

An overview of Artificial Intelligence applications to electrical power systems and DC microgrids

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Abstract. Microgrids are composed of distributed energy resources such as energy storage devices, photovoltaic (PV) systems, backup generators, and wind energy conversion systems. Because renewable energy sources are intermittent, modern power networks must overcome the stochastic problem of increasing the penetration of renewable energy, which necessitates precise demand forecasting to deliver the best possible power supply. Technologies based on artificial intelligence (AI) have become a viable means of implementing and optimizing microgrid energy management. Owing to the sporadic nature of renewable energy sources, artificial intelligence offers a range of solutions based on the growth in sensor data and compute capacity to create sustainable and dependable power. Artificial intelligence (AI) techniques continue to evolve in DC Microgrids with the aim of perfect voltage profile, minimum distribution losses, optimal schedule of power, planning and controlling of grid parameters and lowering unit price. AI methods can improve DC Micro grid performance by monitoring and controlling the grid parameters by reducing the computational and processing time. This paper offers a comprehensive summary of some of the most recent research on artificial intelligence techniques used to DC Micro grids and electrical power system networks.

1 Introduction

In recent years, the increasing demand for energy efficiency, renewable energy integration, and enhanced grid resiliency has propelled the development and adoption of microgrids. Among the various types of microgrids, direct current (DC) microgrids have garnered significant attention due to their inherent advantages in certain applications. DC microgrids offer distinct benefits such as improved efficiency, easier integration of renewable energy sources, and seamless incorporation of energy storage systems. These features make DC microgrids an attractive solution for a wide range of applications, including remote communities, data centres, electric vehicle charging stations, and residential complexes [1].

Despite their promising advantages, DC microgrids also face several challenges like Control, Stability, Protection Coordination, Interoperability and Standardization, Operational Efficiency, Conversion Losses, Cost and Economics that need to be addressed for their widespread implementation and optimal operation. These challenges encompass technical, regulatory, economic, and operational aspects, and overcoming them is crucial for realizing the full potential of DC microgrid technology. [2-4]

AI plays a crucial role in optimizing the operation, management, and performance of DC microgrid systems, enabling them to operate efficiently, reliably, and cost-effectively in diverse applications and

environments. As AI technologies continue to advance, their integration into DC microgrid systems is expected to further enhance their capabilities and accelerate the transition towards sustainable and resilient energy systems [5-7].

2 Role of AI in Electrical Power Systems

The term artificial intelligence (AI) describes how computers, especially computer systems, may simulate human intelligence processes. Learning (the process of acquiring knowledge and applying rules to it), reasoning (using rules to arrive at approximations or conclusions), and self-correction are some examples of these processes. Artificial Intelligence (AI) approaches are utilized in electrical power systems to improve several areas of system control, optimization, and maintenance. a variety of AI methods that can be used in electrical power systems for data collection and analysis. These strategies are more specialized literature in the field and will depend on your particular needs and the complexity of the system.

Data acquisition in electrical power systems involves collecting, processing, and analysing data from various sensors, meters and devices. An intelligent data acquisition techniques helps to enhance the quality of data.

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Table 1. AI applications in electrical power systems

Area of Application	Function	Suitable AI Techniques
Data Acquisition	Gathering information about: Voltage and current levels, Power generations, Load demand, Weather conditions, Equipment status.	Machine Learning algorithms [8, 23, 24, 30, 34, 41] Data Mining [9]
Load Forecasting	Analyse the historical data with constraints like Weather factors, Holidays and Peak hours, and Unit price.	Optimization Algorithms [10] Fuzzy Logic Systems [11, 21, 26] Cyber-Physical Systems [12],
Fault Detection and Diagnosis	Analyse the sensor data to detects and diagnose the faults and abnormality conditions. And analyse the performance degradation of installed devices.	Artificial Neural Networks [13, 14, 19,65]
Energy Management and Optimization	Optimize the operation of generation, transmission, and distribution assets.	Support Vector Machines [15, 20] Time Series Analysis [16] Deep learning [17, 42]
Grid Stability and Control	Dynamically adjusting control parameters. Coordinating distributed energy resources (DERs) Mitigating disturbances	Hybrid AI Models [18, 29] Expert Systems [22]
Renewable Energy Integration	Facilitate the integration of renewable energy sources, Forecasting renewable generation	Reinforcement Learning [25, 31, 35] Genetic Algorithms [27] Particle Swam Organization [28]
Cybersecurity and Threat Detection	Anomaly Detection, Behavioural Analysis, Intrusion Detection, Cyber Threat Intelligence, Robustness, Network Traffic Analysis	Predictive Analysis [32, 36] Optimization algorithms [33, 37] Logistic Regression [38]
Asset Monitoring and Maintenance	Sensor data and historical performance data. Assess the health condition and remaining useful life of power system assets.	Decision Trees [39, 40] Natural Language Processing [43] Adversarial Machine Learning [44]

AI based load forecasting techniques predict the demand based the historical data and enables the optimum planning of generation. AI techniques reduce the complexity of decision-making process in the energy management and optimization. AI techniques play a significant role in enhancing grid stability and control.

The combined and customized AI based algorithms can give optimised solution to solve the challenges of RES integration into the grid. The Services of the AI are extended to the field of asset monitoring and maintenance enhance predictive maintenance capabilities, reduce downtime, and optimize resource utilization in electrical power systems.

Analysing cybersecurity and threat detection in electrical power systems involves understanding and mitigating various cyber threats that can impact the operation and security of power grids. AI techniques play a crucial role in enhancing cybersecurity measures and detecting potential in real-time. The detailed applications of AI methods in electrical power systems given in table 1. AI empowers electrical power systems to become more intelligent, adaptive, and efficient in meeting the growing challenges of modern energy management, grid optimization, and sustainability goals.

3 Applications of AI Techniques in DC Microgrids

The DC microgrids can be efficiently implemented, when the there is effective control on every component of the system. AI technologies positively support the DC microgrid applications. The intelligent approaches can be effectively applied in the control of energy management systems as well as energy storage systems to provide best suitable solutions to microgrid challenges.

One kind of artificial intelligence called machine learning has the potential to enhance microgrid management and operation. ML can be roughly divided into four categories: semi-supervised, supervised, unsupervised, and reinforcement learning. AI approaches improve the resilience, efficiency, and dependability of DC microgrids by providing creative solutions to a range of problems. The applications of AI in DC microgrid extended to the following areas.

1. Optimal energy scheduling.
2. Load forecasting and Demand response.
3. Distribution Energy Resources integration
4. Fault Detection and Diagnostics
5. Cyber security and resilience
6. Optimized control and Coordination
7. Predictive Maintenance
8. Data collection and analysis
9. Reliability and Efficiency analysis
10. Control and Management in DC microgrid
11. Performance analysis
12. Simulation and validation of models

Here are a few AI technologies for DC microgrids that have been covered in the literature.

4 Optimal Energy Management

In DC microgrids, optimal power scheduling and network analysis are often carried out separately. Planning DER output is the goal of optimal power scheduling, and network analysis maximizes voltage stability to provide the output. The difficulty of the task increases when one must maintain both optimal power scheduling and voltage control. Dynamic programming has the advantage of reducing the complexity by dividing complex problem into several stages. The operating cost of the DC distribution system for all possible state combinations is computed by dividing the state by the available SOC range and determining the

status of the dynamic programming approach for each hour of optimal planning. The dynamic programming approach is used to calculate the optimal path, which minimizes the overall cost of each step [45, 46]. Simulation demonstrates that the problem's complexity is decreased when dynamic programming is used, and the outcomes of the best scheduling are realistic

Fuzzy logic and Fuzzy inference systems are another AI solution for optimal energy management in DC microgrids due to their flexibility and computation speed. Fuzzy logic is regarded as an efficient approach when the situation is highly uncertain and requires a quicker answer [47]. The Fuzzy Logic based energy management systems for Microgrid for load shifting application can enable the fast-decision-making process so that system can operate quickly. The fuzzy logic system for energy management systems is the combination of mamdani fuzzy interference systems and genetic algorithms [48].

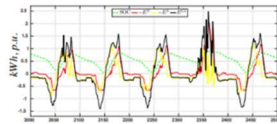


Fig. 1. MG energy profiles on the Test Set for solution [49]

Figure 1 illustrates the effectiveness of the three energy management systems' best-optimized solutions in terms of grid stress and microgrid energy auto-consumption, respectively [49]. The findings indicate that between the 48% and the 28%, auto-consumption performance has been optimized. The reduction in grid stress ranges from 44% to 22%. Furthermore, there is always a significant peak shaving percentage—more than 30%—in relation to the maximum power that is demanded from the grid. Thus, genetic algorithms (GAs) and fuzzy logic systems function well for microgrid energy optimization.

5 Load forecasting and Demand Response

The objective of the load forecasting to provide load forecasting can be used to analyse the grid control and demand response applications [50]. In the smart grid, demand response programs can make the grid more cost efficient and resilient. The forecasting techniques consider the inputs from variables like climate, social, economic and habit related consumables. The gradual integration of intelligence in transmission, distribution and consumer levels of electrical power system maximises the reliability and efficiency of the system. The load forecasting is the one of major problems due to uncertainty in the variables. To address this problem, it is necessary to adopt AI technologies [51]. The horizons of the load forecasting are classified as Very short-term, Short-Term, Medium-Term, and Long-Term.

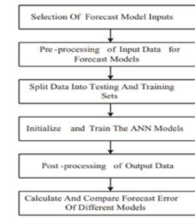


Fig. 2. ANN base load forecast model flowchart [52]

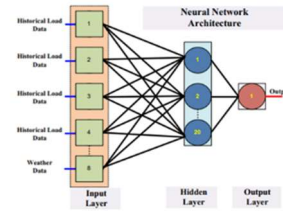


Fig. 3. Multilayer perceptron NN for load forecasting [52]

Since 1980, the ANN proved as a powerful computational tool for load forecasting and prediction problems. The ANN has more advantages as it can extract the nonlinear relationship between input and output variables using training process of network. The primary steps ANN based load forecast model are shown in Fig. 2. Multilayer perceptron neural networks have better flexibility to learn the input constraints and provide best forecast results [54]. The multilayer perception model for load forecasting is presented in figure 3, in which various historical load and weather conditions are fed as input and forecast data as output.

Demand response is the very recent approach to maintain energy balance in the DC microgrids in context of uncertainty of generation from DERs, capacity of energy storage systems. The dynamic pricing, smart metering, and advanced communication technologies make demand response more reliable, which automatically influence the performance of the system. The figure 4 shows how demand response work on the power systems. DR is also called as flexible load shape because of its ability to respond to changes [54].



Fig. 4. Workflow of Demand response in distribution network [54]



Fig. 5. Summary of AI techniques for Demand Response in DC microgrids [54]

Artificial Intelligence (AI) is the study of computer programs that can analyze their environment and take appropriate action to achieve specific goals. For demand response research, supervised learning AI techniques

using tree- and kernel-based methodologies combined with linear regression models are used [55]. When there are uncertainties in the available data or measurement mistakes in demand response research, unsupervised AI approaches are taken into consideration. The most effective unsupervised method for analyzing the disorganized data from the load profiles is clustering. Demand response is made possible by the relayed reward and trial-and-error approach of reinforcement learning, which allows the microgrids to monitor and manage different types of load. The Evolutionary Algorithm (EA) under DR approaches establishes the most economical electricity tariff for customers [56]. DR optimization issues are notoriously non-convex because of their enormous number of variables, quadratic optimization functions, and power flow computation-related constraints. At the home level, rates for the aggregators and the best appliance schedule are determined using the Wind Driven Optimization (WDO), Artificial Immune System (AIS), and Particle Swarm Optimization (PSO) algorithms [57]. Systems with several agents are used to assess pricing, scheduling, and demand response accuracy. Figure 5 summarizes the AI technologies that can be used for DC microgrid load forecasting and demand response.

DER can supply energy to whole distribution systems, serving as a supplement or replacement for the traditional power grid [58]. In addition, DER-based distribution networks guarantee the energy independence of consumers and offer better power quality and service reliability. DER is a great addition to the power generation mix and a component of the green solution for a sustainable environment when it employs any renewable technology. Several technical obstacles must be overcome for DER integration into DC microgrids at the distribution level, including reverse power flow, frequency variation, islanding, grid stability, and power quality problems [59]. In DC microgrids, artificial intelligence (AI) is essential to the integration of distributed energy resources (DERs). In order for AI to provide a better solution for the problems faced by DC microgrids, data analysis, optimization, and control approaches must be combined when integrating Renewable Energy Sources (RES) into DC microgrids.

Predictive modelling with machine learning algorithms, Support vector machines and ANN can predict renewable energy and helps in better resource allocation and scheduling in the DC microgrid [60-63]. Genetic Algorithms can optimize the location and sizing of RES and energy storage systems in the microgrid with respect to the constraints like load demand and unit price [64]. Particle swarm optimization algorithms can optimize the operation of DERs to increase efficiency and grid stability [65]. To increase the efficiency and reduce the line loss of distribution networks in DC microgrids Ant Colony Optimization algorithms effectively worked [66]. Reinforcement learning techniques can be employed for adaptive energy management in DC microgrids. RL agents learn optimal control policies based on feedback from the grid's performance, adjusting energy flows and storage

strategies to meet changing demands and grid conditions [67-69].

By offering enhanced capabilities in load forecasting, energy management, fault detection, optimal control, cybersecurity, and demand response optimization, artificial intelligence (AI) tools are transforming the field of DC microgrids. Microgrid systems can be made more reliable, secure, and efficient by using machine learning, reinforcement learning, genetic algorithms, predictive optimizations, ANNs, and Particle swarm optimization algorithms. Even though there are obstacles like data privacy concerns and integration difficulties, research and development activities are concentrated on getting beyond these barriers to fully realize AI's potential in influencing how energy is distributed and managed in DC microgrids in the future. Altogether AI techniques are instrumental in advancing the capabilities of DC microgrids, paving the way for more efficient, resilient, and sustainable energy distribution systems.

6 Future of AI Techniques in DC Microgrids

The aim of DC microgrids is to obtain a fully autonomous operating system that maintains, reliability, efficiency, fault tolerance and grid stability. And also protects the systems from data theft and cyber-attacks at cost effective level. The future of AI techniques in DC microgrids is poised for significant growth and innovation. As AI technologies continue to evolve, we can expect more sophisticated algorithms and models tailored specifically for microgrid applications. One of the key areas of development will be in real-time adaptive control systems that can dynamically adjust to changing grid conditions and optimize energy flows in response to fluctuating demand and supply patterns. Additionally, AI-driven autonomous operation and decision-making will play a crucial role in enhancing grid resilience, self-healing capabilities, and overall system reliability. Collaborative efforts between researchers, industry stakeholders, and policymakers will drive the adoption of AI techniques, leading to more efficient, sustainable, and interconnected DC microgrid ecosystems that contribute to a cleaner and more resilient energy future.

7 Limitations of AI Techniques in DC Microgrids

Although AI techniques have great promise to optimize DC microgrid administration and operation, there are a few issues that need to be resolved. The need for vast quantities of high-quality data for efficient AI model training is one major obstacle. Data quality and availability may occasionally be restricted, particularly in isolated or underdeveloped places where microgrids are installed. This may impede the efficacy and precision of AI systems, resulting in less-than-ideal choices being made. The intricacy and interpretability of AI models is another drawback. It can be difficult to interpret complex models, such deep learning neural

networks, which makes it tough to comprehend the logic behind AI-driven judgments. This is important since trust and transparency are essential in key energy systems. Additionally, a lot of computational power and energy may be needed for AI techniques, which might be problematic in contexts with limited resources. It will take innovations in data gathering, preprocessing, model interpretability, and optimization algorithms designed with DC microgrids' particular features in mind to overcome these constraints.

8 Conclusions

As the traditional power system transforming to smart microgrid systems, the limitations in processing and analysing the huge amount of data with conventional methods is very difficult. Hence AI algorithms are catching the interest of microgrid researchers. This article presents various AI methods implementation to electrical power systems and DC microgrids. AI techniques represent a promising frontier in the evolution of DC microgrids, offering transformative capabilities in load forecasting, energy management, fault detection, cybersecurity, and demand response optimization. While there are challenges such as data availability, model interpretability, and computational resource requirements, ongoing research and development efforts are addressing these limitations. The future of AI in DC microgrids holds tremendous potential for creating smarter, more efficient, and resilient energy distribution systems. Collaborative endeavours between academia, industry, and policymakers will be instrumental in harnessing the full benefits of AI techniques, driving innovation, and paving the way for a sustainable and reliable energy future. With continued advancements and strategic implementation, AI-powered DC microgrids can play a pivotal role in meeting the growing energy demands while reducing environmental impact and enhancing energy access globally.

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