A Review of Artificial Intelligence Techniques for Sustainable Energy Management in Smart Cities: Trends, Challenges, and Future Directions

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Abstract

Due to rapid urbanisation, increased energy demands and climate change, cities have evolved to be much more intelligent in managing their energy. This is where Artificial Intelligence (AI) comes into play with sustainable smart cities. AI can be used for many purposes including renewable energy forecasting, smart grid optimisation, demand side management and fault detection. This paper provides a structured review of the literature regarding AI and Machine Learning (ML) used in sustainable energy management within Smart Cities. Twenty-two sources (mainly from 2019 to 2026) were reviewed and split into five categories of Renewable Energy Forecasting, Smart Grid Optimisation, Smart Building and Demand Side Management, Explainable AI and Smart City Sustainability. From this literature, it can be seen that deep learning techniques such as Long Short-Term Memory (LSTM) networks, Hybrid Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) and Transformers are dominating in forecasting applications. Reinforcement Learning and Multi-Agent systems are also becoming more popular in real time grid control. Overall though, the literature found that there are many issues surrounding the research and this includes lack of interpretability, scalability, poor quality data and high environmental costs when training large AI models. This paper will outline research gaps, suggest a new conceptual framework around accuracy, interpretability and deployability and suggest future research areas for creating trustworthy, scalable and sustainable AI smart energy systems for Smart Cities.

Keywords — artificial intelligence, machine learning, sustainable energy management, smart cities, smart grid, renewable energy forecasting, explainable AI, deep learning.

I. INTRODUCTION

Cities consume a disproportionate share of global energy and account for a large fraction of greenhouse gas emissions, despite occupying only a small fraction of the Earth's land area. As urban populations continue to grow, energy demand is expected to rise sharply, placing additional strain on existing power infrastructure and complicating efforts to meet international climate commitments. The smart-city concept has emerged as a response to this challenge, combining sensors, connected devices, and computational intelligence to manage urban resources, including energy, more efficiently.

Artificial intelligence (AI), and machine learning (ML) in particular, has become one of the primary technological pillars supporting this transition. AI techniques are now used to forecast renewable energy generation, optimize the operation of smart grids, predict building-level energy consumption, detect equipment faults before they cause outages, and coordinate distributed energy resources across a city. Because AI models can identify complex, nonlinear patterns in large volumes of sensor and weather data, they are often able to outperform traditional statistical or rule-based methods on these tasks.

At the same time, the large and rapidly growing body of literature on this topic makes it difficult to obtain a unified picture of the current state of the field, of which techniques are most effective for which tasks, and of which problems remain unresolved. This paper addresses that need by presenting a structured review of recent literature on AI for sustainable energy management in smart cities. The remainder of the paper is organized as follows. Section II reviews the existing literature across five thematic areas; Section III identifies the research gap that motivates this study; Section IV states the research objectives; Section V presents the guiding research questions; Section VI describes the review methodology; Section VII discusses the expected findings and their implications; and Section VIII concludes the paper with directions for future research.

II. LITERATURE REVIEW

The reviewed literature is organized into five thematic areas, progressing from predictive tasks (renewable energy forecasting) to operational control (smart grids), end-use management (smart buildings), cross-cutting concerns of transparency (explainable AI), and the wider smart-city context. Table I summarizes the techniques, principal findings, and reported limitations in each area.

A. AI and Machine Learning for Renewable Energy Forecasting

A substantial share of the literature addresses the forecasting of solar and wind power output, because the variability of renewable sources is one of the main obstacles to their integration into power grids. Deep learning models, especially Long Short-Term Memory (LSTM) networks and their variants, have become the dominant approach for this task owing to their ability to capture temporal dependencies in weather and generation data [9]–[11]. Hybrid architectures that combine decomposition techniques with attention-based transformer models have reported strong accuracy gains over single-model approaches for long-term wind and solar prediction [10]. Comparative studies evaluating recurrent architectures, such as the Gated Recurrent Unit (GRU) and bidirectional LSTM (BiLSTM), against gradient-boosting methods have generally found that models incorporating memory mechanisms outperform conventional ML baselines on national-scale renewable generation datasets [15].

Other work has examined spatial forecasting, moving beyond single-site prediction toward multi-site and spatio-temporal models that account for correlations between geographically distributed generation assets [16]. Comparative benchmarking studies further emphasize that model performance varies considerably with the dataset, the forecast horizon, and the choice of input features, such as meteorological variables and time-based indicators [14]. A recent review of foundation models for clean energy forecasting suggests that large pre-trained models may offer improved generalization across sites and reduce the need for site-specific retraining, although this direction is still emerging [9].

B. AI in Smart Grid Optimization and Control

Beyond forecasting, AI is widely applied to the operational side of energy systems. Reviews of AI-driven smart grid optimization describe applications spanning load forecasting, real-time operation and control, fault detection and predictive maintenance, demand response, and distributed energy resource management [17]. RL and multi-agent RL (MARL) approaches are increasingly used for tasks such as request scheduling in microgrids and frequency regulation among distributed prosumers, since these methods can adapt to changing grid conditions without requiring a fully specified system model [18]. Graph neural networks combined with deep RL have also been applied to transmission-grid topology and load-flow optimization, in some cases with human-in-the-loop oversight to improve operator trust [18]. Broader systematic reviews of AI for grid stability similarly report that deep learning and RL have improved real-time decision-making and adaptive fault detection, while noting that computational complexity and deployment barriers remain significant obstacles [22].

C. AI in Smart Buildings and Demand-Side Management

At the building level, AI techniques are used to forecast energy consumption, optimize heating, ventilation, and cooling schedules, and support demand response programs. A systematic review and meta-analysis of AI for smart-building energy optimization, synthesizing more than one hundred studies, found consistent evidence that ML and deep learning (DL) models improve the prediction accuracy of building-level energy loads relative to conventional approaches [7]. RL has also been explored for the direct control of building energy systems, allowing an agent to learn energy-saving control policies through interaction with the building environment rather than relying on fixed rules [7]. Federated learning approaches applied to smart-meter data show that decentralized model training can reduce forecast error while preserving household-level data privacy, which is particularly relevant to residential demand-side management in decentralized power networks [3].

D. Explainable AI (XAI) in Energy Systems

As the AI models used in energy systems have grown more complex, a distinct and growing

strand of research has focused on explainability. Because many high-performing models are effectively "black boxes," operators and regulators often struggle to trust or verify their decisions, particularly in safety-critical grid operations [20]. Reviews of XAI applied to smart grids report that RL-based explainable models have improved the interpretability of decisions related to energy storage, demand-side management, and renewable energy forecasting [1]. Explainability has also been examined in the context of predictive maintenance, where physics-informed and hybrid XAI models have been proposed to make fault predictions more transparent and to support Internet of Things (IoT)-enabled digital twins of physical energy assets [23]. Despite this progress, reviewers consistently note that there is no standardized way to measure explanation quality, and that balancing model complexity against interpretability and real-time latency remains an open problem [21].

E. AI in Broader Smart-City Sustainability Applications

Several reviews take a broader view of the role of AI across the smart city, situating energy management alongside transportation, water management, and citizen engagement. A systematic study of AI in sustainable smart cities describes applications across these domains while highlighting persistent ethical and data-governance challenges that cut across all of them [4]. Similarly, reviews focused specifically on the energy sector within smart cities report that AI enables more precise analysis of consumption patterns, weather conditions, and demand forecasts, allowing better optimization of energy distribution; they also caution, however, that most demonstrated benefits come from simulation or pilot studies rather than large-scale, real-world deployment [5], [8].

Across the five areas, a common pattern emerges: the techniques that deliver the strongest reported performance (deep, recurrent, transformer-based, and reinforcement learning models) are also those for which interpretability, computational cost, and deployment readiness are most frequently raised as concerns. This pattern motivates the research gap identified in Section III.

TABLE I
THEMATIC COMPARISON OF THE REVIEWED LITERATURE (SYNTHESIZED FROM SECTION II)

Thematic area	Sources	Dominant techniques	Key reported findings	Reported limitations / open issues
A. Renewable energy forecasting	[9]–[11], [14]–[16]	LSTM and variants; GRU and BiLSTM; decomposition + transformer hybrids; multi-site spatio-temporal models; foundation models	Memory-based models outperform conventional ML baselines on national-scale data [15]; hybrid decomposition–transformer models report strong accuracy gains for long-term prediction [10]; foundation models may improve cross-site generalization [9]	Performance depends on dataset, forecast horizon, and input features [14]; results mostly from curated benchmarks; foundation-model direction still emerging [9]
B. Smart grid optimization and control	[17], [18], [22]	Reinforcement learning (RL) and multi-agent RL; graph neural networks with deep RL; deep learning for load forecasting and fault detection	Methods adapt to changing grid conditions without a fully specified system model [18]; human-in-the-loop oversight can improve operator trust [18]; improved real-time decision-making and adaptive fault detection [22]	Computational complexity and deployment barriers remain significant [22]

C. Smart buildings and demand-side management	[3], [7]	ML and DL load prediction; RL for building control; federated learning on smart-meter data	ML/DL improve building-level load prediction over conventional approaches across 100+ studies [7]; RL learns control policies by interaction [7]; federated learning reduces forecast error while preserving privacy [3]	Not specifically discussed in the reviewed sources as summarized in Section II-C
D. Explainable AI (XAI) in energy systems	[1], [20], [21], [23]	RL-based explainable models; physics-informed and hybrid XAI; XAI within IoT-enabled digital twins	Improved interpretability of storage, demand-side, and forecasting decisions [1]; more transparent fault prediction in predictive maintenance [23]	Black-box models hinder trust in safety-critical operations [20]; no standardized measure of explanation quality; trade-off between complexity, interpretability, and real-time latency [21]
E. Broader smart-city sustainability	[4], [5], [8]	Broad AI applications across energy, transport, water, and citizen engagement	AI enables more precise analysis of consumption, weather, and demand, supporting better energy distribution [5], [8]	Ethical and data-governance challenges [4]; benefits mostly demonstrated in simulation or pilot studies [5], [8]

Sources are identified by their reference numbers in the References section. Entries summarize findings as reported by the cited works.

III. RESEARCH GAP

Taken together, the reviewed literature reveals several consistent gaps. First, although forecasting accuracy has improved substantially through deep learning, most studies report results on curated benchmark datasets rather than on live, real-world deployments, leaving open the question of how well these models generalize under real operating conditions and data-quality issues [9], [14], [16]. Second, there is a persistent trade-off between model accuracy and interpretability: the most accurate deep learning and RL models tend to be the least explainable, and current XAI methods for energy systems lack standardized evaluation metrics, which makes it difficult to compare interpretability claims across studies [20], [21]. Third, scalability and computational cost are frequently identified as barriers, since many proposed architectures are computationally expensive to train and are rarely evaluated for the additional energy consumption they themselves introduce, an important omission for research framed around sustainability [18], [22]. Finally, most existing surveys examine forecasting, grid control, or explainability in isolation; comparatively few synthesize these threads into a single framework that links model accuracy, interpretability, scalability, and real-world deployability for smart-city energy systems. The contribution of this paper is to consolidate these threads and make the gap explicit.

IV. OBJECTIVES

- To systematically review recent literature (2019–2026) on the application of AI and ML techniques to sustainable energy management in smart cities.
- To categorize existing research into thematic areas (forecasting, grid optimization, smart buildings, explainability, and broader smart-city applications) and to summarize the dominant techniques used in each.
- To identify the recurring limitations and unresolved challenges reported across the literature, including those relating to

interpretability, scalability, and real-world deployability.

- To propose a conceptual framework and a set of future research directions that address the identified gaps.

V. HYPOTHESIS / RESEARCH QUESTIONS

As this study is a structured literature review rather than an experimental investigation, it is guided by research questions (RQs) rather than by a testable statistical hypothesis.

RQ1: Which AI/ML techniques are most frequently applied to sustainable energy management tasks in smart cities, and for which specific tasks are they used?

RQ2: What performance and adoption trends emerge across the reviewed literature (e.g., dominant model families and reported accuracy trends)?

RQ3: What limitations and challenges are most frequently reported, and how consistent are they across independent studies?

RQ4: What research directions do existing works propose to address explainability, scalability, and deployment challenges?

VI. METHODOLOGY

This review follows a structured literature search and synthesis process, broadly informed by systematic-review practice while remaining appropriately scaled for an academic project.

A. Search Strategy

Searches were conducted primarily through Google Scholar, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and arXiv, using combinations of the keywords "artificial intelligence," "machine learning," "deep learning," "sustainable energy," "smart grid," "smart city," "renewable energy forecasting," and "explainable AI."

B. Inclusion and Exclusion Criteria

Inclusion: peer-reviewed journal articles, conference papers, and reputable preprints published between 2019 and 2026, written in English, with a clear focus on AI/ML applications in energy management, smart grids, or smart-city sustainability.

Exclusion: studies with no AI/ML component, non-English publications, and sources for which neither the full text nor an abstract was accessible.

C. Screening and Selection

Candidate papers were first identified by title and abstract relevance and were then screened in full, where necessary, to confirm topical fit. This process resulted in twenty-two sources being selected for detailed synthesis in Section II, spanning forecasting-focused studies, grid-optimization reviews, building-level energy management research, and explainability-focused reviews.

D. Synthesis Approach

The selected sources were grouped thematically (Section II, subsections A–E) rather than summarized individually, in order to highlight cross-cutting trends and points of agreement or disagreement between studies. This thematic synthesis directly supports the research questions in Section V.

VII. EXPECTED RESULTS AND DISCUSSION

Based on the patterns observed across the reviewed literature, several consistent trends can be expected to hold as this review is finalized and extended. These are expectations derived from the synthesized literature; they are not experimentally validated results.

Deep learning architectures, particularly LSTM, hybrid CNN-LSTM, and transformer-based models, are expected to remain the dominant approach for renewable energy forecasting, consistently outperforming traditional statistical and shallow ML baselines on accuracy metrics such as root mean square error (RMSE) and mean absolute percentage error (MAPE) [10], [12], [14], [15]. RL and multi-agent systems are expected to account for a rising share of publications on real-time grid control and optimization, reflecting a shift from purely predictive applications toward adaptive, decision-making AI [18], [22]. XAI is expected to appear as a fast-growing but still comparatively small subfield relative to predictive modeling, with most XAI papers concentrated in the last two to three years, reflecting growing regulatory and operational pressure for transparency [20], [21], [23].

A recurring theme across nearly all reviewed sources is the tension between model

performance and practical deployability. Table II summarizes this trade-off across the main technique families identified in the literature.

TABLE II
AI TECHNIQUE FAMILIES IDENTIFIED IN THE REVIEWED LITERATURE: TYPICAL APPLICATIONS, REPORTED STRENGTHS, AND REPORTED LIMITATIONS

Technique family	Typical application	Reported strength	Reported limitation
LSTM / hybrid CNN-LSTM	Solar and wind power forecasting	Captures temporal patterns; high accuracy	Computationally heavy; limited interpretability
Transformer-based models	Long-horizon renewable forecasting	Strong long-range dependency modeling	Large data and compute requirements
Reinforcement learning / MARL	Grid control; microgrid scheduling	Adapts to dynamic, real-time conditions	Training instability; policies hard to explain
Federated learning	Smart-meter and household forecasting	Preserves data privacy; distributed training	Communication overhead; uneven data quality
Explainable AI (XAI) methods	Fault detection; decision transparency	Improves operator trust and regulatory fit	No standardized evaluation metrics

MARL: multi-agent reinforcement learning.

These findings support the research gap identified in Section III: accuracy gains from increasingly complex models are not matched by equivalent progress in interpretability, deployment readiness, or accounting for the energy footprint of the AI systems themselves. This suggests that future work should treat interpretability and deployability as first-class evaluation criteria rather than secondary concerns, and that benchmark datasets alone are insufficient evidence of real-world readiness.

The conceptual framework proposed in this review (Fig. 1) therefore evaluates AI for smart-city energy systems jointly along three dimensions. *Accuracy* refers to forecasting and control performance. *Interpretability* refers to the extent to which operators and regulators can understand and trust model decisions. *Deployability* encompasses scalability, computational and energy cost, and readiness for real-world operation. The reviewed literature indicates that these dimensions are in tension: gains in accuracy are commonly achieved at the expense of interpretability and deployability. Rather than optimizing accuracy alone, the framework is proposed as a direction for future empirical work building on this review. It is a conceptual construct derived from the literature and has not been empirically validated.

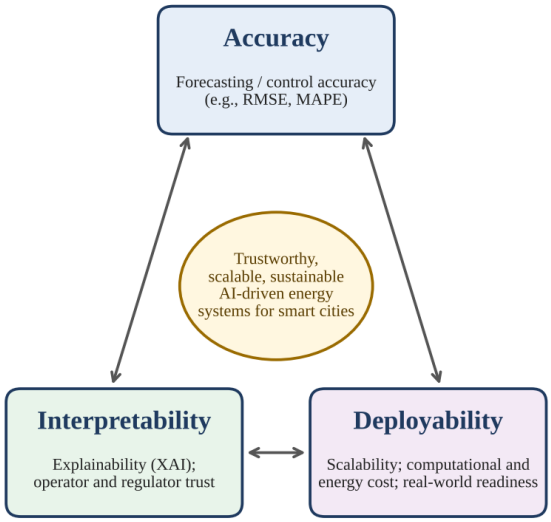


Fig. 1. Conceptual framework linking accuracy, interpretability, and deployability. Double-headed arrows denote the trade-offs reported in the literature. The framework is conceptual and has not been empirically validated.

VIII. CONCLUSION

This paper reviewed recent literature on the application of artificial intelligence to sustainable energy management in smart cities, synthesizing findings across renewable energy forecasting, smart grid optimization, smart building management, explainable AI, and broader smart-city sustainability applications. The review found that, although deep learning and RL methods have substantially advanced prediction accuracy and control capability, the literature consistently

reports unresolved challenges relating to interpretability, scalability, real-world deployment, and the sustainability of the AI models themselves. Addressing these gaps will require future research that jointly optimizes accuracy, explainability, and deployability, supported by standardized benchmarks and real-world pilot evaluations.

As a literature-based study, this review is limited by the availability and scope of the published sources and does not include original experimental validation. Future work could extend this synthesis through a full systematic review with formal quality-assessment scoring, or through empirical evaluation of the proposed conceptual framework on real smart-city energy datasets.

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