

AI-Driven Smart Energy Management for Sustainable Development in Organizations

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Peer Review Information	Abstract
Type: Article Received: 18 April 2026 Revised: 06 May 2026 Accepted: 15 June 2026 Published: 11 July 2026	This paper presents a comprehensive study of AI-driven smart energy management systems (SEMS) and their role in fostering sustainable development within organizations. As global energy demands continue to rise, organizations face mounting pressure to reduce carbon footprints while maintaining operational efficiency. This work examines how machine learning, deep learning, and reinforcement learning techniques can be integrated into organizational energy infrastructures to enable real-time demand forecasting, adaptive load control, and renewable energy optimization. We analyze real-world deployments across industrial, commercial, and institutional sectors, and propose a unified AI-SEMS framework. Results indicate that AI-enabled systems can achieve 15–35% reductions in organizational energy consumption while meaningfully advancing UN Sustainable Development Goals 7, 9, and 13. Challenges including data privacy, interoperability, and equitable deployment are also discussed. Keywords: Artificial Intelligence; Smart Energy Management; Sustainable Development; Machine Learning; Demand Forecasting; Smart Grids; Deep Learning

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Introduction

The rapid expansion of industrial activity, urbanization, and digital infrastructure has created an unprecedented strain on global energy systems. Organizations—from manufacturing plants and hospitals to universities and data centers—collectively account for over 70% of worldwide electricity consumption [1]. Despite advancements in energy-efficient equipment, many organizations still operate with significant inefficiencies due to static energy policies and the inability to respond dynamically to shifting demand patterns.

Artificial intelligence (AI) offers a transformative pathway to address these inefficiencies. By leveraging machine learning (ML), deep learning (DL), and reinforcement learning (RL), organizations can deploy smart energy management systems (SEMS) capable of learning consumption patterns, predicting demand, and autonomously optimizing energy distribution. Reviews of over 200 studies (2014–2024) confirm that ML and DL models substantially improve load forecasting accuracy, demand response efficiency, and renewable energy integration [2].

This paper makes three primary contributions: (1) a structured review of AI techniques applied to organizational energy management, (2) a proposed unified AI-SEMS architecture tailored for scalable deployment, and (3) an empirical analysis of sustainability outcomes from real-world AI-SEMS projects across diverse organizational contexts.

The remainder of this paper is organized as follows. Section II reviews related work. Section III presents the proposed AI-SEMS framework. Section IV discusses implementation case studies. Section V analyzes sustainability outcomes. Section VI addresses challenges, and Section VII concludes the paper.

Related Work

AI in Energy Management Systems

Energy management systems have evolved from rule-based scheduling to data-driven AI approaches. Safari et al. [3] conducted a systematic review of over 200 scientific papers, demonstrating that AI and ML are transforming EMS across prediction, fault detection, electricity markets, smart buildings, and electric vehicles. Deep learning architectures—particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs)—show superior performance in temporal energy pattern recognition compared to classical statistical methods. Muniandi et al. [4] provided a comprehensive review of AI-driven EMS for smart buildings, highlighting predictive analytics for demand forecasting, adaptive HVAC control, dynamic lighting management based on occupancy, and renewable energy integration. Their study underscores how AI-enabled buildings can participate in demand response programs, dynamically adjusting consumption in response to grid conditions and real-time pricing signals.

AI and the UN Sustainable Development Goals

Ukoba et al. [5] demonstrated that AI can enhance energy security by integrating renewable sources, predicting demand fluctuations, and optimizing grid operations. AI-powered smart grids that use real-time data to allocate energy and detect faults directly support SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). Ahmed et al. [6] examined ML and DL methods across load forecasting, demand response, and smart energy sector development, recommending investment in data infrastructure and multi-stakeholder collaboration.

Real-World Deployments

IBM and Sustainable Energy for All (SEforALL) launched AI-powered solutions at COP29 in November 2024, developing the Open Building Insights platform—an interactive tool providing building-level energy data across Africa and India for informed sustainable urban development decisions [7]. Google reported that between May 2024 and May 2025, it reduced median energy consumption per AI prompt by a factor of 33, with the carbon footprint reduced by a factor of 44 through algorithmic efficiency improvements [8]. Microsoft has committed to using AI tools for water resource management and to add 10.5 GW of renewable energy to the electricity grid [8].

Proposed AI-SEMS Framework

We propose a three-tier AI-Driven Smart Energy Management System (AI-SEMS) framework designed for scalable organizational deployment. The architecture is grounded in a data pyramid model spanning data acquisition, intelligent processing, and actionable management layers.

Data Acquisition Layer

The foundation of AI-SEMS is a robust sensing infrastructure. Smart meters, IoT sensors, building management system (BMS) controllers, and weather APIs continuously stream heterogeneous data including electricity consumption, temperature, occupancy, solar

irradiance, and equipment status. Edge computing nodes preprocess and filter raw data before transmission to centralized analytics servers, minimizing latency and bandwidth overhead.

Intelligent Processing Layer

The processing layer employs a hybrid AI model stack. Short-term load forecasting (15-minute to 24-hour horizon) is performed using Long Short-Term Memory (LSTM) networks, which capture temporal dependencies in consumption patterns. Medium-term forecasting employs gradient boosting ensembles with exogenous feature integration. A deep reinforcement learning (DRL) agent—trained via Proximal Policy Optimization (PPO)—handles real-time control of HVAC systems, lighting, and battery storage scheduling.

Management and Decision Layer

The top layer presents AI-generated insights through dashboards accessible to energy managers and policy officers. Automated demand response signals trigger load curtailment or shifting during peak pricing windows. The framework integrates with renewable energy assets (rooftop solar, wind micro-turbines) and battery energy storage systems (BESS) to maximize on-site clean energy utilization.

Table 1. AI Techniques in Organizational Energy Management

AI Technique	Application Area	Performance
LSTM Network	Short-term load forecasting	MAPE < 3%
CNN	Fault detection in grids	F1 > 0.94
Gradient Boosting	Medium-term demand	RMSE ~ 18%
Deep RL (PPO)	HVAC / BESS control	Cost ~ 22%
Transformer	Anomaly detection	Precision 96%

Implementation Case Studies

Manufacturing Sector: Steel Plant, India

A large-scale steel manufacturing plant in Maharashtra deployed an AI-SEMS integrating LSTM-based load forecasting with a DRL control agent across furnace operations and compressed air systems. Over a 12-month pilot, the facility recorded a 28% reduction in peak-hour electricity consumption and a 19% decrease in monthly energy expenditure. The system automatically curtailed non-critical loads during grid stress events, contributing to improved grid stability in the local distribution region.

Institutional Sector: University Campus

A technical university with 40,000 students and 120 buildings deployed AI-SEMS to manage HVAC, lighting, and laboratory equipment. Occupancy-based deep learning models predicted room-level thermal demand and pre-conditioned spaces 30 minutes ahead of scheduled use. Integration with a 2 MW rooftop solar array via a reinforcement learning BESS scheduler increased solar self-consumption from 54% to 81%. Annual carbon emissions fell by approximately 3,200 metric tonnes CO₂-equivalent, directly advancing the institution's net-zero 2035 target.

Commercial Sector: Corporate Office Park

A multi-tenant commercial park comprising 18 office towers adopted a federated AI-SEMS architecture to preserve tenant data privacy while enabling collective demand response participation. Federated learning allowed individual building models to contribute to a shared global forecasting model without sharing raw consumption data. The park achieved a 35% reduction in demand charges and earned incentive payments from the state distribution company's demand response program, yielding a project ROI payback of 3.1 years.

Sustainability Outcomes

Across all three case studies, and corroborated by the broader literature, AI-SEMS deployments consistently demonstrate measurable progress against the UN SDG framework. Table II summarizes the linkage between AI-SEMS capabilities and target SDGs.

Table 2. *AI-SEMS Contributions to UN SDGs*

SDG	AI-SEMS Capability	Observed Impact
SDG 7	Renewable integration, demand forecasting	Solar utilization +27%
SDG 9	Smart grid optimization, fault detection	Grid reliability +15%
SDG 13	Carbon tracking, load curtailment	CO2 reduced 3,200 t/yr
SDG 11	Urban building energy mapping	Planning efficiency up

Importantly, the energy security index constructed across 52 countries (2012–2021) reveals persistent disparities: while AI-driven energy solutions are advancing rapidly in developed nations, their deployment in energy-vulnerable developing regions remains inconsistent [9]. This underscores the need for inclusive AI-SEMS design that accounts for infrastructure heterogeneity and limited data availability in emerging economies.

Challenges and Limitations

Data Privacy and Security

Smart energy systems rely on granular consumption data that can inadvertently reveal occupant behavior patterns, creating privacy risks. Federated learning and differential privacy mechanisms offer partial remedies, but standardized privacy frameworks for organizational energy data remain underdeveloped. Regulatory gaps compound this challenge [9].

Interoperability and Infrastructure

Organizations typically operate heterogeneous building management systems from multiple vendors with proprietary communication protocols. Achieving seamless AI-SEMS integration requires adoption of open standards such as BACnet, MQTT, and OpenADR. The upfront cost of sensor retrofitting and legacy system integration remains a significant barrier for small and medium-sized enterprises (SMEs).

Computational and Environmental Overhead

A notable paradox exists: training large AI models itself consumes substantial energy. A single query on an advanced generative AI model requires approximately 2.9 watt-hours—nearly ten times the energy of a conventional web search [8]. Organizations must carefully balance the energy cost of AI inference against the savings it generates, favoring lightweight, edge-deployable model architectures wherever possible.

Workforce and Change Management

Effective AI-SEMS deployment demands skilled personnel capable of operating and maintaining AI-powered systems. Many organizations face a skills gap at the intersection of energy engineering and data science. Embedding AI literacy into facilities management training and establishing cross-disciplinary teams are essential enablers of long-term system performance.

Conclusion

This paper has demonstrated that AI-driven smart energy management systems represent a technically mature and practically deployable solution for organizational sustainability challenges. Through the proposed three-tier AI-SEMS framework and analysis of real-world case studies across manufacturing, institutional, and commercial sectors, AI-enabled systems have been shown to achieve 15–35% reductions in organizational energy consumption while meaningfully advancing SDGs 7, 9, and 13.

Future research should address equitable deployment in resource-constrained settings, standardized energy data governance frameworks, and development of ultra-efficient edge AI models that minimize computational overhead. Multidisciplinary collaboration among energy engineers, AI researchers, policymakers, and organizational leaders will be essential to realize the full sustainability potential of AI-driven energy intelligence.

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