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AI-Enabled Strategic Management of Smart Energy Grids: Real-Time Algorithmic Optimization and Control

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Abstract
The rapid expansion of renewable energy and the electrification of transport are reshaping electricity demand, exposing the fragility of conventional grids designed for centralized and predictable generation: global electricity demand rose by 4.3% in 2024, adding more than 1,000 TWh in a single year, while renewables now contribute over 30% of global generation, led by wind and solar; traditional grid management systems, built on static models, deterministic forecasting and centralized control, are increasingly inadequate for handling such variability and complexity, creating the need for adaptive, data-driven approaches. Artificial intelligence has addressed this pressure by improving forecasting, predictive maintenance, renewable integration, and operational stability, while easing operator workload through automated optimization and shifting the grid from reactive management to proactive, self-optimizing operation, thereby positioning it as a cornerstone of resilient and sustainable energy systems. This review synthesizes AI applications in smart grids, focusing on learning algorithms, optimization methods, and emerging hybrid approaches, with contributions organized across forecasting, renewable integration, demand-side management, resilience, and cybersecurity, and with analysis of computational trade-offs and real-time performance. By linking these advances with persistent challenges including robustness under extreme events, interoperability, and explainability the review highlights key technical bottlenecks and future research directions and establishes a framework to guide the development of AI-enabled smart grids from experimental models to scalable, resilient, and societally embedded infrastructures that support the global energy transition.

Keywords *Smart Grids, Artificial Intelligence, Machine Learning, Long Short-Term Memory (LSTM), Metaheuristic Optimization.*

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I. Introduction

Artificial Intelligence (AI) is increasingly transforming energy efficiency by providing advanced solutions to the challenges of managing consumption in buildings, transportation, and industry. In the context of climate change, energy security, and sustainability, AI has become a vital tool for optimizing energy use [1]. The electricity grid represents one of the most profound technological milestones in modern civilization, fundamentally shaping industrial development, economic expansion, and societal advancement since its emergence. Serving as the core infrastructure of contemporary energy systems, it facilitates the generation, transmission, and distribution of electrical power to populations and industries on a global scale. However, conventional grid management systems, reliant on simplified or static models, deterministic forecasting, and centralized control, are increasingly inadequate for modern power networks characterized by fluctuating demand, variable renewable generation, and growing cyber–physical vulnerabilities [1]–[3]. These limitations contribute to inefficiencies such as energy losses, higher operational costs, difficulties in accommodating diverse generation sources, and vulnerability to large-scale outages, thereby creating a pressing demand for more decentralized, flexible, and intelligent grid operation [4], [5].

In response to these challenges, the grid has begun to transition from a rigid, centrally controlled system with unidirectional power flow to a more adaptive smart grid paradigm. Enabled by advances in digitalization, automation, and renewable energy integration, smart grids integrate advanced sensors, communication networks, and automated control technologies to optimize electricity generation, distribution, and consumption [6], [7]. Their ability to detect and respond to faults in real time enhances system reliability and minimizes power disruptions, while improved efficiency is achieved by reducing transmission losses and enabling the seamless incorporation of renewable sources such as solar and wind [8]. At the same time, high penetration of distributed and renewable resources increases uncertainty and operational complexity, so that conventional rule-based and model-driven strategies cannot fully exploit the flexibility of modern power systems. This has elevated the need for adaptive, data-driven decision-making that can operate under real-time constraints and support secure, resilient system operation.

Traditional energy management systems relied on basic control mechanisms that are not sufficient for the complexities of contemporary smart grids. To address these challenges, artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools that enhance renewable energy integration and stabilize grid performance. Contemporary smart energy management systems employ predictive analytics, real-time monitoring, and adaptive decision-making to optimize generation, storage, and consumption [9]. Advanced techniques such as deep learning, reinforcement learning, and neural networks process vast streams of historical and real-time data to forecast load and renewable output, support secure dispatching decisions, and enable rapid fault detection and diagnosis in transmission and distribution networks [10], [11], [12]. By aligning energy flows with consumption trends, weather conditions, and system constraints, these methods reduce waste, improve reliability, and enhance the efficiency of storage technologies through optimized charging–discharging cycles, while AI-driven predictive maintenance strengthens grid reliability by identifying potential failures in advance [13].

Within this context, a rapidly growing body of research applies learning algorithms, optimization methods, and emerging hybrid approaches to core smart-grid scenarios, particularly dispatching optimization, load forecasting, and fault diagnosis. Existing studies demonstrate substantial gains in forecasting accuracy, operational stability, and resilience, but often treat these applications in isolation and give limited attention to computational trade-offs, interoperability, and the integration of AI models with physical power-system constraints. This review therefore synthesizes AI applications in smart grids with a specific focus on these three core scenarios, organizing recent contributions in terms of learning paradigms (supervised, unsupervised, reinforcement learning), optimization strategies, and hybrid architectures. By analysing their real-time performance, scalability, and robustness under extreme events, and by emphasizing emerging perspectives such as physics-informed AI and cyber-resilient, edge-deployed intelligence, the paper clarifies the current research status and delineates the key contributions and open challenges that must be addressed to advance AI-enabled smart grids from experimental prototypes to reliable, large-scale infrastructures.

II. Foundations of AI in Smart Energy Grids

The rising global demand for sustainable energy has accelerated progress in renewable energy management, where Artificial Intelligence (AI) and Machine Learning (ML) have emerged as pivotal technologies for enhancing generation, consumption, and grid reliability. Numerous studies highlight the application of AI in forecasting, demand response, storage optimization, and fault detection, all of which contribute to greater efficiency and stability. Machine Learning models such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Long Short-Term Memory (LSTM) networks have demonstrated superior capability in predicting energy demand compared to traditional statistical methods, enabling more accurate load forecasting and improved grid management. Deep learning techniques have also been employed to forecast solar and wind generation, thereby reducing intermittency challenges, while reinforcement learning (RL) facilitates adaptive control strategies that dynamically balance supply and demand in real time. These intelligent systems optimize storage through effective scheduling of charging–discharging cycles, extend battery life, and support decentralized energy trading in smart grids, which lowers transmission losses and enhances distribution [14]–[16].

AI has further advanced predictive maintenance by analysing sensor data to identify failures in wind turbines and photovoltaic systems before they occur, thus minimizing downtime and costs. In parallel, AI-driven optimization of energy markets has introduced dynamic pricing models that adjust electricity tariffs based on consumer behavior, market trends, and weather patterns, incentivizing off-peak usage and supporting grid stability. Despite these benefits, challenges remain in the integration of AI, including the need for robust computational infrastructure, data security, and model transparency [17]–[19]. Research has also emphasized the integration of renewable and conventional sources in hybrid systems to address variability and reliability concerns [20]. Other studies have proposed home energy management frameworks combining renewable sources and storage with intelligent algorithms to minimize costs and reshape peak load demand [21]. Similarly, Paul *et al.,* (2021) reviewed renewable energy development trends across countries, highlighting the importance of policy reforms [22], while Kumar *et al.,* (2022) examined building-integrated microgrid systems as enablers of sustainability in smart cities [23]. More recently, Gorea *et al.,* (2023) investigated renewable energy integration challenges with a focus on management, security, and long-term sustainability through advanced monitoring of grid performance [24].

2.1 Evolution of Grid Management Systems

The contemporary power grid is organized around three fundamental stages: generation, transmission, and distribution that together constitute the regulated structure of modern electricity systems. Electrical energy is produced from diverse sources, including fossil fuels, nuclear, hydroelectric, and increasingly, renewable resources. Once generated, high-voltage transmission networks deliver power across long distances to substations, from where lower-voltage distribution lines supply households and industries [25].

The evolution of alternating current (AC) during the late nineteenth century marked a decisive milestone in grid development. Between 1890 and 1900, large-scale hydroelectric projects in regions such as Oregon, Colorado, Croatia, and Japan showcased AC's advantages, culminating in the establishment of the first complete multiphase system at Niagara Falls in 1895 [26]. Backed by J. P. Morgan and Edward Dean Adams, the Niagara Falls Power Company spearheaded ambitious hydroelectric expansion, while contributions by Charles Curtis in 1896 demonstrated AC's adaptability to both hydro and coal-fired stations [26], [27]. The introduction of the 500-kW Curtis turbine in 1901 and a 5-MW steam turbine in 1903 by General Electric further advanced coal plant efficiency [28].

Institutional consolidation of electricity systems began in 1935 with the Public Utility Holding Company Act (PUHCA), which provided a framework for state regulation under President Roosevelt [29]. Nuclear energy entered the grid with the launch of the Experimental Breeder Reactor I in 1951 [30]. From 1970 to 2013, the deployment of nuclear and renewable energy prevented nearly 163 gigatons of carbon emissions, with nuclear contributing 41% and renewables 6%. Nevertheless, incidents such as Chernobyl in 1986 and Fukushima in 2011 intensified global scepticism toward nuclear power, even as it remained a crucial low-carbon source [31]. Historical data further illustrate the shift in global energy consumption patterns between renewable and non-renewable resources from 1800 to 2022 (Figure 1a, b), as reported by Hannah Ritchie *et al.,* [32].

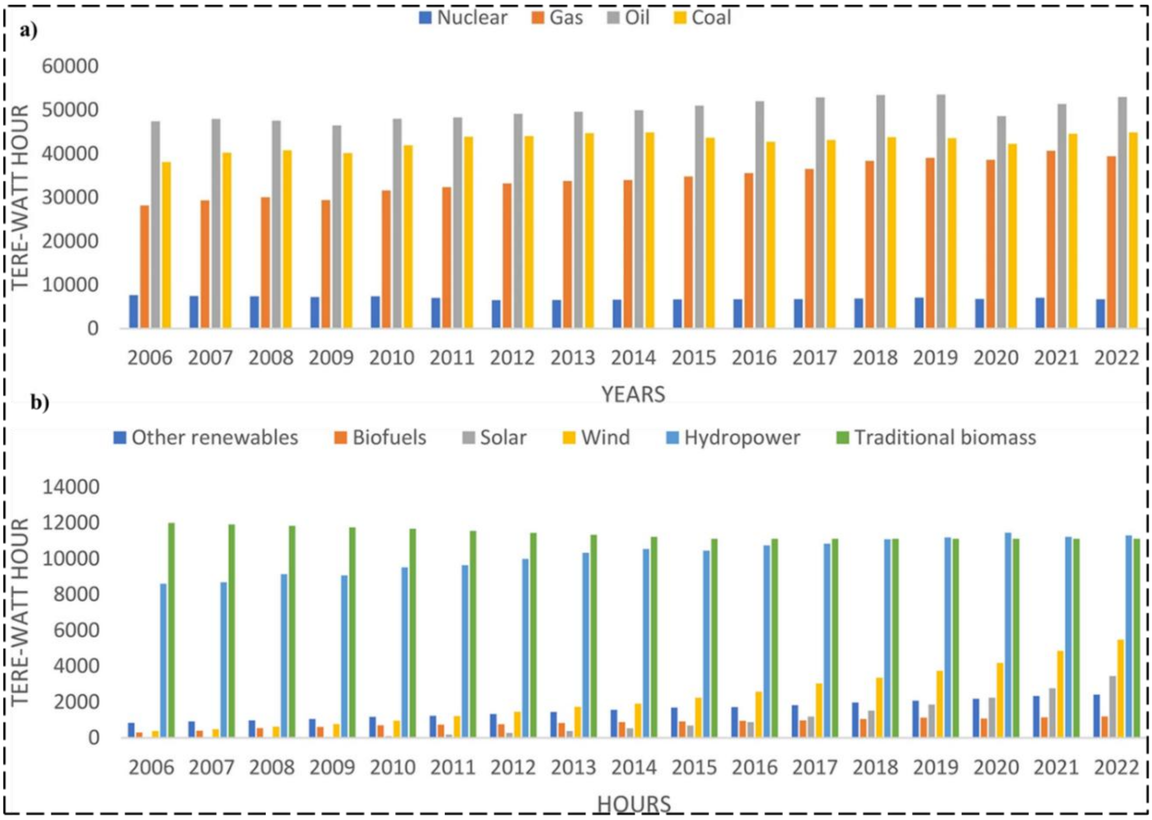

Figure 1 Trends in worldwide energy consumption from 2006 to 2022. **(a)** Non-renewable sources: coal, oil, gas, and nuclear. **(b)** Renewable sources: solar, biofuels, hydropower, traditional biomass, and other renewables [32] .

Figure 2a illustrates the trajectory of energy use across Asia, where industrialization in emerging economies such as China and India have driven a sharp rise in consumption, in contrast to the relatively stable patterns seen in advanced economies like Japan. Figure 2b presents the European context, showing that widespread adoption of renewable energy and efficiency measures has contributed to stable or even declining per capita demand in countries such as France and Germany. These comparisons highlight the divergent regional pathways shaped by both developmental stage and policy orientation. Likewise, Figure 2c demonstrates that per capita electricity consumption in Australia remains consistently high but steady, influenced by population growth alongside the gradual integration of renewable resources.

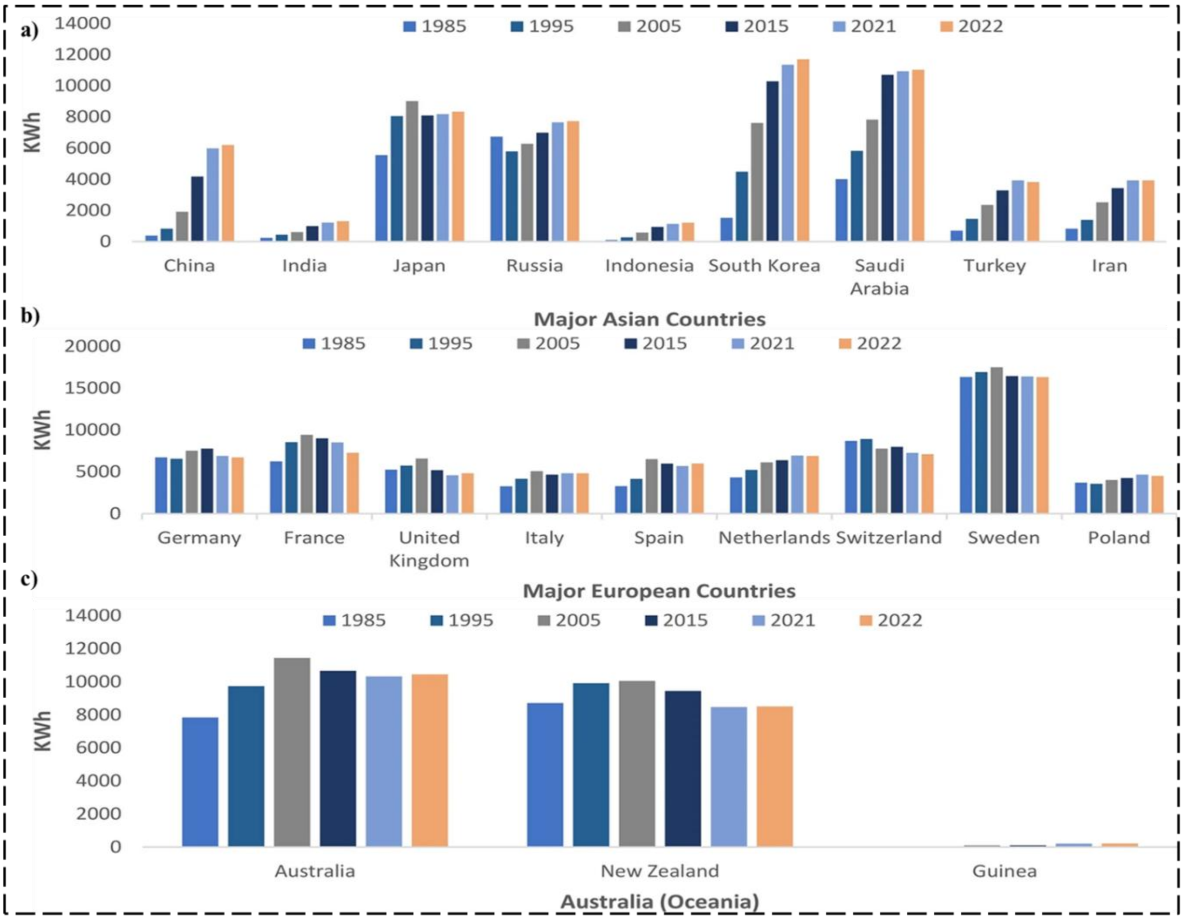

Figure 2 Comparative trends in per capita electricity consumption from 1985 to 2022 across key regions: **(a)** major Asian economies, **(b)** leading European nations, and **(c)** Australia, illustrating divergent developmental pathways and electrification patterns [32].

2.2 Characteristics of Smart Grids as Complex Systems

In many countries, power system infrastructure across generation, transmission, and distribution has reached the end of its operational lifespan, making replacement and refurbishment both technologically demanding and financially burdensome. The shortage of skilled personnel further compounds this challenge, yet it also presents an opportunity to modernize networks in ways that bridge existing gaps in technology and human resources [33]–[35]. The integration of renewable energy sources (RESs) into conventional grids introduces additional complexity, particularly at the transmission level where capacity is already constrained. Variability in renewable output often leads to instability, complicating efforts to align power delivery with the growing global demand for sustainable energy [36].

Thermal limitations in transmission and distribution lines also restrict power transfer capabilities. Exceeding these limits accelerates equipment degradation, increases fault probability, and shortens asset lifespans, underscoring the importance of dynamic line rating strategies that account for environmental influences [37]. Operational stability is further constrained by voltage and frequency boundaries. Over-voltage and under-voltage conditions can result in insulation failure, equipment malfunction, or system-wide tripping, while even small frequency deviations may cause desynchronization. Traditional mitigation strategies such as national and cross-border interconnections, voltage regulation devices, and automatic generation control (AGC) supplemented by emergency load-shedding are proving inadequate in the context of variable renewable generation [38]. To address these challenges, a combination of advanced forecasting, energy storage systems, spinning reserves, and enhanced system flexibility has been recommended to preserve both reliability and cost-effectiveness. However, successful implementation depends on upgrading the grid with modern communication systems capable of real-time data acquisition, processing, and optimization.

Table 1 Characteristics of Smart Grid Technologies as Complex Systems

Category	First-Generation Smart Grid	Second-Generation Smart Grid
Customer Interaction with Energy and Information	Data from smart meters enables basic monitoring and actor-specific electricity management.	Automated and autonomous systems optimize production, storage, and consumption. Interactions exhibit self-organization as consumer behaviours, incentives, and system responses dynamically co-evolve.
Market	Energy trading relies on third-party platforms to manage transactions and enable limited P2P exchanges.	Integration of smart contracts and direct P2P trading allows decentralized control, reducing third-party dependency. The market behaves as a complex adaptive system where multiple actors interact with minimal central intervention.
Operation	Electricity flow managed by operators with limited coordination from actors, based on grid state information.	Real-time data exchange enables collaborative flow management between operators and actors, with plug-and-play capabilities. The system demonstrates emergent coordination through distributed decision-making.
Interoperability	Multiple standards coexist for communication, creating fragmentation.	Adoption of Internet-based universal protocols enhance integration, but increased connectivity leads to higher interdependence and systemic vulnerability.
Generation	Supports centralized or decentralized generation with auxiliary component coordination.	Same foundation, but greater reliance on distributed generation and storage increases nonlinear dynamics and interdependencies between localized and global grid performance.
Transmission	Power flow managed from generation to load with limited flexibility.	Transmission integrates operational support, coordinated asset management, and power quality regulation. Dynamic interactions across assets reflect network-level complexity.
Distribution	Prosumers contribute under third-party and technological limitations.	Prosumers actively participate with diverse energy sources and storage. Distributed inputs increase system heterogeneity and require advanced control to sustain stability.
Physical Controllability	Focused only on the electricity sector.	Extended to multi-energy domains, including transportation and natural gas. This cross-sector integration reflects multi-layered system coupling.
Energy Form	Primarily electrical.	Multi-vector energy (electric, thermal, chemical) integration illustrates complex interdependencies across energy domains.
Optimization Capability	Localized optimization dominates.	Coordination spans both localized and wide-area operations. System-wide optimization relies on adaptive and predictive algorithms to manage uncertainties.
Energy Transferability	Managed through joint power and communication channels.	Layered architecture with P2P modes enhances decentralized supply management, reflecting network resilience and flexibility.
Information Accessibility	Limited to bi-directional communication.	Internet protocol-based access enhances interoperability but increases exposure to cascading risks across the information–power nexus.
Security Concerns	Data leaks and vulnerabilities arise from diverse protocols and third-party reliance.	Machine-to-machine communication mitigates third-party risk, but broad interoperability and device heterogeneity increase cyber-physical vulnerability, requiring adaptive security frameworks.

2.3 Role of AI in Nonlinear and High-Dimensional Grid Dynamics

Artificial intelligence (AI) has emerged as a cornerstone in modernizing distributed energy systems by improving efficiency, optimizing resource allocation, and supporting intelligent decision-making. Core techniques include machine learning (ML), deep learning, and optimization algorithms. ML models process large-scale datasets to identify patterns and forecast demand, proving particularly valuable for demand response programs aimed at predicting and mitigating peak load conditions [39]–[42]. Deep learning approaches, including neural networks, convolutional neural networks (CNNs), and radial basis function networks (RBFnets), are applied to power flow analysis and anomaly detection, where their ability to capture nonlinear relationships enables accurate real-time monitoring and fault diagnosis in complex distribution grids [43]–[46]. Optimization methods, such as genetic algorithms and particle swarm optimization, address challenges in energy distribution and microgrid design, ensuring the efficient integration of renewable and conventional resources [47]–[50].

The increasing penetration of distributed renewable energy sources (RES) fundamentally redefines the mathematical and topological characteristics of power systems. Modern smart grids are characterized by stochasticity and profound non-linearity, rendering traditional analytical methods such as linear approximations and deterministic physical models computationally inefficient and often inaccurate for real-time control. The integration of variable RES, such as photovoltaic (PV) and wind energy, introduces high-dimensional uncertainty, which contributes to power quality disturbances, including harmonic distortion and voltage instability, defying conventional static optimization paradigms.

Artificial Intelligence (AI) addresses these challenges not through mere automation, but by enabling effective dimensionality reduction and feature extraction. AI-driven frameworks leverage deep representation learning to map high-dimensional sensor and operational data (e.g., meteorological inputs, phasor measurements, and market signals) onto low-dimensional manifolds, facilitating the tractable control of intricate system states. This capability is critical because traditional physical models struggle with the curse of dimensionality in state-space estimation. Recent literature demonstrates that hybrid deep learning architectures can autonomously extract hierarchical features from raw time-series data, effectively resolving the non-stationary patterns endemic to high-variability generation. Furthermore, the evolution from offline static optimization to online dynamic adaptation is principally driven by Deep Reinforcement Learning (DRL) agents, which are adept at making robust, sub-second dispatch decisions under uncertainty, a necessary function for maintaining frequency stability in low-inertia environments.

Recent advancements have expanded the role of AI through reinforcement learning (RL), where methods like deep Q-networks optimize electric vehicle (EV) charging schedules to balance supply and demand, an increasingly critical task with rising EV adoption [51]–[54]. Furthermore, coupling AI with emerging technologies, including the Internet of Things (IoT) and blockchain, has fostered the development of more resilient, transparent, and adaptive power grids [55]. Predictive analytics powered by AI enhance demand forecasting, enabling dynamic load management, cost reduction, and improved system reliability [56]–[59]. In addition, real-time processing of smart meter and sensor data allows for adaptive grid control and operational optimization, further strengthening the efficiency and stability of distributed energy networks [60], [61].

2.3.1 Technical Characteristics and Application Scenarios

Effective management of grid complexity requires using AI methods that are specifically designed for different types of problems, from recognizing patterns in network structures to making decisions over time. The approaches discussed below are chosen for their ability to deal with the non-linear behavior and space–time variations of power system operation. Table 2 summarizes these main AI techniques, explaining how they work in basic terms and showing typical ways they are applied in current smart grid research.

Model	Core Mechanism	Applications	Ref.
Convolutional Neural Networks (CNN)	Spatial feature extraction: Employ hierarchical convolutional layers with local receptive fields (kernels) to learn and localize relevant topological and spatial patterns from multivariate input data	Capture spatial dependencies among interconnected grid nodes and distributed energy resources, supporting early detection of abnormal operating conditions. Used in hybrid CNN–LSTM models (e.g., ST-CALNet-type architectures) to extract geographical and meteorological spatial features across distributed PV sites, improving short-term prediction accuracy.	[62], [63]
Long Short-Term Memory (LSTM) networks	Temporal dependency learning: A gated recurrent architecture that maintains a persistent cell state through input, forget, and output gates, thereby mitigating the vanishing gradient problem and capturing long-range sequence dependencies.	Models the sequential, non-stationary, and dynamic evolution of variables such as load, electricity price, and renewable generation. Employed to couple high-frequency operational data with exogenous variables (e.g., temperature, humidity) in regional grids, yielding notable reductions in root-mean-square error (RMSE) for short-term load prediction	[64]
Deep Reinforcement Learning (DRL)	Markov decision process (MDP) formulation: Learns a control policy $\pi(a\|s)$ that maximizes the expected cumulative reward R_t through iterative interaction with the environment, enabling autonomous, model-free decision-making under uncertainty.	Addresses non-convex, large-scale sequential decision-making problems (e.g., unit commitment, corrective re-dispatch) that are computationally challenging for conventional optimization methods. Applied to real-time scheduling of generation and storage resources in distribution and transmission networks with high renewable shares, improving operating cost, constraint satisfaction, and recovery from disturbances in smart grid.	[65], [66]

III. AI Algorithms for Real-Time Optimization

AI techniques have been increasingly applied to forecasting and stability assessment in smart grids, where accuracy and adaptability are critical. Deep neural networks and machine learning models [67]–[70] have been successfully used to predict residential load stability [71]. Recurrent neural networks offer strong potential for precise stability prediction [72], while feed-forward networks improve accuracy over traditional methods. Beyond classical applications, Jindal *et al.,* (2016) compared deep learning algorithms for electricity demand forecasting, reporting that convolutional neural networks integrated with the k-means algorithm achieved the lowest RMSE. These findings demonstrate that AI not only enhances prediction accuracy but also strengthens grid reliability under dynamic conditions [73].

The stability of electrical networks is closely tied to the cost of electricity, as well as the response times of both consumers and providers. Razavi *et al.,* (2019) presented a mathematical model for DSGC systems that links variations in grid frequency to power costs measured over short time intervals, illustrating the role of demand-side control in smart grids. Simulations of production and consumption patterns using analog time gauges, combined with machine learning techniques, revealed that input variables were largely independent [74]. However, when algorithms were trained on large-scale, high-dimensional datasets, accuracy declined. To address this, Chen applied principal component analysis [75] to a machine learning framework proposed by Kotb *et al.,* (2019), demonstrating that dimensionality reduction could enhance grid stability [76].

Multiple AI-based methods have since been developed for stability prediction. Iwendi *et al.,* (2021) employed classification and regression trees within a four-node star topology, achieving 80% accuracy for a simulated DSGC system [77]. Din *et al.,* (2019) implemented a simplified decision tree on a 39-bus power system, reaching 83% accuracy using six dataset samples [78]. Ahmed *et al.,* (2019) introduced a convolutional neural network (CNN) tested on IEEE 118-bus and 145-bus systems, reporting 89.22% accuracy [79]. Xiang *et al.,* (2023) proposed a Bayesian rate algorithm for IEEE 39-bus systems, which achieved 91.6% accuracy but at the expense of significant computational effort [80]. Ghorbanian *et al.,* (2019) developed an XGBoost model with inertial sensors, applied to a 39-bus network, and obtained 97% accuracy, though evaluation relied solely on accuracy as a metric [81].

Real-time modelling approaches have also been explored across diverse grid configurations [13], [82]–[85]. Despite notable progress, studies emphasize that improvements are still needed in prediction accuracy and robustness. Recent efforts focus on refining neural network performance through hyperparameter tuning, as demonstrated by Bassamzadeh and Ghanem (2017), who trained and validated a model on datasets from the Kaggle repository to improve resilience forecasting in smart grids [86].

3.1 Machine Learning Approaches

3.1.1 Advanced Machine Learning Techniques

Recent advancements in artificial intelligence and machine learning have generated a wide spectrum of algorithms that extend beyond conventional forecasting tools, offering robust and adaptive solutions for stability and optimization in smart grids. Among these, swarm-based metaheuristics and bio-inspired algorithms such as the Swarm Hummingbird Optimization model have been introduced for enhancing grid stability prediction, particularly in the context of green energy transition. These approaches are framed as part of a larger effort to provide reliable and sustainable electricity resources that serve as safer alternatives to fossil-fuel-based systems [87]. Complementing these developments, deep learning structures such as LSTM-based recurrent neural networks (RNNs) have been extensively deployed to address electricity demand forecasting challenges in smart grids. The integration of advanced machine learning techniques, including Extra Tree Regressors and feature reduction methods, has enabled not only the ranking of predictive models but also the identification of key variables that drive forecasting accuracy. Furthermore, coupling LSTM models with optimization strategies such as genetic algorithms has facilitated automated hyperparameter selection, revealing optimal layer depths and time lags. Comparative studies against other machine learning baselines consistently demonstrate lower forecasting errors, although recent analyses also highlight potential inconsistencies in deep learning performance across diverse time-series contexts [88], [89].

As smart grids increasingly adopt demand-side service models, consumer load prediction has become more critical, especially in advanced networks characterized by distributed energy and bidirectional flows. Bouktif *et al.,* (2018) investigated photovoltaic power generation forecasting in arid desert climates, using datasets from Adrar, Algeria and Alice Springs, Australia. Their approach relied on nine different modelling configurations in combination with six serial input variations, and the ensemble learning framework employed in this work achieved accuracies surpassing 99% [90]. Hassan *et al.,* (2022) incorporated whale optimization and adaptive particle swarm optimization algorithms for tuning LSTM parameters, successfully improving the precision of metamaterial antenna bandwidth prediction. Their study, benchmarked against standard regression and deep learning approaches, showed superior performance in terms of RMSE, MAE, and mean bias error (MBE) [91]. Similarly, Khafaga (2022) presented a novel framework that integrated Al-Biruni Earth radius optimization with stochastic fractal search to refine deep neural networks for medical image classification, specifically targeting monkeypox detection. Although situated outside energy applications, this study demonstrated the cross-domain adaptability of advanced AI optimizers and underscores their potential relevance for smart grid contexts where complex, high-dimensional data require robust parameter tuning [92].

Parallel efforts in neural network-based forecasting have been explored by Hernández *et al.,* who proposed an artificial neural network (ANN) framework for dynamic time-multiplexed load forecasting (DTMLF). Their methodology employed a three-stage pipeline comprising self-organizing maps (SOMs) for pattern recognition, K-means clustering for load segmentation, and a multilayer perceptron (MLP) for final load prediction. This model was validated on datasets from a Spanish energy company, and its performance was compared against radial basis function neural networks and generalized regression neural networks [93]. Results indicated that the ANN-based pipeline provided superior predictive accuracy, particularly in capturing weekday periodicity and monthly cycles [92], [93].

Another important contribution to this field comes from Ahmed and Chen, who examined short- and medium-term load forecasting for Singapore using three different machine learning models: ANN, AdaBoost, and multiple linear regression (ML). Their design involved disaggregating load forecasts into multiple time windows, ranging from monthly to seasonal horizons, and leveraging aggregated consumption data [94]. Their results highlighted that all three models provided meaningful improvements in predictive accuracy, but the AdaBoost model outperformed the others, particularly in capturing consumer behavioural patterns [93].

Electricity price volatility adds another layer of complexity to load forecasting, since it directly influences consumption patterns and indirectly affects overall demand. Rizk *et al.,* (2023) addressed this by developing a Multi-Input Multi-Output (MIMO) framework that simultaneously forecasts both load and electricity prices. Their model employed a wavelet packet transform (WPT) to decompose load and price series into frequency components, while generalized mutual information was used to identify the most relevant features [95]. The forecasting process was carried out using a Least-Squares Support Vector Machine (LSSVM) applied to the multidimensional input–output matrix, with the Quasi-Joseph Ant Mega Colony algorithm employed to optimize model parameters. Comparative simulations demonstrated that the LSSVM-based approach significantly outperformed ANN baselines in predictive accuracy. Their study also connected these insights to the operation of demand response programs (DRPs), which link consumer participation with electricity markets and are critical to balancing supply-demand mismatches in smart grids.

In a related direction, Ahmad and Chen (2018) examined the application of load forecasting systems (LFSs) to enhance smart grid efficiency, presenting a case study in Texas, USA. Their survey encompassed a wide variety of AI models, including ANN, support vector machines, generalized regression neural networks, recurrent neural networks, ARIMA, probabilistic neural networks, fuzzy logic, and expert systems [94]. Their findings showed that AI-based techniques consistently outperformed conventional statistical methods, especially in contexts requiring high-precision predictions of direct normal irradiation (DNI) for solar power plants. Building on this, Balouch *et al.,* (2022) proposed a hybrid sine–cosine coupled with LSTM algorithm for hourly DNI forecasting using meteorological inputs, achieving highly precise outputs with minimal error and reduced reliance on large input variable sets [96].

With the rise of advanced metering and monitoring technologies, smart grids now generate massive volumes of real-time data. Traditional approaches have struggled to process such high-dimensional inputs, prompting increased interest in scalable AI frameworks. Jiang *et al.,* (2023) conducted a broad survey of AI applications for smart grid load forecasting, grid stability, and fault identification, highlighting how these methods enhance overall grid resilience and operational dependability [97]. Similarly, Djaafari *et al.,* (2022) developed an SVM-based time-series model to predict blackout events, using data from IEEE's 30-bus system. Their framework constructed a knowledge base of both normal and abnormal operating states, trained to identify cascading failures and complex interdependencies. This blackout warning system is presented as an essential component for next-generation smart grids, enabling operators to proactively manage systemic risks and mitigate domino effects from localized faults [98].

Together, these studies demonstrate that advanced machine learning and optimization techniques ranging from swarm intelligence to hybrid LSTM architectures are reshaping the forecasting and operational landscape of smart grids. By improving predictive accuracy across load, renewable generation, price, and stability dimensions, these models provide critical tools for grid operators and policymakers tasked with ensuring sustainable, reliable, and cost-effective energy systems.

3.1.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks, a specialized class of recurrent neural networks, have emerged as one of the most effective tools for modelling sequential and temporal dependencies within complex and nonlinear data streams. Unlike traditional feedforward networks, LSTMs incorporate a gated memory mechanism that enables them to capture both short- and long-term temporal relationships in data, making them particularly well suited to the characteristics of energy systems where demand and generation are influenced by cyclical, seasonal, and stochastic factors [14], [15]. Conventional statistical methods such as ARIMA and SARIMA have historically dominated short-term load forecasting, yet these approaches presuppose stationarity and linearity, both of which are inconsistent with the high volatility, nonlinearity, and nonstationary observed in modern grid conditions, particularly under high renewable penetration [16]. In contrast, LSTM networks retain contextual information across long horizons while mitigating vanishing-gradient issues, allowing them to model the temporal complexity of smart grid data more accurately [99].

The importance of LSTM in the context of smart grid optimization stems from its ability to enhance forecasting accuracy, a cornerstone of reliable grid operation. Forecasts of demand, renewable generation, and market prices directly inform scheduling, unit commitment, and reserve allocation strategies. Even modest improvements in forecast precision translate into significant operational and economic benefits by reducing balancing costs, mitigating the need for excess reserves, and improving the utilization of distributed energy resources [100]. Moreover, LSTM's superiority over classical and even some machine learning methods, including support vector machines and random forests, has been repeatedly demonstrated across diverse grid contexts, with evidence showing reductions in error margins by several percentage points compared to competing models [101]. Its adaptability also makes it suitable for a range of forecasting horizons, from ultra-short-term renewable prediction to day-ahead demand planning, thereby ensuring its relevance across the multiple timescales on which smart grids must operate [102].

Mechanistically, LSTM achieves its performance through a sequence of gating operations that regulate the flow of information through the network (Figure 3). At each time step t, the input, forget, and output gates determine which information is stored, updated, or discarded, while the cell state retains long-term memory. The equations describing these dynamics can be generalized as follows:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), \qquad f_t = \sigma\left(W_f x_f + U_f h_{t-1} + b_f\right),$$
$$\tilde{c}_t = tanh(W_c x_t + U_c h_t + b_c), \quad c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), h_t = o_t \odot tanh(c_t)$$

Here, i_t, f_t and o_t denote the input, forget, and output gates, respectively, while c_t represents the updated cell state. These equations demonstrate how the network selectively propagates relevant temporal information while filtering out noise, a capability central to smart grid forecasting where patterns often embed nonlinear dependencies across hours, days, or seasons. Variations of the LSTM, including convolutional-LSTM hybrids, bidirectional LSTMs, and attention-augmented versions, have been proposed to further refine performance in energy contexts, although their computational costs remain a challenge for real-time deployment [103].

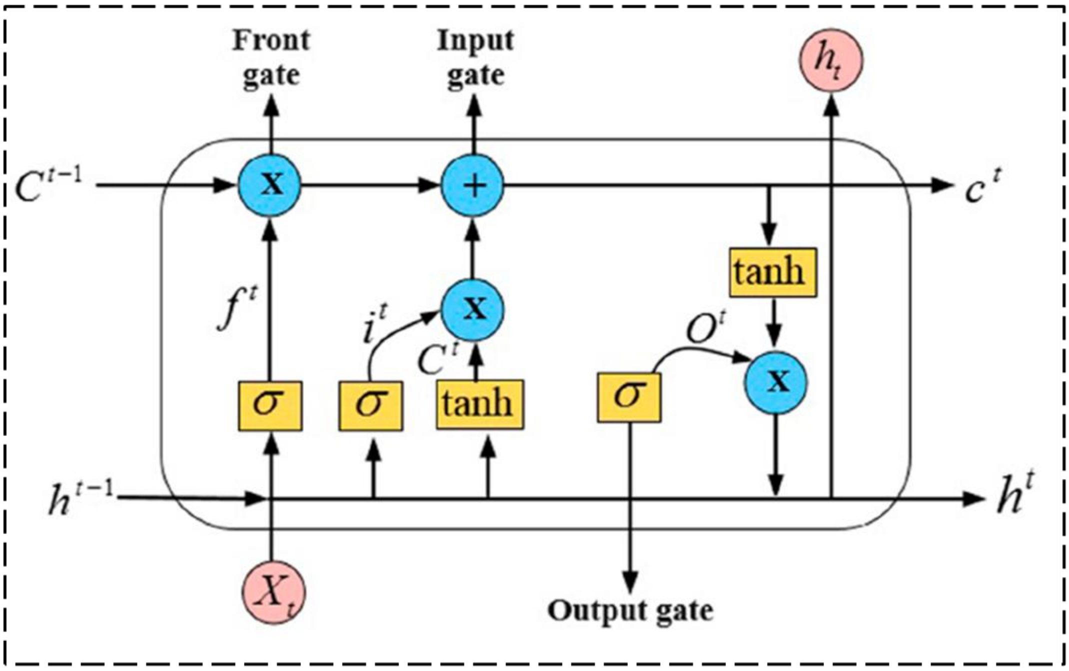

Figure 3 LSTM Model Structure [103] .

Zhou and Zhang developed an ARIMA–LSTM hybrid to forecast hourly load for the Southern China grid, reporting a mean absolute percentage error (MAPE) of 2.83% and an R^2 of 0.973, demonstrating the utility of hybridization for error reduction [104]. Liu *et al.,* combined TimeGAN with a CNN-LSTM model to generate synthetic load sequences for industrial and commercial applications, achieving a MAPE of 4.48% and an R^2 of 0.812; however, the reliance on synthetic data raised concerns regarding generalization [105]. Ibrahim *et al.,* tested dense neural network regression models on Panama's national grid and found LSTM-based variants achieved RMSE values of 50.34 MW with MAPE of 2.90%, outperforming other baselines [106]. Liu *et al.,* proposed integrated CEEMDAN decomposition, K-means clustering, and VMD preprocessing with CNN-BiLSTM-attention models, achieving outstanding forecasting accuracy (MAPE between 1.08% and 1.67%, R^2 between 0.985 and 0.991) on Guangzhou load datasets [107]. Ullah *et al.,* demonstrated the applicability of CNN-LSTM hybrids in Pakistan's NTDC system with simulation results yielding MAPE of 2.72%, although with relatively high RMSE (538.71) indicating sensitivity to noise. In renewable forecasting, bidirectional LSTMs have been applied to wind and solar prediction tasks, consistently outperforming support vector regression and ANN methods [106].

Dakheel and Çevik advanced the field with their hybrid LSTM–XGBoost model for short-term load forecasting on the Belgian Elia grid (Figure 4a). Using 15-minute resolution load data from 2022, they first trained a two-layer LSTM (50 neurons each) to model temporal patterns before applying XGBoost to correct residual errors. Their framework integrated lagged values, rolling statistics, and datetime features as inputs, with min–max normalization applied in preprocessing. Results showed that while standalone LSTM achieved RMSE of 119.41 MW and MAPE of 1.30%, the hybrid approach reduced RMSE to 106.54 MW and MAPE to 1.18%, with R^2 consistently at 0.994 (Figure 4b). Visualization confirmed that the hybrid more effectively captured volatile load fluctuations than either single model (Figure 4c). LSTM when coupled with robust residual learners, provides a highly accurate and computationally efficient solution for short-term load forecasting in modern smart grids [108].

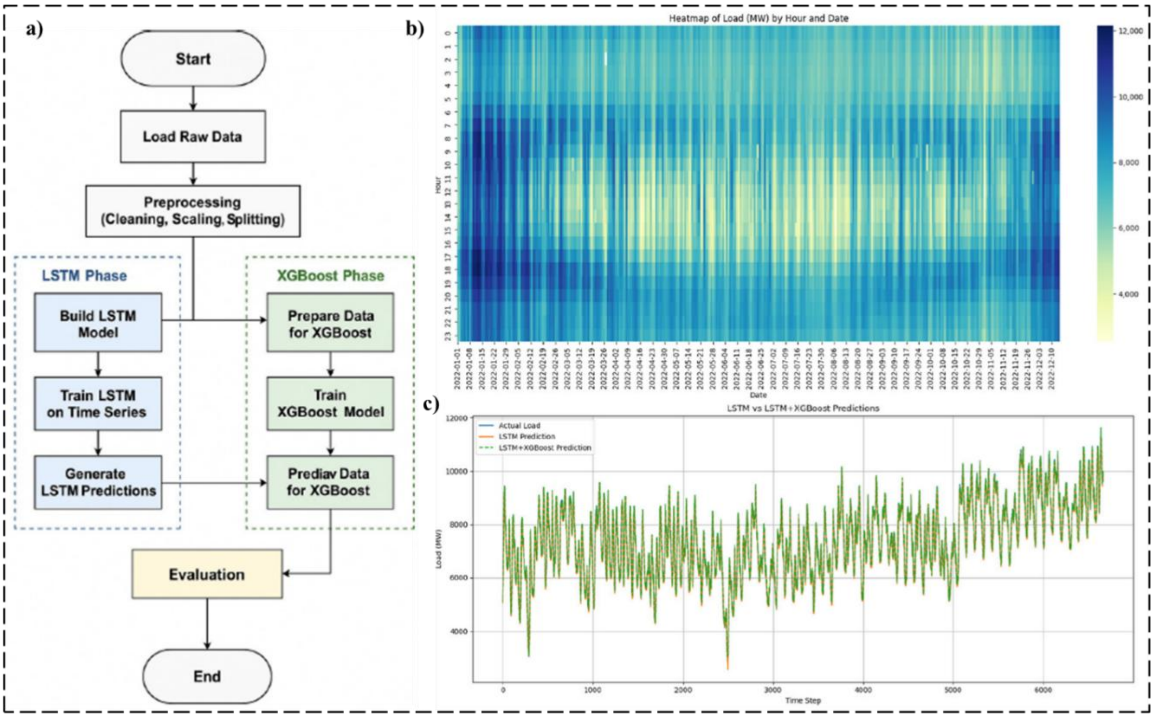

Figure 4 (a) Proposed LSTM and XGBoost hybrid architecture, **(b)** Hourly and date load distribution heatmap, **(c)** Predictive performance of LSTM-only vs. hybrid LSTM–XGBoost models against actual load [108].

Majeed *et al.,* presented an LSTM-based recurrent neural network approach tailored for optimized load forecasting. Their study emphasized the operational significance of accurate demand prediction for enabling renewable integration, demand response, and efficient scheduling. Methodologically, they incorporated weather variables, renewable generation data, and temporal features, with preprocessing via normalization and feature engineering. The LSTM model, constructed with 50 hidden units and trained using the Adam optimizer, was benchmarked against GRU, CNN, and standard RNNs. Results demonstrated clear superiority of LSTM, with RMSE = 2.2889, MAE = 1.1041, and MAPE = 1.538%, alongside rapid convergence time of just 22.19 seconds compared to 42 seconds for GRU and 61 seconds for CNN [109]. This combination of predictive precision and computational efficiency makes their model particularly suitable for real-time energy management applications. Importantly, the study also linked LSTM forecasting outputs to energy management system (EMS) strategies, showing how forecasts could be directly integrated into demand response scheduling and renewable dispatch.

3.1.3 Support Vector Machines (SVM)

SVM have steadily evolved from their early applications in weather prediction to become valuable tools for energy demand modelling in smart grids. Omitaomu and Niu (2021) examined their effectiveness in medium-term forecasting, contrasting their performance with that of artificial neural networks. Their work underscored how SVM, when applied to different load categories such as batch, continuous, and hybrid batch–continuous processes, is able to significantly reduce forecast error rates, recording improvements of around 3% for irregular demand patterns and 1.2% for continuous loads [110]. This advantage becomes especially important in environments where fluctuations are irregular and traditional neural models struggle to adapt. Gupta *et al.,* (2014) further emphasized the importance of external influences such as seasonal variations, temperature, and calendar effects on daily demand, reinforcing the idea that SVM's kernel-based mapping into higher-dimensional feature spaces allows the method to capture nonlinear dependencies often missed by simpler models [111].

The flexibility of SVM is best illustrated through its implementation in support vector regression (SVR), which converts the forecasting problem into a constrained quadratic optimization task. By projecting inputs into complex feature spaces, SVR constructs robust decision boundaries that achieve low root mean square error (RMSE) values even when input data are incomplete. Ali and Azad (2013) demonstrated that SVR consistently outperformed both linear regression and backpropagation-trained neural networks, highlighting its resilience to missing or noisy datasets [112]. This reliability, combined with consistently strong predictive accuracy, makes SVM particularly attractive for real-world grid applications where data gaps are inevitable. The authors also stressed that such models play a critical role not only in providing accurate forecasts for operators but also in empowering consumers to make environmentally responsible choices that align with the transition toward renewable and sustainable energy systems.

Beyond forecasting, SVM techniques are increasingly being integrated into broader decision-making processes for grid optimization. Rizk *et al.,* (2023), for example, extended SVM applications by developing a Multi-Input Multi-Output (MIMO) system that simultaneously predicts both load and electricity prices. Their framework utilized wavelet packet decomposition to separate time-series signals into different frequency bands, followed by feature selection based on generalized mutual information. A least-squares SVM (LSSVM) was then trained on this multidimensional input, while a Quasi-Joseph Ant Mega Colony algorithm was employed to optimize hyperparameters. The study demonstrated that this hybrid approach surpassed ANN-based baselines in predictive accuracy and provided an effective tool for demand response management, linking consumer load adjustments directly to electricity market dynamics [95]. Collectively, these studies position SVM as one of the most dependable methods for load forecasting and price modeling in smart grids, combining accuracy, resilience, and practical applicability.

3.1.4 Artificial Neural Networks (ANN)

ANN has long been applied to energy forecasting tasks due to their capacity to learn complex, nonlinear relationships in large datasets. In contrast to the kernel-based generalization of SVM, ANNs leverage layered architectures of interconnected nodes, making them highly adaptable for diverse forecasting scenarios. Pan and Lee (2012) highlighted their role in stability assessment, showing that trained neural networks could model the operational states of decentralized grids with high reliability [113]. Later, Mitchell *et al.,* (2017) reported accuracy levels above 97% when neural networks were trained to classify grid stability conditions, underscoring their value for monitoring and maintaining resilience in distributed energy systems [114].

In practical load forecasting contexts, Hernández *et al.,* (2014) applied ANN alongside AdaBoost and multiple linear regression (MLR) models for predicting short- and medium-term demand in Singapore. By dividing the task into multiple forecasting horizons, such as monthly and seasonal predictions, they showed that while all three models improved predictive accuracy, ANN consistently captured the underlying behavioural patterns of consumer demand. However, their results indicated that AdaBoost provided the highest accuracy among the models tested, though ANN maintained strong performance in identifying temporal trends [93].

The adaptability of ANN extends beyond load forecasting into hybridized, multi-stage architectures. For instance, Hernández *et al.,* (2014) and Khafaga *et al.,* (2022) described a three-phase forecasting framework integrating self-organizing maps (SOM) for pattern recognition, K-means clustering for data segmentation, and a multilayer perceptron (MLP) for final demand forecasting. Validated against real datasets from Spanish utilities, this system outperformed radial basis function and generalized regression neural networks, particularly in detecting weekday variations and monthly cycles. Such multi-layered ANN-based approaches highlight the capacity of neural networks to not only capture demand fluctuations but also incorporate domain-specific preprocessing stages that enhance predictive accuracy [92], [93].

ANN models have also demonstrated cross-domain adaptability. Recent studies have integrated deep learning architectures such as ResNet and VGG networks, which were initially developed for image recognition, into the energy sector, while also showing their utility in medical applications like MRI-based tumor detection [92]. Within the smart grid context, these advanced architectures provide opportunities to capture spatio-temporal dependencies and incorporate non-traditional data streams, further broadening the range of applications. Moreover, recent work by Li *et al.,* (2024) applied decision-tree-enhanced ANN systems for improving distributed smart grid stability, aligning energy conservation strategies with carbon footprint reduction and enhanced security of supply [115].

The utility of ANN methods also extends into cybersecurity applications. Naeem *et al.,* (2024) [116] and Mohsen *et al.,* (2023a) [117] demonstrated that ANN-based classification frameworks, when combined with metaheuristic optimizers such as the Gray Wolf algorithm, achieved accuracies up to 99% in detecting and classifying cyber-attacks on smart grid infrastructures. These results confirm the dual role of ANN systems in both operational forecasting and security assurance. More broadly, recent ANN-based methods designed to capture both temporal and spatial dependencies in smart grid data have reported predictive accuracies exceeding

95%, surpassing traditional regression and statistical approaches. Such findings reinforce the ongoing relevance of ANN methods in enhancing the efficiency, stability, and resilience of modern smart grids [116], [117].

3.2 Gradient Boosting

Gradient Boosting methods, including XGBoost, LightGBM, and CatBoost, have recently emerged as highly effective techniques for addressing complex optimization and forecasting problems in smart grids. Their ensemble-based structure allows them to combine numerous weak learners into a powerful predictive model, offering both robustness and accuracy in handling the nonlinear and stochastic characteristics of energy data [117]. Unlike many deep learning approaches that require extensive data and computational resources, gradient boosting provides a balance of predictive power, interpretability, and efficiency, making it particularly suitable for the real-time demands of grid management.

In the area of load and generation forecasting, researchers have demonstrated the superiority of boosting methods over traditional statistical models such as ARIMA, achieving significant reductions in error and improved adaptability to changing seasonal and meteorological conditions. For example, Atalay *et al.,* (2023) reported that XGBoost outperformed conventional regression-based techniques in day-ahead load forecasting [118], while Chen *et al.,* (2024) used LightGBM to predict photovoltaic generation and achieved error rates below 5% across different seasons [119]. Similarly, Lee and Kim (2023) applied XGBoost for stability classification in real-time operational data and recorded F1-scores above 0.97 [120], while Singh *et al.,* (2024) integrated CatBoost for line failure detection and achieved more than 98% accuracy [121]. Gradient boosting has also proven valuable for anomaly detection and cybersecurity in smart grids; Sharma and Tiwari (2024), for instance, developed an optimized XGBoost classifier trained on SCADA logs and smart meter consumption data, which identified irregularities with accuracy levels exceeding 95%, thereby providing a practical framework for early fault and cyber-attack detection [122].

Hybrid models further extend the potential of boosting techniques, with Ghous *et al.,* (2025) designing an LSTM–XGBoost ensemble where the neural network captured temporal patterns and XGBoost corrected residuals, yielding accuracies above 98% and allowing explainability through SHAP analysis of feature contributions [123]. While gradient boosting models are already more interpretable than deep neural networks, the integration of explainable AI techniques such as SHAP has made them even more transparent for operators, providing insight into the impact of weather, demand, and temporal patterns on predictive outputs. Recent research demonstrate that gradient boosting has become a cornerstone of smart grid optimization, delivering high predictive accuracy, resilience to noisy or incomplete data, scalability for real-time applications, and adaptability to hybrid and optimized frameworks. Its ability to enhance load and renewable forecasting, improve stability assessment, strengthen cybersecurity, and contribute to transparent decision-making highlights its central role in enabling the next generation of efficient, reliable, and sustainable smart grid systems.

3.3 Metaheuristic Optimization

Metaheuristic search algorithms encompass a wide spectrum of optimization strategies that often draw inspiration from either natural phenomena or artificial processes. While the earliest approaches to metaheuristic optimization emerged in the mid-twentieth century, it is in more recent decades that the field has witnessed an exceptional surge in proposed methods, largely fueled by the rapid advancements in computational power and the increasing demand for efficient problem-solving tools. However, this proliferation of algorithms has not gone without criticism. Scholars have pointed out that many contributions, though framed within elaborate biological or behavioural analogies, sometimes lack genuine methodological innovation, as they emphasize metaphorical inspiration over a deeper exploration of the fundamental mechanisms that drive the search process [124].

3.3.1 Evolutionary Computation

Evolutionary computation (EC) represents a significant branch of computer science that encompasses algorithms designed to simulate the principles of natural evolution, treating each member of a population as a potential solution to a given optimization task. Among the most prominent representatives of this paradigm are genetic algorithms (GAs) [125] and differential evolution (DE) [126], although many other variants have also been developed over the years [127]. GAs have gained popularity due to their robustness and their ability to integrate seamlessly with existing models, as well as their suitability for constructing hybrid optimization frameworks [128], [129]. They are also highly scalable and can be efficiently parallelized [130], [131], and they impose no limitations on the nature of objective functions. Nevertheless, their application can be hindered by the complexity of encoding certain problems and by their sensitivity to parameter tuning. Differential evolution was originally proposed as an alternative aimed at accelerating the often-slow convergence of GAs [132]. Its central innovation lies in the self-referential mutation mechanism, which leverages the differences between randomly selected solution vectors to enhance exploration. Over the last two decades, DE has been extensively analysed and successfully applied to a wide spectrum of problems, ranging from constrained and multi-objective optimization to parallel computing [126], [133], [134]. DE is appreciated for its ease of use, robustness, and reliance on only a few control parameters, though its convergence is also highly dependent on proper parameter settings.

3.3.2 Swarm Intelligence

Swarm intelligence (SI) methods take inspiration from the collective behavior of decentralized, self-organizing biological systems. These techniques operate through populations of simple agents that interact with each other and with their surrounding environment, generating emergent global behaviours from localized exchanges. Examples include algorithms inspired by natural systems such as ant colony dynamics [135], bird flocking [136], herd behavior [137], bee swarming [138], bacterial growth [139], whale hunting [140], dragonfly swarming [141], and the dispersal of seeds by trees [142]. In addition to biological analogies, metaphors drawn from human activities such as the harmony search algorithm (HSA), which models the process of musical improvisation have also been proposed [143]. Among SI techniques, particle swarm optimization (PSO) [144] is one of the most widely studied and applied. Its advantages include a straightforward implementation without the need for special encoding, coupled with strong performance and computational efficiency, making it particularly suitable for problems where speed is a critical factor. These features have contributed to its extensive use, though it suffers from premature convergence, which has prompted numerous modifications and extensions [136], [145]. Another influential SI technique is ant colony optimization (ACO), which has proven highly effective in solving combinatorial optimization problems and has been successfully applied across diverse industrial domains [146]. However, its effectiveness decreases when applied to continuous optimization, leading to multiple algorithmic adaptations and extensions reported in the literature [146]–[148].

3.3.3 Artificial Immune Systems

Artificial immune systems (AIS) are optimization methods inspired by immunological theory, designed to mimic the mechanisms of the biological immune system in responding to external disturbances. These algorithms are characterized by their decentralized structure, relying solely on local information without a central controlling entity. Due to this distributed architecture, AIS approaches are computationally lightweight, requiring minimal memory and CPU resources compared to population-based metaheuristics. However, their adaptability often necessitates problem-specific customization, which can limit general applicability. Despite this, AIS algorithms have been widely investigated and deployed in diverse engineering domains [149], including applications to power grid optimization [150], [151]. Moreover, AIS principles have contributed to the design of hybrid methodologies with enhanced performance characteristics and flexibility [152].

3.3.4 Non–Population-Based Metaheuristics

In contrast to the population- or swarm-based approaches described above, several early metaheuristics operated on the principle of iteratively refining a single candidate solution. The most notable among these are simulated annealing (SA) [153] and tabu search (TS) [154]. Simulated annealing derives inspiration from the metallurgical annealing process, wherein materials are cooled to reach a low-energy crystalline state. Its distinctive feature is the probabilistic acceptance of worse solutions during the search, a mechanism that gradually diminishes over successive iterations. With only a few parameters to tune, SA offers reduced computational requirements as it maintains and updates a single solution, though this efficiency often comes at the cost of lower accuracy compared to population-based methods. Numerous refinements of SA have been proposed in recent years to address its limitations [153]. Tabu search, on the other hand, is grounded in the concept of memory structures known as tabu lists that record the search trajectory to prevent cycling back to previously visited solutions. Over time, many variants of TS have been developed to enhance its performance and efficiency [155], [156]. Owing to its relatively low computational cost and ability to handle large-scale optimization problems effectively, TS has become a valuable tool; however, its accuracy typically falls short of population-based methods, leaving it best suited for problems where computational efficiency outweighs the need for absolute precision.

V. Applications in Smart Energy Grids

5.1 Fog and Edge Computing in IoT-Driven SCADA Systems

The integration of the Internet of Things (IoT) into modern energy infrastructures has introduced transformative possibilities across multiple domains of smart energy systems, including generation asset management, transmission networks governed by SCADA, distribution-level advanced metering infrastructure, environmental and pollution monitoring, as well as intelligent home and building automation. Among these innovations, fog or edge computing has emerged as a particularly powerful enabler for optimizing supervisory control and data acquisition (SCADA) systems, especially within the domain of energy transmission. With the rapid evolution of IoT-driven technologies, household appliances and energy devices are increasingly automated, allowing seamless interaction within smart environments. SCADA remains indispensable for overseeing and controlling the processes of power generation, transmission, and distribution, as it ensures the efficient regulation of operational parameters through continuous data acquisition and supervisory automation [157]. The incorporation of IoT-based paradigms such as fog computing has further enhanced SCADA's efficiency by enabling real-time data handling closer to the source [158].

A typical fog-enabled smart energy SCADA system can be conceptualized as comprising four interconnected layers: terminal devices, fog computing nodes, cloud infrastructure, and the central SCADA platform [157]. The terminal layer is composed of IoT-enabled sensors, actuators, and appliances, linked through wireless sensor networks (WSN) and supported by communication technologies such as Wi-Fi, Bluetooth, and ZigBee. These devices serve as the primary data sources, continuously monitoring and transmitting operational signals. At the intermediate level, fog or edge devices including access points, routers, and switches process and analyse the vast volumes of data generated at the terminal layer, thereby reducing latency and minimizing the reliance on centralized cloud servers [159]. The cloud infrastructure, consisting of distributed data centres, storage systems, and gateways, aggregates and processes information received from the field, enabling large-scale statistical analysis and long-term data management across geographically dispersed networks. Finally, the SCADA interface itself comprising client and server components acts as the decision-making hub. It interprets the results from cloud and fog analytics, supports automated control processes, and provides operators with actionable insights to regulate grid parameters efficiently. Collectively, this layered architecture highlights how IoT-enabled fog computing strengthens SCADA by distributing computational workloads, lowering latency, and enhancing overall system responsiveness (Figure 5).

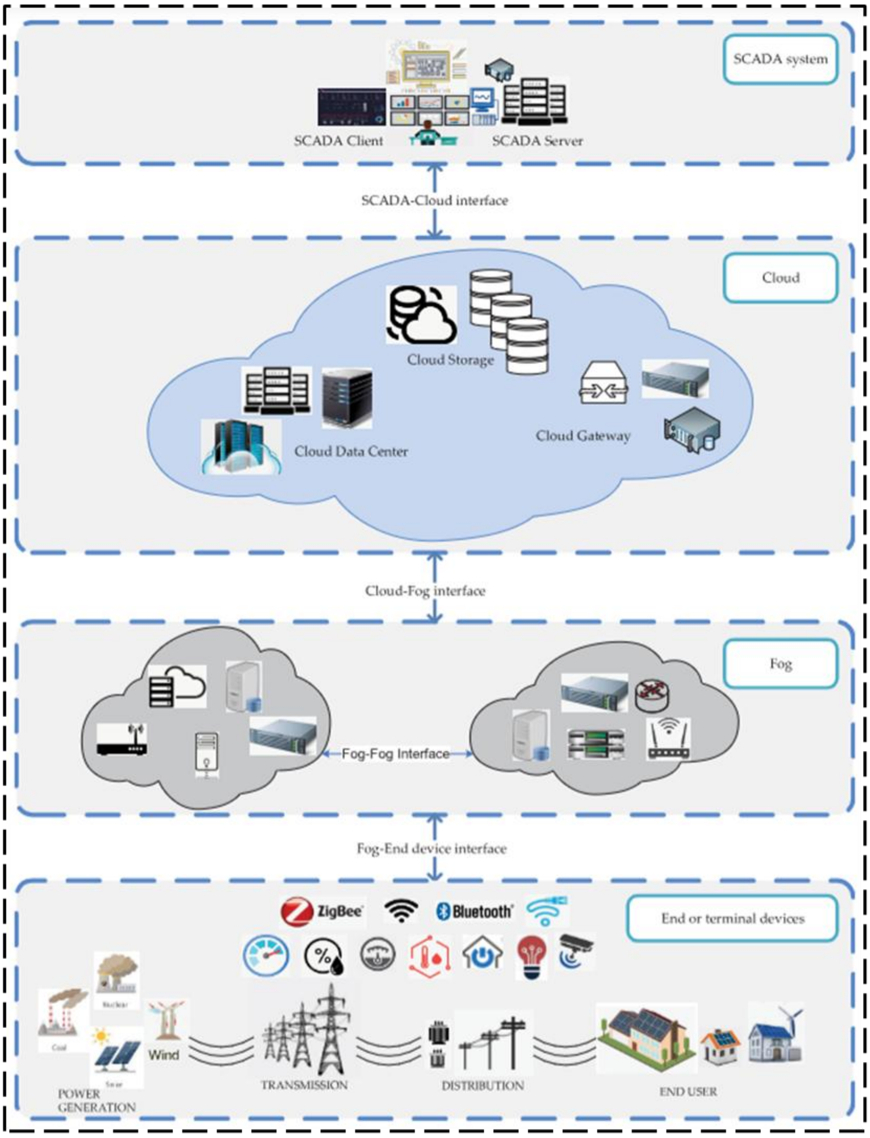

Figure 5 Four-tier SCADA architecture for a smart energy grid, from end devices to Fog, Cloud, and central control [160].

5.2 Renewable Energy Integration

Smart grids play a crucial role in integrating renewable energy sources (RES) into modern power systems. In fact, the smart grid paradigm was conceived to provide the flexibility and advanced control needed for a smooth transition towards renewable-based energy infrastructure. By automating and digitizing grid operations, smart grids can handle the variability and intermittency of resources like solar and wind power while maintaining reliability. Traditional electricity networks are evolving from centralized architectures to more distributed ones as renewable penetration increases, making bidirectional power flow and distributed generation key features of the smart grid [161]. This bidirectional, intelligent network enables active participation of distributed energy resources (e.g. rooftop solar, wind farms) and prosumers, thereby accommodating higher RES shares and reducing greenhouse gas emissions along with reliance on fossil fuels (Figure 6).

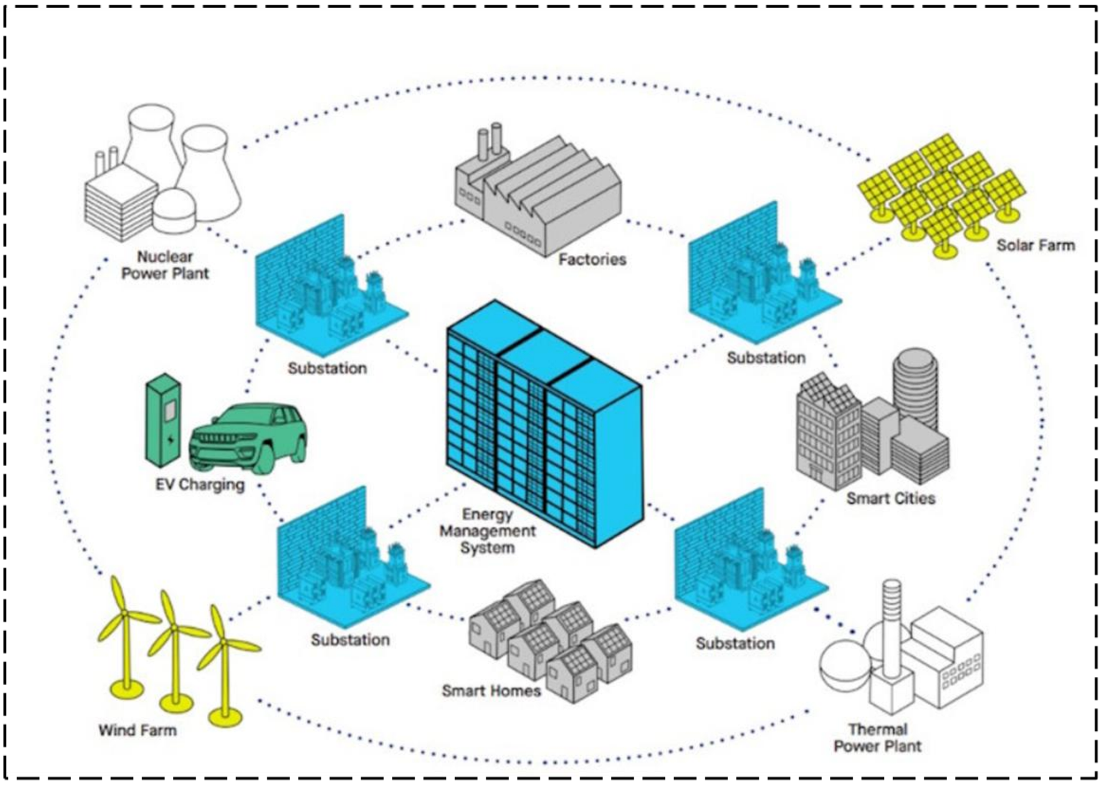

Figure 6 Smart energy management system integrating renewable and conventional power sources with substations and diverse consumer domains [161].

Another promising development is the fusion of digital twin technology with edge-AI to enable real-time microgrid self-optimization. In the NeoGrid project (2024), microgrids deployed decentralized AI agents that continuously adjusted internal control strategies to maximize local solar usage. This architecture reportedly increased RES utilization by 22%, largely by minimizing curtailment and optimizing storage dispatch [162].

However, high levels of RES integration pose challenges that smart grid technologies must address. The output of renewables is inherently unpredictable, which can disrupt real-time supply–demand balance and grid stability. Major obstacles include the need for effective demand-response measures, sufficient energy storage to buffer fluctuations, and maintaining grid resilience amid variable supply . Upgrading grid infrastructure and regulatory frameworks is also critical to support large-scale renewable integration. To overcome these issues, researchers propose enhancements such as advanced forecasting and control systems, innovative energy storage solutions, and cooperative schemes among utilities, policymakers, and consumers. These strategies combined with innovations like smart inverters, adaptive protection, and microgrid systems help ensure that increasing renewable energy contributions can be smoothly integrated into the grid without compromising reliability [163].

5.3 Demand-Side Management

Demand-Side Management (DSM) in smart grids encompasses strategies to adjust and optimize electricity consumption on the customer side in response to supply conditions or price signals. Enabled by two-way communication technologies (e.g. smart meters and IoT devices), DSM allows utilities and consumers to interact in real time to modulate energy usage. Key DSM measures include demand response programs where consumers reduce or shift their electricity use during peak periods in exchange for incentives or dynamic pricing as well as energy efficiency improvements and the integration of distributed generation at customer sites. By leveraging these methods, a smart grid can actively shape the load profile: for example, appliances or EV chargers can be scheduled to run during off-peak hours when energy is cheaper and more plentiful, thereby flattening demand peaks [164].

The benefits of DSM for the grid are substantial. By shifting loads and shaving peak demand, DSM reduces stress on generation and transmission capacity and postpones the need for new power infrastructure. This contributes to improved grid stability and facilitates higher penetration of renewables by aligning consumption with periods of high renewable output. Indeed, effective demand-side management and demand response implementations have been shown to lower overall system costs and curtail emissions, since peak shaving often replaces expensive, carbon-intensive peaking power plants. Consumers also benefit through lower energy bills and greater control over their energy usage, creating a more interactive and efficient energy ecosystem. Realizing DSM at scale, however, requires advanced metering infrastructure, smart appliances, and robust customer engagement to overcome barriers like limited participation and response reliability [165].

5.4 Grid Maintenance and Fault Tolerance

Smart grids significantly enhance grid maintenance and fault tolerance through self-healing capabilities and advanced monitoring. A self-healing grid can automatically detect faults or disturbances, isolate the affected section, and reroute power to restore service all within moments and without human intervention. This automation, often implemented via Fault Location, Isolation, and Service Restoration (FLISR) schemes, minimizes outage durations and improves overall system reliability [166]. Moreover, smart grids employ distributed architectures to bolster fault tolerance. For instance, microgrids (localized networks with their own generation and storage) can disconnect (island) from the main grid during faults and continue supplying local loads independently. This limits the impact of outages and enhances resilience by preventing faults from cascading through the wider network. In short, the grid becomes more robust, able not only to withstand component failures but also to “heal” itself quickly when disruptions occur [165].

In terms of maintenance, smart grids leverage pervasive sensing and AI-driven analytics for predictive asset management. Critical components are outfitted with IoT sensors that continuously monitor equipment health (e.g. measuring temperature, vibration, or electrical parameters). The data is analysed in real time to identify anomalies and forecast potential equipment failures before they happen. By anticipating faults, grid operators can schedule targeted repairs or component replacements proactively, rather than reacting to unexpected breakdowns. This predictive maintenance approach reduces unplanned downtime and maintenance costs while extending the lifespan of infrastructure [165], [166]. Overall, the combination of self-healing automation and predictive maintenance enables a smarter grid that is far more tolerant to faults and quicker in recovery, markedly improving reliability and power quality compared to traditional grids.

5.4 Electric Vehicle Integration

The growing adoption of electric vehicles (EVs) presents both opportunities and challenges for smart energy grids. On one hand, EV charging demand can be very large and concentrated, potentially straining the grid if not properly managed. A surge of EVs plugging in during peak hours could overload local transformers or feeders, leading to voltage drops or even outages. In fact, a U.S. Department of Energy assessment warns that without smart coordination, the added loads from transportation electrification could jeopardize grid reliability and resilience. To prevent this, smart grids employ intelligent charging management [167]. Through time-of-use pricing, demand response signals, and direct control of charging infrastructure, utilities can incentivize EV owners to charge during off-peak times or when surplus renewable power is available. In effect, the smart grid shifts and smooths out the new EV load so that existing infrastructure can accommodate it with minimal stress.

On the other hand, EVs when integrated via smart grid technologies can actively support the grid. The concept of vehicle-to-grid (V2G) enables bi-directional power flow: EVs not only draw power from the grid to charge but can also feed electricity back to the grid when needed. According to the U.S. Department of Energy, this makes EVs into “highly controllable load and mobile storage” units capable of providing valuable grid services to both vehicle owners and utilities. In practice, an aggregated fleet of V2G-enabled EVs functions as a distributed battery system that helps balance supply and demand. During times of high demand or grid stress, plugged-in EVs could discharge energy to reduce peak loads and provide ancillary services like frequency regulation. Likewise, excess renewable energy (for example, midday solar generation) can be absorbed by charging EVs and then returned to the grid during evening peaks, effectively time-shifting energy supply [168].

VI. Technical Bottlenecks and Challenges

While the integration of Artificial Intelligence (AI) into smart grids promises a shift from deterministic to data-driven, adaptive management, this transition is constrained by several critical technical bottlenecks. Existing studies often discuss these issues in isolation; however, a more systematic perspective reveals that they arise across three interconnected layers: the data layer (sparsity, noise, and heterogeneity), the algorithm layer (limited generalization and opacity), and the system layer (cyber-physical security and privacy) [169]. Addressing these challenges requires moving beyond generic problem descriptions toward targeted, methodologically grounded solution pathways.

6.1 Data Layer

The performance of deep learning models in smart grids is fundamentally dependent on the availability of high-quality, labelled datasets. In practice, modern power systems frequently exhibit a "data-rich, information-poor" paradox. Smart meters and monitoring devices generate massive volumes of time-series data, yet the most critical events such as fault signatures, grid responses to extreme weather, or cyber-attack patterns are statistically rare. This severe class imbalance often yields models that perform well under normal operating conditions but fail precisely when they are most needed, during rare but high-impact tail events. Compounding this issue, data streams from heterogeneous sources such as phasor measurement units (PMUs), SCADA systems, and smart meters are susceptible to measurement noise, missing values caused by communication delays, and misaligned timestamps, all of which degrade the reliability of model inputs [169].

To mitigate data scarcity and class imbalance, recent work increasingly explores Generative Adversarial Networks (GANs) and related data-augmentation strategies. By training a generator to produce synthetic samples that are statistically consistent with real fault or disturbance data, GAN-based augmentation can enrich the minority classes and stabilize classifier decision boundaries. In parallel, advanced imputation methods based on denoising autoencoders and similar architectures can reconstruct missing entries in multivariate time-series data, thereby improving data completeness and quality. Together, these approaches enhance the robustness of downstream forecasting, control, and protection algorithms under noisy, incomplete, and imbalanced data conditions [170].

6.2 Algorithm Layer

At the algorithm level, a central challenge is the domain shift problem. Models trained on one system configuration (for example, a particular transmission network or regional grid) often generalize poorly to another due to differences in network topology, impedance characteristics, load profiles, and generation portfolios [171]. This lack of transferability implies that each new deployment may require extensive re-training and re-validation, increasing both computational cost and engineering effort. In addition, many high-performing AI models, particularly deep neural networks, exhibit a pronounced "black-box" character. Their internal representations and decision pathways are difficult to interpret, which poses a significant barrier for grid operators who are accountable for system reliability and must justify automated control decisions within regulatory and operational frameworks [172].

Transfer learning (TL) and Explainable AI (XAI) have emerged as key technical directions to alleviate these issues. Transfer learning enables models to be pre-trained on large, diverse source datasets and then fine-tuned on a specific target grid with comparatively limited data, thereby reducing data requirements and improving adaptation to new environments. At the same time, XAI techniques such as SHAP (SHapley Additive exPlanations) provide granular insight into model behavior by quantifying the contribution of individual features (e.g., temperature, historical load, or line flows) to specific predictions. These explanations help operators understand why a model recommends a given dispatch action or predicts a potential fault, fostering trust, supporting regulatory compliance, and enabling more informed human–AI collaboration in control rooms [172].

6.3 System Layer

At the system level, the increasing reliance on data-driven algorithms significantly expands the attack surface of smart grids. Centralized AI training pipelines typically require the collection of fine-grained consumption and operational data at a central server, raising serious privacy concerns and potentially conflicting with regulations such as the General Data Protection Regulation (GDPR). In parallel, the cyber-physical nature of the grid makes it vulnerable to False Data Injection Attacks (FDIAs), in which adversaries manipulate sensor readings or communication channels to mislead estimation and control algorithms. Such attacks can trigger suboptimal or unsafe dispatch decisions, increasing the risk of line overloads, instability, or cascading failures.

Federated learning (FL) offers a promising architectural response to the joint challenges of privacy and security. In a federated learning framework, model training is performed locally on edge devices (such as smart meters or substation controllers), and only encrypted model updates (gradients) are transmitted to a central aggregator, rather than raw measurement data. This decentralized scheme inherently preserves user privacy while still enabling the training of high-quality global models. Moreover, the incorporation of robust aggregation rules such as Krum or median-based aggregation enables the detection and suppression of anomalous or adversarial gradient updates, thereby limiting the impact of compromised nodes and mitigating the risk of FDIAs propagating into the global model [173]. In this way, federated learning not only reconciles privacy with performance but also strengthens the overall cyber-physical resilience of AI-enabled smart grids.

VII. Future Outlook

The trajectory of AI-enabled smart grids is shifting from isolated, purely data-driven applications toward integrated, physically informed, and decentralized systems. To support reliable large-scale deployment, future research and development should concentrate on three actionable directions: physics-constrained AI, edge AI deployment, and multi-energy complementary systems. Together, these directions aim to ensure that AI methods respect physical laws, operate close to the grid edge with low latency, and coordinate across coupled electricity–heat–gas infrastructures.

7.1 Physics-Constrained AI

Current "pure" deep learning models can generate predictions that are statistically accurate yet inconsistent with fundamental physical laws, such as Kirchhoff's circuit laws or thermodynamic constraints [174]. Such violations are unacceptable in closed-loop control for high-voltage systems, where safety margins and stability criteria must be respected at all times. Future progress therefore depends on combining the flexibility of data-driven learning with explicit representations of power system physics, so that models remain both accurate and physically credible [175].

A central technical pathway in this direction is the development of Physics-Informed Neural Networks (PINNs). Rather than minimizing only a data-based loss (for example, mean squared error), PINNs embed the partial differential equations (PDEs) or algebraic equations that govern power flow directly into the loss function as additional regularization terms [176]. In practical terms, a PINN that forecasts grid states is penalized not only when its outputs deviate from historical measurements, but also when they violate power balance or network constraint equations. This dual penalization helps ensure physical consistency, reduces the amount of labelled data required, and improves stability within the system's operational envelope. As a result, physics-constrained AI provides a more trustworthy foundation for real-time control, protection, and planning in safety-critical power system applications.

7.2. Edge AI Deployment

Traditional cloud-cantered architectures introduce latency and bandwidth limitations that are incompatible with fast grid protection and sub-second frequency regulation. As power systems connect growing numbers of distributed energy resources (DERs), including rooftop photovoltaics, electric vehicles, and battery systems, continuously streaming all data to a central server for processing becomes both computationally expensive and operationally fragile [177]. Future AI-enabled smart grids must therefore push intelligence closer to the devices themselves, enabling decentralized decision-making at or near the grid edge.

The key technical path for this transition is model compression, particularly through quantization and pruning. By converting 32-bit floating-point weights to lower-precision representations (such as 8-bit integers) and systematically removing redundant neurons and connections, large deep learning models can be compressed to run on resource-constrained microcontrollers and embedded processors with minimal loss in accuracy [178]. This enables "intelligence at the socket," where smart inverters, local controllers, and gateways can execute AI inference in milliseconds, autonomously regulating voltage, frequency, and power flows without relying on constant, low-latency connections to a central control centre. Edge AI deployment thus enhances responsiveness, reduces communication overhead, and improves resilience against communication failures and cyber-attacks that target centralized infrastructures.

7.3. Integration of Multi-Energy Complementary Systems

The future energy system is expected to move beyond isolated electricity networks toward integrated energy systems (IES) that jointly manage electricity, heat, and gas. While such multi-energy systems can exploit complementarities such as using surplus electricity to produce heat or hydrogen their tight coupling, nonlinear behaviours, and differing time constants (for instance, slow thermal dynamics versus fast electrical dynamics) make conventional optimization and control methods increasingly inadequate [179].

Multi-Agent Deep Reinforcement Learning (MADRL) offers a promising framework to handle this complexity. In a MADRL setting, different energy subsystems—such as combined heat and power plants, gas turbines, district heating networks, and battery storage units are modelled as autonomous agents that learn to coordinate their actions through interaction with the environment and with each other. A suitable cooperative reward structure encourages these agents to pursue global objectives, such as minimizing system operating cost, reducing emissions, or maximizing renewable utilization. For example, an agent controlling a power-to-heat unit may learn to divert excess wind generation into thermal storage during periods of electrical congestion, storing heat for later use when demand rises. By learning such coordinated strategies, MADRL-based controllers can perform holistic optimization across electricity, heat, and gas networks, thereby improving overall system efficiency and supporting deep decarbonization of both the power and heating sectors [180].

VIII. Conclusion

Artificial intelligence is increasingly redefining the operation and design of smart energy grids, driving a transition from deterministic, centrally managed systems to adaptive, anticipatory, and self-optimizing infrastructures. This review shows that AI-based methods—particularly advanced deep learning for load and renewable forecasting and deep reinforcement learning for control and dispatch—deliver measurable benefits, with reported gains of roughly 25% in short-term forecasting accuracy and up to 30% improvements in energy efficiency for decentralized dispatch and demand response. These advances underline a clear trend toward tighter integration of prediction, decision-making, and real-time actuation through hybrid forecasting architectures, edge-enabled analytics, and decentralized multi-agent control frameworks.

At the same time, the full potential of AI-enabled smart grids remains constrained by interlinked challenges in data quality, algorithmic robustness, and system-level design. The central bottleneck is achieving a coherent synergy across the data–algorithm–system triad. Future progress will depend on the wider adoption of physics-informed neural networks to enforce physical consistency in decision-making, alongside federated learning architectures that preserve privacy and enhance resilience at the grid edge. Addressing limitations in generalizability, interpretability, and cyber-physical security is essential to move beyond current performance plateaus. If these challenges are systematically resolved, AI-enabled smart grids can evolve into resilient, secure, and socially trusted infrastructures capable of reliably integrating high shares of renewables and supporting the broader transition to a low-carbon energy system.

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