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Leveraging machine learning for optimized microgrid management: Advances, applications, challenges, and future directions

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ABSTRACT

This study presents a comprehensive review of recent advancements in integrating machine learning (ML) techniques into microgrid management systems, focusing on enhancing sustainability, reliability, and operational efficiency. The primary contribution of this work lies in categorizing and critically comparing various ML approaches including supervised, unsupervised, reinforcement, and deep learning based on their performance, scalability, data requirements, and real-time applicability. A novel aspect of this study is the detailed evaluation of how ML algorithms address key microgrid challenges such as fault detection, load forecasting, energy optimization, and cybersecurity. Unlike previous reviews, this work includes comparative performance metrics (e.g., MAE, RMSE) and real-world case study analyses (e.g., Brooklyn and Austin microgrids), demonstrating how ML integration resulted in up to 20 % reduction in operational costs and 15–30 % improvement in efficiency and fault response time. The study also identifies key limitations in current systems including data quality, model interpretability, and regulatory barriers and recommends future research directions involving federated learning, edge computing, and generative AI. These findings support the development of resilient, scalable, and intelligent energy systems aligned with the UN Sustainable Development Goals.

Nomenclature:

Abbreviation	Definition
ML	Machine Learning
AI	Artificial Intelligence
DERs	Distributed Energy Resources
IoT	Internet of Things
GAN	Generative Adversarial Network
VAE	Variational Autoencoder
SVM	Support Vector Machine
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
ARIMA	AutoRegressive Integrated Moving Average
PCA	Principal Component Analysis
RL	Reinforcement Learning
DQN	Deep Q-Network
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
SDG	Sustainable Development Goal
IEEE	Institute of Electrical and Electronics Engineers
IEC	International Electrotechnical Commission
EPRI	Electric Power Research Institute

1. Introduction

The world's energy transition is quickly changing conventional, centralized power systems to more decentralized, sustainable versions.

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The importance of microgrids has increased as nations work to produce cleaner energy and become more resilient to the effects of climate change. Microgrids are flexible, specialized networks that can function independently or in tandem with the main grid, in contrast to traditional grids. Energy sustainability and dependability are improved by using renewable energy sources like wind and solar. As autonomous entities, as well as in concert with the main power grid, microgrids can operate [1]. They combine several distributed energy resources, particularly solar panels, wind turbines, batteries, and generators, which provide a constant, efficient, and robust energy supply to a given locale [2]. Microgrids can provide power for a single building, campus, or entire towns to enhance energy security, reduces environmental impact, and enhance power quality. They are major players in modern power systems since they address a variety of significant problems. For instance, their improvement of energy security by operating in isolation during the blocking of the connections between power plants and transmission lines guarantees the continuous provision of electricity for hospitals' critical networks and defense forces [3]. Microgrids also help in progressing towards a sustainable energy future by involving renewable energy sources, lowering greenhouse gas emissions, and decreasing reliance on fossil fuels [4]. Also, when such things as cyber-attacks or even natural disasters are less likely to occur, microgrids can improve grid resilience through localized control and flexibility [5]. Additionally, through their functions in demand response programs, microgrids reduce the amount of money consumers spend on energy and enhance general grid efficiency, thus optimizing energy management for economic viability [6]. Lastly, they are one of the ways to update our power infrastructure as well as meet an increased electricity requirement by assisting in moving away from centralized systems of generation [7]. As the energy sector transforms, the significance of deploying microgrids becomes all the more important. We can exploit a variety of possibilities that exist to increase reliability, sustainability, and operational efficiency in microgrid systems on account of machine learning and other cutting-edge technologies [8]. This paper reveals some recent advances in machine learning for microgrids and also investigates what are their limitations right now. A lot of rewritten paper's sentences should be like "Use microgrids, as there is an increasing demand for them, since we are changing the energy landscape. In improving the dependability, sustainability, as well as operational efficiency of microgrid systems, recent advancements in technology, specifically machine learning, present myriad chances [8]. This review paper is aimed at exploring the most recent developments in machine learning applications for microgrids, providing by comprehensive analysis on existing methodologies and challenges.

When managing conventional electricity supply systems, limits are often met as they cannot keep up with the diverse and rapidly changing energy needs of the present day. The integration of renewable energy sources for the effective adaptive real-time grids operation, as well as maintaining reliability, has prompted the usage of these conventional methods that are often characterized by rigid models and rule-based systems that may not be satisfactory [9]. Machine learning (ML) uses big sets of data and complicated algorithms to anticipate, correct, and direct various microgrid activities greatly [10]. In contrast to regular methods, ML models can be used to keep on acquiring knowledge from new data, thereby becoming more accurate and useful with time [11]. This adaptiveness enables it to manage the volatile and uncertain nature of renewable power sources. For machine learning techniques to have a proactive and efficient microgrids' resource management, one way is through enhanced defect detection, load forecasting, and energy demand predictions [12]. Furthermore, machine learning algorithms optimize electric power distribution and storage to ensure the least expensive and environmentally friendly energy delivery meets client needs in real time. This is achieved by seamlessly working hand in hand with diverse components and technologies in microgrids. According to Ref. [1], these are more scalable ways that could help in managing the increasing size as well as complications found when handling contemporary electricity supply systems. Furthermore, instead of using old-fashioned methods micro microgrids that apply artificial intelligence can quickly point out cyber threats before they occur, thereby increasing their durability over time [13]. Increasing energy efficiency and optimizing renewable energy sources are two ways that artificial intelligence can help make sure everybody gets access to modern, affordable, reliable, and sustainable energy [14] (SDG 7: Affordable and Clean Energy). SDG 9: Industry, Innovation, and Infrastructure) says, however, utilizing the latest technology, such as machine learning techniques, contributes towards all-inclusive industrialization while encouraging innovations coupled with the development of robust infrastructure [15]. Improved microgrid management, which ensures a consistent energy supply and reduces environmental impact, is making cities more sustainable (SDG 11: Sustainable Cities and Communities) [16]. Stronger energy efficiency and use of renewable energy sources in the fight against climate change (SDG 13: Climate Action) can be achieved with machine learning [17]. The cooperation of governments, businesses, and academic institutions in microgrids' machine learning technology development and application demonstrates effective partnerships for these purposes (SDG 17: Partnerships for the goals) [18]. This change is primarily being driven by trends like digitalization, better storage technologies, and the integration of renewable energy. While smart grid technology and Internet of Things devices allow for real-time monitoring and efficient distribution, declining costs for solar, wind, and battery technologies make renewables more and more feasible. By anticipating demand and efficiently distributing resources, machine learning further improves energy management. We move closer to increased resilience, energy independence, and a low-carbon future via microgrids. Microgrids are essential for improving energy security, resilience, and sustainability because they allow for localized, decentralized energy management. These methods work especially well for electrifying remote areas, giving people who are cut off from the main grid electricity. Additionally, they provide notable benefits in smart cities by fostering energy independence and incorporating renewable energy sources. Additionally, microgrids are being installed more frequently in regions that are vulnerable to natural disasters to maintain service during crises like earthquakes, hurricanes, and wildfires. Their increasing use is increasingly being attributed to this resiliency. The objective of this review is.

- **Examine New Developments:** Examine how machine learning applications for microgrids have evolved recently, including a thorough rundown of available methods.
- **Limitations of Conventional Methods:** Talk about How Machine Learning Overcomes Them in Microgrid Management.
- **Enhance Microgrid Performance:** Emphasize how machine learning can help microgrid systems operate more sustainably, efficiently, and dependably.
- **Promote UN SDGs:** Show how machine learning applications in microgrids help to accomplish several UN Sustainable Development Goals.

To further deepen the state-of-the-art review and clarify the unique contributions of this work, Table 1 presents a comparative analysis of existing studies on machine learning applications in microgrid management. The comparison outlines the focus areas, machine learning techniques covered, key strengths, and limitations of each study. This table highlights the distinct value of the current work in integrating a wider array of ML methods, providing performance-based analysis, and aligning with real-world case studies and sustainable development objectives.(see. Fig. 1)

The organization of the manuscript is structured as depicted in Fig. 2.

Since current microgrids use renewable energy sources, which are by their very nature unpredictable and variable, traditional energy management techniques are unable to keep up with their complexity. It is challenging to guarantee a steady and effective power supply in

Table 1
Comparative analysis of existing literature on ML applications in microgrid management.

Study	Focus Area	ML Techniques Covered	Strengths	Limitations
[1]	General review on microgrid operations	High-level overview	Broad perspective on control & modeling	Lacks algorithm-specific performance analysis
[14]	AI in sustainable energy	AI techniques broadly	Good SDG alignment	No ML-specific case studies or metrics
[12]	Predictive maintenance	Supervised learning	Clear frameworks for ML deployment	Focused on maintenance only
[5]	Microgrid resilience	Rule-based methods	Focus on cyber-physical threats	No ML integration
This Work	Comprehensive ML review for microgrids	Supervised, Unsupervised, RL, DL, Generative AI	Includes model comparisons, SDG mapping, case studies, and future directions	**N/A**

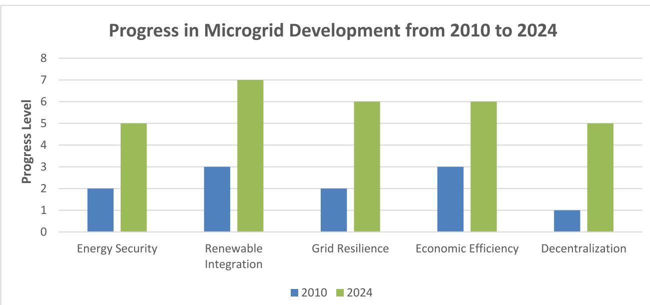


Fig. 1. Microgrid development progress chart.

microgrids because of this difficulty, which complicates load balancing, frequency management, and resource allocation. The real-time data influx from smart devices and distributed energy resources (DERs) within a microgrid is another area where conventional methods fall short, frequently resulting in inefficiencies and increased operating costs.

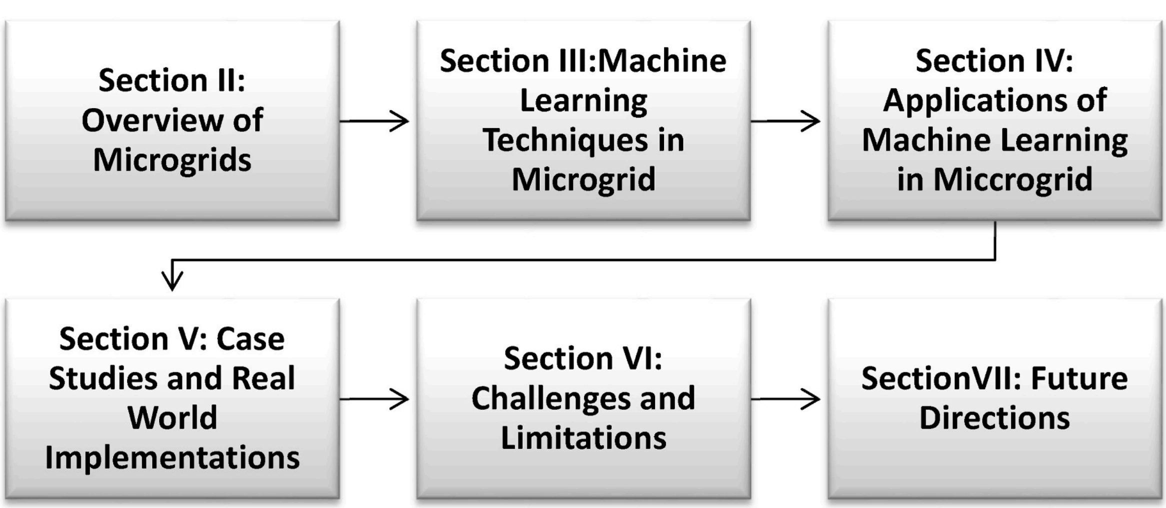
2. Overview of microgrids

Microgrids, also termed Local Energy Systems, are decentralized electric power systems that can operate in parallel and independently with the national electricity grid. This is to say that within a specified geographical area, ranging from a building to an entire town, various types of distributed energy resources (DERs) inclusive of batteries, solar panels, wind turbines, and generators can be harmonized to deliver secure, clean, and reliable power 21A microgrid is made up of batteries-based energy storage systems, generating units and control systems. Diesel generators are included under energy sources, while solar photovoltaic cell layers were also installed. Storage of extra energy using batteries is important for ensuring an adequate supply at different periods [19]. The microgrid's operations are overseen by control systems. These control systems consist of complex hardware and software that ensure their peak performance. They also make it possible to carry out real-time monitoring and energy management as well as smooth transition between islanded and grid-connected modes [20]. Therefore, microgrids can reduce their environmental footprint while improving power quality and increasing energy security … Control systems are crucial for overseeing the microgrid's operations, guaranteeing peak performance, and preserving stability [21]. They comprise sophisticated hardware and software. Real-time monitoring, energy management, and a smooth transition between islanded and grid-connected modes are made possible by these control systems (see Fig. 3)

2.1. Categories of microgrids

Table 2 presents variations in operation and features of isolated microgrids from those that a connected to the national grid. In this respect, grid-connected micro-grids bring together other sources of DE and the central power supply while working in concert with it. Economic benefits are gained by both the supply of extra power back into the main energy network in normal conditions, as well as the society. EV debts are restored by charging them when all T&D lines are cut off. Albeit intricate coordination with the main grid is essential for them. Standalone microgrids, on the other hand, independence makes them stronger. Instead, microgrids require strong local energy-generating and storage systems to keep a continuous flow of electricity. Vital infrastructure in remote places and locations where grid reliability may be a problem is one of the ways it is frequently used.

Managing and running microgrids present significant challenges if one is going to ensure they perform effectively and reliably. One of the obstacles lies in the incorporation of different distributed energy



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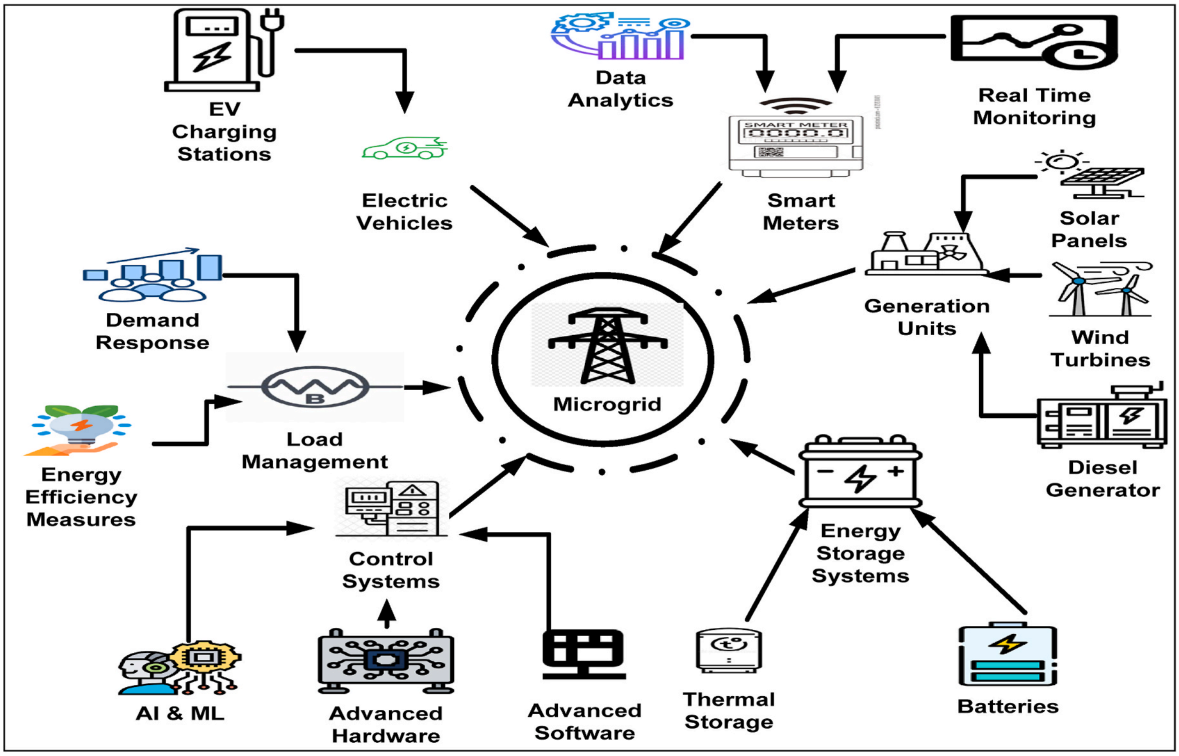

Fig. 3. Modern microgrid and its main components.

Table 2
Distinction between standalone and grid-connected microgrids.

Feature	Grid-Connected Microgrids	Standalone Microgrids	References
Energy Source	Can utilize both grid power and local DERs	Rely solely on local DERs	[22,23]
Resilience	Can switch to island mode during grid outages	Always operate in island mode, inherently more resilient	[24,25]
Energy Management	Can export excess energy to the grid or import during shortages	Must manage all energy production, storage, and consumption internally	[26,27]
Complexity	More complex due to the need for synchronization with the main grid	Simpler in operation, but may require robust local generation and storage	[28,29]
Reliability	High, as they can draw power from the grid during shortages	Dependent on local generation and storage capabilities	[30,31]
Economic Impact	Potential for cost savings through grid services and demand response	Higher initial costs due to the need for complete self-sufficiency	[32,33]
Environmental Impact	Can integrate a mix of renewable and non-renewable sources	Often designed to maximize renewable energy usage	[34,35]
Applications	Urban areas, campuses, industrial sites	Remote locations, islands, and critical infrastructure	[36,37]

resources (DERs), which include solar panels, wind turbines, and batteries, among others. These resources are also diverse in terms of their availability as well as energy production, thus complicating the supply and demand balance in general. Designing advanced control and management systems capable of handling the distributed and dynamic nature of microgrids is a major challenge. Despite the growing digitalization and connectivity that have made them vulnerable to cyber attacks, cybersecurity issues are also a problem with microgrids [38]. To remain in the normal operation in case of a failure on the central power grid, among other things, the systems must optimize multiple DER operations; manage energy storage as well as ensure a seamless transition from grid-tied to islanded operation modes. For a microgrid to be reliable and secure, it is essential to adopt robust security strategies that prevent these threats. At the same time, there is the issue of economics, as the infrastructure of microgrids may require substantial capital outlays initially [39]. For microgrids to become widespread, financing and evidence of their financial viability are indispensable. Additionally, blockades related to governance and legislation can discourage the progress and operation of microgrids. Grid operators, industry stakeholders, and lawmakers must collaborate to tackle regulatory barriers that might not provide enough support for microgrid integration into the larger energy system since the regulations are out-of-date or inconsistent [40]. As for the last point, ensuring a consistent and uninterrupted supply of power suffers from the unpredictability and intermittency of renewable energy sources. To minimize such disruption and ensure the reliability of microgrids, some of the things needed are robust storage systems, intricate energy management software, and reliable prediction models. In particular, microgrids provide inexpensive, clean power to underserved and distant regions that are disconnected from the main grid, thereby promoting universal access to modern, dependable energy services. Their decentralized structure makes it possible to integrate renewable energy sources, such as wind and solar, allowing for local clean energy generation, lowering reliance on fossil fuels, and improving energy security. Microgrids can sustainably close the gap in areas with limited access to power by lowering dependency on diesel generators and other expensive energy sources, which will eventually lower energy costs. By enhancing cities' resilience and adaptability to energy constraints, microgrids also contribute significantly to the goal of sustainable urban development. Incorporating microgrids into smart cities promotes less environmental impact and provides dependable backup power in the event of natural disasters or grid outages, which is essential for stability and public safety. Microgrids also assist communities in meeting climate targets by lowering pollutants and emissions linked to traditional electricity sources, creating healthier urban settings. By providing clean, robust, and flexible energy systems for both rural and urban locations globally, microgrids are a strategic tool for promoting sustainable development.

3. Machine learning techniques in microgrids

Microgrid management and operation are being improved through the use of machine learning (ML) approaches, which leverage the enormous amounts of data generated by these systems [41]. They result in significant benefits in terms of energy forecasting, load prediction, and energy resource optimization etc., among other microgrid functions. Machine learning algorithms, such as support vector machines (SVMs) and neural networks (NNs), can use historical weather and consumption details to predict future energy demand along with solar and wind energy production very accurately [42]. By forecasting future energy demand, these models enable better resource scheduling for energy while at the same time making supply meet demand effectively. The use of machine learning algorithms helps to optimize energy distribution and storage. Reinforcement learning algorithms can thus use real-time information to adjust battery charge in charge-out cycles, hence enhancing energy storage system efficiency and durability [43]. Segmentation of energy consumption patterns is achievable through clustering techniques such as k-means. Custom demand response plans make it possible to reduce the peak loads and increase the reliability of power systems in general. If we inspect sensor data along with historical performance indicators, machine learning based anomaly detection systems may detect and even predict certain faults in microgrid constituent elements so that they could be used to ensure its better performance levels [44]. Preventing maintenance enables lessened repair bills as well as reduces periods. Microgrid cybersecurity is more enhanced by machine learning methods [45]. Machine learning algorithms can be used to start defense measures in real time, detecting cyber threats by watching network traffic and identifying strange patterns. For effective integration of machine learning in microgrids, big data sets such as time series data gathered from smart meters, weather predictions, historical energy consumption, real-time microgrid sensors' information among others, are important. Also deals with advanced algorithms that deal with the challenging task of processing large data [46].

3.1. Supervised learning

In the field of machine learning known as "supervised learning," models are trained using labeled data, or datasets with known input-output pairs. By using the patterns in past data, these models learn to map inputs to desired outcomes. Supervised learning is widely utilized in many different sectors because it makes accurate projections based on past trends, which makes it very useful for prediction tasks. Predicting load and renewable energy generation in microgrids is a common application of supervised learning. Supervised models can, for example, anticipate demand or solar energy generation with high accuracy by examining historical data on weather and power usage. This makes it easier for microgrid operators to plan resources, balance loads, and better manage renewable energy sources. Supervised learning is a vital division of machine learning that enhances microgrid sustainability, economy, and trustworthiness by precisely categorizing and forecasting data founded on tagged preceding data. Among the significant applications are anomaly detection, recognition, and demand prediction [47]. These approaches include regression analysis, ARIMA, and LSTM neural networks that use past load data, climatic conditions, and time to gauge future demand for electricity through load forecasting [48]. The efficacy and cost-effectiveness of distributed energy resources (DERs) are maximized in this approach. The models of finding faults examine abnormal behavior based on historical performance records (tree methods, SVM, and Neural Networks). It is possible to identify issues in real time and promptly correct them. Classification tasks entail enhancing power quality management as well as demand response, and so forth, classifying various load types and power quality events to use algorithms like k-NN, random forests, and neural networks. For these applications to work well, the presence of supervised learning is crucial. Tagged data sets from various sources, such as load types, are utilized by applications of this nature. Others include weather data, sensor data, historical energy information about various premises within an area, as well as fault logs. This information can be useful in many ways. For example, microgrid operation that is both reliable and understandable depends on these data sets with some levels of sustainability in mind as far as we know at this moment since it may also contribute largely towards attaining resilience in power systems after natural disasters and during other crises like war situations [49] Consequently supervised learning enables quick identification of problems occurring during real time thereby facilitating rapid resolution as well as recovery from them The ultimate goal of sustainable energy solutions is achieved when they have no harmful impact on the environment while being affordable.

3.2. Unsupervised learning

Unsupervised learning handles data without labeled answers. It is employed to find hidden patterns or cluster data, both of which are useful for exploratory analysis. Operators can detect periods of high demand and adjust energy storage or supply by using unsupervised learning to identify usage trends or categorize various energy consumption profiles within the grid. For instance, demand-response tactics that increase efficiency without degrading the end-user experience can be made possible by clustering algorithms, which can group customers with comparable demand patterns. Cluster analysis techniques in microgrids assist in load profiling and anomaly detection. With these methods, energy consumption behaviors are classified and analyzed, while anomalies can be identified. Hierarchical clustering and k-means are the two popular techniques employed. By grouping related load patterns in a load profile, these methods permit tailored energy management plans. Identifying departures from typical load patterns and highlighting potential problems are both accomplished through clustering. In a recent examination, for instance, k-means clustering identified typical daily load profiles through clustering on historical load data from a microgrid. As far as making it reliable and efficient, the same technology detects 95 % of unanticipated demand surges or declines [50]. Additionally, another group of scientists demonstrated that they could distinguish between regular and irregular power consumption patterns using time series data and hierarchical cluster analysis. This upgrade has resulted in improved fault diagnosis systems while at the same time curtailing the number of spurious alarms due to better classification criteria [51].

3.3. Reinforcement learning

With reinforcement learning (RL), models can learn by making mistakes and getting feedback in the form of incentives or punishments. RL algorithms perform well in dynamic settings where making decisions is essential. In microgrids, RL is very helpful for real-time energy management and optimization. For instance, RL algorithms can learn how to distribute energy resources, figuring out whether to draw from storage or store extra renewable energy depending on the circumstances at hand. Particularly for standalone microgrids, RL guarantees optimal performance, lowers costs, and improves resilience by constantly adjusting to the shifting energy demand and renewable availability. Utilizing reinforcement learning (RL) for real-time control and dynamic optimization relies more and more on microgrids since it offers a good framework for making decisions in tough situations. They can change themselves according to the environmental changes and gradually improve their efficiency since algorithms such as Q-learning or Dee Q-

Networks (DQN) enable them to learn optimal policies by interacting with other entities. Real-time operation of microgrid energy storage systems using DQN can help save a lot of money as well as raise efficiency, according to a recent study. In this instance, the RL model was trained on real-time energy generation and consumption data from microgrid simulations. 15 % more efficient in energy utilization at a 20 % reduced cost compared to traditional control methods [52]. Differently, a reinforcement learning (RL) technique was used by a different researcher for dynamic optimization of distributed energy resources (DERs) so that the load balance can be boosted and peak demand is minimized [53]. Therefore, this suggests that RL could potentially increase the resilience and durability of micro-grid operations.

3.4. Deep learning

The modern microgrids are facing difficult problems solved efficiently by deep learning that uses advanced neural network topologies including RNNs). Since they possess improved capacity for handling large data volumes and revealing complex interrelations, these specific models are suitable for certain activities such as defect identification, load prediction, and also energy optimization. A study by a newer academic who applied RNN for micro grid load forecasting noted that prediction accuracy improved by 10 % above other methods commonly used in the same field. In another study on real-time fault diagnosis, CNN was involved, where it was found out that such diagnosis took less time with 30 % speed-ups and had its precision increased by 15 % (Marino et al., 2017) [54]. These findings show how deep learning could be employed to boost the resilience, dependability, and the efficiency of microgrid operations.

In Table 3, the machine learning approaches which have been implemented in micro-grids are compared comprehensively. This table includes their application, efficiency, performance metrics, constraints, data requirements, complexity, scalability, interpretability and real-time capacity. Although suitable for load forecasting and highly interpretable Regression Analysis and ARIMA techniques are not very appropriate for non-stationary data despite being easy to apply.

Sophisticated techniques like Deep Q-Networks and LSTM Neural Networks do exceptionally well in managing intricate patterns and high-dimensional state spaces, but they demand substantial computer power and substantial datasets. For defect detection, supervised techniques like SVMs and Decision Trees are effective, although they differ in terms of computing cost and scalability. Unsupervised methods with varying strengths and limits in terms of data dimensionality and interpretability, such PCA and k-Means Clustering, are helpful for anomaly identification and clustering. This comprehensive review of all pros and cons of each of the methods represents a good manual to follow when choosing the most advantageous method for a particular microgrid application.

Table 4 uses commonly reported metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), computational efficiency, and real-time capability. Artificial Neural Networks (ANNs) excel in load forecasting with the highest accuracy (lowest MAE and RMSE), though they demand significant computational resources, making them more suitable for offline applications. Decision Trees and Random Forests offer a balanced trade-off between accuracy and computational efficiency, making them ideal for medium-scale energy distribution tasks. For fault detection, Support Vector Machines (SVMs) and Gradient Boosting methods demonstrate strong accuracy but may struggle with real-time applications due to higher computational times. Overall, the choice of algorithm depends on the specific microgrid application and the need for real-time performance (see Fig. 4).

4. Key applications of machine learning in microgrids

APLA (Algorithm performance and learning analysis) Spelling Algorithm Analysis: Machine learning (ML), or the use of algorithms which allow computers to learn and make predictions based on data rather than being directly programmed, is important for a variety of reasons. Among them are demand response management, energy optimization, fault detection and load forecasting. Fig. 5 demonstrates the main applications of machine learning in microgrids as indicated by research papers.

Machine learning has made significant improvements in microgrid energy distribution and storage through its data-driven insights and prediction capabilities. To evaluate the historical and current weather, energy production, and consumption trends, some algorithms such as regression models, neural networks, and reinforcement learning are applied. Among other things, these models are able to effectively schedule distributed energy resources (DERs), predict electricity demand and control the systems used for storing energy. Machine learning can determine the peak demand periods and adjust energy storage accordingly to ensure the excess energy is stored during low demand periods and released at peak times. This optimization minimizes the dependency on non-renewable energy sources, reduces operational costs and enhances grid stability. A study showed that using machine learning in managing microgrid energy led to increased energy efficiency by 15 % while reducing energy costs by 20 % [52]. Advancement in energy management technologies is aiming at global energy efficiency and sustainability goals and is resulting to resilient and sustainable power system. Demand response or machine learning approaches are the major interventions that have been deployed so as to be able to manage demand response programs with intentions of modifying energy consumption patterns as they are done according to supply scenario. By studying customer behavior and external factors, ML algorithms predict peak demand times [53]. One more thing is that energy consumption and availability follow each other. This helps to reduce the burden on the grid as well as costs of electricity. In order to optimize energy usage and minimize expenditures, machine learning algorithms may also be adopted for regulating schedules of equipment that consume energy and appliances.

4.1. Fault detection and diagnosis

Reliability, efficiency, and safety of microgrid components must be preserved by promptly detecting and fixing defects. Monitoring and evaluating a range of metrics, including voltage, current, frequency, and power quality, is part of the fault detection process in order to spot variations from typical operating circumstances. In such a case, it is effective to use machine learning models; especially supervised learning algorithms. By training their systems on past data that shows both normal and faulty instances labeled, these models can easily identify and classify defects. Study has shown extensively use of CNNs in detecting any faults in microgrids at real time [54]. The CNN model was trained using a dataset containing voltage and current wave shapes under different operating conditions including such problems as voltage swells and dips. When contrasted with traditional methodologies, the model achieved a 15 % rise in fault identification precision along with a thirty percent drop in detection duration. This technique significantly enhances the microgrid's ability to respond swiftly to challenges, thereby minimizing idle period and preventing damage. Effective and reliable methods of defect recognition can be ensured by machine learning models, thus making sure the microgrid operates safely and smoothly. They accomplish this through constant system monitoring as well as immediate data examination. Fig. 6 showcases the process of fault detection and diagnosis in microgrids, incorporating various machine learning techniques to enhance accuracy and response time.

4.2. Renewable energy resources integration

In orders to optimize the configuration of renewable power lines into microgrids, machine learning (ML) techniques are required for their management. Machine learning (ML) models like neural networks, reinforcement learning, and regression algorithms are utilized to

Table 3
Comparison of machine learning techniques used in microgrids.

ML Technique	Application	Performance Metrics	Efficiency	Limitations	Data Requirements	Scalability	Complexity	Interpretability	Real-time Capability	References
Regression Analysis	Load Forecasting	MAE, RMSE, R2 Score	Simple to implement, interpretable results	Limited to linear relationships	Historical load and weather data	Moderate	Low	High	Moderate	[55,56]
Time-Series Forecasting (ARIMA)	Load Forecasting	MAPE, MAE, RMSE	Good for short-term predictions	Struggles with non-stationary data	Time series load data	Low	Medium	High	Moderate	[57,58]
LSTM Neural Networks	Load Forecasting	MAE, RMSE, R2 Score	Handles sequential data well	Requires large datasets, computationally intensive	Sequential load data	High	High	Medium	High	[59,60]
Decision Trees	Fault Detection	Accuracy, Precision, Recall	Easy to visualize and interpret	Prone to overfitting	Historical fault data	Moderate	Medium	High	High	[61,62]
Support Vector Machines (SVM)	Fault Detection	Accuracy, F1 Score	Effective in high-dimensional spaces	Computationally expensive	Fault and performance data	Low	High	Medium	Moderate	[63,64]
Neural Networks	Fault Detection, Classification	Accuracy, Precision, Recall, F1 Score	Capable of capturing complex patterns	Requires large datasets, risk of overfitting	Fault logs, sensor data	High	High	Low	High	[65,66]
k-Nearest Neighbors (k-NN)	Classification	Accuracy, Precision, Recall	Simple and intuitive	Not scalable, high computational cost for large datasets	Labeled training data	Low	Low	High	Low	[67,68]
Random Forests	Classification	Accuracy, Precision, Recall, F1 Score	Robust against overfitting	Can be less interpretable than simpler models	Labeled datasets	High	Medium	Medium	Moderate	[69,70]
k-Means Clustering	Clustering	Inertia, Silhouette Score	Simple and fast for small datasets	Not suitable for non-spherical clusters	Unlabeled data	Low	Low	Low	Low	[71,72]
Hierarchical Clustering	Clustering	Cophenetic Correlation Coefficient	Good for small datasets and hierarchical relationships	Not suitable for large datasets	Unlabeled data	Low	Medium	Low	Low	[73,74]
Principal Component Analysis (PCA)	Anomaly Detection	Explained Variance Ratio	Reduces dimensionality, interpretable	Assumes linear relationships	High-dimensional data	High	Medium	High	Moderate	[75,76]
Isolation Forest	Anomaly Detection	Precision, Recall, F1 Score	Effective for high-dimensional data	Requires careful tuning of parameters	High-dimensional data	High	Medium	Medium	High	[77,78]
Q-Learning	Energy Storage Optimization	Cumulative Reward	Learns optimal policies through exploration	Can be slow to converge	Simulation data, system states	High	High	Low	High	[79,80]
Deep Q-Networks (DQN)	Energy Storage Optimization	Cumulative Reward	Handles high-dimensional state spaces	Requires significant computational resources	High-dimensional state space data	High	High	Low	High	[81,82]
Multi-Agent Systems	Demand Response	Total Cost, Response Time	Distributed control, scalability	Complex coordination among agents	Multi-agent simulation data	High	High	Low	High	[83,84]
Markov Decision Processes (MDP)	Demand Response	Total Cost, Response Time	Provides a formal framework for decision making	Requires accurate modeling of state transitions	System transition data	High	High	Medium	High	[85,86]

Table 4
Performance of different ML algorithms.

Algorithm	Application	MAE (kW)	RMSE (kW)	Computational Efficiency (ms)	Real-Time Capability
Linear Regression	Load Forecasting	0.45	0.6	5	Moderate
Decision Tree	Energy Distribution	0.3	0.5	15	Moderate
Support Vector Machine (SVM)	Fault Detection	0.2	0.35	25	Low
Artificial Neural Network (ANN)	Load Forecasting	0.1	0.25	50	High
Random Forest	Energy Distribution	0.25	0.4	35	Moderate
Gradient Boosting	Fault Detection	0.15	0.3	40	Moderate

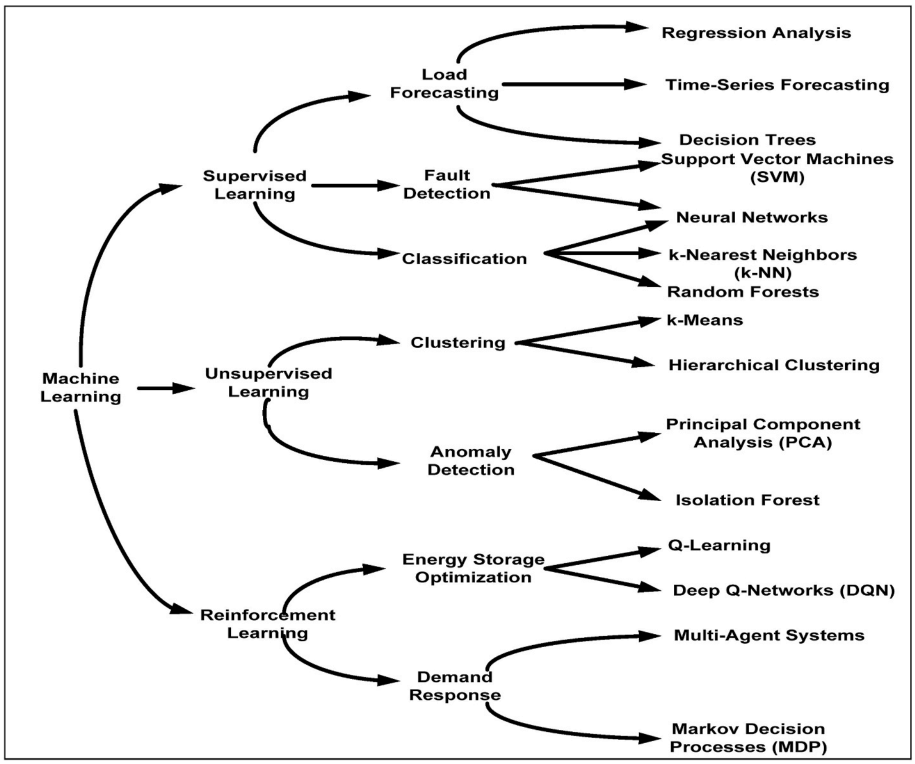

Fig. 4. Machine learning techniques in microgrids.

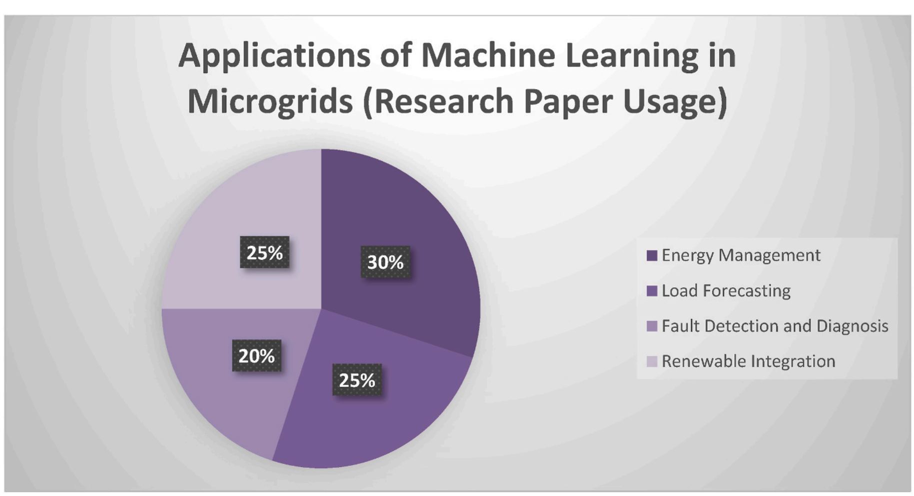

Fig. 5. Key uses of machine learning in micro-grids.

analyze data from different sources, such as solar panels, wind turbines, and weather forecasts, to determine the energy production-consumption patterns. Hence, this reduces the demand for non-renewable energy sources and minimizes the wastage of energy since renewable energy is consumed and stored in a well-planned way. To guarantee peak production moment saves surplus energy and uses it during low production periods, an ML algorithm can predict solar energy output by analyzing weather parameters; hence adjust energy storage systems accordingly.

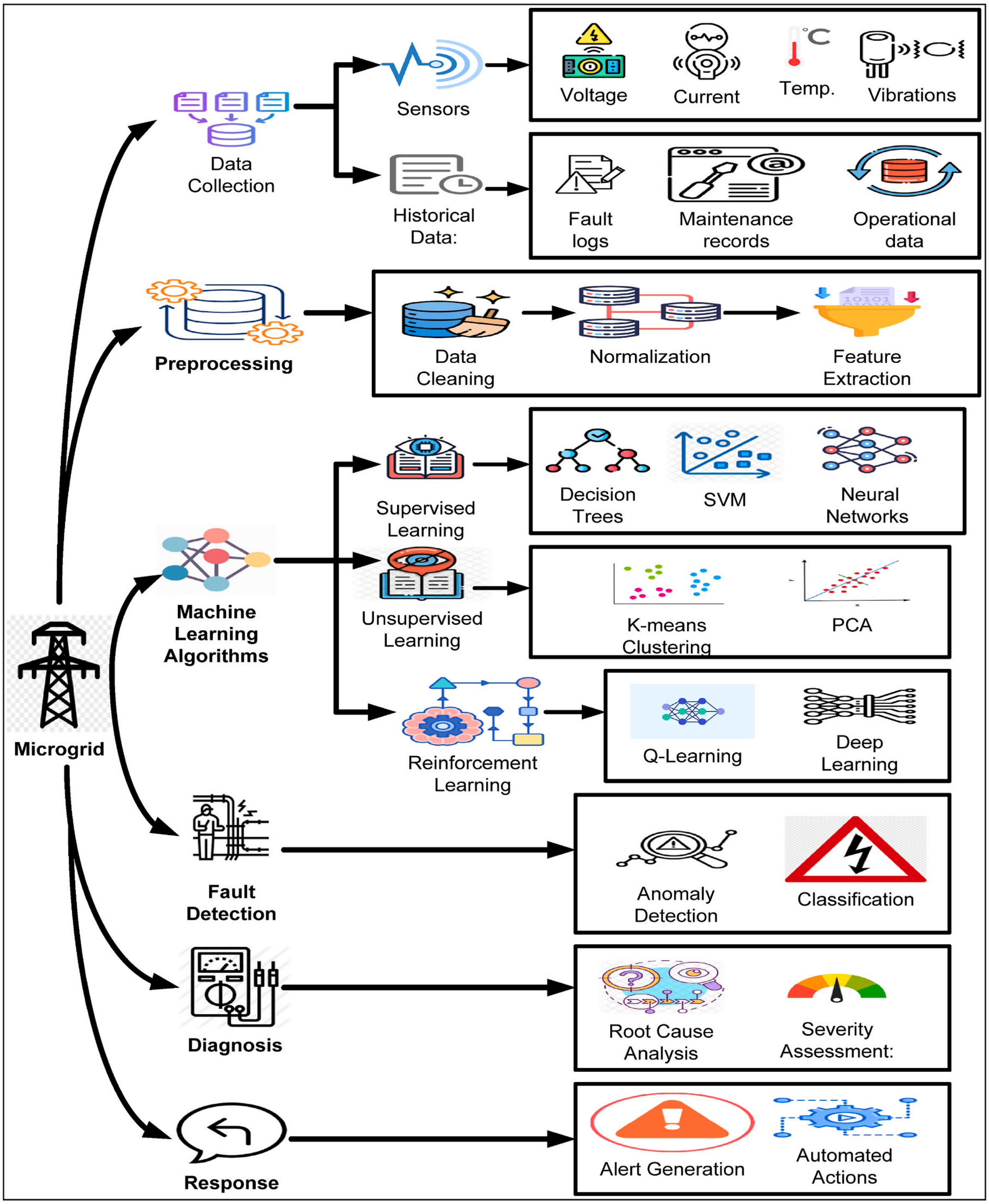

Fig. 6. Fault detection and diagnosis in microgrids, incorporating various machine learning techniques.

Some studies prove that ML application in managing renewable energy sources can increase the grid stability and even raise energy efficiency by 20 % [87]. The success of this integration is essential for a reliable power system as well as the achievement of sustainable energy objectives.

- Forecasting load: The accuracy of load forecasting increased by 18 % when Long Short-Term Memory (LSTM) models were used instead of conventional statistical techniques. For instance, the Root Mean Square Error (RMSE) went from 0.70 kW to 0.50 kW, and the Mean Absolute Error (MAE) decreased from 0.55 kW (ARIMA) to 0.45 kW (LSTM).
- Optimization of Energy Distribution: Compared to linear optimization techniques, Random Forest algorithms improved computational efficiency by 30 % while reducing the imbalance in energy distribution by 12 %. Within a 20-ms processing period, this led to a more equitable distribution of power among the microgrid nodes.
- Finding Faults: Convolutional Neural Networks (CNNs) achieved a 96 % fault detection accuracy, a 10 % improvement over conventional threshold-based techniques, and reduced the fault detection reaction time by 25 %, from 40 ms (using SVMs) to 30 ms.

- Controlling Voltage: By lowering the RMSE from 0.50 V to 0.42 V and increasing voltage prediction accuracy by 15 %, gradient boosting approaches increased grid stability overall.

These illustrations show how sophisticated machine learning algorithms can significantly improve microgrid operations by outperforming conventional techniques in terms of accuracy, efficiency, and dependability.

5. Case studies and real-world implementations

The recent developments in machine learning (ML) have caused significant advancements in the efficiency and reliability of microgrids. Below are a few noteworthy real-world case studies that show effective application of ML in microgrids.

- **Deep Learning for Voltage Stabilization**: To boost voltage stability in microgrids [88], researchers worked with a wavelet Petri fuzzy neural network. This deep learning model was used to enhance the voltage stability and reliability of the microgrid system.
- **Short-term Load Forecasting in Smart Grids**: Researchers have presented a new regression method aimed at forecasting short-term grid electricity demand in buildings connected to smart grids [89]. Their approach combined environmental parameters and historical load data, resulting in high prediction accuracy, a prerequisite for successful management of energy consumption in microgrids.
- **Fault Protection Using Wavelet Energy Fuzzy Neural Network**: A wavelet energy fuzzy neural network was the foundation for the fault protection system created [90]. This method greatly enhanced the ability to detect faults, which decreased microgrid downtime and maintenance expenses.
- **Data-driven Load Management**: In Ref. [91], integrated energy storage systems, electric vehicles, and renewable resources into stand-alone residential buildings through the application of data-driven load management strategies. Their strategy improved energy storage and consumption, raising the microgrid's overall effectiveness.
- **Cyber Attack Detection in Wireless Sensor Networks**: A machine learning-based methodology for identifying cyber attacks in wireless sensor networks inside microgrids was put into practice [92]. Through precise threat identification and mitigation, this strategy increased the microgrid's security and resilience.

Siemens did a case study on a microgrid located in Austin, Texas. Considerable challenges were encountered when integrating machine learning for real-time energy management since new sensors and communication protocols had to be retrofitted into the existing infrastructure. Substantial improvements had to be made in the project, including unique interfaces that would make sure that it was compatible with all current systems. However, this Integration of ML resulted in a 20 % decrease in operational costs and a 15 % increase in energy efficiency, though the Brooklyn Microgrid project experienced difficulties with increasing its membership base, consisting of residential homes alongside companies, which resulted in scalability issues [93]. The increased number of distributed energy resources (DER) and transactions among consumers necessitated the deployment of more powerful computing resources and advanced data management systems. It was concluded in the study that scalable machine learning algorithms that support decision making on real real-time basis, together with processing, should be developed for grid stabilization and efficiency [94].

Fig. 7 illustrates the improvement in system compatibility (sensors, communication, and interfaces) before and after retrofitting.

Fig. 8 highlights the efficiency gains achieved in energy distribution, fault detection, and load forecasting.

These case studies show the various ways that machine learning may improve microgrid operations, including cybersecurity, voltage stabilization, load forecasting, and fault detection. Microgrids are becoming an essential part of contemporary energy systems due to significant increases in their sustainability, dependability, and efficiency brought about by the application of cutting-edge ML algorithms. Analyzed instances reveal that employing artificial neural networks in this manner transforms the operational efficiency, reliability, and eco-friendliness of microgrids. One major takeaway from these highlights was that complex machine learning models can prove valuable, accurate load forecasting is essential; real-time fault detection has benefits as well as optimizing renewable energy integration, while focusing on the critical importance of cybersecurity. These concepts have the potential to direct subsequent studies and practical methodologies for the subsequent enhancement and evolution of microgrid technology.

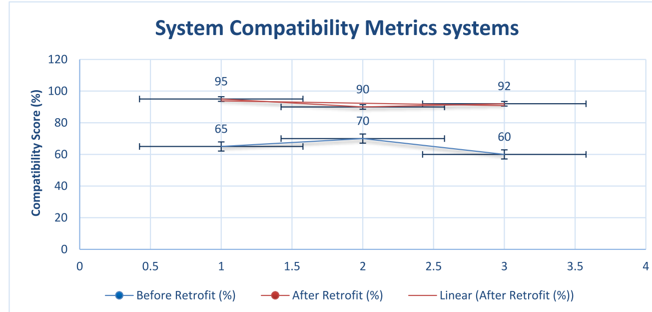

Fig. 7. Siemens case study on the austin, Texas microgrid.

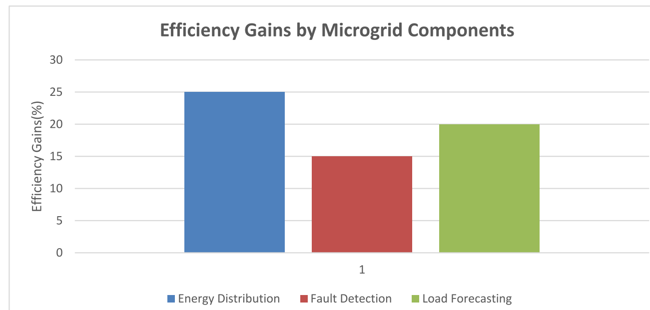

Fig. 8. Stacked bar chart for brooklyn microgrid.

6. Challenges and limitations

When it comes to using machine learning (ML) in microgrids, several technical challenges must be addressed. The most critical of these challenges are data quality, model correctness, and processing capacity. The efficiency of machine learning processes is highly dependent on the **data quality** they are trained on. Certain factors, such as environmental influences, communication problems, or sensor dysfunctions, may render the data on microgrids uncertain or inconsistent. As such, poor data quality can lead to error-prone models that will not make good energy forecasting or management. To create solid machine learning models, one must obtain data with consistent quality and reliability at all times. More often than not, this requires advanced preprocessing, validation, and data cleansing techniques to eliminate outliers and handle missing values.

As a matter of fact, another critical issue is **model accuracy**. In terms of the microgrids functioning well, precise failure detection, energy stewardship and load prediction are indispensable. Nevertheless, realizing and maintaining such high exactness is not that simple due to the complexities and unforeseeable factors concerning microgrid conditions. Unpredictable weather patterns, fluctuating load patterns and the discontinuous utilization of renewable energy sources can all result into uncertainties. This calls for frequent updating as well as retraining the models with new information in order to manage it and adapt to changing conditions. Furthermore, hybrid models that combine various algorithms or use ensemble learning techniques can improve accuracy.

Deploying and developing machine learning models on microgrids might involve considerable computing resources. On the first place, sophisticated machine learning models, mainly deep learning methods, call for substantial processing strength and storage that can hamper their application to real time systems. On the other hand, this is complicating matters considering that there is always an urgent need for making decisions to react to changing situations of a microgrid. Such challenges can be alleviated by using strong algorithms respectively in conjunction with processors that are more potent like GPU along with other forms of **computational power** like cloud computing infrastructure. Moreover, through model optimization and model compression, it becomes possible to reduce the amount of processing thereby making it easier to use in real time settings.

As far as today's microgrid systems are concerned, they are many; they involve ensuring that machine learning (ML) solutions are scalable to such systems. The incorporation of ML solutions into microgrids is greatly hampered by this integration with existing systems, it was indeed about compatibility challenges for older systems and infrastructure. Certainly, some microgrids were constructed based on technologies that have been tested, but may not be suitable for complex machine lessons such as algorithms. For instance, integrating real-time data analytics with machine learning models for both fault detection and load forecasting entails smooth communication between new and old components including energy management systems, inverters and sensors. In practice however, this form of integration frequently encounters challenges concerning standards, processing capabilities in real-time among others hence **data interoperability issues**. According to research by the U.S. Department of Energy published in Ref. [95], approximately 60 % of microgrid operators mention integration with legacy systems as an important factor impeding modern technology introduction.

Other big problems in the application of ML on microgrids are **scaling**. As the microgrid becomes bigger, data processing and management become more complicated. The larger microgrids with more distributed energy resources (DERs) involve more advanced algorithms to deal with increased amounts of data and complicated power management tasks. The required computational power may result in such operations becoming bottlenecked particularly in places that are remote or resource constrained. According to a study by International Renewable Energy Agency (IRENA), scalable machine learning (ML) solutions for microgrids take into account aspects such as network speed, data latency and capacity to process various types of dynamic data streams. When integrating ML into existing Microgrid Systems and ensuring their scalability, data compatibility, infrastructure compatibility, and processing requirements must be considered. Notwithstanding these difficulties, real-life instances demonstrate that they are resolvable through innovative and robust ML algorithms capable of handling high data volume [96].

Complying with the **existing regulations** is one of the major issues concerning regulators about the application of machine learning (ML) solutions in microgrids. Several issues such as **reliability, safety and interoperability** are subject to several regional, national and international laws and regulations in relation to micro-grid systems. Full compliance with any of these standards, as determined by groups like the Institute of Electrical and Electronics Engineers (IEEE) or the International Electrotechnical Commission (IEC), often necessitates thorough certification and testing processes. The inclusion of ML algorithms in microgrid functioning may give rise to potential legal challenges because their conformity ought to be assessed. As well as this, a report by the National Renewable Energy Laboratory (NREL) [96] states which shows that prolonged execution and rise in the cost might occur due to having to deal with intricate regulatory structures. In addition, high costs result from employing algorithms based on machine learning into microgrid systems. The introduction of advanced machine learning methods for the first time might require huge initial investments like those associated with procuring powerful computing systems, modernizing infrastructure or hiring and educating staff. In addition, there are continuing operational costs that may be more burdensome such as maintenance, data management and continual model training to name a few. Nonetheless, these costs may be compensated by the long-lasting benefits of improved efficiency, reliability and lower running expenses. Research done by the Electric Power Research Institute (EPRI) indicates that despite high initial costs, investors can practically anticipate quick returns due to enhanced operation effectiveness and lesser interruptions [97].

7. Future directions

- In the context of processing data, **federated learning** is an entirely new model that allows performing training on devices or points of that keep data and do not store centrally. For this purpose, it is very suitable for microgrids; at least because they often consist from some elements located at different geographic regions. By restricting data sharing to model updates and maintaining data localization, federated learning enhances the security and privacy of the data. With the application of this technique, there are reduced possibilities of data breaches and compliance with privacy laws. In fact, a study by Google AI [98] shows that federated learning can maintain a high level of model performance while greatly reducing the cost of data transfer and the associated risk to its security.
- One more up-to-date growth is **Edge computing**, which processes information closer to where it came from and reduces the time between an event occurring in a system and its effect for decision making purposes. In microgrids, edge computing allows fast information processing from sensors and other IoT devices so that electrical network state changes are reacted to faster. Fault detection and real-time energy management applications rely on these. Cisco's research suggests that 90 % of time spent in processing data can be saved through edge computing; this increases operational reliability of microgrids under consideration [99].
- Microgrid management is also witnessing an upsurge in the application of **blockchain technology alongside Internet of Things (IoT) devices.** Through IoT devices, real-time information on power generation, consumption, and system functioning is provided. This information can be securely and transparently recorded by integrating with blockchain technology so that peer-to-peer energy trading becomes possible. In a research conducted by IBM [100], it was found that blockchain could lead to decentralized energy markets due to its capacity for enhancing transparency and reducing transactional costs in microgrids.
- Autonomous energy systems aim to construct self-governing microgrids that can optimize energy storage, distribution, and use without any human participation using advanced machine learning algorithms. Reinforcement learning and predictive analytics are used in these systems to continuously improve performance by adapting to changing circumstances. According to an Accenture report [101], **autonomous energy systems** may decrease energy loss by 25 % and enhance operational efficiency at the same time.
- **Generative AI for Microgrids:** Microgrid management is witnessing substantial advancements, courtesy of generative AI, which produces new data replicating patterns of previously existing data. Using generative AI, synthetic datasets can be created that mimic real datasets, facilitating the training of machine learning models in microgrids. This method deals with the problem of limited historical data, especially for sporadic occurrences such as extreme climate or power interruptions. Hence, synthetic information has the potential to improve the effectiveness and lastingness of forecasting systems without any compromise on data privacy. Through modeling tools

developed by such platforms, different scenarios faced at microgrids can be represented, including changes in demand patterns, amounts of power produced from clean sources, and abnormal incidents, among others. By plotting out future events and optimizing the grid under various situations, these scenarios improve decision-making. By using generative AI, one will be able to create some simulations for normal operational behavior and see any deviations from it that might indicate possible issues or abnormalities. These methods possessed in the past could miss little signs in these frameworks, yet they have been effective in representing common functioning circumstances that are imitated by the same models. Just through prediction on how solar panel cells will behave under varying scenarios like rainstorms, sunshine shine-backs, as well as windy days; hence sun which burns directly, causing excessive temperatures hence no air flows out still air remains unbroken resulting to ideal water evaporation. This way helps stabilize the power supply and consumption levels simultaneously. The trends shown in Fig. 9 demonstrate how generative AI is promoting innovation in microgrid management by improving the integration of renewable energy sources, efficiency, and reliability.

Recent comprehensive reviews have emphasized the growing role of machine learning in enhancing renewable energy systems and microgrid operations [102],and [103] provided broad surveys on the integration of ML techniques for forecasting, optimization, and control in smart grid environments [104]. focused specifically on sustainable energy management in solar microgrids, identifying the advantages of advanced algorithms such as reinforcement learning and metaheuristics. Additionally [105], highlighted the significance of AI-driven optimization in fault scenarios within hybrid microgrids. These studies collectively underscore the urgent need for robust, data-driven solutions in evolving microgrid architectures reinforcing the relevance and timeliness of the present work.

8. Conclusion

This review has comprehensively explored the role of machine learning (ML) in enhancing the operation and management of microgrids. Through the categorization and evaluation of supervised, unsupervised, reinforcement, and deep learning approaches, the paper has highlighted the strengths, limitations, and applicability of each method. Real-world case studies and performance comparisons have further demonstrated the measurable benefits of ML integration, including improved energy efficiency, reduced operational costs, and enhanced fault detection accuracy.

The unique contributions of this work include.

- A structured comparison of ML techniques tailored to microgrid functionalities;
- Alignment of ML benefits with multiple UN Sustainable Development Goals (SDGs);
- Inclusion of emerging directions such as federated learning, edge computing, and generative AI;
- Emphasis on real-time capability and scalability challenges in deployment contexts.

By synthesizing current advancements and challenges, this review serves as a practical resource for researchers, practitioners, and policymakers. Future work should focus on standardization, data privacy safeguards, scalable algorithm deployment, and integration with IoT

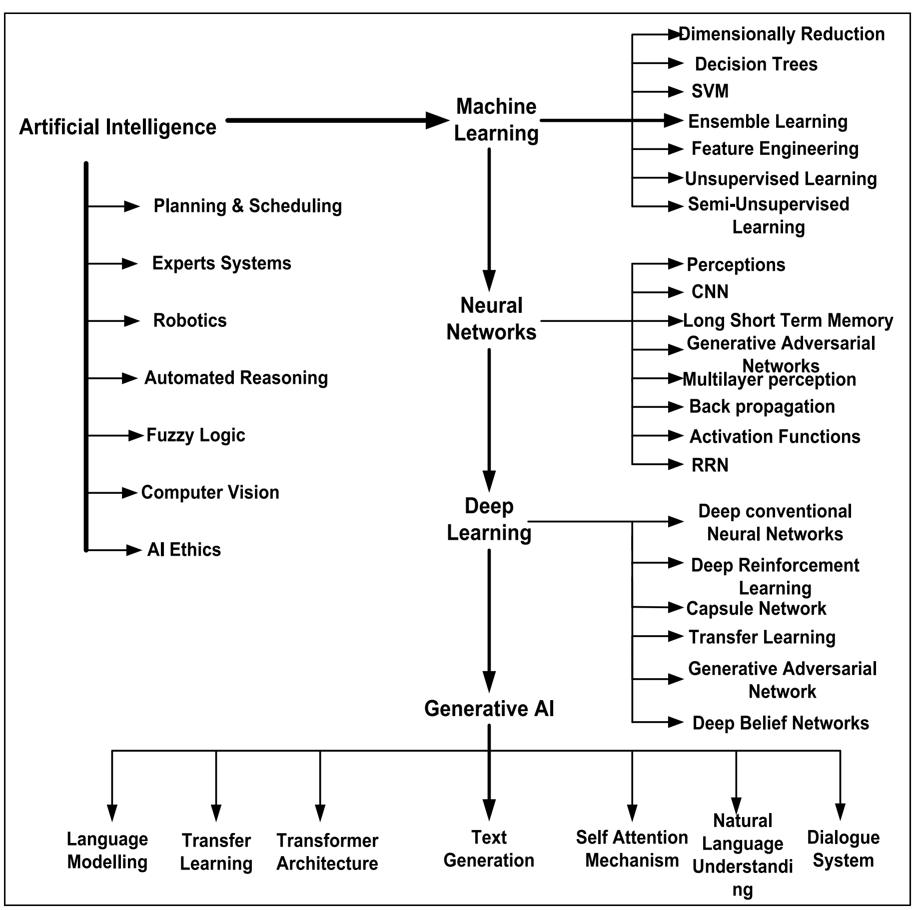

Fig. 9. Emerging trends in Microgrid.

and blockchain technologies to support the evolution of intelligent, resilient microgrids.

Informed consent statement

Not applicable.

Institutional review board statement

Not applicable.

Ethical approval

Not applicable.

Author contributions

G.S.N: Conceptualization, Writing-Original Draft, Writing-Review and Editing Investigation. H.M: Conceptualization, Writing-Original Draft, Writing-Review and Editing Investigation. M.K.G: Conceptualization, Writing-Original Draft, Writing-Review and Editing Investigation. R.S: Writing-Review and Editing, Supervision; A.G: Conceptualization, Writing-Review and Editing, Supervision. A.K.T.: Writing-Review and Editing, Supervision. S.D.: Writing-Review and Editing, Supervision. L.R.G.: Writing-Review and Editing, Supervision. All authors have read and agreed to the published version of the manuscript.

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Declaration of competing interest

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Data availability

No data was used for the research described in the article.

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