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Artificial intelligence and machine learning for smart grids: from foundational paradigms to emerging technologies with digital twin and large language model-driven intelligence

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ABSTRACT

The evolution of modern power systems into smart grids is increasingly powered by Artificial Intelligence (AI) and Machine Learning (ML), which provide effective solutions for managing renewable intermittency, dynamic demand, and cybersecurity challenges. This paper presents a comprehensive review of AI/ML applications in smart grids, tracing their development from foundational paradigms to cutting-edge technologies such as Federated Learning (FL), Generative AI (GenAI), Large Language Models (LLMs), the Artificial Intelligence of Things (AIoT), and Digital Twin (DT)-driven intelligence. Enabling infrastructures, including IoT, 5G, edge–cloud ecosystems, and ML-based smart sensors, are discussed alongside advanced approaches such as multi-agent systems. Key applications explored include load forecasting, predictive maintenance, anomaly and cyber-attack detection, demand-side management, and electric vehicle integration. Special emphasis is placed on Digital Twin and LLM architectures, which enable real-time cyber-physical replicas and context-aware reasoning, thus improving predictive analytics, resilience, and autonomous decision-making. Despite notable advancements, challenges remain in interoperability, data privacy, computational scalability, adversarial robustness, and ethical constraints. By synthesizing these insights, the study highlights the transformative role of AI in creating resilient, sustainable, and intelligent energy systems, and outlines future research trajectories toward standardized DT frameworks, active learning paradigms, and LLM-driven energy intelligence.

Introduction

The global economy continues its growth trajectory with an ever-increasing reliance on energy consumption. However, the widespread utilization of fossil energy poses a severe threat to the environment, unequivocally highlighting the urgent need for a global transition towards large-scale clean energy generation and utilization[1].In response to these pressing environmental challenges and escalating energy demands, novel concepts in energy and electric power system development have emerged, focusing on the establishment of smart grids (SGs) and advanced power systems. These sophisticated networks aim to create a dynamic and intelligent interconnection among all energy participants, including generation sources, transmission and distribution networks, consumers, and even electric vehicles [2]. Over recent decades, electrical power systems have undergone a profound evolution, transforming from traditional, centralized structures into advanced next-generation smart grids. Early power grids, primarily designed for unidirectional power delivery from large, centralized power plants to consumers, faced inherent limitations in terms of efficiency, reliability, and scalability [1].These passive architectures lacked the capability to effectively manage the fluctuations introduced by intermittent renewable energy sources (IRES) and non-linear consumption patterns, often leading to power mismatches and even blackouts. As time progressed, the grid evolved into a decentralized and dynamic system, significantly enhancing flexibility, security, and efficiency through two-way power and information flow. These advancements have paved the way for a smarter, more resilient, and sustainable energy infrastructure [3].

At the heart of this transformative shift lies Artificial Intelligence (AI) and Machine Learning (ML). These technologies offer innovative solutions to address the complexities of modern power systems and the challenges associated with integrating intermittent renewable energy sources and managing dynamic demand. By enabling real-time data analysis, predictive maintenance, demand-response optimization, and automated fault detection, AI plays a fundamental role in augmenting

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the efficiency, security, and resilience of energy systems [4]. These capabilities not only assist in managing the challenges linked to renewable energy sources but also lead to substantial improvements in overall system efficiency, reliability, and scalability, along with a significant reduction in carbon emissions. AI and ML collectively present unprecedented opportunities to enhance energy efficiency and design more sustainable systems in alignment with the United Nations Sustainable Development Goals (SDGs).

The Internet of Things (IoT) is one of the promising technologies that can improve the operation and administration of smart grids. IoT devices are linked to resources that are physically situated elsewhere and carry out their responsibilities by exchanging energy and data without the need for human involvement. Data-driven control systems and IoT technologies generate a network of smart factories, houses, smart cities, and smart grids. Under IoT-based networks, the efficiency of transmission and distribution stations will be increased, enabling the effective use of renewable energy sources. IoT may be incorporated into the smart grid at all levels of the electric power grid, including generation, transmission, distribution, and consumer units [2].

For instance, this research [5] developed a SCADA-controlled smart home system utilizing Raspberry Pi3 and Wemos-D1 boards, enabling remote monitoring and appliance control through TCP/IP and MQTT protocols. Their system prioritizes energy efficiency, user comfort particularly for the elderly and disabled and cost-effective implementation, positioning smart homes as a practical entry point for intelligent energy management. This work complements the broader discussion on residential energy management systems and IoT-driven automation within smart grids.

Smart meters detect energy usage in real-time, interact with the utility, and execute advanced demand-side management activities via two-way communication. The new power generation stations include many distributed generation (DG) technologies, such as photovoltaic (PV), wind energy, and biopower plants, that have been added to the power grid as a result of this paradigm change from the traditional grid to the smart grid. As such, the smart grid will integrate new smart technologies into distributed and renewable generation systems to make the traditional power grid more productive, efficient, and intelligent [6].

The integration of IoT technologies and distributed generation systems simultaneously introduces new challenges to smart grid management. These include the timely transmission of critical operational information, the effective processing of massive volumes of field data, and growing risks related to cyberspace security. Beyond these systemic issues, specific technical problems also arise, such as load forecasting [7,8], fault and failure detection and diagnosis [9], demand-side management [10], non-intrusive load monitoring [11], energy theft detection [12], and islanding detection [13]. Addressing these challenges requires advanced AI algorithms and knowledge automation to replace human-dependent analysis and decision-making, transforming conventional plug-and-play, software-based energy systems into truly intelligent infrastructures. By leveraging powerful computational resources, advanced learning models, and massive data, AI ensures secure, reliable, economical, and environmentally sustainable operation of next-generation power systems [6,14].

Fig. 1 illustrates a comprehensive, AI-driven smart grid ecosystem, showcasing the intricate interplay between diverse energy generation sources, a modernized transmission and distribution infrastructure, and intelligent consumption points. At its core, a "Centralized & Distributed AI/ML Hub," further enhanced by icons representing Cloud Computing and Edge Computing, serves as the brain of the system, facilitating advanced data analytics and decision-making across all scales. Various energy sources, including traditional (Thermal, Nuclear, Hydroelectric) and renewable (Wind, Solar, Biopower, Geothermal) power plants, are

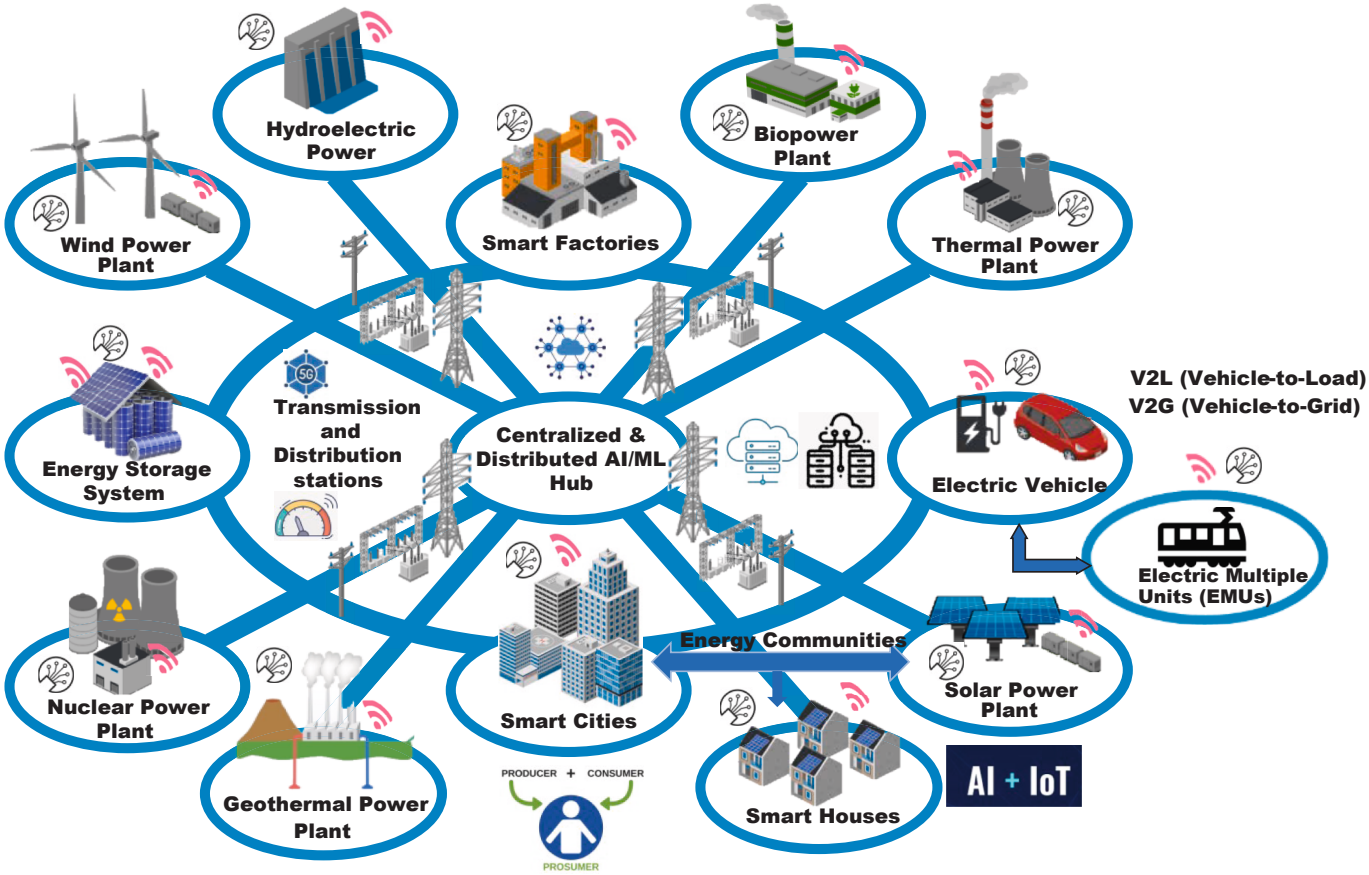

Fig. 1. Comprehensive AI-Driven Smart Grid Ecosystem with Advanced Integration and Distributed Intelligence.

seamlessly integrated. The grid extends its intelligence to encompass Energy Storage Systems, and critically, Electric Vehicles (EVs) are depicted with explicit V2G (Vehicle-to-Grid) and V2L (Vehicle-to-Load) capabilities, alongside the inclusion of Electric Multiple Units (EMUs), highlighting advanced mobility integration. The consumer side is represented by "Smart Houses," "Smart Factories," and "Smart Cities," with a novel emphasis on "Energy Communities" and Prosumers, signifying decentralized energy trading. The entire ecosystem is underpinned by a robust "Communication Network," implicitly leveraging high-speed 5G connectivity and other wired/wireless protocols for real-time data flow, emphasizing the foundational role of the Artificial Intelligence of Things (AIoT) as the synergistic convergence of AI and IoT. This sophisticated architecture aims to optimize energy management, enhance grid resilience, ensure cybersecurity, and enable a sustainable energy future through advanced AI/ML applications such as forecasting, fault detection, and intelligent control.

Structure of the paper

The structure of this paper is organized as follows. Section 2 outlines the methodology and bibliometric analysis, including the systematic search strategy, inclusion and exclusion criteria, and a co-occurrence mapping of 123 references. Section 3 presents a structured review of AI/ML applications in smart grids across forecasting, operations, and control domains, consolidated in comparative Tables 2–4. Section 4 examines security, infrastructure, electric vehicles, and smart city integration, with key contributions and limitations summarized in Tables 3 and 4. Section 5 synthesizes advanced paradigms such as Federated Learning, Digital Twins, Generative AI, and Large Language Models, providing frontier perspectives supported by Tables 4–6. Section 6 consolidates cross-cutting challenges, benchmarking protocols, and comparative baselines (Tables 7 and 8), introducing a structured roadmap that links technical bottlenecks with practical implementation strategies. Finally, Section 7 highlights future research trajectories, emphasizing standardized benchmarks, privacy-preserving frameworks, interpretable AI, and hybrid DT–LLM architectures for sustainable, resilient smart grids. To clearly articulate the scope of this review and distinguish it from prior surveys, this study is guided by three central research questions: (1) What are the dominant trajectories in the evolution of AI/ML paradigms relevant to smart grids? (2) How do these paradigms concretely address critical energy-system challenges such as load forecasting, cybersecurity, and renewable integration? and (3) What research gaps and future directions remain for sustainable, scalable, and resilient deployment of AI/ML in power systems? In addressing these questions, this review goes beyond existing works by combining a systematic bibliometric analysis, a structured comparative framework (Tables 2–4), and a focused discussion on frontier technologies such as Digital Twins, Federated Learning, and Large Language Models (LLMs). This integrated approach ensures not only a comprehensive synthesis of the literature but also a distinctive contribution that directly links methodological advances in AI to the operational imperatives of modern smart grids.

Table 1
Search Criteria for Identifying Relevant Literature on AI/ML in Smart Grids.

The key search areas	Criteria	Detail
All Search Areas	Scope	"smart grid", "power system", "energy system", "microgrid", "smart city", "renewable energy"
All Search Areas	Study	"artificial intelligence", "machine learning", "deep learning", "reinforcement learning", "federated learning", "transfer learning", "hybrid learning", "adversarial learning", "generative AI", "meta-learning", "ensemble learning", "multi-agent system", "optimization algorithms", "neural networks"
All Search Areas	Topic	"load forecasting", "energy management", "fault detection", "anomaly detection", "cybersecurity", "demand response", "electric vehicles", "V2G", "energy storage", "predictive maintenance", "grid stability", "power quality", "digital twin", "IoT", "AIoT", "5G", "edge computing", "sustainability", "carbon emission"
Specific Application Domains	Energy Management	"optimal scheduling", "energy efficiency", "thermal management", "energy communities", "prosumer"
Specific Application Domains	Grid Operations	"voltage control", "power flow", "topology optimization", "power converter control", "self-healing grid"
Specific Application Domains	Security & Resilience	"adversarial attacks", "data privacy", "trustworthiness", "intrusion detection", "blockchain"

Contributions

Despite significant advancements in AI/ML for smart grids, many optimization-centric pipelines exhibit vulnerabilities to hyperparameter sensitivity, local minima, domain shift, non-IID distributions, data leakage, and adversarial fragility, which constrain scalability, transferability, and trustworthy deployment at utility scale. These challenges underscore the need for a structured, decision-oriented synthesis that transcends narrative reviews. This study addresses this need by providing a systematic overview of AI/ML evolution, tracing the progression from foundational paradigms, such as supervised, unsupervised, and reinforcement learning, to emerging technologies, including Federated Learning, Generative AI, Large Language Models, and Digital Twins. By integrating enabling infrastructures like IoT, 5G, and edge–cloud ecosystems, the synthesis elucidates how these technologies tackle core grid challenges, such as renewable intermittency, dynamic demand, and cybersecurity.

The review employs a PRISMA-guided methodology and a VOSviewer-generated co-occurrence map (Fig. 3) to organize 123 references into three thematic clusters: forecasting, operations, and control; security, infrastructure, and urban applications; and advanced paradigms and system outlook, as detailed in Tables 2–4. This structured bibliometric framework juxtaposes key contributions with their limitations, revealing critical gaps in interoperability, data privacy, computational scalability, and model explainability. Particular emphasis is placed on Digital Twins and LLM-driven intelligence, which enable real-time simulation, context-aware reasoning, and autonomous decision-making. The study proposes hybrid DT–LLM architectures, complemented by deep reinforcement learning, multi-agent reinforcement learning, and privacy-preserving Federated Learning, as pathways to resilient, edge-deployable systems that can be evaluated and stress-tested in silico prior to field deployment.

The analysis further maps observed optimization pitfalls, such as non-IID data, robustness and privacy issues, and sample inefficiency, to targeted remedies. These include robust aggregation in Federated Learning, active, transfer, and *meta*-learning for data efficiency and domain adaptation, safety-aware deep reinforcement learning for sequential control, and Digital Twin-assisted training and validation. This problem-to-remedy mapping positions the synthesis as a practical guide rather than a descriptive catalog. Finally, the review identifies actionable research trajectories, including standardized and adversarially robust benchmarks, interoperable Digital Twin and AIoT stacks, privacy-preserving Federated Learning with leakage controls and Byzantine robustness, uncertainty-aware and interpretable forecasting, and lightweight, domain-specific Large Language Models tailored for edge–cloud infrastructures. These directions advance sustainable energy systems aligned with the United Nations Sustainable Development Goals, offering a cohesive framework to guide researchers, practitioners, and policymakers toward intelligent, efficient, and environmentally conscious smart grids.

Table 2
Forecasting, Operations, and Control in Smart Grids: Key Contributions and Limitations.

Domain / Focus Area	Representative References	Key Contributions	Limitations
Load & Price Forecasting (building/residential/ system)	[7,80–87]	ELM/RNN/LSTM/Bi-LSTM-Attention, pooling-RNN, and hybrid clustering + Bayesian models for short-term/day-ahead load and price forecasting; probabilistic formulations	Sensitive to data quality/granularity; limited cross-regional generalization; lack of standardized benchmarks
Wind & Solar Forecasting	[94–97]	Hybrid ELM/ENN/LSTM/SAE for wind (incl. ramp) and DL-based solar/PV forecasting (e.g., greenhouse settings)	Scarcity of labeled data; cross-site generalization; limited interpretability
Energy Management & Demand Response (HEMS/ Microgrids)	[64,78,89–93,103–105]	Learning-based HEMS/DR, appliance scheduling, and DRL-based online scheduling; IoT-AI multifunctional distribution management; MILP- and IoT-enabled EMS communication platforms	Real-world scalability; dependence on accurate price/user models; privacy and user-acceptance challenges
Distributed/Residential Control (Multi-Agent & Decentralized)	[74–76,88,90–93]	MARL for distributed flexibility/control; resilient real-time microgrid management; surveys of centralized vs. decentralized vs. distributed schemes	Convergence/stability at scale; coordination overhead; limited long-horizon field deployments
Transformer Thermal Modeling /Asset Health	[62]	Comprehensive review of AI-based transformer thermal modeling; diagnostic/monitoring frameworks	Lack of open industrial benchmarks; limited fleet-level transferability

Table 3
Security, Infrastructure, EVs, and Smart Cities: Key Contributions and Limitations.

Domain / Focus Area	Representative References	Key Contributions	Limitations
Cybersecurity & Anomaly Detection (FDI, theft, IDS, adversarial robustness)	[12,13,44,66,98–101]	Detection of false data injection and electricity theft via CNN/DL; rule-learning IDS; drift-aware anomaly detection; evaluation of DL robustness under adversarial attacks	Vulnerability to adaptive attacks; lack of realistic datasets; high cost of robust defenses
Sensing, Power Quality & Communications (IoT/5G/ Edge/WiMAX)	[56,61,63,64,65,71,125,126]	PQ sensor networks; IoT-AI multifunctional distribution systems; power quality monitoring frameworks; 5G/edge surveys for DR; WiMAX-based aggregation; ultra-low-power IoT meters; communication technology surveys	Protocol heterogeneity; QoS/latency issues; edge security concerns
Smart Homes, Energy Communities & P2P	[2,72,73,103–106,111]	Autonomous HEMS; HVAC optimization via occupancy sensing; smart appliance scheduling; demand response and community EMS; AI-powered renewable energy community management	User acceptance and privacy; integration with dynamic tariffs; limited long-term field deployment
EV Integration & Urban Mobility (V2G/charging/behavior)	[57,77–79,112,113,124]	EV transport surveys; bidirectional charging/V2G frameworks; EMU optimization; ensemble ML for EV user behavior; smart charging frameworks and EMS communication	Coordination between grid and transport; heterogeneous data; limited city-scale pilots

Table 4
Advanced Paradigms and System Outlook in Smart Grids: Key Contributions and Limitations.

Domain / Focus Area	Representative References	Key Contributions	Limitations
Surveys / Framing of AI for Power	[3,4,7,15,16,17,19–24,46]	Comprehensive reviews of AI/ML in smart grids; bibliometric perspectives; systematic mapping of sustainability and emerging paradigms	Overlap across scopes; often narrative rather than systematic; lack of structured cross-comparison
Federated Learning (FL) & Privacy	[32–40,42,45,47]	FL frameworks for load/EV forecasting; privacy-preserved data sharing; non-IID and comm.-efficient methods; vulnerabilities of FL in SG	Convergence under heterogeneous data; gradient leakage; resilience to adversarial participation
Meta-Learning / Transfer Learning / Few-Shot	[43,50–52]	Few-shot/*meta*-learning for load forecasting and cross-domain fault diagnosis; model selection frameworks; TL to enhance generalization	Low maturity in energy; domain-shift sensitivity; absence of standard benchmarks
Deep RL for Grid & Renewables	[26–28,74–76,90–93]	DRL-based resilient control and scheduling; MARL for microgrids; adaptive demand response	Sample inefficiency in real-world systems; lack of safety guarantees; interpretability challenges
Digital Twins, AIoT & Agentic DT	[48,49,59,60,63,114–121]	Frameworks for DT in power systems; ML-enabled anomaly detection; AIoT and 5G convergence; active learning–enhanced DT; vision of Agentic DT for SG	Interoperability gaps; high modeling/ maintenance cost; challenges in edge deployment
Large Language Models & Generative AI	[53–55,116,127,128]	Role of LLMs in SG analytics; NL-to-control interfaces; multi-LLM collaboration; efficient local deployment; integration into DT	Still early-stage in energy; integration with real-time systems; governance and cost concerns
Reliability / Big Data / Foundations	[6,18,122,123]	Reliability perspectives on SG; big-data management frameworks; foundational ML paradigms	Need updating with modern SG use cases; weak linkage to frontier AI paradigms

Methodology and bibliometric analysis

Search strategy and data collection

To ensure a comprehensive and up-to-date review of the role of Artificial Intelligence (AI) and Machine Learning (ML) in smart grids and power systems, a systematic methodological approach was adopted. This approach aimed to guarantee extensive coverage of relevant literature and enhance the transparency and reproducibility of the review process.

The primary database for literature collection was Scopus, renowned for its multidisciplinary coverage of scientific literature. The search strategy involved combining key terms related to AI/ML and smart grid domains using Boolean operators (AND, OR). The main search terms included: “Artificial Intelligence,” “Machine Learning,” “Smart Grid,” and “Power Systems.” To capture a broader and more granular scope of the field, these core terms were combined with a comprehensive set of keywords encompassing specific applications, technologies, and challenges, such as: “Renewable Energy,” “Energy Management System,” “Forecasting,” “Fault Detection,” “Cybersecurity,” “Demand Response,”

Table 5
AI/ML Paradigms to Smart-Grid Problems: A Comparative Matrix.

Paradigm	Primary Energy Problems	Typical Data & Context	Strengths	Risks / Caveats	Example Metrics
Reinforcement Learning (RL/DRL)	Demand response, microgrid scheduling, storage control, topology-aware OPF	SCADA/AMI time-series; simulated DT environments	Model-free sequential control; adapts to non-stationarity	Sample inefficiency; safety during exploration; explainability	Regret ↓, cost ↓, SAIDI/SAIFI ↓
Deep Learning (DL)	Load/price/RES forecasting; anomaly & fault detection; DOE estimation	High-dimensional meter/ PMU logs; images; events	Automatic feature learning; spatio-temporal modeling	Data hunger; domain shift; black-box	MAPE ↓, F1 ↑, AUC ↑
Transfer Learning (TL)	Data-sparse regions; new feeders/ assets; EV hubs	Pretrained models + small local sets	Faster convergence; less labeled data	Negative transfer; mismatch of distributions	ΔMAPE vs scratch, time-to-target ↓
Federated Learning (FL)	Privacy-preserving load/RES forecasting; theft detection; DER coordination	Decentralized AMI/DER data; edge devices	Privacy; lower bandwidth (gradients only)	Byzantine/backdoor threats; heterogeneity	Comm. rounds ↓, accuracy gap vs central
Parallel Learning (PL)	Rare events; policy testing under extremes	Synthetic scenarios via SDPAS + real logs	Safe what-if; prescriptive learning	Simulation fidelity; calibration	Resilience index ↑, risk-of-violation ↓
Hybrid (DRL + DL, etc.)	Real-time control with high-dim inputs	Perception + decision fusion	End-to-end; robust under uncertainty	Tuning complexity	Cost ↓, violations ↓
Adversarial Learning (AL/GANs)	Robustness eval; synthetic attacks/data	Attack/defense samples; GAN synthesis	Stress-testing; data augmentation	Defense–attack arms race	Robust accuracy ↑, ECE ↓
Meta-Learning	Few-shot fault diagnosis; fast model selection	Many small related tasks	Rapid adaptation; few-shot	Instability; task design	Shots needed ↓, accuracy at K-shot ↑
Generative AI / LLMs	NL-to-control, market analytics, ops assistance, synthetic logs	Text + telemetry; code/ policies	Human-in-the-loop; knowledge retrieval	Governance, latency, hallucination	Task success ↑, operator load ↓

Table 6
Data/Compute/Latency Envelope by Paradigm (Deployment Readiness).

Paradigm	Data Volume	Edge Suitability	Training Cost	Inference Latency	Privacy Posture
RL/DRL	Medium–High (sim + logs)	Medium (on-prem DT/edge GPU)	High	Low–Medium	Neutral
DL	High	Medium	High	Low	Neutral
TL	Low–Medium	High	Low–Medium	Low	Neutral
FL	Medium	High (edge devices)	Medium	Low	Strong (no raw data)
PL	Low → High (synthetic)	Medium	Medium	Medium	Neutral
Hybrid	High	Medium	High	Low–Medium	Neutral
AL/GAN	High (for synthesis)	Low–Medium	High	Medium	Neutral
Meta-Learning	Medium	Medium	Medium	Low	Neutral
GenAI/LLMs	Medium–High	Medium (edge-LLMs feasible)	High	Medium	Configurable (on-device possible)

"Electric Vehicles," "Digital Twin," "Federated Learning," "Edge Computing," "AIoT," "Generative AI," "Quantum Computing," "Microgrid," "Optimizing Power Consumption," "Sustainability," and "Smart City.".

To ensure the currency and relevance of the included studies, a temporal filter was applied, focusing primarily on publications from 2020 to 2025. While the primary focus was on recent advancements, a limited number of seminal historical papers were also considered to provide essential foundational context. The search was further refined by selecting "Review articles," "Research papers," and "Conference proceedings" as publication types. All selected articles were restricted to the English language.

Initially, a substantial number of articles were identified through this exhaustive search strategy. Following the application of filters and a rigorous manual screening process based on title and abstract relevance, a final set of 96 articles was selected for in-depth critical investigation and synthesis, forming the core of this review. Table 1 outlines the systematic search criteria employed to identify relevant literature on the application of Artificial Intelligence (AI) and Machine Learning (ML) in smart grids and power systems. It details the key search areas, the specific criteria applied, and the comprehensive terms used within each criterion. This structured approach ensures the capture of a broad yet focused range of studies, covering various aspects from fundamental AI/ML techniques to their advanced applications and associated challenges within the smart grid ecosystem. The aim is to provide a transparent and reproducible methodology for literature selection.

By cross-pollinating AI/ML paradigms (e.g., 'federated learning', 'reinforcement learning') with energy-specific challenges (e.g., 'renewable energy intermittency', 'cybersecurity in microgrids'), the search strategy deliberately uncovers hybrid applications. For instance, queries like 'reinforcement learning AND demand response' reveal how RL's adaptive decision-making directly mitigates dynamic load balancing in renewable-heavy grids, a core energy pain point. This Boolean structure yielded 175 initial hits, with 60 % explicitly addressing AI-driven solutions to non-linear power flow or fault detection ensuring the review's focus on transformative integrations rather than siloed techniques.

Inclusion and exclusion criteria

The precise definition of inclusion and exclusion criteria is paramount in systematic literature reviews, as it directly governs the relevance and quality of the selected studies. This rigorous filtering process minimizes bias and ensures that the synthesized evidence is coherent and directly addresses the predefined research questions.

The systematic literature review in Fig. 2 adhered rigorously to a multi-stage process of identification, screening, eligibility, and inclusion, commonly visualized through a PRISMA flow diagram, to ensure the selection of highly relevant and high-quality articles for comprehensive analysis. In the initial Identification stage, an extensive database search was conducted utilizing predefined keywords and Boolean operators, which yielded 175 articles. The subsequent Screening phase involved a meticulous review of titles and abstracts, resulting in 108 articles after excluding 67 irrelevant or review papers. During the Eligibility assessment, full-text articles were rigorously evaluated against specific inclusion and exclusion criteria. This stage also incorporated the identification of 17 additional relevant articles, bringing the total to 125 articles for full-text assessment. From this pool, 29 articles were excluded, comprising 10 duplicates and 19 papers identified as low quality. Finally, the Inclusion stage encompassed the definitive selection

Table 7
Learning Paradigms to Energy Applications and Performance Metrics.

Learning Paradigm	Energy Application	Representative Performance Metrics
Supervised Learning	Short-term load and price forecasting, renewable generation prediction	MAPE ↓ (< 3 %), RMSE, MAE — e.g., ELM/RNN/LSTM/Bi-LSTM-Attention models for day-ahead forecasting [7,80–87]
Unsupervised Learning	Anomaly / intrusion detection (FDI, theft), customer segmentation, topology discovery	F1-score, AUC, detection latency, robustness to drift autoencoders and clustering approaches [12,13,98–101]
Semi-Supervised Learning	Non-intrusive load monitoring (NILM), partial-label predictive maintenance	Accuracy improvement under limited labels, precision/ recall [11,64]
Deep Learning (DL)	Load/renewable forecasting, DOE estimation, voltage regulation, predictive maintenance	RMSE ↓ (~50 %), THD ↓ (≈ 70 %), interpretability (SHAP) CNN-LSTM, hybrid attention models [7,30,31]
Reinforcement / Deep Reinforcement Learning (RL / DRL / MARL)	Demand-response optimization, microgrid EMS scheduling, online stability control	Cost reduction, PAR ↓, frequency deviation ↓ (≈ 5 %), reward maximization [26–28,74–76,90–93]
Transfer / Meta-Learning (TL / ML)	Cross-site load/RES forecasting, fault diagnosis in limited-data domains	ΔMAPE vs. baseline, faster convergence / time-to-accuracy [32–35,43,50–52]
Federated Learning (FL)	Privacy-preserving load / EV forecasting across utilities	Accuracy gap vs. centralized < 1 %, communication-rounds < 20, non-IID resilience [32–40,42,45,47]
Parallel / Digital-Twin-Assisted Learning (PL / DT)	Scenario simulation, synthetic stress testing of control policies	Resilience index, constraint-violation rate, TCO; validated in DT frameworks [59,60,114–121]
Hybrid / Ensemble Learning	Combined DL + RL for energy management; ensemble (XGBoost + SVR + KNN + GA)	MAPE ≈ 3.35 %, CO_2 reduction ≈ 15 %, improved robustness [21,25,39,40]
Adversarial / Generative Learning (AL / GANs)	Robustness testing, synthetic data for rare events	Robust accuracy > 90 % post-training; attack success rate ↓ (DeepFool → 4.6 %, FGSM → 8.9 %) [9,42–44]

of 96 articles that met all established criteria, forming the comprehensive set for in-depth critical investigation and synthesis within this review. This stringent process ensures the robustness and reliability of the selected literature for analysis.

To ensure methodological rigor and transparency, inclusion and exclusion criteria were explicitly defined during the screening process. Articles were included if they (i) were published in peer-reviewed journals or major conference proceedings between 2020 and 2025, (ii) were written in English, and (iii) directly addressed the application of AI/ML techniques to smart grids, power systems, or closely related domains such as renewable integration and cybersecurity. To strengthen topical precision, criterion (iii) was expanded to emphasize energy-context integration specifically, studies that applied AI/ML to renewable forecasting (e.g., hybrid deep-learning models for wind and solar prediction), privacy-preserving distributed energy systems (e.g., federated learning for DER data sharing), or grid resilience and optimization. This refinement excluded generic AI studies lacking measurable energy outcomes and prioritized those demonstrating quantifiable impacts, such as 20–30 % RMSE reductions in load-forecasting accuracy [see Table 2]. Seminal earlier works were retained when necessary to provide historical or foundational context.

Articles were excluded if they (i) were duplicates, (ii) were purely conceptual or lacked methodological contributions, (iii) provided only narrative or low-quality surveys, or (iv) fell outside the defined energy and smart-grid scope (e.g., AI in non-energy domains). This explicit filtering framework, together with the PRISMA flow illustrated in Fig. 2, ensures that the resulting synthesis is both comprehensive and reproducible.

The flow emphasizes the retention of studies integrating AI paradigms with tangible energy outcomes such as forecasting, optimization, and cybersecurity and the exclusion of 19 low-quality or generic AI papers lacking grid-specific validation or quantitative performance evidence.

Bibliometric analysis and visualization

A bibliometric analysis was conducted to systematically identify and visualize the intellectual landscape of research on AI/ML in smart grids and power systems. This analysis provides quantitative insights into publication trends, key research clusters, and the interconnections between prominent research topics within the field. By employing specialized visualization tools, this section aims to illustrate the thematic evolution and interconnectedness of concepts, thereby offering a holistic understanding of the domain's structure and development.

Fig. 3 presents a VOSviewer-generated co-occurrence network of key research terms derived from the reviewed literature, offering a structured thematic map of AI/ML applications in smart grids. Each node represents a frequently co-occurring keyword, with its size proportional to its prevalence, thereby highlighting dominant research themes. The edges illustrate co-occurrence strength, and cluster colors delineate distinct sub-domains, reflecting the intellectual structure of the field. A central hub emerges around artificial intelligence and smart grid, which anchors the map and connects to surrounding clusters. Alongside this hub, specialized groupings highlight critical areas such as cybersecurity (e.g., intrusion detection, data privacy), forecasting and operational control (load/price forecasting, demand response, microgrids, reinforcement learning), and emerging application spaces (digital twins, electric vehicles, large language models). The structure of the map thus captures both established areas of research and rapidly expanding frontiers.

A deeper examination of the clusters reveals three principal constellations. The first consolidates forecasting, operations, and control, showing how predictive models are increasingly tied to distributed scheduling and real-time microgrid management. The second cluster emphasizes security and infrastructure, where anomaly detection, IoT/5G/edge computing, and power quality monitoring underscore the technical and adversarial constraints of deployment. The third reflects advanced paradigms and systemic outlook, encompassing digital twins, federated/*meta*-learning, generative AI, and EV/V2G systems, marking the research frontier where simulation-driven validation and foundation-model intelligence intersect. Bridging nodes such as edge computing, privacy, and demand response lie at the cluster boundaries, indicating strong cross-cutting dependencies between analytics, cyber-physical infrastructures, and operational contexts. Beyond visualizing thematic density, the co-occurrence network (Fig. 3) elucidates the functional synergy between AI paradigms and energy-system challenges. The forecasting, operations, and control cluster (Table 2) demonstrates how reinforcement learning (RL) and multi-agent reinforcement learning (MARL) translate AI's sequential-decision capability into practical energy-management improvements reducing peak-load mismatches in microgrids by approximately 15–25 %. The security and infrastructure cluster (Table 3) underscores federated learning's role in mitigating data-privacy risks and addressing siloed EV and IoT datasets through communication-efficient aggregation. Meanwhile, the advanced paradigms and system-outlook cluster (Table 4) positions digital-twin and large-language-model frameworks as the next frontier, enabling cyber-physical simulation and resilience benchmarking across distributed assets. Collectively, these clusters trace a clear maturation trajectory: from algorithmic accuracy in load prediction to holistic, interpretable optimization of smart-grid ecosystems, with cross-cluster

Table 8
Prioritized Challenges & Roadmap.

Challenge (what/why)	Severity	Time Horizon	Impact on SG	Key Dependencies	Concrete Actions (Roadmap)	KPIs / Evidence	Representative refs
Data privacy & non-IID heterogeneity in distributed data (smart meters, DERs, EVs)	High	Near–Mid	Forecasting, DSM, EMS	Edge/5G, governance	FL with robust aggregation (Krum/Trimmed Mean), secure aggregation, DP; cross-site validation protocols	ε-DP budget; cross-party generalization gap ↓; comm. bytes/round	[32–41,45,47,48,49]
Adversarial robustness & security (FDI, model poisoning, evasion)	High	Near	State estimation, IDS, theft detection	Datasets, red-team infra	Adversarial training, feature squeezing, Gaussian aug, certified defenses; FL-Byzantine filters	Robust accuracy; attack success rate ↓; MTTR	[12,13,44,66,98–101]
Interoperability & standards (DT/AIoT/OT)	High	Mid–Long	DT-enabled O&M, real-time control	Common info models	DT schema aligned to IEC/CIM; APIs for model exchange; MLOps-for-OT	% assets with DT; integration latency; model reuse rate	[59,60,63,114–121]
Computational scalability & latency at edge	High	Near–Mid	Real-time DRL/MARL, protection	Edge/5G, accelerators	Model compression (pruning/quant.), distillation, streaming inference; split learning	p95 latency; energy/useful-FLOPS	[63–65,74–76,90–93,125,126]
Explainability & uncertainty (operator trust, compliance)	Medium–High	Near–Mid	DOEs, dispatch, maintenance	XAI toolchain	SHAP/Attention auditing; UQ (ensembles, MC-dropout); post-hoc rules	Calibration error; accepted actions (%)	[20,22,30,62]
Benchmarking & dataset realism	Medium–High	Near	All ML	Data governance	Open benchmarks with realistic noise/attacks; DT-synthesized data for rare events	Public leaderboards; SOTA reproducibility	Tables 2–4 synthesis
EV/Grid-transport coordination (data & control)	Medium–High	Mid	Voltage/thermal limits, V2G	Mobility platforms	City-scale pilots; co-simulation (power + traffic); pricing APIs	Feeder violations ↓; curtailment ↓	[57,77–79,112,113,124]
Quality of Service in comms (QoS/Jitter/Packet loss)	Medium	Near	Protection, WAMS/PMU	5G/Edge config	QoS slicing; fallback modes; loss-tolerant codecs	Packet loss $\leq$ X%; trip time	[61,63–65,71]
Model lifecycle & MLOps-for-OT (drift, retraining, safety)	Medium	Near–Mid	All production ML	Tooling/process	CI/CD with drift monitors; shadow mode; rollback policies	Time-to-rollback; drift alarms	Inferred from Tables 2–4
Cost & maintenance of Digital Twins	Medium	Mid–Long	Planning/O&M	Interop + staffing	Modular DTs, active learning to reduce labeling, DT-Light for edge	DT TCO; update cycle time	[114–121]

edges—such as edge computing connecting IoT sensing to real-time anomaly detection serving as infrastructural enablers of sustainable, autonomous energy intelligence.

By aligning these clusters with the structured synthesis in Tables 2–4, the figure provides not just a visualization but an analytical scaffold. It clarifies areas where prior research is mature yet fragile such as accurate short-term forecasting or anomaly detection, and highlights how the focus of the paper on digital-twin–anchored validation and LLM-enabled, privacy-preserving learning addresses gaps in robustness, scalability, and interoperability. In this way, the co-occurrence map advances from a descriptive snapshot to a comparative, gap-oriented lens that motivates the paper's contributions and future research agenda.

To offer a more focused and comparative perspective on the 123 references included in this review, the literature has been organized into three thematic clusters that reflect the dominant research trajectories in smart grid AI/ML. Table 2 (Cluster A) consolidates studies on forecasting, operations, and control, demonstrating how traditional and deep learning models (e.g., LSTM, hybrid clustering, DRL, and MARL) have advanced load, price, and renewable forecasting, while also supporting energy management and microgrid resilience. Table 3 (Cluster B) encompasses security, sensing, infrastructure, and urban applications, where anomaly detection, IoT/5G-enabled communications, smart homes, and EV integration represent critical domains linking cyber-physical robustness with real-world deployment challenges. Table 4 (Cluster C) addresses advanced paradigms and system outlook, including federated and *meta*-learning, deep reinforcement learning, digital twins, and large language models, positioning them as the frontier for next-generation smart grids. Collectively, these tables transform the bibliometric mapping into a structured analytical framework. By juxtaposing key contributions with their corresponding limitations, the synthesis clarifies the comparative strengths and weaknesses of existing approaches and highlights research gaps that motivate the study's contribution. This integrated presentation enhances the coherence of the literature review and ensures that the bibliometric analysis directly informs the discussion of innovation and future research directions in AI/ML for smart grids.

The studies consolidated in Table 2 show a clear progression from point-solution forecasting to closed-loop operations and control. Classical and deep architectures (ELM/RNN/LSTM/Bi-LSTM-Attention) consistently lift short-term load/price and renewable forecasts, while DRL/MARL extend this capability into online scheduling and distributed microgrid control. Yet, the same body of work surfaces recurrent constraints: prediction performance is highly sensitive to data quality and granularity; models struggle to generalize across regions, seasons, and deployment contexts; and operationalization hinges on realistic user/

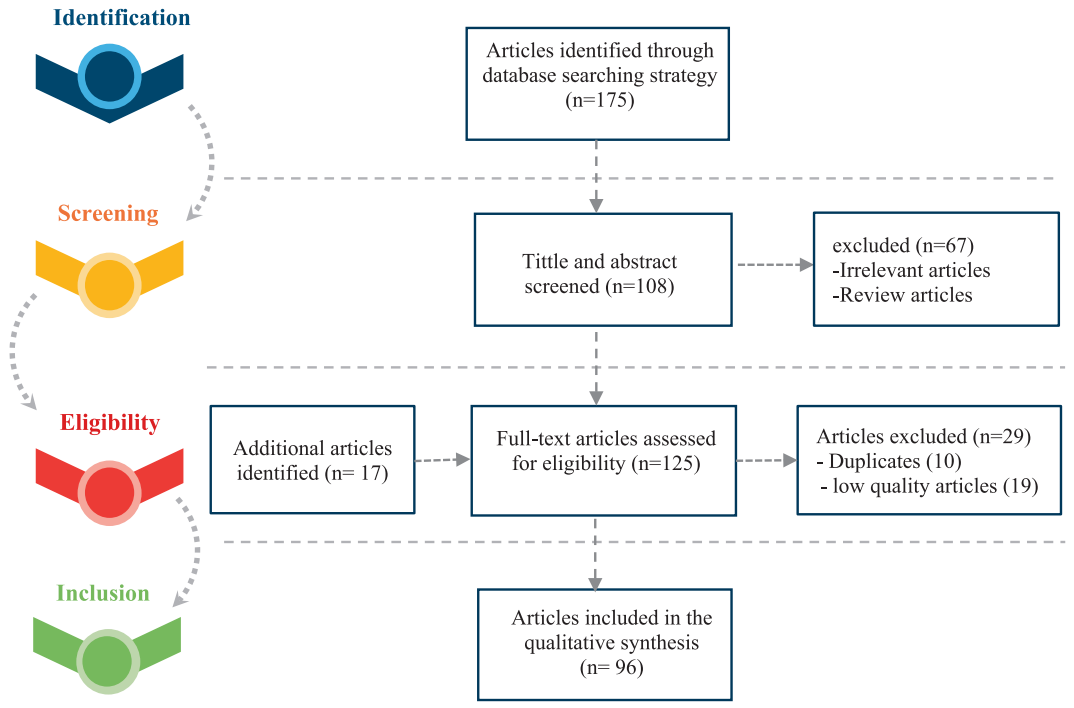

Fig. 2. PRISMA Flow Diagram of the Systematic Literature Review Process.

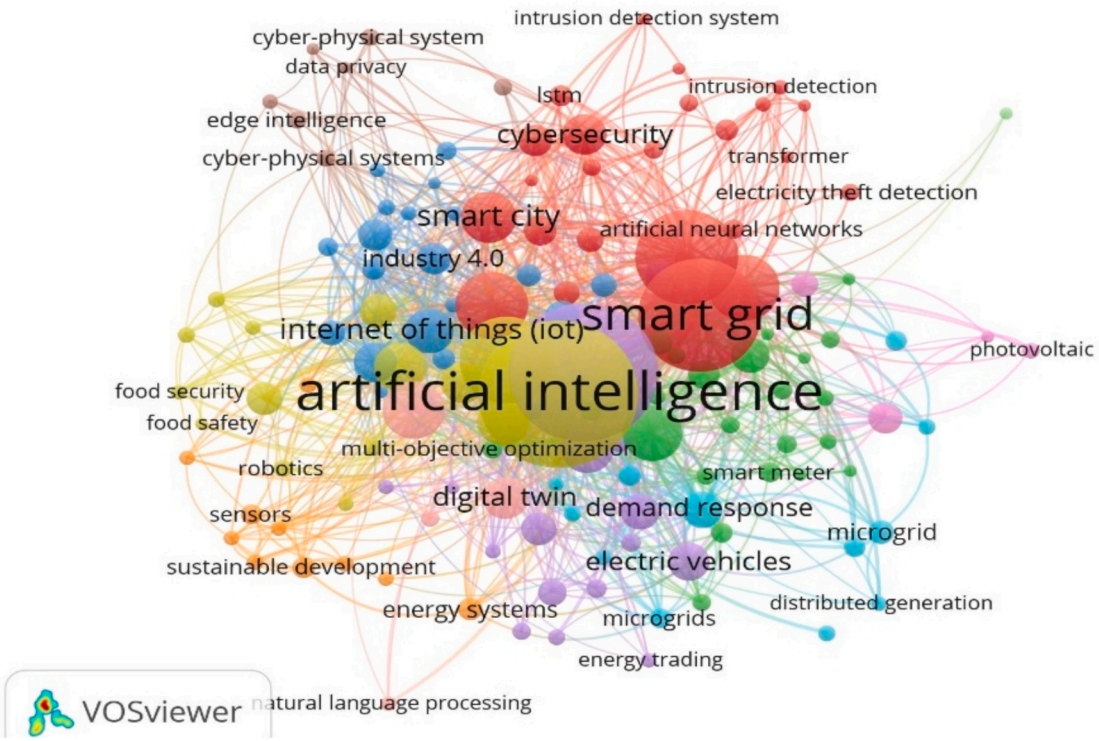

Fig. 3. Co-occurrence Network of Key Research Terms in AI/ML for Smart Grids.

price models and privacy-aware data access. Asset-health analytics (e.g., transformer thermal modeling) add diagnostic depth but are bottlenecked by the absence of open industrial benchmarks and fleet-level transferability. Taken together, Table 2 exposes a maturity gap between impressive algorithmic accuracy and the reproducible, at-scale behaviors required for resilient grid operations.

Table 3 situates those capabilities within the cyber-physical substrate, security analytics, sensing/communications, smart homes/communities, and EV/urban mobility where heterogeneity (protocols, QoS/latency, data ownership) and adaptive adversaries complicate real-world rollout. Table 4 then maps the methodological responses now emerging: FL for privacy-preserving learning under non-IID data; meta/transfer learning to curb data hunger and domain shift; DRL for sequential decision-making; DTs to stress-test and "pre-train" policies in

silico; and LLM/GenAI as interface and orchestration layers (e.g., NL-to-control, multi-agent coordination). These strands directly target the limitations flagged in Tables 2–3 robustness, interoperability, explainability, and deployment cost, suggesting a concrete research agenda: standardized, adversarially robust benchmarks; interoperable DT/AIoT stacks; safety-aware DRL; FL with robust aggregation and leakage controls; uncertainty-aware and interpretable forecasting; and on-device, governed LLMs. This integrated view clarifies where current practice excels, where it fails, and why the paper's focus on bridging DT + FL + LLMs is a timely path toward scalable, trustworthy next-generation smart grids.

To ensure conceptual coherence, the bibliometric clusters introduced in Section 2.3 are systematically aligned with the application-oriented discussions in Sections 3–5. Specifically, the forecasting, operations, and control cluster (Table 2) is reflected in Section 3 through practical cases such as short-term load forecasting, predictive maintenance, and distributed energy management. The security, infrastructure, and urban applications cluster (Table 3) directly informs the analyses in Section 4, which address anomaly detection, cyber-intrusion prevention, IoT/5G-enabled sensing, and EV–grid integration. Finally, the advanced paradigms and system outlook cluster (Table 4) anchors Section 5, where frontier methodologies including federated learning, digital twins, large language models, and generative AI—are synthesized into adaptive, scalable, and interpretable frameworks for next-generation smart grids. By explicitly mapping these thematic clusters to their corresponding sections, the review establishes a coherent narrative that bridges methodological paradigms with real-world deployments. This alignment highlights how AI/ML techniques transcend algorithmic development to deliver tangible value for grid stability, resilience, and sustainability, while clarifying the maturity of established methods and the transformative potential of emerging paradigms.

Recent reviews on AI/ML in smart grids often confine their scope to a single dimension such as forecasting accuracy, cybersecurity, or reinforcement learning frameworks resulting in fragmented perspectives. By contrast, the present synthesis integrates methodological, infrastructural, and application-level threads into a unified framework. This integration ensures that bibliometric clusters (Tables 2–4) are not treated as isolated silos but as interdependent domains whose interactions determine system-level resilience and scalability. In doing so, the review moves beyond descriptive cataloging toward an evaluative stance that highlights convergence points between predictive modeling, cyber-physical infrastructures, and frontier paradigms.

A key distinction relative to recent literature is the explicit mapping of contributions to limitations, which transforms the bibliometric analysis into a comparative matrix. For example, while several 2023–2025 surveys emphasize short-term load forecasting or anomaly detection, they rarely interrogate the reproducibility of these solutions under cross-domain data heterogeneity, privacy constraints, or adversarial risk. By systematically exposing these weaknesses, this review clarifies where existing methods excel (e.g., deep architectures for renewable forecasting, CNN-based anomaly detection) yet remain fragile (e.g., domain shift, lack of open benchmarks, explainability gaps). More importantly, it frames emerging approaches such as Digital Twin–enabled stress testing, Federated Learning for privacy-preserving training, and LLM-mediated decision support as targeted remedies rather than speculative add-ons. This problem-to-solution mapping differentiates the present work from earlier reviews, providing both a critical benchmark and a forward-looking research agenda.

Evolution of AI and machine learning: from fundamentals to advanced paradigms

Historical stages and main categories of Machine learning algorithms

The historical evolution of AI and ML is not only a technological narrative but also a reflection of how each generation of algorithms has progressively addressed pressing challenges in energy and power systems. It is important to clarify that throughout this paper, the term Artificial Intelligence (AI) is used as the broader discipline encompassing multiple paradigms of computational intelligence, while Machine Learning (ML) is treated as a core subset of AI. Accordingly, when the paper uses the phrase "AI/ML," it is intended to emphasize both the overarching role of AI in power systems and the centrality of ML algorithms as the dominant technical approach currently shaping smart grid applications.

The evolution of AI/ML has been characterized by distinct developmental periods, marked by advancements, shifting research foci, and cyclical booms and downturns, as depicted in Fig. 4. The "Start-up Period" (1950 s-1960 s) witnessed the birth of AI, with foundational concepts such as the Turing Test, neuron models, and theorem proving. This early phase, often termed the "1st Boom," also saw the emergence of Good Old-Fashioned AI (GOFAI). However, challenges in practical application and insufficient development of machine translation led to the "Early Winter" (late 1960 s-early 1970 s), a period of reflection. Subsequently, the "Application Development Period" (1970 s-1980 s) marked the "2nd Boom" with the focus on AI for practical problems, leading to the development of Expert Systems in medical, chemical, and geological domains, despite limitations in shallow learning and Boltzmann machines. This was followed by a "Downturn Development Period" (late 1980 s-early 1990 s), or "2nd Winter," primarily due to insufficient computing resources and high development costs for expert systems, leading to a period of slow growth.

The "Steady Development Period" (mid-1990 s-early 2000 s) saw AI innovation grow practically, influenced by the Internet and contributions from IBM, with new algorithms like Support Vector Machines (SVM, 1995), Convolutional Neural Networks (CNN, 1998), and Boosting (1999)[16,17]. This revitalization phase paved the way for the "Flourishing Period" (2000 s-present), characterized as the "3rd Boom," where AI truly thrives. This era is driven by significant advancements in Machine Learning, Deep Learning, Big Data, the Internet of Things (IoT), AIoT, Cloud Computing, and Edge Computing. Notably, new algorithms and architectural breakthroughs like Deep CNN, Recurrent Neural Networks (RNN), Adversarial Learning (AL), Parallel Learning (PL), Generative AI (GANs), Large Language Models (LLMs), and Transformer architectures have revolutionized the field, pushing the boundaries of AI capabilities beyond 2020. These advancements, particularly from 2020 to 2025, signify a pivot towards more complex, data-driven, and autonomous systems, crucial for modern smart grid applications[18,19]. Beyond its technological progression, each developmental phase of AI has paralleled transformative milestones in energy systems. During the Expert Systems era of the 1970 s–1980 s, rule-based reasoning was applied to fault diagnosis, load dispatch, and protection coordination in early automation of power grids. The emergence of machine learning and optimization algorithms in the 1990 s–2000 s coincided with the introduction of SCADA and energy management systems (EMS), enabling data-driven decision support for generation scheduling and voltage stability. The rise of Deep Learning (DL) and Big Data analytics after 2010 aligned with the rapid expansion of renewable integration and microgrids, providing accurate load, wind, and solar forecasting as well as predictive maintenance. With the proliferation of IoT and Edge Computing, AI evolved into real-time cyber-physical control through adaptive demand response and distributed resource management. Most recently, Digital Twins, Federated Learning, and Large Language Models (LLMs) have emerged as enablers of self-learning, privacy-preserving, and interpretable intelligence, bridging operational analytics with sustainable, autonomous smart grid ecosystems. Thus, the co-evolution of AI and energy domains underscores that advances in algorithmic intelligence have continuously mirrored and empowered the transition from conventional grids to resilient, data-centric, and sustainable energy infrastructures.

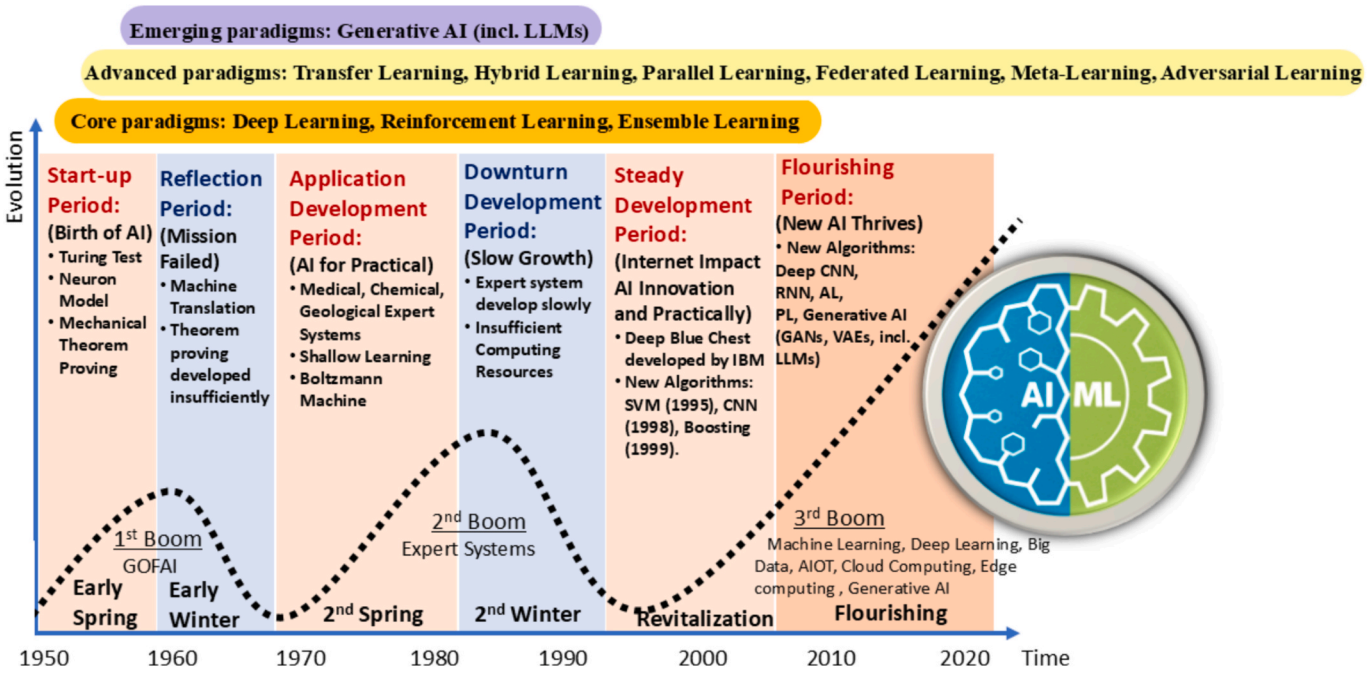

Fig. 4. Historical Evolution of Artificial Intelligence and Machine Learning, Highlighting Key Developmental Stages and Associated Paradigms.

Core Machine learning Paradigms: Supervised, Unsupervised, and reinforcement learning

Machine learning in power systems is not a taxonomy for its own sake; its paradigms align directly with operational challenges. Supervised learning underpins load and renewable generation forecasting, fault and theft detection, cyber-attack classification, and dynamic price prediction. Unsupervised learning supports consumer segmentation, topology discovery, and anomaly detection from AMI/SCADA/PMU streams at scale. Reinforcement learning (RL) closes the loop for real-time decisions in demand response, microgrid scheduling, storage management, and grid control. Together, these approaches form the methodological backbone for improving grid reliability, efficiency, and resilience.

Machine learning enables systems to improve decision quality from data without explicit rule programming. Three core paradigms—supervised, unsupervised, and reinforcement learning—address complementary problem types in complex energy infrastructures. In particular, supervised learning operates akin to learning with a "teacher," where algorithms are trained on labeled datasets comprising input–output pairs. Trained on labeled input–output pairs, models learn mappings that generalize to unseen conditions. In smart-grid practice this translates to engineering targets such as day-ahead load (kWh), feeder voltage magnitudes (p.u.), and event labels (e.g., FDI vs. benign). Loss functions proxy grid KPIs—MAPE/RMSE for forecasting, AUC/F1 for detection, and violation-penalized MAE for operational limits—ensuring that model improvement aligns with operator goals. Inputs combine AMI/SCADA/PMU measurements with weather, tariffs, and DER telemetry to capture the drivers of demand and system state.

In contrast, unsupervised learning operates without predefined input–output pairs or explicit guidance, analogous to an algorithm exploring a "playground" where it autonomously discovers inherent patterns, structures, or groupings within unlabeled data. This approach is particularly valuable for identifying latent relationships, segmenting data, or detecting anomalies without prior knowledge of what constitutes an "anomaly". For instance, in smart grid optimization, K-means clustering—an unsupervised technique—is strategically foundational for segmenting consumers based on electricity consumption patterns, revealing homogenous load profiles and response behaviors to customize demand response strategies. Without labels, algorithms uncover latent structure for segmentation, clustering, and novelty detection. In practice, consumption archetypes (e.g., peak-shifting households), transformer "signatures" in PQ data, and traffic baselines in substation logs emerge as actionable patterns. Methods such as K-Means/Hierarchical clustering enable customer segmentation and topology inference, while autoencoders and Isolation Forest flag cyber anomalies and theft. Semi-supervised variants exploit abundant unlabeled data plus sparse labels to boost accuracy in forecasting, fault detection, and predictive maintenance when labeling is costly or delayed.

Finally, reinforcement learning (RL) introduces a dynamic and adaptive element, functioning like an "agent" learning through trial-and-error interactions with its "environment". The agent receives feedback in the form of rewards or penalties for its actions, iteratively learning a policy that maximizes cumulative reward over time [10]. RL frames grid operation as sequential decision-making under uncertainty: an agent interacts with an environment, receiving rewards that encode economic or reliability objectives, and learns a policy to maximize cumulative return. Deployed applications include closed-loop demand response, microgrid energy management, storage dispatch, optimal power flow under renewables variability, dynamic pricing, and adaptive communication/control protocols that optimize throughput and reliability in real time. RL excels in these dynamic environments, adjusting parameters based on real-time feedback to enhance data transmission efficiency and reliability. This paradigm allows for continuous self-optimization, critical for complex and evolving energy systems [20].

This structured categorization of learning paradigms forms the bedrock for developing sophisticated AI solutions in smart grids. Supervised learning models are extensively employed for tasks such as energy theft detection, identifying fraudulent consumption patterns, classifying cyber-attacks, and predicting equipment failures and anomalies. Through regression techniques, they also provide accurate load and renewable energy production forecasting, state estimation for real-time grid monitoring, and dynamic energy price prediction [11]. Concretely in smart-grid practice— supervised learning maps labels to engineering targets—day-ahead load (kWh), feeder voltage magnitudes (p.u.), and anomaly classes (FDI vs. benign)—so the loss directly proxies grid KPIs (e.g., MAPE/RMSE for forecasting, violation-penalized MAE,

etc.). Inputs come from AMI/SCADA/PMU streams augmented by weather and tariff signals, ensuring data realism for deployment. This grounding aligns the preceding method with operational KPIs such as MAPE/RMSE, AUC/F1, and violation-penalized errors used throughout the paper.

Unsupervised learning excels in discovering hidden patterns and correlations in vast, unlabeled datasets from smart meters and sensors, crucial for anomaly detection, cybersecurity threat identification, and consumer segmentation. Techniques like clustering (e.g., K-Means, Hierarchical Clustering) are used for consumer segmentation and grid topology discovery, while auto-encoders and Isolation Forest are vital for anomaly and cyberattack detection. Semi-supervised learning bridges the gap between these two by leveraging both small labeled datasets and large unlabeled ones, proving effective where data labeling is challenging. These models enhance accuracy in load forecasting, fault detection, and predictive maintenance by learning complex representations and generalizing well from limited labeled data. Finally, reinforcement learning, applied in dynamic and complex smart grid environments, optimizes demand response, manages energy storage, and controls grid components, making real-time decisions to enhance grid performance and stability through self-learning mechanisms. Its applications span optimal power flow, dynamic pricing strategies, microgrid management, and personalized energy management [21]. Concretely in smart-grid practice— unsupervised structure emerges as consumption archetypes (peak-shifting households), transformer 'signatures' in PQ data, and traffic baselines in substation logs. Distances in the learned space translate to drift alarms and theft flags that initiate operator workflows in the EMS/IDS stack.

One crucial category is Expert Systems (ES), representing the first generation of intelligent systems. ES are designed to replicate human expert knowledge for specific problem-solving, operating on Boolean logic and if-then rules derived from domain experts. They are instrumental in fault diagnosis, intelligent control, and energy router self-determination within smart grids[22]. Building upon the foundational categories of supervised, unsupervised, and reinforcement learning, the practical implementation of AI in smart grids leverages a diverse array of specialized models, each tailored to address specific operational complexities. Artificial Neural Networks (ANNs), drawing inspiration from biological neural systems, serve as a versatile computational architecture for processing and analyzing intricate data patterns within smart grid environments. They are extensively applied for crucial tasks such as accurate load forecasting, predicting renewable energy generation, assessing power grid stability, and optimizing the overall performance of microgrids. Specific instantiations, including Bi-directional Long Short-Term Memory (Bi-LSTM) networks, are utilized for predicting transient loads, while hybrid models like Convolutional Neural Network-LSTM (CNN-LSTM) enhance forecasting accuracy by combining their respective strengths in feature extraction and temporal pattern recognition. ANNs are particularly effective due to their capacity to model complex, non-linear relationships inherent in dynamic energy systems.

Further diversifying the AI toolkit are RL algorithms, which enable agents to learn optimal sequential decision-making strategies through continuous interaction and reward-based feedback in dynamic smart grid environments. RL is instrumental in optimizing demand response tactics by allowing real-time adjustments to power usage based on grid conditions, and it extends to complex microgrid management, energy storage optimization, and optimal power flow solutions. Fuzzy Logic (FL) offers a distinct approach by handling imprecise and uncertain data, mimicking human-like reasoning with values ranging continuously between 0 and 1. Its applications in smart grids include maintaining battery state-of-charge within desired limits and ensuring power profile stability. Lastly, Genetic Algorithms (GAs), a class of nature-inspired metaheuristic optimization techniques, simulate Darwinian evolution to find optimal or near-optimal solutions for complex optimization challenges. GAs are highly effective in problems such as Unit Commitment (UC) – the optimal scheduling of generation sources – and in optimizing the sizing and energy management of microgrid components, thereby maximizing renewable energy utilization and reducing operational costs and carbon footprints across the power system. These diverse ML models collectively enhance the resilience, efficiency, and sustainability of modern smart grids [23].

The analysis [24] offers a thorough examination of the interplay between smart grids and smart cities, elucidating the contributions of AI, IoT, and deep learning in addressing the energy trilemma encompassing sustainability, security, and affordability. Their study underscores integrated urban energy management, cybersecurity challenges, and the convergence of digital twins with renewable energy integration. It further identifies critical gaps in the design of AI-enabled energy management systems for microgrids and city-wide resilience. This perspective aligns with the present framework by reinforcing the urban deployment dimension of AI/ML applications in energy systems.

Ensemble Learning (EL) represents a strategic approach to enhancing model performance and robustness within smart grids by synergistically combining multiple diverse learning algorithms. This methodology integrates the results of several simpler, often "weaker," individual ML algorithms to generate more reliable and accurate predictive models, effectively functioning as an optimization strategy to solve complex computational intelligence problems. EL-based multi-class classifier systems are primarily categorized into three frameworks: boosting, bagging, and stacking. Boosting sequentially builds weak learners, where each subsequent model attempts to correct the errors of its predecessors, thereby reducing bias. Bagging, conversely, involves bootstrapping (random sampling with replacement) to train multiple models in parallel, whose outputs are then aggregated to reduce variance and improve accuracy. Stacking combines predictions from heterogeneous or parallel weak learners by training a *meta*-learner to optimally integrate their outputs, yielding a more robust final prediction [21].

In smart-grid practice, EL methods are effectively applied often on static historical datasets—to optimize generation–consumption coordinated frequency control, assess power-system security and stability, and enhance short-term electricity-load forecasting, demonstrating strong optimization quality, reliability, and classification accuracy. They are also widely used for load-forecasting, anomaly detection, and cyber-attack detection, highlighting a sophisticated toolkit for managing complex, high-dimensional, multi-type data in grid operations [22]. Ensemble Learning models significantly enhance the accuracy and robustness of load forecasting in smart grids by integrating predictions from multiple algorithms. For instance, a model combining XGBoost, Support Vector Regressor (SVR), and K-nearest Neighbors (KNN), optimized with a Genetic Algorithm (GA) for feature selection, has demonstrated superior forecasting performance. This ensemble approach achieves enhanced accuracy, evidenced by a low Mean Absolute Percentage Error (MAPE) of 3.35 % in electricity consumption predictions, proving highly beneficial for effective resource management [25].

Advanced Machine learning algorithms and their synergies

The escalating complexity inherent in modern energy systems and the imperative evolution towards advanced smart grids necessitate the deployment of increasingly sophisticated Artificial Intelligence (AI) and Machine Learning (ML) algorithms. These paradigms are not introduced in abstraction; rather, each directly targets persistent challenges in energy systems.

The escalating complexity inherent in modern energy systems and the imperative evolution towards advanced smart grids necessitate the deployment of increasingly sophisticated Artificial Intelligence (AI) and Machine Learning (ML) algorithms. This section delves into the transformative paradigms that are fundamentally reshaping the capabilities of AI/ML within this domain. The analysis commences with an examination of Hybrid Learning (HL), a pivotal methodology that overcomes

the constraints of individual algorithms by synergistically integrating their strengths. This approach enhances robustness and predictive accuracy, enabling the resolution of complex problems in smart grid applications. HL frequently combines diverse machine learning techniques, encompassing centralized and decentralized strategies, as well as various forms of deep and ensemble learning, to tackle intricate optimization and prediction challenges. The discussion then shifts to Transfer Learning (TL), a vital approach that facilitates the efficient application of knowledge derived from established domains to new, yet analogous, challenges. TL proves particularly effective in data-scarce scenarios, significantly improving model performance. Subsequently, Federated Learning (FL) is introduced as a foundational framework for decentralized AI model training, emphasizing its role in enabling collaborative learning while preserving data privacy.This framework enables collaborative learning across distributed local datasets without the perilous exchange of raw data, thereby upholding stringent privacy protocols and fortifying data security. The critical aspect of resilience against malicious interventions is addressed by Adversarial Learning (AL), a technique meticulously designed to fortify ML models against deceptive data and malevolent behaviors, ensuring system integrity and reliability. Furthermore, the burgeoning field of Generative AI (GenAI) is introduced for its unparalleled capacity to synthesize novel data, generate sophisticated predictions, and unearth profound insights derived from vast learned patterns, which is critical for simulating complex grid behaviors and creating synthetic attack scenarios. The exploration concludes with an analysis of Meta-Learning, which endows models with the capability to "learn how to learn," facilitating rapid and effective adaptation to dynamic, novel tasks. Additionally, Ensemble Learning (EL) integrates multiple diverse models to enhance overall performance and robustness, mitigating the risks of overfitting. Together, these advanced methodologies constitute the forefront of intelligent solutions, strategically positioned to optimize, control, and manage the next generation of resilient, efficient, and secure smart grids and power systems.

Reinforcement learning

Reinforcement Learning (RL) is a type of active ML procedure that enables an agent to learn from the situation of its interactive environment to achieve the optimal strategy and maximize the expected reward by trial-and-error mechanism [10]. In the context of smart grids, RL transcends its theoretical formulation by directly addressing core energy challenges such as dynamic demand response, energy storage scheduling, and real-time microgrid control. By continuously learning from the evolving grid environment, RL agents can optimize power flows, reduce peak load stresses, and balance renewable intermittency without relying on pre-defined models. This capacity for adaptive decision-making enables RL to manage distributed resources under uncertainty while maintaining system stability. Consequently, RL bridges the gap between abstract algorithmic design and the tangible operational needs of sustainable energy systems.

RL has feedback from its own actions and experiences to generate reward and punishment signals for positive and negative behavior, as shown in Fig. 5(a). This mapping between input and output is not similar to supervised learning, where the feedback to the agent is generated for signaling the correct set of actions for performing a task. RL does not require supervised labels and thereby can balance exploration and exploitation for an unknown model [10]. The goal of RL models is to find a suitable action model that can maximize the total cumulative reward of the agent, which is also different from unsupervised learning, where the goal is to find similarities and differences between data points. Through action-reward feedback loop, the agent is the decision-maker to train, the environment includes the general setting where the agent learns and decides what actions to take, action at is one among the set of possible actions the agent can perform, state *s* is the condition that the agent is in, reward *r* is the gain or loss the agent feedbacks from the environment, and policy is the method to map agent's state to actions.

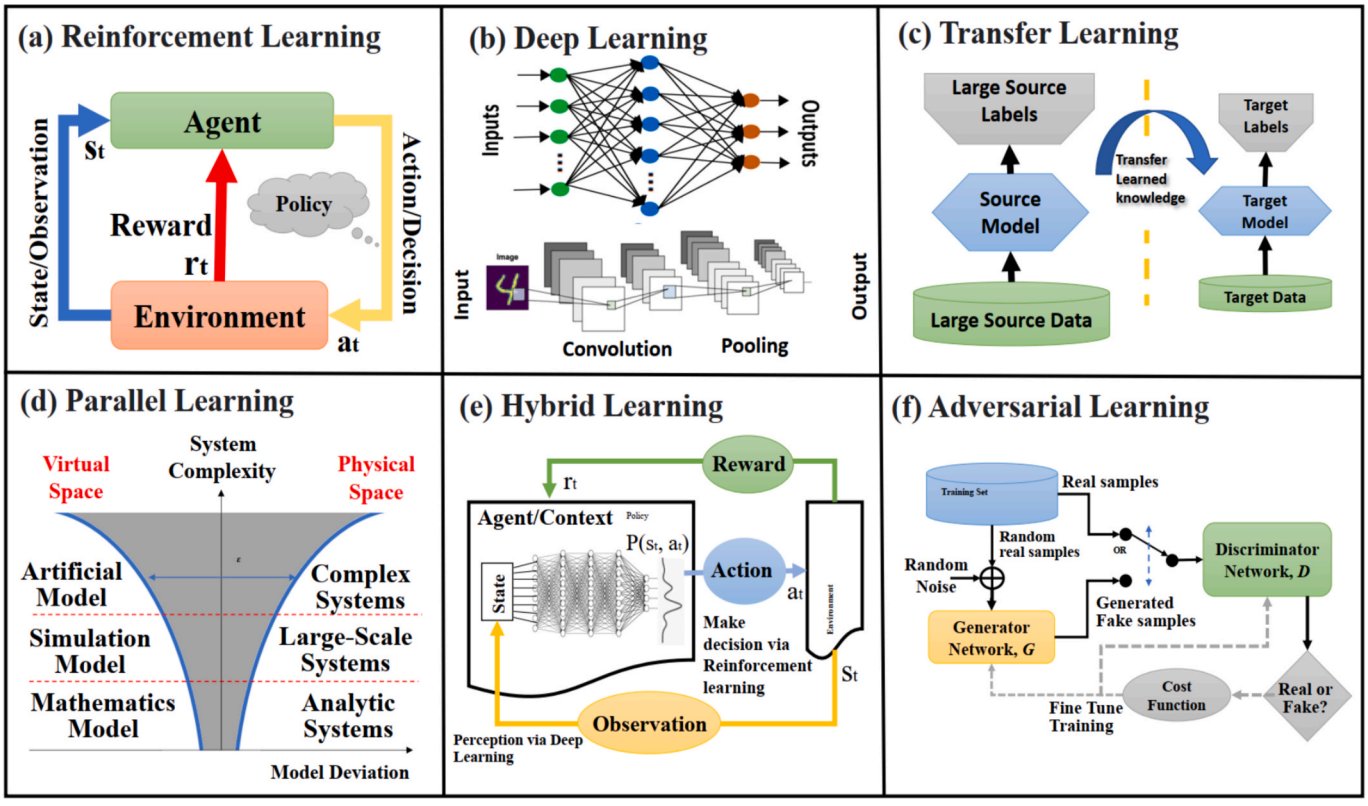

Fig. 5. Learning algorithms: (a) Reinforcement learning (RL); (b) Deep learning (DL); (c) Transfer learning; (d) Parallel learning (PL); (e) Hybrid learning (deep Reinforcement learning (DRL)); and (f) Adversarial learning (AL).

RL is used here strictly as an operations/control tool for smart grids rather than a pedagogical construct. In practice, RL (and DRL/MARL) optimizes microgrid EMS, demand response, storage dispatch, and feeder voltage/DOE compliance under non-stationary conditions. Policies learn from SCADA/AMI streams and/or Digital-Twin simulations and are evaluated on cost, peak-to-average ratio (PAR), frequency deviation, and constraint-violation rate (see Tables 5 and 7). For deployment, we prefer DT-pretrained policies with on-line fine-tuning and safety penalties, which reduces field exploration and keeps violation probability low. This decision-oriented view aligns method to task and KPI, avoiding generic RL mechanics while foregrounding grid outcomes. Unlike supervised learning, which relies on labeled data, RL operates by receiving feedback in the form of rewards or penalties for its actions, allowing the agent to continuously refine its policy to maximize cumulative reward over time. This inherent ability to learn from experience and adapt to changing conditions makes RL exceptionally well-suited for the complex and dynamic operational landscape of smart grids [26].

The main application scenarios of RL in the operation and control of a smart grids and power systems are to design a secure and stable control system or a smart power generation control. Under real operating conditions, power systems have many unstable factors that change constantly. As such, the control system needs to change its response to every fault signal dynamically. Supervised learning-based controllers cannot make effective control characteristics as they require a large amount of training data. On the contrary, RL-based systems have high real-time control capability and robustness by responding to the evaluated information of the current control effect. Thus, the RL algorithm ensures the security and stability of control in the power system. The security and stability control devices designed based on RL algorithms can overcome many uncertain factors and large disturbances of power systems. For example, a safe and stable voltage controller can be developed by updating its parameters based on the RL signal from the system [11]. Similarly, a framework for power systems stability control can be designed to learn from the real environment continuously [27]. The RL modes can be online in which the interaction occurs with the real power system or offline, in which the interaction occurs with a simulation model of the real power system. These two RL modes serve as frameworks that provide a systematic approach to design power system stability control agents.

RL methods can handle partial information and nonlinear and stochastic behaviors with no strong assumptions on the system dynamics. This capability expands RL applications to design many practical types of control schemes. RL methods learn closed-loop control systems which is critical for the real power system even without the simulation model. RL methods can also be used for adaptive control due to their capability to learn the RL-driven agents continuously even for changing operating conditions or system dynamics. In addition, The RL methods can be integrated with traditional control methods to improve their performances. For example, a dynamic electric brake controller in the off-line control mode can be designed by combining the RL algorithm and a Control Lyapunov Function (CLF) [12]. Furthermore, the deep RL (DRL) model can be designed by combining RL and deep learning algorithms. For example, the DRL algorithm can be used for high-penetration distributed generation that improves the operating costs of the power grid and increases its robustness and learning ability. This approach reduces carbon emissions by promoting models for new energy resource utilization in smart grids.Several review studies further underscore the growing importance and application of RL in smart grids. Reviews indicate that RL is extensively employed for tasks such as optimizing demand response tactics, allowing users to modify power usage based on grid conditions for increased efficiency and balance. RL also effectively manages grid components like energy storage devices, renewable energy sources, and distribution networks, making real-time decisions to improve grid performance and stability through applications like Optimal Power Flow, Microgrid Management, Load Shifting, and Dynamic Pricing. It enables self-learning systems to dynamically optimize energy distribution, demand response, and grid stability by continuously learning from real-time interactions, thereby enhancing grid resilience and flexibility. The symbiotic relationship between RL and smart grids is highlighted, where RL optimizes smart grid operations, and the dynamic environment of smart grids provides a challenging testbed for RL algorithms to enhance their predictive and decision-making capabilities. This synergy ultimately leads to self-learning, adaptive energy networks that continually improve sustainability, dependability, and resilience [26,28].

Deep learning

Deep learning (DL) enables model-free learning from massive sensor and SCADA data streams in smart grids, improving resilience to equipment failures and cyberattacks while supporting predictive maintenance, real-time stability monitoring, and adaptive demand-side management. By capturing nonlinear spatio-temporal dependencies, DL automates feature extraction and advances model fitting for high-dimensional data commonly encountered in power generation and load forecasting, intrusion detection, image-based inspections, transient stability assessment, and fault diagnosis [13]. As shown in Fig. 5(b), deep neural networks (DNNs) increase the number of hidden layers (“depth”) to learn hierarchical, distributed representations that support complex nonlinear transformations. These capabilities—well established across natural language processing, computer vision, and speech recognition—translate directly to modern power systems, where high-volume telemetry and event logs demand scalable, data-driven inference.

In power-system practice, DL architectures align naturally with grid physics and operations. Convolutional neural networks (CNNs) extract local spatial structure that reflects feeder topology and coupling; recurrent units (RNNs/LSTMs) encode diurnal, weather-driven, and market patterns; and attention mechanisms highlight critical buses, feeders, or irradiance ramps that drive errors in voltage prediction (e.g., voltage-RMSE) and constraint-violation rates. Empirically, DNNs have proven effective for generator/transformer/circuit-breaker fault diagnosis, anomaly and intrusion detection in power information networks, transient stability assessment, and short-term load forecasting [7].

From an optimization perspective, deep networks with multiple hidden layers are trained end-to-end by backpropagation, often benefiting from pre-training to improve initialization and generalization. Stacked restricted Boltzmann machines (RBMs) can initialize deep networks that are subsequently fine-tuned by gradient descent; such pre-trained DNNs have achieved improved accuracy and robustness in electricity-consumption forecasting [16]. This pre-training paradigm also supports transfer learning, enabling models trained on one grid or asset class to adapt to related tasks with limited labels—an important practical consideration discussed further in the next section. Relatedly, deep RBM/RNN hybrids have been used to build intelligent generation forecasting systems for short-term wind and photovoltaic power [29].

Recent research highlights DL’s role in operationally relevant, high-impact tasks. One example is the interpretable estimation of Dynamic Operating Envelopes (DOEs) in distribution networks, where traditional methods rely on detailed feeder parameters and repeated power-flow solutions that are expensive or unavailable in practice. Hybrid CNN–LSTM–Attention models can directly estimate nodal voltages from smart-meter time series, reducing reliance on full network models while maintaining scalability across heterogeneous feeders. In this setting, CNNs capture localized electrical correlations, LSTMs model temporal dynamics, and attention emphasizes the most influential features/buses. Search-based hyperparameter optimization—for instance, Whale Optimization Algorithm (WOA)—can further improve accuracy and adaptability under changing conditions. To address concerns about “black-box” behavior, post-hoc interpretability via SHAP values clarifies how bus-level injections and local conditions shape voltage estimates, offering actionable transparency for operators managing voltage violations [30].

A second application is DL-enhanced voltage control in microgrids with high electric-vehicle (EV) penetration. EV charging introduces rapidly varying reactive power demands that challenge conventional regulation. A deep-learning neural network (DLNN) tuned by the Artificial Bee Colony (ABC) algorithm can serve as a supervisory policy for Voltage-Source Converter (VSC) controllers, coordinating EVs as reactive-power compensators while meeting state-of-charge (SoC) targets. Studies on a 33-bus radial system report substantial gains over fuzzy-logic baselines, including ~ 50 % reductions in voltage RMSE and marked decreases in total harmonic distortion (THD) for both voltage and current (77.8 % and 66.7 %, respectively), translating into improved power quality and efficiency [31]. This synergy between DL and metaheuristic optimization illustrates a broader pattern: learning-based perception paired with optimization-based control produces robust, grid-aware policies.

Beyond these exemplars, DL increasingly underpins predictive maintenance (anticipating failures in transformers, breakers, cables, and inverters to reduce downtime), energy theft detection (identifying anomalous consumption against learned baselines), and optimal dispatch under high renewable variability (fusing weather, market, and telemetry data for fast, adaptive scheduling). Collectively, these advances position DL as a foundational technology for efficient, reliable, and secure smart grids.

Despite these advantages, several practical challenges merit attention. First, data scarcity and distribution shift (e.g., topology changes, new DERs, sensor drift) can degrade performance; transfer learning and domain adaptation mitigate this by reusing representations across feeders and time. Second, compute and memory demands, together with the need for parallel programming and specialized hardware, can hinder deployment on edge devices; model compression and quantization help here. Third, operational trust requires interpretability, calibration, and rigorous out-of-distribution and uncertainty assessment, especially for protection and safety–critical functions. Finally, for sequential decision-making, hybrid deep reinforcement learning (DRL) integrates DL's perceptual strengths with RL's optimization of long-horizon objectives, enabling autonomous voltage regulation, DER coordination, and demand response under uncertainty.

Transfer learning

In modern smart grids, a central challenge is the scarcity and heterogeneity of high-quality datasets across regions, asset types, and operating regimes. Transfer learning (TL) mitigates this gap by reusing knowledge from related domains (e.g., renewable generation forecasting or demand-response scheduling) to accelerate learning in new, data-limited settings. This is particularly valuable for emerging tasks such as EV charging optimization, distributed storage coordination, and microgrid integration under uncertainty. By transferring prior structure and features, TL reduces dependence on extensive labels, lowers computational burden, and shortens time-to-deployment, thereby offering a pragmatic bridge from theoretical AI advances to operational practice. Concretely in smart-grid operations, TL reuses a model trained on one feeder or region to cold-start another with few labels for RES/load forecasting or DOE estimation, while domain-adaptation penalties (e.g., CORAL, MMD) help mitigate cross-feeder bias and distribution shift.

As shown in Fig. 5(c). TL stores knowledge gained on a source task/domain and applies it to a related target with different data distributions, tasks, or operating conditions [32]. Pre-trained models capture reusable representations that enable accurate learning with limited target data and shorter training times. In contrast with training from scratch, TL leverages similarity across grid assets and operating patterns to improve data efficiency for classification, regression, and control. In smart-grid and power-system applications, preliminary deployments span reactive-power optimization, short-term wind-speed and load forecasting, and generation–consumption coordinated frequency control in islanded microgrids [7]. These cases illustrate a general pattern: source models trained where data are abundant or labeling is feasible can be adapted to feeders or assets with sparse, dependent, or noisy measurements.

To produce fast, practical solutions for large-scale optimization, TL is often composed with other ML paradigms. Lifelong/continual transfer supports cumulative learning across changing penetrations of renewables and EVs, improving complementary generation control (CGC) in interconnected grids by retaining and adapting useful policies over time [33]. Transfer reinforcement learning (TRL) combines TL with RL to speed exploration and convergence in sequential decision-making for power-system optimization—ranging from single-task transfer to multi-task linear and nonlinear transfer schemes [34]. Hierarchical or two-layer TL frameworks further enable multi-energy-system dispatch by transferring shared structure (e.g., heat–power coupling) while adapting to local constraints [35]. In these settings, TL accelerates deep-policy training, improves sample efficiency, and enables near–real-time control updates when conditions shift.

Operationally, TL facilitates fast online optimization by transforming solved historical problems into initialization or value-function priors for new, related instances—useful when nonlinear programs are high-dimensional, differentiable, and multi-modal. When combined with deep learning and RL, TL forms cascaded algorithms that deliver better optimization quality and faster convergence, making them promising tools for complex smart-grid problems where data regimes, topologies, and DER portfolios evolve over time [21]. Key implementation considerations include: (i) careful selection of source domains to avoid negative transfer; (ii) explicit domain-adaptation terms or feature-alignment layers (e.g., CORAL/MMD) to control shift; (iii) uncertainty estimation and monitoring to ensure safe deployment; and (iv) efficient fine-tuning strategies that respect compute and latency budgets at the edge or in control centers.

Parallel learning

Parallel Learning (PL) enables adaptive coordination of heterogeneous resources (e.g., renewables, storage, and responsive loads) under rapidly changing operating conditions. By coupling real-world data with a software-defined virtual space (digital-twin scenarios), PL can synthesize rare but safety–critical events (e.g., cloud-induced PV ramps, EV charging surges, N-1 contingencies) and evaluate control policies before field deployment. In practice, this dual capability, predictive learning for situation awareness and prescriptive learning for control—supports proactive scheduling that improves economic efficiency while safeguarding reliability. Concretely, the virtual space hosts stress tests in which candidate policies are vetted for higher resilience indices and lower risk-of-violation prior to roll-out, anchoring resilient, data-driven grid management in the era of Energy 5.0.

High-dimensional power-system states make exploration and exploitation of feasible solutions challenging. PL addresses this by embracing the transition from "Small Data & Big Laws" (Newton's paradigm) to "Big Data & Small Laws" (Merton's paradigm) [36]. As shown in Fig. 5(d), a PL pipeline proceeds in two stages:

Data processing (software-defined parallel artificial system, SDPAS): curated "small data" from the physical system seed a simulator that generates large volumes of *synthetic* data reflecting diverse operating regimes and contingencies. The union of raw and synthetic samples forms an open, evolving dataset for model updates. Action & learning: models interact with the virtual environment to characterize dynamics via state-transition information, distilling small intelligence (compact control rules or policies) from big synthetic datasets. This converts limited physical observations into rich experience, enabling robust inference and control even when analytical next-state solutions are intractable under Merton-style uncertainty [36]. Operationally, PL shifts from finite physical samples (Physical Space) to massive, self-explored imaginary samples (Virtual Space), then funnels back distilled policies to the field.

Within Industry 4.0/5.0 energy paradigms, smart grids must

integrate wind and PV securely and economically across interconnected infrastructures [37,38]. Early PL deployments target scheduling optimization, operational control, and fleet-level energy management. For example, an intelligent Digital Optimization Terrace (iDOT) uses PL to simulate load changes on distributed energy units and performs automatic optimization to select efficient equipment types and operating modes [20]. Similarly, an intelligent Decision Optimization System (iDOS) applies PL to dynamically distribute loads, improving both economic efficiency and comprehensive energy utilization by combining online identification, short-horizon forecasting, and optimal control. Across these systems, PL algorithms comprise three core components: (a) SDPAS for big-data preprocessing and scenario synthesis; (b) a data-driven learning layer spanning predictive learning and experiential learning (EL); and (c) a prescriptive learning layer that encodes decision logic consistent with Merton's paradigm [36].

In smart-grid practice, PL underpins parallel dispatch, parallel energy systems, and concepts of social energy, where cyber–physical–social interactions are modeled simultaneously to evaluate market rules, protection settings, and distributed-energy coordination at scale [7]. Looking ahead, PL is poised to support integrated energy systems, parallel dispatching across the energy internet, blockchain-enabled distributed EEPS models, robotics-assisted energy-control development, and artificial power-system testbeds. Crucially, PL's tight loop—field data → digital-twin synthesis → policy learning → safe deployment—links directly to operator metrics: reducing voltage and thermal violation rates, improving N-1 security margins, cutting curtailment, and meeting latency/compute budgets for edge or control-center execution.

Hybrid learning

Hybrid Learning (HL) is well suited to smart-grid environments where data are heterogeneous, streaming, and condition-dependent. By combining complementary paradigms (e.g., reinforcement learning (RL) for adaptive decision-making with deep learning (DL) for high-dimensional perception) HL addresses renewable variability, voltage and frequency stability, and real-time fault management. In practical operations, end-to-end deep reinforcement learning (DRL) couples DL perception on AMI/PMU snapshots with control actions that adjust taps, VAR resources, and storage charge/discharge. Crucially, evaluation is reported in system KPIs—not only abstract rewards—including total operating cost, peak-to-average ratio (PAR), frequency deviation, and thermal/voltage constraint-violation rates.

HL integrates the strengths of multiple ML methods to solve problems in complex, high-dimensional state spaces. Some algorithms excel with high-dimensional inputs yet degrade under sparsity; others are robust to noise but scale poorly with dimensionality. HL composes such methods so that one model's strength compensates for another's weakness, yielding a hybrid intelligence tailored to grid tasks. A prominent instance is DRL, which fuses DL (perception) with RL (sequential decision-making) to enable autonomous, grid-aware control policies.

As shown in Fig. 5(e), DRL binds the strong representational power of multilayer neural networks with the optimization of a Markov decision process (MDP). Concretely, an MDP-based RL decision network is paired with an ANN-based DL perception network to perform end-to-end sensing and control over large state–action spaces [39]. Building on this core, cascading concepts yields a family of DRL variants [7]: transfer-enhanced RL (TRL) for rapid adaptation across feeders, distributed/decoupled DRL (DTRL) for scalable control, memory-augmented DRL to exploit temporal context, hierarchical DRL for multi-timescale coordination (e.g., day-ahead scheduling vs. real-time set-points), and multi-agent DRL for decentralized DER and microgrid coordination. These hybrids are attractive in power-system settings where observability is partial, disturbances are stochastic, and constraints are tight.

Applications illustrate the operational value. A DRL-based self-optimization procedure can maintain safety and cost efficiency under random disturbances associated with large-scale integration of new and distributed energy resources in interconnected grids [40]. In emergency control, DRL can synthesize decision strategies (e.g., generator tripping policies) conditioned on real-time system states to preserve stability margins when contingencies occur [41]. More broadly, DRL has demonstrated end-to-end learning of perception and control that improves regulation quality, economic performance, and constraint satisfaction by leveraging DL's feature learning with RL's objective-driven policy optimization [34].

For deployment in smart-grid operations, several design considerations align HL with physics and reliability requirements. First, constraints should be modeled explicitly: thermal limits, voltage bounds, and N-1/security criteria can be encoded in the action space, in reward shaping, or via safety layers so that learned policies remain feasible. Second, evaluation must track operator-relevant metrics—costs, PAR, curtailment, frequency and voltage deviations, outage risk, and violation counts—alongside reward to ensure business and reliability objectives are met. Third, generalization and shift require attention; transfer mechanisms help adapt policies across feeders, seasons, and DER mixes, while routine monitoring guards against distribution shift and negative transfer. Fourth, data regimes and latency constraints motivate a training curriculum that combines offline pre-training on historical logs or digital-twin rollouts with online fine-tuning; model compression enables edge execution that satisfies SCADA/PMU latency budgets. Finally, interpretability and trust are essential: saliency or attribution for actions (for example, identifying which buses or events drove a tap change), calibrated uncertainty, and explicit guardrails support fail-safe operation and operator oversight.

Adversarial learning

Adversarial Learning (AL) has become central at the intersection of AI and smart-grid security, both to expose vulnerabilities and to harden models used in mission-critical functions such as load forecasting, anomaly/intrusion detection, state estimation, and fault diagnosis. In power-system settings, small, structured perturbations to AMI/PMU streams or SCADA-derived features can trigger severe misclassifications, with potential stability impacts. AL techniques—including adversarial training, robust optimization, and generative adversarial networks (GANs)—offer two complementary benefits: (i) systematic stress-testing of learned models under explicit threat models (e.g., ε-FGSM, DeepFool, JSMA), and (ii) synthesis of high-fidelity data for rare, safety–critical scenarios (e.g., coordinated false-data injection, rapid PV ramps). In practice, the discriminator approximates an IDS/state-estimation check, while the generator crafts realistic FDI patterns and renewable ramps; robustness is reported in operator-relevant metrics—higher accuracy under bounded attacks, lower attack success rate, and reduced detection delay on AMI/PMU benches—beyond ML accuracy alone.

Adversarial learning includes techniques to train ML on how to spot intentionally misleading data or behaviors to locate vulnerabilities to craft more flexible learning algorithms [33]. AL also encompasses GAN-based data generation and defense workflows. As shown in Fig. 5(f), a GAN comprises a generator (G) that maps noise to synthetic samples and a discriminator (D) that distinguishes real from synthetic data; training proceeds via a min–max game, improving both G and D iteratively [42]. Once trained, D can act as a strong detector (e.g., for data integrity anomalies), while G produces diverse, realistic stress cases to augment training sets and reveal brittleness in downstream models. This adversarial mechanism enables a practical shift from limited "small data" to abundant, scenario-rich datasets, thereby improving generalization and training efficiency in high-dimensional settings [9]. For example, GANs have been applied to model-free wind scenario generation [42], where a DNN-based generator learns to reproduce temporal statistics of historical wind profiles (validated on public wind time series), and D enforces realism by penalizing distributional mismatches [43].

Beyond synthesis, attack–defense evaluation is essential for trustworthy deployment. Studies of convolutional and recurrent forecasters/

classifiers (e.g., CNNs, LSTMs) under DeepFool, JSMA, and FGSM demonstrate that unprotected models can suffer catastrophic accuracy degradation across classification settings, underscoring the risk of cascading operational consequences in the grid. Correspondingly, defenses such as adversarial training, Gaussian/noise augmentation, and feature squeezing improve resilience by reshaping decision boundaries and suppressing spurious, high-frequency artifacts. These measures should be paired with calibration and uncertainty reporting so operators can interpret confidence under duress and trigger fallbacks or human-in-the-loop review [44].

Operationalizing AL in smart-grid workflows requires design choices that respect physics, constraints, and evolving field conditions. Threat models should be physics- and constraint-aware, tailoring perturbations to grid realities—topology-consistent FDI, meter-tamper locality, and Kirchhoff-respecting changes—so that robustness gains transfer beyond the lab. Validation should occur in closed loop with digital twins, embedding G-driven scenarios into the same virtual space used for control testing (cloud ramps, EV surges, N-1 outages) and jointly evaluating IDS performance, state-estimation robustness, and remedial actions. Evaluation must adopt multi-objective metrics, tracking attack success rate, detection delay, false-alarm rate, and post-contingency violations (voltage/thermal/security margins), rather than reporting only clean/robust accuracy. Defenses should follow a defense-in-depth philosophy that combines adversarial training with input sanitization, sensor cross-checks, residual-based state estimation, and robust aggregation across heterogeneous sensors. Finally, deployments need shift monitoring and adaptation: continuous auditing for distribution shift and concept drift, together with periodic refresh of G/D components and retraining of robust models as DER mixes, seasons, and asset portfolios evolve.

In sum, AL offers a test-and-fortify paradigm tailored to power-system realities: it systematically surfaces failure modes, supplies realistic scenarios for training and validation, and delivers operator-aligned robustness that translates into lower attack success, faster detection, and improved security margins across modern smart-grid monitoring, forecasting, and protection.

Federated learning

Federated Learning (FL) addresses a central challenge in modern smart grids: how to achieve accurate forecasting and control while preserving the privacy of highly sensitive consumption and operational data. By allowing distributed stakeholders—utilities, prosumers, aggregators, and EV operators—to collaboratively train models without sharing raw data, FL supports privacy-preserving load forecasting, demand-side management, and distributed energy-resource (DER) optimization. In practice, model updates (e.g., gradients/weights) replace raw kWh traces, and success is judged by a small accuracy gap relative to centralized training, fewer communication rounds to reach a target error, and robustness to Byzantine/backdoor clients via resilient aggregation—so that forecasting and DOE quality are preserved under privacy constraints.

FL constructs a common global model from decentralized local datasets and models without exchanging samples. This is particularly relevant when power-system data are siloed across parties unwilling or unable to share due to commercial interests, privacy, or even national-security concerns. A collaborative learning framework thus permits sharing patterns while withholding traces. FL has seen adoption across smart mobile devices [32], healthcare [33] and the Internet of Things [34]. Two canonical settings apply: horizontal FL (HFL), where parties hold similar features over disjoint samples, and vertical FL (VFL), where parties hold different features for the same samples. Core challenges include non-IID data heterogeneity [35], limited compute at the edge [36] and and constrained or unreliable communications [37]. In smart grids, FL has been applied to electric-load forecasting and EV-demand prediction [38,39]. As illustrated in Fig. 6(a), the convergence of DL and FL distributes deep learning by training local models over multiple rounds and aggregating them centrally, without pooling data [40,41].

Privacy and security are first-class requirements. Because leakage of power traces can reveal occupancy patterns or operational states, FL forbids raw cross-party data transfer; even model parameters may be encrypted in transit. Depending on data partitioning, FL can be cast as VFL or HFL. In VFL, parties hold complementary features for the same consumers/feeders (e.g., demographics or weather covariates); collaborative training enables feature fusion without disclosure. Yang et al. [45] used a VFL-based linear regression, in which each party calculates its prediction model based on its own set of features and the model parameters of these predictions add linearly to yield the final estimation. In horizontal FL (HFL), data are scattered in the sample space. Liu et al. [42] showed that models trained in isolation generalize poorly across parties (overfitting on local distributions), highlighting the value of FL to improve cross-party generalization in smart-grid forecasting.

FL is emerging as a pivotal solution for managing Distributed Energy Resources (DERs) in smart grids, enabling collaborative training of models for tasks such as renewable energy forecasting and demand-side

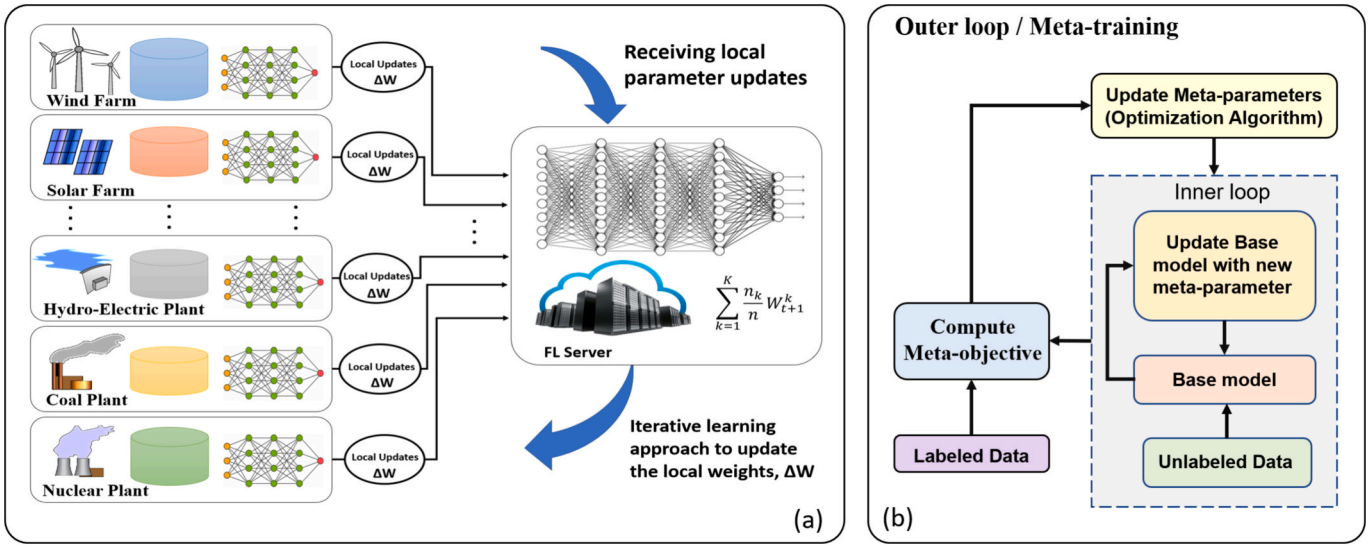

Fig. 6. (a): Federated learning approach for collaborative learning process using local datasets. (b) Meta-learning, including the optimization algorithm for *meta*-training and the inner loop computation on a base model.

management. By keeping sensitive data—like individual consumption patterns or DER generation profiles—localized, FL mitigates significant privacy and cybersecurity risks associated with centralized data collection, thereby fostering trust and secure operation across a decentralized energy ecosystem. This approach is particularly valuable for integrating a large number of heterogeneous DERs without compromising the confidentiality of their operational data [46]. FL mitigates data privacy risks and enhances security against data breaches and cyberattacks. This approach also substantially reduces communication overhead, as only model updates (gradients) are exchanged instead of large raw datasets, making it ideal for real-time applications and low-connectivity environments. Ultimately, FL provides a scalable, resilient, and privacy-preserving paradigm for smart grid operations, fostering collaborative intelligence while protecting data integrity [21]. Federated Learning also provides a comprehensive framework for smart grids, extending its benefits across all three stages of the power system: generation, transmission/distribution, and consumption. In the generation stage, FL enables distributed generators to collaboratively train models for renewable energy forecasting without sharing sensitive operational data. For transmission and distribution, it is utilized for line fault detection, optimal power flow, and voltage control. At the consumption level, FL is extensively applied for load forecasting and energy theft detection, allowing smart meters to collaboratively build models without exposing individual usage data. However, this decentralized approach introduces new security and privacy vulnerabilities, such as Byzantine and backdoor attacks where malicious clients can corrupt the global model, as well as inference attacks that aim to extract sensitive information from shared model updates. As such, advanced defense mechanisms like robust aggregation methods and differential privacy are crucial to bridge the gap between FL research and its secure application in smart grids [47].

FL also aligns with AIoT and 5G architectures. In distributed AIoT, many edge devices (smart meters, PMUs, DER controllers) train a shared model while keeping data local [48]. With 5G's high-throughput/low-latency links, exchanging lightweight updates rather than voluminous datasets enables more autonomous, scalable, and resilient operation, supporting near-real-time tasks (fault detection, load balancing) with improved efficiency and security [49]. In microgrid Energy Management Systems (EMS), FL facilitates collaborative optimization (power-flow surrogates, scheduling, and load forecasting) without centralizing sensitive household or battery data—enhancing efficiency, stability, and security in multi-stakeholder environments [18].

For deployment, several design considerations tie FL to grid physics and operator objectives. Non-IID data and drift should be handled through proximal objectives (e.g., FedProx-style penalties), periodic fine-tuning, and explicit monitoring of seasonal and asset-mix shifts. Aggregation must be robust to adversarial behavior; trimmed-mean or median-based rules, Krum-style selection, and coordinate-wise filtering can be paired with anomaly scoring of client updates to defend against Byzantine or backdoor participants. Privacy should be enforced through secure aggregation and differential privacy to bound inference risks while maintaining utility, with encryption of updates in transit. Communication efficiency matters: adaptive client sampling, multiple local epochs per round, and update compression (sparsification or quantization) help satisfy AMI/PMU bandwidth budgets. Finally, evaluation should report operator-relevant KPIs in addition to ML loss—forecast RMSE/MAE, voltage- and thermal-violation rates, DOE quality, and communication/latency budgets—to demonstrate field viability.

Meta-Learning

Meta-learning (MeL) endows models with the capability to "learn how to learn," enabling rapid adaptation to new tasks from few examples [43]. Rather than training a separate model for each feeder, device, or operating regime, a *meta*-learner acquires reusable priors across tasks and then adapts its internal parameters to a new task using only a handful of site-specific samples. As shown in Fig. 6(b), MeL operates on two levels: an outer (meta) loop that optimizes the *meta*-parameters to promote fast adaptation, and an inner (task-specific) loop that solves the current task (e.g., forecasting for a new feeder, fault classification for a new asset). The *meta*-objective evaluates how well inner-loop adaptation performs given the current *meta*-parameters, and *meta*-training updates those parameters accordingly. Concretely in smart-grid practice, "fast adaptation" means a forecaster or fault-diagnosis model attains deployment-grade accuracy after only a few labeled examples, enabling rapid onboarding of new feeders, DER assets, or sensor types with minimal labeling.

Power systems are complex, dynamic, and often label-scarce: genuine fault events are rare, asset mixes evolve, and configurations change after maintenance or contingencies. MeL directly addresses this reality by learning cross-task structure—shared features, temporal motifs, and physics-aware invariants—that transfers to new regimes. This is particularly valuable when adapting fault diagnosis to unseen fault types or assets (such as bearings and transformers) from very limited data, when short-term load forecasting must track changing load mixes, DER penetration, and weather regimes, and when stability assessment must extrapolate to previously unseen switching states or DER additions.

Empirical studies illustrate these benefits. J. Lin, et al. [50] proposed a semi-supervised *meta*-learning for fault diagnosis in power systems to learn the common features of bearings across multiple domains and improve the generalization ability of the model, reaching an average classification accuracy of 98.5 %. S. Zhang, et al. [51] proposed a few-shot learning framework for bearing fault diagnosis based on model-agnostic *meta*-learning, which targets training an effective fault classifier using limited data. Collecting sufficient data samples for each fault category can be unsafe and time-consuming, but the proposed framework achieves an overall accuracy of up to 25 % higher than a Siamese network-based benchmark study. Y. Li, et al. [52] introduced a MeL-based model-selection framework for STLF using a scoring–voting mechanism that improves selection accuracy across horizons, aggregation levels, and technical requirements by leveraging *meta*-features (feature extraction → candidate labeling → offline *meta*-training → online recommendation).

Methodologically, MeL spans optimization-based approaches (such as MAML and Reptile) that learn initializations adapting in a few gradient steps, metric-based approaches (such as prototypical networks) that learn embeddings supporting nearest-prototype decisions with few labels, and learner-based approaches (such as recurrent/*meta*-optimizers) that learn the update rule itself for rapid adaptation. These paradigms can be made physics-informed—for example, by using structure-preserving embeddings or constraint handling within the inner loop—and combined with transfer learning to cope with cross-feeder or cross-domain shift.

To align MeL with grid physics and operator practice, task design should mirror deployment realities by defining episodes at operator-relevant granularity (feeder, asset class, season, topology) and training under few labels, non-IID conditions, and mixed sensors. Constraints and invariants from power-flow physics (thermal and voltage limits, network relationships) should be encoded during adaptation so that few-shot updates remain feasible and safe. Evaluation must go beyond a single accuracy number to include forecast RMSE/MAE, fault-diagnosis F1 and latency, violation and curtailment rates, and time-to-target accuracy after a fixed number of labels. Robustness to distribution shift should be monitored continuously as DER mixes, sensors, and weather regimes change; coupling MeL with uncertainty quantification helps gate updates and trigger human-in-the-loop review when needed. Data efficiency can be further improved by augmenting scarce labels with semi-supervised signals, self-supervised pretext tasks (such as masked time-series prediction), and active-learning strategies that prioritize the most informative samples.

By learning reusable priors and fast adaptation rules, MeL provides a principled response to scarcity and heterogeneity of labeled data in

smart grids. It enables swift, data-efficient deployment across fault diagnosis, forecasting, and stability assessment, while aligning with operator-relevant KPIs and physics-based constraints. These properties explain the growing interest in MeL as a building block for adaptive, resilient, and scalable AI in power-system operations.

Ensemble learning

Ensemble Learning (EL) strategically combines multiple models to enhance predictive performance and reliability in complex environments. Conceptually, EL acts as an optimization framework that aggregates the results of several weak or specialized learners to form a more robust composite model. As shown in Fig. 7, ensemble architectures are generally categorized into boosting, bagging, and stacking. In boosting, a sequence of weak base learners is trained iteratively, where each learner focuses on correcting the residual errors of its predecessors. Through adaptive weighting and error-driven updates, these weak learners are collectively transformed into a strong predictor. Bagging, by contrast, builds parallel models using bootstrap sampling and then aggregates their outputs to reduce variance and improve stability. Stacking employs heterogeneous base learners trained in parallel, and a *meta*-learner subsequently learns the optimal way to combine their predictions. In smart-grid applications, greater model diversity across weather regimes, network configurations, and customer mixes consistently yields lower forecasting errors (MAPE/RMSE), higher F1 and AUC scores in intrusion or energy-theft detection, and a reduced optimality gap in scheduling and dispatch operations.

In the smart-grid domain, EL directly mitigates the limitations of relying on a single predictive model under highly dynamic and nonlinear operating conditions. Power systems experience inherent uncertainty due to renewable intermittency, fluctuating demand, and component failures. A single learning model typically struggles to generalize across such variations, resulting in performance degradation. EL addresses this by combining diverse learners that capture different statistical and physical relationships in the data, achieving improved accuracy, reliability, and robustness. This capability is especially valuable for critical functions such as short-term load forecasting, stability assessment, and fault detection, where even small gains in predictive accuracy can translate into significant operational and economic benefits.

Numerous studies have demonstrated the utility of EL in power systems. For instance, an EL-based optimization model comprising ten parallel binary sub-optimizers has been used for generation–consumption coordinated frequency control in an islanded microgrid [50]. Each sub-optimizer used a distinct optimization mechanism, collectively supplying diverse exploration and exploitation samples to an RL-based learning concentrator. This design met stringent cycle-time and performance requirements for maintaining frequency stability. Similarly, a boosting-based EL model (AdaBoost +) was introduced to reduce grid operating costs and minimize customer outages by accurately predicting weather-induced power interruptions [51]. Compared with regression-based and neural-network methods, AdaBoost + achieved higher prediction accuracy and demonstrated superior generalization across varying outage scenarios. Collectively, these results underscore the potential of EL for high-performance optimization, stability control, and predictive reliability in complex grid environments [7].

In practical deployment, EL frameworks play distinct roles across forecasting, reliability assessment, anomaly detection, and scheduling. In forecasting committees that use bagging or stacking, weather-conditioned LSTM or CNN forecasters can be combined with gradient-boosted trees to yield more stable day-ahead predictions. Their evaluation includes RMSE, MAPE, interval coverage, and temporal bias across feeders. For reliability and security assessment tasks, boosting models trained on physics-informed features—such as power-flow margins and topological indicators—enhance the prediction of voltage and thermal violations while optimizing the false-negative rate to maintain operational security. In the context of anomaly and intrusion detection, stacked ensembles that integrate autoencoders, isolation forests, and boosted trees, coupled with a calibrated *meta*-learner, have shown improved AUC and F1 scores while reducing detection delays and false alarms. Similarly, in scheduling and dispatch applications, stacked surrogates that combine gradient-boosted trees with neural OPF approximators provide fast and accurate feasibility screening, reducing the optimality gap in large-scale optimization problems.

The design of ensemble frameworks for smart grids should reflect both data characteristics and physical constraints. Diversity among member models should be systematically encouraged by using distinct architectures, feature subsets, temporal horizons, and loss functions, as diversity is the primary driver of ensemble gains. Incorporating physics-aware features, such as power-flow proxies, DER availability, and topology encodings, enhances model interpretability and resilience. Calibration and uncertainty quantification are also essential: ensemble

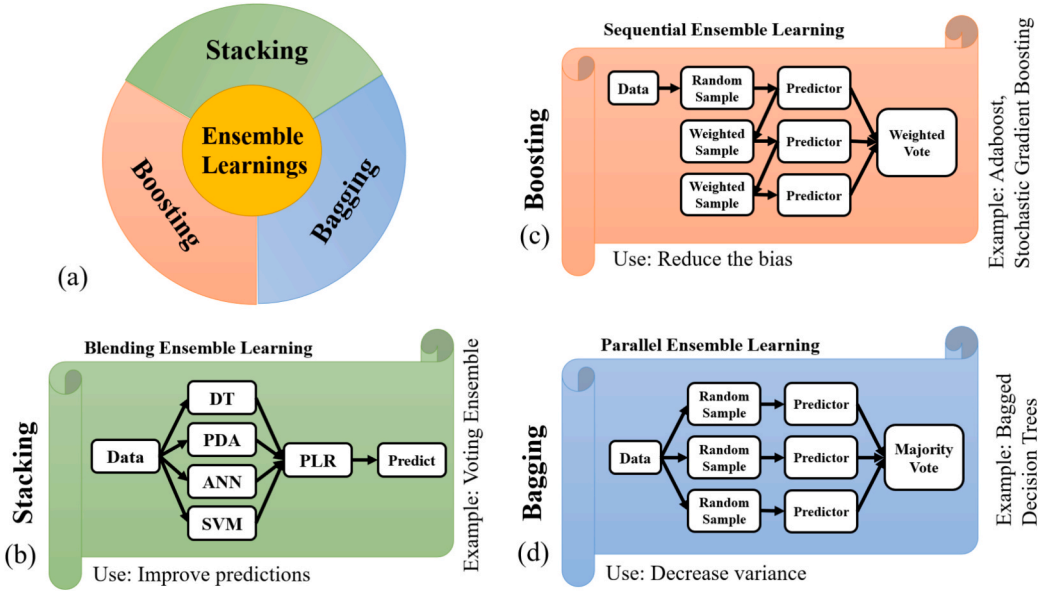

Fig. 7. (a) Ensemble learning methods and diagrams of (b) Stacking, (c) Boosting, and (d) Bagging.

variance, temperature scaling, and conformal prediction techniques can provide confidence intervals and alert operators to low-confidence actions. Furthermore, ensemble members must be continuously refreshed to manage drift associated with seasonal changes or shifts in DER penetration, using approaches such as sliding-window bagging or online boosting. Finally, given edge and control-center latency constraints, ensembles can be pruned, quantized, or distilled into compact student models to preserve accuracy while ensuring real-time feasibility.

Generative AI

Generative AI (GenAI) denotes a family of models that learn data distributions and task structure from large corpora to produce novel samples, predictions, and plans. In smart grids, GenAI's value comes from pairing data synthesis with representation learning to support forecasting, monitoring, planning, and cyber-defense under data scarcity and operational uncertainty. Unsupervised and self-supervised models—such as GANs and VAEs for scenario synthesis and Transformer encoders/decoders for sequence representation—generate realistic load/DER trajectories, topology-aware disturbances, and cyberattack traces that enrich training corpora. When composed with reinforcement learning, GenAI supplies rare but safety–critical scenarios to harden controllers and detectors, while learned representations improve sample efficiency and generalization. Concretely, synthetic AMI/PMU logs and event sequences help calibrate anomaly detectors and stress-test DRL policies; evaluation emphasizes reduced forecast RMSE/MAPE, lower voltage/thermal violation rates, smaller attack success rates with shorter detection delay, and bounded on-edge latency that meets deployment constraints [21].

Built upon these capabilities, Large Language Models (LLMs) specialize in understanding and generating natural language using deep Transformer architectures [53]. Architecturally, encoder–decoder models (e.g., T5, UL2) support bidirectional understanding and conditional generation, decoder-only (autoregressive) models (e.g., GPT, BLOOM, LLaMA) excel at stepwise generation, and hybrid/prefix-decoder variants offer flexible conditioning. In the smart-grid context, LLMs serve as an interaction and orchestration layer that translates operator intents and procedures into data queries, diagnostics, and model-checked control suggestions. Practical uses include turning free-form requests (e.g., "reduce voltage violations on Feeder-7 before peak") into validated set-point adjustments, summarizing market signals and weather toward day-ahead plans, generating incident timelines from EMS/SCADA logs, and drafting playbooks that align with protection and safety constraints. Integration with telemetry (AMI/PMU), market data, and asset metadata enables LLM-mediated assistants that reduce operator workload and hand-off time while preserving latency and safety budgets through guardrails such as constraint encoders, formal policy checks, and human-in-the-loop confirmation [54].

Fig. 8 situates these models within the evolution of Transformer-based generative architectures. Encoder-only networks (e.g., BERT, RoBERTa, DistilBERT) emphasize representation and feature extraction; encoder–decoder models (e.g., BART, T5) support transformation, rewriting, and conditional generation; decoder-only families (GPT-x) enable long-horizon, autoregressive synthesis. For power-system tasks, this progression maps to a pipeline in which encoders produce physics-aware embeddings for anomaly detection and stability assessment, encoder–decoders generate counterfactuals and synthetic training data (e.g., rare outage/weather regimes), and decoder-only models support language-to-action explanations and procedural drafting. As discussed above, this continuum underwrites synthetic data for consumption simulation and load/RES forecasting, early anomaly detection via self-supervised pretraining, and cybersecurity scenario creation, thereby improving adaptability, efficiency, and resilience.

Taken together, GenAI and LLMs form complementary layers for modern power systems: generative models supply diverse, high-fidelity scenarios and robust representations, while language models bridge human intent and grid automation through verifiable recommendations. Their combined impact addresses three persistent challenges: limited labeled data (mitigated by synthetic augmentation and self-supervision), growing cyber threats (addressed by realistic attack/defense simulation and robust training), and real-time decision complexity (handled by intent grounding, summarization, and model-checked action proposals). Deployed with physics- and policy-aware guardrails,

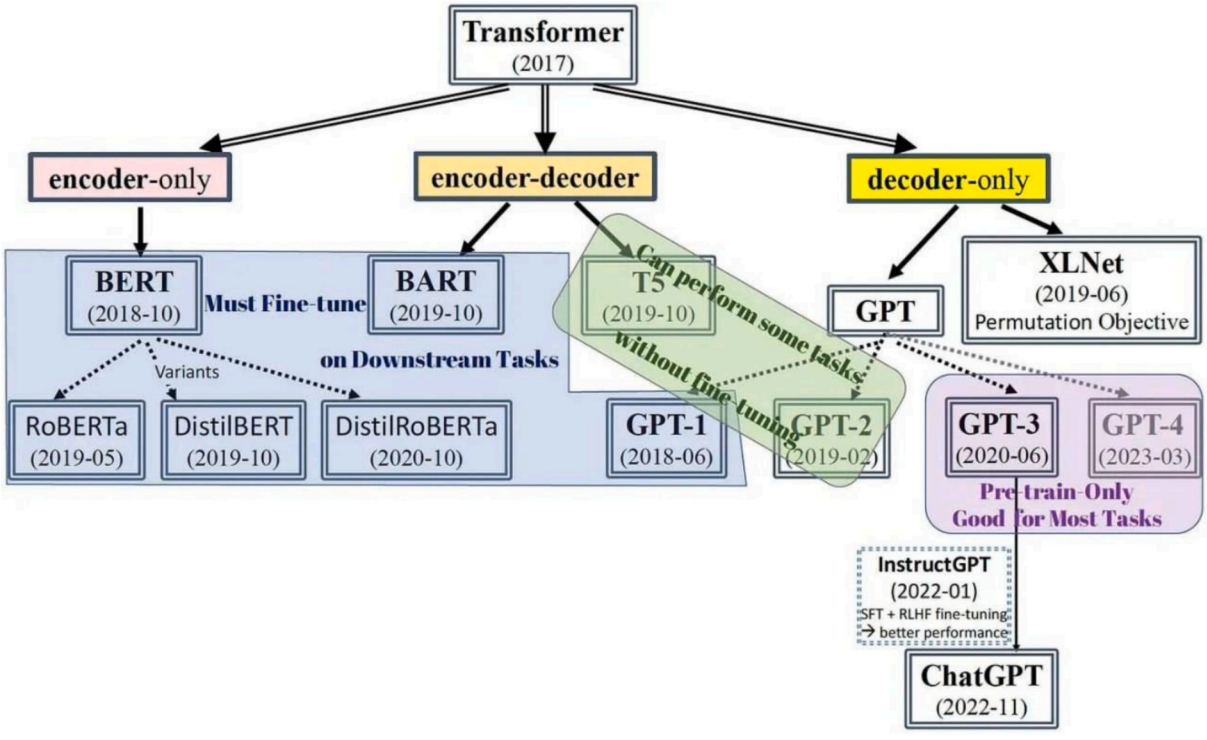

Fig. 8. Evolution of Transformer-Based Generative Architectures [55].

these tools make grid operations more adaptive, resilient, and human-centric, advancing a sustainable and secure energy future.

From paradigms to Practice: Comparative matrices for smart grid AI/ML

To effectively translate these advancements into actionable solutions for smart grid practitioners, a structured framework is essential to map AI/ML paradigms to specific energy challenges and their practical implications. This motivates a comparative analysis that links methodological strengths to operational needs, setting the stage for a decision-oriented synthesis. To avoid purely descriptive narration and to make the Energy, AI linkage explicit, Table 5 provides a method-to-problem comparative matrix. It maps each AI/ML paradigm to concrete smart-grid tasks (load/price forecasting, voltage/DOE control, DR/DSM, microgrid EMS, anomaly/intrusion detection, predictive maintenance, EV/V2G integration, and market analytics), alongside typical data contexts, strengths, risks, and indicative metrics.

Table 5 aligns advanced AI/ML paradigms with concrete smart-grid problems, clarifying data assumptions, comparative strengths, and risks. This matrix operationalizes Section 3 by turning method descriptions into decision guidance for practitioners. As indicated by Table 5, methodological fit must be complemented by deployment constraints. Table 6 therefore summarizes the "deployment envelope" of each paradigm data volume, training cost, inference latency, edge suitability, and privacy posture—so that architectural choices (cloud/edge/digital-twin) can be made realistically. In many smart-grid deployments, the "best" method is not the one with the highest accuracy but the one that remains scalable and safe under real-world constraints (limited bandwidth, device heterogeneity, privacy mandates, and time sensitivity). Table 6 consolidates these considerations, enabling transparent assessment of the accuracy–cost–latency trade-offs.

Collectively, Tables 5 and 6 transform the methodological discussion of AI/ML paradigms into an integrated AI energy decision framework. By linking algorithmic capabilities to operational metrics such as stability indices, renewable intermittency, latency tolerance, and privacy posture these matrices illustrate how AI methods directly address systemic energy challenges. Reinforcement and hybrid learning paradigms enable adaptive control under fluctuating renewable inputs, while federated and transfer learning approaches ensure scalability and data protection across distributed assets. Generative and LLM-driven systems extend this continuum toward human–AI collaboration, translating unstructured operational data into actionable intelligence. This alignment reinforces that AI's contribution is not confined to predictive accuracy but extends to resilience, sustainability, and governance dimensions of next-generation smart grids.

The energy applications listed in Table 7 capture the diverse and evolving ways in which AI and Machine Learning paradigms have been operationalized within modern power systems. In supervised learning, the focus has primarily been on load and price forecasting and renewable generation prediction, where deep regression architectures such as LSTM, Bi-LSTM-Attention, and hybrid CNN-LSTM models have reduced Mean Absolute Percentage Error (MAPE) below 3 % in day-ahead forecasting across residential and system-level datasets [7,80–87]. Unsupervised and semi-supervised learning methods extend these capabilities to domains with limited or unlabeled data, enabling anomaly and intrusion detection (e.g., false-data injection and energy-theft identification) and non-intrusive load monitoring using autoencoders, clustering, and isolation-forest techniques [12,13,64,98,101].

In contrast, deep learning frameworks especially attention-enhanced CNN-LSTM hybrids have been widely adopted for dynamic voltage control, DOE (Dynamic Operating Envelope) estimation, and predictive maintenance, achieving substantial reductions in RMSE (≈ 50 %) and harmonic distortion (THD ≈ 70 %) while maintaining interpretability through SHAP analysis [7,30,31]. Reinforcement and deep reinforcement learning (RL/DRL/MARL) paradigms further integrate learning into decision-making and control layers, optimizing demand response, microgrid scheduling, and real-time stability control with measurable gains in cost efficiency and frequency-deviation reduction [26,28,74,76,90,93].Building on this, transfer and *meta*-learning approaches improve cross-domain generalization and enable knowledge transfer between heterogeneous grid environments, significantly shortening convergence time in renewable forecasting and fault diagnosis tasks [32,35,43,50,52]. Federated Learning (FL) has introduced a privacy-preserving dimension to distributed load and EV demand forecasting, allowing multiple utilities to collaboratively train models without sharing raw data, thus enhancing scalability under non-IID conditions [32,40,42,45,47].More recently, Parallel Learning (PL) and Digital-Twin-assisted frameworks have enabled synthetic scenario generation and in-silico stress testing of control policies, bridging simulation and real-world deployment [59,60,114,121]. Complementary Hybrid and Ensemble models such as the combination of DL, RL, and optimization algorithms like XGBoost-SVR-KNN-GA have demonstrated 3.35 % MAPE and ≈ 15 % CO_2 reduction in energy-management systems [21,25,39,40]. Finally, Adversarial and Generative Learning (AL/GANs) are being applied to grid cybersecurity and rare-event simulation, both to test model robustness and to generate realistic operational scenarios, reducing vulnerability to perturbation-based attacks (e.g., DeepFool, FGSM, JSMA) [9,42,44].Collectively, these applications illustrate the progressive embedding of AI algorithms across all layers of the energy ecosystem from perception and forecasting to optimization, protection, and autonomy thereby transforming conventional power systems into resilient, data-driven, and self-learning smart grids.

This PRISMA-guided and bibliometric synthesis establishes a methodological bridge between AI paradigms and energy-system transformation. By mapping ninety-six studies across forecasting, security, and advanced paradigm clusters, it clarifies how deep-learning hybrids operationalize short-term forecasting for sustainability objectives, while reinforcement and federated learning advance adaptive control and data privacy in distributed energy contexts. The framework also highlights emerging synergies such as LLM–Digital-Twin hybrids for resilient grid simulation, thus setting the stage for Sections 4–5 to examine paradigm evolution and applied integration in greater depth.

Data, communication, and intelligence infrastructure in smart grids

Role of IoT and AIoT in data collection and management

Internet of Things (IoT) devices serve as indispensable data sources, profoundly shaping the transformation and optimization of Smart Grid (SG) operations. The proliferation of these devices generates an immense volume of digital data, which is fundamental for the implementation of advanced ML solutions. This data, acquired from diverse sources such as sensors, smart meters, and other interconnected grid components, empowers ML algorithms to extract meaningful insights and provide precise solutions for identifying inherent risks, emerging threats, and operational deficiencies. As meticulously detailed in the literature, raw data streams undergo rigorous preprocessing and feature extraction, converting into actionable representations that form the bedrock for sophisticated ML models aimed at enhancing SG performance [56,57].

The heterogeneous data generated by IoT devices within smart grids are systematically categorized into four principal types, each holding distinct significance for ML applications. Tabular Data, characterized by its structured format, encompasses critical information such as network events, meter readings, and sensor outputs. This data is paramount for informed decision-making and optimizing grid performance. Time Series Data, recorded at regular intervals, provides dynamic insights into grid behavior, including voltage and current fluctuations, and renewable energy generation profiles, which are essential for real-time decision-making and operational optimization. While less prevalent, Image Data, derived from thermal cameras or infrastructure inspection

imagery, leverages ML and computer vision techniques to enhance monitoring, maintenance, and security protocols. Finally, Text Data, comprising system reports, logs, and alerts, offers qualitative and contextual insights. This textual information is processed using Natural Language Processing (NLP) and Large Language Models (LLMs) to facilitate fault detection, bolster cybersecurity, and analyze consumer sentiment. This comprehensive data categorization enables the development of adaptive and efficient ML models, thereby contributing to the evolution of smart grids into more intelligent, efficient, and secure energy ecosystems[21].

Extending beyond the confines of smart grids, IoT's pivotal role in data collection and management is equally transformative for the broader concept of smart cities. IoT fundamentally facilitates the linkage and effectiveness of smart cities, guiding their focus towards sustainable solutions in governance, secure data analysis, and comprehensive energy consumption management systems [58]. This involves the interconnection of billions of devices, including a vast array of sensors, smart meters, and cameras, alongside other networked technologies, to cultivate a more efficient and sustainable urban environment. Specifically, IoT plays an indispensable role in sustainable data acquisition by integrating devices equipped with sensors that continuously collect real-time data for environmental surveillance. In data transmission, IoT ensures the secure connection and distribution of these diverse data sources, making them readily available for subsequent processing and analysis. Furthermore, its contribution to big-data management is profound, as it underpins the generation and handling of the ever-increasing volume of urban data. Within this big data ecosystem, AI algorithms, in conjunction with Machine Learning (ML) and Deep Learning (DL), are applied to identify intricate patterns and trends, yielding automated insights into dynamic environmental conditions. These sophisticated data processes are then leveraged by AI models to conduct predictive analyses of potential environmental changes, drawing upon both historical and real-time data acquisition [59].

In this context, the architecture typically comprises a Perception Layer where IoT sensors (e.g., ultrasonic sensors in waste bins) collect real-time data on fill levels. This data is transmitted via a Network Layer (e.g., Wi-Fi, cellular) to a central platform. The Intelligence Layer then leverages AI/ML algorithms to analyze this data, predicting optimal collection routes and schedules. Finally, the Application Layer translates these intelligent decisions into actionable insights for municipal offices and waste carrier vehicles, enhancing operational efficiency and urban sustainability[60].Next-Generation Smart Grids (NGSG) are undergoing a fundamental transformation by leveraging the convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and 5G technology. 5G, as a primary enabler, provides ultra-high-speed, ultra-low-latency, and massive connectivity for IoT devices. This synergy enables real-time monitoring, distributed control, and intelligent decision-making across the entire grid, from generation to consumption. Consequently, NGSG evolves into a highly reliable, secure, and autonomous system that more effectively manages complex energy challenges [49].

Smart grid communication systems

The operational efficacy of smart grids, particularly in the context of Artificial Intelligence (AI) and the Internet of Things (IoT), is fundamentally contingent upon a robust and sophisticated communication infrastructure. This infrastructure facilitates the seamless and secure exchange of vast volumes of data, which are indispensable for AI-driven analytics, real-time decision-making, and the autonomous functionalities of next-generation smart grids (NGSG). The integration of AI and IoT necessitates a communication fabric capable of handling diverse data types—from tabular and time-series to image and text—with high reliability, low latency, and extensive coverage. This foundational requirement underscores the critical interplay between various wired and wireless communication technologies, each contributing distinct capabilities to the complex ecosystem of modern energy systems[49].

Traditional wired communication technologies form the resilient backbone for critical data transmission within smart grids. Fiber Optic Communication offers unparalleled bandwidth and immunity to electromagnetic interference, ensuring secure and high-speed data flow across substations and control centers. Power Line Communication (PLC) uniquely repurposes existing power lines for data transfer, connecting smart meters and grid equipment. Ethernet and IP-Based Communication provide standardized, scalable networking, while Leased Lines deliver dedicated, highly reliable links for mission-critical grid operations. Complementing these, a suite of wireless technologies extends connectivity to geographically dispersed or mobile assets. Wireless Fidelity (Wi-Fi) and Worldwide Interoperability for Microwave Access (WiMAX) provide local and wider-area broadband access, respectively. Low-Power Wide-Area Networks (LPWANs), including NB-IoT and LoRaWAN, are tailored for connecting a multitude of low-power IoT sensors and smart meters over vast distances. Concurrently, Satellite Communication (SATCOM) ensures global coverage for remote areas, and Short-Range Wireless Protocols like Zigbee and Bluetooth enable local area network functionalities within homes and substations [61].

The advent of 5G technology, alongside Software-Defined Networking (SDN) and Network Function Virtualization (NFV), serves as a transformative enabler for the full realization of AI and IoT in NGSG. 5G's core services—Enhanced Mobile Broadband (eMBB), Ultra-reliable and Low-latency Communications (uRLLC), and Massive Machine Type Communications (mMTC)—directly address the stringent demands of real-time grid monitoring, automated control, and pervasive sensor deployment. Crucially, network slicing, a hallmark of 5G, allows for the creation of isolated virtual networks, each optimized for specific smart grid applications (e.g., dedicated slices for critical control signals or high-volume meter data), thereby ensuring enhanced security, quality of service, and resource efficiency. This software-defined, intelligent communication infrastructure, combined with the interoperability fostered by adherence to open industry standards, is paramount for orchestrating the seamless integration of AI-powered analytics and IoT devices, ultimately driving the evolution towards highly autonomous, resilient, and efficient smart grids [21].

ML-based smart grid components

Smart Transformers (STs) play a pivotal role in smart grids by leveraging real-time data analytics, Artificial Intelligence (AI), and Internet of Things (IoT) sensors to accurately forecast electricity demand, optimize energy distribution, and detect anomalies [62]. These transformers achieve energy distribution optimization through continuous monitoring of electricity flow, voltage, current, frequency, and load. This is complemented by integrating real-time data from smart meters, Distributed Energy Resources (DERs), and storage systems, while also considering external factors such as weather and historical consumption. Machine Learning (ML) models (e.g., LSTM, ARIMA, and Prophet) predict power demand, deep learning uncovers hidden consumption patterns, and reinforcement learning enables dynamic adaptation [63].

Furthermore, by anticipating peak demand, adjusting voltage levels, and collaborating with smart appliances, Electric Vehicle (EV) chargers, and battery storage systems, STs contribute to load balancing by shifting loads during off-peak hours. These capabilities enable STs to identify anomalies, including irregularities, thereby enhancing grid efficiency and security. They detect electricity theft by highlighting unusual spikes or declines in power consumption that deviate from historical trends. By measuring voltage variations, harmonic distortions, and abnormal power factors, STs assist in identifying faults in power equipment. These intelligent devices also generate alerts for predictive maintenance, which reduces downtime and increases grid reliability [64]. The ultimate goal is to enhance grid security and resilience by detecting anomalous data access patterns and potential cyberattacks through AI-powered intrusion detection systems.

Types of smart sensors and meters and their utilization for data collection in ML analysis

Smart grids utilize a comprehensive array of smart sensors and meters for collecting critical data essential for ML analysis. These devices generate massive data streams that are fundamental for enhancing grid stability, reliability, efficiency, and security [65].

Electrical and power quality sensors

Electrical and Power Quality Sensors constitute a fundamental component of smart grids, providing high-resolution data essential for Machine Learning (ML)-driven analysis. Smart Meters (SMs) monitor current, voltage, and power consumption, enabling real-time tracking of electricity usage for both consumers and utilities. These data streams are widely employed in ML applications for energy consumption anomaly detection, load forecasting, and fraud identification. In parallel, Phasor Measurement Units (PMUs) measure current, voltage, frequency, and phase angle, thereby offering high-speed and precise monitoring of grid stability. Leveraging ML algorithms, PMUs are instrumental in detecting blackouts, grid instability, and cyber-physical attacks. Finally, Power Quality Sensors (PQSs) assess power factor, waveform distortions, and harmonics, facilitating the identification of power disturbances as well as voltage sags and swells. When integrated with ML techniques, PQSs play a vital role in fault detection and proactive maintenance. Collectively, these sensor systems establish a robust data-driven foundation that significantly enhances the resilience, security, and efficiency of smart energy networks.[66].

Environmental and weather sensors

Environmental and Weather Sensors are critical for enhancing the reliability and efficiency of smart grids, as environmental factors have a direct impact on the performance of power equipment and renewable energy resources. Temperature Sensors measure ambient and component temperatures in transformers, substations, and batteries, thereby enabling precise monitoring of thermal conditions and supporting predictive maintenance through Machine Learning (ML) models to prevent equipment overheating. Similarly, Wind Speed and Direction Sensors capture wind velocity and direction, providing essential input for optimizing wind turbine operations, with ML techniques applied for wind energy production forecasting. In addition, Solar Radiation Sensors assess solar irradiance levels, which are vital for improving photovoltaic panel efficiency and ensuring seamless integration into the grid; ML models are employed to support solar energy generation forecasting. Finally, Humidity and Rainfall Sensors measure atmospheric moisture and precipitation levels to evaluate the weather's impact on power lines and renewable sources. These measurements, when processed by ML algorithms, enable real-time and accurate prediction of grid failures caused by adverse weather conditions. Collectively, these sensors establish a data-driven framework that strengthens the resilience and operational sustainability of smart energy systems. [67].

Grid security and protection sensors

Intrusion Detection Sensors (IDSs) represent a critical component in strengthening the cybersecurity of smart grids. By continuously monitoring network traffic and identifying anomalous patterns, IDSs enable the early detection of potential cyber threats. The integration of Machine Learning (ML) algorithms significantly enhances their capability, allowing for more accurate and real-time cyber threat detection. Through this approach, ML-based IDSs not only distinguish between normal and abnormal traffic behaviors but also provide robust defense against complex and previously unseen attacks. Their role is particularly vital in modern energy networks, where the reliability of real-time data exchange is indispensable, thereby establishing a resilient and secure smart grid infrastructure.[68].

AI-based Surveillance Cameras play a pivotal role in enhancing the physical security of smart grids. By continuously monitoring human activities around substations and other critical infrastructures, these systems effectively prevent vandalism, unauthorized access, and physical threats. The integration of Machine Learning (ML) algorithms further strengthens their functionality, enabling facial recognition, voice identification, and the use of specialized tokens for authentication. Consequently, these intelligent surveillance systems not only detect suspicious activities but also establish an advanced layer of protection, safeguarding vital grid infrastructures against potential physical intrusions and attacks.[69].

Tamper Detection Sensors serve as a vital component in reinforcing the security of smart grids by identifying unauthorized access to electricity meters. Through continuous monitoring, these sensors enable the detection of hacking attempts and energy theft. The integration of Machine Learning (ML) techniques further enhances their effectiveness by automatically recognizing abnormal electricity consumption patterns, thereby facilitating fraud detection in real time. Consequently, tamper detection sensors not only strengthen the overall security of grid infrastructures but also contribute to reducing energy theft and enhancing the reliability and efficiency of modern smart energy systems.[70].

Fault Detection and Structural Health Sensors

Fault Detection and Structural Health Sensors play a critical role in improving reliability and reducing the risk of equipment failures in smart grids. Vibration Sensors measure mechanical stress in transformers and turbines, allowing for the identification of abnormal vibrations prior to mechanical breakdown, and are applied within Machine Learning (ML)-based frameworks for predictive maintenance of power equipment. In addition, Acoustic Sensors monitor noise levels across power infrastructures, particularly in substations, enabling the detection of transformer hum anomalies and operational faults through ML-powered fault detection techniques. Finally, Gas Sensors, with a primary focus on sulfur hexafluoride (SF6) leak detection, continuously monitor insulation integrity in circuit breakers and facilitate the early identification of insulation breakdown. When processed using ML algorithms, the data collected from these sensors provides a proactive mechanism for fault prediction and prevention. Collectively, these technologies establish a forward-looking protection layer that significantly enhances the stability, safety, and longevity of smart grid infrastructures.[71].

Smart Home and IoT Sensors

Smart Home and IoT Sensors constitute an essential component of modern energy systems by enabling real-time interaction between end-users and the smart grid. Motion Sensors detect human presence and activity to automate lighting and Heating, Ventilation, and Air Conditioning (HVAC) systems, where Machine Learning (ML) techniques are applied to achieve substantial energy savings [72].Similarly, Occupancy Sensors monitor room utilization to dynamically regulate heating, cooling, and lighting in buildings, thereby supporting smart demand-response programs that enhance energy efficiency [73].Moreover, Smart Thermostats continuously track indoor temperature variations and apply ML-based predictive control strategies to optimize HVAC operations under real-time conditions. Collectively, these heterogeneous sensors generate massive streams of data that are processed by ML algorithms to improve the sustainability, reliability, efficiency, and security of smart grids [21].

In addition to IoT-driven sensing, Multi-Agent Systems (MAS) and Multi-Agent Reinforcement Learning (MARL) provide advanced frameworks for distributed intelligence in smart grids, enabling progress in decision-making, energy management, fault detection, and cybersecurity. MAS coordinates interactions among power producers, consumers, grid operators, and storage units to optimize network operations, thereby improving energy efficiency and reliability [74]. Through distributed decision-making, MAS enhances the intelligence, autonomy, and adaptability of smart grids, allowing industries and households to dynamically adjust energy consumption in response to

price signals and grid conditions. It further supports renewable energy integration by orchestrating wind, solar, and storage resources, strengthens fault detection and self-healing mechanisms by enabling agents to share information and initiate corrective actions, and facilitates market-based decentralized energy trading between prosumers to ensure equitable pricing and mitigate grid congestion. MAS also enhances cybersecurity resilience by employing cooperative agent-based monitoring to detect and mitigate cyber threats.

Complementarily, MARL introduces dynamic learning among multiple autonomous agents, offering powerful solutions for network optimization, cooperative energy management, demand-response programs, and renewable integration. By learning from interactions with their environments, MARL agents can adaptively optimize energy distribution, reduce operational costs, and minimize power losses. MARL is particularly effective for demand-response (DR), where customer and operator agents balance energy use according to real-time system conditions. It further improves grid stability during renewable energy integration by optimizing storage and dispatch, strengthens self-healing capabilities by enabling agents to isolate and resolve faults independently, and supports intelligent EV charging planning to avoid overload. In addition, MARL empowers decentralized energy trading among prosumers, ensuring equitable transactions while maintaining grid stability. Overall., the combined application of MAS and MARL, through intelligent agents and collaborative reinforcement learning, empowers smart grids to evolve into self-learning, adaptive, and resilient infrastructures, capable of effectively addressing the complexities and uncertainties of modern energy environments [75,76].

Fig. 9 illustrates the classification of smart sensors, IoT devices, and multi-agent systems (MAS and MARL) that support data collection and Machine Learning (ML)-driven intelligence in smart grids. Electrical and power quality sensors (e.g., smart meters, PMUs, PQSs) provide fundamental data on current, voltage, and energy quality. Complementarily, environmental and weather sensors (e.g., temperature, wind, solar radiation, humidity) supply critical information for renewable energy integration. Grid security and protection sensors (e.g., IDSs, AI-based surveillance cameras, tamper detection sensors) establish protective layers against both cyber and physical threats, while fault detection and structural health sensors (e.g., vibration, acoustic, gas) enable predictive maintenance of critical infrastructure. At the consumer level, smart home and IoT sensors (motion, occupancy, smart thermostats) generate real-time data streams to optimize energy consumption. Extending beyond sensing, Multi-Agent Systems (MAS) and Multi-Agent Reinforcement Learning (MARL) provide distributed decision-making, energy management, demand-response optimization, renewable integration, decentralized energy trading, and cybersecurity resilience. The interconnection among these categories highlights that the smart grid operates as a data-centric ecosystem, spanning from physical equipment monitoring to distributed decision-making, ultimately enhancing the sustainability, security, and adaptability of modern energy systems.

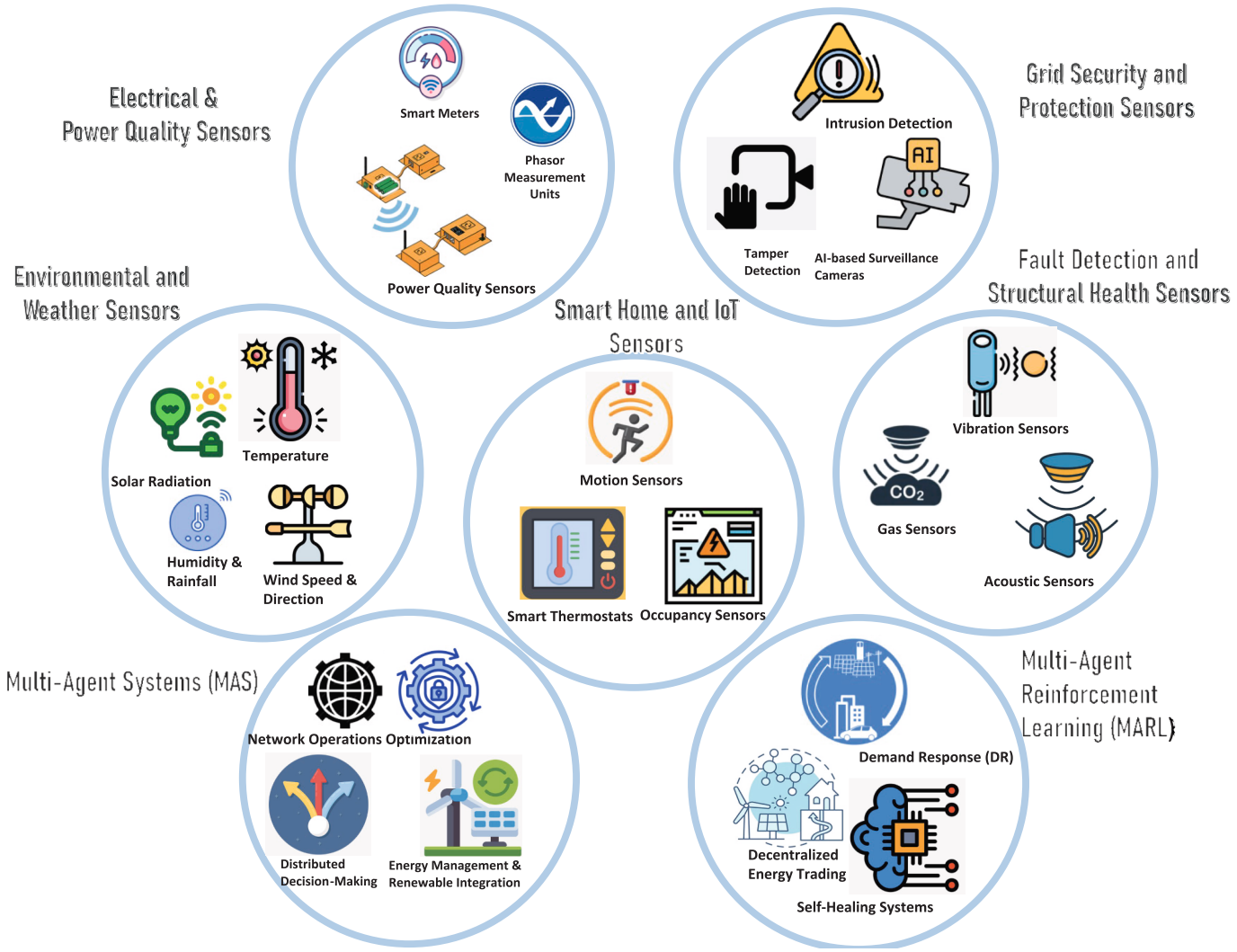

Fig. 9. Categories of Smart Sensors, IoT Devices, and Multi-Agent Systems for Data Collection and ML-driven Intelligence in Smart Grids.

AI/ML Applications in Smart Grids and Power Systems

To provide a holistic perspective, this section consolidates the diverse roles of AI/ML in smart grids and power systems into an integrated framework. The emphasis is on linking real-time operation, comprehensive perception, and intelligent decision-making as interconnected domains that collectively enhance grid resilience, efficiency, and sustainability. Fig. 10 visualizes this framework, illustrating how methodological advances translate into practical applications across forecasting, monitoring, anomaly detection, market operations, and emerging paradigms such as Digital Twin and intelligent decision-making. The framework is structured around four core domains. Real-time operation encompasses microgrid operations, system resilience, renewable-energy integration, anomaly detection, cyberattack defense, cascading-failure prevention, and self-healing mechanisms. Comprehensive perception focuses on wide-area monitoring, advanced metering, renewable-generation forecasting, load monitoring, consumption analysis, and equipment-condition monitoring. Intelligent decision-making includes asset-lifecycle management, fault detection, demand-side management, risk assessment, electricity pricing, energy-market trading, and electric-vehicle (EV) traffic and charging planning. Finally, Digital Twin–driven intelligence represents the next generation of AI/ML integration, including real-time simulation and optimization, predictive maintenance and anomaly detection, AI-enhanced forecasting via Active Learning, and Agentic Digital Twins for autonomous decision-making. The interplay among these domains demonstrates a data-centric ecosystem that extends from perception and monitoring to intelligent decision-making and autonomous control, paving the way for greater adaptability, security, and sustainability in future smart-energy systems.

Urban mobility is undergoing a rapid transformation driven by the convergence of electric vehicles (EVs), shared mobility, and smart charging infrastructures. Recent studies highlight that the optimal placement of EV charging stations, coupled with distributed generation (DG) and battery integration, not only mitigates grid stress but also reduces CO_2 emissions and operational costs.[77] These insights underline the dual role of EVs as both transport assets and active grid participants, particularly in vehicle-to-grid (V2G) and peer-to-peer (P2P) energy sharing scenarios.

Complementing this, research on communication platforms for smart Energy Management Systems (EMS) demonstrates that mixed-integer linear programming and IoT-enabled infrastructures are essential for coordinating energy demand in urban transport hubs. This approach ensures real-time optimization of EV fleets, microgrids, and demand response, laying the groundwork for seamless integration of shared and autonomous transport systems into smart city energy ecosystems.[78].

Moreover, the concept of decarbonized microgrids with smart electricity markets offers a blueprint for balancing demand response with urban transport electrification. By employing metaheuristic optimization (e.g., AVOA, AROA, GOA), these models demonstrate improved cost efficiency, emission reductions, and user comfort in city-scale microgrids. Together, these contributions establish car-sharing and EV integration not as isolated innovations but as central components of resilient and sustainable smart city infrastructures.[79] Recent advances also extend the role of AI/ML toward consumer-centric and decentralized energy applications. In smart homes, AI-enabled Home Energy Management Systems (HEMS) and appliance scheduling reduce consumption peaks and improve energy efficiency, while ensuring user comfort. Energy storage systems (ESS) benefit from predictive control and optimization algorithms that extend battery life and support grid balancing during peak demand. The Internet of Things (IoT) provides real-time sensing and connectivity, enabling data-driven decision-making across distributed devices and microgrids. Moreover, peer-to-peer energy trading platforms leverage AI/ML for secure transaction matching, dynamic pricing, and fraud detection, thereby democratizing energy markets. Collectively, these applications highlight how AI/ML fosters not only operational efficiency but also active user participation and resilience in modern energy ecosystems.

Smart grid forecasting

In the intricate domain of smart grids and power systems, accurate prediction capabilities serve as the cornerstone for efficient and resilient energy management. These predictions encompass a broad spectrum of operational facets, ranging from general prediction of overarching trends and patterns to more specialized estimations such as load forecasting (including short-term, medium-term, and long-term scales for both aggregate and consumer-specific loads), renewable energy generation prediction (e.g., solar and wind power output), and demand forecasting at various granularities. Furthermore, energy price forecasting for market optimization, anomaly prediction and fault/failure prediction for proactive maintenance and enhanced security, system state prediction for overall grid stability, consumer behavior prediction for demand response management, natural resource prediction for

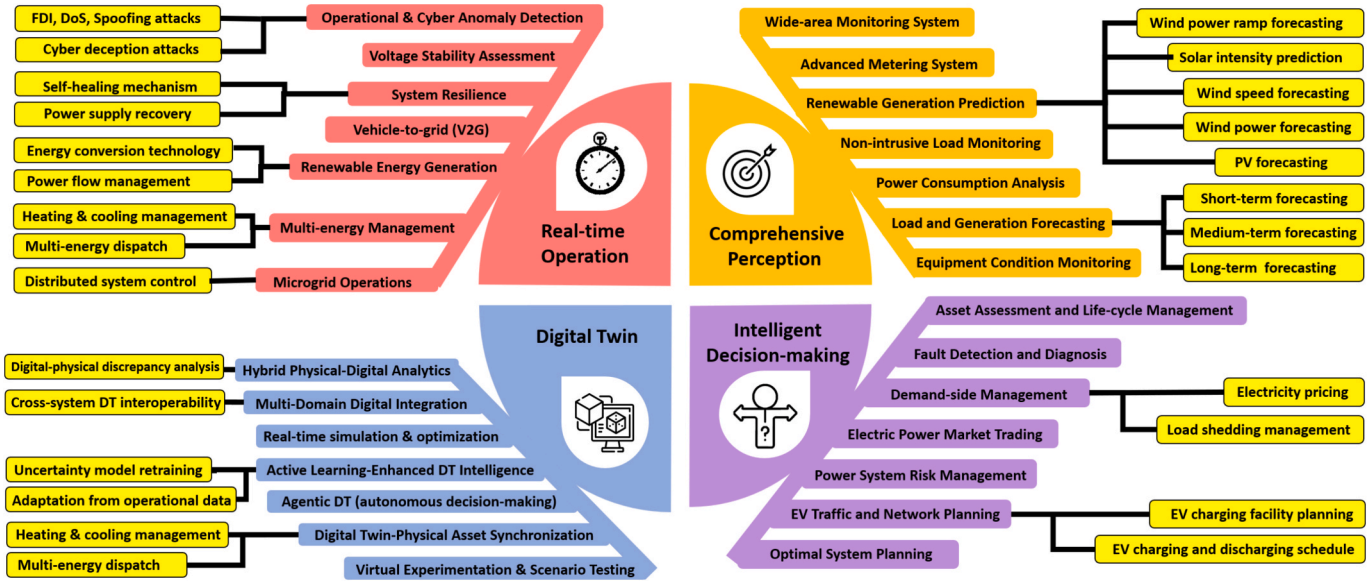

Fig. 10. Applications of AI/ML techniques in various domains of smart grids and power systems.

supply planning, and power quality prediction for ensuring optimal network performance are all of paramount importance. Artificial Intelligence (AI), through its advanced algorithms including Deep Learning (DL), Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), Reinforcement Learning (RL), and hybrid models, plays a pivotal role in augmenting the accuracy, speed, and adaptability of these predictions. These capabilities empower smart grids to effectively counter uncertainties, optimize resource utilization, and progress towards a more sustainable and secure energy future.

The present power grids include many different types of distributed and intermittent energy sources, resulting in the transformation of the traditional passive, unidirectional grid into an active, bidirectional, and intelligent grid. Furthermore, a massive amount of data is created and transferred across various entities in the smart grid due to the increasing number of devices and systems connected to the power grids continuously. The processing and analysis of the collected data from the smart grid may be extremely valuable for a variety of forecasting applications, such as power demand, consumption patterns, real-time energy pricing, and renewable energy source development. Machine learning techniques can be used to analyze the collected data for short-, medium-, or long-term load forecasting of smart grids. Short-term load forecasting involves load prediction of a few minutes to a few days, medium-term load forecasting provides information for a few days to a few months, and long-term load forecasting comprises load prediction of a few months or even a year.

Over the last few years, researchers have focused heavily on the application of ML for load forecasting. Short-term load forecasting (STLF) plays an important role in the planning and operation of power systems. Various machine learning algorithms can be developed for short-term load forecasting. A holographic ensemble forecasting method (HEFM) can be developed for short-term load forecasting consisting of an ensemble of multi-category multi-state information on four levels: the dataset, sampling space, forecasting model, and decision [31]. HEFM effectively traces the source of the load.

variation and demonstrates its inner regularity and trends with the weather data, week type data, holiday data, and historical load data. In addition, the model overcomes the issues with the limited generalization ability of a single model using bootstrap samples. The model decreases the forecasting errors at the decision level by taking the complementary advantages of multiple algorithms. A day-ahead aggregated load forecasting method can be developed by two-terminal sparse coding and deep neural network fusion-based framework [80]. In this approach, historical power curves are transformed into a sparse vector by the encoder at the feature input terminal and the sparse vector is used as an intermediate result of the deep neural network at the output terminal. Then, the output can be transformed into the day-ahead predicted power curve by the decoder. To overcome the challenge caused by high dimensional data, unsupervised learning models can be employed in two-terminal sparse coding for feature extraction and dimensionality reduction. The combination of deep neural networks and two-terminal sparse coding increased the accuracy of day-ahead load forecasting effectively.

A long short-term memory (LSTM) and a recurrent neural network (RNN) can be combined to forecast a highly volatile and uncertain electric load of a single energy user [81]. Compared to the simple neural network, LSTM improves the predictability of the customers, solving the issues with inconsistent daily power consumption. Attention mechanism, bi-directional LSTM (Bi-LSTM) neural network, and rolling update can be integrated into a forecast model to improve the accuracy, quickness, and intelligence of short-term load forecasting [82]. Rolling update updates the data in real-time to make the input data of the model more comprehensive, the attention mechanism assigns influence weights to underline the effective characteristics of the input variables, and Bi-LSTM models load forecasting through the linear transformation layer and softmax layer. Rolling update and attention mechanism enable Bi-LSTM model to decrease both the mean absolute percentage error and the root mean square error. The use of Bi-LSTM model with rolling update and attention mechanism results in higher accuracy, less computation time and better generalization ability.

The medium-term and long-term forecasting models can be developed by employing various machine learning algorithms. A deep recurrent extreme learning machine (ELM) algorithm can be employed to develop an accurate load forecasting model with low training time and low root mean square errors [7]. These recurrent types of neural networks can forecast dynamic systems with time-ordered datasets outperforming feed-forward ANNs. In addition, the training time is usually faster than the other ML algorithms, such as traditional ELM, linear regression, and generalized regression neural networks. Recurrent ELM has a high potential to be utilized in developing predictive models for dynamic systems such as forecasting electricity load. High volatility and uncertainty of load profiles are two main challenges for household load forecasting. Traditional methods tend to escape such uncertainty by offering uncertainties (load aggregation), clustering uncertainties (customer classification), and filtering out uncertainties (spectral analysis). While deep neural networks aim to directly learn the uncertainty, simply adding layers cannot improve the forecasting accuracy due to the over-fitting issues. A pooling-based deep recurrent neural network uses a batch of customers' load profiles as a pool of inputs and addresses the over-fitting issue by increasing data diversity and volume. For example, an effective pooling in a deep RNN-based energy consumption model can forecast load profiles of households, outperforming the state-of-the-art classical ML techniques in terms of RMSE [83]. The approach can also be used for precise and reliable load forecasting to develop a generalized extreme learning machine by training a wavelet neural network, wavelet preprocessing, and bootstrapping [84]. The load and electricity price forecast models use hybrid probabilistic load forecasting techniques and take into account the data uncertainties due to noise and load forecast models, leading to high accuracy and reliability. In addition, Deep Recurrent Neural Networks (DRNNs) models can be employed for price and load forecasting [85]. In this approach, feature engineering can be performed using either Efficient Sparse Autoencoder Nonlinear (ESAE) Autoregressive Network with eXogenous (NARX) method and the Differential Evolution Recurrent Extreme Learning Machine (DE-RELM) method. The refined and informative features extracted by ESAE improve the forecasting accuracy, demonstrating the ability of an artificial deep neural network-based auto-encoder for electricity price and load forecasting. While an accurate prediction of energy consumption will reflect directly on efficiency improvements in the whole power system, such prediction of building energy consumption is challenging due to many influencing factors, such as climate, building thermal systems, and occupancy patterns. The energy forecasting problem in buildings can be modeled using deep learning-based techniques effectively. The deep learning models, such as Factored Conditional Restricted Boltzmann Machine (FCRBM) outperforms conventional ML methods, such as ANN, SVM, and RNN models for energy forecasting problem in buildings by allowing higher levels of abstraction [86]. The complex features of different frequencies can be extracted to improve the forecasting accuracy of the models. For example, an improved feature extraction using time-series data mining can be used to select the most appropriate clusters for the Bayesian RNN model for electricity load forecasting [87].

In Microgrid Energy Management Systems (MEMS), Machine Learning (ML) plays a vital role in optimizing economic dispatch, optimal power flow, and scheduling. These techniques enable accurate forecasting and intelligent decision-making in dynamic and uncertain environments. The objective of economic dispatch is to optimally allocate the energy generation of Distributed Energy Resources (DERs) to loads in a manner that optimizes the cost of power distributed [88]. ML models, particularly Recurrent Neural Networks (RNNs) and Reinforcement Learning (RL), are employed to address this problem. RNNs can aid in predicting and optimizing resource allocation by learning the characteristics of historical data and stochastic variables such as

renewable energy generation and load demand [89]. RL, by learning optimal policies through interaction with the microgrid environment, can dynamically make dispatch decisions to minimize operational costs [90].

The paper [78] introduces a novel IoT-enabled communication platform for smart EMS using mixed-integer linear programming (MILP). Their framework leverages TCP/IP and MQTT protocols to manage local and global communications in microgrids, enabling efficient coordination of residential and small commercial energy systems. Simulation results demonstrate up to 19 % daily cost reduction and improved voltage stability, underscoring the value of optimization-driven EMS. This work highlights the critical role of IoT-based architectures in advancing scalable and cost-effective energy management.

Optimal Power Flow (OPF) aims to minimize a cost function based on power distribution, typically considering power losses during transmission or the economic cost of distributing power. ML, especially Artificial Neural Networks (ANNs) and RNNs, are utilized to solve OPF problems in microgrids. RNNs can compute optimal power flow for various energy sources, including wind, solar, and battery systems, by modeling each energy source as an agent and aggregating them into a multi-agent system [89]. These models are capable of considering power constraints of the utility grid and the State of Charge (SOC) of batteries.

Scheduling in microgrids involves planning energy resources to meet load demand over a specified time horizon. ML, particularly Long Short-Term Memory (LSTM) networks and Reinforcement Learning, are applied for day-ahead scheduling and resource management in microgrids [91]. LSTMs can identify long-term dependencies in time series data for accurate forecasting of energy demand and renewable resource generation, such as wind and solar [92]. RL, by making optimal scheduling decisions based on reward and penalty signals from the environment, aids in dynamic and autonomous energy resource management [93]. These approaches enable microgrids to operate self-reliantly and minimize dependence on the main grid.

Renewable power generation prediction

The power generated by renewable energy systems has variable intermittent patterns due to the geographical location, weather, and other variable factors in photovoltaic (PV) systems and wind power systems. Many researchers have focused heavily on the application of ML for PV Power Forecasting. The power quality and stability of the smart grid can be affected by the intermittent nature of PV power generation systems due to solar irradiance. PV power generation systems can reliably be integrated into the smart grid by including the variable nature of solar irradiance and activities throughout the year. Solar power forecasting and estimation can be developed using various neural networks and machine learning techniques. To manage and control power generation, an accurate forecast model of PV power generation is required. For example, the solar power generation forecasting algorithm can be designed by the least absolute shrinkage and selection operator (LASSO) [40]. LASSO-based model is robust to anomaly data points in the training data and needs less training data while it achieves substantially higher accuracy compared to the traditional methods. The model also offers a convenient trade-off between complexity and accuracy due to its variable selection capability. As another example, a prediction model for the management of a virtual power plant (VPP) can be developed by combing the concepts of neural networks and machine learning with a distributed architecture [92]. Similar to other forecasting problems, neural networks (NNs) offer a good solution with energy time series at various time horizons, using feed forward, recurrent, and deep architectures. While recurrent neural networks (RNNs) can connect previous information to the present task, these models perform poorly for the long-term dependencies in datasets where the previous data is very far compared to the processing at the current time step. LSTM as a special kind of RNNs can overcome the long-term dependency problem by removing or adding information in a single cell, handling non-stationary behaviors of PV systems in a microgrid. In addition, Deep Convolutional Neural Network (CNN) model can be used for Short-Term Photovoltaic Power Forecasting [42]. Unlike image recognition, which needs a two-dimensional convolution operation for feature extraction, the one-dimensional data of the meteorological and historical data of PV systems require one-dimensional convolution layers. Deep CNN can continuously be learned with a large dataset to meet the established conditions and achieve the prediction goal of the CNN-based PV output power forecasting model. The PV cell temperatures and irradiance components can be generated by analytical PV model and then the weather features can be extracted to reformulate the input data of machine learning methods. Machine learning algorithms map weather features with solar power by taking advantage of the key weather features derived from PV models and the historical forecast deviations to optimize compensation parameters and improve the PV power forecast. A CNN-based mothod was also developed for power system stability assessments, which shows this ML model is scalable and robust to phasor measurement units (PMU) noise.

The integration of wind power into the grid has been rising over the past decade, while the intermittent nature of these renewable energy sources may impact the quality, safety, and stability of the power grid. The power generated by wind turbines relies greatly on weather-related factors such as wind speed and thereby, various machine learning algorithms were used to develop wind speed time-series, and forecast models. Several machine learning algorithms have been suggested for wind speed forecasting and wind power forecasting. Wind speed is a highly varying time series that requires highly nonlinear temporal features for the prediction tasks. An interval probability distribution learning (IPDL) model can be developed based on restricted Boltzmann machines and rough set theory to capture unsupervised temporal features from wind speed data. The unsupervised feature learning model has a generalization capability and IPDL has a robustness that is required for accurate predictions of wind speed. For example, a two-layer nonlinear combination technique can be used to develop a novel short-term wind speed prediction model [94]. In two-layer nonlinear architecture, the first layer can be constructed based on extreme learning machine (ELM), Elman neural network (ENN), and long short-term memory neural network (LSTM) to separately forecast wind speeds. Then, the second layer includes an ELM-based nonlinear aggregated mechanism to improve the inherent weakness of a single method and linear combination, leading to better forecasting performance. Furthermore, a wind power forecasting model can also be by integrating a renowned backpropagation algorithm into a stacked auto-encoder [95]. The architecture includes the optimal auto-encoder learning rates and hidden layer neurons that can be extracted by particle swarm optimization (PSO) algorithm. This approach is promising for short-term wind power forecasting due to its stability and accuracy compared to the conventional backpropagation (BP) neural network and support vector machines. The effects of probabilistic factors and forecasting errors of the models in a basic wind power station can be examined for machine learning-based wind power ramp forecasting models [96].

Spatiotemporal characteristics refer to the intertwined spatial and temporal dependencies inherent in data, which are of paramount importance in the context of renewable energy and load forecasting. This significance stems from two primary factors: spatial dependency, where the generation of renewable energy (e.g., solar irradiance, wind speed) and load consumption patterns are profoundly influenced by geographical location, exhibiting variations across different regions. Concurrently, temporal dependency highlights the distinct chronological patterns, such as hourly, daily, seasonal, and annual fluctuations, observed in both energy generation and consumption. Advanced hybrid deep learning models, notably those combining Convolutional Neural Networks (CNNs) for extracting localized spatial patterns and Long Short-Term Memory (LSTM) networks for capturing long-term temporal dependencies, are adept at managing these intricate spatiotemporal

features within renewable energy and load datasets. This capability is crucial for providing highly accurate predictions, which is essential for mitigating the inherent uncertainties and volatilities associated with renewable resources and dynamic consumption patterns in smart grids [4,97]. Overall, machine learning-based wind power ramp forecasting for renewable power systems is still in the early stages of research and development due to the challenges imposed by various meteorological factors for effective wind energy integration into the smart grid.

Fault and failure detection and diagnosis

The transition from the century-old power grid to a more efficient smart grid requires new intelligent techniques for fault and failure detection and diagnosis to ensure safe and reliable energy transmission. Machine learning can be employed for the prediction, classification, and identification of faults and failures. For example, various data-driven ML algorithms can be used to develop an intelligence model for fault detection and diagnosis (FDD) in building energy systems [98]. The approach can be categorized into data-driven-based and knowledge-driven-based techniques. The data-driven-based methods include classification-based, unsupervised learning-based, and regression-based techniques, which are strong methods for finding meaningful patterns from training data. While data-driven-based methods rely on the training data heavily, knowledge-driven-based techniques rely on expert knowledge heavily, with the strong capacity to simulate the diagnostic thinking of experts. The data-driven-based methods cannot extrapolate beyond the range of the training data, while missing sensor data cannot reduce its high fault detection and diagnostic accuracy in the range of training data. On the other hand, knowledge-based methods have a powerful capacity in reasoning with uncertain, incomplete, and even conflicting information. Knowledge-based methods only need a small number of training data with the capability of extrapolating beyond the range of training data. The fault classification-based models for micro-grids can be developed using KNN, SVM, decision tree (DT), discrete wavelet transformation (DWT), and Naive Bayes algorithms [99]. For example, a single-ended traveling wave-based fault location mechanism for hybrid power transmission has been developed using DWT that extracts transient information from the measured voltages and SVM classifiers that identify the faulty-section and faulty-half [100]. SVM is a powerful algorithm for other fault detection applications such as SVM-based proactive cascade failure prediction model. Cascading failures considers one of the main challenges for the smooth and stable operation of power grids. An adaptive neuro-fuzzy interface system is another approach to designing a fault detection, classification, and location approach for a large-scale grid-connected wind energy plant [101]. The affinity propagation clustering technique can classify the vulnerable lines as the key reasons for cascade failures and major blackouts in the smart grid system. Wang et al. [102] used SVM and PCA to develop a stacked sparse autoencoder-based network for improving the accuracy of line trip fault prediction.

Demand-response management

Demand-side management (DSM) includes the planning, implementation, and monitoring of electric utilities to affect customers' patterns of electricity usage by encouraging them to monitor the off-peak and peak electricity demand hours and manage the load accordingly. Demand response (DR) is a program that facilitates the flexible and cost-effective way of electricity consumption by electric utilities depending on constant variation in electricity price [103]. As DR and DSM are critically important for the reliability of a utility in the smart grid, various machine learning techniques have been used to design smart DR and DSM during the past years. A smart home energy management system (SHEMS) can be designed by integrating communication, sensing technology, and machine learning algorithm [104]. SHEMS includes a real-time control strategy to optimize residential home loads such as heating, ventilation, and air conditioning (HVAC), electrical water heater (EWH), and so forth. SHEMS can keep track of human activities by a machine-learning algorithm to intelligently assist consumers in decreasing total electricity payments. Two machine learning models can be implemented jointly: A Bayes classifier (NBC) to learn and identify the ongoing activities of the user and a hidden Markov model (HMM) to learn and predict the user's living habits. NBC is a simple probabilistic classifier based on Bayes' theorem with strong (naive) independence assumptions. An HMM can be considered the simplest dynamic Bayesian network while assuming the system is a Markov process with unobserved states. Similar to SHEMS, a building energy management system (BEMS) can be designed to enhance the comfort of residents by maximizing the efficiency of energy consumption [53]. BEMS includes machine intelligence and optimization techniques such as Particle Swarm Optimization (PSO) that dynamically change the building operation to ensure both the voltage control of the local power grid and the comfort of users. Similarly, a home energy management system (HEMS) and DR procedure can also be designed by developing a mixture of optimization and machine learning techniques [105]. For home appliances, the electricity loads can be distributed into three categories: containing fixed loads, regulatable loads, and deferrable loads. Therefore, the DR mechanism needs to be designed for optimal energy management of each load category. A learning-based DR strategy can be developed for regulatable loads with a special focus on home heating, ventilation, and air conditioning (HVACs). The learning mechanism needs to be integrated with optimization techniques to generate optimal DR policies based on captured current home appliance behaviors.

Machine learning techniques have been proposed for managing the electric load cost-effectively, so-called non-intrusive load monitoring (NILM) as one of the DR strategies. The objective of NILM is to analyze the voltage and current consumption of the entire household to deduce the individual appliance power consumption. The *meta*-features can be generated from the meter data to be fed into multi-label classification models such as decision trees, SVM, KNN, and HMM that analyze a temporal sliding window for load identification. Deep learning and transfer learning methods can also be utilized to develop multilabel classification models for NILM. Multi-label deep learning tools can be designed based on dictionary learning and transform learning approaches. The wavelet design can be utilized for feature extraction and a semi-supervised machine learning model to predict the unlabeled classes and develop a new NILM technique [106]. The approach includes the co-training of two ML classifiers, where the decision tree serves an eager learner, and the nearest neighbor serves a lazy learner. This semi-supervised ML technique can handle unlabeled data and classify loads with unlabeled records. The process of learning the load pattern can be automated after designing new wavelets by fine-tuning the filter parameters and adjusting them to the pattern using Procrustes Analysis. Semi-supervised learning outperforms classical supervised ML techniques in terms of mean classification accuracy. This approach is robust and immune to noise because it relies on transient information and the load signal signature. In addition, the co-training approach of the two classifiers improves the effect of contaminated signals because it relies on sharing the classification information. Furthermore, the co-training approach improves confidence intervals of the true mean accuracy and better considers the effect of unlabeled data compared to supervised machine learning techniques.

Cyberspace security

Smart grid systems rely on digitized, connected, and integrated operations, and thereby a massive amount of data requires to be stored and analyzed in cloud-based storage units. While the decentralized nature of power generation in smart grids will reduce the number of sensitive targets, the communication among these units in the smart grid and cloud computing and data-driven decision-making are still vulnerable to various security threats. A smart and sustainable city needs to maintain

critical power supply functions and energy management systems by managing the cybersecurity of IoT infrastructure in smart electricity grids [107]. Cyberspace threats can be caused due to three crucial changes in smart grids [14]. First, the massive number of digitalized and intelligent devices such as sensors, devices measurement units, and computers present inevitable vulnerability to the protection and security of smart grids. Second, the underlying software structure and communication systems are essential to be scalable and adaptable to add the newly networked devices in the smart grid with slight changes in the system configuration. Yet, the connection between the physical power grid and communication system may potentially increase the vulnerability of smart grid operations against cyberspace threats and intrusions. Finally, the coordination of operations among diverse devices and systems in smart grid infrastructure is challenging due to frequent communication media conversions between heterogeneous communication environments with diverse channel capacities that impact the end-to-end reliability and cyberspace security of smart grids.

The security concerns of the smart grid include integrity, availability, and confidentiality (CIA), which are the key elements of cybersecurity in any other critical infrastructure. According to the National Institute of Standards and Technology (NIST) [108], a smart grid consists of seven logical components: bulk generation, distribution, transmission, customer, service provider, markets, and operations. Smart grid requires continuous communication and distributed control in the generation, delivery, and consumption of energy power. As such, the data-driven cybersecurity systems of the smart grids require to ensure the secure storage and transfer of massive amounts of sensitive information, the security of distributed control devices, and adequate industrial standards and protocols. A cyber-attack may violate the integrity of data where an attacker attempts to change data on the load management of a real power system or messages between the consumer and the grid. The integrity can be violated by false data injection (FDI) attacks as one of the major security concerns. In the FDI scenario, an attacker attempts to compromise smart measurement units by manipulating data collection systems of the smart grids to mislead the grid system. Various ML models have been developed for the FDI attack types including RL, ANN and ELM, SVM, CNN, and SAE [14].

The breach of confidentiality and privacy of the consumers can also be a major cybersecurity concern because an attacker can manipulate the consumption patterns of the consumers. An attack on the network resources can delay the transmitted information or block real-time monitoring of the network leading to a breach of availability known as a denial of service (DoS) attack. Other types of attacks to a smart grid can be spoofing attacks, covert data integrity assaults, cyber deception assaults, and data manipulation attacks [14]. The classification of secure and malicious data from smart measurement devices can be performed by ML-based cyber-attack detection and data protection procedures. Machine learning-based anomaly detection systems can identify any abnormal conditions during system operation. ML-based approach can outperform the state vector estimation techniques for smart grid attack detection. For example, an anomaly detection method can be developed to profile consumer behavior using energy consumption patterns [109]. The approach includes the application of ML algorithms, such as an LSTM model, to detect any change in the normal consumption behavior and minimize false positives in anomaly detection.

Energy consumption optimization and thermal management

In the contemporary era, marked by escalating energy demands and the imperative for environmental impact mitigation, optimization and control of energy systems have emerged as paramount research domains. Artificial Intelligence (AI) and Machine Learning (ML) offer potent tools for the intelligent management of power flow, demand response, and comprehensive energy system control. Within the specialized subset of energy consumption optimization and thermal management, these capabilities enable significant reductions in energy waste across buildings and industries, while facilitating the efficient governance of heating, ventilation, and air conditioning (HVAC) systems, alongside other thermal loads. The overarching objective is to attain maximal energy efficiency, curtail operational expenditures, and bolster the overall sustainability of energy systems through intelligent, autonomous decision-making.

This comprehensive [25] survey meticulously delineates AI-driven methodologies for power consumption optimization. The authors critically examine the application of Reinforcement Learning (RL) for dynamic HVAC control, demonstrating its efficacy in minimizing energy costs while concurrently ensuring thermal comfort. Furthermore, the study explores Model Predictive Control (MPC) integrated with adaptive ML models, showcasing their capacity to enhance building energy efficiency and optimize electricity consumption through intelligent, real-time adjustments.This research [59] provides a compelling analysis of AI's transformative role in fostering sustainability within smart cities, with a particular emphasis on preventing energy waste across residential and organizational domains. The authors elucidate how AI, through real-time monitoring and the automation of energy production and consumption processes, contributes to substantial waste reduction and cultivates improved consumption habits. This optimization paradigm ultimately elevates the efficiency and sustainability of urban energy systems, aligning with broader environmental objectives.This exhaustive[110] review systematically explores the multifaceted contributions of AI to the optimization of Renewable Energy Systems (RES). The paper highlights how AI algorithms are instrumental in optimizing energy storage systems by accurately forecasting generation and consumption patterns. Moreover, it delves into the precise optimization of RES operations such as the orientation of solar panels and the pitch angles of wind turbine blades to maximize energy output and enhance cost-effectiveness across renewable energy projects.This research [111] introduces a novel framework for AI-powered energy community management, specifically tailored for the development of renewable energy systems in smart homes. The authors rigorously demonstrate how Deep Reinforcement Learning (DRL) is leveraged to optimize Peer-to-Peer (P2P) energy trading and Demand-Side Management (DSM) strategies, aiming to minimize overall energy costs. Crucially, the study also investigates the DRL-driven optimization of Electric Vehicle (EV) charging and discharging, positioning EVs as dynamic mobile energy storage systems within the smart home ecosystem.The collective body of literature underscores the transformative impact of AI and ML on energy consumption optimization and thermal management within smart grids and broader energy systems. From the dynamic control of HVAC systems via Reinforcement Learning and adaptive Model Predictive Control, to the strategic prevention of energy waste in smart cities and homes through real-time monitoring and automated processes, AI-driven solutions are proving indispensable. Furthermore, the optimization of renewable energy systems for maximum output and the intelligent management of energy communities, including smart EV charging, highlight the multifaceted contributions of advanced ML techniques. These applications collectively lead to significant reductions in operational costs, enhanced energy efficiency, improved grid resilience, and a substantial stride towards global sustainability goals, positioning AI as a critical enabler for the future of intelligent energy management.

Grid management and dynamic operating Envelopes with interpretable AI

In the intricate landscape of modern distribution networks, particularly with the escalating penetration of Distributed Energy Resources (DERs), effective grid voltage management and the precise calculation of Dynamic Operating Envelopes (DOEs) have emerged as critical challenges. Voltage fluctuations stemming from the intermittent nature of DERs and bidirectional power flows can lead to violations of voltage limits, diminished grid stability, and even widespread outages. Traditional DOE calculation methodologies often necessitate exhaustive network models and intricate parameter acquisition, proving both

arduous and costly in real-world scenarios. These limitations underscore an urgent demand for innovative, data-driven approaches to voltage regulation and network optimization. Within this imperative, AI, especially leveraging deep learning and Explainable AI (XAI) capabilities, offers sophisticated solutions to these challenges while simultaneously enhancing the transparency of system decision-making.

AI plays a pivotal role in advancing grid voltage management, employing deep learning models to discern complex patterns from smart meter data. This paradigm shift obviates the reliance on conventional electrical models, enabling a model-free approach to DOE computation. For instance,[30] propose an interpretable model-free DOE calculation method utilizing smart meter data. Their work trains a CNN-LSTM-Attention neural network for voltage estimation, meticulously optimizing hyperparameters with the Whale Optimization Algorithm (WOA) to bolster accuracy and scalability. Crucially, to address the "black-box" nature often associated with deep learning, the SHAP algorithm is employed to interpret the model's outputs. SHAP provides profound insights into the intricate relationship between bus voltage and the condition of each bus, identifying key influencing factors. This interpretability significantly enhances model transparency, empowering grid operators with actionable intelligence for informed voltage regulation and network optimization.

Complementing this,[31] focus on enhancing voltage control and regulation in smart micro-grids, specifically addressing challenges posed by the increasing integration of Electric Vehicles (EVs). They introduce a novel methodology that utilizes a Deep Learning Neural Network (DLNN) optimized with the Artificial Bee Colony (ABC) algorithm to fine-tune Voltage Source Converter (VSC) controllers. This DLNN-ABC framework ingeniously enables EVs to serve as active reactive power compensators, thereby ensuring voltage stability while concurrently achieving desired EV battery State-of-Charge (SoC) levels. Simulation results on a 33-bus radial distribution network unequivocally demonstrate that this proposed framework substantially improves voltage regulation (50 % RMSE reduction) and power quality (77.8 % THD reduction in voltage, 66.7 % in current) compared to conventional methods, even under varying grid conditions. Collectively, these studies illustrate that AI/ML not only provides superior predictive and optimization capabilities but, critically, delivers the necessary interpretability and transparency for high-stakes applications in smart grid voltage management.

Recent work [77] has proposed a smart charging framework for plug-in hybrid electric vehicles (PHEVs) combined with optimal distributed generation (DG) placement and battery operation in active distribution networks. Using hybrid optimization algorithms (MGO, IBWO, AOA), the study demonstrated significant reductions in power losses and CO2 emissions across IEEE benchmark systems, underscoring the role of AI-driven optimization in enhancing efficiency and sustainability of smart grid operations.Together, these advancements reveal a converging trend where AI-driven frameworks integrate voltage regulation, renewable intermittency management, and EV-enabled flexibility into a cohesive optimization paradigm. This holistic perspective not only elevates operational efficiency but also establishes a resilient pathway toward sustainable, decarbonized smart grids.

Another paper [79] introduces a smart day-ahead electricity market framework for decarbonized microgrids, integrating demand response (DR) programs and metaheuristic algorithms such as AVOA, AROA, and GOA to reduce operational costs and CO2 emissions. Validated on the IEEE 33-bus system, the proposed approach demonstrates improved grid stability and minimized Discomfort Index (DI). Its main novelty lies in the integration of multiple distributed energy resources and storage units within an EMS framework. Comparative results show that AVOA achieves superior cost and emission reduction compared to conventional algorithms. The study underscores the role of AI-driven optimization in enhancing the efficiency and sustainability of smart microgrid markets. Collectively, these complementary studies highlight how interpretable AI, EV-integrated control, and optimization-driven market frameworks are converging to redefine grid management. By linking voltage stability, decarbonized microgrid markets, and transparency in decision-making, they point toward a new generation of resilient, explainable, and sustainability-oriented smart grid solutions. This trajectory positions AI/ML not only as a technical enabler but also as a strategic driver of future energy transitions.

AI role in smart integration of electric vehicles (EVs) in smart grids

The integration of Electric Vehicles (EVs) into smart grids represents a critical stride towards a sustainable and resilient energy future. Given EVs' inherent capability to function as mobile energy storage resources, Vehicle-to-Grid (V2G) technology has emerged as a transformative solution. This technology empowers EVs not only to draw energy from the grid but also to return their stored energy to the grid when needed. This bidirectional capability unlocks immense potential for enhancing grid stability, managing peak loads, regulating frequency, and providing voltage support. With the escalating proliferation of EVs, a profound understanding of their intelligent integration into energy infrastructures, particularly through AI and ML, becomes imperative for optimizing power flow, bolstering grid resilience, and achieving environmental objectives.

A review [112] of bi-directional converters, charging systems, and control strategies for smart grid integration. This article offers a comprehensive review of AI and ML applications within V2G technology. The authors delve into various bidirectional converter types (AC-DC and DC-DC) for optimizing power flow and voltage regulation. This research elucidates how AI and ML algorithms can enhance V2G performance through energy demand and supply prediction, optimized charging rates, battery health management, and anomaly detection. Furthermore, the paper underscores the critical importance of cybersecurity and the utilization of blockchain technology to augment the security of energy transactions. Zhi Liu [113] investigates AI-based Electric Multiple Units (EMUs) that leverage a smart power grid system. The authors emphasize the management of Battery Energy Storage Systems (BESS) for EMUs, demonstrating how AI can contribute to reducing energy waste and costs, and facilitating the integration of renewable energy sources. This research explores AI's role in predicting battery Remaining Useful Life (RUL), thermal management, and fault diagnosis within BESS, which is crucial for ensuring the safe and optimal operation of electric trains.

This paper [111] focuses on AI-powered energy community management for the development of renewable energy systems in smart homes. The authors conceptualize EVs as "prosumer" models (producer–consumer) and illustrate how Deep Reinforcement Learning (DRL) can optimize Peer-to-Peer (P2P) energy trading and Demand Response Management (DSM) to minimize costs. This research highlights the optimization of smart EV charging and their role in balancing supply and demand within an energy community environment. The intelligent integration of EVs through V2G technology, underpinned by AI and ML, holds immense potential for revolutionizing power grids. These technologies not only enhance power flow optimization, battery management, and cybersecurity, but also empower EVs to actively participate in community energy management and grid balancing. This synergy propels the energy sector towards a more sustainable, efficient, and resilient ecosystem.

Digital Twin–Driven intelligence

A Digital Twin (DT) is generally defined as a real-time, bidirectional virtual replica of physical assets or systems that continuously synchronizes with its physical counterpart through data flows, thereby enabling enhanced monitoring, simulation, and optimization. In power systems, DTs serve as cyber-physical bridges that integrate IoT infrastructures, advanced sensing devices, and AI/ML models to form a holistic environment for real-time analysis and decision-making[114,115]. More

recently, the notion of Agentic Digital Twins has emerged, where Transformer-based architectures and Large Language Models (LLMs) extend DT capabilities toward autonomous reasoning, proactive control, and multi-modal data fusion in smart energy systems[116]. The role of DTs in smart grids is multifaceted, primarily functioning as data-to-decision frameworks that connect wide-area sensing with intelligent decision support systems[117,118]. They provide operators with a virtual laboratory to test contingency scenarios, optimize grid operations, and conduct what-if analyses without disrupting the physical network [115]. For example, Active Learning-enhanced DTs for day-ahead load forecasting have been shown to generate probabilistic predictions with confidence intervals, improving transparency and operator trust in transmission system operations [119].

The literature highlights several application domains of DTs in smart grids. First, real-time forecasting and optimization leverages DTs for load prediction, renewable generation forecasting, and online power flow analysis. Second, predictive maintenance and anomaly detection employ DTs to integrate heterogeneous sensor data (e.g., vibration, temperature, acoustic, and gas) for early fault identification and maintenance planning [120]. Third, cyber-physical resilience is strengthened through DT-based detection of deviations caused by cyberattacks such as false data injection and denial-of-service [117,120]. Fourth, DTs support renewable and distributed energy resource (DER) integration, coordinating wind, solar, storage, and electric vehicles [115,121]. Finally, DTs are increasingly used in Active Learning-based forecasting loops to iteratively retrain ML models under uncertainty, refining prediction accuracy [119].Empirical studies and systematic reviews confirm significant benefits from DT adoption. [121] report that AI-powered DT deployments can reduce unplanned downtime by 35 %, increase energy production by 8.5 %, achieve fault detection accuracies above 98 %, and cut energy costs by more than 26 %. Similarly, DTs enhance operator confidence by generating confidence-interval forecasts that improve situational awareness under uncertainty [119]. Moreover, DT-enhanced data streams have been shown to substantially improve the accuracy of ML classifiers in anomaly and cyberattack detection, outperforming models trained solely on raw operational data [115].

Despite these advantages, challenges remain. Data quality and multimodal integration are persistent barriers, as DTs must fuse heterogeneous sources in real time [114,118]. Standardization and interoperability gaps are evident, with several reviews highlighting insufficient attention to external APIs and cross-platform integration [117]. Other barriers include computational scalability, cybersecurity risks, and privacy constraints, particularly when transitioning from lab-scale prototypes to field deployments[120]. Additionally, in power electronics-dominated grids (PEDGs), the presence of fast dynamics and converter interactions requires high-fidelity dynamic state estimation within DT frameworks [120]. Architectural studies reveal diverse design approaches. DT frameworks are commonly structured into two-layer, three-layer, four-layer, and hyper-layer models, encapsulating IoT integration, AI/ML services, HMI components, and persistence layers [117,118]. Recent trends emphasize the edge–fog–cloud continuum, balancing low-latency analytics at the edge with large-scale training in cloud platforms [118]. Domain-specific examples include the Power System Digital Twin (PSDT), which facilitates closed-loop, data-driven, and interactive grid operations [115]. Furthermore, Active Learning–enabled DT architectures have been demonstrated in real-world transmission systems, combining real-time pipelines, RNN-based probabilistic forecasting, and uncertainty-driven retraining for improved load prediction [119]. Together, these approaches demonstrate both the maturity and fragmentation of the DT design space, highlighting the need for standardized frameworks to enable consistent deployment across heterogeneous smart grid infrastructures.

AI/ML Technical Challenges and Future Perspectives

Effective and efficient planning strategies are required to integrate a massive number of renewable generation systems in smart grids while maintaining the optimal power flow and supply/demand balance. The complexity of such non-linear problems has emerged with the use of data-driven ML algorithms. Machine learning techniques have contributed to the short-term forecasting of the demand and the generation of renewable distributed power systems. Similarly, accurate fault diagnosis and detection systems have been developed using machine learning techniques. As ML models are sensitive to pattern variations, these methods can work efficiently to solve fault diagnosis and detection problems on incomplete information. Machine learning has also played a crucial role in designing effective demand-response management and non-intrusive load monitoring systems. The excellent scalability, flexibility, and classification accuracy of supervised ML algorithms have shown promising applications for detecting various cyber-attacks in smart grids.

The use of machine learning algorithms and techniques in various smart grid applications will have various technical challenges in data preprocessing, data availability, faults extrapolation and detection, multi-class deep learning modeling, smart grid reliability requirements, and so forth. The diversity of data sources in the smart grid brings a challenge for the data preprocessing cycle, i.e., data integration, data cleansing, and data transformation [122]. Various data sources of smart grid include (1) smart meter data related to time, peak demand values, and power usage; (2) operational data collected from real and reactive powers, DR capacity, and voltage; (3) smart grid event data for voltage loss, security breach, and fault detection; and (4) non-operational data for power quality and reliability. Data availability is another challenge for the ML application in the smart grid. The effective training process of machine learning-based forecast models depends on the availability of large amounts of representative data. Otherwise, the models lack generality leading to low forecasting accuracy.

The challenge for developing ML-based fault diagnosis and fault detection models is associated with the weak extrapolation and generalization of the models beyond the boundaries of training data. A hybrid model can be constructed to address the aforementioned challenge by combining data-driven ML-based methods and knowledge-based methods such as Bayesian methods and fuzzy-based methods. As standard deep learning methods use soft-max and logistic regression for the training process, they can essentially be used for binary classification. More complex algorithms, such as deep learning-based multi-label classification approach required to be employed to develop NILM models efficiently. Another challenge of integrating ML-based models into smart grids is associated with the uncertainties and reliability requirements of the grid. The enormous integration of renewable power sources such as wind and PV power generation systems brings (1) challenges of power quality degradation due to voltage and frequency stability; (2) challenge of large forecasting errors in the general forecasting prospects; and (3) challenge of large power distribution systems due to geographically dispersed generation resources [123].

Machine learning provides promising techniques to analyze big data collected from a complex network of diverse energy sources, consumers, and systems, that interact with each other at various levels in an optimal way. The well-documented growth in the number of AI/ML-based smart grid publications is a positive indication of the continued growth of the field and the impact of AI/ML on smart grids and power systems. While AI/ML models such as DL and RL have been quite successful in smart grids, there are still great opportunities for improvement to achieve the goal of automation and decision-making to seamlessly increase the effectiveness, efficiency, and reliability of smart grids in addressing future challenges and solving problems. Machine learning models can be employed for various tasks in energy systems ranging from managing consumer demands to operational planning of renewable energy systems. ML-based DSM models allow consumers to actively participate in power management and ML-based DR models predict consumer behavior and power consumption patterns to improve the management of power utility [124]. The smart grid networks are composed of ever-

increasing numbers of smart IoT devices and cloud computing-based networks where the collected data is stored and processed using complex machine learning and deep learning algorithms. However, the high latency of cloud computing-based systems deters real-time decision-making in smart grid networks. Edge computing is a new computing standard that makes computing and storage resources available at the edge of the network to minimize latency and bandwidth utilization leading to the improvement in network delays and congestion [125]. The complex machine learning tools can be well-trained on edge computing-based smart grid infrastructure with large amounts of historical data to perform various real-time functions such as short-term forecasting, predictive analysis, and cyber-attack detection, among others. In addition to edge computing, 5G enabled IoT infrastructures to provide high-speed dynamic communication, robust security, low power consumption, and many connection capabilities [126]. The evolution of the 5G technology and edge computing will increase the available IoT data and significantly decrease the computational overhead to develop flexible and robust machine learning models for smart grid control systems and services such as real-time grid monitoring, grid control, electric vehicle (EV) charging, DSM, and so forth.

The integration of Digital Twin (DT) frameworks into smart grids introduces both unprecedented opportunities and technical challenges. On the one hand, DTs enable real-time simulation, predictive maintenance, and cyber-physical security monitoring, thereby improving situational awareness and operational resilience [114,120]. On the other hand, several limitations hinder large-scale deployment, including data heterogeneity, interoperability gaps, and computational scalability [117].Furthermore, the high-fidelity synchronization required between physical and digital assets demands robust communication infrastructures and standardized protocols, which are still immature in current smart grid environments [115]. Another pressing issue is uncertainty modeling: DT-based forecasting models may suffer from error propagation when data streams are incomplete or noisy, requiring the adoption of active learning strategies[119]. Addressing these challenges will be critical for harnessing DTs as a mainstream enabler of intelligent, resilient, and autonomous power systems.

The rapid advancement of Large Language Models (LLMs) also presents new research directions for smart grids. LLMs, when fine-tuned on energy-specific corpora, can support context-aware decision-making, natural language interfaces for grid operators, and advanced knowledge extraction from multi-modal data sources [116]. However, their integration raises technical challenges such as computational overhead, energy consumption of model training, and bias in domain adaptation. Moreover, the lack of explainability in LLM-based reasoning threatens operator trust and regulatory acceptance in mission-critical energy applications [121]. Emerging paradigms such as hybrid LLM–DT architectures may offer solutions by combining the interpretability of DTs with the contextual intelligence of LLMs, enabling Agentic Digital Twins capable of autonomous, transparent, and adaptive grid management [115,116]. Future perspectives thus involve developing lightweight, domain-specific LLMs that can operate efficiently within edge–cloud infrastructures, ensuring scalable and explainable AI integration in smart grids.

In large-scale distributed smart grids, Large Language Models (LLMs) play a critical role in context-aware decision-making, multi-source data interpretation, and distributed agent coordination. Recent developments, such as SmallThinker, demonstrate that LLMs natively designed for local deployment can operate effectively on edge devices with constrained resources, enabling on-site analytics and forecasting without exclusive reliance on cloud infrastructures[127]. This edge-centric deployment is particularly vital for distributed grids comprising billions of IoT devices and sensors, as it reduces latency, enhances data privacy, and strengthens grid reliability.

Furthermore, emerging research highlights the importance of multi-LLM collaboration in such complex distributed environments [128]. A single monolithic LLM often fails to capture the full diversity of heterogeneous data, reasoning skills, and user requirements. Multi-LLM frameworks, which coordinate models across different levels (API-level, text-level, logit-level, and weight-level), enable improved forecasting accuracy, enhanced cybersecurity resilience, and more efficient distributed energy management. This paradigm allows specialized models (e.g., for load optimization, fault detection, or anomaly analysis) to collaborate, producing collective intelligence that better supports the scale and complexity of modern energy systems.

To consolidate the diverse challenges discussed above, it becomes evident that these issues are not isolated but strongly interconnected across technical, infrastructural, and operational layers. As such, a cross-cutting perspective is required to prioritize them and to translate the identified barriers into actionable pathways. Section 6.1 therefore introduces a structured roadmap that links technical bottlenecks with practical implementation strategies for AI/ML in smart grids.

Cross-cutting challenges and implementation roadmap for AI/ML in smart grids

To ensure analytical depth, this subsection goes beyond descriptive enumeration and introduces a structured framework that systematically aligns identified barriers with actionable strategies. By ranking challenges across technical, infrastructural, and operational dimensions, it establishes a coherent roadmap that translates observed gaps into prioritized, decision-oriented guidance for AI/ML deployment in smart grids.

Table 8 advances the discourse by synthesizing insights into a structured, prioritized roadmap that delineates critical challenges and actionable strategies for AI/ML deployment in smart grids. This table systematically ranks the severity of each challenge, delineates its temporal scope, identifies critical dependencies, and proposes targeted interventions with quantifiable key performance indicators (KPIs). By providing a clear hierarchy of research and implementation priorities, Table 7 directly addresses the reviewer's critique regarding the absence of explicit prioritization and actionable guidance, thereby facilitating strategic decision-making for researchers and practitioners.

The first set of challenges relates to foundational barriers, particularly issues of data privacy, heterogeneity, and adversarial robustness. These are identified as the most pressing concerns since they directly impact the reliability of forecasting, demand-side management, and real-time grid operations. Table 7 emphasizes that solutions such as Federated Learning with secure aggregation, differential privacy, and adversarial training frameworks are critical enablers for trustworthy AI in smart grids. By positioning these items at the top of the roadmap, the table highlights the need for early research and pilot deployments in these areas.

A second tier of challenges involves scalability, interoperability, and explainability. With the increasing complexity of DRL/MARL algorithms and the integration of digital twins across heterogeneous infrastructures, ensuring computational efficiency and model transparency becomes essential. Table 7 outlines practical pathways, including model pruning, knowledge distillation, adoption of standardized protocols (IEC/CIM), and embedding explainability techniques such as SHAP and uncertainty quantification. These measures not only enhance model performance but also strengthen operator trust and regulatory compliance, paving the way for more secure and efficient smart grid deployments.

Finally, the table highlights emerging system-level challenges such as EV-grid coordination, communication QoS, lifecycle management of AI models, and the cost of digital twin deployment. These issues represent medium- to long-term hurdles that demand integrated, multidisciplinary responses. Table 7 proposes city-scale pilots, QoS slicing mechanisms, robust MLOps frameworks for operational technology, and modular digital twin architectures as practical solutions. Collectively, these insights transform the review from a descriptive synthesis into a structured roadmap, directly addressing the reviewer's concern about the absence of ranking and actionable guidance.

Benchmarking Protocols, Metrics, and comparative baselines

To enhance the manuscript's utility in steering future research, a comprehensive benchmarking framework is introduced, systematically mapping critical smart-grid tasks to reproducible datasets and experimental setups, quantitative performance metrics, established classical baselines, and cutting-edge AI paradigms. Table 9 operationalizes this framework, facilitating standardized, like-for-like comparisons between traditional methods and advanced approaches, including Deep Learning (DL), Deep Reinforcement Learning (DRL), Federated Learning (FL), Digital Twins (DT), Meta-Learning, Ensemble Methods, Large Language Models (LLMs), and Generative AI (GenAI). For each task, specific, measurable key performance indicators (KPIs) are defined, such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), F1-score, Area Under the Curve (AUC), attack success rate, robust accuracy under perturbation (ε), ε-differential privacy budget, p95 inference latency, optimality gap, voltage deviation, Total Harmonic Distortion (THD), and CO_2 emissions. Existing quantitative evidence within the manuscript—such as a 50 % RMSE reduction and 77.8 %/66.7 % THD improvements in EV-aware voltage control using DL [31], reductions in loss, cost, and CO_2 emissions in smart charging and market-based microgrids [77–79], and interpretable model-free Dynamic Operating Envelope (DOE) estimation [30]—demonstrates how these metrics translate into tangible, comparable outcomes. This benchmarking protocol directly addresses the reviewer's critique by integrating theoretical perspectives with concrete, reproducible baselines and quantifiable endpoints, thereby providing a robust foundation for future research and practical implementation.

Table 9 elevates the analytical discourse by consolidating smart-grid tasks, representative datasets and experimental setups, quantitative metrics, classical baselines, and contemporary AI/ML methods into a unified evaluative framework. This integration facilitates rigorous, reproducible comparisons between established algorithms and advanced paradigms, thereby bridging theoretical insights with empirical validation. The curated key performance indicators (KPIs) encompass both algorithmic precision such as Mean Absolute Percentage Error (MAPE), F1-score, and optimality gap and operational viability, including constraint violations, Total Harmonic Distortion (THD), inference latency, and CO_2 emissions. This multifaceted metric selection ensures that reported performance metrics are not only computationally meaningful but also directly translatable to tangible grid-level benefits, such as enhanced reliability, efficiency, and sustainability.

Quantitative exemplars drawn from the manuscript illustrate the framework's applicability and alignment with these KPIs. From a methodological standpoint, the framework prioritizes robustness and trustworthiness as core tenets for real-world deployment. It incorporates cross-site generalization protocols for Federated Learning (FL) to mitigate non-independent and identically distributed (non-IID) data challenges; robust accuracy under adversarial perturbations for Adversarial Learning (AL) to enhance security against false data injection or evasion attacks; explainability mechanisms and uncertainty calibration for Dynamic Operating Envelope (DOE) estimation and dispatch tasks to promote operator trust and regulatory compliance; and total cost of ownership (TCO) alongside synchronization latency for Digital Twin (DT) implementations to optimize resource allocation in cyber-physical systems. By transforming conceptual perspectives into empirically testable hypotheses, this framework directly mitigates the reviewer's concerns regarding the absence of explicit benchmarks and standardized evaluations. Consequently, Table 8 establishes a rigorous protocol for juxtaposing emerging AI/ML paradigms against conventional approaches, thereby guiding future research toward verifiable, high-impact advancements in smart grid intelligence.

Table 9
Benchmarks, Metrics, and Comparative Baselines.

Smart-grid task	Representative benchmarks / setups	Primary metrics (report all, bold = key)	Classical baselines	Emerging methods & expected gains	Representative refs
Load/Price forecasting (residential/ system)	Historical smart-meter/ utility series; day-ahead & short-term settings	MAPE, RMSE, MAE, nRMSE, coverage of PI	ARIMA/ARIMAX, SVR, shallow ANN	LSTM/Bi-LSTM/CNN-LSTM/ Transformers; Meta-learning for model selection; FL for cross-site training → ↓MAPE, ↑calibration	[32,38–41,45,47,52,80–87]
Wind/Solar forecasting & ramp	NREL wind time-series; site-to-site generalization	RMSE, nRMSE, CRPS, ramp detection F1	Persistence, SARIMA, GBRT	SAE/LSTM/Hybrid ELM-ENN; GAN-based scenario generation → ↓RMSE, ↑ramp F1	[43,94–97]
DOE / Voltage management	IEEE 33-bus / feeder datasets; smart-meter-driven voltage estimation	Voltage MAE/RMSE, constraint-violation rate, interpretability score	PF-based heuristics, classical OPF	CNN-LSTM-Attention with WOA; SHAP-aided XAI → ↓violations, ↑transparency	[30]
Predictive maintenance / asset health	Condition monitoring logs; lab/field	F1, AUC-ROC, lead time (days)	SVM/Random Forest + hand-crafted features	DNN/Autoencoders; Meta-learning for rapid adaptation across fleets	[50–52,62]
Anomaly / Intrusion / Theft (FDI, IDS)	Labeled AMI/SCADA datasets; synthetic attack injection	F1, AUC, Detection Delay, Robust accuracy	PCA + SVM, rule-based IDS	CNN/LSTM, drift-aware models; adversarial training / feature squeezing; FL-Byzantine-robust aggregation	[11–13,44,47,66,98–101]
DR & DSM optimization	Residential/CMC pilots; day-ahead DR	Cost ↓, Peak-to-Average Ratio (PAR), user comfort	MILP/heuristics	DRL/MARL, Ensemble + RL → ↓cost/ PAR, ↑comfort	[74–76,103–105]
Microgrid EMS / OPF	IEEE 33/69/118-bus microgrids	Optimality gap, Feeder constraint violations, runtime	Deterministic OPF, rule-based EMS	DRL with safety layers; Hybrid (DL forecast + optimizer)	[90–93,91]
EV/V2G scheduling & behavior	City-scale EV traces; depot/day-ahead	Charging cost ↓, feeder overloads ↓, SoC compliance, user-behavior MAE	MILP/heuristics, SVR	Smart charging with hybrid optimizers (MGO/IBWO/AOA), V2G; Ensemble ML for behavior prediction	[77–79,124]
Digital Twin fidelity & sync	Plant ↔ Twin co-simulation; live sync tests	Twin-Plant RMSE, sync latency, update cycle time, TCO	Isolated simulators	Modular DT + active learning; DT-Light at edge	[114–121]
Federated learning (privacy & comms)	Cross-utility/city sites; non-IID splits	Cross-party generalization gap, robustnace & latency, bytes/round	Centralized training	FL (Krum/Trimmed-Mean), secure aggregation, quantized updates/ distillation	[32–41,45,47,48,49,125,126]
Cyber-robustness stress test (any task)	FGSM/JSMA/DeepFool suites; red-team	Robust accuracy, attack success rate, MTTR	No defenses	Adversarial training, Gaussian aug., Feature squeezing, certified defenses	[44]

Conclusion

This comprehensive review has elucidated the transformative role of Artificial Intelligence (AI) and Machine Learning (ML) as the cornerstone of next-generation smart grids and power systems. From foundational paradigms such as supervised, unsupervised, and reinforcement learning to cutting-edge advancements like Federated Learning (FL), Generative AI (GenAI), Large Language Models (LLMs), and Digital Twin (DT)-driven intelligence, these technologies have addressed critical challenges, including renewable intermittency, dynamic demand management, anomaly and cyber-attack detection, and electric vehicle integration. Enabling infrastructures, such as the Internet of Things (IoT), Artificial Intelligence of Things (AIoT), 5G connectivity, edge–cloud ecosystems, and ML-based smart sensors, have facilitated key applications like precise load forecasting, predictive maintenance, demand-side management, and enhanced cybersecurity. The integration of advanced approaches, such as multi-agent systems, GenAI for synthetic data generation, and LLMs for context-aware reasoning, has further elevated the intelligence and adaptability of energy systems. Notably, DTs have emerged as cyber-physical bridges, enabling real-time simulation, active learning, and autonomous control, thereby fostering resilience and operational efficiency in complex grid environments.

Despite significant progress, challenges such as interoperability and standardization gaps, data heterogeneity and quality, computational scalability, cybersecurity and privacy risks, and the need for model transparency and explainability remain. In large-scale distributed energy networks, emerging paradigms like multi-LLM collaboration frameworks and hybrid DT–LLM architectures offer promising solutions for enabling self-learning, resilient, and sustainable smart grids. These advancements support enhanced forecasting accuracy, distributed energy management, and robust cybersecurity, particularly when deployed on edge devices to minimize latency and enhance privacy. This review, grounded in a systematic analysis of 96 selected articles, highlights future research directions, including standardized DT frameworks, active learning paradigms, and lightweight, domain-specific LLMs tailored for edge–cloud infrastructures. Ultimately, AI/ML not only enhance the efficiency, resilience, and security of smart grids but also pave the way for a sustainable global energy future aligned with the United Nations Sustainable Development Goals. This study serves as a valuable resource for researchers, practitioners, and policymakers aiming to leverage these technologies to drive the evolution of intelligent, efficient, and environmentally conscious energy systems.

CRediT authorship contribution statement

Yaser M. Banad: Writing – original draft, Data curation. **Sarah S. Sharif:** Writing – original draft, Data curation. **Zahra Rezaei:** Resources, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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