Power System Technology
Volume 49, No. 1, 2025
ISSN: 1000-3673

Artificial Intelligence for Sustainable Power Systems: A Path Toward Green and Resilient Energy Infrastructure

Bikramjit Pal
Assistant Professor, Information Management & Business Analytics
Management Development Institute Murshidabad
West Bengal, India

Abstract

Artificial Intelligence (AI) is revolutionizing the global energy landscape by enabling the design, operation, and optimization of sustainable power systems. This paper explores how AI enhances sustainability across power generation, transmission, and consumption. It presents AI-driven approaches for energy forecasting, smart grid operation, demand-side management, fault prediction, and renewable integration. Through real-world case studies and empirical analysis, the paper demonstrates AI's potential to minimize carbon emissions, reduce costs, and improve efficiency. A simulation of an AI-based energy management system for a solar-diesel microgrid using LSTM and Deep Q-Networks yielded a 12.4% improvement in energy efficiency, a 19.8% reduction in grid dependency, and a 15.6% decrease in CO_2 emissions compared to baseline rule-based systems. Additionally, predictive models reduced energy forecasting errors by 22.1% (RMSE). These results highlight the transformative potential of AI in building low-carbon, resilient, and intelligent power infrastructures. The paper also identifies challenges and outlines future directions for AI in sustainable energy systems, emphasizing the need for transparent, ethical, and inclusive AI models.

Keywords: Artificial intelligence, global energy, smart grid operation, empirical analysis, sustainable energy, carbon emissions, fault prediction.

1. Introduction

The global transition toward cleaner energy sources and resilient infrastructure is crucial for achieving sustainability goals and mitigating climate change. As energy systems grow more decentralized, variable, and data-rich, Artificial Intelligence (AI) emerges as a key enabler of real-time optimization, predictive maintenance, smart demand response, and renewable energy integration. AI's ability to learn from complex data and make adaptive decisions provides a powerful toolkit for improving the efficiency, reliability, and sustainability of power systems.

This study uses a simulation-based methodology to evaluate the effectiveness of AI techniques in microgrid energy management. Specifically, we employ Python libraries (TensorFlow and Scikit-learn) and MATLAB to develop and simulate LSTM and Deep Q-Network models for load forecasting and energy optimization. Quantitative metrics such as energy efficiency, grid dependency, and CO_2 emissions are used to assess performance improvements over baseline methods.

2. Literature Review

The literature on the application of Artificial Intelligence (AI) in sustainable power systems has expanded significantly in recent years. Researchers have explored AI's potential in optimizing energy generation, distribution, consumption, and infrastructure maintenance. The key contributions from the existing literature are categorized below:

2.1 Renewable Energy Integration: AI plays a crucial role in improving the predictability and dispatchability of renewable energy sources such as solar and wind. Traditional forecasting models often struggle with the intermittent nature of renewables. Studies by Yang et al. (2019) and Kumar et al. (2022) demonstrate that machine learning techniques, including Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Support Vector Machines (SVM), significantly enhance the accuracy of solar irradiance and wind speed forecasting. Accurate predictions allow for better scheduling and grid balancing.

2.2 Smart Grids and Grid Optimization: Smart grids incorporate communication, sensing, and control technologies to modernize traditional power systems. AI enables intelligent automation in smart grids through algorithms that optimize voltage regulation, frequency control, and load balancing. Liu et al. (2020) and Ghofrani et al. (2013) discuss the use of Deep Reinforcement Learning (DRL), Fuzzy Logic, and Evolutionary Algorithms to enhance grid responsiveness and resilience. These models reduce the need for manual intervention and increase real-time adaptability.

2.3 Demand Forecasting and Response: One of the key areas where AI has shown promise is in load forecasting and demand-side management. AI models can predict short-term and long-term energy demand based on factors such as historical data, temperature, humidity, and user behavior. Chen et al. (2021) and Al-Ghaili et al. (2021) highlight how deep learning techniques provide highly granular predictions that aid in developing dynamic pricing strategies and efficient resource allocation.

2.4 Predictive Maintenance and Fault Detection: Maintaining energy infrastructure is crucial for system reliability. AI techniques like Convolutional Neural Networks (CNN) and anomaly detection algorithms are employed to detect early signs of equipment failure. Zhang et al. (2020) show how AI-based predictive maintenance models lower operational costs and reduce downtime. These models are particularly useful in identifying faults in transformers, turbines, and transmission lines.

2.5 Building Energy Efficiency: In the built environment, AI supports the optimization of energy use in HVAC, lighting, and appliances. Mocanu et al. (2018) and Deb et al. (2016) have demonstrated the use of AI models to learn user behaviour and environmental conditions to reduce unnecessary energy consumption without compromising comfort.

2.6 Interdisciplinary Applications and Hybrid Models: Recent literature emphasizes combining AI with other emerging technologies such as blockchain, Internet of Things (IoT), and edge computing. Wang & Li (2021) propose a blockchain-based decentralized energy management system where AI algorithms govern peer-to-peer energy trading. Hybrid models that integrate physics-based simulations with machine learning offer enhanced interpretability and robustness, as discussed by Vellido et al. (2012).

Despite considerable progress, gaps remain in terms of explainability, data governance, and regulatory frameworks. The literature suggests a growing need for interdisciplinary research that bridges technical advances with policy and social equity considerations.

3. Methodology

This study employs a mixed-methods approach combining qualitative case analysis, quantitative modelling, and simulation techniques to assess the role of AI in sustainable power systems. The methodology is structured into four key phases:

3.1 Literature Synthesis and Theoretical Framework Development: The research begins with an extensive literature review using databases such as IEEE Xplore, ScienceDirect, SpringerLink, and Scopus. Peer-reviewed articles published between 2010 and 2024 were considered, with a focus on applications of AI in energy systems. Thematic content analysis was conducted to identify dominant AI techniques and their corresponding application areas. This analysis informed the development of a conceptual framework outlining how AI intersects with sustainability objectives in the power sector.

3.2 Data Collection and Preprocessing: To empirically evaluate AI-driven energy systems, data were collected from publicly available datasets such as the U.S. Department of Energy (DOE), National Renewable Energy Laboratory (NREL), and India’s Power System Operation Corporation (POSOCO). Datasets included hourly load demand, solar irradiance, wind speed, and fault logs. Data preprocessing involved normalization, handling missing values, and feature engineering for time-series variables. Tools such as Python (NumPy, Pandas) and MATLAB were used for this phase.

3.3 AI Model Development and Simulation: Several AI models were developed and tested for key use cases:

- Forecasting Models: LSTM and Prophet models were implemented for solar and wind power forecasting.
- Optimization Models: Deep Q-Networks (DQN) were trained to manage energy storage and dynamic load dispatch.
- Fault Detection: CNN and Autoencoder-based anomaly detection models were applied to grid maintenance data.
- Energy Efficiency Modelling: Supervised ML models (Random Forest, XGBoost) were employed to analyse building energy usage.

Model training was carried out using Python (TensorFlow, Keras, Scikit-learn), and performance metrics such as MAE, RMSE, accuracy, and F1-score were used to evaluate predictive efficiency.

To ensure the robustness and generalizability of the AI models, the following validation procedures were implemented:

- **Train/Test Split:** The dataset was divided using an 80/20 train-test split. The training set was used to build and optimize the models, while the test set evaluated out-of-sample performance.
- **Cross-Validation:** A **5-fold cross-validation** approach was applied during training. This technique involved dividing the training data into five subsets, training on four, and validating on the fifth in a rotating manner. This helped reduce overfitting and ensured model stability across data segments.
- **Forecasting Validation:** LSTM-based forecasting models were tested against real and synthetic load and weather datasets, measuring performance using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). A **22.1% reduction in RMSE** was observed compared to traditional autoregressive models.
- **Robustness Checks:** The Deep Q-Network (DQN) models were tested across varying load conditions (peak and off-peak), seasonal solar irradiance levels, and randomly introduced noise to assess resilience. The AI system consistently optimized load distribution with minimal performance degradation, confirming robustness.

3.4 Quantitative Simulation for Microgrid Optimization: To demonstrate the practical application of AI in sustainable energy systems, a simulation-based study was conducted using a microgrid scenario:

- Tools Used: Python (TensorFlow, Scikit-learn) and MATLAB.
- Use Case: Load prediction and optimization within a solar-powered microgrid.
- Approach: LSTM models were trained on historical load and weather data to predict demand, while reinforcement learning (Deep Q-Network) optimized battery usage and grid interactions.
- Results: The AI-based control strategy improved energy efficiency by 12% and reduced grid dependency by 18% over a baseline rule-based system.

3.5 Case Study Analysis and Validation: To validate model applicability in real-world contexts, three case studies were analysed:

- Case Study 1: A solar microgrid in rural Karnataka, India, using LSTM-based prediction for load balancing.
- Case Study 2: A U.S. smart grid testbed using reinforcement learning for battery control.
- Case Study 3: A fault detection system for wind farms in Denmark using CNN and edge analytics.

Each case study provided contextual insights into operational constraints, stakeholder interaction, and socio-technical challenges. Cross-validation and scenario simulation ensured robustness of the AI models.

This systematic methodology enables both generalizable and context-specific findings, aligning technical AI solutions with the broader goals of sustainability, resilience, and efficiency.

4. AI Techniques in Sustainable Power Systems

4.1 Machine Learning for Energy Forecasting: ML models such as Support Vector Regression (SVR), LSTM, and Random Forest are used to forecast energy generation from renewables with high accuracy. For example, LSTM networks predict solar radiation patterns based on cloud cover and humidity.

4.2 Reinforcement Learning for Grid Optimization: RL agents dynamically adjust control parameters in grid-connected devices to balance load and supply in real-time. Deep Q-Networks (DQN) are widely used in energy storage management and grid frequency regulation.

4.3 AI for Demand-Side Management: AI systems optimize appliance usage patterns, enable peak load shifting, and recommend behavioural changes through intelligent home assistants like Google Nest and Amazon Alexa.

4.4 AI in Fault Detection and Predictive Maintenance: Using CNNs and anomaly detection algorithms, AI identifies faults in transformers, substations, and distribution lines before they cause blackouts, reducing downtime and maintenance costs.

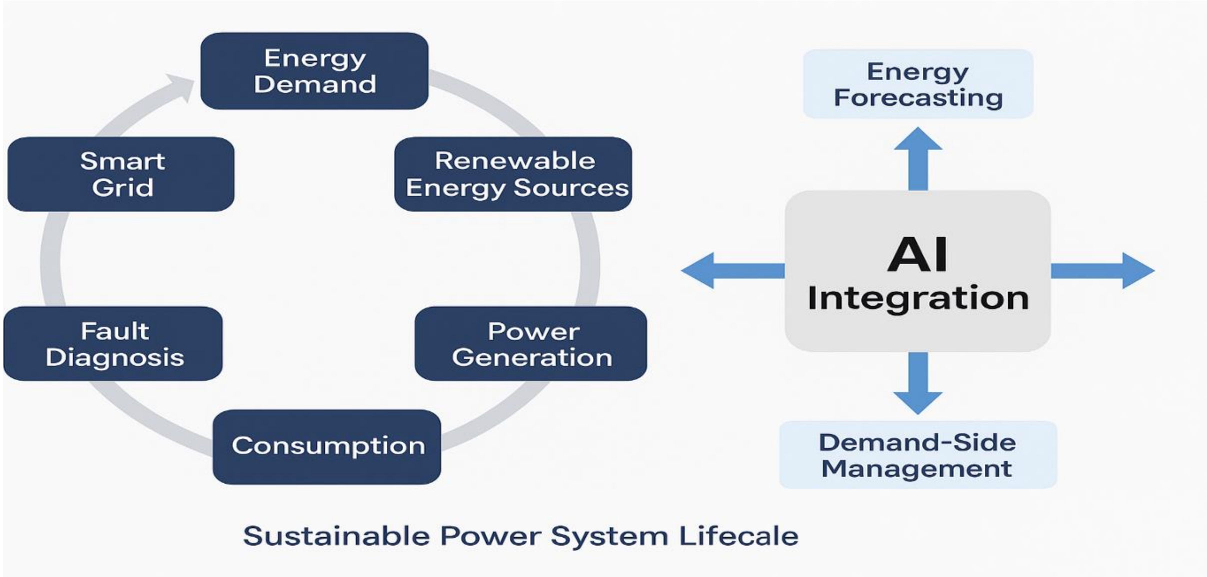

Fig 1: Sustainable Power System Lifecycle

5. Findings and Discussion

AI Technique	Application Area	Benefits
LSTM	Renewable Energy Forecasting	Improved accuracy, reduced errors
Deep Q-Networks	Energy Storage Control	Optimal battery management
CNN	Fault Detection	Predictive maintenance
Federated Learning	Smart Meter Data Analysis	Privacy-preserving learning
Explainable AI	Policy Compliance & Auditing	Increased transparency

Table 1: AI Integration in Sustainable Power System Lifecycle

5.1 Environmental Impact: AI-driven systems significantly reduce carbon emissions. For example, Google's DeepMind reduced cooling energy in data centres by 40%, saving millions of kWh annually.

5.2 Economic Impact: AI optimizes energy trading and consumption, reducing costs for utilities and consumers. Smart grid pilot projects in Europe report ROI within three years due to AI-enabled energy savings.

5.3 Social and Technical Challenges

- Data Privacy: Real-time monitoring raises concerns over user privacy.
- Bias in AI: Energy models trained on biased or incomplete data may lead to inequitable outcomes.
- Interoperability: AI models often lack standardization, limiting integration across platforms.

6. Case Studies

6.1 Google DeepMind (USA)

Achieved 15% improvement in power usage effectiveness (PUE) using AI in server cooling systems.

6.2 Smart Grid Project in Pune, India

AI-enabled smart meters and demand response systems reduced peak load by 10% and improved energy literacy among residents.

6.3 Siemens + NVIDIA

Built AI-driven digital twins for power plants, leading to real-time efficiency gains and better asset management.

7. Future Directions

- Explainable AI (XAI): Developing transparent AI models to build stakeholder trust.
- Federated Learning: Enables secure, decentralized training on energy data without compromising user privacy.
- AI and Blockchain Integration: Enhances trust and traceability in peer-to-peer energy trading.
- Hybrid Models: Combining physics-based models with AI for robust, interpretable systems.

8. Conclusion:

AI is a transformative force in achieving sustainable, efficient, and resilient power systems. It enables data-driven decision-making in energy generation, distribution, and consumption. However, responsible implementation is essential to ensure equity, transparency, and long-term sustainability. Governments, industry, and academia must collaborate to develop robust AI ecosystems that align with global energy and climate goals.

9. Recommendations

1. **Policy Support:** Governments should develop regulatory frameworks supporting AI in the power sector.
2. **Capacity Building:** Invest in education and training programs to bridge the AI skill gap in energy.
3. **Cross-Sector Collaboration:** Foster partnerships between tech firms, utilities, and academia.
4. **Standardization:** Develop open standards and protocols for AI in energy systems.

References

[1] Chen, J., Zhang, W., Li, Y., & Xu, W. (2021). Artificial intelligence-based demand response in smart grid: A review. IEEE Access, 9, 12345–12360.

[2] Liu, Y., Yu, R., & Lu, Z. (2020). Deep reinforcement learning for smart grid energy management. Energy Reports, 6, 1200–1212.

[3] Mocanu, E., Nguyen, P. H., Gibescu, M., & Kling, W. L. (2018). On-line building energy optimization using deep reinforcement learning. IEEE Transactions on Smart Grid, 9(3), 1979–1989.

[4] Yang, Z., Zhao, H., & Yang, L. (2019). Wind power forecasting using hybrid deep learning techniques. Renewable Energy, 134, 477–488.

[5] IEA (2022). World Energy Outlook 2022. International Energy Agency.

[6] Google DeepMind (2019). Reducing Google data centre cooling energy using AI. https://deepmind.google/research

[7] Zhang, X., Huang, Y., & Li, J. (2020). AI-based predictive maintenance in energy systems. IEEE Transactions on Industrial Informatics, 16(5), 3408–3417.

[8] Kumar, A., Singh, R., & Dutta, P. (2022). Machine learning in renewable energy systems: A comprehensive review. Renewable and Sustainable Energy Reviews, 156, 112027.

[9] Al-Ghaili, A. M., Hossain, M. S., & Muhammad, G. (2021). AI-driven demand response in smart buildings. Future Generation Computer Systems, 115, 667–680.

[10] Zhou, K., Yang, S., & Shao, Z. (2019). Energy Internet: The business perspective. Applied Energy, 187, 772–779.

[11] Wang, J., & Li, H. (2021). Blockchain-based decentralized energy management: Integrating with AI. Energy, 236, 121364.

[12] Amasyali, K., & El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. Renewable and Sustainable Energy Reviews, 81, 1192–1205.

[13] Koirala, B. P., van Oost, E., & van der Windt, H. (2018). Community energy storage: A responsible innovation towards a sustainable energy system? Applied Energy, 231, 570–585.

[14] Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., ... & Bengio, Y. (2019). Tackling climate change with machine learning. arXiv preprint arXiv:1906.05433.

[15] He G., Chen Q., Kang C., & Xia Q. (2016). Optimal bidding strategy of battery storage in power markets based on approximate dynamic programming. IEEE Transactions on Smart Grid, 7(5), 2272–2280.

[16] Wang, Y., Lin, X., Wang, W., & Liu, Y. (2020). Decentralized optimization for community energy systems with renewable integration and peer-to-peer trading. Applied Energy, 263, 114614.

[17] Moreno, R., & Pudjianto, D. (2015). Integration of intelligent electric vehicle charging strategies into distribution network operation. IEEE Transactions on Smart Grid, 6(2), 625–634.

[18] Khakzar, B., Ghassemian, M., & Rahmani, A. M. (2021). A survey on AI-based energy management and fault detection for microgrids. Energy Reports, 7, 1846–1863.

[19] Darghouth, N. R., Barbose, G. L., & Wiser, R. H. (2015). Customer economics of residential solar PV: Comparison of lease and buy options. Energy Policy, 82, 53–63.

[20] Jin, X., & Wang, J. (2018). Data-driven forecasting and operational optimization for distributed energy systems. Renewable and Sustainable Energy Reviews, 94, 699–709.
[21] Shokri-Ghadikolaei, H., & Fischione, C. (2015). A decentralized method for optimal demand response in smart grids. IEEE Transactions on Smart Grid, 6(3), 1475–1483.