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The AI-Powered Grid: A Systematic Review of Machine Learning for Optimization and Resilience in Smart Energy Systems

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Abstract
Traditional energy grids are evolving into smart grids (SGs), which incorporate advanced communications, real-time analytics, and two-way power flows due to the global shift in the direction of sustainable energy. Complex problems as a result of this paradigm shift include handling large datasets, integrating intermittent renewable energy resources, and ensuring grid security and reliability. This literature review systematically examines the transformative role of machine learning (ML) and artificial intelligence (AI) in addressing these challenges. In addition to summarizing their use in key domains including demand forecasting, predictive maintenance, resource allocation, and anomaly detection, it also presents a selection of ML algorithms ranging from simple models such as SVM to state-of-the-art deep learning (DRL). The review also examines new hybrid architectures, including AI integration with blockchain to ensure secure transactions and federated learning to ensure data security. Despite significant improvements in efficiency and sustainability, AI adoption faces barriers related to data quality, model scalability, computational complexity, and cybersecurity. The study concludes by identifying critical research gaps and proposing future directions such as the development of explainable AI (XAI), lightweight models, standardized frameworks, and robust policy reforms to realize the full potential of self-adaptive smart energy grids.

Keywords: Smart Grids; Distribution Systems; Renewable Energy Integration; Machine Learning.

1-Introduction

The global energy landscape is undergoing a major transformation driven by the urgent need to reduce carbon emissions and meet increasing energy demand through sustainable practices (Hatcher & Yu, 2018). Traditional power grids, designed for one-way centralized power flow, are becoming inadequate due to aging infrastructure, high transmission losses, and excessive reliance on fossil fuels (Ramadh, 2022). Smart grids (SGs) represent a paradigm shift that integrates digital communication, automation, and real-time data analysis with traditional power grids to enable robust and efficient management of power generation, distribution, and consumption (Gaikwad et al., 2025). However, the complexity of smart grids creates inherent operational challenges. One of the central issues is the integration of variable renewable energy sources (VRES) such as solar and wind, whose intermittent and unpredictable nature endangers the stability of the grid (Arefin et al., 2025). Furthermore, smart grids generate massive, high-frequency big data from IoT devices such as smart meters, which traditional analysis methods cannot process effectively (Xu et al., 2025). Artificial intelligence (AI) and machine learning (ML) have emerged as key technologies to process these massive amounts of data, identify patterns, make predictions, facilitate independent decision-making, and improve network efficiency, reliability, and security (Long et al., 2023; Zhang et al., 2018).

1.1. Research Methodology and Purpose

This literature review adopts a systematic approach to summarize and evaluate research related to machine learning for smart grid management.

- **Database Search:** Primary searches were conducted in Scopus, IEEE Xplore, and Web of Science.
- **Keywords:** Search strings included combinations of: ("Machine Learning" OR "Deep Learning") AND ("Smart Grid" OR "Power Grid") AND ("forecasting" OR "optimization" OR "proactive maintenance" OR "security").
- **Inclusion/Exclusion:** The review focused on peer-reviewed scientific articles and conference proceedings published between 2020 and 2025. The initial research resulted in more than 63 research papers, categorized by title, abstract, and full text, resulting in 35 studies cited in this review.

Figure 1 illustrates the annual distribution of the final set of papers included in this survey, showing a clear upward trend in research interest in this field.

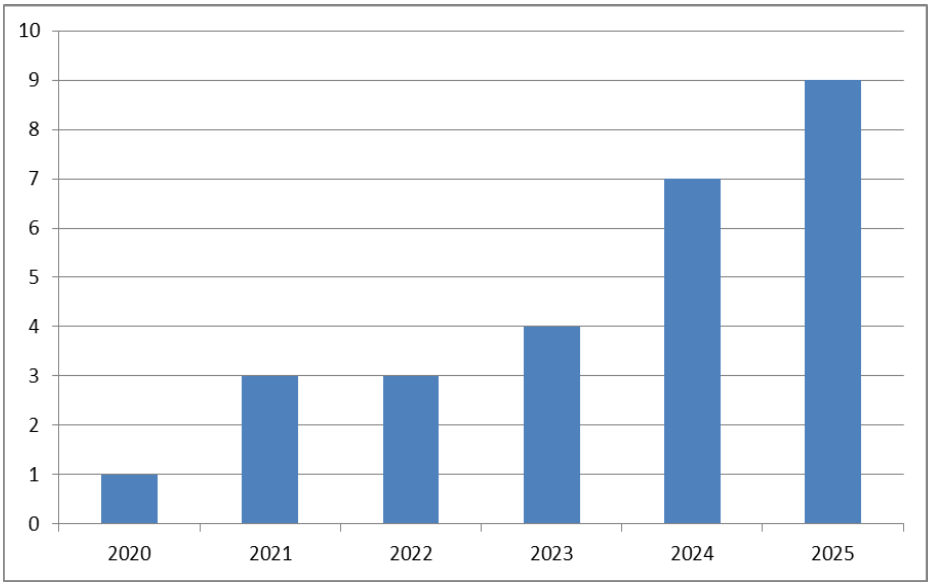

Figure 1: The number of surveyed papers over years

The main objective is to examine how machine learning models can enhance operational efficiency, network stability, and sustainability by solving key issues such as renewable energy integration and data security. The scope of research ranges from basic machine learning algorithms, cutting-edge deep learning (DL) models, and deep reinforcement learning (DRL) models, as well as new hybrid models.

2. The Smart Grid Paradigm: Challenges and Data Foundations

The foundation of AI-powered power generation systems is the transition from one-way power flow to a smart grid that provides two-way communication and power flow between utility companies and consumers (Klasari & Aly, 2024). This transformation is enabled by the Internet of Things (IoT), a network of interconnected devices like smart meters that generate real-time, high-resolution data on energy consumption (Tannahill & Jamshidi, 2014). The size, speed, and variety of these data make up what is known as "big data", necessitating advanced analytical methods that go beyond traditional tools.

The fundamental problem that AI must address is the uncertainty caused by variable renewable energy sources (VRES). Unlike conventional sources, VRES like solar and wind are weather dependent and intermittent in nature, and pose a persistent challenge of maintaining demand-supply balance and grid stability (Bayindir et al., 2014). It is within the context of data abundance and operational complexity that ML is a compelling solution.

3. A Taxonomy of AI and ML Techniques for Smart Grids

Machine learning tools in learning clusters (SGs) use different models, each suitable for specific tasks. Table 1 provides an overview of the most prominent AI/machine learning technologies, their areas of application and their main strengths, as reported in previous studies.

Table 1. Taxonomy of AI/ML Techniques and Their Applications in Smart Grids

AI Technique	**Application Area**	**Key Advantages**	**Reference(s)**
Traditional ML (SVM, ANN, Decision Trees)	Energy demand forecasting, tariff optimization, fault detection, and classification	Effective for managing large, continuous, complex data sets and non-linear relationships.	(Niu et al., 2023), (Sadiq et al., 2024)
Deep Learning (DL) (LSTM, CNNs)	Predictive maintenance, network stability enhancement, anomaly detection, and pattern recognition	It handles massive amounts of data, has greater predictive accuracy, understands raw data, uncovers hidden patterns, and is powerful for sequential and high-dimensional data.	(Jiang et al., 2017), (L. Zhou et al., 2017), (Huang et al., 2025)
Deep Reinforcement Learning (DRL) (DQN, PPO)	Autonomous control, real-time load balancing, demand response control, optimal power scheduling, distributed generator operation optimization, renewable energy systems, flexible loads, resource allocation, voltage and frequency control, virtual power plants (VPPs) for multi-objective optimization	Self-organizing, continuously learning and optimizing power distribution in real time, robust under highly dynamic and changing conditions, handles complex smart grid operations, maximizes renewable energy utilization, reduces grid losses, improves economic distribution efficiency, and dynamically adapts to real-time conditions.	(Yang et al., 2020), (Aslam et al., 2025), (Tang & Wang, 2025), (Manbachi et al., 2014), (Khosravi et al., 2025), (Lu et al., 2023)
Hybrid Frameworks (AI/Blockchain Integration)	Safe and sustainable energy management, reliable energy trading, and secure data handling	It provides a secure and immutable record of transactions, enhances transparency and trust, verifies data integrity, prevents tampering and fraud, analyzes patterns, predicts consumption, and enables real-time data-driven insights.	(Thopate et al., 2024), (Kolivandi et al., 2024)
AI/ML for Proactive Maintenance & Anomaly Detection	Fault detection, predictive maintenance, anomaly detection, and pattern recognition to ensure system integrity	Reduces system failures, enhances power flow efficiency and overall network resilience, reduces energy waste, identifies faults and prevents their escalation, and reduces downtime and	(Ramadh, 2022), (Ojadi et al., 2024), (Singh et al., 2025)

		technical losses.	
Federated Learning (FL)	Distributed systems, data privacy, and decentralized optimization	It enables high data privacy, distributed computing efficiency, operations closer to the source (edge computing), reduces latency, and supports real-time operation in geographically distributed energy systems.	(Akbari et al., 2024)

The preferred technology depends on the problem being addressed: classical machine learning provides powerful solutions to well-defined problems, deep learning is able to handle high-dimensional data, deep learning enables independent control of dynamic settings, and hybrid frameworks address system-level problems such as security and decentralization.

4. Core Application Domains of AI in Smart Grids

4.1. Demand Forecasting and Load Management

Predictive analytics using AI is critical to demand-supply balance. Machine learning algorithms, especially LSTM algorithms, analyze historical and live data to predict energy consumption with high accuracy, outperforming traditional algorithms (Ogadi et al., 2024). This supports demand-side management (DSM), where AI optimizes energy usage through scheduling high-power loads in accordance with grid conditions and dynamic prices, reducing peak demand and operation charges (Gaikwad et al., 2025; Singh et al., 2025).

4.2. Grid Reliability and Proactive Maintenance

Artificial intelligence supports the transition from reactive to predictive maintenance. Historical sensor data-based machine learning algorithms can predict equipment failures before they occur, reducing downtime and network resilience. Studies indicate that predictive maintenance with AI can achieve a downtime savings of up to 20% (Ogadi et al., 2024; Singh et al., 2025). Anomaly detection via unsupervised learning-based models, i.e., autoencoders (AE), needs to identify abnormal patterns that indicate failures or breaches and, therefore, ensure system integrity (Jiang et al., 2017).

4.3. Component-Level Monitoring and Diagnostics: A Zeta Converter Case Study

Power converters are critical to the integration of renewable energy sources. One of the most prominent researches focuses on machine learning-based predictions for DC-DC converters, such as the zeta converter in photovoltaic systems (Katche et al., 2023). Studies detect parametric faults in passive components (inductors and capacitors) and classify them into distinct fault classes. Comparative evaluations show that quadratic SVM classifiers achieve superior performance (e.g., 99.2% accuracy) in diagnosing these faults compared to K-Nearest Neighbors (KNN) classifiers and decision trees, due to their ability to model nonlinear degradation patterns (Sadiq et al., 2024; Wang et al., 2021).

4.4. Resource Allocation and Dynamic Optimization with DRL

The complexity of dynamic power systems requires the use of advanced artificial intelligence techniques to improve performance. Deep reinforcement learning (DRL) is particularly effective for real-time tasks, such as load balancing, power scheduling, and managing distributed energy generation and storage. In virtual power plants (VPPs), deep reinforcement learning frameworks dynamically adapt to grid conditions to maximize renewable energy utilization and increase economic efficiency. One study showed a 15% reduction in grid losses and a 22% increase in renewable energy use, outperforming traditional genetic algorithms (Tang & Wang, 2025).

4.5. Security and Fraud Detection

Machine learning is a powerful tool in combating electricity theft and non-technical losses. AI algorithms analyze consumption patterns to detect any anomalies that indicate fraudulent activity (Mostafa et al., 2022). Furthermore, machine learning models, such as support vector machines (SVMs), are used to detect subtle cyber-attacks, such as false data injection, which may affect load predictions and compromise network stability (Esmalifalak et al., 2017).

5. Advanced Architectures for Future Grids

5.1. Decentralized Management: VPPs and Multi-Agent Systems

The future of centralized power plants. Artificial intelligence enables the coordination of virtual power plants (VPPs) and multifactor reinforcement learning (MARL) systems, which efficiently manage distributed energy resources (DERs). These systems enable coordinated optimization between virtual power plant operators and distribution system operators, enhancing local energy balance and flexibility (Iqbal et al., 2021).

5.2. Secure Frameworks: AI-Blockchain Integration

AI supports blockchain technology as a secure, transparent, and non-manipulable record, for energy trading among peers, and for ensuring data integrity. Smart contracts are used through embedded blockchain and AI systems to conduct automated and secure transactions, while AI is used for predictive modeling, resulting in a flexible system that enables "producers" to operate efficiently and reduces the risk of energy theft (Jamil et al., 2021; Singh et al., 2025; Thopate et al., 2024).

6. Synthesis, Critical Gaps, and Future Directions

It has been fundamentally agreed that AI and more specific machine learning methods, such as deep learning and more specific deep learning, can work much better than traditional methods in solving the size and complexity of SG data, thereby achieving measurable gains in predictive accuracy, anomaly detection, and operational efficiency (Huang et al., 2025).

6.1. Critical Research Gaps

- **Data Rigidity and Quality:** The ability to generalize is hampered by the fact that models are repeatedly trained on sporadic or artificial data, ignoring real-world noise and latent time (Dehaghani et al., 2025).
- **Computational Complexity and Scalability:** Because advanced DRL and DL models require a lot of resources, they cannot be used in small-scale or time-sensitive settings (F. Zhou et al., 2022).
- **Interoperability with Legacy Systems:** The absence of standardized interfaces and protocols makes it difficult to integrate AI with existing network infrastructure (e.g. SCADA) (Shoaei et al., 2024).
- **Security and Adversarial Vulnerabilities:** Because machine learning models are vulnerable to adversarial attacks, the stability of the network can be compromised due to precise data manipulation.

6.2. Future Research Directions

- **Explainable AI (XAI):** Developing transparent models is important to increase trust, regulatory compliance and operator intervention in safety-critical energy systems.
- **Federated Learning (FL) and Edge Computing:** By facilitating distributed model training and reducing latency for real-time operations, FL can address data privacy and centralization barriers.
- **Lightweight and Quantum AI:** Energy-efficient architectures and shrinking models require further research. In the long run, hybrid quantum AI frameworks can solve complex optimization problems at unprecedented speed.
- **Policy Reform and Governance:** And for AI to be widely adopted, robust regulatory frameworks for cybersecurity, operational compatibility, and ethical deployment are essential.

7. Conclusion

Integration of machine learning and artificial intelligence is revolutionizing smart grids, as their reliability, efficiency, and ability to use renewable energy are significantly improved. AI provides the intelligence needed to manage state-of-the-art power systems, from accurate demand forecasting and predictive maintenance to dynamic optimization with DRL systems. And while data, scalability, and security challenges continue to emerge, work in exponential artificial intelligence (XAI), federated learning, and secure hybrid models is paving the way to building a robust, efficient, and sustainable smart energy grid.

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