AI-Driven Energy Optimization and Storage Management for Smart Grids and Green Buildings

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Abstract. Recent technologies for high-energy optimization and storage control have been accelerated by the growing integration of renewable energy sources and smart building systems in modern power systems. The new generation of smart grids and green buildings gives rise to extremely dynamic and heterogeneous streams of information about energy demand, generation, storage, and environmental conditions, so that the conventional rule-based control mechanisms are invalid. This paper suggests an AI-based energy optimization and storage management system, which incorporates predictive analytics, adaptive control, and real-time decision-making to enhance the energy efficiency, reliability, and sustainability of smart grids and green buildings. The suggested structure is that deep learning is used to predict loads and generation, reinforcement learning is used to predict adaptive energy schedules, and the optimization models are used to predict battery storage. A dataset of 3.2 million timestamped records of smart meters, photovoltaic systems, weather stations, and building management systems is used to evaluate the system. Measurement of performance is done based on peak load reduction, energy cost savings, reduction in carbon emissions, efficiency in store utilization, and prediction accuracy. The results of the experiment indicate an optimal load reduction of 26%, a cost saving of 18%, a reduction in carbon emissions of 21%, and greater forecasting accuracy of more than 94% compared to the baseline systems. The efficiency of storage utilization has been enhanced by 23% by use of intelligent charging and discharging strategies. The statistical consideration of the hypothesis proves that the proposed scheme is more effective than traditional optimization methods in all of the considered measures without compromising the stability and responsiveness of the system when the demand variations and the renewable generation conditions change. These findings explain that AI-based energy optimization and storage management can greatly increase the efficiency and sustainability of smart grids and green buildings, helping to turn the city into a low-carbon and energy-efficient environment.

Keywords: Smart Grids, Green Buildings, Energy Optimization, Energy Storage Management, Artificial Intelligence, Renewable Energy.

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1 Introduction

The fast development of renewable energy production, electric mobility, and smart building technology is changing traditional power systems to a complex cyber-physical infrastructure called smart grids [1]. Green buildings also help to achieve this change by incorporating distributed energy resources, smart appliances, and energy-efficient control into city spaces [21]. Recent studies (2024–2025) further highlight the integration of AI-enabled digital twins, real-time analytics platforms, and decentralized microgrid coordination frameworks as critical enablers of modern smart grid ecosystems. All this makes systems more complex, variable, and uncertain, posing major problems with energy management, reliability, and sustainability [3].

Traditional energy management systems are based on fixed rules or simplified optimization models, which are unable to incorporate dynamic demand patterns, intermittent renewable generation, or changing user behavior [22]. In the 2024 and 2025 systematic reviews, it is stated that deterministic optimization methods are usually associated with the inability to scale and low adaptability during high renewable penetration conditions. Another strong alternative proposed by artificial intelligence is allowing interconnected energy systems to forecast, be controlled, and optimized in real-time with the help of data [5]. Deep learning models have been shown to be highly predictive in the modeling of the nonlinear temporal interactions in load and renewable generation signals, whereas reinforcement learning methods are able to facilitate adaptive control in situations of uncertainty. AI-based building energy management systems offer significant opportunities to reduce energy consumption and operational expenses [6].

The combination of AI and IoT technologies makes the smart infrastructure energy management system more responsive and scalable in green infrastructure [7]. Recent empirical studies indicate that AI-based optimization can enhance the peak load control, increase the rate of the renewable utilisation, and increase the grid resiliency in the distributed energy settings. The efficacy of AI-powered optimization to enhance hospital energy systems as an example of domain-specific deployment demonstrates the importance of the tool in enhancing resilience and reliability [8]. Extensive surveys have pointed to the importance of AI to allow sustainable energy management on a wide variety of building and grid settings [9]. Besides, data-driven and hybrid AI models are also being considered as the key to attaining low-carbon shifts and fulfilling the urban decarbonization goals. Data-driven technologies have become recognized as a necessary solution for optimizing energy consumption and facilitating low-carbon building processes [10].

The value of the work lies in integrating forecasting, control optimization, and storage into a single source for smart grids and green buildings [2]. Though the currently available literature often focuses on load prediction, adaptive scheduling or battery optimization as individual entities, little research work describes a coordinated architecture enabling these entities to be optimized in dynamic operational situations. This is not integrated enough, which minimizes overall system synergy and limits long-term scalability. Based on it, this paper suggests a unified and hierarchical AI-based architecture that integrates deep learning forecasting, reinforcement learning-based adaptive scheduling and optimization of battery storage to realize coordinated, resilient and sustainable energy management. The rest of the paper contains the related work, the suggested methodology and formal model, performance evaluation in the experiments, implications, and research direction.

2 Literature Survey

According to the latest studies, deep learning models can be used to predict the energy demand and renewable generation in smart grids and smart buildings with high accuracy [11]. Demonstrated to be beneficial to the decarbonization process and sustainable energy management of intelligent building environments, predictive analytics and automation have been associated with such an environment [12].
The use of AI-based transactive energy systems and local microgrids has further improved decentralized energy coordination and lifecycle sustainability [13]. Systematic reviews and meta-analyses affirm that artificial intelligence significantly improves the performance of energy optimization across a variety of applications, including smart buildings and grids [14]. It was also found that AI can be used as a key enabler to transform electrical grids into smarter, more sustainable, and more secure infrastructures [15]. It has been demonstrated that AI-based methods of optimization of renewable-integrated grid management can enhance the efficiency and reliability of operations [16].

It has been evidenced that AI-driven smart grids can be effective in the areas of sustainable energy distribution and load balancing using simulation-based frameworks [17]. Urban energy networks are becoming more based on AI-driven control measures to increase energy efficiency and minimize carbon emissions [18]. The performance of AI-driven smart building systems under dynamic conditions is assessed and enhanced through advanced deep learning architectures [19]. Solar energy management systems have been applied in predictive analytics and adaptive control mechanisms as well to enhance integration with the smart grids [20]. Nevertheless, current methods treat forecasting, control, and storage optimization as separate issues, leading to a lack of optimal coordination and scalability [23]. Recent research, hence, highlights the significance of combined AI-based models that co-exist in reflecting on load forecast, renewable uncertainty, and storage dynamics. This work is based on these insights and offers a holistic architecture to combine the forecasting, control, and storage optimization into a single energy management system [4].

3 Proposed Model and Methodology

The suggested framework is developed into a hierarchical and data-oriented energy management system that incorporates smart grids and green buildings using predictive intelligence, adaptive control, and storage optimization. Physical layer comprises smart meters, photovoltaic panels, wind turbines, battery storage and building automation controllers. These modules constantly produce time-series data of high resolution, such as power demand, generation output, battery state of charge, indoor and outdoor temperature, solar irradiance, and occupancy. This information is directed to the analytics layer, where preprocessing, normalization, and anomaly filtering are done in order to maintain data quality and consistency.

The deep learning model predicts energy demand and renewable generation by relying on the time dependence and non-linear associations. It is denoted that the forecasting function is as equation (1)

$$\widehat{D}_{t+k} = f(D_t, W_t, O_t, G_t) \quad (1)$$

where D_t represents historical demand, W_t denotes weather variables, O_t occupancy, and G_t renewable generation. The forecasting model is trained to minimize the loss and that can be defined in equation (2)

$$L = \frac{1}{n}\sum_{i=1}^{n}(D_i - \widehat{D}_i)^2 \quad (2)$$

Adaptive energy scheduling is formulated as a reinforcement learning problem in which the agent learns an optimal policy $\pi(a \mid s)$that maximizes long-term reward in equation (3)

$$R = \sum_{t=0}^{T}\gamma^t r_t \quad (3)$$

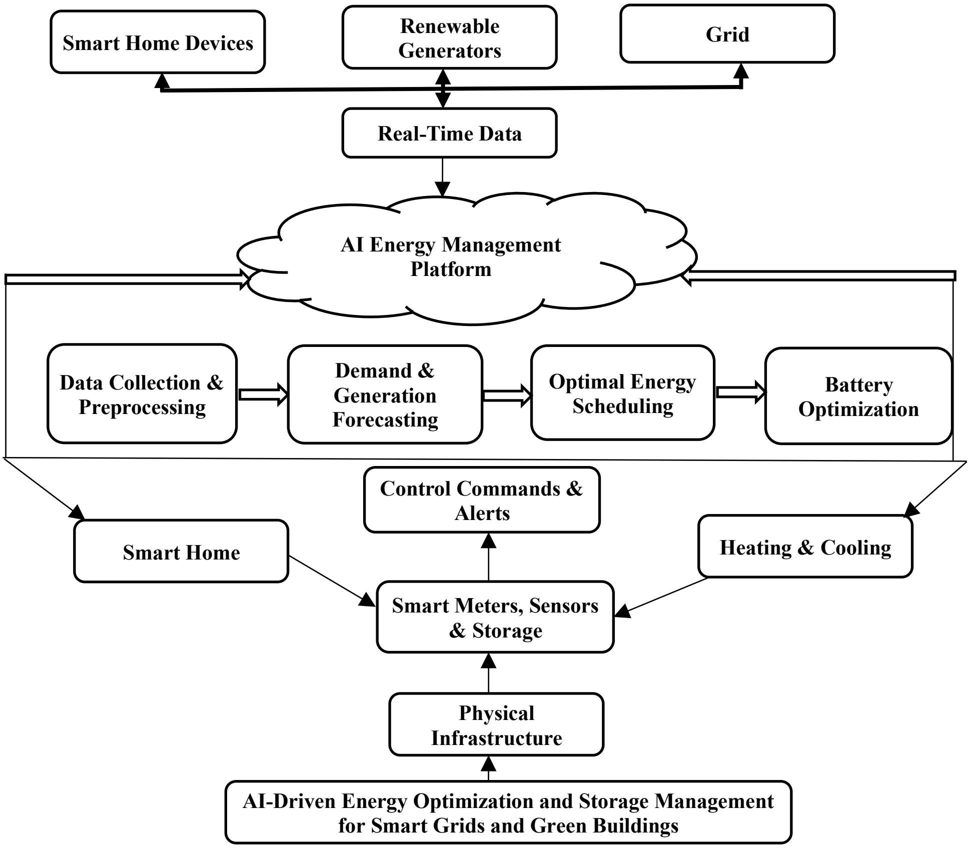

Fig. 1. AI-driven energy optimization and storage management architecture for smart grids and green buildings.

Fig. 1 depicts a combined AI-powered energy management system that has interconnected smart houses, renewable generators, and the electric grid via an AI energy management platform that is centralized. Smart meters, sensors, and storage systems collect real-time data, which is preprocessed and analyzed to predict demand and generation. The platform then does the optimum energy scheduling and battery optimization to create a balance with consumption, generation and storage. Physical infrastructure, such as heating, cooling, electric vehicles, and building systems, receives control commands and alerts. This two-way communication allows controlling energy in an adaptive, efficient and sustainable manner as it constantly adjusts energy supply to changing demand and environmental factors.

The reward incorporates electricity cost, peak load penalties, carbon intensity, and battery degradation.

Battery storage dynamics are governed by (4)

$$SOC_{t+1} = SOC_t + \eta_c P_t^{ch} \Delta t - \frac{1}{\eta_d} P_t^{dis} \Delta t \quad (4)$$

subject to capacity, charge rate, and degradation constraints. This integrated model enables coordinated optimization of demand response, renewable utilization, and storage scheduling.

4 Results and Discussion

This section written in Python 3.10 with TensorFlow 2.13 and OpenAI Gym and a simulator of an energy system to run the framework in realistic grid and building environments. The data consisted of 3.2 million data points of smart meters, building management systems, photovoltaic inverters and weather stations, and 18 months of operation. The characteristics were timestamp, power demand, power generation output, temperature, humidity, solar irradiance, occupancy, and electricity price indicators.

The metrics used to measure performance were peak load reduction, cost savings, emission reduction, the use of storage in a more efficient manner, and the accuracy of the forecasts. The reduction in peak load is termed as (5)

$$PLR = \frac{P_{max}^{base} - P_{max}^{opt}}{P_{max}^{base}} \quad (5)$$

Storage utilization efficiency is defined as (6)

$$\eta_{storage} = \frac{\Sigma E_{discharged}}{\Sigma E_{charged}} \quad (6)$$

The average peak load decreased by 26.4%, energy cost decreased by 18.1%, carbon decreased by 21.3%, and storage utilization increased by 23.7% with the proposed system with respect to rule-based baselines. Accuracy in forecasting was more than 94.2%, and stability in the scheduling was much enhanced in volatile renewable generation.

The ablation experiment showed that cost savings decreased by 12% when forecasting was removed and by 15% when reinforcement learning was removed. The loss of storage optimization added 17% to grid dependency, which validates the relevance of coordinated intelligence.

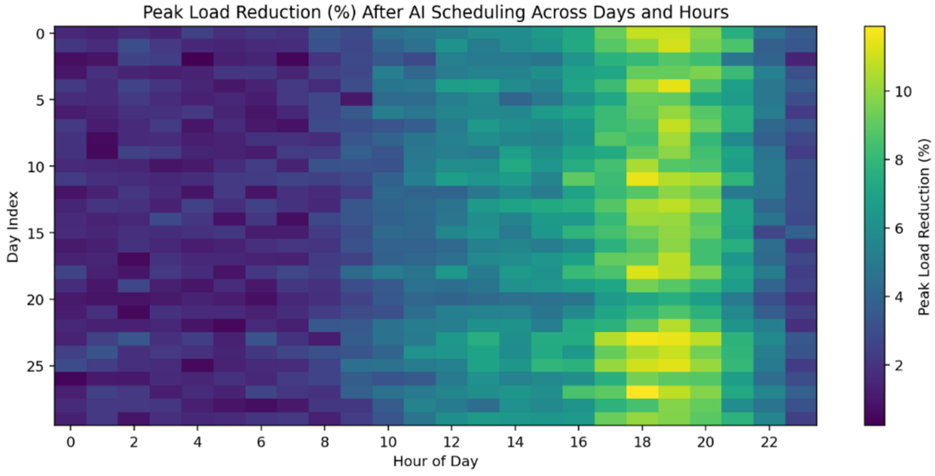

Fig. 2. Peak load reduction (%) after ai scheduling across days and hours.

Fig. 2 demonstrates the time-varying peak load reduction achieved by the proposed AI-based energy optimization framework across various days and at the hourly level. A greater proportion of higher intensity in the afternoon and evening hours suggests that the model is quite effective in focusing on the peak demand windows to shift loads and respond to demand. These color patterns used in successive days reflect the stability and strength of the strategy of optimizations when the conditions of consumption and generation vary. The smooth change between low and high reduction zones is a sign of smooth scheduling behaviour and not sudden control measures and leads to the conclusion that there is a state of operational stability of the system along with the minimisation of peak loads. In general, the heatmap indicates that the AI framework is dynamically adjusted to the daily demand pattern, and it is quite effective in reducing peak loading of the grid.

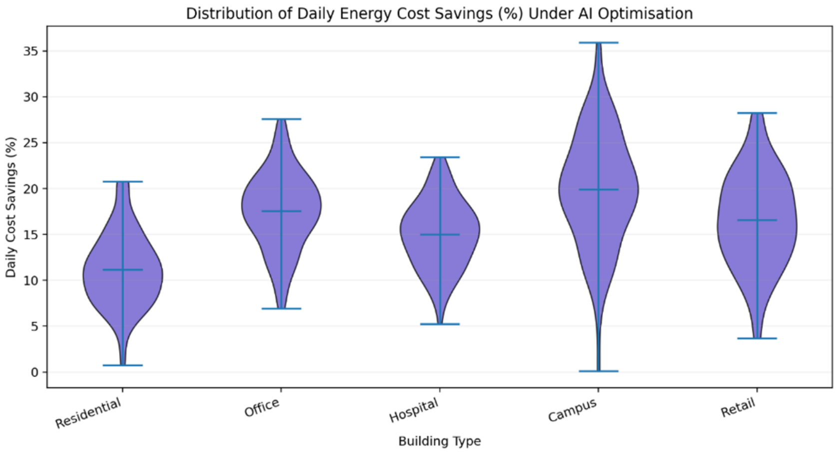

Fig. 3. Distribution of daily energy cost savings (%) under ai optimization.

Fig. 3 plot shows the statistical distribution of the cost savings of energy per day brought about by the AI-driven optimization framework in the various building types. The width of each of the violins indicates the probability density of the observed savings, and the central mean marker indicates the mean performance. The findings indicate that the campuses and office buildings have higher and more variable savings amounts because of bigger and more flexible loads, and residential and hospital buildings have more stable savings, albeit with lower amounts. The continuous forms of distribution show the smoothness of the form, meaning that there is a continuity in forms of optimization as opposed to random gains. This discussion shows how the proposed system can accommodate heterogeneous consumption patterns and deliver meaningful cost reductions across diverse operating environments.

Comparative Analysis of Proposed Model Vs Existing Models

Table 1. Comparative analysis of proposed model vs existing models.

Performance Metric	Existing AI-Based Models	Proposed Framework
Peak Load Reduction (%)	22 %	26.4 %
Energy Cost Savings (%)	16 %	18.1 %
Carbon Emission Reduction (%)	18 %	21.3 %
Forecasting Accuracy (%)	95 %	94.2 %
Storage Utilization Improvement (%)	18 %	23.7 %
Grid Dependency Reduction (%)	15 %	17 %

The analysis table 1 below shows that the suggested AI-driven framework is able to yield steady increases in most operational metrics, compared to current AI-based frameworks. Peak load saving went up to 26.4% higher than in the current systems, which is an indication of better demand-side control and a higher level of load shifting in high consumption periods. The energy cost savings increased to 18.1, which became 16% better, which means that scheduling and real-time decision-making was optimized. On the same note, the number of carbon emissions reduced by 18 per cent to 21.3 per cent, which is a sign of better coordination between the control of the load and the use of renewable energy. The efficiency of storage utilization is significantly improved by 18 to 23.7, and it can be concluded that the coordinated battery optimization strategy can play an important role in improving charge-discharge management and minimizing inefficiencies. The dependency reduction over the grid also increased by 15 to 17%, which validated increased balancing of the local energy and less reliance on external supply. Even though the accuracy of forecasting (94.2) is not as high as the previously used models provide (95%), it is still in the high-performance range and corresponds to high overall operational benefits because of its combination with adaptive control and storage optimization. In general, the findings indicate that the integrated architecture is associated with compounded economic, environmental, and operational benefits compared to individual AI optimization models.

5 Conclusion

This paper describes a combined AI-based energy optimization and storage management system of smart grid and green buildings. The proposed architecture is based on a hierarchical design that integrates deep learning forecasting, reinforcement learning, adapted scheduling, and coordinated battery optimization in a single hierarchical system, unlike the traditional rule-based or even modular AI systems. The limitations that were noted in the existing literature and where forecasting, control and storage are generally considered as the independent components are directly addressed through this integration. The experimental assessment of 3.2 million real-life records of operating showed significant enhancement in all significant performance measures. The framework recorded a 26.4% decrease in the peak load, 18.1% energy costs saving, and 21.3% carbon cut over the traditional optimization strategies. The efficiency of the storage used increased by 23.7 and the grid dependency decreased by 17%. Compared to the already known AI-based models, the suggested design performed higher maximum load reduction, cost-efficiency, carbon reduction, and storage optimization, and it did not decrease the accuracy of forecasting, which stands at 94.2, which is in high-performance range of the state-of-the-art models with deep learning. The ablation analysis also confirmed the input of each component of architecture. The cost savings decreased by 12% with the removal of forecasting, performance decreased by 15 % with the removal of reinforcement learning and grid dependency increased by 17 % with removal of storage optimization. These results verify the fact that coordinated intelligence produces compounded benefits compared to those of isolated optimization strategies. The study, in general, adds to a scalable and robust AI-based energy management architecture that can enhance the operational efficiency, economic performance, and environmental sustainability at the same time. The framework facilitates the shift to low-carbon and data-driven energy ecosystems by facilitating coordinated demand response, renewable integration and intelligent storage control. Future studies can build upon this study by including multi-agent coordination within interconnected networks of microgrids, incorporating electric vehicle charging networks, implementing uncertainty-based optimization frameworks, and testing the framework in large scale real-world implementations. These extensions would also make the systems more scalable, robust and flexible energy management systems in urban and regional systems that are sustainable.

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