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Review Article

Artificial Intelligence Applications in Smart Grids and Modern Power Systems: A Comprehensive Review

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Abstract

The rapid digitalization of the power sector, coupled with increasing penetration of renewable energy sources and distributed energy resources, has fundamentally transformed the structure and operation of modern power systems. Traditional model-based and rule-driven approaches are increasingly challenged by the growing complexity, uncertainty, and scalability requirements of smart grids. In this context, artificial intelligence (AI) has emerged as a key enabling technology for enhancing forecasting accuracy, operational efficiency, system resilience, and cybersecurity. This paper presents a comprehensive review of AI applications in smart grids and modern power systems, covering methodological advances and practical implementations across multiple domains. A structured taxonomy of AI techniques-including machine learning, deep learning, reinforcement learning, and hybrid and explainable AI-is provided, along with a critical discussion of their suitability for power system applications. Key application areas such as load and renewable energy forecasting, power system operation and control, fault detection and predictive maintenance, demand response, distributed energy resource management, and grid resilience and security are systematically reviewed. Furthermore, the paper examines performance evaluation practices, benchmarking challenges, and deployment barriers related to data availability, scalability, interpretability, and regulatory constraints. Emerging research directions, including AI-driven digital twins, federated learning, foundation models, and AI-enabled net-zero grid operation, are also discussed. By synthesizing recent advances and identifying open research challenges, this review aims to provide valuable insights for researchers and practitioners seeking to develop reliable, scalable, and trustworthy AI solutions for next-generation power systems.

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1. Introduction

The global power sector is undergoing a profound transformation driven by the rapid digitalization of energy infrastructures, the large-scale integration of renewable energy sources, and the increasing electrification of end-use sectors. Traditional power systems, which were historically designed around centralized generation and unidirectional power flows, are no longer sufficient to meet modern requirements related to efficiency, flexibility, sustainability, and resilience. Advances in sensing, communication, and computing technologies such as phasor measurement units, smart meters, and high-speed communication networks have enabled the emergence of data-rich, cyber-physical power systems, commonly referred to as smart grids [1–3].

The evolution from conventional grids to smart grids represents a paradigm shift in how electricity is generated, transmitted, distributed, and consumed. Smart grids incorporate distributed energy resources, active consumers (prosumers), electric vehicles, and microgrids, while supporting bidirectional power and information flows. Although these features enhance system flexibility and reliability, they also introduce significant operational challenges, including high-dimensional decision spaces, strong nonlinearities, stochastic behavior due to renewable generation, and complex interactions between physical and cyber layers. Managing such complexity using conventional model-based and rule-based approaches has become increasingly difficult, particularly under real-time and large-scale operating conditions [4, 5].

Artificial Intelligence (AI) has emerged as a powerful enabler for addressing these challenges. By leveraging data-driven learning, adaptive decision-making, and pattern recognition capabilities, AI techniques offer new tools to model uncertainty, capture nonlinear dynamics, and support scalable and autonomous control in modern power systems. Machine learning, deep learning, and reinforcement learning methods have demonstrated promising results in a wide range of applications, including load and renewable generation forecasting, optimal power system operation, fault diagnosis, demand response, and cybersecurity. Moreover, recent developments in explainable and physics-informed AI have opened new pathways for enhancing model transparency, reliability, and trustworthiness critical requirements for safety-critical power system applications [6, 7].

Despite the growing body of literature, existing studies are often fragmented, focusing on specific applications, AI techniques, or grid layers, with limited cross-comparison and synthesis. Furthermore, there remains a lack of consensus on benchmarking practices, deployment challenges, and the integration of AI with physical power system models and regulatory frameworks. These gaps motivate the need for a comprehensive and critical review that systematically organizes existing research and provides clear insights into current trends and future opportunities.

The main contributions of this review are threefold. First, it presents a comprehensive taxonomy of AI techniques and their applications across different domains of smart grids and modern power systems. Second, it provides a critical comparative analysis between AI-based approaches and traditional methods, highlighting performance gains, limitations, and practical considerations [8]. Third, it identifies key research gaps and outlines future directions, with particular emphasis on scalability, interpretability, real-world deployment, and the role of AI in enabling resilient and low-carbon power systems.

The remainder of this paper is organized as follows. Section 2 provides an overview of smart grid architectures and the key challenges of modern power systems. Section 3 reviews the main AI techniques relevant to power system applications. Section 4 discusses AI-driven applications in smart grids, followed by Sections 5 and 6, which focus on distributed energy resources, microgrids, and grid resilience and security, respectively. Section 7 addresses performance evaluation and benchmarking issues. Section 8 outlines open challenges, and Section 9 discusses future research directions. Finally, Section 10 concludes the paper with key insights and perspectives.

This review is based on peer-reviewed journal articles published primarily between 2015 and 2025, selected from major scientific databases including IEEE Xplore, Scopus, and Web of Science. Studies were included if they applied artificial intelligence techniques to smart grid or power system applications with clear relevance to forecasting, operation, control, resilience, or security.

2. Smart Grids and Modern Power Systems: An Overview

To provide a systems-level view of how artificial intelligence supports monitoring, analysis, and control across modern power systems, Figure 1 presents an integrated AI-enabled smart grid framework that captures the interaction between physical infrastructure, cyber layers, and decision-making processes.

Figure 1 presents an integrated cyber–physical framework for AI-enabled smart grid operation, showing how data from physical power system assets and sensing infrastructures are processed by AI-based analytics to support forecasting, optimization, control, resilience, and security through closed-loop decision-making.

2.1. Architecture of Smart Grids

Smart grids represent an integrated and intelligent evolution of conventional power systems, characterized by the seamless interaction between physical power infrastructures and advanced information and communication technologies. From a structural perspective, smart grid architecture can be broadly decomposed into four interconnected layers: generation, transmission, distribution, and consumption [9].

The generation layer increasingly comprises a heterogeneous mix of conventional power plants and renewable energy sources such as wind and solar. Unlike traditional centralized generation, modern systems emphasize decentralization, flexibility, and low-carbon operation. The transmission layer is responsible for bulk power transfer over long distances and relies on advanced monitoring technologies, such as wide-area measurement systems, to maintain system stability and situational awareness. The distribution layer has evolved from a passive network into an active and dynamic subsystem, integrating distributed energy resources, electric vehicles, and local storage while supporting bidirectional power flows. Finally, the consumption layer includes residential, commercial, and industrial users who actively participate in grid operation through demand response programs and prosumer-based energy management [10, 11].

A defining feature of smart grids is their cyber-physical nature, where physical power components are tightly coupled with cyber layers responsible for data acquisition, communication, computation, and control. Sensors, intelligent electronic devices, and embedded controllers continuously collect high-resolution data, which are processed and acted upon in near real time. This coupling enables enhanced observability, automation, and adaptive control, but it also increases system complexity and vulnerability to cyber disturbances.

Communication, sensing, and control infrastructures play a central role in enabling smart grid functionality. Advanced metering

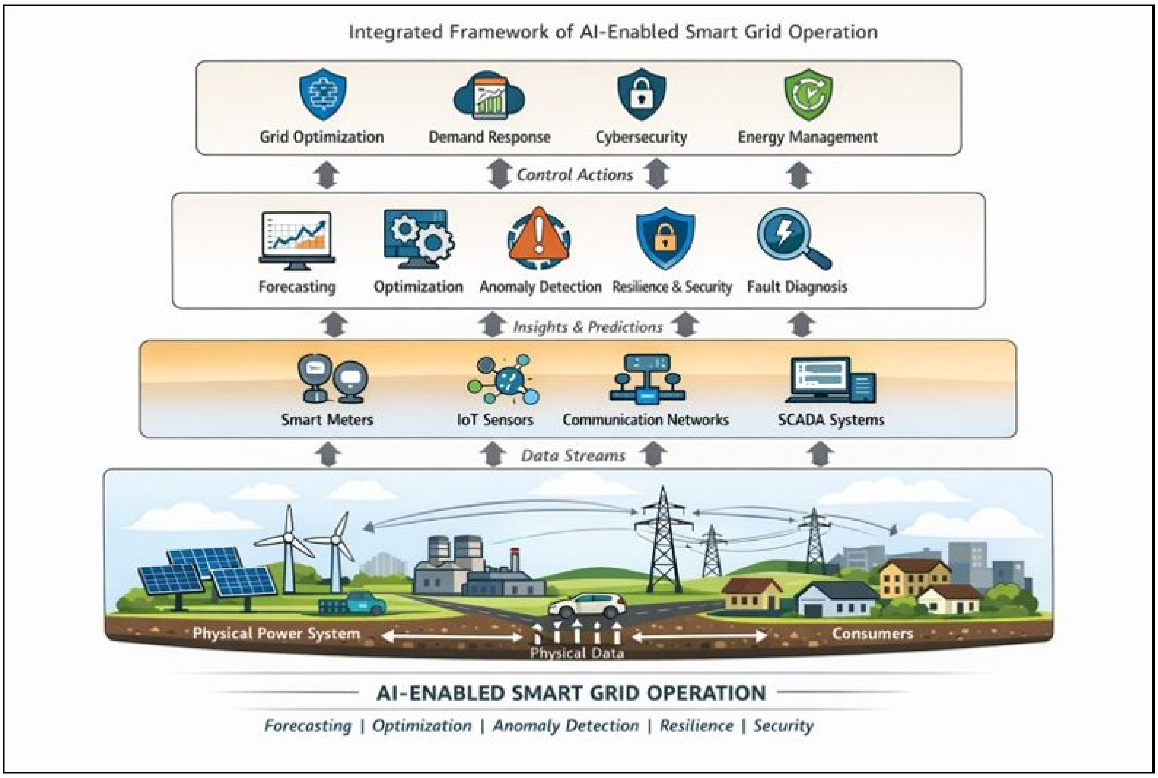

Figure 1: Integrated Framework of AI-Enabled Smart Grid Operation

infrastructure, phasor measurement units, and Internet of Things–based sensors provide granular visibility into system states. High-speed and reliable communication networks facilitate data exchange across grid layers, while distributed and hierarchical control architectures enable coordinated decision-making. Together, these infrastructures form the technological backbone that allows smart grids to operate efficiently, securely, and autonomously under dynamic operating conditions [12].

2.2. Key Challenges in Modern Power Systems

Despite their advantages, smart grids and modern power systems face several fundamental challenges that complicate planning, operation, and control. One of the most critical issues is the high penetration of renewable energy sources, which introduces significant uncertainty and variability due to their weather-dependent nature. Unlike conventional generators, renewable sources exhibit limited controllability, leading to fluctuations in power balance and increased requirements for flexibility and reserve management [10, 13].

The widespread integration of distributed energy resources and microgrids further increases system complexity. While DERs enhance local reliability and reduce transmission losses, their large-scale coordination poses challenges related to protection, voltage regulation, and optimal resource scheduling. Microgrids, which can operate in both grid-connected and islanded modes, require sophisticated control strategies to ensure stable and seamless transitions under varying conditions.

Another major challenge is demand uncertainty and load variability, driven by changing consumer behavior, electrification of transportation and heating, and the growing adoption of smart appliances. Traditional load models and forecasting techniques often struggle to capture these nonlinear and time-varying patterns, particularly at fine spatial and temporal resolutions [14].

Finally, grid reliability, resilience, and security have become paramount concerns. Modern power systems must withstand extreme weather events, equipment failures, and cascading disturbances while maintaining acceptable levels of service. At the same time, increased digitalization exposes the grid to cyber threats, such as data manipulation and coordinated attacks on control systems. Ensuring reliable and resilient operation in the presence of both physical and cyber risks requires advanced monitoring, predictive, and adaptive capabilities that go beyond conventional engineering approaches [15].

These architectural characteristics and challenges collectively underscore the need for intelligent, data-driven methods such as artificial intelligence to support the operation and evolution of next-generation power systems.

3. Artificial Intelligence Techniques for Power Systems

Building on the system challenges outlined in Section 2, this section reviews the core artificial intelligence techniques that form the methodological foundation for smart grid and power system applications.

Artificial intelligence techniques provide a diverse set of tools for modeling, prediction, optimization, and control in modern power systems. Unlike traditional analytical and optimization-based methods, AI approaches can learn complex relationships directly from data, adapt to changing system conditions, and scale to high-dimensional problems. This section reviews the major classes of AI techniques that have been widely adopted in smart grid and power system applications, highlighting their fundamental principles and suitability for different problem settings.

3.1. Machine Learning (ML)

Machine learning constitutes the foundation of most data-driven approaches in power systems. ML techniques aim to extract patterns and knowledge from historical and real-time data to support prediction and decision-making tasks.

- **Supervised learning methods** learn a mapping between input features and labeled outputs and are extensively used in applications such as load forecasting, renewable generation prediction, and fault classification. Common algorithms include linear and nonlinear regression models, support vector machines, decision trees, random forests, and ensemble learning techniques. These methods are particularly effective when sufficient labeled data are available and the system behavior remains relatively stationary [16].
- **Unsupervised learning** focuses on discovering hidden structures or patterns in unlabeled data. In power systems, unsupervised techniques such as clustering, dimensionality reduction, and anomaly detection are often applied to load profiling, customer segmentation, power quality assessment, and early fault detection. These approaches are valuable in scenarios where labeled data are scarce or expensive to obtain [4].
- **Semi-supervised learning** bridges the gap between supervised and unsupervised learning by leveraging a small amount of labeled data together with a large volume of unlabeled data. This paradigm is especially relevant for power systems, where labeling events such as faults or cyberattacks can be costly and time-consuming. Semi-supervised approaches improve generalization performance while reducing the reliance on extensive labeled datasets [17].

3.2. Deep Learning (DL)

Deep learning extends conventional machine learning by employing multi-layer neural network architectures capable of learning hierarchical and highly nonlinear representations. DL methods have gained significant attention in power systems due to their strong performance in large-scale and high-dimensional problems [18].

- **Convolutional Neural Networks (CNNs)** are primarily used for spatial feature extraction and pattern recognition. In power systems, CNNs have been applied to tasks such as fault localization, power quality disturbance classification, and image-based analysis of infrastructure assets. Their ability to automatically extract relevant features reduces the need for manual feature engineering [19].
- **Recurrent Neural Networks (RNNs)** and their advanced variants, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, are well suited for sequential and time-series data. These models are widely used for short-term and long-term load forecasting, renewable energy prediction, and dynamic state estimation, as they can effectively capture temporal dependencies and long-range correlations [20].
- **Graph Neural Networks (GNNs)** have recently emerged as a powerful tool for modeling the topological structure of power systems. By representing power networks as graphs, GNNs can naturally encode electrical connectivity and spatial dependencies, making them particularly suitable for applications such as state estimation, topology identification, and optimal power flow approximation [21].

3.3. Reinforcement Learning (RL)

Reinforcement learning addresses sequential decision-making problems by enabling agents to learn optimal control policies through interaction with an environment. RL is especially attractive for power system operation and control, where explicit system models may be incomplete or highly nonlinear [22].

- **Model-free reinforcement learning** methods learn policies directly from data without requiring an explicit system model. These approaches have been applied to voltage and frequency control, energy management, and demand response, but often require large amounts of training data and careful reward design.
- **Model-based reinforcement learning** incorporates an explicit or learned model of the environment, which can significantly improve sample efficiency and stability. In power systems, model-based RL is gaining interest for safety-critical applications where operational constraints and system dynamics must be explicitly considered.
- **Multi-agent reinforcement learning (MARL)** extends RL to systems with multiple interacting agents, such as distributed energy resources, microgrids, and peer-to-peer energy markets. MARL enables decentralized and coordinated decision-making but introduces challenges related to scalability, convergence, and communication among agents.

3.4. Hybrid and Explainable AI Models

To address the limitations of purely data-driven approaches, recent research has focused on hybrid and interpretable AI models that combine learning capability with physical insight and transparency [23, 24].

- **Physics-informed AI** integrates power system physics, constraints, and domain knowledge into learning models. By embedding physical laws or engineering constraints into the training process, these approaches improve generalization, reduce data requirements, and enhance reliability, making them particularly suitable for safety-critical grid applications.
- **Explainable AI (XAI)** aims to improve the transparency and interpretability of AI models by providing insights into their decision-making processes. In power systems, explain ability is essential for building operator trust, ensuring regulatory compliance, and supporting human-in-the-loop decision-making. XAI techniques enable stakeholders to understand why a model produces certain predictions or control actions, thereby facilitating practical deployment in real-world grid environments [24].

Together, these AI techniques form a comprehensive methodological foundation for addressing the diverse and complex challenges of smart grids and modern power systems.

To provide a structured synthesis of existing methodologies, Table 1 presents a comparative taxonomy of the principal artificial intelligence techniques applied in smart grids and modern power systems, highlighting their typical data requirements, representative applications, key advantages, and inherent limitations.

Table 1: Taxonomy and Comparative Analysis of AI Techniques for Smart Grids and Modern Power Systems

AI Technique	Typical Data Type	Representative Applications	Key Advantages	Key Limitations
Machine Learning (ML)	Time-series, tabular data	Load forecasting, fault classification, demand response	Low computational complexity; mature algorithms; partial interpretability	Limited capability in modeling highly nonlinear dynamics; feature engineering required
Deep Learning (DL)	Time-series, images, spatial data	Renewable energy forecasting, power quality analysis, predictive maintenance	High predictive accuracy; automatic feature extraction	Data-intensive; high computational cost; limited interpretability
Reinforcement Learning (RL)	Sequential decision data	Voltage and frequency control, energy management systems, optimal power flow	Model-free control; adaptive and autonomous decision-making	Training instability; safety and convergence concerns
Multi-Agent Reinforcement Learning (MARL)	Distributed agent data	Microgrid coordination, DER management, peer-to-peer energy trading	Scalable and decentralized control; enhanced flexibility	Communication overhead; non-stationarity; convergence challenges
Physics-Informed AI	Hybrid physical and data-driven models	State estimation, control, resilience enhancement	Improved generalization; physical consistency;	Increased modeling complexity; integration effort
Explainable AI (XAI)	Model outputs and feature relevance	Fault diagnosis, cybersecurity, operator decision support	Improved transparency; enhanced trust and regulatory compliance	Possible trade-off between interpretability and performance

Table 1. Comparative taxonomy of artificial intelligence techniques applied in smart grids and modern power systems, summarizing their typical data characteristics, representative application domains, primary strengths, and key limitations. The table highlights methodological trade-offs relevant to forecasting, control, resilience, and security applications.

4. AI Applications in Smart Grids

Having introduced the principal AI techniques in the previous section, this section examines how these methods are applied across key functional domains of smart grids.

Artificial intelligence has been widely adopted across multiple functional layers of smart grids, where it enables data-driven forecasting, adaptive control, enhanced reliability, and active consumer participation. This section reviews the major application domains of AI in smart grids, emphasizing methodological advances, performance benefits, and practical implications.

4.1. Load Forecasting

Load forecasting is one of the earliest and most extensively studied applications of AI in power systems, as accurate demand prediction is fundamental to planning, operation, and market activities. Depending on the time horizon, load forecasting is typically categorized into short-term, medium-term, and long-term forecasting.

- **Short-term load forecasting** focuses on time horizons ranging from minutes to days and is critical for real-time operation, unit commitment, and economic dispatch. AI-based methods, particularly deep learning models such as recurrent neural networks and hybrid architectures, have demonstrated superior accuracy in capturing nonlinear load patterns and temporal dependencies compared to traditional statistical approaches.
- **Medium-term load forecasting** covering weeks to months, supports maintenance scheduling and fuel planning, while long-term load forecasting, extending over years, is essential for capacity expansion and infrastructure investment decisions. In these settings, AI models can integrate diverse exogenous variables, such as weather conditions, socioeconomic indicators, and electrification trends, improving robustness under evolving demand patterns [25].

Comparative studies consistently show that AI-based forecasting techniques outperform conventional statistical methods, such as auto regressive models, especially in environments characterized by high variability and complex consumer behavior. However, challenges related to interpretability, data quality, and model generalization remain active research issues.

4.2. Renewable Energy Forecasting

The increasing penetration of renewable energy sources has intensified the need for accurate generation forecasting. AI techniques have become central to solar and wind power prediction, where output variability is strongly influenced by meteorological conditions.

Machine learning and deep learning models are widely used to capture nonlinear relationships between weather variables and renewable generation output. Advanced architectures, including convolutional and recurrent neural networks, enable the extraction of spatial and temporal features from numerical weather prediction data, satellite imagery, and historical generation records. These models significantly enhance forecasting accuracy across multiple time scales, from minutes ahead to day-ahead horizons [26].

Spatio-temporal modeling has emerged as a key research direction, particularly for geographically distributed wind farms and photovoltaic plants. By jointly modeling spatial correlations and temporal dynamics, AI-based spatio-temporal approaches improve situational awareness and support more reliable grid operation under high renewable penetration.

4.3. Power System Operation and Control

AI is increasingly being applied to operational and control tasks in smart grids, where fast decision-making and adaptability are essential. In voltage and frequency control, AI-based controllers can learn optimal control policies that respond dynamically to system disturbances and fluctuating operating conditions. Reinforcement learning, in particular, has shown promise in managing complex control problems without requiring explicit system models.

For optimal power flow (OPF), AI techniques are being explored as alternatives or complements to traditional optimization solvers. Data-driven OPF approximations enable near real-time solutions by learning mappings between system states and optimal operating points, significantly reducing computational burden. These approaches are especially valuable in large-scale and highly dynamic systems.

AI also supports real-time decision-making in power system operation by enabling adaptive responses to uncertainties, contingencies, and changing system topologies. While these methods offer substantial speed and flexibility advantages, ensuring stability, feasibility, and compliance with operational constraints remains a critical challenge [27].

4.4. Fault Detection, Diagnosis, and Protection

Enhancing grid reliability is a core objective of smart grids, and AI has become a key enabler for advanced fault management. AI-based anomaly detection techniques can identify abnormal system behavior by learning normal operating patterns from historical data, enabling early detection of faults and disturbances.

In predictive maintenance, AI models analyze sensor data and equipment condition indicators to anticipate failures before they occur. This proactive approach reduces unplanned outages, extends asset lifetimes, and lowers maintenance costs. Deep learning and unsupervised learning methods are particularly effective in extracting subtle degradation patterns from large volumes of monitoring data [28].

Cyber-physical fault identification addresses the growing interdependence between cyber and physical layers in smart grids. AI-based methods can distinguish between physical faults and cyber-induced anomalies, such as data manipulation or communication failures, thereby supporting robust protection and security mechanisms in digitally enabled power systems.

4.5. Demand Response and Energy Management

Demand response and energy management represent key mechanisms for enhancing flexibility and efficiency in smart grids. AI-driven approaches enable intelligent coordination of energy consumption across residential, commercial, and industrial demand response programs.

By learning consumption patterns and user preferences, AI models can optimize load shifting, peak shaving, and energy cost minimization while maintaining user comfort. In industrial settings, AI-based energy management systems support complex scheduling decisions that balance production requirements with energy constraints.

AI-driven consumer behavior modeling plays a crucial role in these applications, as it enables more accurate representation of human-in-the-loop dynamics. By capturing behavioral uncertainty and heterogeneity, AI enhances the effectiveness of demand response strategies and supports the transition toward more participatory and flexible power systems.

Overall, AI applications in smart grids demonstrate substantial potential to improve forecasting accuracy, operational efficiency, reliability, and consumer engagement, while also highlighting the need for careful integration with physical models, regulatory frameworks, and human decision-making processes [29].

5. AI in Distributed Energy Resources and Microgrids

The rapid proliferation of distributed energy resources (DERs), including renewable generation, energy storage systems, and controllable loads, has fundamentally reshaped the structure and operation of modern power systems. Microgrids, which integrate multiple DERs within a localized electrical network, offer enhanced reliability, resilience, and operational flexibility. However, their decentralized and dynamic nature introduces significant challenges in coordination, control, and optimization. Artificial intelligence has emerged as a key enabling technology for addressing these challenges by supporting autonomous, adaptive, and scalable decision-making [30].

5.1. Energy Management Systems (EMS)

AI-driven energy management systems play a central role in the optimal operation of DERs and microgrids. Traditional EMS solutions rely heavily on deterministic optimization models that require accurate system parameters and forecasts. In contrast, AI-based EMS leverage historical and real-time data to learn complex relationships among generation, storage, load demand, and market signals. Machine learning and reinforcement learning techniques enable adaptive scheduling of DERs, optimal charging and discharging of energy storage systems, and real-time balancing of supply and demand under uncertainty. These data-driven EMS improve operational efficiency, reduce energy costs, and enhance the ability of microgrids to respond to fluctuating renewable generation and load profiles [31].

5.2. Islanding Detection and Control

Islanding detection and control are critical for ensuring the safe and reliable operation of microgrids. Conventional islanding detection methods often face challenges related to detection speed, accuracy, and robustness under varying operating conditions. AI-based approaches address these limitations by learning discriminative patterns associated with islanding events from measurement data. Supervised and deep learning models can rapidly detect islanding conditions with high accuracy, while minimizing false positives. Beyond detection, AI techniques also support intelligent islanding control by enabling smooth transitions between grid-connected and islanded modes, maintaining voltage and frequency stability, and coordinating DERs during isolated operation [32].

5.3. Peer-to-Peer Energy Trading

Peer-to-peer (P2P) energy trading has gained increasing attention as a mechanism for enabling prosumers within microgrids and local energy communities to directly exchange energy. AI plays a pivotal role in facilitating P2P trading by supporting price prediction, participant matching, and transaction optimization. Learning-based models can adapt to dynamic market conditions, user preferences, and network constraints, enabling efficient and fair energy exchanges. When combined with decentralized optimization and distributed ledger technologies, AI-driven P2P trading frameworks enhance market transparency, improve local energy utilization, and incentivize active participation in distributed energy markets [33].

5.4. Multi-Agent Coordination Strategies

The decentralized nature of DERs and microgrids naturally lends itself to multi-agent system formulations, where individual resources or controllers act as autonomous agents. Multi-agent reinforcement learning and cooperative learning frameworks enable these agents to coordinate their actions while pursuing local and global objectives. Such strategies support scalable and resilient control architectures, allowing microgrids to operate efficiently without centralized supervision. AI-based multi-agent coordination facilitates tasks such as distributed voltage control, resource sharing among neighboring microgrids, and collective response to disturbances. Despite their promise, these approaches face challenges related to convergence, communication overhead, and stability guarantees, which remain active areas of research [34].

Overall, AI-driven solutions for DERs and microgrids provide the intelligence required to manage decentralized, uncertain, and interactive energy systems. By enabling adaptive energy management, robust islanding operation, innovative market mechanisms, and coordinated multi-agent control, AI contributes significantly to the realization of flexible, resilient, and consumer-centric power systems.

6. AI for Grid Resilience, Reliability, and Security

As power systems become increasingly complex and digitally interconnected, ensuring resilience, reliability, and security has emerged as a critical priority. Extreme weather events, aging infrastructure, and growing cyber threats pose significant risks to grid operation. Artificial intelligence offers powerful tools for enhancing situational awareness, enabling proactive risk mitigation, and supporting rapid recovery from disturbances. This section reviews key AI-driven approaches for improving grid resilience and security in modern power systems.

6.1. Resilience Enhancement

Grid resilience refers to the ability of a power system to anticipate, withstand, adapt to, and rapidly recover from disruptive events. AI-based methods have demonstrated strong potential in enhancing resilience across different stages of disturbance management.

- Extreme weather event prediction is a vital application of AI, as weather-related incidents are among the leading causes of large-scale power outages. Machine learning and deep learning models can analyze historical weather data, climate patterns, and grid performance records to predict the likelihood, location, and severity of weather-induced disruptions. By providing early warnings and probabilistic risk assessments, AI-driven prediction tools support preventive actions such as resource pre-positioning, adaptive network reconfiguration, and proactive maintenance [35].
- Self-healing grids represent an advanced resilience paradigm in which the power system autonomously detects, isolates, and mitigates faults with minimal human intervention. AI plays a central role in enabling self-healing capabilities by supporting fast fault localization, intelligent switching, and adaptive restoration strategies. Reinforcement learning and multi-agent approaches allow grid components to learn optimal recovery actions through experience, improving restoration speed and minimizing service interruption. These intelligent mechanisms significantly enhance reliability, particularly in distribution networks with high levels of automation and distributed resources [36].

6.2. Cybersecurity Applications

The increased reliance on communication and control technologies exposes smart grids to a wide range of cyber threats, making cybersecurity a fundamental component of reliable power system operation. AI-based techniques have become essential for detecting, analyzing, and mitigating cyber attacks in real time.

- **Intrusion detection systems** based on machine learning can identify abnormal network behavior by learning normal traffic patterns and system states. Supervised, unsupervised, and hybrid learning models are employed to detect known and unknown attack signatures, offering improved detection accuracy and adaptability compared to rule-based security mechanisms. These AI-driven systems enhance situational awareness and enable timely responses to cyber intrusions [27, 37].
- **False data injection attack mitigation** addresses one of the most critical cyber threats to power system operation, where malicious actors manipulate measurement data to mislead control and estimation processes. AI techniques can detect inconsistencies between

physical system behavior and reported data by learning underlying system correlations and constraints. By identifying and isolating compromised measurements, AI-based mitigation strategies help preserve the integrity of state estimation, protection, and control functions [38].

Collectively, AI-driven resilience and cybersecurity solutions strengthen the ability of modern power systems to operate securely and reliably under both physical and cyber disruptions. While these approaches offer substantial benefits, their deployment in real-world grids requires careful consideration of robustness, interpretability, and integration with existing operational and regulatory frameworks.

7. Performance Evaluation and Benchmarking

Most AI-based power system studies rely primarily on simulation platforms and benchmark test systems for validation, while a smaller subset has been evaluated using real-world utility or field data. Although simulation-based studies are essential for controlled experimentation, limited access to operational data constrains empirical validation, underscoring the need for increased collaboration with utilities to support real-world deployment and testing.

Robust performance evaluation and systematic benchmarking are essential for assessing the effectiveness, reliability, and practical viability of AI-based methods in smart grids and modern power systems. Given the safety-critical nature of power system operation, AI models must be evaluated not only in terms of predictive accuracy or control performance, but also with respect to robustness, scalability, and compliance with physical and operational constraints. This section discusses commonly used datasets and simulation platforms, evaluation metrics, and the key challenges related to reproducibility and comparability [6].

7.1. Datasets and Simulation Platforms

The availability of high-quality data is a fundamental prerequisite for developing and validating AI-based power system applications. Commonly used datasets include historical load demand records, renewable generation data, weather information, and system measurements from supervisory control and data acquisition and phasor measurement unit infrastructures. While such datasets enable realistic modeling and validation, access to real-world operational data is often restricted due to privacy, security, and commercial concerns.

As a result, simulation platforms play a crucial role in AI research for power systems. Transmission and distribution system simulators, often combined with communication and market models, allow researchers to generate synthetic yet realistic datasets under a wide range of operating scenarios. These platforms support controlled experimentation, sensitivity analysis, and stress testing of AI algorithms under extreme events, high renewable penetration, and fault conditions [39]. However, discrepancies between simulated environments and real-world systems may limit the transferability of learned models, highlighting the need for careful validation and domain adaptation techniques.

7.2. Evaluation Metrics

The choice of evaluation metrics significantly influences the interpretation of AI model performance. In forecasting applications, error-based metrics such as mean absolute error, root mean square error, and normalized error indices are widely used to quantify prediction accuracy across different time horizons. For classification and detection tasks, including fault diagnosis and cybersecurity applications, metrics such as accuracy, precision, recall, F1-score, and receiver operating characteristics provide insight into detection capability and false alarm behavior.

For control, optimization, and energy management applications, evaluation extends beyond prediction accuracy to system-level performance indicators. These include operational cost, energy efficiency, constraint violation rates, voltage and frequency deviations, response time, and reliability indices. In resilience and security studies, metrics related to disturbance recovery time, service continuity, detection latency, and robustness against adversarial conditions are particularly important. A comprehensive evaluation framework should therefore integrate both data-driven metrics and power system–specific operational criteria [40].

7.3. Reproducibility and Comparability Challenges

Despite significant progress in AI-based power system research, reproducibility and comparability remain major challenges. Reported results often vary due to differences in datasets, preprocessing methods, model architectures, hyperparameter tuning strategies, and experimental setups. In many studies, limited disclosure of data sources, model configurations, and training procedures further complicates independent verification and fair comparison.

Addressing these challenges requires greater emphasis on standardized benchmarking practices, open-access datasets, and transparent reporting of experimental details. The development of common test systems, reference scenarios, and shared evaluation protocols would significantly enhance the credibility and impact of AI research in power systems. Improving reproducibility and comparability is also critical for accelerating the transition of AI-based solutions from academic research to real-world deployment in operational power grids [41].

8. Challenges and Open Research Issues

Among the challenges discussed in this section, data availability and quality and scalability under real-time operational constraints currently represent the most critical barriers to near-term deployment, while interpretability, regulatory alignment, and ethical considerations are increasingly important for sustained adoption.

Despite the rapid advancement and growing adoption of AI techniques in smart grids and modern power systems, several fundamental challenges and open research issues continue to limit their widespread and reliable deployment. Addressing these challenges is essential for ensuring that AI-based solutions are not only technically effective but also operationally feasible, trustworthy, and aligned with regulatory and societal requirements.

8.1. Data Availability and Quality

AI models rely heavily on large volumes of high-quality data for training and validation. In power systems, however, data availability is often constrained by privacy concerns, proprietary ownership, incomplete measurements, and heterogeneous data formats. Measurement noise, missing data, and labeling errors further degrade data quality, potentially leading to biased or unreliable AI models. Developing robust data preprocessing techniques, privacy-preserving learning frameworks, and standardized data-sharing mechanisms remains an open research challenge [42, 43].

8.2. Scalability and Real-Time Deployment

Many AI algorithms demonstrate strong performance in offline studies or small-scale test systems but face significant difficulties when deployed in large-scale, real-world power networks. High-dimensional state spaces, strict latency requirements, and limited computational resources at the edge complicate real-time implementation. Ensuring scalability while meeting real-time operational constraints requires advances in model compression, distributed learning, edge–cloud coordination, and efficient inference strategies tailored to power system environments [44].

8.3. Model Interpretability and Trustworthiness

The black-box nature of many AI models, particularly deep learning architectures, poses a major barrier to adoption in safety-critical power system applications. System operators and regulators require transparent and explainable decision-making processes to ensure accountability and operational confidence. Enhancing model interpretability, quantifying uncertainty, and establishing trust in AI-driven decisions remain key research priorities. Explainable AI techniques and human-in-the-loop frameworks offer promising directions but are still in early stages of development for power system applications [45].

8.4. Integration with Physical Models

Purely data-driven AI approaches may struggle to generalize beyond observed operating conditions, especially under rare or extreme events. Integrating AI with physics-based power system models offers a pathway to improving robustness, data efficiency, and physical consistency. However, achieving seamless integration between learning-based methods and established analytical models presents methodological and computational challenges.

Developing hybrid frameworks that balance physical insight with data-driven adaptability is an important open research area [23].

8.5. Regulatory and Ethical Considerations

The deployment of AI in power systems raises important regulatory and ethical questions related to accountability, safety, data privacy, and fairness. Existing regulatory frameworks are often not designed to accommodate autonomous and learning-based decision-making systems. Establishing clear guidelines for validation, certification, and liability is essential for enabling large-scale adoption. Ethical considerations, including bias in data-driven models and the impact of automation on workforce roles, must also be addressed to ensure socially responsible and equitable implementation of AI technologies [46].

Collectively, these challenges highlight the need for interdisciplinary research efforts that combine advances in artificial intelligence, power system engineering, cybersecurity, and policy development. Addressing these open issues will be critical for realizing the full potential of AI in next-generation power systems.

9. Future Research Directions

The continued evolution of smart grids and modern power systems, driven by decarbonization, decentralization, and digitalization, opens a wide range of opportunities for advanced AI-based solutions. While existing research has demonstrated the potential of AI in numerous applications, several emerging directions are expected to play a pivotal role in shaping next-generation power systems. This section highlights key future research avenues that are likely to have significant scientific and practical impact.

9.1. Digital Twins and AI-Driven Grid Virtualization

Digital twins' high-fidelity virtual replicas of physical power system sare emerging as a powerful paradigm for planning, operation, and asset management. When combined with AI, digital twins enable real-time grid virtualization, allowing continuous monitoring, predictive analysis, and what-if scenario evaluation under evolving operating conditions. AI-driven digital twins can support proactive maintenance, adaptive control, and resilience assessment by learning from real-time data and historical system behavior. Future research should focus on scalable architectures, real-time data integration, and the co-simulation of physical, cyber, and market layers to fully realize the potential of AI-enhanced digital twins [11, 47].

9.2. Federated and Decentralized Learning

As power systems become increasingly distributed and data privacy concerns intensify, federated and decentralized learning frameworks offer promising alternatives to centralized AI training. These approaches enable multiple grid entities such as substations, microgrids, and prosumers to collaboratively train AI models without sharing raw data. Federated learning can enhance data privacy, reduce communication overhead, and improve model generalization across heterogeneous environments. Key research challenges include handling non-identically distributed data, ensuring communication efficiency, and maintaining robustness against unreliable or malicious participants [48].

9.3. Foundation Models for Power Systems

The concept of foundation models, characterized by large-scale pretraining on diverse datasets followed by task-specific fine-tuning, has recently gained traction in other domains and holds significant promise for power systems. Foundation models could enable transferable representations across multiple grid applications, such as forecasting, fault diagnosis, and control, thereby reducing the need for task-specific data and training [49]. Future research is needed to develop domain-adapted pretraining strategies, integrate physical constraints, and evaluate the scalability and interpretability of such models in power system contexts.

9.4. AI for Net-Zero and Carbon-Neutral Grids

Achieving net-zero and carbon-neutral energy systems is a central global objective, and AI is expected to play a critical role in this transition. Future AI applications will increasingly focus on optimizing renewable integration, coordinating sector coupling, and enhancing energy efficiency across electricity, transportation, and heating systems. AI-driven tools can support long-term planning, real-time operation, and policy analysis by quantifying emissions impacts and identifying cost-effective decarbonization pathways. Advancing AI methodologies that explicitly account for sustainability objectives, environmental constraints, and societal impacts represents a crucial research direction for next-generation power systems [50].

In summary, these emerging research directions underscore the transformative potential of AI in enabling intelligent, resilient, and sustainable power systems. Addressing the associated technical, regulatory, and ethical challenges will be essential for translating these innovations into practical, large-scale deployments.

10. Conclusion

This paper has presented a comprehensive review of artificial intelligence applications in smart grids and modern power systems, highlighting the transformative role of data-driven and learning-based techniques across forecasting, operation, control, resilience, and security domains. By systematically categorizing AI methodologies and their applications, the review has demonstrated that machine learning, deep learning, reinforcement learning, and hybrid AI approaches offer substantial performance improvements over conventional methods, particularly in managing complexity, uncertainty, and large-scale system dynamics.

From an academic perspective, the findings of this review underscore the importance of developing AI models that are not only accurate but also interpretable, robust, and grounded in power system physics. The analysis reveals a growing need for standardized benchmarking practices, open datasets, and rigorous evaluation frameworks to enhance reproducibility and comparability across studies. Furthermore, emerging research directions such as digital twins, federated learning, and foundation models highlight promising opportunities for advancing theoretical foundations and methodological innovation in AI-enabled power systems.

For industry stakeholders, AI offers practical solutions for enhancing operational efficiency, reliability, and resilience in increasingly decentralized and renewable-rich grids. Applications such as predictive maintenance, adaptive control, demand response optimization, and cybersecurity monitoring have the potential to reduce costs, improve service continuity, and support the integration of low-carbon energy resources. However, successful deployment requires careful consideration of real-time constraints, regulatory compliance, and integration with existing infrastructure and operational practices.

In the near term, research efforts should prioritize scalable implementations, access to real-world operational data, and interpretable AI models that can be integrated into existing grid workflows. Longer-term research directions include AI-driven digital twins, federated and foundation models, and holistic optimization frameworks to support fully autonomous, net-zero power systems.

In conclusion, artificial intelligence is poised to become a cornerstone of next-generation power systems, enabling intelligent, flexible, and sustainable grid operation. Realizing this potential will require close collaboration between researchers, utilities, technology providers, and policymakers to address technical, regulatory, and ethical challenges. With continued interdisciplinary effort, AI-driven solutions can play a decisive role in shaping resilient, efficient, and carbon-neutral power systems of the future.

Article Information

Disclaimer (Artificial Intelligence): The author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.), and text-to-image generators have been used during writing or editing of manuscripts.

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