# Role of artificial intelligence in smart grid – a mini review

M. Balamurugan[1], Kamala Narayanan[2], N. Raghu[3],
G. B. Arjun Kumar[1]* and V. N. Trupti[3]

[1]Department of EEE, Dayananda Sagar College of Engineering, Bangalore, India, [2]Department of ECE,
University of Nevada, Las Vegas, Las Vegas, NV, United States, [3]Department of EEE, Faculty of
Engineering and Technology, JAIN (Deemed-to-be University), Bangalore, India

A smart grid is a structure that regulates, operates, and utilizes energy sources that are incorporated into the smart grid using smart communications techniques and computerized techniques. The running and maintenance of Smart Grids now depend on artificial intelligence methods quite extensively. Artificial intelligence is enabling more dependable, efficient, and sustainable energy systems from improving load forecasting accuracy to optimizing power distribution and guaranteeing issue identification. An intelligent smart grid will be created by substituting artificial intelligence for manual tasks and achieving high efficiency, dependability, and affordability across the energy supply chain from production to consumption. Collection of a large diversity of data is vital to make effective decisions. Artificial intelligence application operates by processing abundant data samples, advanced computing, and strong communication collaboration. The development of appropriate infrastructure resources, including big data, cloud computing, and other collaboration platforms, must be enhanced for this type of operation. In this paper, an attempt has been made to summarize the artificial intelligence techniques used in various aspects of smart grid system.

KEYWORDS

smart grid, demand management, machine learning, deep learning, artificial intelligence

## Introduction

The cumulative demand for electricity has directed to a widespread deployment of high-capacity and long-transmission power networks in recent decades (Dranka and Ferreira, 2020). However, difficulties arise from fluctuating and inconsistent energy distribution and the continuous pursuit of enhancing the standards. Incorrect behavior of particular failures can quickly directed to accidents and severe chain reactions, ultimately resulting in a significant outage. The world of today needs a reliable, secure, scalable, interoperable, and economically feasible power system (Bari et al., 2014; Khan et al., 2022). In the future, electrical power systems will be a "smart grid" (Fan et al., 2021), capable of self-healing and providing high-quality, energy-efficient, and reliable electricity.

A smart grid can strengthen the present electrical system by using sustainable sources of energy, which include solar, wind, etc. (Feng et al., 2021; Iris and Lam, 2021). Power transmission and distribution grids need to be upgraded to enhance reliability, economy, efficiency, and security. Need to upgrade the power distribution and transmission grids to improve reliability, economy, efficiency, and security. Introducing excellent communication and control technologies optimizes transmission and distribution grid efficiency. Smart metering, quicker problem analysis, and enhanced network process and management are all altering conventional grid (Shi et al., 2021; Alarifi et al., 2021).

Power supply was compelled to stimulate these methodologies in all of their consequences due to the over-reliance on technology, which increased the need for asset management and tripled productivity. Conventional energy sources are very expensive than smart grid technology. As a consequence, prices for energy have decreased with the advancement of smart grid technology (Iris and Lam, 2021; Kapitonov and Patapas, 2021; Moretti et al., 2017; Panda and Das, 2021). The evolution of traditional grid into smart grid will introduce job opportunities for qualified and unqualified people, in accumulation to supporting advanced technology solutions and financial growth (Acakpovi et al., 2019; Cheena et al., 2020; Matisoff et al., 2020). According to (Sareen et al., 2024), a smart grid reduces power interruptions, improves efficiency, and provides users with

more control over distribution of energy and usage (Adamec et al., 2011; El-Hawary, 2016). Customers are more satisfied due to the reduced reliance on conventional grids and the resulting savings (Gungor et al., 2011; Hossain et al., 2016; Wang and Lu, 2013).

Figure 1 explains the structure of smart grids. Smart grids are classified as transmission and distribution systems based on their roles. The components of an electrical transmission system are arranged in a circular network with several electrical power generators. A single component breakdown does not significantly affect the transmission network's performance. The distribution system utilizes radial topology to offer electricity directly to consumers. Minor distribution system failures can severely impact QoS for individual costumers. A distribution system's self-healing
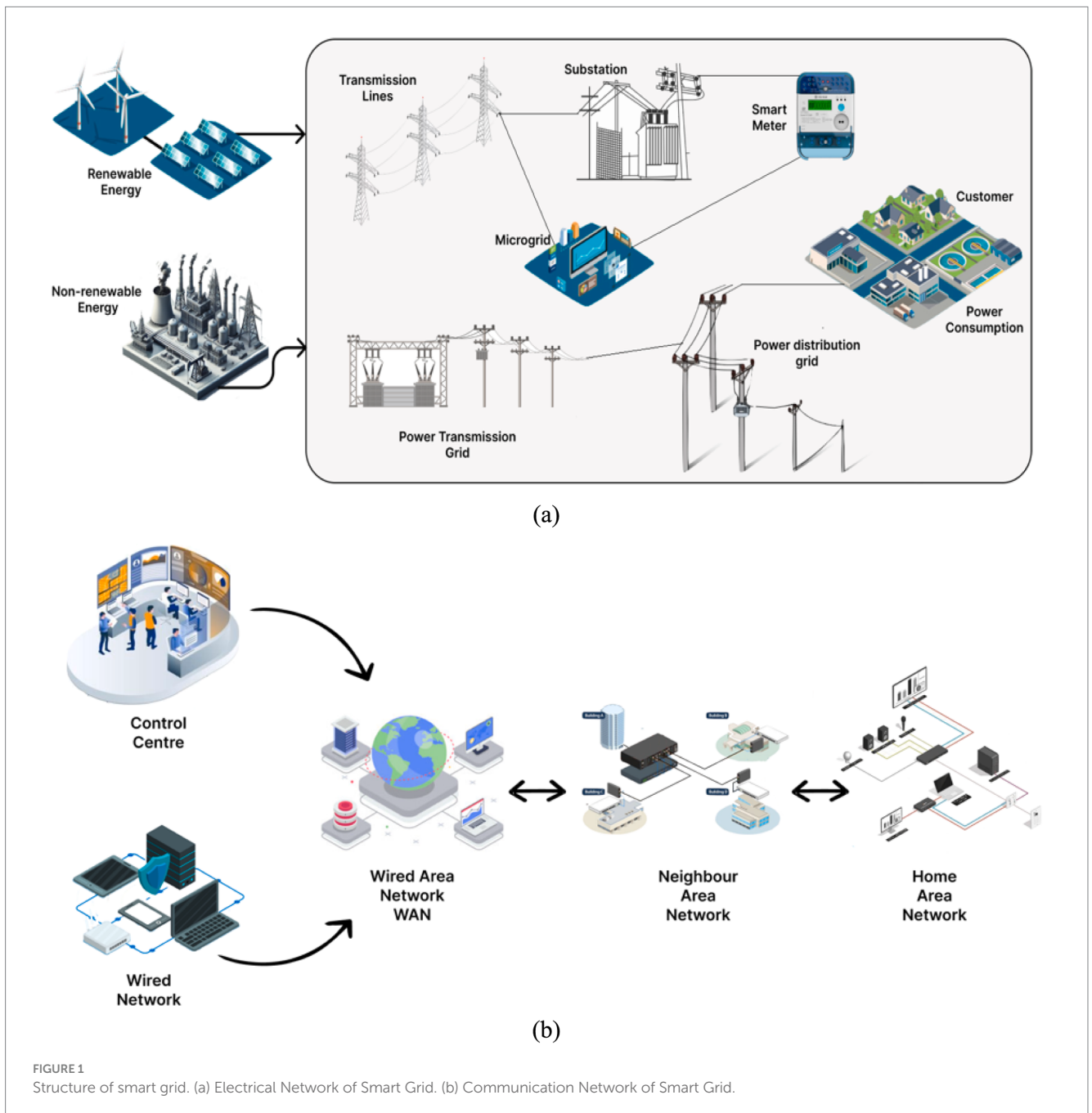


(a)

(b)

FIGURE 1
Structure of smart grid. (a) Electrical Network of Smart Grid. (b) Communication Network of Smart Grid.

feature isolates defective components from grid and allows for automatic return to regular functioning (Gungor et al., 2013; Wang et al., 2011). A self-healing grid can eliminate power supply disruptions, shorten refurbishment time, and increase renewal load to ensure availability and stability of system. Several international standards have been suggested to provide suitable recommendations for load shedding (IEEE C37.117–2007), condition monitoring analysis (IEC TR 61850–90), connectivity structure (NIST release 3.0), and isolating fault (IEEE C37.114–2004) in context of implementation of smart grid restoration. Smart grids are incorporating emerging technologies, including sensor expertise, microgrid frameworks, energy storage systems, and distributed renewable generation, as well as associated management approaches (Kabalci, 2016; Salkuti, 2020). An energy management system (EMS) in a smart grid (SG) is a computer system that helps balance energy supply and demand while keeping electrical system operations safe, reliable, and cost-effective. EMSs use software and hardware to collect, analyze, and visualize data in real time to control energy flows. The incorporation of Artificial Intelligence (AI) techniques in smart grids has revolutionized the way electricity is produced, transmitted, and distributed. With growing demand for competent and reliable energy supply (Allal et al., 2024), AI has become a crucial component in optimizing grid operations, improving energy efficiency, and enhancing customer experience.

## Artificial intelligence in smart grid

The use of AI in smart grids also enables the incorporation of non-conventional energy sources, such as wind and solar power, into the grid. AI algorithms can analyze data from weather forecasts and energy demand to optimize the output of non-conventional energy sources, reducing the dependence on fossil fuels and improving overall sustainability (Biswal et al., 2024). For instance, a utility company can use AI to analyze data from weather forecasts to predict when solar panels will produce the most energy, and adjust energy production accordingly (Balamurugan et al., 2017). Furthermore, AI can also be used to maximize the use of energy storage devices, such as batteries, to store extra energy produced by non-conventional sources and release it when demand is high. This not only reduces the stress on grid during peak hours and also helps to stabilize the grid and prevent power outages (Balamurugan and Sahoo, 2017).

The benefits of AI in smart grids are numerous, including improved efficiency, reliability, and sustainability. AI can support utilities to lessen energy waste, improve energy efficiency, and enhance customer experience. Additionally, AI can assist to decrease the risk of power outages and brownouts, improving overall grid reliability (Lamnatou et al., 2024). However, the implementation of AI in smart grids also comes with challenges and limitations. One of the significant issues is the readiness and value of data, which is important for training and validating AI terminologies. Utilities must ensure that they have access to high-quality and relevant data, and that they have the necessary infrastructure and resources to progress and examine large quantity of data. Summary of AI techniques in smart grid along with its benefits, challenges and applications is provided in Table 1.

Another challenge is the need for standardization and interoperability, as AI systems must be able to communicate and incorporate with existing grid infrastructure and systems. Utilities must work together to develop industry standards and guidelines for AI implementation in smart grids, and ensure that AI systems are designed to be compatible with existing systems. Despite these challenges, the use of AI in smart grids is becoming progressively widespread, and is anticipated to play a critical role in the energy production and distribution (Kumar and Shivashankar, 2022). As the demand for effective and consistent energy supply continues to grow, AI will become an essential component in optimizing grid operations, improving energy efficiency, and enhancing customer experience.

## AI application in smart grid

The integration of AI and big data analytics in enhancing discretion and safety for demand response modeling within smart grids. Their research emphasizes the critical part of machine learning in managing large-scale information for dynamic pricing and load forecasting while addressing potential cybersecurity threats. The study explores various machine learning frameworks' efficacy in mitigating risks associated with cyber-physical systems in smart grids, outlining future directions in developing secure, efficient, and resilient energy systems (Reka et al., 2024). The transformative impact of AI in sustainable energy segment, detailing its pivotal roles to enhance operative efficiency, grid optimization, and incorporation of non-conventional energy sources. The study emphasizes AI's capabilities in managing big data, protect from cyberattacks, and also improves energy management. It outlines three core AI applications: hydrogen and solar power production, management of demand and supply, and AI technology advancement, advocating for stronger regulatory frameworks to harness AI's full potential in a rapidly evolving energy market (Ahmad et al., 2021).

The deployment of ML and DL within the framework of Industry 4.0, focusing particularly on smart manufacturing and smart grid applications. Their study presents a new architecture for Industrial AI (IAI) and explores the usage of ML and DL in optimizing operations, enhancing cybersecurity, and managing big data challenges in the smart grid sector (Kotsiopoulos et al., 2021). The use of ML and computer vision to determine the angular velocity of wind turbine blades in smart grids. This method not only offers precise localization of turbine hubs and blades but also aids in predicting energy output, which is crucial for planning and optimizing new wind energy facilities (Bahaghighat et al., 2021). A comprehensive review of ML applications across key sustainability sectors including no-conventional energy, smart grids, catalysis, and storage. Their study underscores the predominant use of artificial neural networks due to their superior generalization capabilities and forecasts a rise in ML demand within the energy sector, driven by advances in academia and technology. The review highlights the importance of data generation, management, and security, anticipating that unsupervised and reinforcement learning will play increasingly central roles. Future ML technologies are expected to enable real-time, multi-task processing and integration of various energy systems, enhancing efficiency and promoting sustainable energy management practices. Additionally, the authors point to emerging concerns over data security and ethical standards in the deployment of AI technologies in sustainable development (Rangel-Martinez et al., 2021).

TABLE 1 Artificial intelligence (AI) techniques in smart grid.

| AI technique | Problem addressed | Benefits | Challenges | Applications |
|---|---|---|---|---|
| Machine learning (ML) | Analyses data to forecast energy demand and enhance energy supply | Improves energy efficiency, reduces energy waste, enhances customer experience | Requires high-quality data, can be complex to process. | Load forecasting, demand response, energy storage optimization |
| Deep learning (DL) | Analyzes complex data sets to detect anomalies and predict energy demand | Improves grid reliability, reduces power outages, enhances customer experience | Requires large amounts of data, can be computationally intensive | Fault detection, predictive maintenance, energy demand forecasting |
| Natural language processing (NLP) | Analyzes customer feedback and complaints to improve customer experience | Enhances customer experience, improves customer engagement | Requires high-quality data, can be challenging to implement | Customer service chatbots, sentiment analysis |
| Computer vision | Analyzes images to detect signs of wear and tear on grid infrastructure | Improves grid reliability, reduces power outages, enhances customer experience | Requires high-quality images, can be challenging to implement | Transmission line inspection, equipment monitoring |
| Reinforcement learning | Optimizes energy storage and release to stabilize the grid | Improves grid stability, reduces energy waste, enhances customer experience | Requires complex algorithms, can be challenging to implement | Energy storage optimization, grid stability management |
| Transfer learning | Applies pre-trained models to new data sets to improve energy demand forecasting | Improves energy demand forecasting, reduces energy waste, enhances customer experience | Requires high-quality data, challenge to implement | Energy demand forecasting, load forecasting |
| Clustering | Groups similar data points to identify patterns and drifts in energy dissipation to consumers. | Improves energy efficiency, reduces energy waste, enhances customer experience | Requires high-quality data, can be challenging to implement | Customer segmentation, energy consumption analysis |
| Decision trees | Analyzes data to make decisions about energy supply and demand | Improves energy efficiency, reduces energy waste, enhances customer experience | Requires high-quality data, can be challenging to implement | Energy supply and demand management, grid optimization |

The DL applications in smart grid methodology, highlighting current improvements and prospects. They explore the integration of DL in smart grid for enhanced grid reliability and efficient energy management, emphasizing decentralized decision-making and also discusses state-of-the-art DL paradigms like merged learning, edge intelligence, and distributed computing, identifies the main challenges in deploying these technologies. It advocates for interdisciplinary approaches to overcome computational and communication bottlenecks, suggesting a future focus on Explainable DL to enhance transparency in smart grid systems (Massaoudi et al., 2021). Expert systems (ESs) are artificial intelligence-based systems meant to replicate human knowledge in tackling challenging tasks. Expert systems are being used in SGs for fault diagnostics and decision-making. These technologies can track the grid in real-time, spot abnormalities, and pinpoint the underlying causes of failures such grid instability or equipment breakdown. Usually loaded with a knowledge base covering information about the components of the grid and their behavior under various running situations, the ESs in SGs. The system detects possible problems by means of inference rules, so analyzing data. For instance, the expert system can advise corrective action or immediately reroute electricity to stop harm if a given transformer starts to show indicators of overload. Apart from defect diagnostics, expert systems guide grid management decisions. The ES can advise, for instance, best load distribution plans, preventative maintenance schedules, and grid integration of renewable energy sources. Expert systems help grid operators to save their effort by automating these

chores and raise the general system dependability. The application of big data analytics and ML in managing no-conventional energy within smart grids. They develop a framework employing five distinct ML methods to forecast grid stability, utilizing data from a distributed smart grid system. The study reveals high predictive accuracies, highlighting the efficacy of methods like penalized linear regression and convolutional neural networks. Despite the relatively small dataset size, the research demonstrates the potential of cloud computing and real-time analytics in enhancing grid management. Future research is encouraged to expand dataset diversity and include more comprehensive non-conventional energy sources and demand profiles across different countries, aiming to further validate and refine the predictive capabilities of big data analytics in smart grid applications (Mostafa et al., 2022). Deep reinforcement learning is the combination of reinforcement learning and neural networks. It is one of the most effective AI techniques to make optimal choices based on the available data. Deep reinforcement learning technique is used in various stages of smart grid like renewable energy generation, voltage regulation, demand response and resilience enhancement.

The potential of Demand Side Storage (DSS) within smart grids employs a Extreme Learning Machine (ELM) and Genetic Algorithm (GA) to optimize dispatch schedules, aiming to increase generation efficiency and extend the operational lifetime of water pump systems. This multi-objective approach minimizes operational costs and switching frequencies, thereby improving pump longevity. The study showcases the effectiveness of the ELM-GA model through real-time

simulation on an IEEE 24 bus test system, highlighting its superiority in handling complex, non-linear optimization problems in smart grid management (Nandkeolyar and Ray, 2022). A novel machine learning-based demand-side management (DSM) engine designed for IoT-enabled smart grids, focusing on improving grid security and energy efficiency. Their proposed system leverages ML classifiers within a resilient agent model to spot and control interruptions, optimizing energy use through advanced management of IoT devices within the grid. Study demonstrates through simulation that their DSM engine not only enhances security against cyber threats but also effectively reduces energy consumption in smart grid environments, proving the incorporation of communication technologies and ML in enhancing grid resilience and efficiency (Babar et al., 2020). The incorporation of technologies within Energy Smart Grids (ESG) by proposing a Multi-Objective Particle Swarm Optimization Algorithm with Competitive Mechanism (MOPSO-CM). This algorithm is designed to optimize the alignment's extensiveness and exactness in ESG's Ontology Matching Problem (ESG-OMP), a crucial task for monitoring and efficient energy distribution in smart city environments. The study utilizes a hybrid resemblance measure to differentiate heterogeneous ontology entities and employs competitive updating of particles to enhance solution diversity and convergence. Tested across various standard datasets, MOPSO-CM demonstrates effectiveness in resolving heterogeneous ontology matches, outperforming other Particle Swarm Optimization (PSO) methods. However, the approach faces challenges with complex mappings and large-scale ontologies, suggesting future improvements could include pre-processing strategies and efficiency-enhancing measures (Xue and Tsai, 2022). Classification method comes under the category of supervised learning approach. There are many classifications methods, but mainly linear regression and support vector machines are used for smart grid applications. Especially for optimization problems the outcome can be predicted based on the data availability.

An innovative management approach for smart grids using cloud-fog (CF) technology, which enhances performance through lower delay, better safety, and reduced costs. Their research integrates smart grids with a CF environment, utilizing a novel Honeybee Mating Optimization Algorithm for optimal resource allocation across six fog regions, each containing 500 smart homes. This method is compared to Particle Swarm Optimization (PSO), demonstrating superior performance in load balancing through Digital Twin Virtual Machines (DTVMs). The study, conducted within a digital twin framework on the Eclipse platform, highlights the assistances of DTVMs in smart grid systems, such as scalability, visibility, and collaborative efficiency. This CF-driven scheme significantly improves the management of demand and supply in smart grids, offering a realistic and scalable solution for future grid technologies (Massaoudi et al., 2021; Zhang and Sun, 2023).

The vulnerabilities of smart grid cyber-physical systems, specifically addressing prevalent threat of false data injection (FDI) attacks. These attacks pose serious challenges to grid stability, sustainability, and reliability by corrupting data integrity within smart grids. The study presents a mathematical model of FDI attacks, illustrating their potential impacts on grid operations, economics, and societal trust. It categorizes and evaluates various detection algorithms developed to identify and mitigate such attacks. The study identifies current issues and challenges within this domain and

suggests directions for future research, emphasizing the need for a robust cybersecurity framework to enhance resilience against FDI threats in smart grids (Habib et al., 2023).

The incorporation of Industry 4.0 technologies like AI, IoT, and ML in fostering environmental sustainability within manufacturing sectors. Their research highlights how digitalization and smart technologies not only enhance operational efficiency but also significantly contribute to sustainable environmental practices. The study identifies 20 applications where Industry 4.0 can positively impact sustainable production, supply chains, and resource consumption, underscoring the pivotal role of advanced technologies in achieving greener manufacturing processes (Javaid et al., 2022).

## Limitations

However, there are also challenges and limitations to consider, such as:

1. Data quality and accessibility: AI requires high-quality and relevant data to make exact forecasts and decisions.
2. Cybersecurity risks: AI systems can be susceptible to cyber threats, which can negotiate the security and reliability of the grid.
3. Regulatory frameworks: Regulatory frameworks may need to be updated to accommodate the usage of AI in smart electric grids.
4. Public acceptance: There may be concerns about the usage of AI in smart electric grids, particularly around data privacy and job displacement.

Overall, the incorporation of AI techniques in smart electric grids has the potential to transform the way electricity has been generated, transmitted, and distributed, improving efficiency, reliability, and sustainability.

## Conclusion

This paper summarizes the role of AI in smart grid in various stages like control algorithm, optimization strategies and demand side management. In each stage, various AI techniques like DL, ML, Natural language processing techniques utilized by researchers to resolve the problems in smart grid. Although evaluating each method's standard according to specific performance metrics is difficult, the effectiveness of the approach in resolving the issue has been summarized. Based on the discussion, it is anticipated that AI methods will eventually be a useful instrument for resolving complex smart grid issues. These capabilities would be helpful when considering the importance of AI approaches.

## Author contributions

MB: Writing – original draft, Writing – review & editing, Conceptualization, Methodology. KN: Writing – original draft, Formal analysis. NR: Writing – original draft, Investigation. GA:

Writing – original draft, Writing – review & editing. VT: Project administration, Supervision, Writing – original draft.

## Funding

## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

## Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

## References

Acakpovi, A., Abubakar, R., Asabere, N. Y., and Majeed, I. B. (2019). Barriers and prospects of smart grid adoption in Ghana. *Proc. Manufact.* 35, 1240–1249. doi: 10.1016/J.PROMFG.2019.06.082

Adamec, M., Pavlatka, P., and Stary, O. (2011). Costs and benefits of smart grids and accumulation in Czech distribution system. *Energy Procedia* 12, 67–75. doi: 10.1016/J.EGYPRO.2011.10.011

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., et al. (2021). Artificial intelligence in sustainable energy industry: status quo, challenges and opportunities. *J. Clean. Prod.* 289:125834. doi: 10.1016/J.JCLEPRO.2021.125834

Alarifi, A., Ali AlZubi, A., Alfarraj, O., and Alwadain, A. (2021). Automated control scheduling to improve the operative performance of smart renewable energy systems. *Sustain Energy Technol Assess* 45:101036. doi: 10.1016/J.SETA.2021.101036

Allal, Z., Noura, H. N., Salman, O., and Chahine, K. (2024). Leveraging the power of machine learning and data balancing techniques to evaluate stability in smart grids. *Eng. Appl. Artif. Intell.* 133:108304. doi: 10.1016/J.ENGAPPAI.2024.108304

Babar, M., Tariq, M. U., and Jan, M. A. (2020). Secure and resilient demand side management engine using machine learning for IoT-enabled smart grid. *Sustain. Cities Soc.* 62:102370. doi: 10.1016/J.SCS.2020.102370

Bahaghighat, M., Abedini, F., Xin, Q., Zanjireh, M. M., and Mirjalili, S. (2021). Using machine learning and computer vision to estimate the angular velocity of wind turbines in smart grids remotely. *Energy Rep.* 7, 8561–8576. doi: 10.1016/J.EGYR.2021.07.077

Balamurugan, M., and Sahoo, S. K. (2017). A novel islanding detection technique for grid connected photovoltaic system. *Appl. Solar Energy* 53, 208–214. doi: 10.3103/S0003701X17030057

Balamurugan, M., Sahoo, S. K., and Sukchai, S. (2017). Application of soft computing methods for grid connected PV system: a technological and status review. *Renew. Sust. Energ. Rev.* 75, 1493–1508. doi: 10.1016/j.rser.2016.11.210

Bari, A., Jiang, J., Saad, W., and Jaekel, A. (2014). Challenges in the smart grid applications: an overview. *Int. J. Distrib. Sens. Netw.* 10:974682. doi: 10.1155/2014/974682

Biswal, B., Deb, S., Datta, S., Ustun, T. S., and Cali, U. (2024). Review on smart grid load forecasting for smart energy management using machine learning and deep learning techniques. *Energy Rep.* 12, 3654–3670. doi: 10.1016/J.EGYR.2024.09.056

Cheena, K., Amgoth, T., and Shankar, G. (2020). Emperor penguin optimised self-healing strategy for WSN based smart grids. *Int. J. Sens. Netw.* 32, 87–95. doi: 10.1504/IJSNET.2020.104924

Dranka, G. G., and Ferreira, P. (2020). Towards a smart grid power system in Brazil: challenges and opportunities. *Energy Policy* 136:111033. doi: 10.1016/J.ENPOL.2019.111033

El-Hawary, M. E. (2016). The smart grid—state-of-the-art and future trends. 2016 Eighteenth International Middle East Power Systems Conference (MEPCON), 17

Fan, D., Ren, Y., Feng, Q., Liu, Y., Wang, Z., and Lin, J. (2021). Restoration of smart grids: current status, challenges, and opportunities. *Renew. Sust. Energ. Rev.* 143:110909. doi: 10.1016/J.RSER.2021.110909

Feng, C., Wang, Y., Chen, Q., Ding, Y., Strbac, G., and Kang, C. (2021). Smart grid encounters edge computing: opportunities and applications. *Adv. Appl. Energy* 1:100006. doi: 10.1016/J.ADAPEN.2020.100006

Gungor, V. C., Sahin, D., Kocak, T., Ergut, S., Buccella, C., Cecati, C., et al. (2011). Smart grid technologies: communication technologies and standards. *IEEE Trans. Industr. Inform.* 7, 529–539. doi: 10.1109/TII.2011.2166794

Gungor, V. C., Sahin, D., Kocak, T., Ergut, S., Buccella, C., Cecati, C., et al. (2013). A survey on smart grid potential applications and communication requirements. *IEEE Trans. Industr. Inform.* 9, 28–42. doi: 10.1109/TII.2012.2218253

Habib, A. A., Hasan, M. K., Alkhayyat, A., Islam, S., Sharma, R., and Alkwai, L. M. (2023). False data injection attack in smart grid cyber physical system: issues, challenges, and future direction. *Comput. Electr. Eng.* 107:108638. doi: 10.1016/J.COMPELECENG.2023.108638

Hossain, M. S., Madlool, N. A., Rahim, N. A., Selvaraj, J., Pandey, A. K., and Khan, A. F. (2016). Role of smart grid in renewable energy: an overview. *Renew. Sust. Energ. Rev.* 60, 1168–1184. doi: 10.1016/J.RSER.2015.09.098

Iris, Ç., and Lam, J. S. L. (2021). Optimal energy management and operations planning in seaports with smart grid while harnessing renewable energy under uncertainty. *Omega* 103:102445. doi: 10.1016/J.OMEGA.2021.102445

Javaid, M., Haleem, A., Singh, R. P., Suman, R., and Gonzalez, E. S. (2022). Understanding the adoption of industry 4.0 technologies in improving environmental sustainability. *Sustain. Operat. Comput.* 3, 203–217. doi: 10.1016/J.SUSOC.2022.01.008

Kabalci, Y. (2016). A survey on smart metering and smart grid communication. *Renew. Sust. Energ. Rev.* 57, 302–318. doi: 10.1016/J.RSER.2015.12.114

Kapitonov, I. A., and Patapas, A. (2021). Principles regulation of electricity tariffs for the integrated generation of traditional and alternative energy sources. *Renew. Sust. Energ. Rev.* 146:111183. doi: 10.1016/J.RSER.2021.111183

Khan, N., Shahid, Z., Alam, M. M., Bakar Sajak, A. A., Mazliham, M. S., Khan, T. A., et al. (2022). "Energy management systems using smart grids: an exhaustive parametric comprehensive analysis of existing trends, significance, opportunities, and challenges" in International transactions on electrical energy systems (Hindawi Limited), 1–38.

Kotsiopoulos, T., Sarigiannidis, P., Ioannidis, D., and Tzovaras, D. (2021). Machine learning and deep learning in smart manufacturing: the smart grid paradigm. *Comput Sci Rev* 40:100341. doi: 10.1016/J.COSREV.2020.100341

Kumar, G. B. A., and Shivashankar (2022). Optimal power point tracking of solar and wind energy in a hybrid wind solar energy system. *Int. J. Energy Environ. Eng.* 13, 77–103. doi: 10.1007/s40095-021-00399-9

Lamnatou, C., Cristofari, C., and Chemisana, D. (2024). Artificial intelligence (AI) in relation to environmental life-cycle assessment, photovoltaics, smart grids and small-island economies. *Sustain Energy Technol Assess* 71:104005. doi: 10.1016/J.SETA.2024.104005

Massaoudi, M., Abu-Rub, H., Refaat, S. S., Chihi, I., and Oueslati, F. S. (2021). Deep learning in smart grid technology: a review of recent advancements and future prospects. *IEEE Access* 9, 54558–54578. doi: 10.1109/ACCESS.2021.3071269

Matisoff, D. C., Beppler, R., Chan, G., and Carley, S. (2020). A review of barriers in implementing dynamic electricity pricing to achieve cost-causality. *Environ. Res. Lett.* 15:093006. doi: 10.1088/1748-9326/ab9a69

Moretti, M., Djomo, S. N., Azadi, H., May, K., De Vos, K., Van Passel, S., et al. (2017). A systematic review of environmental and economic impacts of smart grids. *Renew. Sust. Energ. Rev.* 68, 888–898. doi: 10.1016/J.RSER.2016.03.039

Mostafa, N., Ramadan, H. S. M., and Elfarouk, O. (2022). Renewable energy management in smart grids by using big data analytics and machine learning. *Mach. Learn. Applicat.* 9:100363. doi: 10.1016/J.MLWA.2022.100363

Nandkeolyar, S., and Ray, P. K. (2022). Multi objective demand side storage dispatch using hybrid extreme learning machine trained neural networks in a smart grid. *J. Energy Stor.* 51:104439. doi: 10.1016/J.EST.2022.104439

Panda, D. K., and Das, S. (2021). Smart grid architecture model for control, optimization and data analytics of future power networks with more renewable energy. *J. Clean. Prod.* 301:126877. doi: 10.1016/J.JCLEPRO.2021.126877

Rangel-Martinez, D., Nigam, K. D. P., and Ricardez-Sandoval, L. A. (2021). Machine learning on sustainable energy: a review and outlook on renewable energy systems, catalysis, smart grid and energy storage. *Chem. Eng. Res. Des.* 174, 414–441. doi: 10.1016/J.CHERD.2021.08.013

Reka, S. S., Dragicevic, T., Venugopal, P, Ravi, V., and Rajagopal, M. K. (2024). Big data analytics and artificial intelligence aspects for privacy and security concerns for demand response modelling in smart grid: a futuristic approach. Heliyon, 10). doi: 10.1016/j.heliyon.2024.e35683, e35683

Salkuti, S. R. (2020). Challenges, issues and opportunities for the development of smart grid. *Int. J. Electr. Comput. Engineer.* 10, 1179–1186. doi: 10.11591/ijece.v10i2.pp1179-1186

Sareen, K., Panigrahi, B. K., Shikhola, T., and Nagdeve, R. (2024). Cla learning solar forecasting for green hydrogen production in India: a case study. *Int. J. Hydrog. Energy* 50, 334–351. doi: 10.1016/J.IJHYDENE.2023.08.323

Shi, Y., Tuan, H. D., Savkin, A. V., Lin, C. T., Zhu, J. G., and Poor, H. V. (2021). Distributed model predictive control for joint coordination of demand response and optimal power flow with renewables in smart grid. *Appl. Energy* 290:116701. doi: 10.1016/J.APENERGY.2021.116701

Wang, W., and Lu, Z. (2013). Cyber security in the smart grid: survey and challenges. *Comput. Netw.* 57, 1344–1371. doi: 10.1016/J.COMNET.2012.12.017

Wang, W., Xu, Y., and Khanna, M. (2011). A survey on the communication architectures in smart grid. *Comput. Netw.* 55, 3604–3629. doi: 10.1016/J.COMNET.2011.07.010

Xue, X., and Tsai, P. W. (2022). Integrating energy smart Grid's ontologies through multi-objective particle swarm optimization algorithm with competitive mechanism. *Sustain Energy Technol Assess* 53:102442. doi: 10.1016/J.SETA.2022.102442

Zhang, H., and Sun, R. (2023). A novel optimal management method for smart grids incorporating cloud-fog layer and honeybee mating optimization algorithm. *Sol. Energy* 262:111874. doi: 10.1016/J.SOLENER.2023.111874