Leveraging Artificial Intelligence for Enhanced Distributed Control Strategies in Low-Inertia Microgrids: Current Approaches, Challenges, and Quantitative Assessment Methods

Aakash Shukla[1], Aaditya Singh[1], Akash Singh[1], Ayush Sahu[1], Tushar Khandelwal[1], and Yuvraj Singh Thakur[1]

Bhilai Institute of Technology, Bhilai House, Durg, Chhattisgarh, India

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ABSTRACT

With the trend of accelerated integration in power systems having renewable energy sources, low-inertia microgrids have become one of the most significant points of interest in modern energy management. The aim of this paper is to investigate how AI can help improve distributed control methods within these systems. To better analyze this topic, we outline what low-inertia microgrids are, look at distinctive characteristics of these systems, and discuss challenges with stability in frequency control. The paper contributes to several AI methodologies, including machine learning and predictive analytics, which resolve the above mentioned problems through better decision-making processes and optimal energy management. A review of the current AI-driven control frameworks undergoes detailed analysis regarding the indicators for measuring stability and efficiency of operations. Quantitative metrics to explain effectiveness, simulation tools, and comparative analyses are applied to show greater efficacy of approaches based on AI against conventional means. A crucial aspect related to microgrid systems is that there arise technical and practical challenges associated with AI : such urgency requires robust data governance and algorithm reliability. Such emerging trends and possibilities of collaboration across disciplines are the avenues that the authors propose for further work to bridge some gaps in the use of AI for low-inertia microgrids. Ultimately, such a review offers extreme value for researchers and practitioners in contributing to the advancement of sustainable energy management practices.

Introduction

Low-inertia microgrids are systems with high penetration of IBRs and renewable energy sources, which reduce system inertia compared to traditional microgrids. According to Dhople (2017), the kind of reduction in inertia leads to some challenges regarding frequency control and stability, thus making the task more difficult. According to Awda et al. (2023), with the aim of counteracting this, grid-forming and grid-following inverters can offer frequency support; this depends on microgrid size and level of grid inertia. Low-inertia microgrids require energy storage for the preservation of frequency and voltage stability, and according to Toliyat and Kwasinski (2015), proper sizing of the energy storage is necessary to ensure sufficient margins in stability are achieved. More importantly, dynamics of the end-use loads would be more important in the low-inertia microgrid; therefore, multi-state models that are electromechanical will be required for the detailed and cost-effective equipment sizing that supports resilient operations (Tuffner et al., 2019). Generally, it will be required to integrate all of these elements for proper operation of the low-inertia microgrid (Dhople, 2017; Awda et al., 2023; Toliyat & Kwasinski, 2015).

With the increased penetration of renewable energy sources and power electronic inverters, inertial responses in power systems have declined, making it troublesome to sustain frequency stability. As Ratnam Kamala Sarojini et al. quoted, "The recent tendency toward low-inertia systems has ignited research on microgrids, which provide many merits but require careful control and management.". Toliyat and

Kwasinski (2015) recommend that energy storage systems ought to be integrated in a network to maintain the frequency as well as voltage stability during low-inertia microgrid. Moreover, transitioning traditional fossil fuel-based power stations to renewable energy sources necessitates deeper understanding of generation accompanied by power electronics, to interact with the power supply grid, as noted by Milano et al. (2018). The significance of end-use load dynamics grows, especially to support resilience-based operations, in low-inertia microgrids. Accurate modeling of these load dynamics helps in cost-effective size of equipment while supporting loads that are critical for each operation scenario (Tuffner et al., 2019). Overall, managing low-inertia microgrids would require solving some of these challenges (Ratnam Kamala Sarojini et al., 2020; Toliyat & Kwasinski, 2015; Milano et al., 2018).

Artificial intelligence is a promising solution to the problems of low-inertia microgrids. According to Mohammadi et al. (2022), AI techniques can enhance the efficiency, stability, security, and reliability of microgrids by solving problems such as uncertainties in renewable energy resources, sudden load variations, and energy management. As stated by Wu and Wang, "Deep learning and deep reinforcement learning have recently appeared promising in solving the intricacy of microgrid energy management problems, especially low inertia and high penetration scenarios of renewable energy." Therefore, the AI in a microgrid comprises applications related to energy management, prediction related to load and generation, protection, and the control of power electronics; as cited in Mohammadi et al. (2022).

Joshi et al. (2023) further stated that machine learning techniques like artificial neural networks, federated learning, and reinforcement learning are used for economic dispatch, optimal power flow, and scheduling in the microgrid energy management systems. However, challenges are still there, especially in developing economies, where limitations such as limited communication infrastructure and technical skills must be considered when adapting AI methods for microgrid applications (Bodewes et al., 2024). Overall, using AI in microgrid management offers much promise while also posing challenges that must be approached with care (Mohammadi et al., 2022; Wu & Wang, 2021; Joshi et al., 2023).

Thus, AI has emerged as a promising approach toward energy management in microgrids towards tackling issues of uncertainties over renewables and sudden load fluctuations. According to Mohammadi et al. (2022), AI techniques like machine learning, neural networks, and reinforcement learning can be exploited to improve microgrid performance in various sectors such as economic dispatch as well as optimal power flow and scheduling. According to Joshi et al. (2023), research suggested the possible use of AI-driven microgrid energy management systems that would enhance the efficiency, reliability, and real-time responsiveness of microgrids.

AI application in microgrids extends into load and generation forecasting, protection, control of power electronics, and cybersecurity among others. With AI technology comes several benefits to managing energy in microgrids. But as Joshi et al. (2023) pointed out the issues remain those of data privacy, security, and scalability. Overall, the application of AI technology in the management of energy systems in microgrids promises immense potential toward reaching sustainability and resilience in decentralized systems (Altin & Eyimaya, 2023; Oudinga, 2023).

AI techniques are increasingly being applied in the search for better control and management strategies in microgrids. AI applies promising solutions in solving problems in microgrid environments, specifically regarding the integration of distributed energy resources, energy management, and control of power electronics. According to Trivedi and Khadem (2022), the application of these techniques will enhance the accuracy of forecasting, optimize resource allocation, and ensure stability in the face of uncertainties associated with renewable energy sources and load variations. There are several areas that fall under AI applications in microgrids, which include energy management, load and generation forecasting, protection, and cybersecurity. According to Mohammadi et al. (2022), some AI methods utilized include machine learning, artificial neural networks, and fuzzy logic. There is still much promise in the way that further study in hierarchical control structures and networked microgrid environments unlock the capabilities of the AI implementation, according to several authors, such as Talaat et al. (2023) and Guerrero Sánchez et al. (2024).

Recent research work identifies the growing importance of artificial intelligence in optimizing distributed control strategies for microgrids. The AI-based approach is particularly useful for ensuring stable and optimal energy management with high uncertainties when the complexity of the system includes nonlinear components. In this context, Hua et al. have noted that such an approach is most beneficial where challenges are related to the intermittent nature of renewable energy sources: wind speed and changes in solar irradiation. AI can be applied across the hierarchical control layers, and therefore it may enhance performance both in the single and networked microgrid environments. According to Trivedi and Khadem (2022), multiple AI technologies are being developed for realizing and optimizing energy management in microgrids, including machine learning and optimization algorithms. This integration of AI with distributed control systems has made microgrids intelligent, safe, and efficient and is a significant direction in future research on energy management, as highlighted by some authors (Altin & Eyimaya, 2023; Bilal et al., 2023).

Understanding Low-Inertia Microgrids

Definition and Characteristics

Low-inertia microgrids have a high penetration of renewable energy sources and energy storage devices interfaced through power electronic inverters with limited or no synchronous generators. According to Dhople et al. (2017), such systems are already compounded with problems of stability due to a reduced system inertia hence, frequency and voltage control more demanding. Toliyat and Kwasinski et al. (2015) emphasize that such problems can be solved by proper sizing of energy storage systems that maintain stability margins. Microgrids can provide frequency responses to supplement low-inertia grids, and for this reason, it is worthwhile to compare the effectiveness of grid-forming and grid-following inverters. Virtual inertia controllers, which include high-pass filters-based ones, have been proposed to maintain the frequency stability of AC microgrids while ensuring the stability of DC voltage in hybrid AC-DC systems, as stated by Awda et al. (2023). These strategies relate to facilitating the integration of renewable energy sources and improving overall stability and performance of low-inertia microgrids, according to several authors (Toliyat & Kwasinski, 2015; Afifi et al., 2023).

Low-inertia microgrids, mostly based on renewable energy sources and power electronic interfaces, introduce specific challenges in control and stability. These elements, according to Dhople et al. (2017), include voltage source inverters converting the energy and virtual inertia control for enhanced stability. Kerdphol et al. (2019) highlighted that virtual inertia control is necessary because the system inertia is low, and they further supported the idea that the robust H∞ control scheme is superior to other schemes in dealing with measurement effects of frequency and uncertainties. The third aspect is the frequency droop control because it allows the generators to adapt to the changes in loading without losing stability as claimed by Bollman et al. (2010). As inverter-based generation is on the rise, end-use dynamics of loads become increasingly important in the design of microgrids in a way that will ensure a resilient yet cost-effective system. Tuffner et al. (2019) report "Components combined are essential to operate microgrids with low inertia stability and efficiency across conditions with various authors concluding to have an agreement".

Low-inertia microgrids are much more operationally challenging than high-inertia systems. These are usually inverter-based, with very little or no inertia, so end-use load dynamics have to be considered in designing resilient operations, as noted by Tuffner et al. (2019). The limited generation capacity and rotating inertia in low-inertia systems can lead to generator overloading during significant disturbances, which Feng et al. (2013) argues is a critical concern.

There have been proposed novel control strategies in addressing these challenges. The dynamic balancing technique may obtain real-time generation and load balancing while meeting operational constraints in low-inertia systems (Feng, 2013). Moreover, voltage source inverters are essential for interfacing DC-energy resources with the AC network in islanded microgrids (Dhople, 2017). The integration of both Grid-Forming and Grid-Following control strategies in the inverters may also lead to further frequency regulation in low-inertia systems, hence ensuring enhanced stability and resilience (Zhang, 2020).

Stability Challenges

Low-inertia microgrids are prone to issues related to stability, in particular frequency control. It is the rising penetration of RESs such as wind and solar power that often lack the physical inertia normally provided by synchronous generators. According to Afifi (2024), without physical inertia, islanded microgrids are at a higher risk of frequency instability whenever there is a sudden change in load or when a generation unit becomes disconnected.

Adding to the complexity of low-inertia dynamics is the rapid fluctuation of RES output. Kerdphol et al. (2019) mention that the absence of mechanical inertia in high RES-based power electronic-based microgrids might lead to severe voltage and frequency oscillations, hence instability in the system. Nour (2023) mentions that sudden load or generation changes may cause a sudden increase in RoCoF and deviation in frequency, which may cause instability in the system.

These should be adapted control strategies toward these challenges in low-inertia microgrids. The traditional control strategies would not be enough because of the distinctive characteristics of inverter-based resources. This sense, Ojo et al. (2021) discuss frequency and voltage regulation using grid-forming inverters, which have inherently low inertia and introduce new operational challenges. Various innovative control strategies proposed toward facing these challenges include virtual inertia control. The VIC aims at emulating the inertial response of conventional generators using ESS for damping frequency support (Roudi et al., 2021; Amiri, 2023).

The integration of energy storage systems is important in alleviating the adverse impacts of low inertia. According to Roudi et al. (2021), the use of ESSs can help in mitigating frequency deviations and, by extension, stability within microgrids characterized by a low-inertia power profile. In the same vain, Kerdphol et al. (2019) presented several strong virtual inertia control strategies capable of withstanding various uncertainty sources such as measurement delay. Developing such advanced control strategies is very crucial for maintaining the integrity of the operational sustainability of microgrids as they transition towards higher renewable energy integration.

In summary, low inertia microgrids are challenging to control in terms of frequency because of reduced mechanical inertia, which is more or less a by-product of high RES penetration. The need for inverter-based generation requires the advent of innovative control strategies that can mimic the effect of virtual inertia control to maintain frequency stability. Energy storage systems form a crucial enabler to overcome these challenges and allow microgrids to be operated reliably as the energy landscape becomes progressively dominated by renewable energy (Afifi, 2024; Kerdphol et al., 2019).

Variations in renewable energy sources are significant causes of instability in low-inertia microgrids. This is mainly because renewable energy sources vary inherently, and hence the task of maintaining frequency becomes very challenging. The overall inertia of a microgrid gets reduced when the penetration levels of RESs like wind and solar increase, thus making the microgrid sensitive to any disturbance. According to Banki et al. (2020), the microgrid may face extreme energy shocks from irregular wind speeds and variable solar irradiation, which worsen frequency oscillations and instability. Moreover, reduced system inertia of traditional diesel generators is a problem because of their poor response to such oscillations, and their contribution to the system inertia is negligible when high RES penetration is in place.

The intermittency of RESs is therefore the key challenge to frequency stability. This is because, according to Qi and Tsuji (2023), replacement of synchronous generators using asynchronous RESs reduces the overall inertia in microgrids, thus rendering frequency regulation tougher. Since inertia decreases, even the slightest disturbances can lead to significant frequency deviations as the system no longer has the usual buffer capability associated with synchronous generators. This same author argues that Fadheel (2024) even underlines this by claiming that the higher penetration of RESs might raise fragile frequency oscillations, making the very problem to be tackled to solve the problem of system instability much harder to solve.

Apart from this, the fact that RESs cannot participate in frequency modulation due to interconnection through inverters aggravates the situation. As Santra (2023) puts it, absence of natural inertia in the generation based on RES sources causes frequency deviations and so effective LFC mechanisms should be in place for keeping the system stable. These fluctuations not only have theoretical but also practical issues in that sudden changes in loads or the generation might create instability within low-inertia microgrids (Nour, 2023).

Integration of energy storage systems is generally considered an alleviation solution to such fluctuations. Coordination between demand response and energy storage can be utilized for minimizing frequency excursions in hybrid microgrids and hence improve the stability of the system, as observed by Babaei et al. (2020). Advanced control strategies such as model predictive control are also being implemented to better manage the stochastic nature of RESs and ensure frequency stability (Zhao, 2023). These strategies aim to emulate the damping and inertia characteristics of traditional systems, providing a buffer against the rapid fluctuations associated with high RES penetration (Criollo, 2024; Magdy et al., 2021).

In conclusion, such instability caused by the fluctuation of renewable sources of energy has a great influence on low-inertia microgrids. As maintained by Banki et al. (2020) and Qi and Tsuji (2023), replacing the traditional generators with RESs demands new approaches involving energy storage integration and new control methods to guarantee reliability within an increasingly variable energy context.

AI Techniques in Distributed Control Strategies

Overview of AI in Microgrid Control

More AI techniques are applied in the control strategies of microgrids in addressing problems related to uncertainties, energy management, and system stability. According to Wu and Wang (2021), deep learning and deep reinforcement learning can be promising approaches to solving decision-making problems in microgrid operations. AI methods like machine learning, artificial neural networks, and fuzzy logic are used in several tasks including energy management, load forecasting, and protection in microgrids (Mohammadi et al., 2022).

Espina et al. (2020) note that linear consensus and finite-time consensus protocols are currently being used to explore primary, secondary, and tertiary control of microgrids for distributed cooperative control systems. Additionally, Trivedi and Khadem (2022) assert that the application of AI will be a good remedy to boost the control and operation of microgrids in the future smart grid networks with applications in the hierarchical control layers and networked microgrid environments. These AI-based methods are developed with the focus of achieving improved efficiency, stability, and reliability in microgrid systems.

The integration of AI in microgrid control enhances decision-making processes by solving complex challenges in energy management and control. According to Wu and Wang (2021), AI techniques, such as deep learning and reinforcement learning, offer promising solutions for optimizing microgrid operations, improving energy efficiency, and enhancing system reliability. Oudinga (2023) observes that AI-driven systems exhibit superior performance in real-time adaptability, power efficiency, and reliability compared to conventional control methods.

Hasani et al. (2024) pointed out that sophisticated predictive AI-based control strategies like deep neural networks are apt enough to predict the precise and accurate power demand generation and will lead to effective advance planning and optimization for managing microgrids. Such an AI-based method addresses issues like voltage deviation or frequency deviation in an efficient manner during islanding, minimizes the communication dependent devices, and brings forth the unification between the primary and secondary controlling methods.

Overall, the integration of AI in microgrids promises significant advancements in sustainability, resilience, and operational efficiency (Trivedi & Khadem, 2022; Oudinga, 2023).

Machine Learning Approaches

Machine learning techniques have shown promise for the microgrid load forecasting; it works in the face of dynamic demand and scarce availability of data. Devender Singh and Suneet Singh, (2002) and E. Mele, (2019) show the use of supervised as well as unsupervised learning using artificial neural networks, support vector machines, and k-nearest neighbors, respectively by S. N. B. Rao et al. (2022) indicate that ANN models, particularly optimized with the Levenberg-Marquardt algorithm, are superior compared to other models in the case of day-ahead load forecasting for urban community cluster microgrids. Additionally, E. Genov et al. (2021) report that FFNN and RNN models were competitive in short-term load forecasting, while cross-learning methods improved accuracy in certain cases. These methods are typically judged based on their root mean square error, mean absolute percentage error, and R-square values. However, even though the best approach is machine learning, it can be expected that a particular microgrid would prefer another depending on specific performance metrics for a microgrid.

RL has very promising solutions for adaptive microgrid control in real-time. Boukas and Ernst (2019) explain that methods based on RL are able to integrate a multiplicity of control tasks such as parameter estimation, forecasting, planning, and real-time control, with automatic adaptation to system changes without any tuning. Hasan et al. (2022) reported that these methods were shown to be effective for regulating frequency and voltage in a wide range of operating conditions. In addition, Younesi et al. (2020) explain how RL controllers can complement the existing control systems through adaptive offset signals, yielding an improved dynamic response relative to traditional controllers in terms of damping voltage and frequency oscillations. Chen et al. (2023) also assert that the problems of modern microgrid systems, where inertia is low and damping relatively low, are overcome with RL techniques since they allow a fast adaptive control through real-time interaction with the environment. This approaches are useful particularly for renewable energy microgrids as well as electric vehicles systems and enhance stability and resiliency in the systems (Hasan et al., 2022).

Predictive Analytics

Predictive analytics is essential in the process of improving demand forecasting as well as supply optimization of microgrids. Machine learning techniques, which include artificial neural networks as well as deep learning techniques, are widely used by Wazirali et al. (2023) for short-term load forecasting and renewable energy prediction. These methods leverage information from smart meters, as well as weather and past consumption data, according to Mirowski et al. (2014). Furthermore, Mehdipour Pirbazari (2021) observes that lagged loads, air temperature, and time variables are significant in household consumption and generation behavior. Yin et al. (2019) argue that big data analytics of smart grid data sources can improve demand response estimation, event detection in synchrophasor data, and peak demand management. This integration reduces the risks and enhances microgrid reliability by having better estimation of energy supply and demand, thereby helping to maintain power system stability (Mehdipour Pirbazari, 2021; Wazirali et al., 2023).

Data quality forms the backbone of the functionality of predictive analytics in the management of microgrids. According to Queiroz et al. (2015), high-quality data is required for exact renewable energy production and consumption forecasting. Sundararajan et al. (2022) explain that factors of data quality include completeness, missing observations, epistemic uncertainties, and data drift, which determine generalization in forecasting models. Low data quality generates a low-level of accurate predictive analysis which affects decision making and strategic planning at an organizational level. Indeed, Nugroho 2023 explains that improvements are needed with regard to data quality. In terms of this fact, there has been research on proposed frameworks for being data-quality aware, based on existing data quality techniques such as handling missing values, implementing divergence tests and continuous generalized performance monitoring in Sundararajan et al (2022). Empirically, the quantity versus error relationship, according to Cui et al. (2021), is due to a power law that validates the necessity of appropriate quantification of data in conjunction with quality of data associated with online energy dispatch management into microgrids, thus achieving robustness in proper handling and evaluating the prepared as well as quality of data, which is essential for proper microgrid management.

Enhancing Stability and Control with AI

AI-Driven Control Strategies

A plethora of recent studies indicate potential in AI-based control architecture for low-inertia microgrids. According to Wu and Wang (2021), deep learning and deep reinforcement learning has been shown useful in challenging situations like inertia, uncertainties in generation, and other complexities in the network structure. Trivedi and Khadem (2022) discuss AI methods as applied to enhance microgrid control and operation, such as in hierarchical control layers and networked environments. Afifi et al. (2024) also present reinforcement learning agents, TD3 and DDPG, to aid in frequency support for low-inertia microgrids, where the former provides better performance than conventional control schemes. According to Chandna (2023), AI-based methods attempt to bypass the limitation of the classical control techniques at its failure to manage the integration and coordination of the dispersed resources in dynamic environments. As microgrids become more prevalent, there is much promise in the use of AI to better control and analyze the operational performance of future smart grids.

Several case studies illustrate the successful integration of AI technologies in microgrid systems, demonstrating improvements in energy management, stability, and resilience.

A case worth mentioning is the optimization of low-inertia islanded microgrids' frequency stability using AI algorithms. The case is discussed by Hamanah (2024) in how optimized virtual inertia control, through AI capabilities, can significantly improve the dynamic stability and restore a very important factor in virtual inertia for reliable power system maintenance. This addresses typical problems of DG systems commonly replacing conventional synchronous generators with negative impacts on the frequency stability. Advanced control strategies have been proved as promising factors that can improve the stability of microgrids in terms of both frequency and voltage.

In that case, the most evident one pertains to the implementation of EVs in microgrids. Johansson et al. (2019) highlights the horizon for broad-scale integration of EVs towards the development of an AC/DC microgrid. In that respect, the use of optimal charging controllers and decentralized control architectures can be effective to make the respective microgrid more stable, thus establishing evidence for AI implementation in complex energy system management. It will balance the energy supply and demand while contributing to the resilience of the microgrid as a whole. The third most important application of AI relates to microgrid stability, which is based on energy forecasting. Islam (2024) emphasizes AI has proven significantly efficient in the use of ANN and ANFIS systems for capturing the underlying relationships within renewable energy data that are complex in nature. Better accuracy in the prediction process leads to operational decisions, which allow a greater share of renewable energies while ensuring overall stability within microgrid operations.

Further, the application of AI in detecting and mitigating cyber attacks is significant for the stability of microgrids. Beg (2023) has discussed various AI-based techniques, such as neural networks that are applied in designing resilient control systems withstanding cyber threats. The application of AI in this aspect is more important due to the increasing interconnectedness of microgrids, which makes them more susceptible to cyber attacks and, therefore, requires a stronger security system to operate continuously.

Additionally, the concept of digital twins, as discussed by Irmak et al. (2023) (Irmak et al., 2023), illustrates how AI can optimize microgrid performance and enhance stability. By creating virtual replicas of microgrids, operators can simulate various scenarios and optimize energy management strategies, leading to improved operational efficiency and stability.

In summary, the integration of AI in microgrid systems has led to significant advances in stability and efficiency. From optimizing frequency control to integrating EVs, increasing forecasting accuracy, and guaranteeing cybersecurity, AI technologies are proving essential in the evolution of microgrids toward more resilient and efficient energy systems.

Performance Improvement Metrics

AI-driven techniques are now becoming integral in microgrids due to the low inertia developed in this system. They use numerous KPIs for proper assessment of techniques. It is mentioned in Hasani et al. (2024) that the techniques include voltage deviations and frequency deviations, since these problems are highly prevailing during the islanding processes. As per Hasani et al. (2024), deep neural networks are further used for developing predictive algorithms for power generation and demand patterns to determine efficiency, reliability, and sustainability. Zahraoui et al. (2024) further highlight that resilience metrics play a critical role during pre-event, event, and post-event phases. Pirani et al. (2017) have also highlighted that system-theoretic performance metrics, such as eigenvalue damping ratios, H2 and H∞ norms are used to quantify grid stability and performance in low-inertia systems. This extends the argument presented by Yegon and Singh (2023) that it explains how the technique-based adaptive virtual inertia control strategies deploy performance indices to assess their enhancement for achieving microgrid frequency stability with ITAE, IAE, ISE, and ITSE. Together, these KPIs determine the stability of microgrid AI-based strategies.

KPIs are very important in measuring the operating efficiency and reliability of microgrid systems. According to Gabbar et al. (2016), such KPIs comprise economic efficiency, reliability, environmental conservation, and power quality. Other researchers, such as Wang et al. (2013), have also produced several metrics to measure the performance of microgrids. These metrics comprise reliability parameters for islanded mode operation, distributed generation and load characteristics indices, economic indices, and customer-based reliability indices. Skowronska et al. (2015) present an MSOM which can be applied to optimization of design and maintenance for a microgrid to obtain minimum failure-free period, failures, and cost. In order to evaluate the entire performance cycle of a microgrid, Tsolakis et al. (2020) proposed a full set of KPIs from an economic, environmental, and technical point of view. In addition, dynamic metrics and customized reference models will become data-driven assessment methodologies for identifying periods of suboptimal operation by emerging as a promising means through which microgrid performance could be classified.

Quantitative Assessment of AI Approaches

Assessment Metrics

With the latest developments, AI has emerged as a means to enhance the controllability and performance of microgrids. According to Mainaa Oudinga (2023), some of the measurable parameters that are utilized for measuring the effectiveness of AI include energy efficiency, reliability indices, and real-time adaptability. Yao et al. (2023) also focus on resilience metrics. The existing event-based corrective scheduling and online model predictive control models reveal a positive side of grid resilience. In addition, Mohammadi et al. (2022) mentioned that machine learning, artificial neural networks, and fuzzy logic techniques have been applied to the microgrid in various ways, including energy management, load forecasting, and protection. Wu and Wang (2021) report that deep learning and deep reinforcement learning have particular promise for complex microgrid challenges like generation uncertainty and network topology optimization. Such approaches have shown potential towards the enhancement of efficiency, stability, and reliability in microgrids. Yet, empirical evidence and experiences based on real data will be needed to confirm the results and address the many challenges that are still surfacing with regard to operating and controlling microgrids.

Key towards the assessment and optimization of resilience in microgrid implementations lies in the standardization of metrics across various deployments. Definition of the primary functions and designing the specifications of those functions must outline the function of control systems of microgrid deployments, as outlined as part of best practice procedure by Joss and Reilly (2018). Yao et al. (2023) established a framework for the quantitative measures of microgrid resilience: a set of quantitative metrics describing the resilience properties for physical interpretation through optimization formulations applied to the microgrids. Chanda and Srivastava (2016) also offer a method of quantifying the resiliency of a distribution system through analytical hierarchical process and percolation theory applicable to systems with several microgrids. Ramezani et al. (2020) present a "MetaMetric" approach. Such approach aggregates multiple performance objective functions into a single metric based on operational preferences and goals. These methodologies are envisioned to offer standardized ways for assessing microgrid performance, enhancing resilience, and supporting decision-making in planning and operations across the different implementations.

Simulation Models and Tools

Several simulation tools are used to simulate AI interventions on low-inertia microgrids. Afifi et al. (2024) state that Matlab/Simulink is used to design and test reinforcement learning-based virtual inertia controllers for frequency support. According to Henri et al. (2020), the open-source Python package pymgrid generates and simulates various microgrids and has been applied to different reinforcement learning applications. In addition to that, Henriquez-Auba et al. (2020) define LITS.jl, an open-source Julia-based toolbox specifically designed for low-inertia power systems modeling. Other popular simulation tools used in power systems are reported by Kondoro et al. (2017) as Anylogic, Repast, GridLAB-D, and RAPSim, which differ regarding features and approaches to their implementation. These tools permit researchers to model microgrid components, optimize configurations, and study transient responses in high renewable energy penetration scenarios. The choice of simulation tool will depend on the ease of implementation, model accuracy, and the capability to visualize the results (Kondoro et al., 2017).

Simulation models are very crucial in determining the impact of AI on microgrid stability. You et al. (2020) and Wu & Wang (2021) mention that AI techniques, such as machine learning and deep reinforcement learning, can provide efficient alternatives to the traditional simulation-based approach for assessing grid stability. Men et al. (2020) also mention that these methods can improve computational efficiency and provide accurate stability assessments for both AC and DC microgrids. Moreover, Zahraoui et al. (2024) proposed the AI applications in microgrids capture all the phases of event occurrence with enhanced resilience while maintaining power stability. Men et al. (2020) further discussed Kernel Ridge Regression algorithms that are implemented to determine the stability boundaries with increased efficiency. The AI-based tools have also shown accuracy in transient stability, frequency stability, and small signal stability assessments (You et al., 2020). Lastly, Wu & Wang (2021) emphasize that AI techniques show promise in addressing challenges unique to microgrids, such as lack of inertia, generation uncertainty from distributed energy resources, and complex network topologies.

Comparative Analysis

Low-inertia microgrids appear to come with promising benefits when deployed using AI-driven strategies instead of traditional control techniques. According to Wang and Saraswat (2022), it is also stated that a higher percent of grid-forming inverters will improve system stability, but AI will only improve the performance capabilities in complex microgrid conditions. Wu and Wang (2021) asserted further that deep learning, deep reinforcement learning provide insights to manage generation uncertainty as well as lack of inertia, and even complex topologies of networks. Additionally, Hasani et al. (2024) further mentioned that AI-based predictive control, especially deep neural networks, can precisely predict the power demand and generation patterns, thus causing a minimum deviation in voltage and frequency in islanding operation. Such intelligent control systems ensure stability with minimal dependency on communication devices. As indicated by Trivedi and Khadem (2022), AI implementation in the hierarchical control layers and in networked microgrid environments has a potential for improving coordination between distributed generators as well as optimizing efficiency in the operation. In total, AI-based strategies seem to outperform conventional methods when performance and stability for low-inertia microgrids are concerned.

Artificial Intelligence (AI) might significantly improve microgrid management compared to traditional methods. According to Mainaa Oudinga (2023), AI-based energy management systems show better energy efficiency, reliability, and real-time adaptability in microgrids. According to Aditya Joshi et al. (2023), machine learning, neural networks, and reinforcement learning techniques have been employed to achieve various microgrid objectives like economic dispatch, optimal power flow, and scheduling. All the methods note that they address challenges associated with uncertainties in renewable energy resources, sudden load variation, and energy management from multiple resources, according to E. Mohammadi et al. (2022). Tao Wu and Jianhui Wang (2021) also state that deep learning and deep reinforcement learning have been particularly promising in solving complex microgrid energy management problems, including lack of inertia, generation uncertainty, and diverse network topologies. AI-based approaches improve efficiency, reliability, and scalability in microgrid management; however, Aditya Joshi et al. (2023) also point out that challenges related to data privacy, security, and explainability must be addressed for real-world implementation.

Challenges and Limitations of AI Implementation

Technical Challenges

Various technical challenges are associated with the implementation of AI algorithms in low-inertia microgrids. According to Simoes et al. (2023) and Mohammadi et al. (2022), some of the technical challenges include power quality and stability issues, energy resources management, handling uncertainties of loads and generations, and cybersecurity. According to Wu and Wang (2021), energy management is further complicated by the lack of inertia required for system stability and the complex network topology of microgrids. Techniques under AI include machine learning, artificial neural networks, and deep reinforcement learning and are being applied to break through these hurdles through efficiency, stability, and reliability (Mohammadi et al., 2022; Wu & Wang, 2021). Bodewes et al. (2024) note that these AI methods can support energy management systems, fault detection, generation sizing, and load forecasting. However, implementing AI in developing economies presents additional hurdles due to limited access to high-quality power, reliable communication infrastructure, and technical skills (Bodewes et al., 2024). Adapting AI solutions to meet these constraints remains an important area for future research.

Practical Limitations

There are many constraints when developing AI solutions for microgrids that already exist. These are more challenging when dealing with developing economies. Challenges He et al. (2019) pointed out data sharing and privacy issues, lack of transparency in algorithms, standardization of data, and the issue of interoperability of different platforms. Although AI techniques have been deployed for energy management, fault detection, and load forecasting, Bodewes et al. (2024) believe that it still remains a difficult task to adapt these technologies to suit the needs of developing countries due to scarce infrastructure as well as technical expertise in these areas. Talaat et al. (2023) added that there is difficulty in the interconnection of renewable energy in microgrids since it presents an intermittent nature, meaning that more complex control strategy and optimization techniques are also needed. Further, Kelly et al. (2019) describe the challenge of AI research to the clinic and have put together barriers on clinical translation as they discuss in-depth those concerning the challenges in evaluating strongly, the right regulatory mechanism, and controlling and handling the risk of possible algorithmic bias and overfitting problems. In such a manner, addressing these would be of crucial interest for the right utilization of AI in microgrid systems.

The use of AI-based strategies in managing microgrids can further optimize energy resources and enhance performance. According to Joshi et al. (2023), deep learning and reinforcement learning have proven techniques for the complicated issues encountered in microgrid control such as generation uncertainty and the optimization of network topology (Wu & Wang, 2021). Scalability is still a big challenge for the implementation of AI-based microgrid management strategies. According to Suk et al. (2018), when the community evolves and the energy demand changes, then the power supply will not be sufficient from the microgrid, and thus adaptive design techniques are required. Scalability factors also determine the development of smart city microgrids, wherein Khan et al. (2018) argue that AI frameworks can alleviate the difficulty posed by the challenges of distributed energy generation and optimization in such a system. Therefore, it is suggested to develop mathematical frameworks and design methodologies supporting adaptability so that increasing energy demands could be handled in the microgrid systems (Suk et al., 2018).

Future Directions and Opportunities

Emerging AI Trends

Some new research shows it is possible that artificial intelligence can improve low-inertia microgrid control strategies. According to Wu and Wang (2021), there are promising candidates for solutions in deep learning and deep reinforcement learning for the solution of the challenges related to inertia-less and uncertain generation with microgrid energy management problems. Besides, Trivedi and Khadem (2022) point out that AI techniques are being researched to improve several aspects of microgrid control, ranging from hierarchical control layers to networked microgrid environments. Afifi et al. (2024) present reinforcement learning agents, such as TD3 and DDPG, for frequency support in low-inertia microgrids with better performance than traditional controllers. In addition, Ngamroo and Surinkaew (2024) claim that there is a high likelihood by robust deep learning neural networks to control distributed resources of converter-based microgrids. Such aspects include low computational time for a fast stabilizing response coupled with high robustness. These emerging AI technologies highly promise to be a huge improvement in enhancing control strategy in low-inertia microgrids.

Current trends in AI significantly impact research in the management of microgrids. Joshi et al. (2023) and Oudinga (2023) discussed how AI techniques, mainly machine learning, are implemented for improving EMSs of the microgrid with better efficiency, reliability, and adaptability in real time. Yousef et al. (2023) point out that this technology will further enhance power generation forecast, demand prediction, and variable renewable sources integration in the power grids. In addition, Beg et al. (2023) present the development of AI-driven approaches for dealing with cybersecurity challenges in microgrids, especially on attack detection and mitigation strategies. Future research directions include explainable AI, quantum AI, and coupling AI with digital twin technology (Yousef et al., 2023). Furthermore, Beg et al. (2023) highlight that transfer learning and explainable AI techniques are being considered to increase trust in AI-based models for microgrid applications. However, challenges such as data privacy, security, and scalability need to be addressed for the successful implementation of AI in microgrid management (Joshi et al., 2023).

Research Gaps

Artificial intelligence has recently been applied to the quest of solving problems in low-inertia microgrids. According to Wu and Wang (2021) and Mohammadi et al. (2022), AI methods, including deep learning and reinforcement learning, have great promise in energy management, load forecasting, and fault detection for microgrids. However, Bodewes et al. (2024) also mention gaps to be adapted in these techniques to the specific constraints found in developing economies, with limited communication infrastructure and the technical skills of the manpower. Low-inertia microgrids face unique AI application challenges, including absence of inertia for system stability and uncertainty in generation, which may arise from diverse distributed energy resources (Wu & Wang, 2021). Recent work has explored reinforcement learning-based virtual inertia controllers for frequency support in islanded microgrids, demonstrating potential improvements over conventional methods (Afifi et al., 2024). While AI shows promise in addressing microgrid challenges, further research is needed to adapt these techniques to specific contexts and overcome implementation barriers in developing economies.

Interdisciplinary Collaboration

Significantly, AI experts and power system engineers have collaborated over the management of microgrid EMS with intelligence. More recent works in Tajjour and Chandel (2023) state that advanced techniques for optimal power flow, peak-shaving in peak demands, and network optimization through AI-based techniques using machine learning and metaheuristics have been emerging recently, and such techniques shall provide a solution to renewable energy sources intermittency to optimize efficiency (Joshi et al., 2023). Chaouachi et al. (2013) note that artificial neural networks can be used for accurate forecasting of renewable energy generation and load demand, while fuzzy logic expert systems can optimize battery scheduling. Altin and Eyimaya (2023) further emphasize that AI technologies enable microgrids to achieve sustainable and reliable power management, and they conquer the challenges due to variables like wind speed and solar irradiation. However, Joshi et al. (2023) have pointed out that data privacy, security, and scalability are to be addressed for the successful implementation of AI-based EMS in real-world microgrid applications.

The integration of data science and AI insights into the microgrid application has quite a number of benefits. Wu and Wang (2021) and Mohammadi et al. (2022) point that the AI techniques, which include machine learning, deep learning, and reinforcement learning methods, can solve the complex issues in microgrid energy management, load forecasting, and control. These could make the microgrids efficient, stable, and reliable by handling uncertainties when there are renewable energy sources and sudden load variations (Mohammadi et al., 2022). Additionally, AI can enhance microgrid protection, power electronics control, and cybersecurity. Atique and Bayne (2020) suggest that applications of machine learning and game theory in microgrids can provide autonomous solutions for detection, system design, and prediction. Khan et al. (2018) emphasized the fact that AI frameworks could optimize the benefits from microgrids at various levels, ranging from residential to community levels, through the use of deep learning in data centers and AI inference at edge computing nodes and IoT sensors. All these advances contribute a lot toward developing smart cities and self-sustaining smart grid systems.

Conclusion

The review delivers keynote insights about applications of AI in low-inertia microgrids; these might help to enhance stability and performance along with techniques like machine learning and deep learning, which increase efficiency and reliability by handling uncertainties in renewable energy resources and sudden load variations. Despite these positive outcomes, the implementation challenges - more so in developing economics - brought about by insufficient communication infrastructure and deficient technical skills hinder the adoption of AI techniques. In addition, strong data governance and reliable algorithms are required to manage frequency and voltage stability issues for effective deployment of AI. Quantitatively, it has also been proven that AI techniques work better than conventional controls regarding the anticipation of demand for power, optimization of resources in distribution, and the use of communication devices. Some future research directions include the development of AI solutions appropriate for low-inertia microgrids, such as dealing with generation uncertainty and reinforcement learning for frequency support. It has also underscored the need for very close interdisciplinary collaboration between AI and energy system experts in developing intelligent systems and energy management that optimize the performance of microgrids. In summary, it's a great review emphasizing the transformative potential of AI towards low-inertia microgrid management while pointing to potential barriers that require more research to overcome.

The results of the study highlighted several practical implications for the stakeholders involved in microgrid management, especially with regards to the integration of AI technologies. AI-driven strategies will optimize energy management systems and improve reliability, enhance operational efficiency, and allow real-time adaptability to dynamic conditions in low-inertia microgrids, which effectively addresses challenges such as uncertainties in renewable energy sources and load fluctuations. Developing economies have to be more sensitive to such limitations as lack of communication infrastructure and technical skills. Hence, there is a need for AI experts to collaborate with energy systems engineers to develop intelligent energy management solutions that can address the unique challenges while promoting sustainability and resilience in decentralized energy environments.

Further studies will be conducted based on findings of this review to build the knowledge in AI and microgrid applications in these three key areas. The former one is improving on the technical and practical issues to design robust algorithms on AI, particularly targeting key problems of power quality and stability issues, energy management in a microgrid context, and strong cyber security. Further research should be done in AI applications specifically designed in consideration of the conditions of developing economies, with special attention to limited communication infrastructure and a lack of technical skills regarding models created for reduced computational resources yet high efficiency. Improving the reliability of algorithms and governing data requires strict standards for the proper testing of such AI applications in microgrids for stability and security. Besides, the deployment of AI techniques such as explainable AI, quantum AI, and AI/digital twin technology will evolve towards highly sophisticated management systems with increasing trust and transparency in the decision-making processes. The innovation for the solution comes through interdisciplinary collaborative works of AI, experts of energy systems, and other related fields while designing a shared framework for and tools of simulation over many management challenges of a microgrid. In-depth, quantitative analyses should also be carried out to compare how an AI-driven strategy does as well as a classical strategy against established metrics on the lines of energy efficiency, resilience, and near-real-time adaptability; in such a way as to build a case in support of AI applications. Finally, case studies in real-world applications may bring out the successful implementations of AI in microgrid systems, which can then help distill best practices and guidelines for future implementations. Addressing these areas, future research can greatly improve the integration of AI technologies in microgrids to make energy management systems smarter, more efficient, and resilient.

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