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Renewable Energy Transition in India: Role of Artificial Intelligence in Optimising Renewable Energy Generation and Distribution

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***Abstract:** India is prioritising the deployment of renewable energy as a central pillar of its sustainable development policy and climate action plan. This shift towards renewable energy systems presents complex operational constraints arising from the intermittency of renewable energy sources, information asymmetries in forecasting power requirements, and the need for smart and robust energy infrastructure. In this context, this review paper aims to explore the evolving role and potential of Artificial Intelligence (AI) in facilitating sustainable energy transitions. Drawing on interdisciplinary literature, this paper explores the application of AI to data-driven decision-making to enhance renewable energy forecasting and intelligent energy storage management, thereby improving grid stability. Further, by drawing on theoretical and empirical insights, the paper seeks to contribute to the identification of key pathways, limitations, and policy-oriented considerations for shaping the future deployment of AI in sustainable energy production and distribution. The paper finds that recent developments in AI models and machine learning-based technologies, and their deployment in the renewable energy ecosystem, hold great potential for advancing renewable energy generation and distribution.*

***Keywords:** Green Energy, Energy Storage System, Grid Balancing, Artificial Intelligence, Machine Learning, Forecasting Techniques.*

Nomenclature:
GW: Gigawatts
AI: Artificial Intelligence
GoI: Government of India
KNN: k-Nearest Neighbours
SVR: Support Vector Regression
LSTM: Long Short-Term Memory
CNNs: Convolutional Neural Networks
LightGBM: Light Gradient Boosting Machine
XGBoost: eXtreme Gradient Boosting
EMD: Empirical Mode Decomposition
MAPE: Mean Absolute Percentage Error
TL: Transfer Learning
AHA: Artificial Hummingbird Algorithm
ANNs: artificial neural networks
GRU: Gated Recurrent Unit
SOC: State of Charge
BMS: Battery Management Systems
SoP: State of Power
SoH: State of Health
FDD: Fault Detection and Diagnosis
SoC: State of Charge
RDSS: Revamped Distribution Sector Scheme
NSGM: National Smart Grid Mission
RL: Reinforcement Learning
DL: Deep Learning
XAI: Explainable Artificial Intelligence
VGF: Viability Gap Funding
ML: Machine Learning

I. INTRODUCTION

A. Green Energy Generation in India

To mitigate the impacts of climate change, the Government of India is prioritising the deployment of renewable energy sources as an essential component of its sustainable development strategy and climate action plan. The renewable energy market has seen significant growth in recent years, driven by ambitious national targets, technological advancements, and supportive government policies. As of 31st October 2025, India's total installed electricity generation capacity has reached 505 gigawatts (GW), which comprises 259 GW from non-fossil fuel sources (including 200 GW from renewable energy sources, i.e., Solar, Wind, Bio Power and Small Hydro). It is relevant to note that in some regions, large hydro power plants (with more than 25-megawatt capacity) are not counted as renewable sources. However, the Government of India (GoI) has now declared large hydro power plants as a renewable energy source [1]. To fulfil its commitment to combat climate change, GoI has set an ambitious target to install 500 GW of renewable capacity by 2030 and to achieve net-zero carbon emissions by 2070 [2]. The present status of the total installed capacity of energy generation by different sources in India is as follows:

Table I: India's Power Generation Capacity by Source (in %)

Source	Electricity Installed Capacity (as on March 2026)	Electricity Generation Capacity (April 2025 – March 2026).
Coal (including lignite)	43.80	70.73
Oil & Gas	4.00	
Large Hydro	9.80	9.05
Nuclear	1.7	2.99
Solar	27.0	9.46
Wind	10.5	5.77
BM Power/ Cogen/ Waste to Energy	2.3	0.93
Small Hydro	1.0	0.65

Source: (a) For Installed Capacity: Ministry of Power, GoI. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2238921&reg=3&lang=1
(b) For Generation capacity: Central Electricity Authority, GOI, https://cea.nic.in/wp-

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content/uploads/resd/2026/03/Monthly_RE_Generation_report_March_2026.pdf

The above table provides data on installed electricity generation capacity and actual electricity generation by different sources in India. The data shows that coal remains dominant in terms of the actual electricity generation (70.73%). It is also striking that actual electricity generation from coal is much higher than its installed capacity (43.80%). This indicates that coal-fired electricity generation plants operate at a very high capacity factor. Conversely, Solar and Wind energy generation show different patterns, as their installed capacity (27.0% and 10.5%, respectively) is significantly higher than their actual generation (9.46% and 5.77%, respectively). This gap arises from the intermittent nature of renewable energy sources, which leads to lower capacity factors than those of dispatchable sources.

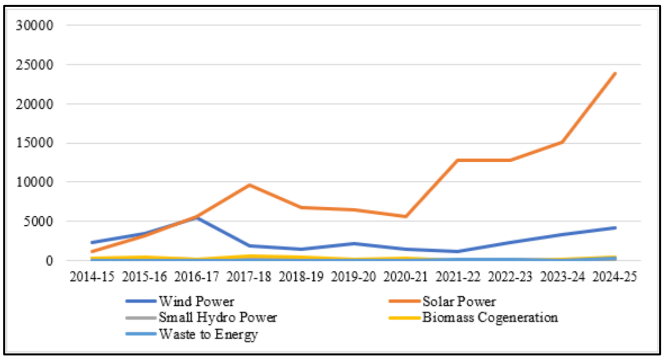
The trajectory of electricity generation capacity in India over the last decade shows an outstanding transformation in the renewable energy landscape. Solar energy capacity observed exponential growth, rising from very small levels in 2012 to around 132 GW in 2025, surpassing all other renewable sources. The growth in renewable energy sources in the last decade can be seen from the table below:

Table II: Installed Renewable Energy Capacity (MW)

Sector	Cumulative Achievements (as on 30.11.2014)	Cumulative Achievements (till 30.11.2025)
Solar Power	2821.91	132848.25
Wind Power	21042.58	53986.02
Small Hydro Power	3803.68	5158.61
Biomass Cogeneration	7951.05	10757.31
Waste to Energy	230.37	856.62
Total Renewable Energy	35849.59	203606.81

Source: Ministry of New and Renewable Energy, Government of India. Available at: https://mnre.gov.in/en/year-wise-achievement/

The table above shows the total installed renewable energy production capacity in India for 2014 and 2025. The table shows a significant expansion in renewable energy production capacity over the last decade. The table also shows that solar energy has experienced exponential growth and has emerged as a significant contributor to renewable energy in India. The installed capacity of solar energy increased more than 40 times during the aforesaid period. Wind is the second-largest contributor to renewable energy and has experienced an approximately 2.5-fold increase over the last decade. The year-wise trend of renewable energy capacity, reflecting the changing contribution from various renewable sources, can be seen from the table below:



[Fig.1: Year-Wise Achievements in Installed Renewable Energy Capacity (in MW)]

Source: Ministry of New and Renewable Energy, Government of India. Available at: https://mnre.gov.in/en/year-wise-achievement/ (accessed on 06th January 2026).

The above figure shows the rapid growth in India's installed solar energy capacity, which surpassed that of all other renewable energy sources over the last decade. Wind energy capacity increased steadily until around 2018, then plateaued. The capacity to generate hydropower and bioenergy, and to store waste, remained relatively stable over the last decade. This trend indicates India's strategic focus on harnessing abundant, cost-effective solar energy.

The growth of renewable energy, particularly solar energy, in India has been promising in recent years, but sustaining this momentum in the long run may face some technical challenges. The data suggest that GoI missed the target of installing 175 GW of renewable energy capacity by 2022. Now, India has a target of achieving 500 GW of renewable energy by 2030, which is technically feasible if we convert installed capacity into sustained renewable generation. Meeting such ambitious goals necessitates integrating renewable energy into the electrical grid to ensure a reliable supply for household, business, and industrial use. This integration with the grid requires the use of efficient technologies to forecast energy demand and renewable energy supply, minimising power supply uncertainty and improving operational efficiency.

At the same time, enhanced planning of energy storage infrastructure and intelligent grid integration are essential to ensure efficient transmission, grid stability, and long-term energy security. While the Central Electricity Authority (CEA) has projected a massive requirement of 336 GWh of energy storage by 2029-30 to maintain grid stability, the operational reality as of late 2025 remains in its infancy at roughly 500 MWh to 700 MWh of battery capacity [1]. This means that, with only four years remaining until the target of 500 GW of renewable energy capacity, India has commissioned less than 0.25% of the needed battery storage infrastructure. However, GoI has recently launched the Viability Gap Funding (VGF) scheme to provide financial support for the development of battery energy storage systems, particularly for integrating renewable energy into the grid. This may take significant time to increase the battery storage system's production capacity. The literature suggests that the gap in energy storage capacity may be addressed by optimising the storage system using AI [3,4,5].

In this context, AI's role in enabling sustainable energy transitions assumes paramount importance, particularly for India’s rapidly transforming energy sector. Drawing on findings from interdisciplinary research, the following sections of the article conceptualise AI within theoretical frameworks of data-driven decision-making and systems optimisation, highlighting its capacity to improve the accuracy of renewable energy forecasting, strengthen grid stability, and support intelligent energy storage management.

II. ARTIFICIAL INTELLIGENCE (AI)

John McCarthy introduced the concept of AI in 1956. According to him, AI is the science of creating intelligent machines capable of performing tasks associated with human cognition [6]. This introductory understanding of AI has evolved significantly since its inception. Currently, AI can learn from data, adapt to changing situations, and support goal-oriented decision-making [7,8]. In the context of environmental sustainability, AI is considered a technology that enables the efficient use of natural resources through data-driven optimisation and predictive analytics [9]. By processing large volumes of real-time and historical data, AI-based tools can help us accurately forecast energy consumption and production from green sources, thereby improving decision-making in the energy sector. Similarly, AI tools can enhance energy efficiency, reduce material waste, and support environmentally friendly decision-making across sectors [10].

AI-based technology is being used in industrial applications aligned with sustainability objectives, specifically in areas such as energy management, resource optimisation, and environmentally friendly production systems [11,12]. This shift has supported environment-oriented research and development by fostering new approaches to improve the efficiency of innovation while mitigating adverse environmental and social externalities associated with industrial activity [13,14]. These outcomes are achieved mainly through AI’s ability to reduce information asymmetries by processing and analysing large volumes of heterogeneous data, thereby generating timely, accurate, and context-specific insights for operational and strategic decision-making [15].

In the energy sector, AI has become a key enabler of sustainability by transforming traditional energy production and distribution systems. AI-based forecasting and control techniques have been widely applied to enhance grid stability with high penetration of variable renewable energy sources, such as solar and wind, by improving load prediction, frequency regulation, and fault detection [16, 17]. Furthermore, AI plays a critical role in the management of energy storage systems by optimising charging–discharging cycles, extending battery life, and supporting the integration of distributed energy resources, thereby enabling more flexible, resilient, and sustainable electricity networks [19,20].

The literature suggests that integrating renewable energy requires AI-enabled smart grids that leverage real-time monitoring and demand response to maintain stability and optimise resource utilisation. Further, to counter the intermittent nature of renewables, storage solutions such as lithium-ion batteries, supercapacitors, pumped hydro storage, etc., capture surplus energy during peak production to ensure a continuous supply. Together, these technologies form a cohesive ecosystem that strengthens grid reliability and secures a resilient, carbon-free power future. Details of these systems are discussed in the section below.

III. ARTIFICIAL INTELLIGENCE IN OPTIMISING GREEN ENERGY GENERATION

Renewable power output is highly dependent on dynamic factors such as cloud cover, environmental temperature, and variations in daylight hours. In contrast, wind power generation depends on wind speed, direction, and atmospheric turbulence. The complex interplay of these variables introduces substantial uncertainty, making it difficult for conventional modelling techniques to accurately forecast energy generation, especially under rapidly fluctuating meteorological conditions and climatic variability [21]. The conventional forecasting models for energy generation and consumption are based on statistical methods and historical time-series data, which are often inadequate to capture the stochastic and non-linear characteristics inherent in renewable energy generation [21]. As a result, renewable power generation remains difficult to forecast for grid operators and energy planners, leading to suboptimal dispatch decisions, greater reliance on reserve capacity, and higher operational costs [22].

The aforesaid limitations, as well as the complexity and volatility of renewable energy-linked power systems, necessitate the adoption of sophisticated forecasting techniques. AI and machine learning (ML)- related technologies offer practical solutions, as tools based on these technologies can process large volumes of heterogeneous data and generate reliable forecasts even in the presence of significant uncertainty. Further, AI/ML-based tools can learn complex relationships among factors/variables affecting energy production, storage, and distribution. Therefore, these tools not only improve predictions of electricity generation but also contribute to optimising energy storage charge–discharge cycles and grid load balancing, thereby facilitating the integration of renewable energy with traditional energy systems and improving operational reliability [23,24].

Furthermore, AI-driven control systems improve the performance of renewable energy technologies by continuously regulating parameters to maximise efficiency. For example, AI can help us identify the optimal positioning of solar panels to capture the maximum sunlight throughout the day. Similarly, for wind turbines, AI algorithms can adjust blade positions to optimise energy capture while minimising system pressure [25].

Broad AI techniques for predicting renewable energy generation can be categorised into: statistical and classical ML methods; deep learning approaches; ensemble learning models; and hybrid AI frameworks. A brief about these techniques is mentioned below:

A. **Statistical and Classical ML Techniques**: It employs mathematical functions to directly map historical meteorological variables such as solar irradiance, temperature, and humidity. These techniques rely on well-established statistical prediction and pattern-recognition techniques, viz., Support Vector Regression (SVR) and k-Nearest Neighbours (KNN), to suggest the correlation between meteorological factors and energy generation. The main advantage of these techniques is that they help select variables, thereby simplifying model formulation by identifying the most significant weather parameters affecting solar generation. The literature suggests that these methods provide a low-cost and reliable model for forecasting under stable and clear-sky conditions. However, their prediction quality degrades in highly non-linear or noisy weather scenarios [26].

B. Deep Learning (DL): This approach utilises multi-layer neural network architectures, such as those in the human brain, to learn complex patterns from data. DL models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) are effective at capturing temporal dependencies. In contrast, Convolutional Neural Networks (CNNs) extract spatial features from meteorological and satellite data. The recent literature suggests that transformer-based models have demonstrated strong capability in developing long-range dependencies through attention mechanisms that assign varying importance to historical inputs. These characteristics make DL models critical for intra-day solar forecasting and energy trading, where rapid weather fluctuations significantly impact electricity generation. However, the deployment of these techniques requires large datasets and is limited in interpretability due to their 'black-box' nature, i.e., inherent opacity in the decision-making process [27].

C. Ensemble Learning (EL): EL techniques improve prediction accuracy by associating multiple weak learners into a single, more accurate model. Approaches such as Random Forest, eXtreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) are particularly effective at capturing the stochastic and non-linear behaviour of solar irradiance across diverse climatic regions. By allowing individual models to compensate for one another when noise or uncertainty is present, ensemble methods reduce spikes in forecast error and help prevent sudden grid imbalances. However, the literature suggests that these models are computationally intensive because they require training multiple learners simultaneously [28,29].

D. Hybrid AI Models: The hybrid AI models are an evolving paradigm in this field, which integrates physical knowledge of photovoltaic (PV) systems with the adaptive learning capabilities of AI. Examples include CNN–LSTM architectures, Empirical Mode Decomposition (EMD)-based ML models, and physics-informed AI frameworks. These approaches not only improve forecasting accuracy but also enhance interpretability by enabling attribution of power losses to specific physical mechanisms within the PV system. Hybrid models are particularly valuable under extreme weather conditions, such as monsoons or sandstorms, where purely data-driven models may be misleading. Nevertheless, their practical application is constrained by complex architecture design and high implementation difficulty [30].

Recent literature highlights a shift toward ML and Ensemble frameworks to address challenges associated with classical models. For instance, research by Tandon and Others demonstrates that tree-based ensemble methods, specifically Random Forest, excel at capturing non-linear meteorological patterns, with the latter achieving a Mean Absolute Percentage Error (MAPE) as low as 2.28% in Indian climatic conditions [31]. Chakraborty and others further validate the scalability of these approaches [28], who achieved 96% accuracy with their stacking and voting frameworks for rooftop solar installations.

The literature also emphasizes that combining diverse models via Support Vector Regression (SVR) reduces forecast bias and variance for day-ahead scheduling [32]. To combat data scarcity in remote regions, Transfer Learning (TL) significantly outperforms standalone deep learning models by leveraging pre-trained knowledge [33]. Furthermore, the optimization of PV system design is being refined through hybrid metaheuristics. It is noteworthy that algorithms such as the Chaotic Sand Cat Optimiser and the Artificial Hummingbird Algorithm (AHA) offer superior stability in identifying unknown PV cell parameters across single-, double-, and triple-diode configurations [34]. Collectively, the aforesaid advancements underscore that, while no single optimisation technique is universally perfect, integrating ensemble architectures and adaptive learning is important for the economic and operational viability of large-scale renewable energy systems.

IV. ARTIFICIAL INTELLIGENCE IN IMPROVING ENERGY STORAGE SYSTEMS

An energy storage system is a crucial component for achieving a sustained renewable energy transition. By storing surplus energy during peak generation and discharging it during periods of low production, these storage systems mitigate the inherent variability of solar and wind power. Thus, the energy storage systems facilitate higher renewable penetration and smoother grid integration. However, the increasing complexity of modern technologies, particularly lithium-ion batteries, presents significant challenges regarding performance optimisation, safety management, and lifecycle prediction [35].

To address the inherent problems of modern energy storage, AI integration has emerged as an important transformative solution. AI enables data-driven optimisation of charging and discharging cycles by synthesizing historical patterns with real-time operating conditions [36]. These control strategies do more than manage power; they improve battery utilization efficiency, extend operational lifespans, and enhance economic performance by aligning storage dispatch with dynamic market signals [36]. The recent literature suggests that hybrid AI models, including artificial neural networks (ANNs) and specialized optimization algorithms are now essential for delivering more precise estimations of battery health and power quality [37].

Significant advancements in time-series modelling have specifically focused on improving the accuracy of State of Health (SOH) predictions. ML-based SOH estimation for lithium-ion batteries has gained substantial momentum due to its ability to detect degradation patterns using practical, data-efficient methods [38]. Further, an optimised bi-directional long short-term memory (LSTM) model demonstrates better SOH and capacity-fade predictions than standard feedforward networks, traditional LSTMs, and other metaheuristic models [39].

A major frontier in AI-enhanced storage is balancing high-precision estimation with the limited computational resources of onboard hardware. Some researchers addressed this by developing a hybrid CNN-GRU-LSTM model [40]. By combining the long-term dependency modelling of LSTM with the structural efficiency of the Gated Recurrent Unit (GRU) and the spatial feature extraction of Convolutional Neural Networks (CNNs), the system achieved State of Charge (SOC) estimation errors as low as 0.41% across a range of temperatures. Remarkably, this high accuracy is maintained while keeping processing time to just 0.000113 seconds per sample, making it ideal for real-time onboard integration with Battery Management Systems (BMS).

Conceptually, an AI-enabled BMS delivers superior performance and reliability through four interlinked functional layers that transition from real-time operational awareness to long-term systemic resilience. At the core, State of Charge (SoC) and State of Power (SoP) estimation provide the precision necessary for optimal energy dispatch and safety, overcoming the accuracy limitations of traditional methods under varying environmental conditions [41]. This operational data feeds into State of Health (SoH) monitoring, where AI identifies non-linear degradation patterns, such as capacity fade and increases in internal resistance, to predict battery lifetimes and optimise charge cycles [42]. These insights facilitate a third layer of predictive maintenance, utilizing ensemble methods and neural networks to shift from reactive repairs to proactive failure prevention and load optimisation [5]. Finally, these capabilities culminate in an Intelligent Fault Detection and Diagnosis (FDD) layer by employing advanced pattern recognition and reinforcement learning. This system can autonomously detect and respond to anomalies like thermal runaway or cell imbalances, fostering the development of self-healing grids that ensure the long-term safety and sustainability of the renewable energy landscape [43].

V. THE ROLE OF AI IN GRID BALANCING

Balancing electricity supply with demand is the primary requirement for maintaining a stable and reliable power grid. Grid operators achieve this complicated balance through a combination of automated systems, manual interventions, and strategic reserves. Normally, ‘spinning reserve’ or ‘operating reserve’ is utilised to ramp up power generation to meet a sudden increase in demand or to compensate for an unexpected decrease in supply [44]. However, the increasing reliance on variable renewable energy sources has introduced new complications in maintaining grid stability. On the one hand, integrating renewable energy with conventional power plants offers some relief; on the other hand, it creates problems due to intermittent generation. For example, the effects of solar energy amplify challenges across broader temporal and spatial scales, necessitating faster and more flexible responses from system resources. To address the aforesaid challenges, energy storage technologies provide a solution by storing the surplus electricity and releasing it when needed [44,50].

Smart Grids, which utilise sensors, software, and digital technologies, help improve the efficiency, reliability, and resilience of electricity networks by matching supply and demand in real time. The smart grid operates through three interconnected layers that support intelligent operation and two-way electricity communication. The foundation layer, called the Perception Layer, collects raw data from physical devices such as sensors, smart meters, and data acquisition units. This data is transmitted through the second layer of the smart grid, i.e., ‘Network Layer’, which works as a communication backbone. The network layer uses a range of wired and wireless tools to ensure efficient data exchange within the grid system. Thereafter, the third layer, i.e., ‘Application Layer’, processes and analyses the data collected through the first two layers, using advanced tools such as big data analytics and ML, to provide practical, operational intelligence for tasks such as power demand forecasting, anomaly detection, consumer interaction, and grid management. Thus, this layered structure of the smart grid ensures efficient data collection, transmission, and analysis, thereby improving the grid’s performance and intelligence [18] [44,45].

AI and ML algorithms are essential for the effective operation of smart grids, as they facilitate the collection and analysis of complex datasets, which support real-time decision-making across various layers of the power grid [46]. ML builds algorithms and models that help computers learn and recognise patterns in large, complex datasets. ML algorithms have significant potential to optimise the generation, distribution, and consumption of electricity. Furthermore, these techniques perform a crucial role in detecting data anomalies and distortions, as well as maintaining the overall stability of the grid system [47]. Thus, AI/ML-related technologies help improve grid balancing and stability, especially when integrating variable renewable energy sources, such as solar and wind, with traditional energy sources, such as coal.

Keeping in mind the importance of smart grids, the GOI has launched various initiatives under the National Smart Grid Mission (NSGM) and the Revamped Distribution Sector Scheme (RDSS), which are actively laying the groundwork for integrating AI/ML technologies into electricity distribution operations. Preliminary projects in cities like Bhubaneswar, Chandigarh, and Puducherry have demonstrated the viability of AI-enabled grid automation, demand-side management, and real-time monitoring [44].

VI. CONCLUSION AND WAY FORWARD

Renewable energy is essential to combat climate change and promote sustainable development. However, the inherent variability and uncertainty of renewable

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energy sources pose a substantial obstacle to widespread adoption. One approach to tackling this hurdle is to develop precise forecasting models for predicting renewable energy generation. Accurate forecasting techniques can help minimise the negative impact of variability and uncertainty in renewable energy generation and its integration with the power grid. This will allow widespread adoption of green energy in electricity production and consumption. The above discussion shows that AI and ML-based technologies have emerged as powerful tools for renewable energy forecasting. They have significantly improved smart grid capabilities by enabling real-time decision-making, adaptive fault detection, and optimised energy management. Though these technologies have made significant improvements, several challenges remain in the precise forecasting of power generation and grid balancing. One important limitation is the availability of high-quality, comprehensive datasets for forecasting model training and validation, as renewable energy data are often sparse or incomplete. Furthermore, many AI/ML-based models are like black boxes, making it difficult to understand how they make predictions [48]. Therefore, future research in this field should focus on developing hybrid and explainable AI models that can simultaneously handle multiple renewable energy sources while effectively addressing the uncertainty and variability inherent in renewable generation. Integrating weather, grid, and environmental data, along with advances in Deep Learning (DL) and Reinforcement Learning (RL), holds strong potential to improve forecasting accuracy and enhance grid resilience.

A critical technical evolution within this space is the emergence of Explainable Artificial Intelligence (XAI), which seeks to mitigate the 'black box' nature of traditional models by improving interpretability and stakeholder transparency. The data suggest that 43% of Indian Generative AI (Gen AI) startups use a hybrid architecture, synthesising open-source and proprietary models to balance flexibility with performance. Recent developments in the domestic 'Model Layer' indicate a transition toward specialized deployment. Significant contributions include federated machine learning platforms for secure collaborative research (e.g., Npluslabs), edge-based optimization for hardware-independent deployment (e.g., EDGE Neural), and the integration of ethical auditing services for small-to-medium enterprises (e.g., Aqeeq Technologies) [49]. These advancements signify a maturing ecosystem of computational efficiency that may contribute to advances in renewable energy systems.

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I must verify the accuracy of the following information as the article's author.

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REFERENCES

1. PIB (Press Information Bureau), Government of India. (2019). The Cabinet approves measures to promote the hydro power sector. https://www.pib.gov.in/PressReleaseIframePage.aspx?PRID=1567817&reg=3&lang=2
2. PIB, Government of India. (2023) India is committed to achieving the Net Zero emissions target by 2070. https://www.pib.gov.in/Pressreleaseshare.aspx?PRID=1961797&reg=3&lang=2
3. Krishnamurthy, S., Adewuyi, O. B., & Salimon, S. A. (2026). Recent advances in artificial intelligence-based optimization for power system applications: A review of techniques, challenges, and future directions. Renewable and Sustainable Energy Reviews, 226, 116340. DOI: https://doi.org/10.1016/j.rser.2025.116340
4. Kumaresh, S. S., Devarapalli, R., García Márquez, F. P., & Acaroğlu, H. (2025). A comprehensive review of optimization, market strategies, and AI applications in energy storage systems. *Evolutionary Intelligence*, *18*(4), 1-23. DOI: https://doi.org/10.1007/s12065-025-01066-2
5. Cavus, M., Ayan, H., Bell, M., & Dissanayake, D. (2025). Advances in Energy Storage, AI Optimisation, and Cybersecurity for Electric Vehicle Grid Integration. *Energies (19961073)*, *18*(17). DOI: https://doi.org/10.3390/en18174599
6. Mintz, Yoav, and Ronit Brodie (2019). Introduction to artificial intelligence in medicine. Minimally Invasive Therapy & Allied Technologies 28.2 (2019): 73-81. DOI: https://doi.org/10.1080/13645706.2019.1575882
7. Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business horizons, 62(1), 15-25. DOI: https://doi.org/10.1016/j.bushor.2018.08.004
8. Mitchell, M. (2019). Artificial intelligence: A guide for thinking humans. Penguin UK.
9. Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., ... & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and machines, 28(4), 689-707. DOI: https://doi.org/10.1007/s11023-018-9482-5
10. Brynjolfsson, E., & McAfee, A. N. D. R. E. W. (2017). The business of artificial intelligence. Harvard Business Review, 7(1). https://people.dsv.su.se/~perjons/AI%20and%20Healthcare/The%20Business%20of%20Artificial%20Intelligence.pdf
11. Liu, P., Lai, Y., & Liu, D. (2024). Artificial intelligence research in organizations: a bibliometric approach. DOI: https://doi.org/10.1080/23311975.2024.2408439
12. Kusiak, A. (2018). Smart manufacturing. International journal of production Research, 56(1-2), 508-517. https://doi.org/10.1080/00207543.2017.1351644
13. Feng, F., Li, J., Zhang, F., & Sun, J. (2024). The impact of artificial intelligence on green innovation efficiency: Moderating role of dynamic capability. International Review of Economics & Finance, 96, 103649. DOI: https://doi.org/10.1016/j.iref.2024.103649
14. Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big-data analytics-powered artificial intelligence, sustainable manufacturing practices, and circular-economy capabilities. Technological Forecasting and Social Change, 163, 120420. approach. Cogent Business & Management, 11(1), 2408439. DOI: https://doi.org/10.1016/j.techfore.2020.120420
15. Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. American Economic Journal:

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Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

Macroeconomics, 13(1), 333-372.
DOI: https://doi.org/10.1257/mac.20180386

16. Bazionis, I. K., & Georgilakis, P. S. (2021). Review of deterministic and probabilistic wind power forecasting: Models, methods, and future research. Electricity, 2(1), 13-47.
DOI: https://doi.org/10.3390/electricity2010002
17. Vázquez-Canteli, J. R., & Nagy, Z. (2019). Reinforcement learning for demand response: A review of algorithms and modelling techniques. Applied energy, 235, 1072-1089.
DOI: https://doi.org/10.1016/j.apenergy.2018.11.002
18. Divakar, B., Ali, A., Sengupta, D., Sebastiao, B. G., Priyatharsini, G. S., & Babu, B. H. (2025, May). Big data analytics in renewable energy management for intelligent smart grid operation. IEEE.
DOI: https://doi.org/10.1109/icSmartGrid66138.2025.11071786
19. Gupta, R., & Chaturvedi, K. T. (2023). Adaptive energy management of big data analytics in smart grids. Energies, 16(16), 6016.
DOI: https://doi.org/10.3390/en16166016
20. Choudhary, S. K., & Mondal, A. (2025). Utilization of computer vision and machine learning for solar power prediction. In *Computer Vision and Machine Intelligence for Renewable Energy Systems* (pp. 67-84). Elsevier. DOI: https://doi.org/10.1016/B978-0-443-28947-7.00004-5
21. Mucomole, F. V., Silva, C. A. S., & Magaia, L. L. (2025). Parametric Forecast of Solar Energy over Time by Applying Machine Learning Techniques: Systematic Review. Energies, 18(6), 1460.
DOI: https://doi.org/10.3390/en18061460
22. Rajaperumal, T. A., & Christopher Columbus, C. (2025). Enhanced wind power forecasting using machine learning, deep learning models and ensemble integration. Scientific Reports, 15(1), 20572.
DOI: https://doi.org/10.1038/s41598-025-05250-3
23. Oladapo, B. I., Olawumi, M. A., & Omigbodun, F. T. (2024). Machine learning for optimising renewable energy and grid efficiency. Atmosphere, 15(10), 1250.
DOI: https://doi.org/10.3390/atmos15101250
24. Rodríguez-Aburto, C., Montaño-Pisfil, J., Santos-Mejía, C., Morcillo-Valdivia, P., Solís-Farfán, R., Curay-Tribeño, J., ... & Arroyo-Paz, A. (2025). Machine Learning for Photovoltaic Power Forecasting Integrated with Energy Storage Systems: A Scientometric Analysis, Systematic Review, and Meta-Analysis. Energies, 18(23), 6291.
DOI: https://doi.org/10.3390/en18236291
25. Al-Dahidi, S., Hammad, B., Alrbai, M., & Al-Abed, M. (2024). A novel dynamic/adaptive K-nearest neighbor model for the prediction of solar photovoltaic systems' performance. Results in Engineering, 22, 102141.
DOI: https://doi.org/10.1016/j.rineng.2024.102141
26. Runge, J., & Zmeureanu, R. (2021). A review of deep learning techniques for forecasting energy use in buildings. Energies, 14(3), 608.
DOI: https://doi.org/10.3390/en14030608
27. Chakraborty, D., Mondal, J., Barua, H. B., & Bhattacharjee, A. (2023). Computational solar energy–Ensemble learning methods for prediction of solar power generation based on meteorological parameters in Eastern India. Renewable energy focus, 44, 277-294.
DOI: https://doi.org/10.1016/j.ref.2023.01.006
28. Mohan, R., & Pachauri, N. (2025). An ensemble model for the energy consumption prediction of residential buildings. Energy, 314, 134255.
DOI: https://doi.org/10.1016/j.energy.2024.134255
29. Zemouri, N., Mezaache, H., Zemali, Z., La Foresta, F., Versaci, M., & Angiulli, G. (2025). Hybrid AI-based framework for renewable energy forecasting: one-stage decomposition and sample entropy reconstruction with least-squares regression. Energies, 18(11), 2942.
DOI: https://doi.org/10.3390/en18112942
30. Tandon, A., Awasthi, A., Pattnayak, K. C., Tandon, A., Choudhury, T., & Kotecha, K. (2025). Machine learning-driven solar irradiance prediction: advancing renewable energy in Rajasthan. Discover Applied Sciences, 7(2), 107. DOI: https://doi.org/10.1007/s42452-025-06490-8
31. Dewangan, C. L., Singh, S. N., & Chakrabarti, S. (2020). Combining forecasts of day-ahead solar power. Energy, 202, 117743.
DOI: https://doi.org/10.1016/j.energy.2020.117743
32. Tajjour, S., Chandel, S. S., Malik, H., Márquez, F. P. G., & Alotaibi, M. A. (2025). Daily power generation forecasting for a grid-connected solar power plant using transfer learning technique: S. Tajjour et al. Applied Intelligence, 55(6), 383.
DOI: https://doi.org/10.1007/s10489-024-06090-w
33. Navarro, M. A., Oliva, D., Ramos-Michel, A., & Haro, E. H. (2023). An analysis of the performance of metaheuristic algorithms for the estimation of parameters in solar cell models. Energy Conversion and Management, 276, 116523.
DOI: https://doi.org/10.1016/j.enconman.2022.116523
34. Ngoy, K. R., Lukong, V. T., Yoro, K. O., Makambo, J. B., Chukwuati, N. C., Ibegbulam, C., ... & Jen, T. C. (2025). Lithium-ion batteries and the future of sustainable energy: A comprehensive review. *Renewable and Sustainable Energy Reviews*, *223*, 115971.
DOI: https://doi.org/10.1016/j.rser.2025.115971
35. Tang, Z., Yang, Y., & Blaabjerg, F. (2021). Power electronics: The enabling technology for renewable energy integration. CSEE Journal of Power and Energy Systems, 8(1), 39-52.
DOI: https://doi.org/10.17775/CSEEJPES.2021.02850
36. Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T. C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and prospects. Energy & Environment, 35(7), 3833-3879. DOI: https://doi.org/10.1177/0958305X241256293
37. Miraftabzadeh, S. M., Longo, M., Di Martino, A., Saldarini, A., & Faranda, R. S. (2024). Exploring the synergy of artificial intelligence in energy storage systems for electric vehicles. *Electronics*, *13*(10), 1973.
DOI: https://doi.org/10.3390/electronics13101973
38. Lanubile, A., Bosoni, P., Pozzato, G., Allam, A., Acquarone, M., & Onori, S. (2024). Domain knowledge-guided machine learning framework for state of health estimation in Lithium-ion batteries. *Communications Engineering*, *3*(1), 168.
DOI: https://doi.org/10.1038/s44172-024-00304-2
39. Wang, X. T., Wang, J. S., Zhang, S. B., Liu, X., Sun, Y. C., & Shang-Guan, Y. P. (2025). Capacity prediction model for lithium-ion batteries based on bi-directional LSTM neural network optimized by adaptive convergence factor gold rush optimizer. *Evolutionary Intelligence*, *18*(2), 1-30.
DOI: https://doi.org/10.1007/s12065-024-01013-7
40. Shahriar, S. M., Bhuiyan, E. A., Nahiduzzaman, M., Ahsan, M., & Haider, J. (2022). State-of-charge estimation for electric vehicle battery management systems using a hybrid recurrent learning approach with explainable artificial intelligence. *Energies*, *15*(21), 8003.
DOI: https://doi.org/10.3390/en15218003
41. Oloyede, M. O., Akpakwu, G. A., Myburgh, H. C., De Freitas, A., & Kunatsa, T. (2024). A review on state-of-charge estimation methods, energy storage technologies and state-of-the-art simulators: recent developments and challenges. *World Electric Vehicle Journal*, *15*(9), 381. DOI: https://doi.org/10.3390/wevj15090381
42. Sylvestrin, G. R., Maciel, J. N., Amorim, M. L. M., Carmo, J. P., Afonso, J. A., Lopes, S. F., & Ando Junior, O. H. (2025). State of the art in electric batteries' state-of-health (soh) estimation with machine learning: A review. *Energies*, *18*(3), 746. DOI: https://doi.org/10.3390/en18030746
43. Andriani, T., Hudaya, C., & Garniwa, I. (2025, February). Integration of Artificial Intelligence into Battery Energy Storage System Fault Diagnosis: A Review. In *International Congress on Information and Communication Technology* (pp. 137-154). Singapore: Springer Nature Singapore. DOI: https://doi.org/10.1007/978-981-96-6432-0_12
44. Supriya, Sweety (2025), Integrating Solar Energy into Power Grids: India's Path to a Sustainable Energy Future; International Journal of Emerging Science and Engineering (IJESE)
DOI: https://doi.org/10.35940/ijese.A1050.13100925
45. Abrahamsen, F. E., Y. Ai, and M. Cheffena (2021). Communication technologies for smart grid: A comprehensive survey. Sensors 21, no. 23 (2021) DOI: https://doi.org/10.3390/s21238087
46. Anjana, K. R., & Shaji, R. S. (2018). A review of the features and technologies for energy efficiency of the smart grid. International Journal of Energy Research, 42(3), 936-952.
DOI: https://doi.org/10.1002/er.3852
47. Allal, Z., H. N. Noura, O. Salman, and K. Chahine (2024). Leveraging the power of machine learning and data balancing techniques to evaluate stability in smart grids. Engineering Applications of Artificial Intelligence 133 (2024).
DOI: https://doi.org/10.1016/j.engappai.2024.108304
48. Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., ... & Hussain, A. (2024). Interpreting black-box models: a review on explainable artificial intelligence. Cognitive Computation, 16(1), 45-74.
DOI: https://doi.org/10.1007/s12559-023-10179-8
49. CCI (Competition Commission of India) (2025). Market study on Artificial Intelligence and competition. Government of India. https://www.cci.gov.in/images/marketstudie/en/market-study-on-artificial-intelligence-and-competition1759752172.pdf
50. Sahoo, S., and P. Timmann. (2023) Energy storage technologies for modern power systems: A detailed analysis of functionalities, potentials, and impacts. DOI: https://doi.org/10.1109/ACCESS.2023.3274504

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