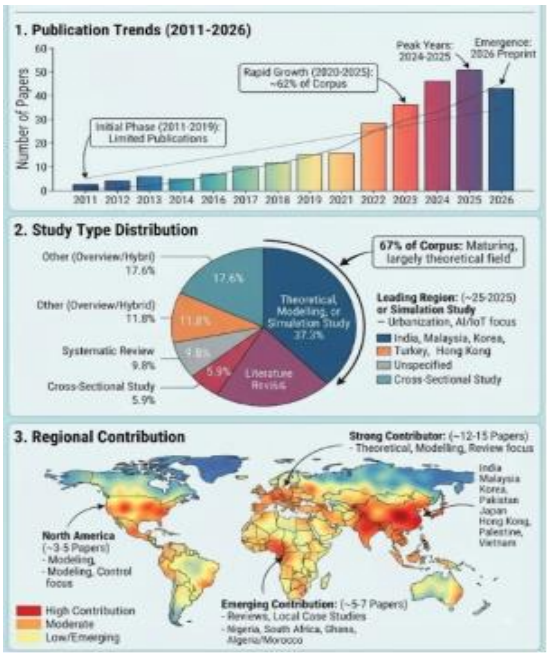


Figure 3: Key Attributes of the Systematic Review
Source: Author's Compilations, 2026

These questions have been addressed in relation to IoT architecture, demand response solutions, the integration of renewable energy and electric vehicles, and cybersecurity issues (Page et al., 2021; Poyyamozhi et al., 2024). The systematic review process involved searches of the Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar databases, using Boolean operators to retrieve relevant peer-reviewed, English-language papers from journals published between 2015 and 2026, with some additional early literature (Fei et al., 2022; Halim et al., 2026). The inclusion and exclusion criteria for the selection process were as follows: non-peer-reviewed materials, macro-grid analysis, and industrial establishments where no IoT-based demand response approach was in use in smart buildings (Javed et al., 2023; Teixeira et al., 2022). Four PRISMA stages were followed to select articles (Page et al., 2021; Yusoffdeen, 2025).

Descriptive Statistics of Included Studies

The number of publications has increased dramatically in recent years, owing to the importance of energy optimisation in smart buildings, with academia largely driven by advances in sensor technologies and machine learning methods (Poyyamozhi et al., 2024; Akbulut et al., 2025). However, bibliometric analysis reveals that empirical studies on the topic are clustered around digitally advanced urban centres (Toderean et al., 2024; Yusoffdeen, 2025). Table 1 shows that 62% of all publications were published between 2020 and 2025, with one published as a preprint in 2026.

Table 1. Publication Year Distribution

Year	Number of Papers	%
2011	1	2.0
2014	1	2.0
2015	1	2.0
2016	5	9.8
2017	2	3.9
2018	2	3.9
2019	1	2.0
2020	6	11.8
2021	4	7.8
2022	6	11.8
2023	6	11.8
2024	7	13.7
2025	8	15.7
2026	1	2.0
Total	**51**	**100**

Source: Author's Compilations, 2026

The corpus is dominated by modelling, simulation, and review papers, which together account for approximately 67% of studies (Table 2), whereas empirical and cross-sectional work remains comparatively limited. This skew reflects a maturing but predominantly theoretical research landscape and a relative scarcity of large-scale empirical deployments; the same distribution underlies the taxonomy of DR framework types discussed in Section 4.2.

Table 2. Distribution of Study Type

Study Type	Number of Papers	%
Theoretical, modelling, or simulation study	19	37.3
Literature review	9	17.6
Others	9	17.6
Systematic review	6	11.8
Unspecified	5	9.8
Cross-sectional study	3	5.9
Total	**51**	**100**

Source: Author's Compilations, 2026

Globally, the leading continents in the body of literature are Asia, with notable examples including India, Malaysia, Korea, Taiwan, Pakistan, Japan, Turkey, and Indonesia; Europe, which offers many papers in theory, modelling, and review (Italy, Romania, Greece, Germany, and the Nordic countries); and Africa, which mostly includes reviews and case studies (Nigeria, South Africa, Ghana). North America provides modelling and control studies. These trends imply that the research agenda is predominantly influenced by concerns for energy security and sustainability in Asia and Europe, with emerging input from Africa (see Fig. 3 and Table 3).

Table 3. Approximate Regional Distribution

Region	Approx. Papers	Notes
Asia	~25-28	India, Malaysia, Korea, Taiwan, Pakistan, Japan, Turkey, Indonesia, Vietnam
Europe	~12-15	Italy, Romania, Greece, Germany, Slovakia, Spain, Nordic countries
Africa	~5-7	Nigeria, South Africa, Ghana, Algeria/Morocco
North America	~3-5	Primarily USA, with some Canadian contributions
Other/multi-regional	~3-5	Mixed-author teams or unclear affiliation

Source: Author's Compilations, 2026

Classification of IoT-Enabled DR Frameworks

T-supported DR framework designs can be distinguished by their objectives, response types, and architectures (Javed et al., 2023; Fei et al., 2022). This taxonomy distinguishes price-based tariffs, such as RTP and ToU, from incentive-based mechanisms that use an automatic feedback loop enabled by IoT rather than human intervention (Hafeez et al., 2020). Table 2 shows that most classified research works are modelling/simulation and review studies, indicating a gap between methodology development and the empirical testing of IoT-supported DR.

Architectural Models: Centralised, Decentralised, Hierarchical, and Multi-Agent

The choice of architectural structure determines the configuration of building energy systems, including system architecture and data routing within the network. Centralised architecture enables straightforward management but introduces serious problems, including a single point of failure and high communication latency (Alhasnawi et al., 2020; Halim et al., 2026). The decentralised, hierarchical, and multi-agent system architecture addresses these issues through autonomous processing by edge nodes, in conjunction with global coordination with grid operators (Spanoudakis et al., 2023; Toderean et al., 2024) (see Fig. 4).

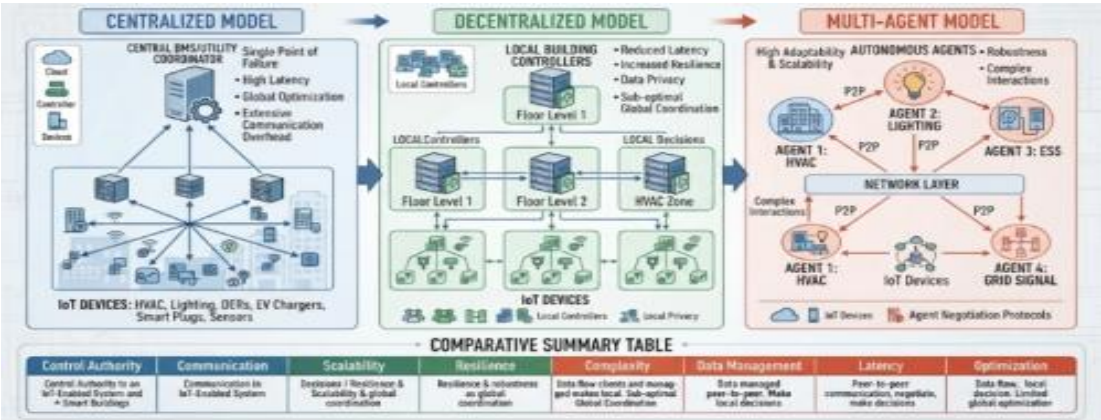


Figure 4: Architectural Comparison: IoT-Enabled Demand Response Framework in Smart Buildings

Source: Author's Compilations, 2026

Communication and Data Management

As shown in Table 4, robust, low-latency, and secure communication is essential for interoperability among heterogeneous building devices. Lightweight publish-subscribe protocols such as MQTT efficiently handle cloud-bound telemetry, while short-range wireless standards (e.g., ZigBee) and wide-area networks (e.g., LoRaWAN) provide local and regional connectivity (Nguyen et al., 2022; Ben Dhaou et al., 2022). Edge-computing platforms and cloud middleware normalise disparate streams, including weather forecasts, dynamic pricing, and occupancy patterns, thereby preventing congestion and maintaining responsiveness (Sittón-Candanedo et al., 2019; Alijoyo, 2024). Table 4 summarises the principal protocols used in the reviewed literature.

Table 4. Communication Protocol Comparison for IoT-Enabled Demand Response

Protocol	Data Flow / Transport	Typical Application	Key Trade-offs
MQTT	Publish-subscribe over TCP/IP	Real-time telemetry from meters, sensors, and HVAC controllers to a central BEMS	Lightweight and scalable; needs a persistent TCP connection
HTTP/REST	Request-response over TCP/IP	Cloud-to-cloud integration, historical data retrieval, dashboards	Universally compatible; high overhead for high-frequency updates
CoAP	RESTful request-response over UDP	Battery-operated sensor nodes monitoring indoor conditions	Low overhead for constrained devices; needs added reliability layer
ZigBee/Thread	Multi-hop mesh (IEEE 802.15.4)	Local device communication for plugs, lighting, sub-meters	Low power, self-healing mesh; needs a gateway to reach the cloud
BACnet/Modbus	Master-slave / peer-to-peer, wired	Legacy building automation and HVAC/power-meter integration	Mature and standard for BAS; limited native security, rigid topology

Source: Author's Compilations, 2026

Control Strategies and Algorithms

Control intelligence has evolved from static heuristics to adaptive machine learning. Traditional rule-based controllers rely on fixed set points that do not adapt to changing environmental and market conditions (Tepe & Irmak, 2024; Ali et al., 2024). By contrast, optimisation-based methods (GA, PSO) and AI/ML-based approaches, such as MPC and DRL, improve multi-objective performance by forecasting renewable energy generation and dynamically scheduling devices (Yusoffdeen, 2025). Table 5 summarises the control strategies discussed in the corpus.

Table 5. Comparative Performance of Control and Optimisation Algorithms

Approach	Optimisation Focus	Scalability	Typical Application	Strengths / Limitations
Deep Reinforcement Learning (DDPG, PPO, DQN)	Real-time policy learning under uncertainty	High, once trained	Adaptive HVAC control, dynamic EV charging	Handles non-linear dynamics well; needs extensive training data

Approach	Optimisation Focus	Scalability	Typical Application	Strengths / Limitations
Model Predictive Control (MPC)	Constrained optimisation over a prediction horizon	Moderate	Thermal comfort, battery/microgrid dispatch	Explicitly handles constraints; sensitive to model accuracy
Genetic Algorithm (GA)	Global metaheuristic search	Moderate, slower convergence	Day-ahead scheduling, microgrid sizing	Escapes local optima; computationally heavy, not real-time
Mixed-Integer Linear Programming (MILP)	Exact optimisation for linearised problems	Low-to-moderate	Economic dispatch, CCHP unit commitment	Guarantees global optimum; rigid, NP-hard at scale
Rule-Based Control (RBC)	Heuristic threshold logic	High for basic use, poor adaptability	Peak shedding, basic thermostat scheduling	Simple and transparent; sub-optimal, no forecasting

Source: Author's Compilations, 2026

Applications in Smart Buildings

Fig. 5 shows that IoT-based DR comprises a number of interrelated subsystems designed to maximise building performance. Current implementations automate sensing and control to balance consumption across all parts of a building while ensuring operational efficiency (Poyyamozhi et al., 2024; Akbulut et al., 2025). These macro-scale implementations include specific subsystems, most notably HVAC, lighting, and appliance control.

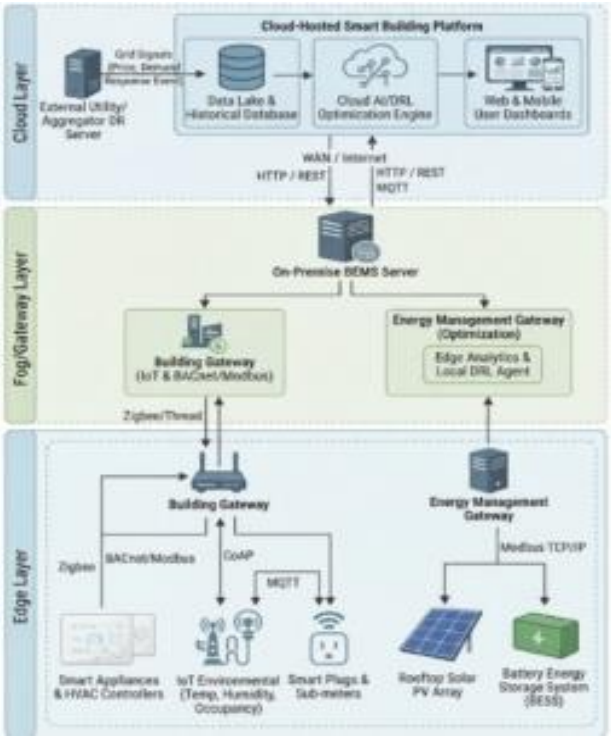


Figure 5: Application of Architectural Schematic: IoT-Enabled Smart Buildings BEMS with Demand Response
Source: Author's Compilations, 2026

HVAC, Lighting, and Appliance Control

As shown in Table 6, HVAC systems, lighting, and large appliances are the primary controllable loads whose energy use must be reduced. The HVAC system alone accounts for 30-60% of a building's energy use, making it the most crucial component for improving efficiency (Kamal et al., 2023; Ali et al., 2024). With automatic IoT-based sensing and AI-based control, the system can adjust temperature and lighting setpoints based on occupancy and tariffs, reducing energy use by 37% in commercial areas (Ali et al., 2024; Rocha et al., 2015).

Table 6. Building Subsystem Energy Share and Demand-Response Potential

Subsystem	Energy Share	DR / Flexibility Potential	Primary IoT Control
HVAC	40-50%	High: pre-cooling/heating, setpoint adjustment, thermal storage	Smart thermostats, VRF controllers, occupancy zoning
Lighting	15-20%	High: instantaneous shedding, daylight harvesting	Smart luminaires, DALI/Zigbee controllers, PIR sensors
Plug loads & equipment	15-20%	Moderate: automated shutdown, smart-plug scheduling	Smart sockets, sub-meters, edge relays
Water heating (DHW)	5-10%	High: off-peak load shifting	Smart immersion heaters, tank sensors, relays
Elevators, pumps, auxiliary	5-10%	Low-to-moderate: speed reduction where safety permits	VFD monitors via Modbus/TCP, energy meters

Source: Author's Compilations, 2026

Integration with On-Site Renewable Energy Sources

The combination of on-site renewable energy sources, such as solar photovoltaic panels and batteries, is crucial for achieving zero-net energy in smart buildings. Integrating on-site generation with IoT-based microgrids minimises costs and protects against grid disruptions (Fei et al., 2022; Kanakadhurga & Prabaharan, 2024). Given the intermittency of solar generation, load scheduling and forecasting systems help shift consumption to peak production hours (Halim et al., 2026).

EV Charging Management and Bidirectional Energy Flows

EV charging management and V2G technology are emerging areas for enhancing building flexibility. Two-way electricity flow can charge electric vehicle batteries during periods of excess generation and then return electricity to the building during periods of high demand (Kanakadhurga & Prabaharan, 2024; Marinakis & Doukas, 2018). Using scheduling algorithms and IoT technologies, V2G can help manage peak grid load and provide additional services, such as frequency regulation (Fei et al., 2022; Spanoudakis et al., 2023).

Occupant Comfort and Behaviour Modelling

Occupant comfort is a crucial factor in determining the success of the DR, as any automated system should ensure users' well-being. AI-based occupancy detection systems increase thermal comfort by 43-73%, thereby supporting efficient office operations (Ali et al., 2024; Marinakis & Doukas, 2018). As people's behaviour is unpredictable and energy consumption habits vary, semantic models and machine learning algorithms analyse historical data on people's actions to generate personalised energy plans (Javed et al., 2023; Tepe & Irmak, 2024).

Performance Evaluation Metrics

Quantified performance metrics, as shown in Table 7, are used to assess the effectiveness of IoT-DR system operations. These include operating cost savings of up to 58%, peak load shedding of 45%–55%, and improvements in renewable resource utilisation efficiency (Fei et al., 2022; Akbulut et al., 2025). Additional metrics include communication delay, reliability, and algorithm convergence speed (Minh et al., 2022; Toderean et al., 2024). The main performance metrics are summarised in Table 7 below.

Table 7. Performance Metrics Summary

Performance Domain	Baseline Approach	IoT/AI-Enabled Approach	Reported Outcome
Total energy consumption	Fixed scheduling, static setpoints	Dynamic multi-zone predictive control	Reduced 13.3%-18%+
Peak demand	Unmanaged coincident peaks	Automated shedding, thermal pre-cooling	Reduced 10%-30%
Occupant comfort compliance	Frequent temperature overshoot	Constraint-aware optimisation	Comfort-violation duration reduced 19% (up to 98% in DRL trials)
Operating cost	Standard ToU tariffs, unoptimised	Price-responsive economic dispatch	Reduced up to 21.6% via predictive control

Source: Author's Compilations, 2026

Comparative Analysis of Frameworks

Table 8 compares architectures and highlights a trade-off. Decentralised multi-agent systems offer better scalability and fault tolerance, yet entail greater complexity and make interoperability harder to achieve. Centralised systems are easier to manage but are vulnerable to attacks and create single points of failure (Toderean et al., 2024; Akbulut et al., 2025; Manic et al., 2016). Table 8 extends the algorithm comparison (Table 5) to architecture evaluation.

Table 8. Framework Strengths, Weaknesses, and Scalability

Framework	Core Strength	Key Limitation	Scalability
Rule-Based Control	Low overhead, transparent, simple to deploy	Sub-optimal, cannot anticipate pricing or load shifts	High for basic setups; poor adaptability
Model Predictive Control	Handles physical constraints; strong for thermal storage	Sensitive to model accuracy; high runtime complexity	Moderate; bottlenecked by state-space size
Deep Reinforcement Learning	Handles non-linear, stochastic dynamics; low online latency	Needs extensive offline training data	High after training, for complex multi-zone settings
Metaheuristic Optimisation (GA)	Escapes local optima in complex search spaces	Not real-time adaptive; computationally heavy	Moderate-to-low; slow convergence

Source: Author's Compilations, 2026

Case Studies and Pilot Implementations

Case studies bridge simulation and validation in practical applications, yet few studies in the literature review provide information on deployment in large-scale commercial buildings or across multiple energy generation systems (Yusoffdeen, 2025; Toderean et al., 2024). Although simulations consistently demonstrate perfect load shifting and V2G optimisation, pilots face compatibility issues with legacy hardware, a lack of a regulatory framework, data protection concerns, and high initial costs (Teixeira et al., 2022; Mustapha et al., 2025). These and other factors are summarised in Table 9.

Table 9. Pilot Implementation Scale and Identified Barriers

Deployment Scale	Typical Assets	Key Barriers	Mitigation / Lessons Learned
Micro-scale (single-zone residential)	Smart plugs/thermostats, residential PV, local storage	Consumer apathy toward manual DR; unreliable legacy Wi-Fi	Automated plug-and-play scheduling; self-healing mesh protocols
Medium-scale (commercial office)	Multi-zone VRF HVAC, DALI lighting, smart sub-meters	BACnet/Modbus interoperability friction; manager reluctance to cede control	Dual-protocol edge gateways; human-in-the-loop override options
Macro-scale (industrial/microgrid cluster)	Centralised BEMS, utility-scale BESS, RES farms, EV fleets	High capital expenditure; cybersecurity and regulatory complexity	Public-private funding; standardised protocols (OCPP, IEC 61850); zero-trust security

Source: Author's Compilations, 2026

How IoT Enhances DR Effectiveness

IoT fundamentally transforms DR by replacing slow, manual consumer intervention with automated, closed-loop control. Dense sensing grids, edge-cloud computing, and advanced telemetry enable continuous monitoring and near-instantaneous responses to dynamic pricing signals (Hafeez et al., 2020; Teixeira et al., 2022). This approach overcomes the latency and unpredictability of traditional DR, enabling systems to modulate loads autonomously during peak events (Alhasnawi et al., 2020; Toderean et al., 2024).

Realised Benefits

IoT-enabled DR delivers measurable benefits across efficiency, resilience, renewable integration, and cost. Review studies report up to a 30% reduction in overall energy consumption, a 20% drop in operating expenses, and cost savings of up to 58% under real-time pricing (Fei et al., 2022; Poyyamozhi et al., 2024). Intelligent scheduling of HVAC and EV charging around solar generation windows further stabilises local grids and reduces dependence on fossil fuels (Kanakadhurga & Prabaharan, 2024; Halim et al., 2026).

Interplay of Technical, Economic, and Social Factors

Scaling depends on the interplay among technical feasibility, economic sustainability, and social acceptability. High upfront costs, heterogeneity in existing infrastructure, and privacy concerns often constrain adoption of these technologies, despite their technical efficiency (Mustapha et al., 2025;

Akbulut et al., 2025). Although optimisation and vehicle-to-grid (V2G) algorithms may perform well in simulations, real-world success requires end-user behavioural compliance and financial incentives (Teixeira et al., 2022; Tepe & Irmak, 2024).

Comparison with Conventional (Non-IoT) DR Approaches

Traditional DR relies on static set points, manual human intervention to limit consumption, and fixed time-of-use schedules that do not account for real-time weather and market conditions (Rocha et al., 2015; Hannan et al., 2018). By contrast, smart IoT-based technology utilises dynamic set points and automatic controls, resulting in a 40% reduction in heating demand and effective load management beyond what policies can achieve (Rocha et al., 2015; Toderean et al., 2024).

Implications for Stakeholders

IoT-driven demand response poses distinct challenges for different stakeholders. For building owners, there are lower costs and an extended lifespan; for utilities, greater flexibility of the power grid and better management of peak congestion; for policymakers, the need to establish regulatory policies and incentives to close the gap between simulations and implementation; and, finally, for occupants, a comfortable indoor climate and automatic cost savings without any behavioural intervention (Yusoffdeen, 2025; Phan et al., 2025; Marinakis & Doukas, 2018). The implications, challenges, and solutions for stakeholders are summarised in Table 10.

Table 10. Stakeholder Impact Mapping

Stakeholder	Key Benefits	Key Risks	Mitigation Strategy
Occupants & tenants	Better comfort/IAQ; lower utility cost via automated DR	Perceived loss of control; occupancy-tracking privacy concerns	Human-in-the-loop overrides; strict data anonymisation
Facility managers	Reduced workload via automated fault detection; longer equipment life	Steep learning curve; legacy/IoT interoperability friction	Intuitive dashboards; hybrid manual-automated control
Building owners/developers	Higher property valuation; lower long-term OpEx	High CapEx for retrofits; uncertain ROI timelines	Energy-efficiency grants; phased ROI via pilots
Utilities/grid operators	Flattened load curves; grid flexibility via V2G	Voltage fluctuation after DR events; regulatory complexity	Standardised protocols (OCPP, IEC); dynamic pricing
Technology vendors	Expanded market for IoT/BEMS; recurring SaaS revenue	Cybersecurity exposure; rapid technology obsolescence	End-to-end encryption; open interoperability standards

Source: Author's Compilations, 2026

Conclusions

This systematic review shows that IoT-based demand response schemes play a vital role in the shift from traditional building energy management systems to data-driven, highly adaptable models (Akbulut

et al., 2025; Halim et al., 2026). In turn, integrating real-time IoT solutions, machine-learning forecasts, and multi-objective optimisation methods enables buildings to coordinate intermittent renewable generation with EV charging schedules (Fei et al., 2022; Kanakadhurga & Prabaharan, 2024). However, implementing large-scale smart building energy management and demand response systems entails multiple challenges, including technical incompatibility, high economic barriers, regulatory problems, behavioural barriers, cybersecurity risks, and a lack of empirical validation (Akbulut et al., 2025; Mustapha et al., 2025; Toderean et al., 2024; Teixeira et al., 2022). Hence, this systematic review identifies a critical lack of real-world application of smart building energy management systems and demand response schemes in empirical settings (Toderean et al., 2024; Yusoffdeen, 2025).

To address these shortcomings, future research should prioritise edge intelligence, digital twins, blockchain-enabled peer-to-peer transactions, district-level coordination, and the integration of simulation models with practical implementation (Alijoyo, 2024; Halim et al., 2026; Javed et al., 2023; Fei et al., 2022). Scholars should focus on multi-building and district-level coordination and on privacy-preserving edge systems; practitioners should focus on interoperability guidelines and security measures to prevent implementation problems (Teixeira et al., 2022; Javed et al., 2023); policymakers should develop the necessary regulatory framework, dynamic pricing systems, and incentives to reduce capital investment for property owners (Mustapha et al., 2025; Phan et al., 2025). Finally, empirically optimised IoT-based systems can play a significant role in improving sustainable smart buildings and reducing grid congestion (Poyyamozhi et al., 2024; Halim et al., 2026).

References

Adhikari, S., Nguyen, T. D., & Silverman, E. (2025). A review of smart building energy management systems (BEMS) to enhance building sustainability. *EPiC Series in Built Environment*. https://doi.org/10.29007/sgfr

Akbulut, L., Taşdelen, K., Atılgan, A., Malinowski, M., Çoşgun, A., Şenol, R., Akbulut, A., & Petryk, A. (2025). A systematic review of building energy management systems (BEMSs): Sensors, IoT, and AI integration. *Energies*, *18*(24), Article 6522. https://doi.org/10.3390/en18246522

Ali, D., Motuzienė, V., & Džiugaitė-Tumėnienė, R. (2024). AI-driven innovations in building energy management systems: A review of potential applications and energy savings. *Energies*, *17*(17), Article 4277. https://doi.org/10.3390/en17174277

Alijoyo, F. A. (2024). AI-powered deep learning for sustainable industry 4.0 and internet of things: Enhancing energy management in smart buildings. *Alexandria Engineering Journal*, *104*, 711–725. https://doi.org/10.1016/j.aej.2024.07.110

Alhasnawi, B., Jasim, B. H., Esteban, M. D., & Guerrero, J. (2020). A novel smart energy management as a service over a cloud computing platform for nanogrid appliances. *Sustainability*, *12*(22), Article 9686. https://doi.org/10.3390/su12229686

Balakumar, P., Vinopraba, T., & Chandrasekaran, K. (2023). Machine learning based demand response scheme for IoT enabled PV integrated smart building. *Sustainable Cities and Society*, *89*, Article 104260. https://doi.org/10.1016/j.scs.2022.104260

Barwińska-Małajowicz, A., Banaś, M., Piecuch, T., Pyrek, R., Szczotka, K., & Szymiczek, J. (2024). Energy and ecological concept of a zero-emission building using renewable energy sources—Case study in Poland. *Energies*, *17*(23), Article 5817. https://doi.org/10.3390/en17235817

Bayasgalan, A., Park, Y. S., Koh, S. B., & Son, S.-Y. (2024). Comprehensive review of building energy management models: Grid-interactive efficient building perspective. *Energies*, *17*(19), Article 4794. https://doi.org/10.3390/en17194794

Ben Dhaou, I. S., Kondoro, A., Kakakhel, S. R. U., Westerlund, T., & Tenhunen, H. (2022). Internet of things technologies for smart grid. In *Research anthology on smart grid and microgrid development* (pp. 805–832). IGI Global. https://doi.org/10.4018/978-1-6684-3666-0.ch035

Bianchini, G., Casini, M., Vicino, A., & Zarrilli, D. (2016). Demand-response in building heating systems: A model predictive control approach. *Applied Energy*, *168*, 159–170. https://doi.org/10.1016/j.apenergy.2016.01.088

Ciano, J. K., & Zou, T. (2025). A systematic review of circular economy of artificial lighting and global sustainability. *Energy and Buildings*, *347*, Article 116314. https://doi.org/10.1016/j.enbuild.2025.116314

Das, D. K. (2025). Integrating IoT and AI for sustainable energy-efficient smart building: Potential, barriers and strategic pathways. *Sustainability*, *17*(22), 10313. https://doi.org/10.3390/su172210313

de Oliveira Cavalcanti, G., & Pimenta, H. C. D. (2023). Electric energy management in buildings based on the internet of things: A systematic review. *Energies*, *16*(15), Article 5753. https://doi.org/10.3390/en16155753

Digitemie, W. N., & Ekemezie, I. O. (2024). A comprehensive review of building energy management systems (BEMS) for improved efficiency. *World Journal of Advanced Research and Reviews*, *21*(3), 0746. https://doi.org/10.30574/wjarr.2024.21.3.0746

Fei, L., Shahzad, M., Abbas, F., Muqeet, H. A., Hussain, M. M., & Bin, L. (2022). Optimal energy management system of IoT-enabled large building considering electric vehicle scheduling, distributed resources, and demand response schemes. *Sensors*, *22*(19), Article 7448.

https://doi.org/10.3390/s22197448

Hafeez, G., Wadud, Z., Khan, I., Khan, I., Shafiq, Z., Usman, M., & Khan, M. U. A. (2020). Efficient energy management of IoT-enabled smart homes under price-based demand response program in smart grid. *Sensors*, *20*(11), Article 3155.

https://doi.org/10.3390/s20113155

Halim, H. H. A., Alias, D., Arsad, A., Looi, L. T. J., Nordin, R., & Ng, D. K. S. (2026). IoT-driven building energy management systems (BEMS) for net zero energy buildings: Concept, integration and future directions. *arXiv*. https://doi.org/10.48550/arxiv.2602.20453

Hannan, M., Faisal, M., Ker, P., Mun, L. H., Parvin, K., Mahlia, T., & Blaabjerg, F. (2018). A review of internet of energy-based building energy management systems: Issues and recommendations. *IEEE Access*, *6*, 38997–39014.

https://doi.org/10.1109/access.2018.2852811

Hernández, J. L., de Miguel, I., Vélez, F., & Vasallo, A. (2024). Challenges and opportunities in European smart buildings energy management: A critical review. *Renewable and Sustainable Energy Reviews*, *199*, Article 114472.

https://doi.org/10.1016/j.rser.2024.114472

IoT-based smart plug-in device for home energy management system. (2018). In *Proceedings of the 4th International Conference on Green Technology and Sustainable Development (GTSD)*. Ho Chi Minh City, Vietnam. https://doi.org/10.1109/GTSD.2018.8595615

Javed, S., Tripathy, A., Deventer, J. V., Mokayed, H., Paniagua, C., & Delsing, J. (2023). An approach towards demand response optimization at the edge in smart energy systems using local clouds. *Smart Energy*, *10*, Article 100123.

https://doi.org/10.1016/j.segy.2023.100123

Kamal, T., et al. (2023). Integrating smart energy management system with internet of things and cloud computing for efficient demand side management in smart grids. *Energies*, *16*(12), Article 4835. https://doi.org/10.3390/en16124835

Kanakadhurga, D., & Prabaharan, N. (2024). Smart home energy management using demand response with uncertainty analysis of electric vehicle in the presence of renewable energy sources. *Applied Energy*, *355*, Article 123062.

https://doi.org/10.1016/j.apenergy.2024.123062

Khan, M. H., Asar, A., Ullah, N., Albogamy, F. R., & Rafique, M. (2022). Modeling and optimization of smart building energy management system considering both electrical and thermal load. *Energies*, *15*(2), Article 0574. https://doi.org/10.3390/en15020574

Khan, M. A., Khan, T., Waseem, M., Saleh, A. M., Qamar, N., & Muqeet, H. A. (2024). Investigation and analysis of demand response approaches, bottlenecks, and future potential capabilities for IoT-enabled smart grid. *IET Renewable Power Generation*, *18*(15), 3509–3535. https://doi.org/10.1049/rpg2.13011

Liu, J., et al. (2022). Internet of things technologies for smart grid. In *Research anthology on smart grid and microgrid development* (pp. 805–832). IGI Global. https://doi.org/10.4018/978- 1-6684-3666-0.ch035

Manic, M., Wijayasekara, D., Amarasinghe, K., & Rodríguez-Andina, J. (2016). Building energy management systems: The age of intelligent and adaptive buildings. *IEEE Industrial Electronics Magazine*, *10*(1), 25–39. https://doi.org/10.1109/mie.2015.2513749

Mannini, R., Darure, T., Eynard, J., & Grieu, S. (2024). Predictive energy management of a building-integrated microgrid: A case study. *Energies*, *17*(6), Article 1355.

https://doi.org/10.3390/en17061355

Marinakis, V., & Doukas, H. (2018). An advanced IoT-based system for intelligent energy management in buildings. *Sensors*, *18*(2), Article 610. https://doi.org/10.3390/s18020610

Minh, Q. N., Nguyen, V.-H., Quy, V. K., Ngoc, L. A., Chehri, A., & Jeon, G. (2022). Edge computing for IoT-enabled smart grid: The future of energy. *Energies*, *15*(17), Article

6140. https://doi.org/10.3390/en15176140

Moghimi, K. S. M., Gulliver, T. A., & Thirumai Chelvan, I. (2024). Energy management in modern buildings based on demand prediction and machine learning—A review. *Energies*, *17*(3), Article 555. https://doi.org/10.3390/en17030555

Munck, L.; Bansi, A.C.; Dias, B.G.; Cella-de-Oliveira, F.A. Em Busca (2013). Da Sustentabilidade Organizacional: A Proposição de um Framework. Rev. *Alcance 2013, 20*, 460–477.

Mustapha, Z., Akomah, B., Abilgah, T., & Tieru, C. K. (2025). Enhancing energy efficiency and management in smart buildings: A holistic approach. *Journal of Applied Science and Technology Trends, 6*(1), 206. https://doi.org/10.38094/jastt61206

Nguyen, V.-H., Quy, V. K., Ngoc, L. A., Chehri, A., & Jeon, G. (2022). IoT-based smart grid: Architecture, communication protocols, and applications. *Energies*, *15*(19), Article 7116.

https://doi.org/10.3390/en15197116

O'Neill, Z. N., Chen, Y., Zhang, J., Cheng, H., & Dong, B. (2023). Adopting occupancy-based HVAC controls in commercial building energy codes: Analysis of cost-effectiveness and decarbonization potential. *Applied Energy*, *349*, Article 121594.

https://doi.org/10.1016/j.apenergy.2023.121594

Page, M. J., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, Article n71. https://doi.org/10.1136/bmj.n71

Pan, J., Jain, R., Paul, S., Vu, T. N., Saifullah, A., & Sha, M. (2015). An internet of things framework for smart energy in buildings: Designs, prototype, and experiments. *IEEE Internet of Things Journal*, *2*(6), 527–537. https://doi.org/10.1109/jiot.2015.2413397

Phan, T. T. H., Huy, T. H. B., Khan, W., Walker, S., Nghia, H. L., & Nguyen, P. H. (2025). Comparative review of energy management strategies for building energy flexibility. In *Proceedings of the Asia Meeting on Environment and Electrical Engineering (EEE-AM)* 1–6. https://doi.org/10.1109/eee-am66675.2025.11473419

Poyyamozhi, M., Murugesan, B., Rajamanickam, N., Shorfuzzaman, M., & Aboelmagd, Y. (2024). IoT—A promising solution to energy management in smart buildings: A systematic review, applications, barriers, and future scope. *Buildings*, *14*(11), Article 3446.

https://doi.org/10.3390/buildings14113446

Rocha, P., Siddiqui, A., & Stadler, M. (2015). Improving energy efficiency via smart building energy management systems: A comparison with policy measures. *Energy and Buildings*, *88*, 203–213. https://doi.org/10.1016/j.enbuild.2014.11.077

Sayed, K., & Gabbar, H. (2018). Building energy management systems (BEMS). In *Energy conservation in residential, commercial, and industrial facilities* (Chapter 2). Wiley.

https://doi.org/10.1002/9781119422099.ch2

Shaqour, A., & Hagishima, A. (2022). Systematic review on deep reinforcement learning-based energy management for different building types. *Energies*, *15*(22), Article 8663.

https://doi.org/10.3390/en15228663

Sittón-Candanedo, I., Alonso, R. S., García, Ó., Muñoz, L., & Rodríguez-González, S. (2019). Edge computing, IoT and social computing in smart energy scenarios. *Sensors*, *19*(15), Article 3353. https://doi.org/10.3390/s19153353

Sivakumar, S., Kanagachidambaresan, G. R., & Mwanandiye, E. S. (2025). An effective IoT-based demand response for energy-efficient smart homes. *Energy Informatics*, *8*, Article 5. https://doi.org/10.1186/s42162-025-00590-w

Spanoudakis, N. I., Akasiadis, C., Iatrakis, G., & Chalkiadakis, G. (2023). Engineering IoT-based open MAS for large-scale V2G/G2V. *Systems*, *11*(3), Article 157.

https://doi.org/10.3390/systems11030157

Teixeira, N., Barreto, R., Gomes, L., Faria, P., & Vale, Z. (2022). A trustworthy building energy management system to enable direct IoT devices' participation in demand response programs. *Electronics*, *11*(6), Article 897. https://doi.org/10.3390/electronics11060897

Tepe, İ. F., & Irmak, E. (2024). Optimizing real-time demand response in smart homes through fuzzy-based energy management and control system. *Electrical Engineering*, *107*, 2121–2145. https://doi.org/10.1007/s00202-024-02613-3

Toderean, L., Cioara, T., Anghel, I., Sarmas, E., Michalakopoulos, V., & Marinakis, V. (2024). Demand response optimization for smart grid integrated buildings: Review of technology enablers landscape and innovation challenges. *Energy and Buildings*, *308*, Article 115067. https://doi.org/10.1016/j.enbuild.2024.115067

Udayakumar, R., Preethi, R., Al-Fatlawy, R., Omirbayevna, T. G., Thandapani, K., Sharma, K., & Rao, H. K. (2023). Smart grids and demand responses strategies for efficient energy management in IoT based urban environments. In *Proceedings of the International*

Conference on Technology, Engineering and Applications for Sustainable Development (ICTEASD) (pp. 325–331). https://doi.org/10.1109/icteasd57136.2023.10585021

Yusoffdeen, K. (2025). A survey of methods and architectures for efficient energy management in IoT-enabled large buildings: Giant Trevally Optimizer (GTO) based electric vehicle scheduling, distributed resource integration, and demand response strategies. *International Journal of Electrical, Electronic and Computer System*, *14*(1), 2682.

https://doi.org/10.65521/ijeecs.v14i1.2682

Zhuang, D., Gan, V. J., Tekler, Z. D., Chong, A., Tian, S., & Shi, X. (2023). Data-driven predictive control for smart HVAC system in IoT-integrated buildings with time-series forecasting and reinforcement learning. *Applied Energy*, *338*, Article 120936.

https://doi.org/10.1016/j.apenergy.2023.120936