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Review Article

Artificial Intelligence and Machine Learning in Electrical Power Systems: A Review of Applications and Future Directions

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Abstract

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in electrical power systems has transformed the way energy is generated, transmitted, and distributed. AI and ML techniques enable predictive analytics, fault detection, and optimization of power system operations. With the increasing complexity and decentralization of power systems, AI and ML play a crucial role in ensuring reliability, efficiency, and sustainability. This review explores the current applications of AI and ML in electrical power systems, including load forecasting, renewable energy integration, grid management, and cybersecurity. It also discusses future directions, challenges, and opportunities for AI-driven innovation in the energy sector. The review employed a comprehensive methodology, involving a literature review of AI and ML applications in power systems, analysis of case studies, evaluation of techniques (machine learning and deep learning models), and examination of applications (grid stability assessment, predictive maintenance, fault diagnosis, and renewable energy integration). Findings from this study revealed that AI and ML have transformative potential in electrical power systems, enhancing efficiency, reliability, and sustainability. Key findings include: AI-driven predictive analytics and fault detection improve grid stability and reduce downtime; ML models optimize renewable energy output and integration; and AI-powered control systems enhance grid management. The review also identified challenges, such as data quality and cybersecurity concerns, and highlighted future research directions, including developing more advanced AI algorithms and integrating AI with emerging technologies like IoT and blockchain. The integration of AI and ML in electrical power systems has transformative potential, enhancing efficiency, reliability, and sustainability. While challenges exist, ongoing research and development can address these issues. As the energy sector evolves, AI and ML will play a crucial role in shaping its future, driving innovation and improvement. Overall, AI and ML can revolutionize power system operations, but require careful implementation and ongoing research.

Keywords: Machine learning, Artificial intelligence, Energy, Sustainability, Blockchain, and Power systems

Introduction

The global energy landscape is undergoing a profound transformation, driven by the escalating demand for reliable, efficient, and sustainable electricity. Traditional power systems, long characterized by centralized generation and

manual control mechanisms, are increasingly inadequate for meeting the dynamic requirements of modern society (Errandonea *et al.*, 2020). These legacy infrastructures often suffer from inefficiencies, limited adaptability, and heightened vulnerability to faults and cyber threats. Consequently, there is a growing imperative for grid modernization a strategic shift

toward intelligent power systems that harness digital technologies to enhance performance, resilience, and flexibility (Gao *et al.*, 2024). Intelligent power systems represent a convergence of advanced sensing, communication, and computational capabilities, enabling real-time monitoring, control, and optimization across the entire energy value chain from generation to consumption. This evolution is not merely technological but also systemic, supporting the integration of renewable energy sources, electric vehicles, and distributed energy resources while maintaining grid stability and operational reliability. As the energy ecosystem becomes more decentralized and data-intensive, the role of intelligent automation becomes indispensable (Ghorbanian *et al.*, 2021). Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative enablers in this context. These technologies facilitate data-driven decision-making by allowing power systems to learn from historical and real-time data, thereby improving forecasting accuracy, fault detection, and operational efficiency. For example, ML algorithms can

anticipate equipment failures before they occur, enabling predictive maintenance strategies that reduce downtime and extend asset lifespans (Heluany *et al.*, 2024). AI also contributes to energy efficiency by optimizing load dispatch, voltage regulation, and demand response mechanisms. Deep learning models can uncover complex patterns in energy consumption and generation, offering actionable insights to grid operators and consumers alike. In protection systems, AI enhances fault classification and isolation, minimizing the impact of disturbances and bolstering system resilience. Beyond operational enhancements, AI and ML play a critical role in cybersecurity (Su and Zhao, 2025). As power systems become increasingly digitalized and interconnected, the ability to autonomously detect anomalies and respond to cyber threats is essential for safeguarding infrastructure integrity. Intelligent algorithms can monitor network behavior, identify deviations, and initiate protective measures in real time, thereby fortifying the grid against malicious intrusions (Helal *et al.*, 2022).

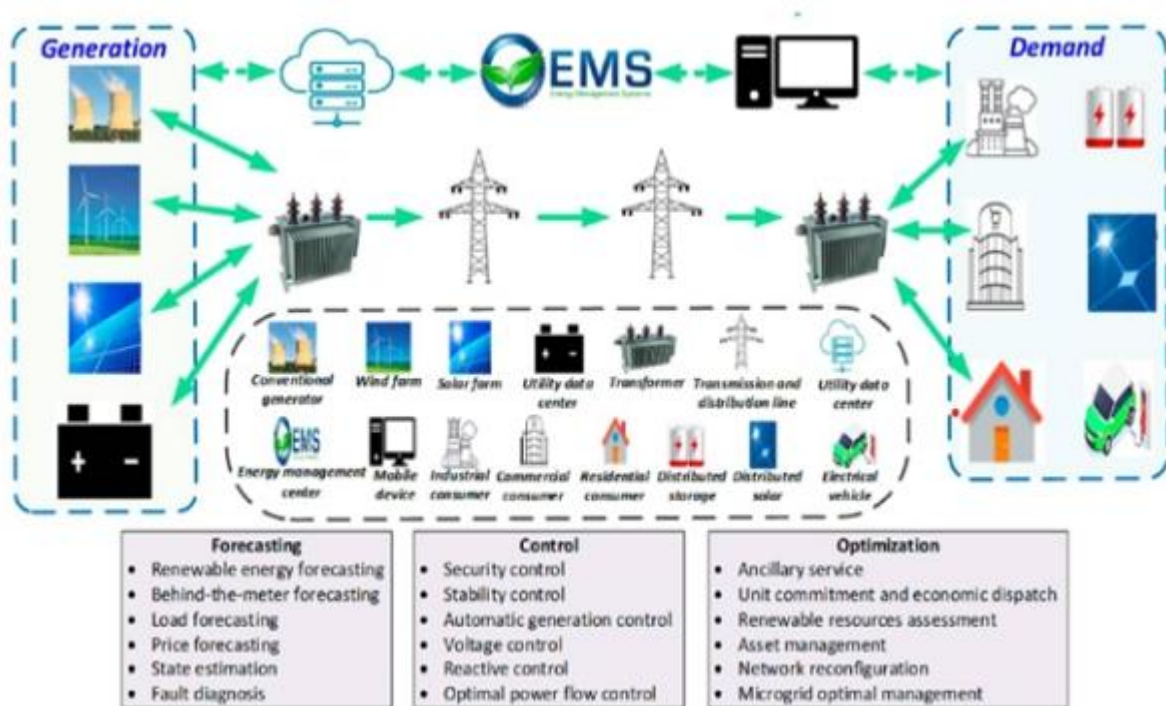


Figure 1. Overview of AI/ML integration in electrical power systems **Source:** Ghorbanian *et al.* (2021)

Figure 1 illustrates a seamless integration of AI and machine learning across the electrical power system, beginning with the generation of electricity from diverse sources such as conventional thermal plants, wind farms, solar arrays, and utility-scale energy storage. These generation assets feed into the transmission infrastructure, where high-voltage lines and transformers channel energy toward the distribution network. At the heart of this system lies the Energy Management System (EMS), which serves as the digital and operational bridge between supply and demand. Within this EMS layer,

AI/ML algorithms are embedded to perform a range of intelligent functions renewable energy forecasting, state estimation, fault diagnosis, and optimal power flow control ensuring that electricity is delivered efficiently and reliably (Heluany *et al.*, 2024). As electricity moves toward the demand side, encompassing residential homes, commercial buildings, industrial facilities, and utility data centers, AI/ML continues to play a pivotal role. It enables accurate load forecasting, facilitates demand response strategies, and supports asset management, all while maintaining system stability and optimizing resource allocation (Errandonea *et al.*,

2020). The figure also reflects how control mechanisms such as voltage regulation, reactive power control, and automatic generation control are enhanced through intelligent automation. These capabilities are not isolated but interwoven, forming a dynamic feedback loop that allows the grid to adapt in real time to fluctuations in generation, consumption, and market conditions. However, this review aims to provide a comprehensive synthesis of current and emerging applications of AI and ML in electrical power systems. It explores recent advancements across key domains, including generation, transmission, distribution, and protection, while also examining future trends that are likely to shape the next era of intelligent grid operations. In the generation sector, AI/ML techniques are used to forecast renewable energy output, optimize generator dispatch, and manage hybrid energy systems. In transmission, these technologies enhance grid stability, facilitate congestion management, and improve fault localization. Within distribution networks, AI supports load forecasting, voltage control, and outage management. Protection systems benefit from intelligent fault detection, relay coordination, and automated system restoration. Looking ahead, innovations such as edge computing, federated learning, and AI-driven market operations are poised to redefine how power systems are designed and managed.

Fundamentals of Artificial Intelligence and Machine Learning in Power Systems

Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing the operation and control of electrical power systems. As the global energy sector shifts toward decentralization, decarbonization, and digitalization, traditional power systems once reliant on deterministic models and manual interventions are increasingly inadequate for managing the complexity and variability of modern grids (Heno *et al.*, 2025). These conventional systems often struggle with real-time decision-making, fault tolerance, and integration of renewable energy sources. In contrast, AI and ML offer adaptive, data-driven approaches that enhance forecasting, optimization, and system resilience across generation, transmission, distribution, and protection layers.

AI, broadly defined as the simulation of human intelligence in machines, has evolved from early rule-based systems to sophisticated neural networks capable of autonomous learning and reasoning. In the context of engineering control systems, AI enables predictive diagnostics, intelligent automation, and real-time optimization. Its relevance in power systems is particularly evident in applications such as load forecasting, fault detection, and contingency analysis, where rapid and accurate decisions are essential for maintaining grid stability (Ghorbanian *et al.*, 2021). By enabling machines to mimic cognitive functions such as learning and problem-solving, AI transforms the grid from a reactive infrastructure into a proactive, self-healing network.

Within the AI domain, ML focuses on algorithms that learn from data to make predictions or decisions without being explicitly programmed. ML techniques are typically categorized into supervised, unsupervised, and reinforcement

learning. Supervised learning involves training models on labeled datasets and is widely used in power systems for tasks like energy price prediction, load classification, and equipment fault diagnosis. For example, support vector machines (SVMs) have been effectively applied to classify fault types using historical sensor data (Heluany *et al.*, 2024). Unsupervised learning, which identifies patterns in unlabeled data, is useful for anomaly detection and customer segmentation. Reinforcement learning (RL), where agents learn optimal strategies through trial and error, has shown promise in dynamic energy management and adaptive protection schemes, particularly in microgrids and smart distribution networks (Hossain and Kumar, 2023).

Deep learning, a subset of ML, employs multi-layered neural networks to model complex, nonlinear relationships in large datasets. Convolutional Neural Networks (CNNs) are particularly effective for image-based diagnostics, such as identifying faults in photovoltaic panels through thermal imaging. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are well-suited for time-series forecasting, enabling accurate predictions of load demand and renewable energy generation. Hybrid models, such as neuro-fuzzy systems and genetic algorithms, combine the strengths of multiple techniques to handle uncertainty and optimize multi-objective problems. These models are especially valuable in scenarios where data is noisy or incomplete, and decisions must balance competing priorities like cost, reliability, and sustainability (Ghorbanian *et al.*, 2021).

Table 1 provides a comparative overview of these algorithms, highlighting their typical use cases, advantages, and limitations. For instance, ANNs are commonly used for load forecasting and fault detection due to their ability to model nonlinear relationships, while SVMs are preferred for classification tasks with limited data. Decision Trees offer simplicity and speed but may overfit, whereas ensemble methods provide robustness at the cost of interpretability. Deep learning models like CNNs and LSTMs are powerful but data-intensive, and hybrid models offer flexibility in handling complex, uncertain environments. Ultimately, the importance of AI and ML in power systems lies in their ability to outperform conventional mathematical models. Traditional approaches often rely on fixed parameters and assumptions that may not hold in dynamic environments. In contrast, AI and ML models continuously adapt to changing conditions, refine their predictions, and optimize control strategies based on real-time feedback (Strielkowski *et al.*, 2023). This adaptability leads to improved reliability, efficiency, and resilience in grid operations. For example, ML-based fault detection systems can identify anomalies more quickly and accurately than rule-based systems, reducing outage durations and maintenance costs. AI-driven load forecasting enables better demand-side management, while reinforcement learning optimizes energy dispatch in microgrids with minimal human intervention (Errandonea *et al.*, 2020).

Table 1. Common AI/ML algorithms and their applications in power systems

<i>Algorithm</i>	<i>Type</i>	<i>Typical Use Case</i>	<i>Advantages</i>	<i>Limitations</i>
<i>ANN</i>	Supervised	Load forecasting, fault detection	Nonlinear modeling, flexible	Requires large data, risk of overfitting
<i>SVM</i>	Supervised	Fault classification	High accuracy with small data	Computationally intensive
<i>Decision Tree</i>	Supervised	Outage prediction, asset health	Easy to interpret, fast	Prone to overfitting, sensitive to noise
<i>Random Forest</i>	Ensemble	Reliability assessment	High accuracy, robust	Complex tuning, less interpretable
<i>CNN</i>	Deep Learning	Image-based diagnostics	Feature extraction, spatial analysis	Requires labeled image data
<i>LSTM</i>	Deep Learning	Time-series forecasting	Captures long-term dependencies	Training complexity
<i>Genetic Algorithm</i>	Optimization	Network planning, loss minimization	Multi-objective optimization	Slow convergence, parameter tuning
<i>Neuro-Fuzzy</i>	Hybrid	Uncertainty modeling	Handles imprecise data	Complex architecture

Source: Li et al. (2024)

AI and ML in Power Generation Systems

Artificial Intelligence (AI) and Machine Learning (ML) are reshaping the landscape of power generation, offering intelligent solutions to optimize performance, forecast demand, and maintain assets with greater precision than ever before. As power systems evolve to accommodate renewable energy sources and decentralized grids, the complexity of managing generation assets has increased. Traditional models, often based on static equations and manual oversight, struggle to adapt to fluctuating conditions. AI and ML, by contrast, provide dynamic, data-driven approaches that learn from historical and real-time data to improve operational efficiency and system reliability (Gao et al., 2024).

One of the most critical applications of AI and ML in power generation is load and demand forecasting. Accurate forecasting ensures that generation meets consumption without overproduction or shortages, which is vital for grid stability and economic efficiency. Neural networks, particularly multilayer perceptrons, have been widely used to model nonlinear relationships between variables such as temperature, humidity, time of day, and historical load data. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, have proven especially effective in capturing temporal dependencies in energy consumption

patterns, making them ideal for short- and medium-term forecasting (Inturi et al., 2024). Regression models, including

support vector regression and ensemble methods like gradient boosting, also contribute to forecasting accuracy, especially when combined with feature selection techniques that reduce noise and improve model interpretability.

The integration of renewable energy sources such as solar and wind has introduced new challenges due to their intermittent nature. AI and ML help mitigate these challenges by enhancing the accuracy of generation forecasts and enabling smarter dispatch strategies. Deep learning models trained on meteorological data and historical output can predict solar irradiance and wind speed with high precision, allowing operators to anticipate fluctuations and adjust generation accordingly. Hybrid approaches that combine physical models with ML algorithms offer even greater robustness, especially under uncertain weather conditions (Inturi et al., 2024). These predictive capabilities are essential for maximizing the use of clean energy while maintaining grid reliability. AI also plays a pivotal role in optimizing power plant operations. In thermal plants, AI algorithms are used to regulate combustion processes, adjust air-fuel ratios, and fine-tune turbine performance. Reinforcement learning models have demonstrated the ability to learn optimal control policies that reduce fuel consumption and emissions while maintaining output. Fuzzy logic systems and genetic algorithms have been applied to boiler control and heat rate optimization, resulting in measurable improvements in efficiency and environmental compliance. In gas turbine and combined-cycle plants, digital twins powered by AI simulate plant behavior under various operating conditions, enabling operators to test strategies and anticipate performance issues without disrupting actual operations (Jones et al., 2020).



Figure 2. Schematic of AI-based generation optimization system Source: Inturi *et al.* (2024)

Figure 2 illustrates a schematic of an AI-based generation optimization system, highlighting how data from sensors, weather forecasts, and historical records feed into a centralized AI engine (Gao *et al.*, 2024). This engine processes inputs using a combination of machine learning models such as long short-term memory (LSTM) networks for forecasting, reinforcement learning for control, and decision trees for diagnostics to generate actionable outputs. These outputs are used to adjust generator setpoints, schedule maintenance, and coordinate renewable integration in real time, forming a

closed-loop system that continuously learns and adapts (Ukoba *et al.*, 2024).

To highlight the breadth of research in this field, Table 2 demonstrates the application of AI and ML in power generation. These studies span various technologies and methodologies, from deep learning-based solar forecasting to hybrid optimization of thermal plant operations. Collectively, they underscore the growing maturity of AI/ML solutions and their potential to redefine how generation assets are managed in the era of smart grids and sustainable energy (Trull *et al.*, 2022).

Table 2. Selected Studies on AI/ML in power generation (2018–2025)

Study	Focus Area	AI/ML Techniques	Key Contribution
Forecasting renewable energy generation with ML and DL	Solar and wind forecasting	LSTM, CNN, hybrid models	Improved accuracy in short-term renewable output prediction
AI for smart grid operations and renewable energy management	Grid-integrated generation	Reinforcement learning, ANN	Real-time control and dispatch of distributed energy resources
ML applications in energy systems	Load forecasting and maintenance	SVR, LSTM, ensemble methods	Enhanced demand prediction and predictive maintenance

With intelligent solutions that improve fault identification, stability analysis, equipment monitoring, and real-time grid operation, artificial intelligence (AI) and machine learning (ML) are becoming more and more important in the modernization of power transmission networks. Traditional monitoring and control techniques are failing to keep up with the complexity of transmission networks brought about by the integration of dispersed generation, electric vehicles, and renewable energy sources. Reliability and resilience throughout high-voltage infrastructure are ensured by AI and ML, which offer the computational agility required to control \

these dynamic systems (Gao *et al.*, 2024). One of the most critical applications of AI in transmission systems is fault detection and localization. Transmission line faults caused by weather events, equipment failure, or external interference can lead to cascading outages if not identified and isolated promptly. ML algorithms such as Support Vector Machines (SVMs) have demonstrated high accuracy in classifying fault types based on voltage and current waveforms. Convolutional Neural Networks (CNNs), typically used in image recognition, have been adapted to analyze waveform patterns and detect anomalies in real time. Fuzzy logic systems, which handle uncertainty and imprecise data, are particularly effective in modeling fault conditions where crisp boundaries are difficult to define (Li *et al.*, 2024). These AI-driven approaches

outperform traditional threshold-based methods by learning from historical fault data and adapting to evolving grid conditions.

Beyond fault detection, AI and ML are instrumental in power flow and voltage stability analysis. Maintaining voltage stability is essential for preventing blackouts and ensuring efficient power delivery. Data-driven models trained on historical grid behavior can predict voltage collapse scenarios and suggest corrective actions before instability occurs

(Mchirgui *et al.*, 2024). Techniques such as deep learning and ensemble learning have been used to model nonlinear relationships between load, generation, and reactive power, providing more accurate stability assessments than conventional power flow equations. In particular, hybrid models that combine physical simulations with ML algorithms offer robust predictions under varying load and generation conditions (Li *et al.*, 2024). These models enable grid operators to anticipate stress points and deploy reactive power compensation or load shedding strategies proactively.

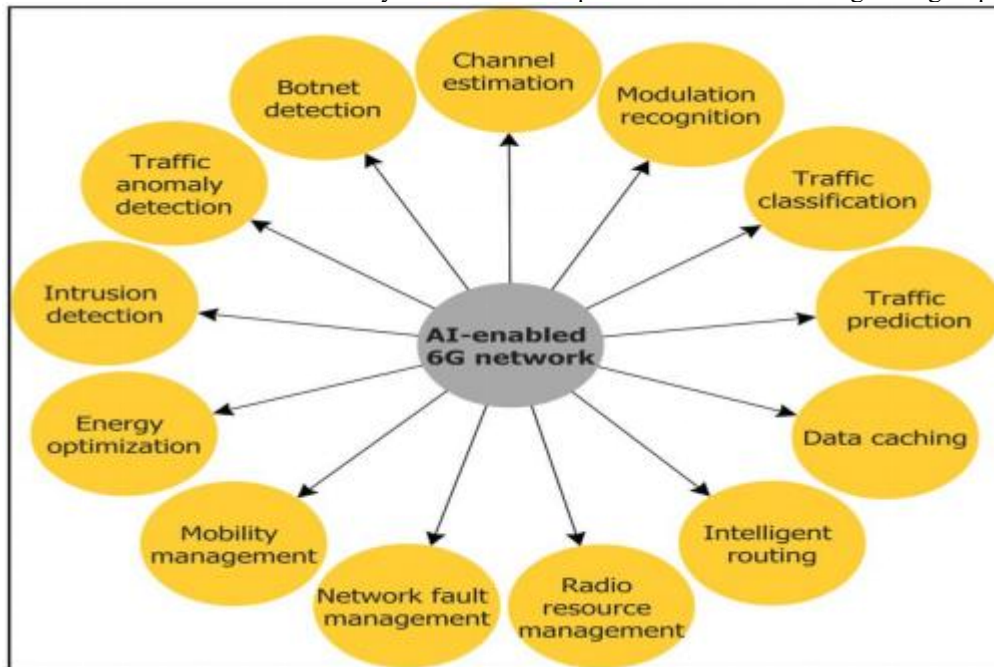


Figure 3. Architecture of AI-enabled transmission network .Source: Mchirgui *et al.* (2024)

Figure 3 presents the architecture of an AI-enabled transmission network. It illustrates how data from sensors, phasor measurement units (PMUs), and SCADA systems feed into a centralized AI engine. This engine processes the inputs using ML models for fault detection, stability analysis, and equipment diagnostics. Outputs from the AI engine are used to trigger control actions, update asset health dashboards, and coordinate grid operations across multiple zones. The architecture highlights the integration of real-time data acquisition, intelligent processing, and automated decision-making in a closed-loop system that continuously learns and adapts (Gao *et al.*, 2024)

As power transmission systems continue to evolve, the role of AI and ML will become even more critical. Their ability to process vast datasets, uncover hidden patterns, and make real-time decisions positions them as indispensable tools for grid modernization. While challenges remain such as data interoperability, cybersecurity, and model transparency the trajectory of research and deployment suggests a future where

intelligent transmission networks are the backbone of resilient and sustainable power systems (Mchirgui *et al.*, 2024).

AI and ML in Power Distribution and Smart Grid Systems

The architecture and operation of contemporary power distribution systems are being redefined by artificial intelligence (AI) and machine learning (ML), especially in the context of smart grids (Oelhaf *et al.*, 2025). Traditional distribution models based on static infrastructure and manual oversight are becoming less and less suitable as energy networks adapt to decentralized generation, dynamic demand, and real-time control. AI and ML are essential tools for next-generation grid operations because they provide intelligent, flexible solutions that improve data analytics, resource management, load balancing, and automated decision-making (Pandey *et al.*, 2023).

One of the most transformative applications of AI in smart grids is smart meter data analytics. Smart meters generate vast amounts of granular consumption data, which, when processed through ML algorithms, can reveal patterns in load profiles, predict consumer behavior, and detect anomalies (Wang *et al.*,

2024). Techniques such as clustering, decision trees, and neural networks have been used to segment consumers based on usage habits, enabling personalized energy services and targeted demand-side management. Anomaly detection models, including autoencoders and isolation forests, identify irregular consumption patterns that may indicate meter tampering, energy theft, or equipment malfunction (Kulkarni *et al.*, 2025). These insights not only improve operational efficiency but also empower consumers with real-time feedback and dynamic pricing options.

Smart grid automation is perhaps the most comprehensive application of AI, encompassing outage management, fault restoration, and network control. Decision-support systems powered by ML analyze sensor data, fault logs, and weather forecasts to predict outages and recommend restoration strategies (Strielkowsk *et al.*, 2023). Multi-agent systems coordinate across substations and control centers to isolate faults, reroute power, and restore service with minimal human

intervention. Digital twin virtual replicas of grid infrastructure simulate network behavior under various scenarios, allowing operators to test contingency plans and optimize control actions without affecting live operations (Gao *et al.*, 2024). These capabilities are essential for building resilient, self-healing grids that can adapt to changing conditions and recover from disruptions swiftly.

Figure 4 illustrates the data flow in an AI-driven smart grid network. It shows how data from smart meters, DERs, and historical records feed into a cloud-based AI engine. This engine performs functions such as demand forecasting, load profiling, fault detection, and optimization. The outputs are used to control microgrids, balance loads, and manage outages in real time. The schematic highlights the integration of edge devices, centralized intelligence, and automated control in a closed-loop system that continuously learns and evolves (Pandey *et al.*, 2023).

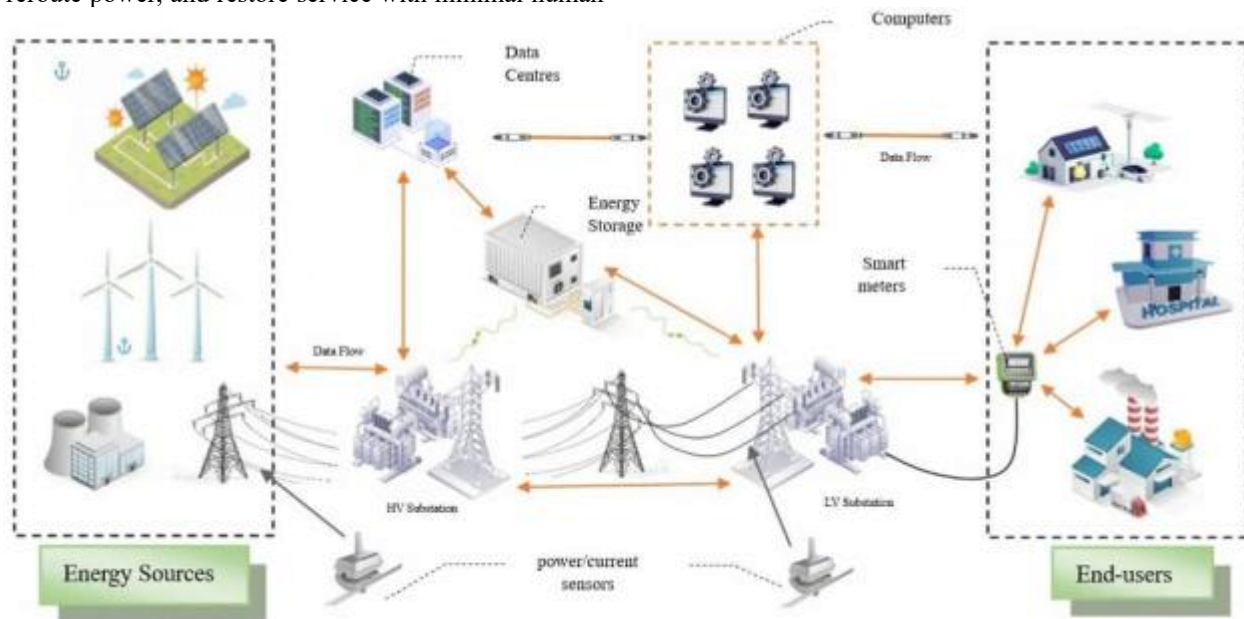


Figure 4. Data Flow in an AI-Driven Smart Grid Network **Source:** Li *et al.* (2024)

To provide a structured overview of AI techniques used in smart grid operation and control, Figure 3 offers a visual representation of how energy and data flow through a modern smart grid system, integrating renewable sources, substations, smart meters, data centers, and end-user facilities. The diagram emphasizes the role of AI in managing this complex ecosystem, where algorithms analyze real-time data from sensors and smart meters to optimize energy distribution,

detect faults, and coordinate energy storage. For example, decision trees are widely used for fault classification due to their interpretability and speed, while neural networks excel in load forecasting and anomaly detection. Reinforcement learning models are preferred for dynamic control tasks such as demand response and distributed energy resource (DER) coordination. Ensemble methods, including random forests and gradient boosting, offer robustness and accuracy in complex prediction tasks. Each technique has its strengths and limitations, and their selection depends on the specific operational context and data availability.

Table 3. Summary of AI techniques in smart grid operation and control

<i>AI Technique</i>	<i>Application Area</i>	<i>Strengths</i>	<i>Limitations</i>
<i>Decision Trees</i>	Fault classification	Fast, interpretable	Prone to overfitting
<i>Neural Networks</i>	Load forecasting, anomaly detection	Nonlinear modeling, high accuracy	Requires large datasets
<i>Reinforcement Learning</i>	Demand response, DER control	Adaptive, learns optimal policies	Complex training, slow convergence
<i>Ensemble Methods</i>	Prediction, diagnostics	Robust, high accuracy	Less interpretable, tuning required
<i>Autoencoders</i>	Anomaly detection	Unsupervised, efficient	Sensitive to noise
<i>Clustering Algorithms</i>	Consumer segmentation	Unsupervised, scalable	May require manual interpretation

Sources: [Oelhaf et al. \(2025\)](#)

AI and ML in Power System Protection and Cybersecurity

Modern power systems' resilience, security, and protection are being improved by the application of artificial intelligence (AI) and machine learning (ML). Grids face increasing risks from both physical malfunctions and cyberattacks as they become more digitalized and networked. Because of the dynamic and intricate nature of today's power networks, traditional safety solutions that rely on static thresholds and predefined logic are frequently insufficient. In order to improve the grid's resilience to disturbances and speed of recovery, artificial intelligence (AI) and machine learning (ML) provide intelligent, adaptable systems that can identify faults, anticipate threats, and coordinate responses in real time ([Oelhaf et al., 2025](#)). For power system protection, intelligent fault classification is one of the most significant uses of machine learning. Faults in transmission and distribution lines

whether caused by equipment failure, environmental conditions, or human error must be identified and isolated quickly to prevent cascading outages. ML models such as support vector machines (SVMs), decision trees, and convolutional neural networks (CNNs) have demonstrated high accuracy in classifying fault types based on voltage and current waveforms ([Rahmani-Sane et al., 2025](#)). These models learn from historical fault data and can distinguish between transient, permanent, and symmetrical faults with minimal latency. In addition, AI algorithms are being used to optimize relay coordination, ensuring that protective devices operate selectively and efficiently during fault conditions ([Shen et al., 2023](#)). This intelligent coordination reduces unnecessary tripping and enhances system reliability.

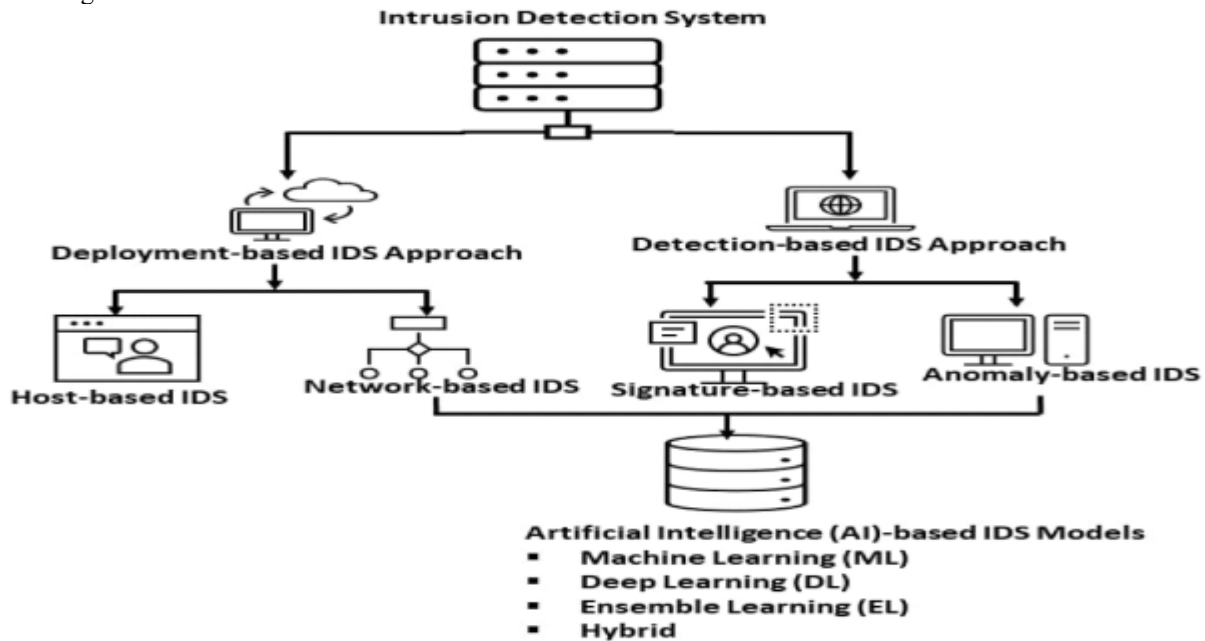


Figure 5. AI-based intrusion detection and protection model Source: [Kuyumani et al. \(2023\)](#)

Figure 5 illustrates an AI-based intrusion detection and protection model, offering a structured view of how intelligent systems enhance cybersecurity in real time [Kuyumani et al.](#)

(2023). The schematic shows how data from network traffic and system logs is continuously fed into a central AI engine, which applies deep learning techniques to perform anomaly detection, threat prediction, and classification. These

analytical outputs are then routed to network security modules and protection systems, which execute automated fault isolation, relay coordination, and alert generation. The model underscores the integration of real-time data processing, intelligent analysis, and automated response within a closed-loop cybersecurity framework, reflecting the growing role of AI in safeguarding digital infrastructure. AI is also central to the development of self-healing grids systems that can detect faults, isolate affected sections, and restore service autonomously (Shen *et al.*, 2023). These grids rely on a combination of sensor networks, intelligent control algorithms, and distributed decision-making. ML models analyze data from phasor measurement units (PMUs), smart meters, and fault indicators to pinpoint fault locations and assess system health. Once a fault is detected, AI algorithms determine the optimal isolation strategy and reroute power through alternate paths. This process minimizes downtime and reduces the need for manual intervention. Digital twins, which simulate grid behavior under various fault scenarios, are increasingly used to test and refine self-healing strategies before deployment (Rahmani-Sane *et al.*, 2025).

Challenges and Limitations of AI/ML in Power Systems

Artificial intelligence and machine learning promise significant advances for power systems, but their deployment faces a constellation of technical, ethical, and infrastructural barriers that must be understood and mitigated. A primary challenge is data quality and availability: many AI/ML methods depend on large, standardized, and labeled datasets, yet power utilities often store data in heterogeneous formats across SCADA, PMU, and smart meter systems, with gaps, noise, and inconsistent labeling that degrade model performance (Shen *et al.*, 2023). Securing representative datasets that capture rare events extreme weather, cascading failures, cyberattacks remains difficult, and sharing data across organizations is constrained by confidentiality and regulatory concerns, which together limit reproducibility and slow research-to-deployment cycles (El Rhatrif, 2024)

Closely linked to data issues are problems of model generalization and overfitting. Models trained on historical or region-specific data may perform well in-sample but fail when exposed to new operating regimes, different equipment, or unseen adversarial conditions. Overfitting is especially problematic for deep learning architectures that have large parameter counts but limited labeled examples of critical events; such models can learn spurious correlations that break down in deployment. Developing robust ML models therefore requires careful cross-validation strategies, data augmentation,

domain adaptation techniques, and hybrid approaches that embed physical laws or engineering constraints into learning algorithms to improve transferability across sites and scenarios (Kuyumani *et al.*, 2023). The computational cost and infrastructure required for real-time AI deployment present another set of barriers. Training state-of-the-art models demands substantial computational resources, while inference for time-critical tasks fault detection, protection relays, or real-time optimization must meet stringent latency and reliability requirements. Many utilities operate legacy control centers with limited edge-compute capabilities and constrained communication bandwidth, making it difficult to place complex models where they are most effective. Solutions such as model compression, pruning, quantization, and edge-cloud hybrid architectures help reduce latency and costs, but they introduce trade-offs in accuracy and maintenance complexity that must be managed carefully (El Rhatrif, 2024).

Interpretability and trust issues amplify the reluctance of operators to rely on black-box AI models for safety-critical decisions. Deep neural networks and ensemble methods often provide accurate predictions but offer limited insight into how those predictions are formed, complicating validation, certification, and operator acceptance. The need for transparent, explainable AI is acute in power systems where regulatory compliance and human-in-the-loop oversight are required. Techniques such as explainable models, surrogate explanations, sensitivity analysis, and the integration of physics-informed constraints can improve interpretability, but establishing standards for verification and validation in operational environments remains an open challenge (Rahmani-Sane *et al.*, 2025).

Regulatory and ethical concerns form an additional layer of complexity. The use of consumer consumption data, asset health information, and operational telemetry raises privacy considerations and data governance questions. Regulations differ between jurisdictions, creating uncertainty for multinational deployments and cross-utility collaborations. Furthermore, safety standards for AI-driven control actions especially those that can trip protection devices or change control setpoints are still evolving. Ensuring that AI systems comply with existing grid codes, cybersecurity standards, and ethical norms requires coordinated efforts among researchers, utilities, regulators, and standards bodies (El Rhatrif, 2024).

Table 4 summarizes these core challenges alongside representative mitigation approaches, providing a concise map from problem to practical response.

Table 4. Challenges of AI/ML in Power Systems and Possible Mitigation Approaches.

Challenge	Impact on Power Systems	Representative Mitigation Approach
Data quality and availability	Reduced model accuracy and robustness	Data standardization; anonymized shared repositories
Model generalization	Poor transferability across sites	Physics-informed ML; domain adaptation
Computational costs	Latency, high deployment cost	Model compression; edge-cloud hybrid architectures
Interpretability and trust	Operator reluctance, certification gaps	Explainable AI; surrogate models; human-in-the-loop
Regulatory and ethical issues	Privacy, safety, and compliance risks	Governance frameworks; privacy-preserving ML

Source: El Rhatri (2024)

Future Directions: Provide strategic insights into upcoming trends and research directions.

Emerging paradigms in artificial intelligence and machine learning are poised to reshape how power systems are designed, controlled, and secured, offering pathways to greater transparency, scalability, and resilience. Explainable AI (XAI) is becoming essential as operators demand interpretable models that can justify automated decisions in safety-critical contexts; XAI techniques such as attention mechanisms, rule extraction, and surrogate models bridge the gap between high-performing black-box predictors and the transparency required for certification, operator trust, and regulatory compliance, enabling clearer audit trails for actions such as relay coordination, load-shedding decisions, or automated dispatch (Chen *et al.*, 2023). Federated learning and Edge-AI address privacy, bandwidth, and latency constraints by moving training and inference closer to data sources: distributed learning frameworks allow local models at substations, microgrids, and smart meters to collaborate without exposing raw data, while lightweight inference at the edge supports

real-time control and reduces the need for centralized computation, an attractive approach for geographically dispersed utilities and latency-sensitive protection schemes (Dudek *et al.*, 2023).

Quantum machine learning (QML) offers long-term prospects for tackling combinatorial optimization and high-dimensional state estimation problems that challenge classical algorithms. Early QML formulations and quantum-enhanced optimization routines could accelerate solutions for unit commitment, optimal power flow, and robust grid planning under deep uncertainty, although practical QML deployment remains contingent on quantum hardware maturity and hybrid quantum-classical workflows (Boukhris *et al.*, 2023). Parallel to computational advances, integrating AI with blockchain can strengthen data provenance, secure telemetry, and enable decentralized energy markets. Blockchain’s immutable ledgers combined with AI-driven analytics can support transparent peer-to-peer energy trading, automated settlement, and provenance tracking for renewable attributes while providing tamper-evident records that enhance trust among prosumers, aggregators, and system operators (Alsaigh *et al.*, 2022).



Figure 6. AI and ML paradigms for future power systems Source: Afridi *et al.* (2021)

Figure 6 shows these trends by depicting Explainable AI, Federated Learning and Edge-AI, Quantum ML, and AI–Blockchain integration as interlinked paradigms feeding into future power systems. The figure highlights data flow between edge devices, distributed learning nodes, centralized analytics, and secure ledgers, illustrating how combined approaches can deliver low-latency control, privacy-preserving collaboration, and auditable decision-making. Practically, near-term research should prioritize hybrid architectures that combine physics-based models with ML, scalable federated training for cross-utility learning, and XAI toolchains tailored for control-room workflows. Mid-term efforts must address operational integration: mature digital twins, standard interfaces for model deployment, and field trials that validate safety and performance at scale. Long-term initiatives can explore quantum accelerators for optimization and tightly coupled AI–blockchain platforms for decentralized market mechanisms (Afridi *et al.*, 2021).

Realizing this vision requires overcoming research and deployment challenges in data governance, model verification, and workforce capability. Standards for dataset formats, labeling conventions, and anonymization protocols will enable wider sharing of benchmark datasets that accelerate reproducible research. Robust verification and validation pipelines, including synthetic stress testing and digital-twin-based certification, are necessary to demonstrate safety under edge-case scenarios (Wang *et al.*, 2023). Investments in workforce training and interdisciplinary curricula will equip engineers and operators with the skills to oversee AI-enabled infrastructures and to interpret model explanations during real-world contingencies (Zheng *et al.*, 2020).

Conclusion

Artificial intelligence and machine learning are transforming electrical power systems across generation, transmission, distribution, protection, and market layers by enabling data-driven forecasting, adaptive control, and proactive resilience. Across the grid, AI/ML has demonstrably improved forecasting accuracy for both load and renewable generation, enabled predictive maintenance that reduces unplanned outages, and supported intelligent protection schemes that shorten fault detection and isolation times. The integration of explainable and distributed learning paradigms promises to reconcile operational needs with privacy and regulatory requirements, while emerging approaches such as quantum machine learning and AI–blockchain hybrids point to new capabilities for optimization and secure decentralization.

Real-world benefits include enhanced operational efficiency through optimized dispatch and reduced fuel consumption, stronger resilience via early fault detection and self-healing routines, and greater sustainability through improved renewable integration and reduced curtailment. However, turning research into practice requires coordinated effort: engineers must partner with data scientists to embed domain knowledge into models; policymakers and standards bodies

must codify testing and certification pathways; and utilities must invest in data infrastructure, edge computing, and workforce development. By aligning technical innovation with governance and human expertise, AI and ML can deliver a more reliable, efficient, and sustainable power system for the future.

Authors' Contributions

The authors of this research have significantly contributed to the study's conception, data collection, and manuscript development. All authors were involved in writing the manuscript or critically reviewing it for its intellectual value. They have reviewed and approved the final version for submission and publication and accepted full responsibility for the content and integrity of the work.

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Conflicts of Interest

The authors state that there are no financial, personal, or professional conflicts of interest associated with this research.

Ethical Approvals

This research did not involve the use of human participants or animal subjects and therefore did not require ethical clearance

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