AI-Based Energy Management Systems for Optimizing Renewable Energy and Enhancing Grid Stability

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ABSTRACT

Artificial Intelligence (AI)-based Energy Management Systems (EMS) have revolutionized energy efficiency and sustainability in modern electrical systems. By integrating machine learning, deep learning, and reinforcement learning, these systems optimize energy consumption in smart grids, microgrids, and smart buildings. With the increasing reliance on renewable energy sources like solar and wind, AI enhances grid stability and minimizes energy wastage through predictive analytics and adaptive control. Despite challenges in computational cost, data quality, and real-world deployment, AI-based EMS remains a promising solution for improving resource utilization and advancing sustainability in energy systems.

Keywords: *Artificial Intelligence (AI), Energy Management Systems (EMS), Smart Grids, Renewable Energy.*

I. INTRODUCTION

Artificial Intelligence (AI)-based Energy Management Systems (EMS) have emerged as a transformative solution for addressing the growing challenges associated with energy efficiency, sustainability, and optimal power utilization in modern electrical systems. With the rapid increase in global energy demand driven by industrialization, urbanization, and digital transformation, traditional energy management approaches have proven insufficient in handling the complexity, variability, and scale of contemporary power systems. As a result, the integration of AI technologies—such as machine learning (ML), deep learning (DL), and reinforcement learning (RL)—into energy management frameworks has gained significant attention in recent years. Energy management systems are designed to monitor, control, and optimize energy consumption across various domains, including buildings, smart grids, microgrids, industrial systems, and renewable energy networks. Conventional EMS relied heavily on rule-based control strategies and static optimization techniques, which lacked adaptability and predictive capabilities. However, AI-based EMS introduces intelligent decision-making by leveraging real-time data, predictive analytics, and adaptive control mechanisms. These systems can dynamically respond to fluctuations in energy demand, renewable generation variability, and operational uncertainties, thereby improving overall system efficiency and reliability. One of the key drivers behind the adoption of AI-based EMS is the increasing penetration of renewable energy sources such as solar and wind power. While these sources contribute significantly to reducing carbon emissions, their intermittent and unpredictable nature poses challenges for grid stability and energy balancing. Lin et al. (2026) addressed this issue by proposing an AI-driven integrated energy system combining photovoltaic, thermal, electric, and hydrogen subsystems. Their study demonstrated that AI techniques such as Long Short-Term Memory (LSTM) networks and Deep Reinforcement Learning (DRL) could significantly improve prediction accuracy and optimize energy dispatch, resulting in enhanced self-consumption and reduced energy wastage. Similarly, the application of AI in microgrid energy management has shown promising results. Hoummadi et al. (2025)

utilized a Genetic Algorithm-based EMS to optimize energy flow in a microgrid supplying residential loads. Their findings indicated a substantial reduction in wasted energy, highlighting the effectiveness of AI in improving resource utilization. Despite the increase in initial system cost, the long-term benefits in terms of efficiency and sustainability make AI-based EMS a viable solution for future energy systems. In the context of smart buildings, AI-based EMS has been widely adopted to enhance energy efficiency and occupant comfort. Buildings account for a significant portion of global energy consumption, making them a critical area for optimization. Ali et al. (2024) reported that AI-driven Building Energy Management Systems (BEMS) could reduce energy consumption by up to 37% in office buildings through optimized heating, ventilation, and air conditioning (HVAC) control. Additionally, Rizvi (2023) emphasized that AI-based systems could predict energy demand using historical data and real-time inputs, enabling proactive energy management and reducing unnecessary energy usage.

Another important application of AI-based EMS is in smart grids and energy distribution networks. Peters and Kamrul (2025) developed an AI-powered solar energy management system that utilized predictive analytics and reinforcement learning for adaptive control. Their system improved solar energy utilization and reduced dependency on conventional grid power, demonstrating the potential of AI in achieving sustainable and resilient power systems. Furthermore, Javed et al. (2025) highlighted that ML and DL models have significantly enhanced load forecasting accuracy, which is crucial for effective demand response and grid stability. Wireless sensor networks (WSNs) and Internet of Things (IoT) technologies also play a vital role in enabling AI-based EMS. These technologies facilitate real-time data collection and communication between system components, allowing AI algorithms to make informed decisions. White and Scott (2022) discussed the integration of AI with next-generation WSNs to improve energy efficiency and data analytics capabilities. Similarly, Farzaneh et al. (2021) emphasized the role of IoT-enabled smart buildings in achieving intelligent energy management through automation and predictive modeling. Despite the numerous advantages, the implementation of AI-based EMS is not without challenges. One of the major concerns is the high computational and energy requirements of AI models, particularly during the training phase. Jackson et al. (2026) noted that improving the energy efficiency of AI systems themselves remains a critical challenge, especially for resource-constrained applications such as robotics. Additionally, issues related to data quality, cybersecurity, and system scalability must be addressed to ensure reliable and secure operation of AI-driven energy systems (Aderibigbe et al., 2023). Another significant challenge is the lack of real-world deployment and standardization of AI-based EMS. While many studies have demonstrated promising results through simulations and controlled experiments, large-scale implementation in practical environments is still limited. Javed et al. (2025) pointed out the need for improved collaboration between academia, industry, and policymakers to bridge this gap and accelerate the adoption of AI technologies in energy management. Furthermore, ethical and regulatory considerations must be taken into account when deploying AI-based systems. Issues such as data privacy, algorithm transparency, and decision accountability are critical in ensuring user trust and system acceptance. As AI continues to evolve, developing explainable and interpretable models will be essential for gaining stakeholder confidence and facilitating widespread adoption.

II. RESEARCH BACKGROUND

Jackson et al. (2026) examined the growing need for improved power efficiency in robotic platforms as their computational capabilities and applications had expanded significantly. The authors reviewed several intelligent power management techniques and energy-efficient control strategies used in untethered battery-powered robotics. Their study discussed approaches such as Dynamic Power Management (DPM), Dynamic Voltage and Frequency Scaling (DVFS), AI-assisted Adaptive Dynamic

Programming (DP) control systems, AI-assisted Model Predictive Control (MPC) systems, and Hybrid Energy Storage Systems (HESS), which were considered suitable for multi-objective AI integration. The review further highlighted that robotic neural networks and AI-based enhancements had been identified as promising directions for future robotic development. However, the authors also noted that improving the training power efficiency of AI systems remained a significant challenge for their onboard implementation. Through background discussions and case study implementations across different developmental scales, the study quantified efficiency improvements and outlined potential opportunities for advancing power-efficient robotic systems.

Lin et al. (2026) investigated the challenge of intermittency in photovoltaic (PV) power generation, which had previously resulted in significant PV curtailment and limited large-scale deployment. The authors proposed and implemented a Photovoltaic–Thermal–Electric–Hydrogen Integrated Energy System (IES) that integrated multi-energy storage with artificial intelligence technologies. Their study introduced an AI-based "prediction–optimization–diagnosis" framework deployed on edge hardware (STM32) for real-time system control. In this framework, long short-term memory (LSTM) networks were used for PV power prediction, achieving a mean absolute percentage error (MAPE) of 4.7%, while deep reinforcement learning (DRL) was applied for optimal power dispatch, which improved self-consumption to 95.8% and reduced PV curtailment by 5.2 percentage points. Furthermore, a one-dimensional convolutional neural network (1D-CNN) was utilized for fault diagnosis, reaching an accuracy of 98.8%. The lightweight deployment on the STM32 platform was reported to enhance operational efficiency. Experimental findings indicated that the proposed approach outperformed model predictive control (MPC) in terms of energy efficiency, economic performance, reliability, and sustainability outcomes.

Hoummadi et al. (2025) investigated the potential of integrating sustainable energy sources with advanced energy management systems supported by Internet of Things (IoT) and artificial intelligence technologies. The authors reported that the empirical analysis had been conducted using a Genetic Algorithm model implemented in Python on a typical microgrid system supplying electricity to approximately 100 homes with an average load of 47 kW. The simulation results indicated that the proposed system had significantly reduced waste power by nearly 93%, although the total microgrid cost had increased by about 25%. The study also highlighted that such an integrated approach was technically viable and economically promising for improving energy efficiency and resource utilization. Furthermore, the authors examined the economic implications associated with the implementation and maintenance of energy management systems. Cybersecurity challenges in interconnected microgrids were also identified as a critical concern affecting operational reliability. The research additionally discussed battery consumption losses and emphasized the importance of addressing these factors to enhance overall microgrid performance.

Javed et al. (2025) examined the application of innovative machine learning (ML) and deep learning (DL) techniques in smart energy management systems with particular emphasis on load forecasting, demand response, and the development of smart energy sectors. The authors reviewed more than 200 studies published between 2014 and 2024 to evaluate the role of ML and DL models within electrical network energy management systems. Their analysis indicated that these models had significantly improved prediction accuracy in load forecasting and had effectively supported demand response mechanisms in modern energy systems. The study further highlighted that ML and DL technologies had contributed to the advancement of smart and sustainable energy infrastructures. Based on the survey findings, the authors recommended strengthening data infrastructure, improving model training and validation processes, and encouraging collaboration among researchers, industry experts, and policymakers. However, the review also identified several limitations in existing research, including limited real-world implementations, data quality challenges, and the need for improved interpretability of ML and DL models in energy management applications.

Peters and Kamrul (2025) examined the development of smart, sustainable, and efficient power distribution through advanced energy networks supported by artificial intelligence technologies. The authors proposed an AI-powered Solar Energy Management System for smart grids, known as SEMS-PA2C, which integrated predictive analytics and adaptive control mechanisms to enhance energy sustainability and grid reliability. The system utilized historical solar generation data and weather information to train prediction models based on Gradient Boosting and Long Short-Term Memory (LSTM) networks. Furthermore, adaptive control was implemented using Reinforcement Learning to optimize energy distribution by balancing grid demand and battery storage utilization. The proposed framework was evaluated through simulations using smart grid datasets that incorporated real-world solar energy metrics and grid load profiles. The findings indicated that the model improved solar energy utilization by approximately 20% and reduced grid dependency by about 15% compared with conventional control systems. Additionally, the adaptive control mechanism decreased energy losses during peak hours by nearly 10%, thereby contributing to improved grid stability and demonstrating a scalable approach for sustainable power grid management.

Ali et al. (2024) examined the challenges associated with achieving the Net Zero Emissions (NZE) target for buildings by 2050 despite the implementation of stricter energy performance standards and the increasing adoption of renewable and energy-efficient technologies. The authors observed that a major issue faced by many buildings during operation was the energy performance gap, where actual energy consumption significantly exceeded the levels predicted during the design phase. This gap was largely attributed to ineffective management of Building Energy Management Systems (BEMS). The study reviewed various Artificial Intelligence (AI) models that had been proposed for improving BEMS performance and reducing building energy consumption. Different AI-based approaches were compared based on their accuracy and error rates across several building types. The findings indicated that office buildings demonstrated the highest potential for energy savings, achieving reductions of up to 37% through AI-based HVAC optimization, while residential and educational buildings showed comparatively lower savings of about 23% and 21%, respectively.

Rizvi (2023) emphasized the growing necessity for efficient energy consumption in buildings, noting that rapid economic growth and increasing pollution had significantly raised global energy demand. The study highlighted the importance of implementing real-time energy management systems to address inefficiencies in energy consumption and to enhance overall energy performance in buildings. It was reported that the adoption of modern architectural frameworks integrated with artificial intelligence had helped in identifying critical factors involved in optimizing building energy use. The paper reviewed various machine learning–based algorithms applied for data cleaning, processing, and analysis in energy management systems. These included reinforcement learning, rule-based approaches, and mixed integer linear programming models. The reviewed studies indicated that AI-driven techniques had the potential to reduce energy consumption by approximately 20–30%. The author concluded that AI-based energy management systems could effectively predict future energy demand using historical data and building characteristics, thereby improving efficiency compared with traditional monitoring and alert-based systems.

Aderibigbe et al. (2023) examined the influence of artificial intelligence (AI) and machine learning (ML) in improving energy efficiency, with particular emphasis on electricity demand forecasting. The authors reported that the emergence of AI had significantly transformed traditional forecasting techniques by introducing advanced data-driven models capable of handling complex and nonlinear energy patterns. The review analyzed various ML models by discussing their theoretical foundations, selection criteria, and performance across different forecasting environments. The study indicated that ML-based approaches, particularly deep learning models supported by big data analytics, had demonstrated higher accuracy and adaptability compared with conventional forecasting methods. Furthermore, the authors highlighted the importance of selecting appropriate ML models based on factors such as prediction accuracy, forecasting horizon, data-processing capability, and environmental considerations. The review also discussed technological, economic, and environmental implications of ML-based forecasting. However, challenges related to data privacy, cybersecurity, and the shortage of skilled professionals were identified as significant concerns requiring further research and policy support.

Xiang et al. (2022) examined the role of artificial intelligence in improving energy management in green buildings. The authors explained that green buildings were designed to minimize negative environmental impacts and promote environmental benefits through sustainable construction and operation. It was observed that although smart buildings supported sustainability goals, excessive use of electronic devices could hinder the achievement of overall green objectives. The study emphasized that effective demand-side management depended on accurate prediction of building energy consumption. To address this issue, the researchers proposed an Artificial Intelligence-based Energy Management Model (AI-EMM) capable of adapting to human preferences while enhancing user comfort, safety, and energy efficiency. The model incorporated a universal infrared communication system, smart user identification, and environmental monitoring subsystems. Long Short-Term Memory (LSTM) techniques were applied to improve energy consumption prediction. The findings indicated that the model achieved high performance, improved energy management efficiency, reduced energy consumption, and demonstrated that economic benefits could coexist with environmentally sustainable building practices.

Enjam (2022) examined the increasing dependence of the insurance industry on digital platforms and highlighted the growing requirement for robust, scalable, and energy-efficient IT infrastructures. The study noted that distributed insurance systems were expected to handle dynamic workloads, especially during peak operational periods such as claims processing and policy renewals. It was observed that traditional rule-based load balancing techniques were insufficient for managing the complexity and energy demands of modern distributed systems. The author proposed an AI-optimized switching framework designed to improve load balancing while reducing energy consumption. The framework integrated machine learning techniques including reinforcement learning, Long Short-Term Memory (LSTM) networks, and clustering algorithms to forecast demand and optimize switching decisions. A smart switching controller was introduced to dynamically reassign workloads based on predictive insights and real-time performance feedback. Simulation results indicated significant improvements, including reduced processing delays, lower energy consumption, decreased latency, and enhanced system reliability and resource utilization.

White and Scott (2022) examined the emerging role of Next-Generation Wireless Sensor Networks (NG-WSNs) in transforming diverse sectors such as environmental monitoring and industrial automation through real-time data collection and analysis. The study highlighted that the effectiveness of NG-WSNs largely depended on overcoming major challenges related to energy efficiency and advanced data analytics. The authors reviewed recent developments in energy-efficient system architectures and artificial intelligence–based analytical techniques designed for NG-WSNs. Their analysis included energy-harvesting mechanisms, low-power communication protocols, and intelligent algorithms aimed at improving data processing, network optimization, and decision-making capabilities. Through an extensive review of prior research and empirical findings, the study identified both the opportunities and limitations associated with these technological advancements. Furthermore, the authors proposed an integrated framework combining energy-efficient architectures with AI-driven analytics to improve network performance and sustainability. The paper also outlined several future research directions and emphasized the practical significance of adopting intelligent and energy-aware NG-WSN systems.

Farzaneh et al. (2021) examined the emerging concept of smart buildings, emphasizing the integration of sensors, big data (BD), and artificial intelligence (AI) as a means to enhance urban energy efficiency. They highlighted that AI technologies in smart buildings could reduce energy consumption by enabling better control, improving reliability, and facilitating automation. The study reviewed recent research on AI applications within building management systems (BMS) and demand response programs (DRPs), focusing on the principles and implementation of AI-based modeling approaches for predicting building energy use. An evaluation framework was presented and employed to assess contemporary studies across major AI domains, including energy, comfort, design, and maintenance. Moreover, the authors discussed open challenges and potential future directions, noting the need for more comprehensive, adaptive, and scalable AI solutions to optimize building operations. Their review underscored the transformative potential of AI in achieving sustainable and intelligent building environments.

Yan et al. (2021) examined the role of artificial intelligence (AI) in enhancing building energy efficiency, a field that had long relied on diverse traditional methods. They investigated how AI applications could advance building energy performance, particularly in the context of zero energy building initiatives promoted by multiple countries. Their study reviewed and analyzed existing research to identify the effectiveness of AI-based solutions in managing energy consumption and improving building operations. They first assessed potential impacts of AI approaches on laws, regulations, and standards related to energy efficiency. Subsequently, they compared infrastructures supporting AI in buildings, including IoT-based sensors for thermal comfort, platforms and algorithms for multi-energy management, and forecasting methods for building load, subsystem performance, and structural safety. The research further highlighted AI-driven strategies for zero energy buildings, emphasizing occupant presence and behavior patterns. Finally, they summarized future research directions for AI applications aimed at optimizing zero energy building implementation.

Senjaliya and Tejani (2020) examined the integration of artificial intelligence (AI) with renewable energy sources in residential energy management systems, emphasizing its potential to transform household energy practices. They proposed an AI-powered autonomous energy management system aimed at optimizing the performance of hybrid heat pumps coupled with solar thermal systems in residential buildings. The study adopted a methodology that involved designing a hybrid energy system architecture, implementing machine learning algorithms for demand prediction, and optimizing energy distribution between the solar thermal and heat pump components. Their simulations indicated that the system could significantly enhance energy efficiency compared to conventional approaches, with potential energy savings reaching approximately 35%. The authors highlighted that leveraging real-time data processing and predictive analytics not only improved operational efficiency but also contributed to cost reduction and carbon footprint minimization. This work was presented as a notable contribution to sustainable energy research, demonstrating the transformative role of AI in achieving carbon-neutral residential energy solutions.

Jana and Saha (2019) investigated the integration of artificial intelligence (AI) into energy management systems to address the increasing global demand for sustainable and energy-efficient buildings. The study examined the existing knowledge on AI applications in energy management and explored how such technologies could transform smart building infrastructures. Through the utilization of sensors and Internet of Things (IoT) devices, real-time data were collected, enabling AI algorithms to make dynamic decisions. The research emphasized machine learning, neural networks, and reinforcement learning approaches, highlighting their capacity to adapt to real-world conditions. A comprehensive case study was conducted to demonstrate the practical implementation of an AI-powered energy management system, showing improvements in energy efficiency and occupant satisfaction. The findings illustrated that AI could optimize energy consumption within smart buildings, providing insights into the potential of AI-driven sustainable infrastructure and paving the way for future advancements in the field.

III. KEY FINDINGS FROM STUDY

Author & Year	Methodology	Key Findings	Objective
Jackson et al. (2026)	Review of AI-based power management in robotics	Identified DPM, DVFS, AI-DP, MPC, HESS as efficient methods; challenge in training efficiency	Improve robotic energy efficiency
Lin et al. (2026)	LSTM, DRL, CNN-based integrated system	95.8% self-consumption; 98.8% fault accuracy	Optimize PV energy utilization
Hoummadi et al. (2025)	Genetic Algorithm in microgrid	93% reduction in wasted energy; cost increased by 25%	Improve microgrid efficiency
Javed et al. (2025)	Review of 200+ ML/DL studies	Improved forecasting and demand response	Analyze AI in energy systems
Peters & Kamrul (2025)	RL + LSTM + Gradient Boosting	20% better solar utilization; 15% less grid dependency	Smart grid optimization
Ali et al. (2024)	AI-based BEMS analysis	Up to 37% energy savings in offices	Reduce building energy consumption
Rizvi (2023)	ML-based real-time EMS	20–30% energy reduction	Improve building energy efficiency
Aderibigbe et al. (2023)	ML forecasting review	Higher accuracy than traditional methods	Enhance demand forecasting
Xiang et al. (2022)	AI-based green building model	Improved prediction and energy efficiency	Sustainable building management
Enjam (2022)	RL + LSTM switching system	Reduced latency and energy consumption	Optimize distributed systems
White & Scott (2022)	AI + WSN integration	Improved data analytics and energy efficiency	Enhance sensor networks
Farzaneh et al. (2021)	AI in smart buildings	Improved automation and control	Optimize building operations
Yan et al. (2021)	AI for zero-energy buildings	Improved performance and policy insights	Promote sustainable buildings
Senjaliya & Tejani (2020)	AI hybrid energy system	35% energy savings	Residential energy optimization
Jana & Saha (2019)	AI-based smart building system	Improved efficiency and comfort	Smart energy control

IV. CONCLUSION

Artificial Intelligence-based Energy Management Systems have demonstrated immense potential in transforming traditional energy systems into intelligent, adaptive, and efficient frameworks. The reviewed studies collectively highlight that AI techniques such as machine learning, deep learning, and reinforcement learning significantly enhance energy forecasting, demand response, and system optimization. These systems are particularly effective in applications such as smart grids, microgrids, renewable energy integration, and building energy management, where dynamic decision-making and real-time adaptability are essential. The findings indicate substantial improvements in energy efficiency, with reductions in energy consumption ranging from 20% to 37% across different domains. Moreover, AI-based approaches have been shown to improve renewable energy utilization, reduce energy wastage, and enhance system reliability. However, challenges such as high implementation costs, data quality issues, cybersecurity risks, and limited real-world deployment must be addressed to fully realize the benefits of AI-based EMS.

V. FUTURE SCOPE

The future of AI-based Energy Management Systems is highly promising, with several research and development opportunities:

- **Integration with Smart Cities** – AI-based EMS can be integrated into smart city infrastructure for holistic energy optimization.
- **Edge Computing and IoT Expansion** – Deployment of lightweight AI models on edge devices for real-time decision-making.
- **Explainable AI (XAI)** – Development of transparent AI models to improve trust and adoption.
- **Cybersecurity Enhancement** – Advanced security frameworks to protect energy systems from cyber threats.
- **Hybrid Energy Systems** – Further exploration of multi-energy systems combining solar, wind, hydrogen, and storage.
- **Real-World Implementation** – Large-scale deployment and validation of AI-based EMS in practical environments.
- **Energy-Efficient AI Models** – Designing low-power AI algorithms to reduce computational energy consumption.
- **Policy and Standardization** – Development of global standards and regulatory frameworks for AI-based energy systems.

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