International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 10, NCREHAASTE - 2026

Sustainable Artificial Intelligence for Energy Management: A Comparative Review of Machine Learning and Deep Learning Approaches

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Abstract

Artificial Intelligence (AI), including Machine Learning (ML) and Deep Learning (DL), is becoming an important component of modern energy-management systems. These techniques support energy-demand forecasting, demand response, renewable-energy integration, fault detection, and automated decision-making. The growing adoption of solar and wind power introduces greater variability and uncertainty, creating challenges for conventional energy-management methods. This review compares SVM, RF, ANN, LSTM, CNN, autoencoders, and reinforcement learning across prediction performance, computational cost, scalability, interpretability, data requirements, and practical deployment. DL models, particularly LSTM networks, are well suited to nonlinear and sequential energy-forecasting tasks, whereas SVM and ensemble-based methods can achieve competitive performance with lower computational requirements. Nevertheless, data dependency, computational overhead, limited deployment in real-world environments, and interpretability remain significant concerns. To address these issues, an AI-based sustainable energy-management framework is proposed that combines data-quality assessment, model selection, forecasting, explainable AI, and adaptive control.

Keywords: Sustainable AI, Artificial Intelligence, Machine Learning, Deep Learning, Energy Management System.

1 Introduction

The growing demand for electricity, rapid expansion of renewable-energy generation, and pressure to minimize environmental impacts have introduced significant challenges for energy-management systems (EMSs). Modern energy networks increasingly integrate distributed renewable sources, battery storage, electric vehicles, smart meters, intelligent buildings, and responsive consumers, making energy production and consumption more dynamic and difficult to predict.

Artificial Intelligence (AI) offers a means of developing EMSs that can respond more effectively to these changing conditions. Machine Learning (ML) techniques identify patterns in historical data to support forecasting and operational decisions, while Deep Learning (DL) employs multilayer neural networks to learn complex representations from large datasets. Existing studies have applied

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these approaches to load forecasting, demand response, renewable-energy prediction, photovoltaic fault detection, building energy management, and smart-grid applications.

Renewable variability is particularly important because solar output depends on irradiance, cloud conditions, temperature, and panel performance, whereas wind generation is influenced by wind speed, direction, terrain, and weather. ML and DL can model these relationships to improve scheduling and resource utilization. A key distinction is that conventional ML often depends on engineered features, while DL can learn relevant representations directly from raw data. However, DL typically demands larger datasets and greater computational resources.

The main contributions of this paper are:

- A structured comparison of major ML and DL techniques used in energy management.
- A classification of their applications in forecasting, demand response, renewable-energy management, and fault detection.
- A comparative analysis of accuracy, computational complexity, scalability, interpretability, and data requirements.
- Identification of major challenges affecting practical implementation.
- A proposed sustainable AI-based EMS framework.
- A set of research directions for practical and environmentally responsible AI deployment.

2 Related Work

Artificial Intelligence (AI) encompasses computational methods designed to perform tasks that typically require intelligent analysis, learning, and decision-making. Machine Learning (ML) constitutes a major branch of AI in which algorithms identify patterns and relationships from data rather than depending solely on explicitly programmed rules. Deep Learning (DL), a specialized subset of ML, uses multilayer neural networks to learn increasingly complex representations from data. Existing research has demonstrated the application of ML and DL to renewable-energy forecasting, energy-demand prediction, equipment fault detection, and intelligent energy control.

2.1 Machine Learning

ML techniques used in energy-management applications can broadly be categorized into supervised, unsupervised, semi-supervised, and reinforcement learning.

Supervised learning relies on labeled datasets to learn a relationship between input variables and a predefined target. Regression techniques can estimate continuous quantities such as energy consumption or renewable-energy generation, whereas classification methods can distinguish equipment faults, operating conditions, or system states.

Unsupervised learning analyzes data without predefined target labels to identify underlying structures, clusters, or unusual patterns. In energy-management systems, such methods can support consumer segmentation, discovery of energy-use patterns, and anomaly detection.

Reinforcement learning (RL) follows a different learning paradigm in which an agent interacts with an environment, performs actions, and receives corresponding rewards or penalties. Through repeated interaction, the agent learns a policy intended to maximize cumulative rewards. Research has explored RL for energy-optimization tasks, including photovoltaic maximum-power-point tracking and automated energy-control applications.

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2.2 Deep Learning

Deep Learning is particularly relevant to energy-management problems involving nonlinear relationships, high-dimensional inputs, and temporal dependencies. Frequently applied architectures include:

- Artificial Neural Networks (ANNs)
- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs)
- Long Short-Term Memory (LSTM) networks
- Autoencoders
- Deep Reinforcement Learning
- Transformer-based architectures

Among these approaches, LSTM networks are well suited to sequential energy data because both electricity demand and renewable generation exhibit temporal dependencies. CNNs, in contrast, can effectively process spatial information and have consequently been applied to image-based photovoltaic (PV) fault identification. The reviewed literature reports LSTM-based approaches for load forecasting and CNN-based methods for PV fault detection.

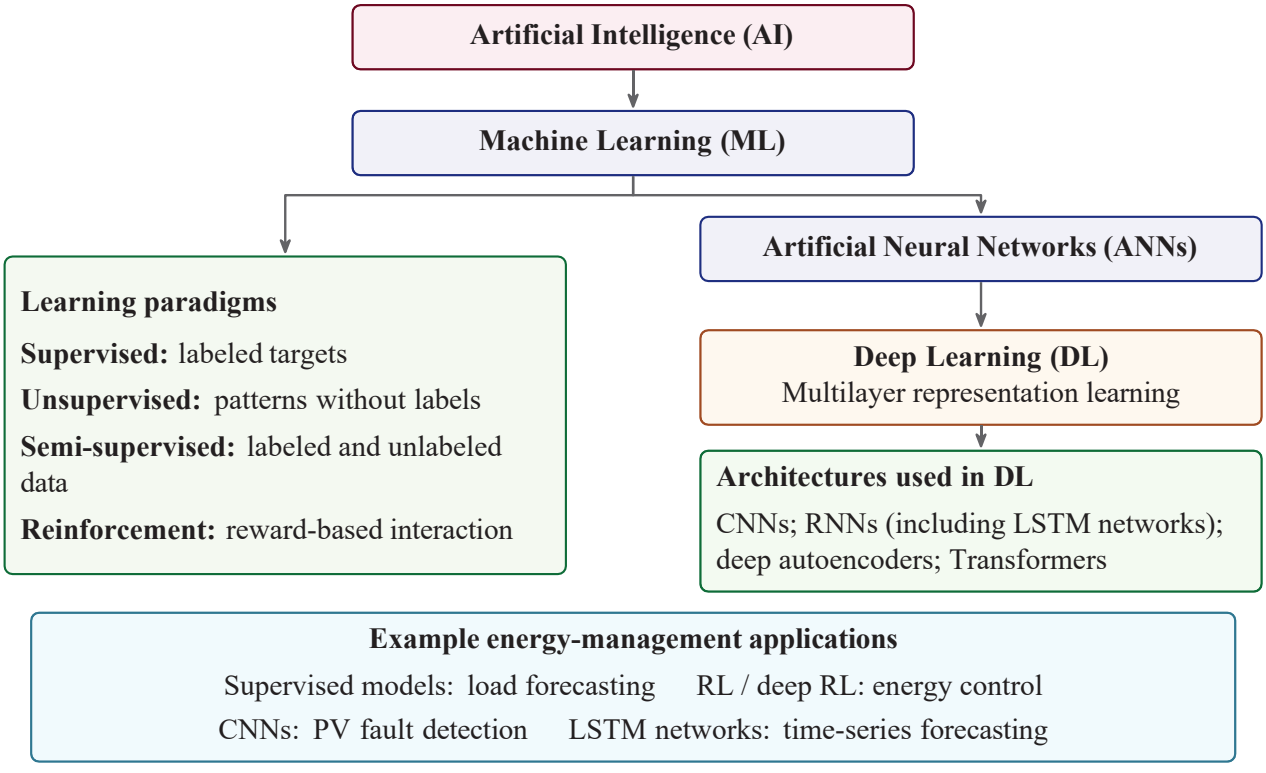


Figure 1: AI–ML–DL hierarchy and example energy-management applications. Arrows indicate increasing specialization or grouped examples. Learning paradigms and neural architectures are complementary views: DL can be used across learning paradigms, and LSTM is a recurrent architecture [8, 9].

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3 Applications of ML and DL in Energy Management

3.1 Load Forecasting

Load forecasting is one of the most important applications of AI in EMSs. Accurate prediction of future electricity demand supports generation scheduling, battery operation, load balancing, and demand-response planning. SVM, ANN, regression models, Random Forest, MLP, RNN, and LSTM have all been used for energy prediction. The reviewed literature reports that ML and DL methods can improve predictive capability compared with conventional approaches, although performance depends strongly on data quality and model selection.

For a load-forecasting problem, a general formulation can be represented as:

$$\hat{L}_{t+h} = f(L_t, L_{t-1}, W_t, T_t, D_t, H_t) \quad (1)$$

where:

- $\hat{L}_{t+h}$ = predicted load,
- L_t = historical load,
- W_t = weather information,
- T_t = temperature,
- D_t = day-related variables,
- H_t = time-related variables.

The model learns the function $f(\cdot)$ from historical observations.

3.2 Renewable-Energy Forecasting

Renewable-energy forecasting is another major AI application. Solar and wind generation fluctuate because of environmental conditions. ML can estimate generation based on historical power output and meteorological variables. The literature reports ML and DL approaches for solar, wind, hybrid PV-wind, and microgrid applications. However, sudden weather changes, incomplete historical datasets, and limited real-time sensor information can reduce prediction performance.

3.3 Demand Response

Demand response dynamically adjusts electricity consumption in response to grid conditions, electricity prices, or supply availability. AI models can predict consumer behavior and identify suitable loads for shifting. Random Forest and other ML models have been investigated for demand-response applications. The supplied literature highlights demand response as an important area in which ML/DL can improve resource utilization and grid stability.

3.4 Photovoltaic Fault Detection

PV systems can experience faults caused by damaged modules, abnormal electrical behavior, shading, or environmental conditions. CNN-based approaches can analyze PV images and identify defective or anomalous components. The reviewed literature identifies CNN as particularly useful for image-based fault detection because of its ability to automatically learn visual features.

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3.5 Building Energy Management

Buildings generate large volumes of energy-consumption data through smart meters, sensors, HVAC systems, lighting, and other devices. ML models can learn occupancy and consumption patterns and predict short-, medium-, and long-term energy demand. The reviewed work notes applications of ANN, SVM, decision trees, and DL to building-energy data.

4 Comparative Analysis of ML and DL Techniques

Table 1 summarizes the major techniques based on their characteristics and applications reported in the reviewed literature.

Table 1: Comparison of AI techniques for sustainable energy management

Technique	Main Application	Accuracy	Comp. Cost	Data Req.	Interpret.
Linear Regression	Basic load forecasting	Medium	Low	Low–Med	High
Decision Tree	Energy decisions/fault class.	Med–High	Low	Medium	High
Random Forest	Demand response, prediction	High	Medium	Medium	Medium
SVM/SVR	Load and renewable forecasting	High	Medium	Medium	Medium
ANN	Energy prediction	High	Medium	Med–High	Low–Med
CNN	PV image/fault detection	High	High	High	Low
RNN	Sequential forecasting	High	High	High	Low
LSTM	Load/renewable forecasting	Very High	High	High	Low
Autoencoder	Anomaly detection	High	High	High	Low
Reinforcement Learning	Energy control/optimization	High	High	High	Low
Hybrid ML/DL	Complex EMS optimization	Very High	Very High	Very High	Low

Note: The table represents a qualitative synthesis of the supplied literature rather than a new experimental benchmark.

The source literature reports that ANNs have been used for energy prediction, load forecasting, and power-flow calculations, while SVMs have been applied to energy prediction and power-system problems.

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International Journal of Engineering Research & Technology (IJERT)
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Table 2: Application-oriented comparison

Energy Problem	Recommended Model	Reason
Small-scale load	SVM/Regression	Lower complexity and good performance
Complex load	LSTM/RNN	Captures temporal dependencies
PV generation	ANN/LSTM	Handles nonlinear and temporal relationships
Wind forecasting	LSTM/Hybrid	Suitable for changing time-series patterns
PV image fault	CNN	Automatic visual feature extraction
Consumer clustering	K-Means/Clustering	Finds consumption groups
Demand-response	Random Forest/Decision Tree	Effective and relatively interpretable
Energy control	Reinforcement Learning	Learns actions through interaction
Anomaly detection	Autoencoder	Learns normal operating patterns
Large heterogeneous EMS	Hybrid ML/DL	Combines complementary capabilities

5 Proposed Sustainable AI-Based EMS Framework

Based on the limitations identified in the literature, this paper proposes a sustainable AI-EMS framework that considers not only prediction accuracy but also computational efficiency, data quality, explainability, and environmental impact.

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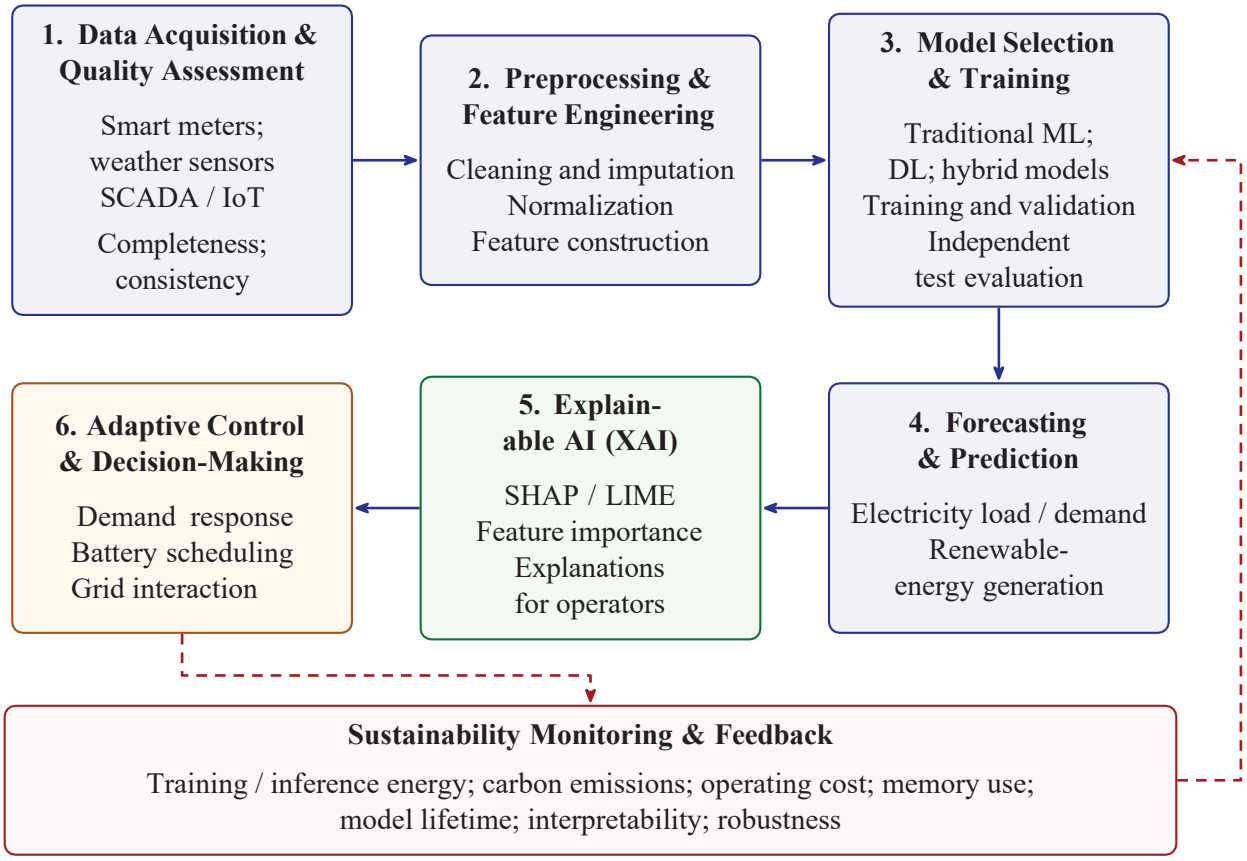


Figure 2: Proposed sustainable AI-based EMS framework. Solid arrows show the six-stage workflow, read left to right across the top row and right to left across the second row. Dashed arrows show sustainability monitoring and feedback to model selection and retraining.

The proposed framework follows the training and validation principles discussed in the supplied literature, where training data are used to construct the model, validation data are used for model selection, and independent test data are used for final evaluation.

6 Sustainable AI Evaluation Metrics

Traditional AI evaluation frequently emphasizes predictive accuracy. However, a sustainable AI system must consider several additional dimensions. For regression-based energy forecasting, common metrics include:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3}$$

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n} \frac{y_i - \hat{y}_i}{y_i} \tag{4}$$

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However, sustainable AI should additionally consider:

- Training energy consumption;
- Inference energy consumption;
- Training time;
- Memory utilization;
- Number of model parameters;
- Hardware requirements;
- Carbon emissions;
- Model lifetime and retraining frequency;
- Interpretability;
- Robustness.

A conceptual sustainability score can therefore be represented as:

$$S_{AI} = w_a A + w_e E + w_c C + w_i I + w_r R \quad (5)$$

where A represents predictive accuracy, E computational/energy efficiency, C carbon efficiency, I interpretability, and R robustness. The weights w_a, w_e, w_c, w_i, w_r can be selected according to the application.

7 Results and Comparative Discussion

The literature synthesis demonstrates that no single AI algorithm is optimal for every energy-management problem.

Table 3: Qualitative performance comparison

Criterion	Trad. ML	ANN	LSTM/RNN	CNN	RL
Forecasting	High	High	Very High	Medium	Medium
Temporal learning	Medium	Medium	Very High	Low–Med	High
Image analysis	Low	Medium	Low	Very High	Low
Comp. efficiency	High	Medium	Low	Low	Low
Scalability	High	Medium	Medium	Medium	Medium
Interpretability	Med–High	Medium	Low	Low	Low
Data requirement	Medium	High	High	High	Very High
Real-time control	High	Medium	Medium	Medium	Very High

The comparison suggests three important observations.

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7.1 Accuracy versus Computational Cost

DL models can achieve strong predictive performance for complex energy data but generally require more computational resources. The supplied source explicitly notes that highly accurate predictive models can require more computing power and larger datasets. Therefore, the highest-accuracy model is not necessarily the most sustainable model.

7.2 Importance of Data Quality

Data quality is one of the most important determinants of AI performance. The literature identifies data availability and quality as significant challenges, particularly for renewable-energy prediction and LSTM-based forecasting. Poor-quality data can result in:

- inaccurate forecasting;
- model instability;
- biased decisions;
- increased retraining;
- unnecessary computational expenditure.

Consequently, preprocessing and data-quality management should be considered fundamental components of sustainable AI.

7.3 Interpretability

Deep neural networks can behave as black-box models, making it difficult for operators to understand why a particular energy decision was produced. This can limit adoption in safety- and reliability-critical applications. The reviewed literature emphasizes Explainable AI (XAI) as an important research direction and reports increased acceptance when explainability is incorporated into DL-based PV fault detection.

8 Challenges

8.1 High Computational Requirements

Large DL models can require substantial CPU/GPU resources for training and inference. This can conflict with the objective of sustainable computing.

8.2 Data Availability

Energy AI systems depend heavily on historical and real-time data. However, comprehensive datasets covering different geographical regions, weather conditions, consumer behaviors, and equipment states are not always available.

8.3 Dynamic Renewable Generation

Solar and wind generation can change rapidly. A model trained under one environmental distribution may perform poorly under different weather or operating conditions.

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8.4 Model Generalization

An AI model may perform well on its training and validation datasets but fail when deployed in a different building, geographic region, or energy network.

8.5 Interpretability

Complex DL and reinforcement-learning models can be difficult to explain. This creates challenges for grid operators and other stakeholders who require understandable decisions.

8.6 Limited Real-World Deployment

One of the strongest limitations identified in the supplied literature is the gap between simulation-based research and practical deployment. The review notes that many ML/DL solutions have promising results but relatively limited large-scale real-world implementation.

9 Recommendations

Based on the comparative review, the following recommendations are proposed.

Table 4: Challenges and recommended solutions

Challenge	Recommended Solution
Poor-quality data	Data cleaning, validation and sensor-quality monitoring
Missing data	Imputation and data augmentation
High DL computation	Model compression and lightweight architectures
Large energy consumption	Efficient hardware and optimized training
Black-box decisions	XAI and interpretable ML
Weather uncertainty	Adaptive and ensemble models
Poor generalization	Transfer learning and diverse datasets
Limited deployment	Industry–academia pilot projects
Scalability	Distributed and cloud/edge architectures
Rapid changes	Online/adaptive learning
Cybersecurity	Secure data and model-management mechanisms
High retraining cost	Selective retraining and model monitoring

The supplied literature similarly recommends stronger industry–academia collaboration, improved data-management infrastructure, open data initiatives, and increased research into explainable AI.

10 Future Research Directions

Future research should move beyond isolated prediction tasks toward integrated sustainable AI systems.

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First, hybrid AI models should combine the strengths of conventional ML and DL. For example, an SVM or Random Forest model could be used for computationally efficient prediction, while LSTM could be applied when long-term temporal dependencies are important.

Second, edge AI represents an important direction for smart meters and local energy-management devices. Processing data close to the source can reduce communication requirements and latency.

Third, federated learning could allow multiple buildings or energy systems to collaboratively train models without transferring all raw data to a centralized server.

Fourth, explainable AI should become a standard component of energy-management applications rather than an optional addition.

Fifth, researchers should evaluate AI models using multi-dimensional sustainability metrics rather than accuracy alone. A model with marginally higher accuracy but substantially higher energy consumption may not be the best choice for a sustainable EMS.

Finally, long-term field trials are required. The supplied literature recommends moving from laboratory and pilot-scale studies toward broader real-world implementations and emphasizes collaboration among researchers, industry, and policymakers.

11 Conclusion

This paper presented a comparative review of Machine Learning and Deep Learning approaches for sustainable energy management. The analysis demonstrates that AI can significantly contribute to energy forecasting, renewable-energy prediction, demand response, PV fault detection, building energy management, and intelligent control.

Traditional ML approaches such as SVM, Random Forest, and decision trees offer advantages in terms of computational efficiency and, in some cases, interpretability. DL architectures such as CNN and LSTM provide powerful capabilities for image analysis and complex temporal forecasting, respectively. Reinforcement learning provides an alternative for sequential decision-making and energy-control problems.

Nevertheless, sustainable AI requires a broader evaluation framework. Prediction accuracy alone cannot determine whether an AI system is suitable for sustainable deployment. Computational cost, energy consumption, data requirements, scalability, robustness, interpretability, and real-world applicability must also be considered.

The reviewed literature, covering more than 200 studies, identifies improved predictive capabilities and opportunities for more efficient demand response and smart energy development, while also highlighting persistent challenges involving data quality, limited real-world implementation, and model interpretability. Therefore, this paper proposes that future energy-management systems should adopt a *Sustainable AI-by-Design* philosophy in which model accuracy, computational efficiency, environmental impact, reliability, and explainability are jointly optimized. Such an approach can help transform AI from a prediction technology into a practical component of resilient, intelligent, and sustainable energy infrastructure.

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