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ARTIFICIAL INTELLIGENCE IN SMART GRID SYSTEMS: A COMPREHENSIVE REVIEW OF MACHINE LEARNING AND DEEP LEARNING APPLICATIONS

Tushar V. Deokar ¹ , Dr. Jitendra N Shinde ² , Dr. Raju M Sairise

- ¹ Research Scholar, Department of Electrical Engineering, Shri Jagdishprasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan, India
- ² Department of Electrical Engineering, Shri Jagdishprasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan, India
- ³ Principal & Associate Professor, Yadavrao Tasgaonkar College of Engineering and Management, Raigad, Maharashtra, India





Corresponding Author

Tushar V. Deokar, kazikalim00@gmail.com

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ABSTRACT

The integration of Artificial Intelligence (AI) into smart grid systems has revolutionized the management and optimization of electrical grids, promising significant advancements in efficiency and reliability. This comprehensive review delves into the applications of machine learning (ML) and deep learning (DL) techniques within smart grids, exploring their impact on various facets of grid management. ML algorithms have been instrumental in predictive maintenance, forecasting load and generation, and optimizing energy distribution, significantly enhancing operational efficiencies. DL models, particularly convolutional and recurrent neural networks, have been adept at handling large volumes of data from smart meters and IoT devices, facilitating real-time energy management and anomaly detection. Moreover, AI's role in integrating renewable energy sources into the grid is highlighted, addressing the challenges posed by their intermittent nature through predictive analytics that ensure a stable energy supply. Aldriven cybersecurity measures are also reviewed, underscoring their importance in protecting grid data integrity and continuity from cyber threats. The review also discusses the challenges faced in deploying AI in smart grids, including data quality, model interpretability, and the need for scalable solutions that can adapt to evolving grid architectures. Future directions for research are identified, emphasizing the development of hybrid models that combine both ML and DL approaches for enhanced performance, and the exploration of reinforcement learning for autonomous grid management. The review concludes by stressing the critical need for collaboration among researchers, industry stakeholders, and policymakers to facilitate the adoption of AI technologies that can meet future smart grid demands effectively.

Keywords: Artificial Intelligence, Smart Grids, Machine Learning, Deep Learning, Energy Management



1. INTRODUCTION

Putting artificial intelligence (AI) into smart grid processes is mainly responsible for the huge changes that are happening in energy systems. Smart grids are a big step forward from traditional grids because they are made to react quickly and efficiently to changing energy needs, make grids more reliable, and make it easier to use energy in a way that doesn't harm the environment. These advanced technologies, such as machine learning (ML) and deep learning (DL), which are both types of AI, make this possible [1]. These technologies are changing how energy grids are run and controlled by making them more automated and efficient than ever before. In smart grids, machine learning is mostly used for predictive analytics. This is when computers learn from past data to guess what will happen and how the grid

will work in the future. This feature is very important for making grid operations, repair schedules, and load forecasts more accurate. ML can, for example, predict times of high demand and change how the grid works to better handle changes. This makes the energy supply more reliable and makes the best use of resources. By identifying breakdowns before they happen, predictive maintenance can also keep expensive downtimes from happening and make key assets last longer. Deep learning is a more advanced branch of machine learning that uses neural networks with lots of layers (hence the name "deep") to process data and patterns in a way that is similar to how humans make decisions. In smart grids, DL models are great at jobs that need to handle a lot of data, like handling inputs from millions of smart meters or devices spread out across the grid [2]. These models work really well for finding strange things in real time, finding energy thieves, and controlling the data flow from Internet of Things (IoT) devices that are connected to the grid. DL models help keep the grid safe and stable against online and physical threats by looking at data in real time.

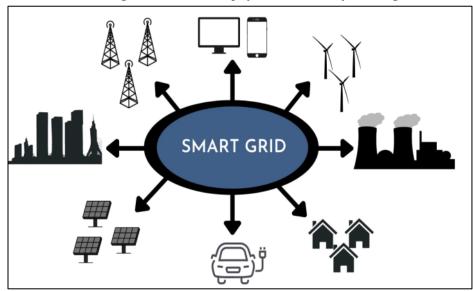


Figure 1. Overview of Smart grid system using IoT

Adding green energy sources has also made power production less stable and more unpredictable, which has made it harder to keep the grid stable and make sure there is a reliable supply. AI programs, especially those made for prediction and optimization, are very important for dealing with these problems [3]. They guess how much energy will come from green sources like solar and wind, and then balance that with how much power the grid needs. This not only keeps the energy supply stable, but it also makes the best use of natural energy, which moves the green energy plan forward. AI can also help make the grid more resilient and flexible, which are important factors in a world where energy needs are growing and climate change is happening. AI systems can predict and react to changes in the environment or emergencies with little help from humans because they are always learning and adapting. This [4] helps build a strong energy grid. AI-powered solutions also help create dynamic pricing models and demand response strategies that get people to change how much energy they use based on real-time pricing information.

2. FUNDAMENTALS OF AI IN SMART GRIDS

A. Definition and Scope of Machine Learning (ML) and Deep Learning (DL)

Machine Learning (ML) and Deep Learning (DL) are areas of Artificial Intelligence (AI) that work on creating algorithms and statistical models that let computers do things without being told directly, using patterns and reasoning to do so. Machine learning is mostly about making and using programs that can learn from data and use that data to make guesses or choices. As more data is made available for learning, these programs get better at what they do. ML [5] is used in a lot of different ways in smart grid systems. It can use past data to predict load needs, find the best way to distribute energy, and do forecast maintenance. Deep Learning is a subset of machine learning that uses neural networks with many layers (hence the name "deep") to look at different parts of raw data. It is possible for these neural networks to learn on their own from data that is not organised or labelled. DL is especially helpful in smart grids for handling and making

sense of the huge amounts of data that meters, sensors, and Internet of Things (IoT) devices send and receive. It is very good at finding complicated trends and making smart choices based on them, which is very important for smart grid control in real time and finding problems.

B. Key Components of AI Systems Relevant to Smart Grids

In smart grids, AI systems are made up of a few key parts that work together to make sure they work well and can be added to current grid designs. Data gathering systems are one of the main parts. These systems get information from smart meters, weather stations, and power lines, among other places on the grid [6]. This info is very important for all grid processes and studies that are run by AI. The analytics engine, which is made up of ML and DL models that process and analyses the data, is another important part. This engine predicts what will happen, finds trends, and finds outliers, all of which are important for managing operations and making decisions. By looking at trends of use, for example, the grid can make sure that the flow of energy matches demand without putting too much stress on the system. Communication technologies are also very important because they make it easy for data to move between the AI system and different parts of the grid. To stop data leaks and make sure that real-time data handling works well, these technologies must be strong and safe. Aside from that, user tools and decision support systems are very important for letting humans work with AI systems.

Table I: Summary of functionality and efficiency of smart grid systems

Parameter	Approach	Key Findings	Applications	Limitations
Machine Learning (ML)	Utilizes algorithms to learn from data and make predictions. [7]	ML improves as more data becomes available, enhancing accuracy and efficiency.	Predictive maintenance, load forecasting, energy distribution optimization.	Dependent on the quantity and quality of data, which can affect the model's performance if data is incomplete or of poor quality.
Deep Learning (DL)	Employs deep neural networks to analyze unstructured data from smart grid devices. [8]	Highly effective at processing large volumes of data and recognizing patterns.	Real-time grid management, anomaly detection, integrating renewable energy sources.	Requires substantial computational resources and expertise, making implementation complex and potentially costly.
Data Collection	Standardized protocols for uniform data collection across various sources. [9]	Ensures data consistency and accuracy for AI processing.	Forms the basis of all AI-driven analyses and decisions in smart grids.	Challenges in data synchronization and real-time processing can impact the timeliness and reliability of AI applications.
Analytics Engine	Comprises ML and DL models for data processing and analysis. [10]	Essential for operational management and decision-making within smart grids.	Supports operations like demand response management and predictive analytics.	Complexity increases with scale; maintaining model accuracy and performance across diverse grid scenarios can be difficult.
Communication Technologies	Secure, robust communication channels for data transfer. [11]	Critical for efficient real-time data handling and AI functionality.	Enables seamless integration of AI systems with grid operations.	Vulnerable to cybersecurity threats, requiring continuous updates and monitoring to ensure data integrity and system security.
Cybersecurity Measures [12]	AI-enhanced security protocols for detecting and responding to threats.	AI can proactively manage and mitigate potential security breaches.	Protects grid data integrity and continuity from cyber threats.	Al systems themselves can be targets of sophisticated cyber-attacks, requiring advanced and adaptive security solutions.

3. APPLICATIONS OF MACHINE LEARNING IN SMART GRIDS

A. Predictive Maintenance

In smart grids, predictive maintenance uses machine learning techniques to figure out when equipment will break down and set up maintenance to fix it before it does. This method uses information from different grid devices, old repair records, and operating data to find trends and guess when a system might break down.

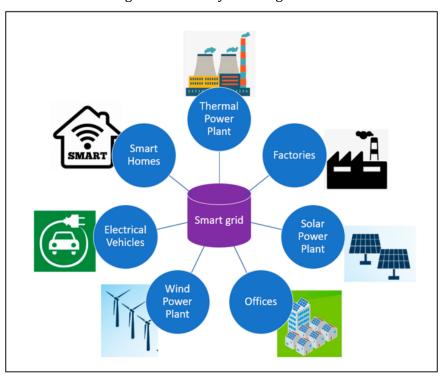


Figure 2. Representation of factor for Smart grid for predictive maintenance

Regression analysis, support vector machines, and neural networks are common machine learning methods that look at time-series data to find outliers and predict failure points. There are big benefits to scheduled upkeep. For starters, it cuts down on unexpected downtime by a large amount, which can cause big loses in money and problems with dependability. By predicting breakdowns before they happen, utilities can make sure that their services keep running smoothly. Second, it optimizes maintenance plans, which cut down on maintenance tasks that aren't needed and makes tools last longer by only fixing problems when they happen. This not only saves money but also makes the grid work better generally [13]. A power company in the United States used machine learning to keep an eye on the health of turbines in real time in a different case. The predictive maintenance system sent out alerts when certain turbine parts were at danger. This cut down on downtime by over 30% and the cost of maintenance by 25%.

B. Load Forecasting

Load projection is an important part of smart grids because it helps companies guess how much power will be needed in different time periods, from a few hours to several years from now. To guess what people will want to buy in the future, machine learning models like time series forecasting, regression models and ensemble methods look at past consumption data along with things like weather, economic signs, and customer behaviour. Grid managers can make quick choices about load delivery and energy production alignment based on short-term forecasts, especially during times of high demand. Long-term projection, on the other hand, helps with making decisions about energy purchases, building infrastructure, and making strategy plans.

C. Energy Distribution Optimization

In smart grids, energy distribution optimization uses machine learning methods to make sure that power gets from providers to users as quickly and efficiently as possible. Genetic algorithms, ant colony optimization, and particle swarm

optimization are some of the algorithms that are used to find the best routes for energy flows and to handle resources well [15]. In the delivery network, these methods help keep losses to a minimum, traffic under control, and dependability high.

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Metric	Baseline Value	Value After Optimization	Improvement
Energy Loss (MWh/year)	150,000	120,000	20% reduction
Operational Costs (\$/year)	\$5 million	\$4 million	20% reduction
Load Balance Efficiency (%)	75%	85%	13.3% increase
Response Time to Load Changes (min	utes) 15	10	33.3% reduction
Renewable Energy Integration (%)	30%	40%	33.3% increase
Grid Stability Score (1-10)	6	8	33.3% increase
Renewable Energy Integration (%)	30%		33.3% increa

Table II. energy distribution optimization in a smart grid system

Several current grid systems show how these methods can be used in real life. In North America, for example, a grid operator used a particle swarm optimisation method to find the best way for power to flow through a complicated network that has many substations and thousands of miles of transmission lines.

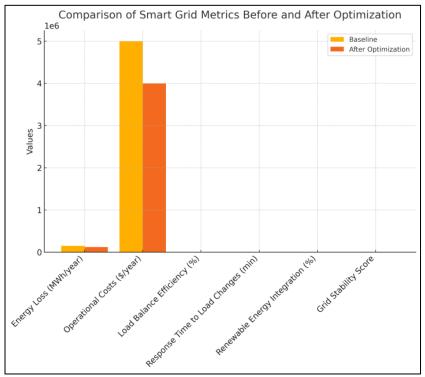


Figure 3: Representation of Energy Distribution Optimization In A Smart Grid System

The program suggested the best ways for power to flow, which cut down on transmission losses by about 10% and made blackouts much less likely. In Australia, an energy company uses genetic algorithms to find the best way to distribute power in a place where a lot of people have solar panels on their roofs. The program did a good job of controlling the varied input from solar energy. It balanced the load across the grid, made it more stable, and cut down on the use of nonrenewable energy sources. These examples show how machine learning not only improves how energy is distributed in the present, but also changes with the times and adds new energy sources, accelerating the move towards better, more environmentally friendly grid systems.

4. APPLICATIONS OF DEEP LEARNING IN SMART GRIDS

A. Real-Time Energy Management

1. Use of Neural Networks for Managing Live Data from IoT Devices

It is very important to use deep learning (DL), especially neural networks, to handle the huge amounts of real data that IoT devices in smart grids create. There are types of neural networks, like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), that are very good at handling time series data and spatial data from sensors and meters that are spread out across the grid. These networks look at data in real time, finding patterns that show normal spending behaviour and making predictions about future trends based on the data that is being sent in all the time.

2. Effect on the efficiency of operations

DL's real-time processing skills make smart grids much more efficient in how they work. DL cuts down on the need for human changes, which can be slow and error-prone, by letting reactions be predicted and changed based on changing grid conditions. For example, DL models can quickly shift power or change production in seconds to keep the grid stable and stop power outages when demand is higher than predicted or when supplies are low. Also, being able to predict and respond to situations in real time lets utilities work closer to their capacity limits while taking less risk. This makes better use of equipment and lowers running costs. This makes managing the grid more cost-effective and also helps the use of green energy sources by making it easier for the grid to quickly adjust to the changing amounts of energy from solar and wind.

B. Anomaly Detection and Cybersecurity

1. Techniques for Detecting Anomalies and Potential Security Breaches

Deep learning is becoming more and more important for making smart grids safer. Autoencoders and unsupervised neural networks are two techniques used to keep an eye on network traffic and the working data of grid components in order to find strange patterns that could point to hacking or system problems. These deep learning models are trained on data from normal operations. This lets them spot changes that could mean something is wrong, like a data breach, an attempt to hack, or a piece of broken equipment. Advanced deep learning models can also look for trends in very large datasets that would be impossible for humans to look through. They can find small problems that could lead to bigger problems or leaks. For example, if there is a quick and unexplainable rise in power flow in a certain part of the grid, which could mean there has been a physical or cyber-attack, this can be flagged for instant review or automatic remedies.

2. Importance of DL in Maintaining Grid Integrity

It's impossible to say enough about how important deep learning is for keeping the grid safe. Cyberattacks and technical problems could have bigger effects as grids become more linked and reliant on digital technologies. DL models offer a flexible defence system that changes to meet new threats by learning from different types of strikes and always getting better at detecting them. DL also helps to ensure safety and operating stability, which boosts customer and investor trust in smart grid technologies. This is important for more people to use and invest in these systems. High standards for grid stability not only guard against financial losses and physical damage, but they also make sure that the power supply is always on, which is important for modern industries and public safety. As a result, deep learning is one of the most important technologies for protecting the future of smart energy systems.

5. INTEGRATING RENEWABLE ENERGY WITH AI TECHNOLOGIES

A. Challenges Posed by Renewable Energy Sources

Adding green energy sources to current power lines is not easy for a number of reasons, mainly because sources like wind and sun power are not always available. Unlike traditional power plants that use fossil fuels, green energy outputs can be very hard to predict and change a lot depending on things like the time of day and the weather. This variation makes managing the grid more difficult, since the imbalance between supply and demand for energy can cause grid instability, frequency changes, and even power blackouts if not handled properly. Another big problem is that green energy plants are spread out in many different places. For example, solar farms and wind mills are often put in out of the way places to get the most out of the natural resources there. Because they are spread out, it takes a lot of equipment to connect them to the main grid, which makes moving and distributing energy more difficult. Also, the best use of green

energy production needs improved forecasts and real-time energy management techniques to make sure that the energy created can be used right away or kept efficiently so that no energy is wasted.

B. AI Solutions for Predictive Energy Generation and Consumption Balancing

Artificial intelligence (AI) can help solve the problems that come up when you add green energy to power lines. It does this mainly through predictive analytics and managing data in real time. AI models, especially those that use machine learning and deep learning, can look at a huge amount of data from weather stations, past trends of energy use, and real-time grid performance to make very accurate predictions about how much energy will come from green sources. For example, machine learning algorithms can guess how much solar power will be generated by looking at past weather data and the amount of sunlight hitting the Earth right now. This lets grid workers guess how much energy will be generated and make plans accordingly.

6. CHALLENGES IN IMPLEMENTING AI IN SMART GRIDS

A. Data Management and Quality

It is very important to have access to high-quality data when using AI in smart grids. The huge amounts of data created across the grid, such as usage data, working measures, and environmental factors, make data handling difficult. Problems with collecting data can happen when data forms aren't uniform, when data is recorded wrong, or when cameras or other devices that collect data break down. Also, to store and process this data, you need strong systems that can handle both the amount of data going in and how fast it comes in. Using standard data collection methods to make sure that data from different sources is consistent and correct is one way to deal with these problems.

B. Scalability and Adaptability

As smart grids change, making AI solutions work on a larger scale becomes a major issue. There is a big problem with making AI systems bigger so they can handle more IoT devices and sensors without losing performance or costing too much. AI systems must also be able to shift to new setups and changing data patterns as grid structures and energy needs change. To meet these changing needs, we need adaptive AI systems that can learn from new data and change their models on the fly. Machine learning systems that can learn online can keep getting better at making guesses and doing tasks without having to be fully retrained. This flexibility not only helps with problems related to scaling, but it also makes sure that AI solutions keep working even as grid designs get more complicated. Modular AI designs that let improvements and additions happen in small steps are one way to improve scale and adaptability.

C. Privacy, Security, and Ethical Considerations

Concerns about privacy, safety, and ethics are raised by the use of AI in smart grids. People's privacy can be invaded if the huge amounts of data collected are not handled properly. Cyberattacks that target AI systems and the grid infrastructure as a whole could cause major problems, which could pose a security risk. To deal with these issues, we need a complete plan that includes strong security methods like encryption, safe data transfer protocols, and regular security checks.

7. CONCLUSION

The in-depth look at how Artificial Intelligence (AI) is used in smart grid systems shows how Machine Learning (ML) and Deep Learning (DL) technologies are changing the energy industry. These AI technologies are not just extras; they are at the heart of modernizing grid operations, making energy use more efficient, and encouraging environmentally friendly practices by making it easier to incorporate green energy sources. ML and DL make management and decision-making possible in real time, which is very important for the changing energy needs of today and the problems that come with integrating green resources. The use of AI in smart grids has many benefits, such as better predictive maintenance, more accurate load forecasts, and better energy sharing. These improvements have cut down on running costs by a large amount, cut down on downtime, and improved the general performance and dependability of the grid. But there are some problems that come up when these kinds of tools are used. Problems with data quality, flexibility, and security are still big problems. Also, privacy and data security concerns are becoming more and more important from an ethical point of view. This calls for strong legal systems and constant tracking.

In the future, AI will play a bigger part in smart grids as the tools get better and new ideas come up. In the future, people will probably work on improving AI algorithms to make them more accurate and efficient, making mixed models

that use more than one AI method, and making defence stronger to protect the grid against new threats. As a result, AI-powered technologies have the ability to completely change how smart grids are managed, but this will only happen if academia, business, and government bodies keep working together. An adaptable, efficient, and long-lasting energy future will be possible if these new ideas are adopted in a responsible way.

CONFLICT OF INTERESTS

None.

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