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Data-Driven Energy Optimization for Intelligent Buildings with Clean Energy Integration

Arman Petrosyan
Department of Computer Engineering, National Polytechnic University of Armenia, Yerevan, Armenia

ABSTRACT: The rapid transformation of modern buildings into intelligent energy ecosystems has created a critical need for advanced optimization approaches capable of integrating heterogeneous energy resources, renewable generation, energy storage, and dynamic consumption patterns. Traditional building energy management strategies often rely on static operational rules that cannot effectively address uncertainty arising from renewable energy intermittency, occupant behavior variations, electricity price fluctuations, and complex interactions between distributed energy resources. This research paper investigates a data-driven energy optimization framework for intelligent buildings with clean energy integration, emphasizing artificial intelligence-enabled decision-making, stochastic optimization, demand response, and coordinated energy management. The study develops a conceptual framework combining data acquisition, predictive analytics, optimization algorithms, and adaptive control mechanisms to improve building energy efficiency while increasing renewable energy utilization.

The research synthesizes existing optimization methodologies in active distribution networks, integrated energy systems, distributed generation planning, and uncertainty-aware scheduling to establish their applicability within intelligent building environments. Previous studies have demonstrated the effectiveness of chance-constrained optimization, robust optimization, stochastic scheduling, and distributionally robust approaches in addressing uncertain energy system conditions (Akhavn-Hejazi & Mohsenian-Rad, 2018; Álorc & Sun, 2017; Ning & You, 2018). Building upon these foundations, this paper proposes an integrated data-driven optimization architecture where machine learning-based forecasting supports real-time energy allocation, renewable energy coordination, storage management, and demand response decisions.

The proposed framework considers intelligent buildings as interconnected cyber-physical energy systems rather than isolated consumption units. It incorporates photovoltaic generation, battery energy storage, flexible loads, electric vehicles, and grid interaction mechanisms to achieve improved operational reliability and reduced carbon emissions. The methodology analyzes optimization objectives including energy cost minimization, renewable energy consumption maximization, peak demand reduction, and enhancement of system resilience. The findings indicate that data-driven optimization can significantly improve the adaptability of building energy management systems by transforming historical and real-time operational data into actionable control strategies.

The study further discusses practical implementation challenges, including data quality requirements, computational complexity, privacy concerns, interoperability limitations, and uncertainty management. The integration of artificial intelligence with clean energy technologies represents a significant pathway toward sustainable intelligent buildings. Recent research has highlighted the increasing role of AI-based energy optimization in smart building management and renewable integration, particularly from a project implementation and operational perspective (Philip, 2026). This paper contributes a comprehensive analytical framework for researchers, engineers, and policymakers seeking to develop next-generation intelligent building energy systems capable of achieving efficiency, sustainability, and resilience.

Keywords: Data-driven optimization; Intelligent buildings; Renewable energy integration; Artificial intelligence; Energy management systems; Demand response; Energy storage; Smart grid; Sustainable buildings

1. INTRODUCTION

1.1 Background

Reimbursement Buildings represent one of the largest energy-consuming sectors globally, with increasing demand driven by urbanization, technological advancement, and improved living standards. Conventional building energy systems have historically been designed around predictable consumption patterns and centralized electricity supply structures. However, the transition toward sustainable energy systems has introduced new operational complexities due to the increasing penetration of renewable energy resources, distributed generation technologies, and flexible energy assets. Intelligent buildings have emerged as a promising solution by combining sensing technologies, communication infrastructure, automation systems, and advanced computational techniques to optimize energy utilization.

The concept of intelligent buildings extends beyond automated control of lighting, heating, ventilation, and air-conditioning systems. Modern intelligent buildings function as integrated energy platforms where renewable generation, storage devices, electric vehicles, and flexible loads interact dynamically with external power networks. Such buildings require advanced optimization methodologies capable of processing large-scale operational data and making real-time decisions under uncertainty. The uncertainty originates from multiple sources, including weather-dependent renewable generation, variable occupancy behavior, energy price changes, and unpredictable grid conditions.

Data-driven optimization has become an important research direction for addressing these challenges. Unlike conventional deterministic approaches, data-driven methods utilize historical operational information, sensor measurements, and predictive models to identify patterns and optimize energy decisions. In uncertain energy environments, these approaches enable adaptive scheduling and improved resource coordination. Research on uncertain power system optimization has demonstrated that data-based methods can enhance decision quality by incorporating probabilistic information and learning-based prediction mechanisms (Lu et al., 2020).

The integration of clean energy technologies further increases the importance of intelligent optimization. Renewable energy sources such as solar photovoltaic systems introduce variability because their output depends on environmental conditions. Without appropriate optimization strategies, renewable generation may create operational challenges, including power imbalance, excessive curtailment, and inefficient storage utilization. Therefore, intelligent buildings require coordinated strategies that combine renewable generation forecasting, energy storage optimization, demand response management, and grid interaction control.

1.2 Problem Statement

Although intelligent building technologies have advanced considerably, several challenges remain unresolved. First, traditional energy management systems frequently operate using predefined control rules that lack adaptability under changing environmental and operational conditions. These systems may perform adequately under normal conditions but often fail to achieve optimal performance when facing uncertainty.

Second, renewable energy integration creates a complex optimization problem involving multiple conflicting objectives. Increasing renewable utilization may require additional storage capacity, while minimizing operational costs may require strategic interaction with electricity markets. Similarly, reducing peak demand through demand response may influence occupant comfort and operational requirements. Therefore, intelligent building energy management requires multi-objective optimization frameworks capable of balancing economic, environmental, and technical considerations.

Third, the large volume of data generated by smart meters, sensors, building automation systems, and renewable energy devices introduces both opportunities and challenges. While data availability enables advanced analytics, extracting meaningful information requires sophisticated artificial intelligence and optimization techniques. The development of computational frameworks capable of transforming raw data into reliable operational decisions remains a significant research challenge.

Existing studies in power system optimization provide valuable theoretical foundations but are primarily focused on distribution networks and large-scale energy systems rather than building-level energy ecosystems. For example, stochastic and robust optimization techniques have been widely applied for energy storage planning, unit commitment, and renewable generation management (Akhavn-Hejazi & Mohsenian-Rad, 2018; Álorc & Sun, 2017). However, adapting these methodologies to intelligent buildings requires consideration of building-specific characteristics, including occupant behavior, thermal dynamics, and local energy flexibility.

1.3 Research Relevance

The development of data-driven energy optimization frameworks for intelligent buildings is highly relevant to achieving sustainable energy transition goals. Buildings equipped with renewable energy generation, storage technologies, and intelligent control systems can contribute to reduced carbon emissions, improved energy efficiency, and enhanced grid flexibility.

Recent research emphasizes that artificial intelligence-based optimization approaches can provide significant improvements in smart building energy management by enabling predictive decision-making and improved renewable integration (Philip, 2026). Such approaches are particularly important as buildings increasingly become active participants in energy networks rather than passive consumers.

Furthermore, intelligent buildings can support broader smart grid objectives by providing demand flexibility and distributed energy management capabilities. Research on integrated energy systems has shown that coordinated optimization among multiple energy carriers and flexible resources can improve system reliability and economic performance (Li et al., 2018). These findings suggest that building-level optimization should be considered as part of a larger energy ecosystem.

1.4 Research Objectives

This paper aims to develop a comprehensive analytical framework for data-driven energy optimization in intelligent buildings integrated with clean energy resources. The specific objectives are:

1. To analyze the theoretical foundations of data-driven optimization approaches for uncertain energy systems.

2. To develop an intelligent building energy management framework integrating renewable generation, storage, and demand response.

3. To examine the role of artificial intelligence and predictive analytics in improving building energy decisions.

4. To evaluate optimization strategies for reducing energy costs, improving renewable utilization, and enhancing operational resilience.

5. To identify implementation challenges and future research directions for intelligent building energy optimization.

1.5 Scope and Significance

The scope of this research focuses on intelligent buildings equipped with renewable energy resources, energy storage systems, flexible loads, and digital monitoring infrastructure. The study does not examine a single commercial building implementation but develops a generalized optimization framework applicable to various building types, including residential complexes, commercial facilities, educational institutions, and industrial buildings.

The significance of this research lies in connecting advanced energy optimization theories with practical intelligent building applications. By integrating concepts from stochastic optimization, robust decision-making, machine learning, and renewable energy management, the proposed framework provides a foundation for future sustainable building energy systems.

2. LITERATURE REVIEW

2.1 Evolution of Data-Driven Energy Optimization Research

The transition from conventional energy management approaches toward data-driven optimization has been influenced by increasing uncertainty in modern energy systems. Traditional optimization methods generally assume predictable operating conditions, fixed demand patterns, and deterministic resource availability. However, the integration of renewable energy sources, distributed generation, and flexible energy resources has introduced significant uncertainty, requiring advanced mathematical and computational techniques.

Research on uncertain energy system optimization has progressively shifted from deterministic scheduling toward stochastic, robust, and data-driven decision frameworks. Lu et al. (2020) provided an overview of data-driven optimal scheduling methods in uncertain power system environments and emphasized that increasing data availability has enabled new approaches for improving operational decisions. According to their analysis, data-driven methods can reduce dependence on predefined assumptions by extracting hidden patterns from historical and real-time operational information.

The theoretical foundation of these methods is closely connected with uncertainty modeling, predictive analytics, and optimization under incomplete information. Ning and You (2018) developed a general computational framework for data-driven stochastic robust optimization and demonstrated how machine learning techniques can enhance optimization performance under uncertainty. Their research established that combining data analytics with mathematical optimization allows energy systems to achieve improved adaptability compared with conventional robust approaches.

For intelligent buildings, these developments provide important theoretical support because building energy systems contain multiple uncertain variables, including renewable generation availability, occupancy behavior, thermal conditions, and energy market variations. The ability to process and learn from operational data becomes essential for achieving efficient and reliable building energy management.

2.2 Optimization Under Renewable Energy and System Uncertainty

Renewable energy integration represents one of the major challenges in intelligent energy management due to its intermittent nature. Solar and wind generation depend strongly on environmental conditions, making accurate prediction and flexible scheduling necessary. Several studies in power system optimization have addressed similar challenges through probabilistic and robust optimization techniques.

Akhavn-Hejazi and Mohsenian-Rad (2018) investigated energy storage planning in active distribution grids using chance-constrained optimization with non-parametric probability functions. Their study demonstrated that storage planning can be improved by considering uncertainty distributions derived from operational data rather than relying exclusively on predetermined probability assumptions. This approach is highly relevant to intelligent buildings because energy storage is a key mechanism for balancing renewable generation and consumption.

Similarly, Álorc and Sun (2017) proposed a multistage robust unit commitment framework incorporating dynamic uncertainty sets and energy storage. Their research highlighted the importance of adaptive decision-making when system conditions evolve over time. The concept of dynamic uncertainty management can be transferred to intelligent buildings where energy decisions must continuously adjust according to changing weather, occupancy, and electricity pricing conditions.

Ding et al. (2018) examined data-driven stochastic reactive power optimization considering uncertainty in active distribution networks. Their research demonstrated the effectiveness of combining operational data with stochastic optimization methods for improving system performance. Although their study focused on distribution networks, the underlying principle is applicable to intelligent buildings because building energy systems increasingly interact with distribution grids through distributed generation and flexible demand.

These studies collectively demonstrate that uncertainty-aware optimization is essential for clean energy integration. However, existing research has primarily concentrated on grid-level applications, creating a need for customized frameworks that consider the unique characteristics of intelligent buildings.

2.3 Distributed Generation and Integrated Energy System Optimization

The expansion of distributed generation has significantly changed the structure of energy systems. Buildings equipped with photovoltaic panels, combined heat and power systems, batteries, and electric vehicle charging infrastructure can operate as distributed energy nodes. Effective coordination of these resources requires integrated optimization models capable of balancing multiple energy flows.

Gao et al. (2017) proposed a multi-objective bilevel coordinated planning approach for distributed generation and distribution network development using multi-scenario techniques. Their study emphasized that planning decisions should consider temporal characteristics and different operational scenarios. This perspective is valuable for intelligent building applications because building energy investments, such as renewable installations and storage systems, require long-term planning under uncertain future conditions.

He et al. (2019) developed a distributionally robust optimal distributed generation allocation model considering flexible demand response. Their research highlighted the importance of incorporating demand-side flexibility into renewable energy planning. In intelligent buildings, demand response provides an effective mechanism for adjusting consumption patterns according to energy availability and grid requirements.

Muñoz-Delgado et al. (2016) investigated multistage generation and network expansion planning under uncertainty and reliability constraints. Their work demonstrated that energy infrastructure decisions require consideration of both technical reliability and uncertain future scenarios. This concept supports the development of intelligent building frameworks where renewable integration strategies must consider long-term operational stability.

The integration of multiple energy carriers has also received increasing attention. Li et al. (2018) studied stochastic operation optimization of integrated low-carbon electric power, natural gas, and heat delivery systems. Their research demonstrated that coordinated management of different energy forms can improve efficiency and reduce environmental impacts. For intelligent buildings, similar principles apply through coordination between electricity, heating, cooling, storage, and renewable generation systems.

2.4 Demand Response and Flexible Energy Management

Demand response has become a fundamental component of intelligent energy optimization because it enables consumers to actively participate in energy management. Unlike traditional systems where demand is considered fixed, modern optimization approaches treat consumption as a flexible resource.

Zhang et al. (2016) investigated electricity-natural gas operation planning with hourly demand response for flexible ramp deployment. Their findings showed that demand flexibility can enhance system reliability by improving resource balancing. This concept is particularly relevant for intelligent buildings because flexible loads, including HVAC systems, water heating, and electric vehicle charging, can be scheduled according to energy availability.

Zeng et al. (2014) examined integrated planning for low-carbon distribution systems considering renewable generation and demand response. Their research indicated that combining renewable energy deployment with flexible demand strategies can improve the transition toward low-carbon energy systems.

Ruan et al. (2019) proposed a distributionally robust reactive power optimization model considering distributed generation support and switch reconfiguration. Their research demonstrated that advanced optimization methods can improve system flexibility while managing uncertainty. Such approaches provide theoretical foundations for intelligent building controllers that must coordinate renewable resources and grid interaction.

The application of demand response in buildings also requires consideration of user comfort and operational constraints. Excessive energy reduction strategies may negatively affect occupants, making multi-objective optimization necessary. Therefore, future intelligent building systems must balance energy efficiency with human-centered operational requirements.

2.5 Artificial Intelligence and Smart Building Energy Management

Artificial intelligence has become increasingly important in intelligent building energy optimization because it enables predictive analysis, pattern recognition, and adaptive control. AI techniques can analyze large volumes of building operational data and generate optimization decisions that respond to changing conditions.

Recent work on AI-based energy optimization in smart buildings has highlighted the importance of combining artificial intelligence with renewable energy management, particularly for improving operational efficiency and supporting sustainable construction management practices (Philip, 2026). The study emphasizes that AI-driven approaches can assist in predictive energy scheduling, renewable integration planning, and project-level energy performance improvement.

Jia et al. (2022) investigated multi-layer coordinated optimization of integrated energy systems with electric vehicles based on feedback correction. Their research demonstrated that layered optimization structures can improve coordination between multiple energy resources. This approach has direct relevance to intelligent buildings where electric vehicles, storage systems, and renewable resources must operate together.

However, despite significant progress, several challenges remain. AI-based approaches require high-quality datasets, reliable communication infrastructure, and computational resources. Furthermore, optimization models must address privacy concerns because building energy data can reveal sensitive information about occupant behavior.

Recent advances in privacy-preserving artificial intelligence have demonstrated that federated deep reinforcement learning combined with homomorphic encryption can support secure distributed model training without exposing sensitive operational data. Such architectures are particularly valuable for intelligent building energy management, where cloud-based optimization requires strong protection of occupant and infrastructure information while maintaining high analytical performance (Kodela et al., 2025).

2.6 Research Gap and Theoretical Positioning

The reviewed literature demonstrates substantial progress in uncertain energy optimization, renewable integration, demand response, and distributed energy management. However, several research gaps remain.

First, many existing studies focus on distribution networks or large-scale energy systems rather than building-level integrated energy environments. Intelligent buildings require optimization models that consider unique characteristics such as occupancy patterns, thermal behavior, and localized renewable generation.

Second, existing optimization approaches often address individual challenges separately, such as storage planning, distributed generation allocation, or demand response management. A comprehensive framework integrating these elements through data-driven intelligence remains insufficiently developed.

Third, while AI-based approaches provide significant opportunities, practical integration between machine learning prediction models and mathematical optimization frameworks requires further investigation.

Therefore, this research positions intelligent buildings as dynamic cyber-physical energy systems where data analytics, optimization algorithms, renewable resources, and flexible energy assets operate as an integrated framework. The theoretical foundation combines stochastic optimization, robust decision-making, artificial intelligence, and integrated energy management principles derived from the reviewed studies.

3. METHODOLOGY

3.1 Research Framework Development

This study develops a data-driven energy optimization framework for intelligent buildings integrated with clean energy resources. The proposed methodology considers an intelligent building as a cyber-physical energy system composed of physical energy assets, digital monitoring infrastructure, computational intelligence, and adaptive control mechanisms. Unlike traditional building energy management approaches that focus primarily on reducing consumption, the proposed framework aims to optimize the complete energy ecosystem by coordinating generation, storage, consumption, and grid interaction.

The methodology is established through the integration of four major functional layers: data acquisition, predictive analytics, optimization decision-making, and intelligent control. The data acquisition layer collects information from smart meters, renewable generation units, environmental sensors, energy storage systems, building automation platforms, and external grid signals. The predictive analytics layer processes collected data using statistical and artificial intelligence-based methods to estimate future energy demand, renewable generation availability, and operational conditions. The optimization layer determines the most efficient energy scheduling strategy, while the control layer implements optimized decisions through automated building management systems.

The framework is theoretically supported by uncertainty-aware optimization approaches developed for modern energy systems. Previous research has demonstrated that stochastic and robust optimization methods can improve operational decisions under uncertain conditions by incorporating probabilistic information and adaptive strategies (Akhavn-Hejazi & Mohsenian-Rad, 2018; Álorc & Sun, 2017). In intelligent buildings, similar principles are applied to address uncertainties associated with occupancy behavior, weather conditions, renewable generation fluctuations, and electricity market variations.

The proposed methodology follows a closed-loop optimization process. Operational data continuously updates prediction models, prediction outputs guide optimization decisions, and actual system performance provides feedback for model improvement. This adaptive mechanism allows intelligent buildings to continuously improve their energy performance rather than relying on fixed operational rules.

3.2 Intelligent Building Energy System Architecture

The intelligent building energy system considered in this research consists of multiple interconnected components:

1. Renewable energy generation system
2. Energy storage system
3. Flexible building loads
4. Electric vehicle charging infrastructure
5. Grid interaction interface
6. Artificial intelligence-based optimization controller

The renewable energy subsystem primarily includes photovoltaic generation due to its increasing adoption in buildings. Renewable generation is modeled as a variable energy source influenced by environmental conditions such as solar radiation, temperature, and weather patterns. Since renewable output cannot be directly controlled, forecasting and adaptive scheduling mechanisms are required.

The energy storage subsystem acts as an intermediate balancing resource between renewable generation and consumption. During periods of high renewable production and low demand, excess energy can be stored. During renewable shortages or peak electricity price periods, stored energy can be discharged to reduce grid dependency. Storage planning and operational optimization are critical because inappropriate charging and discharging decisions can reduce economic benefits and battery lifespan.

The flexible load subsystem represents energy-consuming devices whose operation can be adjusted without significantly affecting user requirements. Examples include heating, ventilation, air-conditioning systems, water heating, lighting systems, and electric vehicle charging. Demand flexibility enables intelligent buildings to respond dynamically to renewable availability and electricity market conditions.

Electric vehicles are considered mobile energy resources capable of both consuming and supplying electricity through vehicle-to-building or vehicle-to-grid interactions. Jia et al. (2022) demonstrated that coordinated optimization of integrated energy systems involving electric vehicles can improve system flexibility through feedback-based control mechanisms.

3.3 Data Acquisition and Processing Framework

Data availability is the foundation of data-driven optimization. The proposed framework utilizes multiple categories of data:

Energy Consumption Data

Historical electricity consumption data is collected from smart meters and building energy management systems. This data provides information about daily consumption patterns, peak demand periods, and load variability. Machine learning models use historical consumption trends to predict future demand.

Environmental Data

Environmental information, including temperature, humidity, solar radiation, and weather forecasts, is incorporated because building energy demand is strongly influenced by external conditions. For example, cooling demand increases during high-temperature periods, while photovoltaic output varies according to solar availability.

Renewable Generation Data

Real-time and historical renewable generation data is used to develop prediction models for photovoltaic output. Accurate renewable forecasting improves energy scheduling decisions and reduces unnecessary grid dependency.

Operational and User Data

Occupancy patterns and equipment operation information are included to improve demand prediction accuracy. However, the collection of user-related data introduces privacy challenges requiring appropriate data protection mechanisms.

To enhance data security during cloud-based analytics, privacy-preserving machine learning techniques can be integrated into the proposed framework. Homomorphic encryption enables encrypted computation, while federated deep reinforcement learning allows distributed model optimization without transferring raw operational data, thereby improving both privacy protection and intelligent decision-making (Kodela et al., 2025).

Data preprocessing involves cleaning incomplete datasets, removing abnormal measurements, identifying consumption patterns, and transforming raw information into optimization-compatible formats. High-quality data is essential because inaccurate input information can negatively influence optimization outcomes.

Ning and You (2018) emphasized that effective data-driven stochastic optimization depends on combining machine learning capabilities with mathematical optimization frameworks. Therefore, the proposed methodology does not replace optimization models with AI prediction alone but integrates both approaches.

3.4 Artificial Intelligence-Based Energy Forecasting Model

The forecasting module represents the intelligence component of the proposed framework. Its objective is to predict future energy conditions and provide optimization inputs.

The forecasting process includes:

Load Demand Prediction

Building electricity demand is predicted using historical consumption data combined with environmental and operational variables. Machine learning models identify relationships between external factors and energy consumption patterns.

For example, during summer periods, predicted temperature increases can indicate higher cooling demand. The optimization system can use this prediction to schedule energy storage discharge or modify HVAC operation before peak demand occurs.

Renewable Generation Prediction

Renewable generation forecasting estimates future photovoltaic availability. Accurate prediction enables better coordination between renewable production and energy consumption.

If high solar generation is expected during daytime hours, the system may schedule battery charging or increase flexible load operation during this period. Conversely, predicted low renewable output may trigger preventive energy conservation measures.

Price and Grid Condition Prediction

Electricity price signals and grid conditions are included to support economic optimization. When electricity prices are high, the system can reduce grid consumption through storage utilization and demand response.

The forecasting framework follows the principle that improved prediction accuracy enhances optimization quality. However, forecasting errors remain unavoidable due to unpredictable environmental and human factors. Therefore, uncertainty management mechanisms are integrated into the optimization stage.

3.5 Uncertainty-Aware Optimization Model

The mathematical foundation of the proposed framework combines stochastic optimization and robust optimization principles. The objective is to determine optimal energy management decisions under uncertain operating conditions.

The optimization problem can be represented as:

Minimize:

F=Ce+Co+Cs+CpF = C_e + C_o + C_s + C_pF=Ce+Co+Cs+Cp

where:

- CeC_eCe represents electricity purchasing cost,
- CoC_oCo represents operational cost,
- CsC_sCs represents storage degradation cost,
- CpC_pCp represents penalty cost associated with renewable energy curtailment or demand violations.

The optimization considers multiple constraints:

Energy Balance Constraint

The total energy supplied by renewable generation, storage discharge, and grid electricity must satisfy building demand:

Prenewable+Pstorage+Pgrid=PloadP_{renewable}+P_{storage}+P_{grid}=P_{load}Prenewable+Pstorage+

Pgrid=Pload

Storage Operation Constraint

Battery charging and discharging operations must maintain technical limitations:

SOCmin≤SOCt≤SOCmaxSOC_{min}\leq SOC_t \leq SOC_{max}SOCmin≤SOCt≤SOCmax

where SOC represents battery state of charge.

Renewable Integration Constraint

The system attempts to maximize renewable utilization while avoiding excessive curtailment.

Comfort Constraint

Building operation must maintain acceptable indoor environmental conditions. Energy savings cannot be achieved at the expense of unacceptable occupant comfort.

This multi-objective structure reflects the complexity of intelligent building optimization. Similar multi-objective approaches have been applied in distributed generation planning and integrated energy systems (Gao et al., 2017; Li et al., 2018).

3.6 Demand Response Optimization Strategy

Demand response is integrated as an active optimization component rather than a passive energy-saving measure. The proposed framework classifies building loads into three categories:

1. Fixed loads
2. Adjustable loads
3. Shiftable loads

Fixed loads include essential systems that cannot be interrupted. Adjustable loads allow limited operational modification, while shiftable loads can be rescheduled according to energy availability.

The optimization controller determines appropriate demand response actions based on predicted conditions. For example, during periods of high electricity prices and low renewable generation, non-critical loads can be delayed. During periods of excess solar production, flexible loads can operate to increase renewable utilization.

Research on demand response integration has shown that flexible demand can improve renewable energy adoption and reduce system operational pressure (He et al., 2019; Zeng et al., 2014).

3.7 Energy Storage Optimization Mechanism

Energy storage is considered a critical component for achieving renewable energy integration. The optimization controller determines charging and discharging schedules based on:

- Renewable generation forecast
- Building demand prediction

- Electricity price signals
- Battery operating limitations

The storage strategy follows three operational principles:

First, charging should occur when renewable generation exceeds immediate demand or when electricity prices are low.

Second, discharging should occur during high-cost electricity periods or renewable generation shortages.

Third, unnecessary cycling should be avoided to reduce battery degradation.

The approach extends storage optimization principles developed for active distribution systems toward building-level applications (Akhavn-Hejazi & Mohsenian-Rad, 2018).

3.8 Integrated Decision and Control Mechanism

The final stage of the methodology involves converting optimization results into practical building control actions. The intelligent controller communicates with building automation systems to implement decisions.

3.9 Hypothetical Implementation Scenario and Validation Framework

To evaluate the practical applicability of the proposed data-driven energy optimization framework, a hypothetical intelligent commercial building scenario is considered. The building represents a medium-to-large facility equipped with rooftop photovoltaic generation, battery energy storage, smart meters, automated HVAC systems, electric vehicle charging stations, and a building energy management platform.

The building operates under variable energy conditions, including changing occupancy levels, fluctuating solar availability, and dynamic electricity pricing. The proposed optimization framework receives continuous data from installed sensors and energy devices. Machine learning-based forecasting models estimate short-term electricity demand and renewable generation availability, while the optimization engine determines the most suitable operational strategy.

During high solar generation periods, the framework prioritizes direct renewable energy consumption. If renewable generation exceeds immediate demand, the optimization algorithm schedules battery charging or activates flexible loads. During evening peak periods, when renewable production decreases and electricity prices increase, stored energy is discharged to reduce grid electricity consumption. Similarly, electric vehicle charging schedules are adjusted according to renewable availability and grid conditions.

The implementation scenario demonstrates how intelligent buildings can transition from passive energy consumers to active energy participants. Instead of simply minimizing electricity consumption, the building operates as a flexible energy resource capable of supporting grid stability and renewable energy integration.

The validation framework evaluates the effectiveness of the proposed methodology through several performance indicators:

Energy Cost Reduction

The first evaluation criterion is the reduction in electricity purchasing costs. The optimization model compares intelligent scheduling strategies with conventional building operation methods. Cost savings are achieved through renewable utilization, peak demand reduction, and optimized storage operation.

Renewable Energy Utilization Rate

The second indicator measures the percentage of renewable generation directly consumed or stored within the building. Higher renewable utilization indicates improved integration performance and reduced dependence on conventional energy sources.

Peak Demand Reduction

Peak demand reduction evaluates the ability of the system to minimize high-load periods. Through demand response and storage coordination, intelligent buildings can reduce stress on distribution networks.

Carbon Emission Reduction

The environmental performance of the system is assessed by estimating reductions in grid electricity dependence and associated emissions. Increased renewable utilization contributes to long-term decarbonization objectives.

System Reliability and Adaptability

The final indicator evaluates whether the optimization framework can maintain stable operation under uncertain conditions. Robustness against forecasting errors, renewable variability, and demand fluctuations represents an important measure of practical effectiveness.

These evaluation criteria align with previous research emphasizing the importance of balancing economic efficiency, reliability, and environmental performance in integrated energy systems (Li et al., 2018; Muñoz-Delgado et al., 2016).

3.10 Methodological Limitations and Research Considerations

Although the proposed framework provides an integrated approach for intelligent building energy optimization, several limitations must be considered.

First, the effectiveness of data-driven optimization depends strongly on data availability and quality. Inaccurate sensor measurements, incomplete historical records, or communication failures may reduce prediction accuracy and negatively affect optimization outcomes. Therefore, reliable data management systems are essential for practical implementation.

Second, artificial intelligence-based forecasting models require sufficient computational resources and training data. Smaller buildings with limited monitoring infrastructure may experience difficulties in implementing advanced optimization systems.

Third, uncertainty remains a fundamental challenge. Even advanced forecasting methods cannot completely eliminate unpredictability caused by extreme weather events, unexpected occupancy changes, or sudden grid disturbances. Therefore, future optimization systems should continue improving adaptive uncertainty management approaches.

Fourth, cybersecurity and privacy concerns require attention. Intelligent buildings collect extensive operational information that may reveal occupancy patterns and user behavior. Secure communication protocols and privacy-preserving data management strategies are necessary for widespread adoption.

Finally, economic feasibility must be considered. The installation of renewable systems, storage technologies, sensors, and intelligent control infrastructure requires significant investment. Future research should investigate optimal investment planning approaches that consider both technical benefits and financial constraints.

4. RESULTS

The analysis of the proposed data-driven energy optimization framework demonstrates that intelligent buildings can achieve improved energy performance through coordinated management of renewable generation, storage systems, and flexible demand. The findings indicate that integrating predictive analytics with optimization algorithms provides a more adaptive approach compared with conventional rule-based energy management strategies.

The first major finding is that data-driven forecasting significantly improves energy scheduling decisions. By utilizing historical consumption patterns, environmental information, and renewable generation data, the optimization system can anticipate future operating conditions and adjust energy strategies accordingly. This reduces the impact of uncertainty and enables more efficient utilization of available resources.

The second finding is that energy storage plays a central role in renewable energy integration. Storage optimization allows intelligent buildings to overcome the mismatch between renewable generation and consumption periods. During renewable energy surplus conditions, stored energy prevents unnecessary curtailment, while during high-demand periods, stored energy reduces grid dependency.

The third finding is that demand response enhances system flexibility. Flexible loads provide additional optimization opportunities by allowing energy consumption to be shifted according to renewable availability and electricity price conditions. This approach supports both economic optimization and grid reliability improvement.

The fourth finding is that multi-objective optimization is necessary because intelligent building energy management involves competing goals. Reducing operational costs, maximizing renewable utilization, maintaining occupant comfort, and extending storage lifespan cannot always be achieved simultaneously. Therefore, optimization models must identify balanced solutions rather than focusing on a single performance indicator.

The research also indicates that artificial intelligence-based approaches provide significant advantages in handling complex energy interactions. AI models enable continuous learning from operational data and improve decision-making through adaptive prediction. This supports findings that AI-driven energy optimization can enhance renewable integration and smart building operational performance (Philip, 2026).

However, the findings also reveal several practical challenges. The effectiveness of optimization depends on reliable data infrastructure, accurate forecasting, and appropriate system integration. Furthermore, computational complexity increases as more energy resources and operational constraints are included.

Overall, the results demonstrate that data-driven optimization provides a viable pathway for developing sustainable intelligent buildings. By integrating renewable energy, storage technologies, demand response, and artificial intelligence, buildings can achieve improved efficiency, flexibility, and environmental performance.

5. DISCUSSION

The findings highlight that intelligent building energy optimization represents a transition from conventional energy conservation toward active energy management. The proposed framework demonstrates that buildings can function as dynamic components of future energy systems by coordinating renewable generation, storage, and flexible consumption.

From a theoretical perspective, the research extends uncertainty-aware optimization concepts from power system applications to building-level energy management. Previous studies on stochastic and robust optimization have primarily focused on distribution networks and large-scale energy systems (Akhavn-Hejazi & Mohsenian-Rad, 2018; Álorc & Sun, 2017). This study demonstrates that similar principles can be adapted to intelligent buildings where uncertainties occur at smaller but highly dynamic scales.

The integration of artificial intelligence introduces significant opportunities for improving operational decisions. AI-based forecasting allows optimization models to move beyond static assumptions and respond to changing conditions. As emphasized by Philip (2026), AI-supported energy optimization can contribute to more effective renewable energy integration and sustainable building management.

However, several trade-offs must be considered. Increasing renewable utilization may require larger storage capacity, which increases investment costs. Similarly, aggressive demand response strategies may reduce energy costs but could affect occupant comfort if operational constraints are not properly managed. Therefore, optimization frameworks must maintain a balance between economic, environmental, and human-centered objectives.

The comparison with existing literature shows that distributed generation planning, demand response optimization, and integrated energy management studies provide valuable foundations for intelligent building applications (Gao et al., 2017; He et al., 2019; Zeng et al., 2014). However, a major limitation of current research is the lack of fully integrated frameworks combining prediction, optimization, and real-time control.

Practical implementation also faces challenges related to cybersecurity, interoperability, investment requirements, and data management. Future intelligent building systems must adopt standardized communication architectures and secure data-processing mechanisms.

Despite these limitations, the proposed framework provides important implications for sustainable energy development. Intelligent buildings equipped with data-driven optimization capabilities can contribute to renewable energy adoption, reduced emissions, and improved grid flexibility. The combination of artificial intelligence and clean energy technologies represents a significant direction for future energy management research.

6. CONCLUSION

The increasing complexity of modern energy systems has created a strong requirement for intelligent optimization approaches capable of managing uncertainty, renewable energy variability, and dynamic consumption patterns. This research presented a comprehensive data-driven energy optimization framework for intelligent buildings with clean energy integration. The proposed framework conceptualizes intelligent buildings as adaptive cyber-physical energy systems where renewable generation, energy storage, demand response, artificial intelligence, and grid interaction mechanisms operate through coordinated decision-making processes.

The study demonstrates that data-driven optimization provides a significant advancement over traditional energy management strategies. By combining historical operational data, real-time monitoring information, predictive analytics, and optimization algorithms, intelligent buildings can achieve improved energy efficiency, reduced operational costs, and enhanced renewable energy utilization. The methodology integrates principles from stochastic optimization, robust optimization, distributed energy planning, and artificial intelligence-based control to address the uncertainties associated with renewable energy systems.

A major contribution of this research is the development of an integrated perspective that connects building-level energy management with broader smart energy system optimization concepts. Previous research has primarily focused on distribution networks, energy storage planning, distributed generation allocation, and integrated energy systems. This study extends these concepts toward intelligent building applications by incorporating building-specific factors such as flexible loads, occupant-related energy variations, and localized renewable resources.

The findings indicate that renewable energy integration alone is insufficient to achieve optimal building sustainability. Effective coordination among photovoltaic generation, storage systems, demand response mechanisms, and intelligent control platforms is essential. Energy storage provides flexibility by reducing the mismatch between renewable production and energy demand, while demand response enables buildings to actively participate in energy management. Artificial intelligence further strengthens this process by improving forecasting accuracy and enabling adaptive operational decisions.

The research also identifies important limitations that require further investigation. The effectiveness of data-driven optimization depends on data quality, computational capability, communication infrastructure, and cybersecurity protection. Additionally, real-world implementation requires consideration of economic feasibility, technology compatibility, and user acceptance. Future research should focus on developing lightweight optimization models suitable for different building scales, improving privacy-preserving AI techniques, and creating standardized frameworks for intelligent building integration with smart grids.

Future developments may also explore digital twins, reinforcement learning-based controllers, peer-to-peer energy trading mechanisms, and coordinated multi-building energy communities. Such approaches could further enhance the role of intelligent buildings as active contributors to sustainable energy networks.

In conclusion, data-driven energy optimization represents a critical pathway toward achieving efficient, resilient, and low-carbon intelligent buildings. The combination of artificial intelligence, renewable energy technologies, and advanced optimization methods provides a foundation for next-generation energy management systems capable of supporting global sustainability objectives.

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