ELECTRICAL ENGINEERING

Artificial Intelligence for India's Energy Transition: Integrating Smart Grids, Renewable Energy, Green Hydrogen and Battery Energy Storage

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Abstract

India's rapid expansion of renewable energy capacity has increased the need for flexible, intelligent coordination among electricity generation, grid infrastructure, energy storage, and emerging green hydrogen systems. This paper reviews the application of artificial intelligence (AI) to renewable energy forecasting, smart grid operation, battery energy storage system (BESS) management, and green hydrogen production, with particular attention to the Indian energy transition. The review identifies a gap in the largely separate treatment of these domains and proposes an AI-Integrated Energy Transition Framework (AIETF). The framework comprises renewable energy sources, a data-acquisition layer based on Internet of Things sensors, phasor measurement units and smart meters, a shared AI intelligence layer, and integrated energy assets including smart grids, BESS, green hydrogen production, electric-vehicle charging and demand response. It conceptualises the allocation of renewable electricity among grid export, battery charging and electrolysis as a coordinated decision problem. Indian initiatives are examined to assess the extent to which the framework's constituent elements are emerging in practice. The paper also discusses data quality, cybersecurity, explainability, infrastructure cost, skills and interoperability challenges, and identifies future research directions involving virtual power plants, digital twins, vehicle-to-grid integration and multi-agent energy management. The proposed framework is conceptual and requires subsequent validation using simulation and operational Indian grid data.

Keywords: artificial intelligence; battery energy storage; green hydrogen; renewable energy; smart grid

1 Introduction

India's energy transition is being shaped by the twin requirements of expanding electricity access and reducing the carbon intensity of energy supply. At the twenty-sixth Conference of the Parties (COP26), India announced the Panchamrit commitments, including net-zero carbon emissions by 2070 and a target of 50% cumulative installed electric power capacity from non-fossil sources by 2030. The source material reports that the 50% milestone was achieved five years ahead of schedule and that, by June 2026, non-fossil capacity had reached approximately 297 GW, including nearly 289 GW of renewable energy capacity, with solar power contributing more than 162 GW [1]. Annual renewable capacity additions reportedly exceeded 48 GW in 2025, while the national target remains 500 GW of non-fossil capacity by 2030 [2].

The rapid growth of renewable generation, however, creates operational requirements that extend beyond the addition of generating capacity. Variable solar and wind output must be balanced against

demand, transmission constraints and the availability of flexible resources. Battery energy storage capacity, reported at approximately 5–5.5 GW as of mid-2025, remains below the estimated requirement of about 16 GW for 2026–27 [3]. Deployment has also been affected by tariff expectations and power-purchase-agreement bottlenecks associated with viability-gap-funding initiatives [4]. In parallel, the National Green Hydrogen Mission, approved in January 2023 with an outlay of approximately ₹19,744 crore, seeks to establish a domestic green hydrogen ecosystem and targets annual production of 5 million tonnes by 2030 [5, 6].

These developments create an interconnected planning and control problem. Surplus renewable electricity may be exported to the grid, stored in batteries or directed to electrolysers for hydrogen production. The preferred action changes with generation forecasts, demand, network conditions, battery state of charge, electrolyser operating limits and system prices. Conventional rule-based control can manage defined operating conditions, but coordinated optimisation across geographically distributed and technologically diverse assets requires extensive data processing and adaptive decision-making. Artificial intelligence can support this coordination through forecasting, optimisation, anomaly detection, predictive maintenance and decision support [7, 8].

This paper synthesises literature on AI applications in renewable integration, smart grids, BESS and green hydrogen, and examines Indian initiatives relevant to these domains. Its central contribution is the AI-Integrated Energy Transition Framework (AIETF), which places a shared intelligence layer between data acquisition and integrated energy assets. The paper addresses four questions: (i) which AI techniques are applied across the four domains and what effects are reported; (ii) how these applications may be coordinated through a shared intelligence layer; (iii) how far Indian initiatives reflect the proposed framework; and (iv) which challenges and research directions will influence implementation at scale. The paper is a literature-based conceptual synthesis; the proposed framework is not presented as an experimentally validated control system.

2 Literature review and AI foundations

Research on AI-enabled smart grids has examined demand forecasting, fault detection, automated reconfiguration and self-healing operation. These applications are reported to improve grid reliability compared with conventional threshold-based supervisory control [7]. Recent work also surveys AI and machine-learning applications across generation, transmission and distribution [8]. For the Indian context, the availability and quality of digital communication infrastructure, legacy equipment and workforce readiness are identified as important conditions affecting adoption [9]. Cloud–fog architectures combined with metaheuristic optimisation have been proposed for renewable dispatch and grid balancing [10]. At the microgrid level, hierarchical AI-based control has been studied across primary, secondary and tertiary control layers [11, 12].

A second stream of literature concerns battery monitoring and lifecycle management. Battery-health reviews distinguish model-based, data-driven and hybrid methods for estimating state of health (SoH) and remaining useful life (RUL) [13]. Internet of Things (IoT)-enabled monitoring supports the collection of operating data for battery-health assessment in electric vehicles and stationary storage applications [14]. Research on lithium-ion battery technologies further highlights degradation processes and thermal safety as important considerations for storage deployment [15].

AI applications in green hydrogen production are an emerging research area. Computational modelling and optimisation methods have been examined for water electrolysis, including the use of AI to support operating-point selection and maintenance planning [16]. Related work on digital twins

considers renewable generation, smart grids, energy storage and vehicle-to-grid (V2G) integration as connected components of an evolving energy system [17]. In India, the development of phasor measurement unit (PMU) and smart-meter infrastructure provides a potential sensing foundation for more advanced grid analytics and digital-twin applications [18]. Research on virtual power plants (VPPs) and AI-driven EV charging similarly points towards the aggregation and coordinated management of distributed energy resources [19, 20].

The AI methods discussed across these studies serve complementary functions. Machine-learning and deep-learning models, including long short-term memory (LSTM) and gated recurrent unit architectures, are used for time-series forecasting of renewable generation, demand and battery degradation. Reinforcement learning represents sequential operating decisions and is relevant to storage scheduling and coordination among distributed energy resources. Digital twins provide virtual representations of physical assets for monitoring, prediction and scenario analysis. Computer vision can support inspection, while IoT sensing and edge AI enable data acquisition and device-level response. Explainable AI can help make model outputs more interpretable in operational and regulatory settings. These techniques provide the technical basis for the integrated application model proposed in this paper.

3 AI applications across the energy value chain

3.1 Renewable energy integration

AI-based renewable forecasting uses satellite imagery, numerical weather prediction and historical generation data to estimate short-term and day-ahead solar and wind output. Improved forecasts can support the scheduling of thermal, hydro and storage resources and reduce the uncertainty associated with variable generation [7]. AI-based congestion prediction and redispatch optimisation can identify emerging network constraints before they result in renewable curtailment. Cloud–fog management architectures combined with metaheuristic optimisation provide one approach to coordinating distributed information processing and grid-level decisions [10]. In the Indian distribution context, real-time, cloud-based AI applications have been reported to reduce scheduled-deviation penalties and power-purchase costs [21].

3.2 Smart grid operation

AI supports smart-grid operation through load forecasting, anomaly detection, fault identification and network reconfiguration. LSTM-based short-term load forecasting can improve estimates of demand and support time-of-use strategies intended to shift discretionary consumption away from peak periods. Machine-learning models applied to voltage, current and frequency measurements can identify abnormal operating patterns and support faster fault detection. When integrated with automated switching and control, these functions contribute to self-healing grid operation [7]. Hierarchical AI-based control can coordinate distributed energy resources and microgrids across primary, secondary and tertiary levels [11, 12]. In India, legacy equipment, uneven data quality and varying workforce capabilities remain important deployment constraints [9].

3.3 Battery energy storage systems

The limited scale of deployed BESS relative to projected requirements increases the importance of efficient operation and lifecycle management [3]. Data-driven and hybrid estimation methods use voltage, current and temperature time-series to estimate state of charge (SoC), SoH and RUL [13].

IoT-based monitoring can provide the operating data required for battery-health assessment in both electric-vehicle and stationary applications [14, 15]. AI-based dispatch can determine charging and discharging schedules for applications such as peak shaving and frequency regulation. Predictive thermal monitoring can also identify abnormal temperature patterns and provide an early warning of overheating, supporting safer operation as storage deployment expands.

3.4 Green hydrogen production

The National Green Hydrogen Mission targets annual production of 5 million tonnes by 2030. The cited source material reports that, by May 2025, allocations covered approximately 862,000 tonnes per annum of production capacity and 3,000 MW of electrolyser manufacturing capacity [5, 6]. AI can support the hydrogen value chain by predicting suitable electrolyser operating set-points, optimising energy use and anticipating maintenance requirements [16]. At the system level, optimisation methods can coordinate the allocation of available renewable electricity among battery charging, grid export and electrolysis. This makes electricity and hydrogen linked energy carriers within a common operational decision problem rather than independent planning domains.

4 Proposed AI-integrated energy transition framework

The preceding applications are interdependent. For example, a decision to curtail solar generation affects the energy available for battery charging and electrolysis; a battery's state of charge influences its ability to support the grid during a demand peak; and an electrolyser's operating condition affects the amount of renewable electricity that can be converted into hydrogen. The AI-Integrated Energy Transition Framework (AIETF) is proposed to represent these relationships through four connected layers.

Layer 1—Renewable Sources: This layer comprises the renewable generation resources, principally solar, wind and hydro, that supply variable and dispatchable low-carbon electricity to the wider system.

Layer 2—Data Acquisition: IoT sensors, PMUs and smart meters collect operational measurements from generation assets, networks, storage systems and end users. The data-acquisition layer provides the observability required for forecasting, state estimation, anomaly detection and coordinated optimisation.

Layer 3—Shared AI Intelligence: This is the coordinating layer of the framework. It performs renewable-generation and demand forecasting, operational optimisation, predictive maintenance and decision support. Rather than assigning isolated AI applications to individual assets, the framework envisages a shared intelligence layer that considers system-level objectives and constraints.

Layer 4—Integrated Energy Assets: The intelligence layer interacts with smart-grid infrastructure, BESS, green hydrogen production facilities, EV charging infrastructure and demand-response resources. These assets provide the controllable flexibility through which the system can respond to changing renewable output and demand.

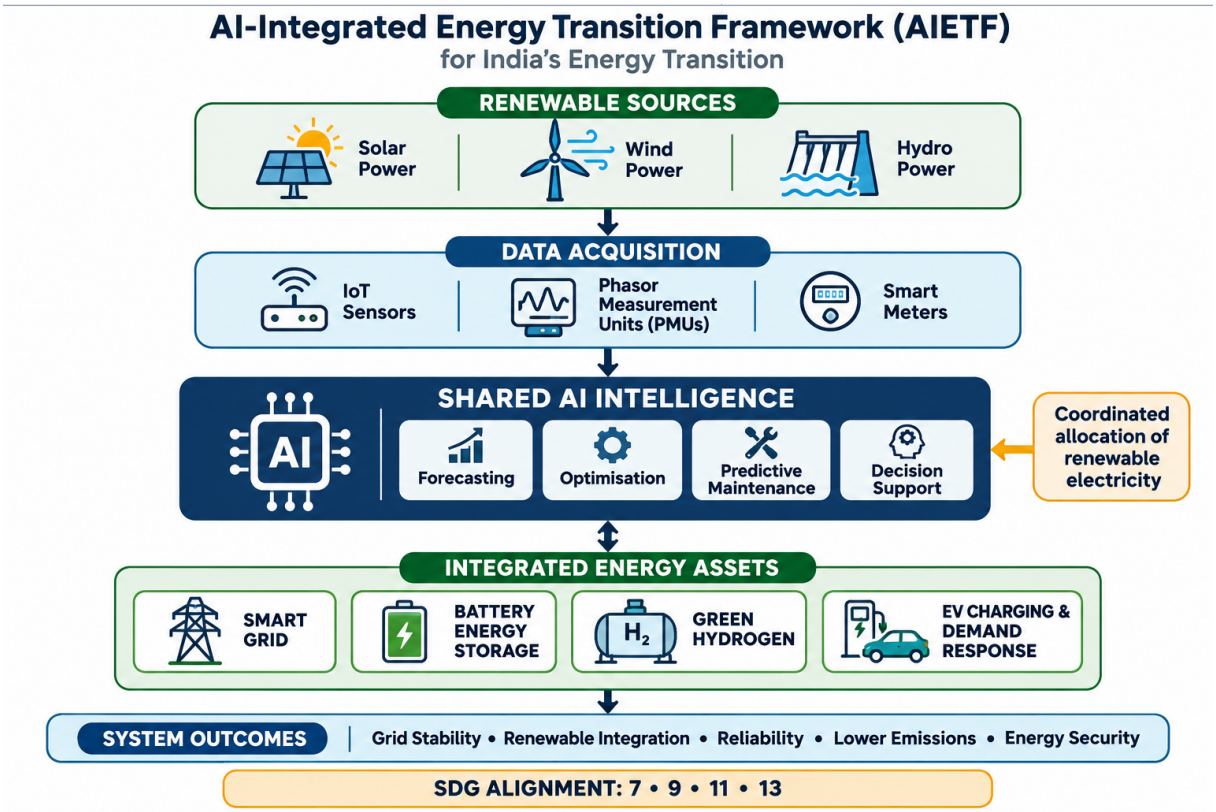


Figure 1. AI-Integrated Energy Transition Framework (AIETF) and its alignment with the Sustainable Development Goals

The framework seeks to coordinate the allocation of available renewable electricity among grid export, battery charging and hydrogen production, subject to network conditions, storage limits, electrolyser requirements and demand. Its intended outcomes include improved grid stability, higher renewable penetration, reduced emissions, improved reliability, lower operating costs and enhanced energy security. These outcomes correspond to four Sustainable Development Goals (SDGs): SDG 7 (Affordable and Clean Energy), through renewable integration and storage; SDG 9 (Industry, Innovation and Infrastructure), through digital grid and electrolyser infrastructure; SDG 11 (Sustainable Cities and Communities), through more reliable urban energy networks; and SDG 13 (Climate Action), through reduced fossil-based generation and green hydrogen. The framework's principal contribution is the shared coordination layer linking assets that are otherwise often planned and operated separately.

5 Indian initiatives and framework assessment

Several Indian initiatives illustrate individual components of the AIETF. The National Green Hydrogen Mission, approved in January 2023 with an outlay of approximately ₹19,744 crore, is being implemented in phases, with an initial emphasis on domestic manufacturing capacity and a subsequent focus on cost competitiveness and adoption in sectors such as refining, fertiliser, steel and mobility [5]. BESS deployment has also advanced through pilot projects and viability-gap-funding support. The source material reports approval of more than ₹9,160 crore for over 43 GWh of storage capacity, while power-purchase-agreement delays and tender cancellations indicate continuing market and implementation constraints [4].

Expansion of PMU and smart-meter infrastructure provides part of the sensing foundation required for data-driven grid operation [18]. Real-time, cloud-based AI in distribution operations, including the reported Mumbai application, illustrates the potential operational value of data-enabled optimisation [21]. These developments indicate that elements corresponding to the data-acquisition and integrated-asset layers are emerging in India. However, the cited initiatives do not establish that a unified AI layer is already coordinating renewable generation, grid operation, storage and hydrogen production at national or system-wide scale.

In relation to the research questions, the reviewed studies identify forecasting, machine learning, deep learning, reinforcement learning, digital twins and optimisation as relevant techniques across the four domains. The AIETF addresses the coordination question by placing these functions within a shared intelligence layer. Indian initiatives demonstrate progress in renewable generation, hydrogen policy, storage procurement and grid sensing, but the available evidence points to component-level development rather than comprehensive cross-domain coordination. The extent of integration, therefore, remains an issue for implementation and empirical investigation.

6 Implementation challenges and future research

The deployment of AI-enabled integrated energy systems faces several interrelated challenges. First, inconsistent data quality across distribution utilities can limit the reliability and transferability of trained models. Second, increased dependence on sensors, communication networks and connected control devices expands the cybersecurity attack surface; intrusion detection and secure communication therefore need to be incorporated into system design. Third, deep-learning models used in critical control applications may raise explainability and accountability concerns, particularly where operators and regulators must justify automated decisions. Fourth, the capital cost of BESS, PMUs, communication infrastructure and electrolysers can constrain deployment even where AI methods are technically mature. Finally, shortages of professionals with combined power-systems and data-science expertise, together with evolving certification and interoperability standards, create additional uncertainty for developers and investors.

Future research can extend the AIETF in several directions. AI-enabled VPPs could aggregate distributed generation, storage and flexible demand into dispatchable resources [19]. Digital twins could evolve from descriptive monitoring and predictive analysis towards prescriptive and more autonomous operation [17]. V2G systems could use demand forecasting and deep reinforcement learning to coordinate EV charging and treat vehicle fleets as mobile storage resources [20]. Decentralised multi-agent energy management could allow grid, storage and hydrogen assets to coordinate decisions while respecting local constraints and system-wide objectives. Further work is also warranted on AI-supported price discovery and market mechanisms for a developing green hydrogen economy.

The next stage of research should move beyond conceptual integration towards simulation-based and data-driven validation. The AIETF can be operationalised through test cases using Indian grid, renewable-generation, storage and electrolyser data. Such studies should define objective functions, operating constraints, data requirements and performance indicators, and compare coordinated control against independent asset-level strategies. The present paper proposes the architecture and identifies these validation needs; it does not claim measured performance improvements from an implemented AIETF.

7 Conclusion

Artificial intelligence can contribute to India's energy transition not only through individual applications in forecasting, grid operation, battery management and hydrogen production, but also by coordinating these domains as an integrated energy ecosystem. The review indicates that relevant AI techniques are being developed across each domain, while Indian initiatives are expanding renewable capacity, storage programmes, green hydrogen infrastructure and digital grid sensing. However, the coordination of these assets through a common intelligence layer remains an important gap.

The proposed AIETF addresses this gap through four layers: renewable sources, data acquisition, shared AI intelligence and integrated energy assets. By coordinating grid export, battery charging, electrolysis, EV charging and demand response, the framework provides a conceptual basis for improving flexibility, reliability and renewable utilisation. Its intended outcomes align with SDGs 7, 9, 11 and 13. Realising this potential will require progress in data quality, cybersecurity, explainability, infrastructure investment, skills and interoperability. Simulation and validation using Indian operational data are necessary next steps before the framework can be considered an operationally verified solution.

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