

Artificial Intelligence for Smart Grid and Renewable Energy Management: A Review of Techniques, Applications, and Future Directions

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Abstract: *Intermittent renewable generation, volatile loads, and concerns over grid stability have become defining features of modern power systems. Addressing these challenges with Artificial Intelligence (AI) and Machine Learning (ML) is attracting growing attention, including through better forecasting, automated demand response, optimized energy storage, and smart grid fault detection. This paper highlights the various AI-based techniques developed across the smart grid landscape, ranging from solar and wind forecasting to short-term load forecasting, demand-side management, electricity price forecasting, energy storage and battery management, grid resilience, and digital twins. It offers an overview of recently published work, including the major approaches, namely deep learning (LSTM and Transformer models), explainable AI, multi-agent systems, reinforcement learning, and federated learning, together with their strengths and limitations. The paper also presents a conceptual three-layer framework comprising edge sensing, federated forecasting and control, and explainable operator support at the distribution-utility level; the framework is not validated empirically. Challenges such as data privacy, model interpretability, scalability, and cybersecurity are explored, together with future research directions and the relevance of these technologies to India's energy transition goals.*

Keywords: Artificial Intelligence, Smart Grid, Renewable Energy, Load Forecasting, Demand Response, Deep Learning, Federated Learning, Energy Management

I. INTRODUCTION

The electricity transition is taking place on a structural basis, driven by decarbonization targets, growing electricity demand, and the rapid growth of distributed and renewable energy sources (RES) such as solar photovoltaics and wind power. RES generation is not steady and depends on factors such as weather, which makes balancing supply and demand more challenging than with conventional fossil-fuel generation [1], [2]. At the same time, the proliferation of smart meters, IoT sensors, and bidirectional communication technologies has introduced a huge volume of operational data across generation, transmission, and distribution systems [3].

The nonlinear, high-dimensional relationships found in modern grid data are not easily modeled by traditional rule-based and statistical approaches to grid operation, such as classic time-series forecasting and static dispatch heuristics. Artificial Intelligence (AI), specifically Machine Learning (ML) and Deep Learning (DL), is thus playing an increasingly prominent role in the smart grid of the future, enabling data-driven prediction, optimization, anomaly detection, and control with less human intervention.

This paper provides an overview of current AI applications across the smart grid value chain. It is a narrative review: no formal systematic search protocol or screening procedure was applied, and sources were selected from recent literature on AI for smart grids, renewable energy forecasting, demand response, and energy storage. The main AI techniques used in this area are covered in Section II. Section III presents a taxonomy diagram (Fig. 1) that gives an



overview of applications in renewable energy forecasting, load forecasting, demand response, grid fault detection, price forecasting, energy storage, and digital twins. Section IV puts forward an integrated conceptual framework, illustrated in Fig. 2. The relevance of these technologies to India's energy policy context is discussed in Section V. Open challenges are summarized in Section VI, future research directions are given in Section VII, and the paper is concluded in Section VIII.

II. AI METHODOLOGIES IN THE CONTEXT OF SMART GRIDS

A. Machine Learning and Deep Learning

Simpler supervised learning models, including support vector regression, random forests, and gradient-boosted ensembles, are still widely used for short-term load and generation forecasting because they are easy to interpret and have relatively small data requirements [4], [5]. For load and price time series, deep learning models, particularly Long Short-Term Memory (LSTM), Bidirectional LSTM, and hybrid ARIMA-LSTM models, have been shown to be superior in capturing the temporal dependence of the data [6], [7]. More recently, Transformer-based architectures have been reported to deliver better performance than LSTM and Prophet baselines in demand-response prediction, owing to their ability to model long-range dependencies in high-frequency load data [8].

B. Reinforcement Learning and Multi-Agent Systems

Given the sequential decision-making nature of energy management tasks under uncertainty, such as home energy scheduling and battery dispatch, reinforcement learning (RL) is a suitable AI approach. In home energy management systems (HEMS), multi-agent RL frameworks have been applied in which agents learn to cooperate or compete in order to achieve the best demand-side outcomes without a central controller [9].

C. Explainable AI

With the growing use of AI models in critical grid operations, the need for model interpretability is increasing. Explainable AI (XAI) has been applied in solar power forecasting to give grid operators insight into how predictions are produced, which enhances trust and decision-making [10].

D. Federated and Privacy-Preserving Learning

A growing number of studies on federated learning (FL) address the tradeoff between performance and privacy, with models trained across many distributed devices and utilities without centralizing the raw data. FL has been used to identify electricity consumer characteristics directly from smart-meter data without sharing consumption records with a central station [11]. Combining FL with reinforcement learning has also been suggested for distributed energy storage networks (DESNs), where federated reinforcement learning (FRL) selects representative subsets of devices and reduces the bias caused by non-IID data at energy storage nodes [12]. Moreover, a generalized policy-learning framework for smart grids that integrates Trust-Region Policy Optimization with FL (FL-TRPO) has been proposed to reduce emissions and operating costs while maintaining data locality [13]. This line of work has been extended to federated battery diagnosis and prognosis, in which battery health management is performed from locally acquired information without centralized data collection [14].

III. APPLICATIONS OF AI IN SMART GRID AND RENEWABLE ENERGY MANAGEMENT

A. Renewable Energy Forecasting

Solar and wind forecasting is vital for ensuring the proper generation mix on the grid and for correct unit commitment. Explainable AI tools have been studied to improve the transparency of PV solar power forecasting [10], and ensemble learning has been shown to be more accurate than single-model baselines for wind power forecasting [15].

B. Load Forecasting

Short-term load forecasting (STLF) is one of the most widely investigated applications of AI in power systems. Several studies show that combining models such as ARIMA and LSTM in an ensemble deep learning model gives beneficial results [6], and that updating an attention-based Bi-LSTM model with a rolling architecture makes it more robust to changing load patterns [7]. Other work has used periodicity decomposition and machine learning to explicitly model



seasonal and daily cycles and thereby improve short-term forecast accuracy [16]. In the Indian context, Gaussian Process Regression has been employed to predict peak load at the distribution-transformer level for grid stability and peak-load control in the Jajpur (Odisha) grid [17].

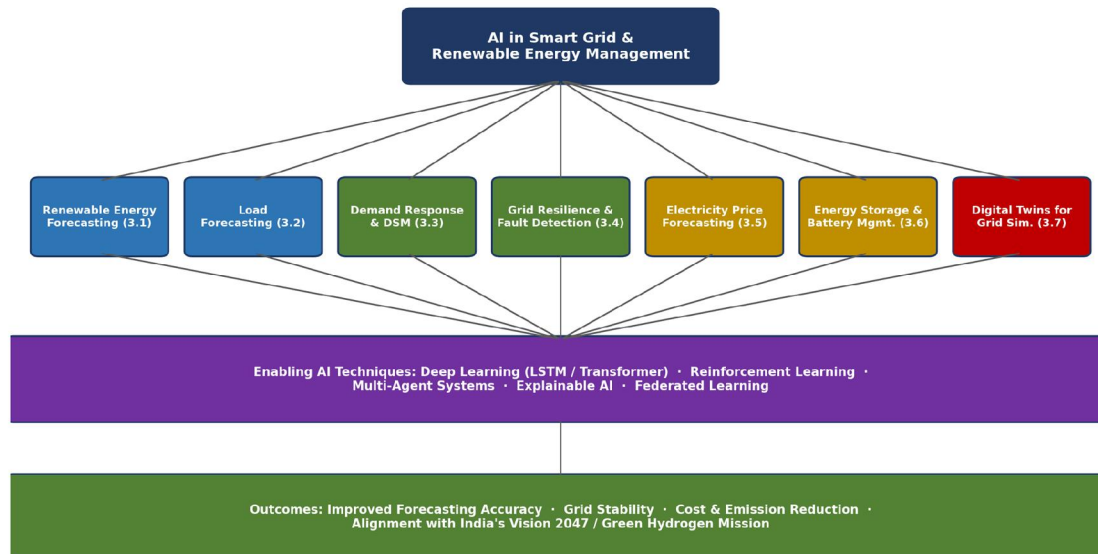


Fig. 1. Taxonomy of AI applications across the smart grid and renewable energy management value chain.

C. Demand Response and Demand-Side Management

AI-based demand response (DR) systems predict load and use consumer behavior patterns to recommend or automatically enroll consumers in DR programs. To align consumers with suitable dynamic-pricing DR programs, a clustering-based recommendation system that combines time-series forecasting with consumer segmentation has been proposed [18]. The combination of IoT, cloud computing, and AI-driven optimization has been put forward as a way to achieve effective, scalable demand-side management (DSM) [4], and multi-level energy management architectures have been suggested to provide more autonomous, hierarchical control of the grid [5].

D. Grid Resilience and Fault Detection

Common AI use cases in distribution networks include fault detection, fault location, and self-healing. Such functions rely on a sensing and communication foundation at the distribution-grid level, which digital and automation technologies can provide to enhance situational awareness and outage response times, thereby improving grid resilience as the share of renewables grows [1]. The sources reviewed here provide more detail on this automation layer than on AI-specific fault classifiers, which suggests a need for focused research.

E. Electricity Price Forecasting

Accurate day-ahead price forecasting influences consumer behavior and generation dispatch in electricity markets, and improved forecasts lead to better trading and dispatch decisions. In one study, deep learning models were found to be more suitable than traditional econometric models for day-ahead electricity price forecasting, although further comparisons across different markets and time periods are needed before this can be generalized [19].

F. Energy Storage and Battery Management

Optimal planning, health monitoring, and fault diagnosis of Battery Energy Storage Systems (BESS) are vital for mitigating the intermittency of renewable energy and are increasingly being addressed with AI methods. Federated reinforcement learning for scheduling residential battery storage using electricity-pricing signals and smart-meter data has been reported to lower household energy costs and the associated carbon emissions [20]. At the system level, an AI-based optimization framework that combines deep learning for load and generation forecasting, reinforcement-



learning-based scheduling, and mathematical optimization for battery dispatch is claimed to achieve double-digit reductions in peak load and operating cost, with better forecasting accuracy, in smart-grid and green-building applications [21]; as this is a conference-level result, independent validation would be welcome. Beyond scheduling, AI-based Battery Management Systems (BMS) are used for thermal management and state-of-health estimation in lithium-ion batteries, tasks that are difficult for rule-based or physics-based approaches because they depend on battery chemistry and operating conditions [22]. Reviews of AI-based BESS also underscore that machine-learning-based fault diagnosis and predictive health estimation are key enablers of safer, longer-lasting battery storage assets in electric vehicles and grid-scale deployments [23].

G. Digital Twins for Grid Simulation

Digital twin technology is an emerging technology that represents real-world grid assets in a virtual, continually updated model, providing another pathway for deploying AI-driven forecasting and control. A meta-analysis of studies conducted between 2020 and 2025 indicates the greatest potential benefit for decentralized, zero-carbon grid optimization when AI-driven digital twins are coupled with federated learning, particularly in microgrid deployments [24]. Digital twins can simulate the deployment of AI-based control policies to reduce operational risk, and can also be used for scenario analysis when planning grids with high renewable penetration.

TABLE I: Comparative Summary of AI Techniques in Smart Grid and Renewable Energy Management

AI Technique	Primary Grid Application	Key Strength	Reported Limitation
LSTM / Bi-LSTM	Short-term load and price forecasting [6], [7]	Captures long-range temporal dependencies	High training cost; limited interpretability
Transformer-based models	Demand-response prediction [8]	Outperforms LSTM/Prophet baselines on complex sequences	Requires large training datasets
Ensemble learning	Wind power and load forecasting [15], [6]	Robust to noise; combines weak learners	Slower inference for real-time use
Reinforcement Learning / Multi-Agent RL	Home energy management, battery scheduling [9], [20]	Learns adaptive control without hand-crafted rules	Sample inefficiency; safety constraints needed
Explainable AI (XAI)	Solar PV forecast interpretation [10]	Improves operator trust and regulatory acceptance	Added computational and design overhead
Federated Learning / FRL	Privacy-preserving load and battery modeling [11], [12], [13]	Preserves data privacy across distributed nodes	Communication overhead; non-IID data bias

IV. PROPOSED CONCEPTUAL FRAMEWORK: AN INTEGRATED AI PIPELINE FOR DISTRIBUTION-LEVEL GRID MANAGEMENT

Building on the gaps identified across the reviewed literature, particularly the fragmentation between forecasting, storage optimization, and privacy-preserving deployment, this section outlines a conceptual, three-layer framework proposed by the authors for integrated AI-based management at the distribution-utility level. Its closest antecedents are the federated reinforcement learning approaches in [12], [20], and [13]; the contribution here is the explicit combination of edge pre-processing, federated forecasting, multi-agent control, and an explainable operator interface in a single pipeline, rather than any new algorithm. The framework is intended as a synthesis and planning tool rather than a reproduction of any single reviewed system.



Proposed Three-Layer AI Framework for Distribution-Level Grid Management

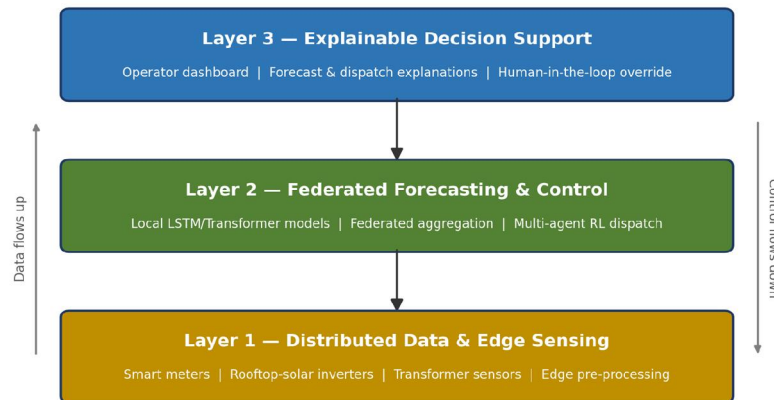


Fig. 2. Proposed three-layer AI framework for distribution-level grid management.

A. Layer 1: Distributed Data and Edge Sensing

At the lowest layer, smart meters, rooftop-solar inverters, and distribution-transformer sensors continuously relay consumption, generation, and grid-health telemetry. Lightweight edge-AI models pre-process data locally, for example by flagging anomalies, estimating missing values, and predicting short-term load trends, before any data leaves the node. This design choice helps address the scalability concern raised in Section VI and lessens the latency and bandwidth burden of centralized processing, since the volume of data that must pass through communication networks is reduced.

B. Layer 2: Federated Forecasting and Control

The second layer trains models in a federated manner across distribution nodes using a federated learning protocol, following the approaches surveyed in Section II-D. A local forecasting model (e.g., an LSTM or a Transformer variant, per Section III-B) is trained at every node, and only model updates, not raw consumer data, are shared with a central aggregator. A multi-agent reinforcement learning controller then uses the aggregated forecasts to coordinate demand-response signals and battery dispatch decisions across neighboring nodes, keeping localized decisions (e.g., a single feeder's storage schedule) consistent with feeder- and substation-level constraints.

C. Layer 3: Explainable Decision Support for Operators

An explainable-AI interface at the top layer presents forecasts, dispatch recommendations, and anomaly alerts to human grid operators, identifying the key features (e.g., temperature, historical peak, solar irradiance forecast) behind each recommendation. The layer is intentionally designed to be human-in-the-loop: operators can override automated dispatch decisions, and each override is recorded and used in subsequent model retraining, creating a continuous improvement loop.

This three-layer structure is deliberately modular, allowing any of the individual techniques described in Sections II and III (e.g., replacing the LSTM with a Transformer-based forecaster, or the RL controller with a rule-based safety shield) to be swapped without redesigning the entire pipeline. The framework is proposed for future prototyping only and is not tested with field data in this review; Section VII outlines the empirical validation required to test it.

V. RELEVANCE TO INDIA'S ENERGY TRANSITION AND VISION 2047

India's long-term strategy is framed by the Viksit Bharat vision of a developed India by 2047 and by climate commitments that include a net-zero target for 2070 [25] and a goal of meeting about half of installed electric power capacity from non-fossil sources by 2030 [26]. In line with this, complementary initiatives such as the National Green Hydrogen Mission [27] and the IndiaAI Mission place renewable energy integration and the digital transformation of



the grid at the center of India's path toward energy self-reliance (Atmanirbhar Bharat). AI-powered load forecasting and demand-response systems are especially relevant for India's distribution utilities, where demand is highly variable and strongly influenced by weather and socioeconomic factors [17]. As India scales up rooftop solar, distributed renewable generation, and electric vehicle (EV) adoption, the AI-based forecasting, storage optimization, and grid-balancing techniques discussed in Section III can help achieve policy goals around sustainable infrastructure, green building integration, and low-carbon power systems. Evidence from the Indian context remains limited in the reviewed literature [17], which motivates validation on Indian distribution-feeder data.

VI. CHALLENGES

- *Data privacy and governance:* Privacy concerns about smart meter and consumer usage data limit data sharing across utilities and researchers [28].
- *Model interpretability:* Deep learning models are often treated as black boxes, so operators may hesitate to trust their predictions in safety-critical grid decisions [10].
- *Scalability:* Developing and deploying AI models across millions of distributed sensors and meters demands substantial computational infrastructure [28].
- *Data quality and variability:* Renewable generation and consumer load data are highly variable and weather dependent, which makes it difficult to generalize models across regions and seasons [2].
- *Cybersecurity:* As smart grids become more digitized and interconnected through two-way communication, their attack surface grows [3].

VII. FUTURE RESEARCH DIRECTIONS

- Explainable AI (XAI) for operator-facing forecasting and control systems, to build trust and regulatory acceptance [10].
- Federated and federated-reinforcement learning approaches that enable utilities to train shared forecasting and control models without centralizing sensitive consumer or battery data [11], [12], [13], [14].
- Edge-AI deployment at substations and smart meters for real-time inference with minimal latency and communication overhead, as outlined in the Layer 1 design of the proposed framework (Section IV-A).
- Digital-twin-based grid simulation combined with reinforcement learning for proactive, scenario-based grid management, especially for microgrids [24].
- Empirical validation of integrated, multi-layer AI pipelines (such as the framework proposed in Section IV) on real distribution-feeder data, to move beyond single-technique benchmarks toward end-to-end system evaluation.
- Integration of AI-based forecasting with electric vehicle charging infrastructure and green hydrogen production scheduling, in line with national priorities such as the National Green Hydrogen Mission [27].

VIII. CONCLUSION

The complexity created by integrating renewable energy into the power grid has made Artificial Intelligence an important technology for grid management. Across forecasting, demand response, and storage optimization, the reviewed studies generally show improvements over statistical and rule-based baselines, although direct comparisons are difficult because datasets, horizons, and metrics differ; evidence for AI-based fault detection is thinner. Realizing the full potential of AI-enabled smart grids depends on addressing persistent challenges around interpretability, data privacy, and computational scalability. The proposed conceptual framework can serve as a first step toward integrated, privacy-preserving deployment, but it remains to be validated with field data. For countries such as India, where distribution networks face heterogeneous demand patterns and renewable energy adoption is accelerating, AI-driven grid management could prove to be a strategic enabler of long-term energy security and sustainability.



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