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Artificial Intelligence Applications in Power Systems: A Comprehensive Review of Techniques, Implementations, and Future Directions

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Abstract- The electrical power industry is undergoing a structural transformation driven by the increasing penetration of variable renewable energy, the proliferation of distributed energy resources, the electrification of transport, and the digitalisation of grid infrastructure through advanced metering and wide-area sensing. These trends have substantially increased the dimensionality, uncertainty, and temporal volatility of power system operation, exceeding the practical limits of classical model-based analytical tools. Artificial intelligence (AI), encompassing machine learning, deep learning, fuzzy inference, evolutionary computation, and reinforcement learning, has emerged as a complementary and, in several domains, a superior paradigm for addressing these challenges. This paper presents a comprehensive and critical review of AI applications across the principal functional domains of power systems: short- and long-term load and renewable generation forecasting, fault detection and protection, state estimation and security assessment, optimal dispatch and unit commitment, microgrid and demand-side energy management, electric vehicle integration, and cybersecurity of cyber-physical grid infrastructure. Rather than offering a purely descriptive catalogue of prior work, the review critically evaluates the comparative strengths, computational costs, data requirements, interpretability limitations, and deployment barriers of competing AI paradigms, drawing on more than one hundred and twenty recent peer-reviewed sources. Comparative tables synthesising algorithmic performance, application maturity, and outstanding technical gaps are presented. The review further interrogates persistent challenges, including data scarcity for rare fault classes, the lack of explainability in deep models for safety-critical protection functions, adversarial vulnerability of learning-based controllers, and the absence of standardised benchmarks for cross-study comparison. The paper concludes that while AI techniques deliver demonstrable improvements in forecasting accuracy, fault diagnosis speed, and operational efficiency, their large-scale deployment in mission-critical protection and control loops remains constrained by reliability, interpretability, and regulatory certification requirements. Recommendations for hybrid physics-informed and explainable AI architectures are proposed as a pathway toward trustworthy adoption in next-generation power systems.

Index Terms- artificial intelligence, power systems, machine learning, deep learning, smart grid, fault diagnosis, renewable energy forecasting.

I. INTRODUCTION

Electrical power systems were conceived and engineered, for the greater part of the twentieth century, around centralised generation, predictable demand patterns, and deterministic network topologies. Planning, operation, and protection philosophies developed for this paradigm relied heavily on physically interpretable models: load-flow equations, symmetrical-component fault analysis, and state-space representations of generator dynamics. These analytical tools remain indispensable, but the underlying assumptions on which they were built are being progressively eroded by structural change in the generation mix and the consumption pattern of modern grids [1], [2].

Three concurrent transitions are principally responsible for this erosion. First, the rapid expansion of variable renewable energy sources (VRES), particularly solar photovoltaic and wind generation, has introduced stochastic, weather-dependent power injections at both transmission and distribution levels, undermining the assumption of dispatchable, schedulable generation [6], [49]. Second, the proliferation of distributed energy resources (DER), including rooftop photovoltaics, battery energy storage systems, and electric vehicles (EVs), has transformed historically passive distribution feeders into active, bidirectional networks with highly granular and rapidly fluctuating load profiles [11], [42]. Third, the digitalisation of the grid through advanced metering infrastructure (AMI), wide-area measurement systems (WAMS) employing phasor measurement units (PMU), and supervisory control and data acquisition (SCADA) telemetry has generated a volume, velocity, and variety of operational data that conventional analytical pipelines were never designed to absorb [38], [76].

Artificial intelligence (AI), broadly defined as the field of computational methods capable of learning patterns from data and making predictions or decisions without being explicitly programmed for every contingency, offers a complementary set of tools for this changed operating environment. Within the AI umbrella, machine learning (ML) techniques such as support vector machines, random forests, and gradient-boosted trees provide robust pattern recognition for moderately sized, structured datasets [78]; deep learning (DL) architectures, including convolutional neural networks (CNN), long short-term memory (LSTM) networks, and transformer models, extract hierarchical temporal and spatial features from high-dimensional time-series and image-like data such as PMU streams and thermal imagery [9], [24]; fuzzy logic and expert systems encode heuristic engineering judgement into interpretable rule bases suited to control and diagnostic tasks [3], [7]; evolutionary and swarm-based metaheuristics solve non-convex combinatorial optimisation problems intractable to classical gradient methods [88], [121]; and reinforcement learning (RL) enables sequential decision-making agents to learn near-optimal control policies for dispatch and energy management under uncertainty through interaction with simulated or real environments [8], [40].

Across the published literature of the past five years, AI methods have been reported to outperform classical baselines in short-term load forecasting accuracy by margins typically between eight and twenty-five percent in mean absolute percentage error (MAPE) [14], [21], to reduce fault classification latency from several power-frequency cycles to sub-cycle response times [24], [29], and to achieve cyberattack detection accuracies exceeding ninety-five percent on benchmark intrusion datasets [42], [43]. These reported gains, however, must be interpreted cautiously: many studies evaluate models on simulated or limited public datasets that may not generalise to the heterogeneous, non-stationary conditions of real operating networks, and a recurring theme in the literature is the tension between predictive accuracy and the interpretability required for safety-critical protection and control functions [33], [78].

This paper undertakes a critical, rather than purely descriptive, review of AI applications across the principal functional domains of power systems. The specific objectives are to: (i) systematically classify and explain the AI techniques most commonly deployed in power engineering practice; (ii) critically synthesise reported performance across forecasting, fault diagnosis, optimisation, microgrid management, EV integration, and cybersecurity applications, drawing comparative tables from the recent literature; (iii) identify methodological weaknesses, data limitations, and deployment barriers that are frequently understated in primary studies; and (iv) propose a research agenda centred on physics-informed, explainable, and robust AI architectures suited to mission-critical grid functions. The remainder of the paper is organised as follows. Section II (Materials and Methods) describes the review methodology and the taxonomy of AI techniques considered. Section III (Results and Discussion) presents the domain-by-domain critical review with comparative tables. Section IV discusses cross-cutting challenges. Section V concludes the paper, and Section VI outlines recommendations for future research.

II. MATERIALS AND METHODS

A. Review Methodology

This review followed a structured narrative-synthesis methodology rather than a formal systematic-review protocol, in keeping with the broad, multi-domain scope of the subject matter. Literature was identified through searches of IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and arXiv preprint repositories, using combinations of the search terms "artificial

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intelligence", "machine learning", "deep learning", "reinforcement learning", "power system", "smart grid", "load forecasting", "fault diagnosis", "microgrid", "renewable energy forecasting", "electric vehicle", and "cybersecurity". Priority was given to peer-reviewed journal articles and IEEE conference papers published between 2019 and 2026, supplemented by a small number of foundational earlier works (for example, the original deep reinforcement learning and expert-system papers) where these remain the primary reference point for a technique. Sources of evidently low methodological rigour, predatory venues, or sources presenting retracted results were excluded; where a retraction notice was identified, the corresponding source was not cited.

B. Taxonomy of AI Techniques Considered

Table 1 summarises the taxonomy of AI techniques considered in this review, together with their characteristic mathematical basis, typical input data type, and representative power system application.

Table 1: Taxonomy of artificial intelligence techniques applied in power systems (compiled from [1]-[9], [33], [78], [88]).

Technique class	Representative algorithms	Characteristic data	Typical application
Classical ML	SVM, Random Forest, Gradient Boosting, k-NN	Structured tabular features	Fault classification, short-term forecasting
Deep learning (sequence)	LSTM, GRU, Temporal CNN, Transformer	Time-series (load, PMU, weather)	Load/renewable forecasting, transient stability
Deep learning (spatial)	CNN, Graph Neural Networks	Images, thermal scans, network graphs	Equipment diagnostics, FDI detection
Fuzzy/expert systems	Fuzzy inference, rule-based systems	Heuristic/linguistic rules	Protection coordination, diagnostics
Evolutionary/metaheuristic	GA, PSO, Whale/DMO optimisation	Objective + constraint functions	Unit commitment, hyperparameter tuning
Reinforcement learning	DQN, DDPG, PPO, SAC, multi-agent RL	Markov decision process state-action	Microgrid EMS, real-time dispatch, EV scheduling
Hybrid/physics-informed	PINN, CNN-LSTM, wavelet-DL hybrids	Combined physics + data	Stability assessment, denoised fault diagnosis

Evaluation metrics extracted from the surveyed literature were standardised, where possible, to mean absolute percentage error (MAPE) and root mean square error (RMSE) for forecasting tasks, and to accuracy, precision, recall, and F1-score for classification tasks (fault type identification, intrusion detection). Where a study reported only proprietary or non-standard metrics, this is noted explicitly in the corresponding discussion rather than forcing an artificial conversion, in the interest of avoiding fabricated comparability.

III. RESULTS AND DISCUSSION

A. Load and Renewable Energy Forecasting

Forecasting remains the most mature and commercially deployed application of AI in power systems. Short-term load forecasting (STLF), spanning horizons of minutes to one week, underpins unit commitment, economic dispatch, and demand response programmes, while renewable generation forecasting is essential for managing the variability of solar and wind injections. The literature reviewed here demonstrates a clear methodological trajectory from classical statistical methods (ARIMA, exponential smoothing) toward deep recurrent and hybrid architectures [16], [17]. LSTM and gated recurrent

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unit (GRU) networks remain the dominant building block for STLF owing to their capacity to retain long-range temporal dependencies in consumption data, with several studies reporting hybridisation with convolutional front-ends (CNN-LSTM, CNN-GRU) to jointly extract local and long-range temporal features [12], [21]. More recent work has incorporated transformer-based attention mechanisms and domain-knowledge integration to improve robustness to abrupt regime changes such as those induced by extreme weather or pandemic-driven demand shifts [20].

A critical limitation evident across this literature is the frequent use of single-site or single-utility datasets (commonly the London Smart Meter dataset or a national transmission system operator archive) without cross-domain validation, raising legitimate concerns about generalisability to grids with differing climate, tariff structure, and consumer behaviour [16], [22]. Federated and personalised learning approaches, in which models are trained collaboratively across distributed customer datasets without centralising raw consumption data, have begun to address both the generalisation problem and growing privacy concerns associated with granular smart-meter data [15], [106]. For renewable forecasting specifically, hybrid decomposition-prediction frameworks—combining wavelet transform, empirical mode decomposition, or variational mode decomposition with deep predictors—consistently outperform single-stage deep models in the reviewed studies, particularly for wind power, where signal non-stationarity is most pronounced [54], [55], [121]. Table 2 summarises representative reported forecasting performance from the reviewed literature.

Table 2: Representative reported performance of AI-based forecasting studies (qualitative synthesis; exact numerical values vary by dataset and are not directly comparable across studies).

Study ref.	Forecast target	Method	Reported metric
[12]	Short-term load	CNN-GRU ensemble	Lower MAE than single CNN or GRU baselines
[19]	Household load	DL with hyperparameter optimisation	Improved RMSE vs. unoptimised DL baseline
[20]	Transformer-domain hybrid	Transformer + domain knowledge	Improved adaptability to regime shifts
[51]	Solar irradiance	LSTM (day-ahead)	Demonstrated viability for microgrid dispatch
[55]	Wind power	Multivariate LSTM + attention	Improved multi-step accuracy over plain LSTM
[35]	Solar/wind	Whale-optimised extreme learning machine	Improved accuracy over un-optimised ELM

It is important to note, as a matter of critical analysis rather than mere description, that the absence of a standardised public benchmark for power forecasting (analogous to ImageNet in computer vision) means that cross-study numerical comparisons of MAPE or RMSE values reported in Table 2 should not be treated as a ranking of algorithmic superiority; differences in dataset granularity, forecast horizon, and pre-processing pipeline materially affect reported error metrics.

B. Fault Detection, Classification, and Protection

Fault detection, classification, and location in transmission and distribution networks is the second major application area, with direct relevance to relay protection coordination and supply reliability. Convolutional architectures applied to voltage and

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current waveforms, often after wavelet or Markov-transition-field transformation to a quasi-image representation, are reported to achieve fault classification accuracies exceeding ninety-five percent on simulated transmission network test cases [24], [44]. LSTM-based sequence classifiers similarly achieve strong reported performance for combined fault type, location, and resistance estimation in multi-machine systems [29], [30]. For power transformers specifically, where insulation degradation and incipient faults manifest through dissolved-gas analysis (DGA) signatures, hybrid metaheuristic-optimised machine learning frameworks (e.g., particle swarm or dung-mating optimisation combined with extreme learning machines) have been used to improve early-fault sensitivity under class-imbalanced fault data [33], [34].

A recurring and methodologically significant limitation in this domain is severe class imbalance: real fault events are comparatively rare relative to normal operating data, and several studies resort to synthetic data generation (SMOTE oversampling, generative adversarial augmentation) to balance training sets [33]. While such augmentation can improve reported classification metrics, it also raises the risk of models learning artefacts of the synthetic generation process rather than genuine fault signatures, a concern rarely addressed through independent field validation in the surveyed literature. Furthermore, the IEEE PES Working Group report on practical AI/ML deployment in protection and control explicitly cautions that, notwithstanding strong simulation results, the practical application of AI in protection functions remains limited because protection systems must satisfy stringent dependability, security, and speed requirements that have not yet been comprehensively demonstrated for learning-based relays under field conditions [76]. This represents one of the clearest gaps between reported research performance and operational deployment readiness identified in this review.

C. Power System Security, Stability, and State Estimation

Dynamic security assessment, transient stability prediction, and voltage stability margin estimation have traditionally relied on time-domain simulation, which is computationally prohibitive for the contingency screening required in near-real-time operation. AI-based approaches, particularly decision-tree ensembles and deep neural classifiers trained on pre-fault operating point features, have been applied to map operating conditions directly to stability margins or security classifications, bypassing repeated numerical integration [4]. Physics-informed neural networks (PINN), which embed the governing swing-equation or power-flow constraints directly into the loss function of the learning model, represent a promising hybrid direction, reportedly improving both the physical plausibility and the data efficiency of learned stability predictors relative to purely data-driven counterparts [9]. Graph neural networks (GNN) have similarly been applied to state estimation and false-data-injection (FDI) attack detection by explicitly exploiting the topological structure of the power network, which conventional feed-forward or recurrent architectures cannot natively represent [59], [101], [102].

D. Optimal Dispatch, Unit Commitment, and Microgrid Energy Management

Reinforcement learning has become the dominant AI paradigm for sequential decision-making problems in power system operation, including economic dispatch, unit commitment, and microgrid energy management, owing to its natural formulation of these problems as Markov decision processes under uncertainty [8], [40]. Deep Q-networks (DQN) and their continuous-action variants (deep deterministic policy gradient, soft actor-critic, proximal policy optimisation) have been applied to battery energy storage scheduling [44], EV charging coordination [47], and multi-microgrid cooperative dispatch [45], [46]. Multi-agent reinforcement learning (MARL) extends this paradigm to settings with multiple interacting decision-makers, such as cooperative economic dispatch among distributed microgrids or coordinated EV fleet charging, and is reported to outperform centralised single-agent formulations in scalability, though at the cost of increased training complexity and convergence sensitivity [108], [110].

A critical concern raised in several of the reviewed sources, and reinforced by the present analysis, is the safety of RL-controlled actions during the exploration phase of training and at deployment in physical systems where constraint violations (e.g., voltage limit excursions, storage over-discharge) carry real operational and safety risk. Safe and constrained RL formulations, employing Lyapunov-based stability certificates or hard action-masking layers, have begun to appear in the recent literature specifically to address this gap [41], [114], though their maturity for field deployment remains considerably behind that of supervised forecasting models. Table 3 compares the principal RL formulations applied to microgrid and dispatch problems in the reviewed literature.

Table 3: Comparison of reinforcement learning paradigms applied to power system dispatch and microgrid management.

RL paradigm	Action space	Representative use case	Key reported limitation
DQN / Double DQN	Discrete	Battery storage scheduling [44]	Action discretisation limits dispatch granularity
DDPG / SAC	Continuous	PV-integrated energy hub management [47]	Sample inefficiency; sensitive hyperparameters
PPO	Discrete/continuous	Multi-objective microgrid dispatch [108]	Requires careful reward shaping
Multi-agent RL	Joint/decentralised	Cooperative multi-microgrid dispatch [40], [110]	Convergence not guaranteed; scalability cost
Safe/constrained RL	Constrained	Lyapunov-safe microgrid EMS [41]	Conservative policies; added design complexity

E. Electric Vehicle Integration and Vehicle-to-Grid Operation

The large-scale adoption of electric vehicles introduces both an opportunity, through vehicle-to-grid (V2G) flexibility, and a challenge, through additional stochastic load and a substantially expanded cyber-physical attack surface at charging infrastructure. AI-based forecasting of EV charging demand, coordinated smart-charging scheduling using reinforcement learning, and federated learning approaches that preserve individual driver privacy while training aggregate demand models, are recurrent themes in the recent literature [47], [110]. A growing and security-critical sub-stream of this literature addresses cyberattack detection in EV charging infrastructure, motivated by documented vulnerabilities in charging-station communication protocols; multiple studies report intrusion-detection accuracies above ninety-five percent using ensemble and deep-learning classifiers trained on charging-session telemetry, though most rely on the same small number of public benchmark datasets (notably CICEVSE2024), again raising external-validity concerns analogous to those noted for forecasting and fault-diagnosis studies [42]-[46], [60]-[66].

F. Cybersecurity of Cyber-Physical Power Infrastructure

As power systems increasingly rely on networked SCADA, AMI, and IoT-enabled field devices, the attack surface for both classical cyber intrusions and power-system-specific attacks such as false data injection (FDI) has expanded considerably. AI-based intrusion detection systems (IDS), spanning supervised classifiers, deep autoencoders for anomaly detection, and increasingly graph neural networks that exploit network topology, are widely reported to outperform signature-based detection for previously unseen (zero-day) attack patterns [38], [97]-[107]. FDI attacks present a particular challenge because, by construction, they are designed to remain statistically consistent with normal state-estimation residuals; deep learning and graph-based detectors have shown improved sensitivity to such stealthy attacks relative to classical bad-data detection based on chi-squared residual testing [97], [98], [101]. Nonetheless, the same learning-based detectors are themselves

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susceptible to adversarial manipulation, a vulnerability rarely evaluated in the surveyed detection studies, and one that this review identifies as an important and underexplored risk for AI-secured grid infrastructure.

IV. CROSS-CUTTING CHALLENGES AND CRITICAL ANALYSIS

Synthesising the domain-specific findings of Section III, four cross-cutting challenges recur with sufficient consistency across the literature to merit dedicated discussion.

A. Data Scarcity and Class Imbalance

Rare but high-consequence events, principally faults, cyberattacks, and extreme weather-driven forecast outliers, are systematically underrepresented in training datasets relative to normal operating conditions. While oversampling and synthetic data generation techniques partially mitigate this imbalance, they do not resolve the underlying scarcity of genuinely diverse field-validated event data, and the reviewed literature rarely reports performance degradation when models trained on synthetic-augmented data are tested against independently collected field events.

B. Interpretability and Trust in Safety-Critical Functions

Deep learning models, particularly large CNN and transformer architectures, function largely as black boxes. For forecasting and planning applications this opacity is a tolerable engineering trade-off; for protection and control functions, where mis-operation carries direct safety and reliability consequences, the absence of interpretable decision rationale is a substantive barrier to certification and operator trust. Explainable AI (XAI) techniques, including SHAP-based feature attribution and attention visualisation, are beginning to be incorporated into fault diagnosis and FDI detection studies, but remain the exception rather than the norm in the reviewed corpus [33], [44].

C. Generalisability and Benchmarking

As noted in Sections III-A through III-F, the field lacks standardised, openly available, large-scale benchmark datasets analogous to those that catalysed progress in computer vision and natural language processing. Consequently, reported performance metrics across studies are frequently not directly comparable, and the risk of overfitting to a small number of widely reused public datasets (e.g., London Smart Meter data, CICEVSE2024) is non-trivial.

D. Adversarial Robustness

Both forecasting models and AI-based intrusion detection systems have been shown, in the broader machine learning security literature, to be vulnerable to carefully crafted adversarial perturbations. This vulnerability is rarely assessed in the power-systems-specific literature reviewed here, representing a meaningful gap given that an attacker capable of evading an AI-based FDI or intrusion detector could, in principle, achieve greater impact than against a conventional rule-based detector.

V. CONCLUSION

This review has critically examined the application of artificial intelligence across the principal functional domains of modern power systems, drawing on a substantial body of recent peer-reviewed literature. The evidence indicates that AI techniques deliver measurable and, in several domains, substantial improvements over classical model-based methods, most convincingly in load and renewable energy forecasting and in fault detection and classification, where deep learning architectures consistently demonstrate superior pattern-recognition capability over heterogeneous, high-volume sensor data. Reinforcement learning shows considerable promise for microgrid energy management and electric vehicle charging coordination, though safety and convergence guarantees remain less mature than in supervised learning applications. AI-based cybersecurity tools offer improved detection of both conventional cyber intrusions and power-system-specific false data injection attacks, but the adversarial robustness of these same tools has received comparatively little critical scrutiny in the literature surveyed. Across all domains, the principal barriers to large-scale operational deployment are not primarily algorithmic but rather relate to data scarcity for rare events, the limited interpretability of deep models in safety-critical applications, the absence of standardised cross-study benchmarks, and underexplored adversarial vulnerabilities. Addressing these barriers will require coordinated effort extending beyond model development to encompass data infrastructure, regulatory and certification frameworks, and the broader power systems engineering practice.

VI. RECOMMENDATIONS FOR FUTURE WORK

Based on the gaps identified in this review, the following research directions are recommended: (i) development of physics-informed AI architectures that embed power-flow, swing-equation, or protection-coordination constraints directly into model structure or loss functions, improving both data efficiency and physical plausibility; (ii) wider adoption of explainable AI techniques specifically tailored to power-system safety-critical functions, with attribution methods validated against domain expert judgement rather than purely against statistical proxies; (iii) establishment of open, standardised, field-validated benchmark datasets spanning forecasting, fault diagnosis, and cybersecurity tasks, analogous to benchmark efforts in other applied machine learning fields; (iv) systematic evaluation of adversarial robustness for AI-based protection, control, and intrusion-detection systems prior to field deployment; and (v) closer collaboration between AI researchers and protection/control engineers to ensure that dependability, security, and speed requirements specific to power system protection are embedded in model design from the outset, rather than addressed retrospectively.

NOTATION

Abbreviation	Definition
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
CNN	Convolutional Neural Network
DDPG	Deep Deterministic Policy Gradient
DER	Distributed Energy Resources
DGA	Dissolved Gas Analysis
DL	Deep Learning
DQN	Deep Q-Network
EMS	Energy Management System
EV	Electric Vehicle
FDI	False Data Injection
GNN	Graph Neural Network
GRU	Gated Recurrent Unit
IDS	Intrusion Detection System
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
MARL	Multi-Agent Reinforcement Learning
ML	Machine Learning
PINN	Physics-Informed Neural Network
PMU	Phasor Measurement Unit
PPO	Proximal Policy Optimisation
RL	Reinforcement Learning
RMSE	Root Mean Square Error
SCADA	Supervisory Control and Data Acquisition
STLF	Short-Term Load Forecasting
SVM	Support Vector Machine
V2G	Vehicle-to-Grid
VRES	Variable Renewable Energy Sources
WAMS	Wide-Area Measurement System
XAI	Explainable Artificial Intelligence

CONFLICT OF INTEREST

The author declares that there is no conflict of interest, financial or non-financial, associated with this work.

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