Received: 14 December 2023 | Revised: 28 May 2024 | Accepted: 1 July 2024

IET Renewable Power Generation

DOI: 10.1049/rpg2.13056

The Institution of Engineering and Technology WILEY

REVIEW

A review of control strategies for optimized microgrid operations

Shaibu Ali Juma | Sarah Paul Ayeng'o | Cuthbert Z. M. Kimambo

Department of Mechanical and Industrial Engineering, College of Engineering and Technology, University of Dar es Salaam, Dar es Salaam, Tanzania

Correspondence
Shaibu Ali Juma, Department of Mechanical and Industrial Engineering, College of Engineering and Technology, University of Dar es Salaam, P. O. Box 35091, Dar es Salaam, Tanzania.
Email: juma.s@mzuni.ac.mw

Abstract

Microgrids (MGs) have emerged as a promising solution for providing reliable and sustainable electricity, particularly in underserved communities and remote areas. Integrating diverse renewable energy sources into the grid has further emphasized the need for effective management and sophisticated control strategies. This review explores the crucial role of control strategies in optimizing MG operations and ensuring efficient utilization of distributed energy resources, storage systems, networks, and loads. To maximize energy source utilization and overall system performance, various control strategies are implemented, including demand response, energy storage management, data management, and generation-load management. Employing artificial intelligence (AI) and optimization techniques further enhances these strategies, leading to improved energy management and performance in MGs. The review delves into the control strategies and their architectures, and highlights the significant contributions of AI and emerging technologies in advancing MG energy management.

1 | INTRODUCTION

In recent years, there has been accelerated growth in energy demand that has led to an emergent need for utilities to plan properly for their future when expanding the electrical generation capacity. Renewable energy sources (RESs) and energy efficiency development programmes have been popular initiatives to contribute to global warming mitigation [1–3]. According to [4], three-fifths of the Sub-Saharan African (SSA) countries have inadequate energy access, especially in remote areas. Microgrids (MGs) have significantly contributed to the development of rural electrification programmes to bridge the energy access gap and meet the Sustainable development goal (SDG) 7 [5]. A remarkable number of MG developments have seen a rise in off-grid or isolated MG systems, especially in developing countries [6].

Mostly, MGs have played a huge role in incorporating additional energy into the utility grid as distributed generation (DG) [7–9]. This has increased power generation, however, understanding the possible impacts on the networks is of utmost importance. There can be major drawbacks associated with DGs due to their intermittent nature and unpredictable demand [10]. Thus, leading to the development of energy storage technologies to overcome these challenges [11]. DG technologies have contributed to reducing power utility charges and providing ancillary services at both the transmission and distribution levels due to their optimization nature. However, the integration and hybridization of various energy sources in MGs normally bring challenges that require resilient optimum control strategies to be implemented [12].

To achieve optimal technical and economic operations in MGs, it is inevitable to do without energy management systems (EMSs). EMSs play an important role in operational planning and energy scheduling. Various researches have been conducted to come up with novel methodologies and tools that can extract nearly all the available energy resources [13]. Optimization of EMS operations can solve MG control problems by mitigating any other inefficiencies and ensuring available energy utilization is maximised whilst minimising cost [14]. It has been noted how significant advances in artificial intelligence (AI) and optimization methods have been exploited to ascertain optimal solutions in MG control strategy applications [15]. The MG depends on proper control of various decision variables to achieve successful optimal operations. In [16–19], they highlight how MG control strategy studies have predominantly been conducted in developed countries. Despite the acute growth in community-based MG systems in developing countries, there is a need to pay more attention in researching on MG energy management.

1.1 | Motivation behind the increased interest in control strategies and energy management

The research interest focuses on identifying issues and gaps concerning control strategies and energy management operations in MG systems [20]. It also explores the role of AI and optimization tools in MG control strategies and emerging advanced technologies. Despite the benefits of hybrid energy sources (HESs) in MG systems, the uncertainty in generation and load changes can contribute to instability issues and other complexities if not managed properly [21]. Solving these challenges requires the use of simultaneous multiple operations, which may further introduce issues of controllability, scalability, and real-time collaboration of RESs at the component level [22]. Thus, the motivation behind this study is to see coordinated energy utilisation in a secure, reliable and economical manner within MGs. Further description has been provided below:

1. To satisfy the generation-load demand energy balance considering the non-linearity of a hybridized system.
2. To guarantee a secure quality of service that fulfils the consumers' needs while reducing cost operations and making profits.
3. To regulate the voltage and frequency requirements of the MG system.
4. To provide an interactive energy management system in which end users may also play an active role, especially in daily energy consumption.
5. To acquire adequate data analysis that will positively impact the daily operational running of the MG for both the operator and the consumer.

1.2 | Overview of microgrid (MG) systems and their benefits

A microgrid is a small-scale power system operated as a standalone or grid-connected mode to facilitate power provisions for a defined area [23]. MGs can be divided into three main sections; generation, transmission and distribution, depending on the size of the system. MGs connected to the distribution network level will directly feed electric energy to the distribution loads; thus, the transmission will not be involved in this case [24]. The structure of an MG system consists of five major components: (1) energy source(s), (2) loads, (3) energy storage, (4) control unit, and (5) point of common coupling (PCC) of components. Figure 1 shows the components of the MG system [25]. An MG that operates autonomously without connecting to the main grid is referred to as an "isolated or off-grid microgrid." Isolated MGs have been gaining popularity because they supply electricity with less environmental implications, less complex instalments, and are presumed to be extremely reliable and efficient, especially for HESs [26, 27]. These isolated MGs are typically found in off-grid communities, where there are challenges in extending the main grid infrastructure due to technical, economic, and geographical conditions [28]. They can also operate autonomously and disconnect from the traditional grid as localized grids. These MGs are typically found in remote areas where it is not economically feasible to extend the main grid. They rely on standalone power sources, such as solar photovoltaic (SPV) panels, wind turbines (WTs), or small diesel generators, to meet their energy demand.

MGs can be differentiated into residential, commercial or industrial depending on the type of loads to be connected. When various technologies are introduced to MGs, they can form advanced smart grids composed of producers and consumers and/or prosumers. Some of the elements that are considered when designing a reliable MG system are [29]:

1. Microgrid sizing and technologies used;
2. Control strategies and switch modes;
3. Voltage/frequency control;
4. Active and/or reactive power balance;
5. Types of integrated RESs and their positioning.

Due to their nature of being small in size as compared to the main grid, MGs tend to have a minimal CO_2 footprint and less complex power quality issues. The clustered hybrid MGs have recently become an interesting research area, looking at the scattered nature of the systems [13]. However, there are still several unresolved MG behaviours that are yet to be thoroughly and methodically investigated. Some are issues of optimal sizing, data security and advanced management that require intelligent entities to take part in decision-making and control.

1.3 | Overview of hybrid energy systems (HESs) in MGs

In the last decade, there has been a trend of increasing the energy market with a mix of various renewable energy (RE)-based MG systems [30]. When two or more energy sources are combined with or without energy storage to manage power production variations supplied to the load, it is referred to as a hybrid energy system (HES). HESs increase MG system reliability when designed and managed properly, therefore, it is important to pay close attention to the type of source, energy conversions and efficiencies, and optimization methods, when coming up with hybrid system configurations. According to [31], renewable energy technologies (RETs) are the most favourable and cost-effective solutions to deliver clean energy while minimizing the effects of global warming in low electricity access areas. Most countries in Sub-Saharan Africa (SSA) have recently shifted their focus to promoting sustainable energy and constructing resilient ecosystem-based MGs using RETs, mostly targeting off-grid rural communities without access to the utility grid [32].

Recent studies have explored the implementation of HESs in MGs to complement one another to improve the systems' reliability and effective use of energy [13, 33–35]. The commonly used energy sources in hybrid systems are; SPV-WT-battery energy storage system (BESS)-diesel generators [9]. The most common configurations in the SSA have been a combination of

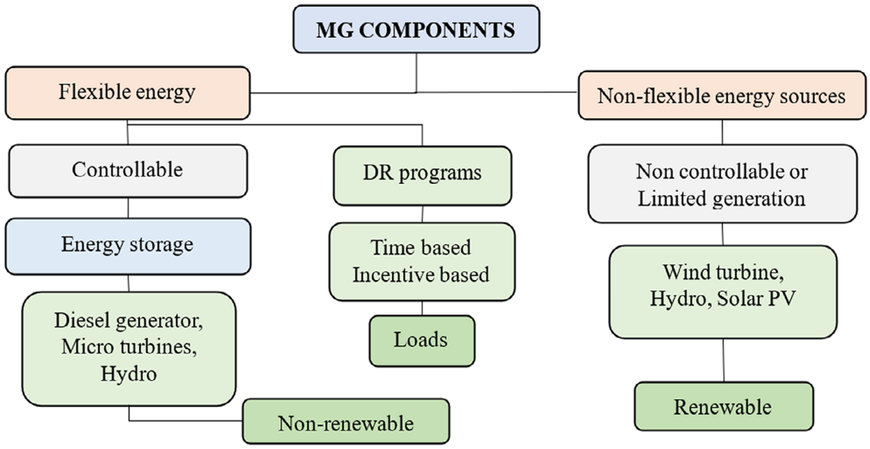

FIGURE 1 Schematic structure of the MG system components. DR, demand response; MG, minigrid; PV, photovoltaic.

SPV and BESS with diesel generators. Especially in cases where the MGs are completely inaccessible to the main utility grid [36].

Power electronics interfacing has also led to significant advancements in integrating RESs leading to a paradigm shift from conventional power systems. The RE integration challenges when in operation due to the intermittency nature are normally suppressed by introducing an energy storage system (ESS) to improve reliability and for efficient operations [37]. The integration of ESS has been rapidly increasing due to their valuable prospects in improving the power system stability and mitigating intermittent RESs in MGs. Thus, elevating overall system performance.

In essence, this has necessitated the implementation of control strategies that can achieve optimum MG management operations from the generation point to the load demand [38]. A comprehensive study will help identify some of the effective and efficient control approaches employed in MGs. A retrospection of existing studies conducted on various control strategies and MG management systems will be discussed, leading to the fulfilment of this review. Therefore, an overview of the review's main contributions is as follows:

1. Describing the implementation of control strategies in the context of MG systems and energy management systems.
2. Assessing control strategy architectures in MG systems.
3. Demonstrating the importance of AI, optimization and emerging technologies in MG control strategies.

1.4 | Methodology

The research has used a scoping review approach which aims to map the key concepts of optimal control strategies in MGs. There was a comprehensive coverage of available literature which was searched from different sources in electronic databases and hand searching of key journals and conferences. Figure 2 illustrates how the documents were filtered leading to article selection considered in the study. A combination of key thematic words that included the following terms "microgrids," "smart grids," "hybrid energy sources," "optimization," "control strategy," "energy management" and "artificial intelligence" and others were searched in the search engines. The study was limited to published articles from 2010 to 2024, that covered recent novel control strategies and emerging technologies in optimizing MG operations and its components. The material was limited to English articles only due to the cost and time involved in translating foreign text material. Having adopted these limits for practical reasons, it is worth pointing out that potentially relevant papers could have been missed. About 130 technical papers, 41 review articles, 41 conferences, 4 internet sources, 5 reports, 2 books, and 5 book chapters discussing various case studies were considered.

The paper is organized as follows: Section 2 introduces the control strategies for MGs which is further categorized into the MG integration and control challenges, control strategy models, multi agent systems, virtual power plants, digital twin concept, MG management and an in-depth analysis of some of the reviews, respectively. Section 3 discusses the application of AI and optimization techniques. Finally, the conclusion and key findings are presented Section 4.

2 | CONTROL STRATEGIES FOR MG SYSTEMS

Control strategies for MGs play a crucial role in improving the management of HESs [39–42]. It refers to the methods employed to optimize energy generation, storage, and distribution within MG system applications. Control strategies encompass a variety of techniques and technologies to effectively manage these domains [43–45]. These strategies ensure a reliable and efficient energy supply, maximize the use of RESs, minimize grid disturbances, and optimize the overall system performance. Most strategies are employed by understanding how to model a resilient MG system that can achieve minimum cost operations whilst meeting the demand securely and reliably [25]. The available resources must be optimally scheduled considering all the uncertainties that can be experienced by the system [4]. Implementation of any form of control technique requires understanding the mode of application and/or operation to identify the most suitable control strategy. The following subsections discuss the integration of some of the

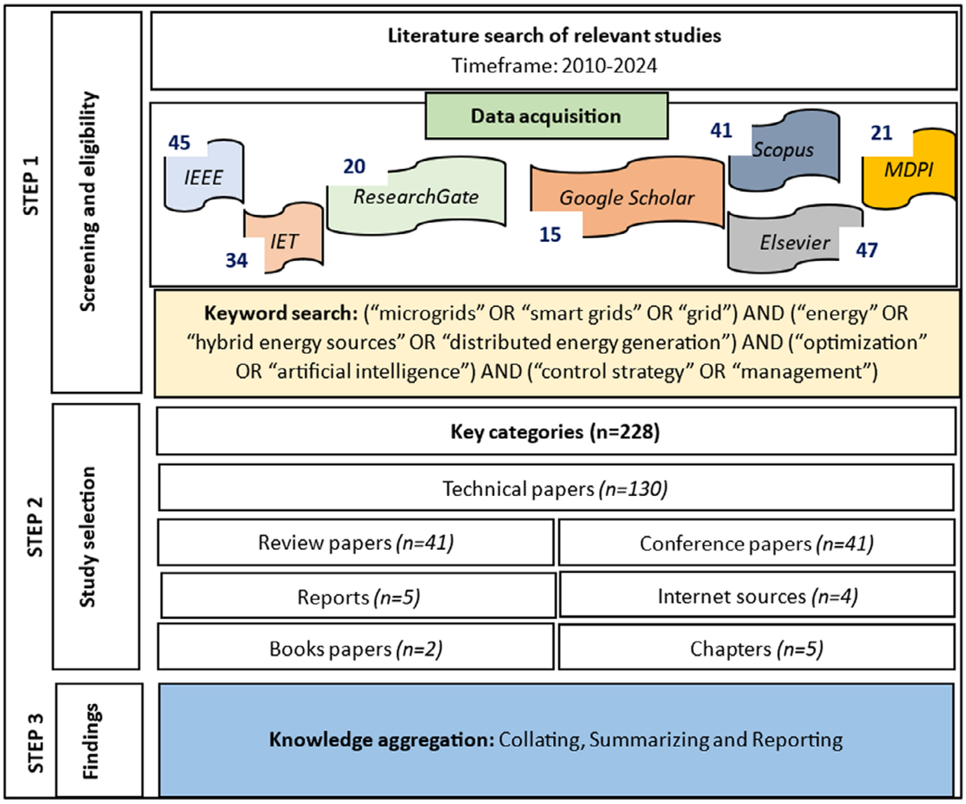

FIGURE 2 Overview of methodology for literature analysis.

control strategies and control challenges in MGs, control architectures and various management methods. It also highlights some of the emerging technologies employed in MGs.

2.1 | MG integration and control challenges

As discussed earlier, energy sources in MG setups are connected to form HESs that share power with various load points. Usually, they are connected to a common bus via converters with varying topologies which raises an important issue of controlling the resources for appropriate power sharing. Maintaining appropriate frequency and voltage magnitudes, and MG power balance can pose challenges if there is no support from the utility grid [46, 47]. Due to the non-existence of an infinite bus in isolated MG systems, they are required to independently maintain the reactive power [48]. Other technical and economic challenges that may arise in MGs include power quality, operational cost, poor resource integration, underutilization, and instability issues [49–52]. Under normal circumstances, a sizeable MG system is designed to have additional contingency reserves and adequate dispatchable generation that satisfies the demand's needs at all times.

MGs can be further classified into alternating current (AC), direct current (DC) and/or hybrid systems, which are further sub-classified depending on the following: architecture, operation, source, application, and size. Table 1 presents a comparison between the AC and DC MGs. Normally, DC MGs are more reliable and efficient when connected to different energy resources compared to AC MGs. Despite being able to connect all RESs and loads to a common AC bus, AC MGs tend to face control and operation challenges. Many studies have investigated system protection, MG stability, HESs in MGs, and the incorporation of energy storage systems (ESSs) [53–57].

The authors in [58] conducted a comprehensive study on some of the existing types of MG models, including the applicability and principles behind each model depicted in Figure 3. MG modelling techniques were classified into four categories which are helpful to researchers especially when designing MG controllers and stability analysis tasks. Each MG model depends on the configuration and type of components to be used. The *component-wise* modelling concept captures the least order possible of each component in individual sources, storage devices, loads and network parameters which are aggregated to obtain the complete MG model. *Lumped models* normally have microsources, ESS units, loads and networks modelled in a modular single state-space model. The *dynamic equivalent* modelling can be modelled using five different techniques to obtain a simplified model which explores related aspects from within. The involvement of generation uncertainties from some RESs prompted *predictive models* to be developed for the operational planning of the MG.

The types of connected energy sources need to be designed with appropriate control measures when integrating MGs with

TABLE 1 Comparison of DC and AC MG-based distribution systems.

AGENT	Power converters	Reconfiguration of the existing system	Control approach	Power electronic interface	Complexity level of interface	Energy storage management	Protection system	Stability	Grid compliance
DC	Yes	No	Simple	Medium	Low/ Medium	Yes	Complex and costly	Unaffected by external effects	No
AC	No	Yes	Complex control process	High	High	No	Simple, mature and cheap	Affected by external disturbances	Yes

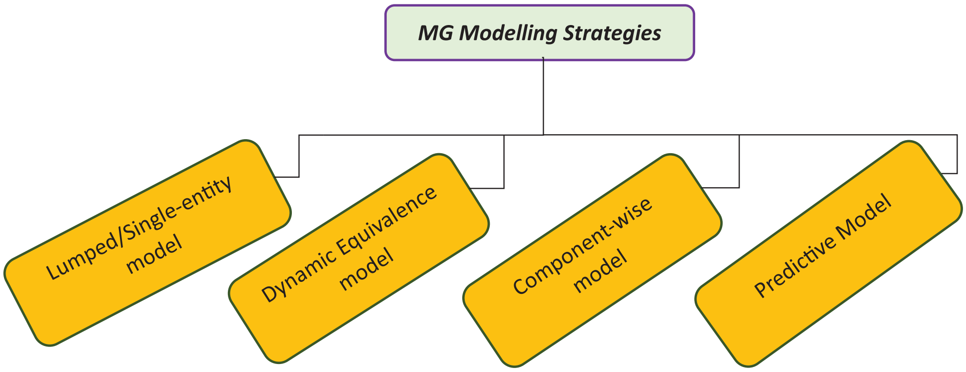

FIGURE 3 MG modelling techniques.

HESs. A good example is of instability challenges faced by wind power due to varying speed operations and power control. There will be a need to take into account the various control layers tasked for each component in MGs so that appropriate measures are considered when transient events occur. Ref. [59] researched the centralized supervisory architecture of an EMS of a tidal turbine, SPV system, diesel generator, and Li-ion battery, for a hybrid energy-isolated marine MG system. The central controller received information from local controllers and determined optimal decision strategies for each energy system. The main objective was to ensure optimal MG operations by minimizing its operations and maintenance (O&M) costs. Ref. [60] proposed a control scheme with enhanced fault ride capabilities which reduced the overvoltage and overcurrent challenges. The strategy ensured smooth operations that satisfied the grid code operations. However, there are still limited improvements in system parameters that can achieve nearly perfect operations, especially during fault conditions.

Some MG control strategies have been employed to stabilize the output that utilizes *real power-frequency* and *reactive power-voltage* control modes for the grid and islanded modes [2]. Smooth switching operations render stable operation in each mode within a series of strategies. Some researchers have looked at how to deal with under-frequency load shedding during power grid failure [61]. However, load-shedding schemes that consider frequency only normally face several challenges, such as unnecessary load tripping. Thus, using conventional load-shedding approaches will not obtain the optimal solution or efficiently overcome the complexity of ever-evolving MG systems [62]. It can be noted how various factors have an influence, including time and transients, as depicted in Figure 4.

It is also important to consider time scales when developing and implementing control strategies, which brings hierarchical modelling of the control scheme to meet flexible and multiple modes of operations. The hierarchical MG control method consists of an autonomous system that ensures cooperation and good scheduling of the controllers [25]. It also depends on the time response and complexities experienced in the MG.

2.2 | Control strategy models

The coordination of various energy systems in supplying high-quality power within a stable voltage and frequency is of utmost importance [63, 64]. Proper control strategies are required to ensure that the appropriate MG operations are implemented. The three main objectives of an MG control strategy in control systems are as follows: (a) to control the active and reactive power, (b) to fulfil the load dynamic requirements and (c) to rectify voltage sag and system imbalances. Thus, the MG control functions to protect and control the integral system. To achieve this, the MG control must consist of a centralized controller, distribution system management, and the generation-load controller [35]. However, this only depends on the type of category the MG will be under based on topography, structure, controller type and type of communication connection. Figure 5 shows an overview of some control strategy methods grouped using a tree diagram and the linkage among the categories which should

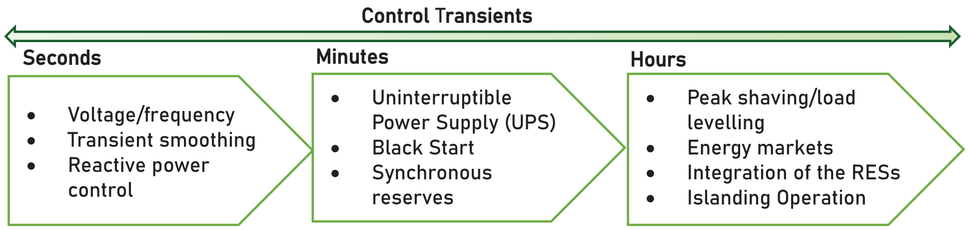

FIGURE 4 Layers of control tasks in MGs.

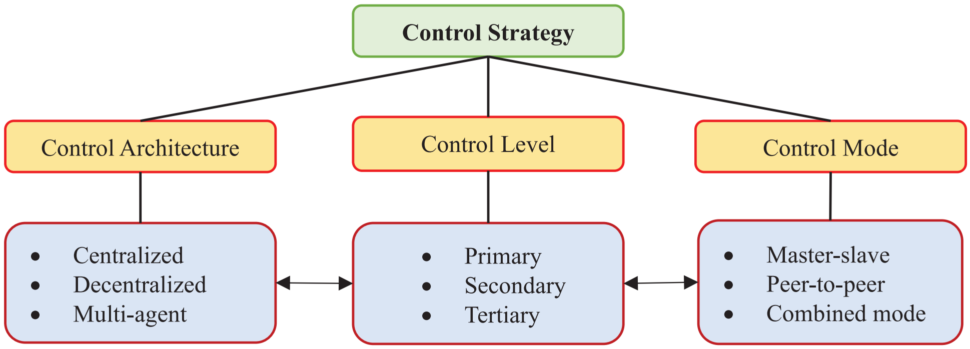

FIGURE 5 Overview of MG control strategy methods.

be considered when designing a robust control system in MGs. Each control method normally has its advantages and disadvantages. That is why it is important to understand the MG system requirements that determine the most suitable control to choose [65].

The hierarchical structure can be split into three control levels as follows: primary, secondary and tertiary control. Within the primary control level, droop control has been identified as the commonly used method for stabilizing the voltage and frequency, power demand sharing and ensuring power quality among several generators connected in the MG [66–73]. It emulates the behaviour of the synchronous machine. The secondary control level aims to restore the voltage and frequency variables to their nominal values while improving the shared power. Finally, the tertiary control level ensures that the EMS is to achieve optimal operations in MGs [23]. It attends to economic dispatch, generation management and congestion management including demand-side management (DSM).

A summary of some studies on the primary control layer is discussed: [74] proposed a modified reverse droop control scheme for proportional power sharing in low voltage MG systems. The proposed controller provided better performance in terms of response and guaranteed system stability. As reported in [62], droop control still exhibits some limitations in application with modern MG systems. This has seen many proposed solutions researched to overcome some problems. The authors in [75] documented research on modelling and simulation tools used for MGs based on SPVs. In addition, they also discussed how droop control methods were more suitable in isolated MG systems than in grid-connected MGs. Ref. [76] studied control methods for inverter-based MGs and focussed on droop control techniques, and voltage and frequency regulation. The main objective of the study was to optimize energy scheduling operations and reliability in MGs for sustainability.

The agents mentioned in Table 1, such as the operating mode and type of supply determine the type of control architecture and suitable topology that will be adopted in the MG system. Centralized control requires communication in all the connected agents and must have enough capacity to process all the required information. The controllers in such a system are usually not considered to be very robust. In decentralized control, each agent will have its local control which only utilizes local measurements with limited communication with the central control unit. Thus, the main disadvantage of this type of architecture is the lack of secondary and tertiary control layer systems since it is only limited to primary control at localized levels. The multi-agent or distributed control system operates in a cooperative way to obtain global objectives in the MG system. The subsection below expands further to get a brief understanding of multi-agent-based systems and how they were applied in some studies.

2.3 | Agent and multi-agent-based systems in MGs

An agent is an entity that learns and analyses the external environment whilst autonomously reacting to local events as it updates local databases [29]. When multiple agents collaborate and communicate with each other to achieve specific goals or objectives in solving a given problem, they become a multi-agent system (MAS). There has to be a central entity that receives information from all the agents in the system to get a complete picture of the coordination problem and the signals to be broadcast. One of the main advantages of MAS is the collective interaction among various agents for the best outcome from the system. They are smart systems that have been identified as viable tools for optimal control and management in MG operations [77]. The various agents in a control system autonomously react to changes in a given environment and make decisions without human intervention. Studies that considered agents in MG energy management systems are discussed below.

Ref. [78] developed coordination strategies using multi-agent-based reinforcement learning to address scalability issues in distributed control of domestic residential systems. The combination of off-line optimization with the used MAS provided high and stable coordination performance at scale. In [79], a BESS management agent was proposed for total operation cost reduction while managing the charge and discharge states. In modern systems, agents are usually capable of learning and updating control strategies through repetitive interactions within the environment. A MAS was proposed in [80] for energy cost optimization of a community with high electric vehicle (EV) penetration. The system had EMS agents with a central coordinator that focused on the energy supply and demand balance. The optimization problem was formulated using mixed integer linear programming (MILP) for day-ahead energy usage. This was used to determine the best peer-to-peer (P2P) household energy transactions. Agents were modelled in a decentralized approach considering the types of available resources in the system.

An agent-based control and management MG system was used in a community in Tanzania [81]. The proposed method examined an MG system with challenges in automatic load shedding and fault detection in electrical networks, focussing on the control and monitoring of a solar-driven DC MG. The study's objective looked at the usage of an agent-based system model consisting of solar energy, storage, and load agents to be developed and simulated before real system implementation. The system considered demand response (DR)-based energy pricing based on energy availability and consumption by the load user.

An investigation of a similar study on how P2P energy transactions can encourage prosumers to regulate their trading behaviour, ensuring efficiency and reliable usage of DESs, is seen in [82]. The strategies employed in the P2P transactions required complete information dynamics, therefore, a MAS game model was used in prioritizing and controlling the transactions that had a great turnover. Ref. [83] presents a study on a decentralized autonomous control approach that used MAS to manage energy transactions in grid-connected MGs. Transactive energy systems in MGs require interactive networks with good communication among various entities, thus, a MAS framework plays a huge role in achieving the desired tasks.

The authors in [84], established how integrating MAS with virtual power plants (VPPs) in taking part in the electricity market could benefit the MGs. The energy trading effects of sharing energy storage with multiple VPPs were explored in an energy trading model. Effective management within the VPP was realized through a coordinated strategy with a dynamic game of electricity pricing. This allowed more flexibility on the demand side, improving the RESs utilization and effective load management. A VPP can be regarded as a MAS in a way. A brief overview of the emerging usage of the VPP concept and how it relates to MG control strategies is discussed in the subsection below.

2.4 | Virtual power plants (VPPs)

A virtual power plant (VPP) can be defined as a decentralized network for small or medium-scale power generation with several sources pooled together with flexible storage and power consumers [85]. The main objective of VPPs is to monitor, forecast, optimize and trade the power in a well-networked system. This requires centralized control to manage all the operations effectively. VPPs networks have recently been considered in MGs with the main focus being to minimize the operational cost in integrated generation units while improving the utilisation of RERs and storage systems [86, 87] However, VPPs highly depend on web-connected systems in a unified network with intelligent energy management (IEM) system software that has several advanced functions.

A VPP with a novel real-time active power dispatch scheme based on distributed model predictive control was proposed in [88]. The scheme permitted independent optimization functions among agents as they sought information from the connected agents. This overcame the optimal scheduling problem in massive VPP distributed resources by disintegrating the global optimization problem into several sub-problems. It then led to improved system stability operations and a reduced impact on peak load since there was a fast response in scheduling time in real-time. In [89], a study was conducted on the dynamic optimal power flow (OPF) in multi-operated VPPs that considered uncertainty from RESs and DSM. The objective function was to maximize the net profit of VPPs as multi-operator depending on cost (O&M cost, operational cost, real power cost) and revenue. Three VPPs with different proprietorships were interconnected through tie lines and the problems were solved using various optimization methods.

A risk-based stochastic MILP model in a VPP was proposed in [90], for optimal operation of a day ahead electricity scheduling. The VPPs utilised the conditional value at risk to measure the risks caused by various uncertainties in MGs. The operations of the VPP were compared between the grid-connected mode and the island mode. Higher generation was noted in the grid-connected mode since the MG exchanged power with the main grid, thus, any excess generation was sold to the grid. It should be noted that the study only focused on DC VPP with a small number of DG units and there is a need to consider other unexpected outages from equipment failure as well as the capital expenditure in the modelling of the daily operations and long-term planning in the future. [91] presented a VPP-based optimal day-ahead electricity market model with hybrid renewable DERs and energy storage. Minimal worst-case scenarios were mapped using an optimization framework, which allowed for a VPP operator to set minimum profit constraints. Two

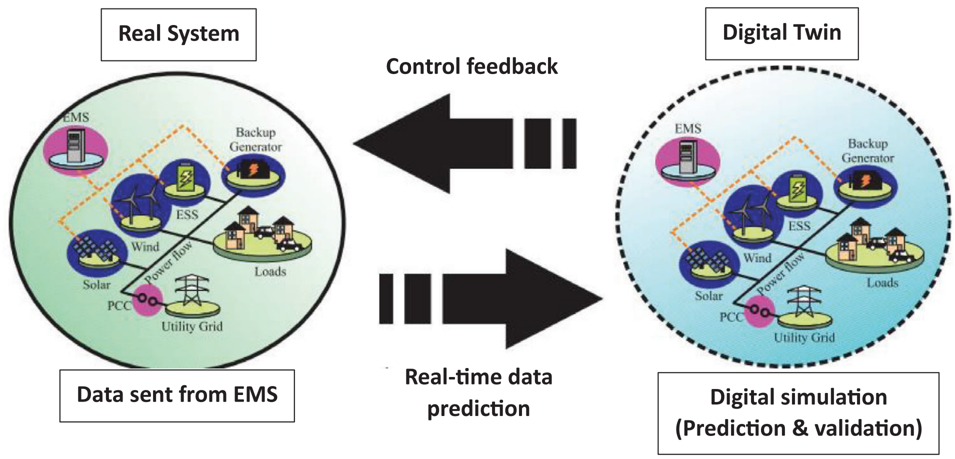

FIGURE 6 A representation of the digital twin model with the real MG system [92].

uncertainty models were considered by the VPP combined with scenario-based stochastic approaches for day-ahead market pricing and wind generation uncertainty. The study showed how VPP is capable of developing strategies in different price scenarios.

VPPs have contributed to solving the intermittency challenges in most renewable DERs, therefore, indirectly participating in the electricity markets and energy scheduling. Soon, VPPs will contribute to competitive electricity markets that will supply an energy mix with reliable power supplies and stable operating conditions. Optimized strategies were considered in most of the studies that had VPP participation in the MG electricity market.

2.5 | Digital twin (DT) concept in MGs

Digital twin (DT) technology has also penetrated its way into MG systems, enabling a digital presentation of an entire MG capable of performing technical feasibility studies, safety measures, reliability and control strategies [92]. DT can validate the MG before operations and show the interaction among various agents, giving control to make improvements on resiliency and reliability, since the operator will have had better foresight of MG control operations [93]. DT in MGs would also overcome the over- and underestimation problems where MG projects are oversimplified in models providing less technically detailed loads or sources. Researchers have seen the benefit of DT MG controllers to be better in managing the MG operations and automation of DERs [94–97].

MGs with DT technology in a simulation environment mimic the actual response, giving better insights with more accurate replication of dynamic complex systems in real life. The aid of DT with a data-driven approach has improved the EMS and control strategies in MGs for real-time applications. However, the development of DT models has presented some challenges in framework connectivity, security, data analysis and standardization. The DT framework in MG systems mainly comprises of the physical system, the virtual system and the data management layer to facilitate data exchange and engage in interaction between the two systems, as illustrated in Figure 6. Due to some unexpected changes that may lead to system faults in MGs, it may cause difficulties in the EMS processes to correctly make informed decisions about the assessed problem. Thus, cyber-physical systems play a huge role in MGs nowadays. The use of DT in MGs is of high benefit in operation, planning, state of health monitoring, and control, among others. Some studies that have considered the use of DT are discussed below.

Ref. [92] established a fault identification framework that used a DT concept for real-time preventive and corrective actions for low-level components in an MG system. The operation considered an artificial neural network (ANN) and a self-organizing map model-based identification strategy to achieve the fault identification process. The coping mechanism of the DT model digital replica of the power converter was compared to a real system in fast response to identify a fault. The results demonstrated how having a DT scheme in a real-time environment through a hardware-in-loop (HIL) approach led to a more reliable fault identification process.

Ref. [93], investigated the use of DT in MGs to estimate the power consumption and communicate with the EMS in making decisions on the suitable energy source to utilize. The support that DT had in EMS's decision-making improved the MG's overall performance, especially in the operational cost. The work presented a methodological framework for developing DT models that can incorporate the actual technical characteristics and complexities of small productive processes (SPPs) used in MGs. Load complexities such as in SPPs for socio-economic developments of communities were recommended in DT advancement and MGs' future developments.

A framework that ensured the development of DT schemes in MGs with a high percentage of RESs was proposed in [95]. DT was identified as an effective way that ensure optimal control strategies in MGs since it would be able to virtually analyse and compare the dynamic behaviour of components in MGs. The collaboration in the entire DT and the actual MG system can be seen to be mostly dependent on communication among components and accurate decision-making. Thus, high-precision simulations and accurate parameters in real time are very important. Ref. [96] introduced a DT-based ESS operation scheduling model in an MG to minimize electricity costs using supervised learning methods. The proposed system had an improvement in cost as compared to an actual ESS operation without the DT scheme. However, more MG model parameters still need to be studied when implementing operation schedules. The verification of the ESS model accuracy will require continued data to be collected. Refs. [94] and [97] did a comprehensive review of studies that applied DT schemes in MG systems to address various challenges by virtual models of the physical entities. The articles also identify the important gaps that still need to be addressed as DT technology gets widely adopted in MGs. The goal is to ensure an ongoing improvement in the quality of service, efficiency optimization, resilient operations, longevity of energy systems, and better control and management of assets in MGs.

Existing studies [73, 98–101] have investigated many control strategies and MG architecture designs so far, with some of the studies [4, 10, 102], mainly focusing on DSM strategies. Table 2 illustrates an overview of various components and areas where some control strategies were implemented. There are different approaches to solving control strategy problems in MGs. Some of the strategies considered are load schedule planning (LSP) [40], demand response (DR) [103], MAS [104], frequency control [105] and smart grid technologies among others.

It can be noted that most studies in Table 2 have had HESs and optimization strategies employed in different MG system components. Limited studies have looked at EVs and forecast models, however, it has recently started to become a trending research area with the new emerging technologies that are getting widely accepted and applicable to integrate in MGs around the globe. A few studies have looked at DC grid systems as compared to AC grid systems which normally have more complex issues when connecting various components, due to the nature of the system. Most sources usually supply the power in AC with most system components operating in AC form. Energy storage has also been highly encouraged in MG systems due to its role when strategizing on effective use of the energy with other sources and making sure there is a supply-demand balance. A centralized approach in control strategies has been widely used. We have also seen the benefits of a decentralized or hybrid control approach in MGs. Most studies seem to have applied a combination of both aspects in their studies with a few applying either one of the two approaches depending on implementation, applicability and what the researchers were trying to achieve. The following subsection will discuss some of the management systems that are commonly considered alongside the control strategies employed in the context of MGs.

2.6 | MG energy management

An energy management system (EMS) is required to manage the various components of MGs. An optimum power flow from the supply source to the load demand is one of the requirements expected at any moment. Thus, an EMS is introduced to observe that the employed strategies are met in the following stages: generation, distribution, and load demand side. The classification of some of the energy management approaches employed in MGs is shown in Figure 7. Justo [112] reported how the management of energy in MG systems involved determining the most economic dispatch of renewable energy resources (RERs) with a minimum total operating cost while satisfying the operating constraints and demand. Most findings were on the IEM of hybrid systems using AI techniques. The techniques employed various advanced intelligent algorithms from real-time energy pricing, generation control, and energy resource forecasting among others. EMS penetration in MGs of different levels was promoted to complement other schemes such as congestion management and DR.

2.6.1 | Data management

Data management in MG systems plays a huge role in managing, transmitting, and storing useful MG data. It is important to understand the energy consumption by the consumer and the power produced from the energy sources to effectively use the system in an optimum manner [113]. The use of smart meters has enabled customers to be involved in managing power usage, allowing the utility to monitor voltage and frequency, measure electricity usage, and identify faults and outages with ease. However, this data handling must be dealt with some level of privacy that has proper structures and policies [114]. The reference architecture in Figure 8 shows a data management system (DMS) that manages electricity and load information in MG utilities. Such a system relies on information from the data collected from communication technologies. The data can provide valuable insights into the MG system operations in all stages. The information layer is embedded in the MG system to allow two-way communication between the controllers, utility operators, and local actuators [86].

Ref. [115] presented the latest key findings that focussed on practical developments of MG operation optimization using blockchain, smart meters, and energy monitoring systems, among other advanced communication and control technologies. The analyzed data is essential for determining electricity market behaviour, power scheduling, operation of MG subsystems, and equipment maintenance. An integral interface of data mining with optimization techniques is anticipated in the near future. Stewart et al. [116] developed a proactive MG control strategy that used *micro*-phasor measurement units (PMUs) to assist with real-time data handling of the controllers. The *micro*-PMUs were able to detect undesirable events such as faults and quickly relay the information in real time, allowing for decisions to be made on time without damage to the equipment.

Guzhov and Krolin [117] assessed how the implementation and use of data technology contribute significantly to energy and cost savings in renewable energy technology (RET) applications. There have been advancements in metering infrastructure to communicate with sensors and controllers in MG systems [118]; however, data handling and management have always

TABLE 2 Reviews of different aspects considered using different strategies.

Ref.	Year	Strategy	MG systems	Grid-connected	Centralized	Decentralized	Energy storage	Optimization strategies	Forecast model	EVs	Single source	Hybrid sources	Utility grid	AC grids	DC grids
[26]	2022	Power flow management	√	✗	√	√	√	√	✗	✗	✗	√	✗	√	✗
[38]	2023	Probabilistic EM scheme	√	√	√	√	√	√	✗	✗	✗	√	√	√	✗
[39]	2022	MG operation using SSA	√	√	√	✗	√	√	✗	✗	✗	√	√	√	✗
[40]	2020	Load shedding	√	√	√	✗	√	√	✗	✗	✗	√	√	√	✗
[41]	2020	Energy management system	√	√	√	✗	✗	√	✗	✗	√	√	√	√	✗
[42]	2023	GA-ANFIS-based control	√	✗	√	√	√	✗	✗	✗	✗	√	✗	√	√
[43]	2022	Intelligent load control	√	√	√	√	√	√	√	✗	√	✗	√	√	√
[44]	2023	State-machine-based EMS	√	√	√	√	√	✗	✗	✗	✗	√	√	√	✗
[45]	2017	Hybrid energy system	√	√	√	√	√	√	✗	✗	✗	√	√	√	✗
[67]	2017	Droop control	√	✗	√	√	√	√	√	√	✗	√	√	✗	√
[101]	2020	Prediction-based optimization	√	√	✗	✗	√	√	√	✗	✗	√	√	√	✗
[103]	2012	Demand response	√	√	√	✗	√	√	✗	✗	✗	✗	√	√	✗
[106]	2019	Optimal distributed control	√	√	√	√	✗	✗	✗	✗	✗	√	√	√	✗
[104]	2018	Voltage control using MAS	√	√	✗	√	√	✗	✗	✗	✗	√	√	√	√
[107]	2021	RNN-based load demand	√	√	√	√	√	√	√	✗	✗	√	✗	√	✗
[108]	2019	Grid-side converter control	√	√	√	√	√	✗	✗	✗	√	✗	√	√	√
[105]	2023	Dual-stage frequency control	√	√	✗	✗	√	√	✗	✗	✗	√	√	√	√
[109]	2021	Two-stage fuzzy logic EMS	√	√	√	√	√	√	✗	√	✗	√	√	√	✗
[110]	2020	Multi-agent based EMS	√	✗	✗	√	✗	√	✗	✗	✗	√	✗	√	✗
[111]	2020	Model predictive control	√	√	√	√	√	√	√	✗	✗	√	√	✗	✗
[81]	2018	Agent-based control system	√	✗	√	√	√	√	✗	✗	√	✗	✗	✗	√

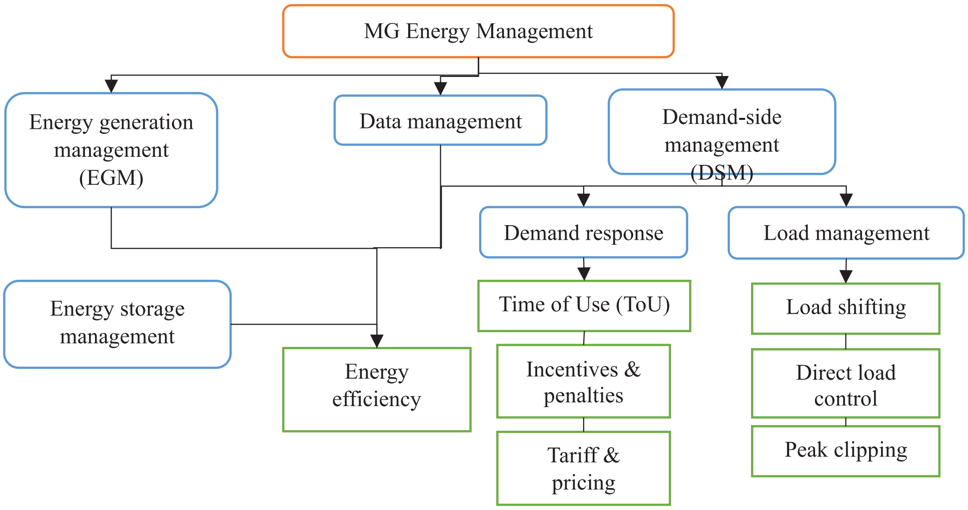

FIGURE 7 General classification of the MG energy management approaches [12].

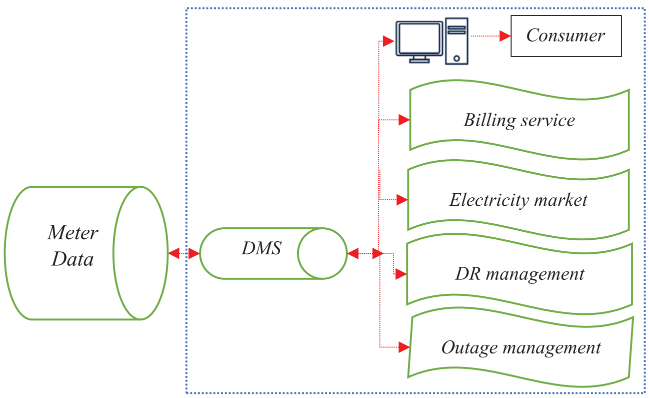

FIGURE 8 Data management system architecture [120].

been a challenge. The generation of big data, data visualization, and transmission speeds require models that fit perfectly into the context of the model application. The growth of electricity consumption will also demand data management in the systems to keep up with the development [119].

2.6.2 | Demand-side management (DSM)

Demand-side management (DSM) modifies the shape of the load patterns by shifting the controllable loads from peak hours to off-peak hours. DSM has activities that influence the behaviour of customers regarding their power consumption, making them aware of various scheduling schemes [121]. When the peak demand is lowered, the mismatch between the generation and demand will be reduced. There will also be a reduction in electricity costs because the utility company will maintain an average power supply during the expected peak hours. Case studies were conducted in [122] to evaluate the effectiveness of different control strategies in improving EMS in isolated MGs, such as the implementation of an optimization-based DSM in a remote village MG. The results showed that the demand management strategy significantly reduced energy consumption during peak hours, resulting in improved reliability and stability of the MG system. It was found that peaker plants charge higher prices per kWh. According to [76], the EMS of an MG encompasses both generation and DSM while satisfying system constraints to realize an economical, sustainable, and reliable operation. In addition, the benefits provided by EMS include the following: power dispatch to save energy, reactive power support for frequency regulation, reliability to loss cost reduction, energy balance to reduce greenhouse gas (GHG) emissions, and customer participation to customer privacy [123].

Razzaq et al. [124] proposed a cooperative DSM that used a prosumer-based energy management model with an energy-sharing scheme. Note that DSM balanced the load as it conserved the energy available. This mechanism influenced how DR programs can be implemented. Load management is one of the methods employed under DSM, with controllable load management (CLM) allowing customers to actively participate in managing their loads using smart devices [87]. Controllable loads can be divided into three types: (a) Active: Have greater flexibility and can be charged or discharged by the grid; (b) Passive: Interruptible and can be shifted, and (c) Broad: MGs and VPPs. DR is a critical control strategy under DSM, which involves adjusting electrical loads in response to changes in electricity prices or grid conditions [103]. This allows for more flexibility in EMS, as consumers can voluntarily shift their electricity usage to times when there is excess RE generation or lower electricity prices. Some strategies aim to match the electricity demand with the available RE generation, thereby maximizing the utilisation of clean energy sources [106].

Ref. [18] proposes a DSM strategy based on price elasticity and incentives for an isolated SPV MG. DSM has been considered an important method for both energy and demand management, with different strategies such as policies, power-saving products, incentives and penalties and the inclusion of electricity tariffs being implemented to positively improve electricity consumption. It should be noted that the unpredictable

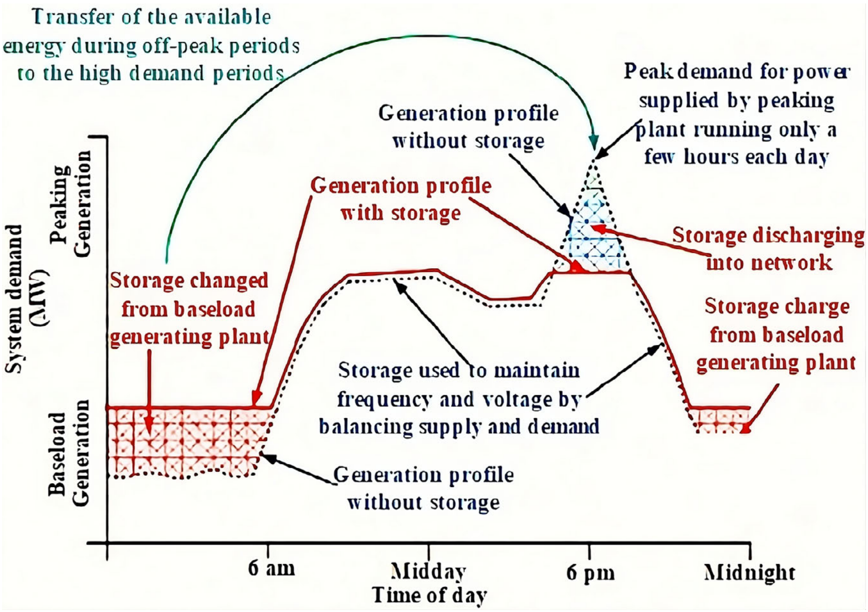

FIGURE 9 Impact of energy storage in the MG system [125].

consumers' behaviour to price sensitivity may differ significantly between developing and developed countries, and from community to community. This is mostly influenced by socioeconomic welfare and factors controlling the energy market. The authors expressed how there were limited studies on DSM in SSA, and encouraged for more research to be conducted. The proposed strategy looked at an isolated Ngurdoto SPV MG in Tanzania and considered the customers' behaviour.

2.6.3 | Energy storage management

The MG system is usually integrated with an energy storage system (ESS) to complement it during peak hours and when the generation fails to supply power to the load user [125]. The expanding growth of RETs has endorsed the wide usage of ESSs to assist in managing the power balance and stability of the MG system. However, the ESS technology experiences challenges such as cost, reliability, battery life cycle, charging, and/or discharging. This calls for solutions to improve the performance of the ESS using appropriate energy management systems (EMSs) for effective and optimum MG operations [126]. According to [127], various studies have examined energy storage management as a control strategy for isolated MGs. Fluctuating RES are normally smoothened with ESSs to provide quality power at all times. ESSs are classified depending on the type, usage, materials used and formation. A detailed classification of ESS has been discussed in [125, 126].

Figure 9 illustrates the impact of energy storage on the generation and load profile in an MG system. The generation with storage ensures that the demand meets adequate energy needs whereby during the peak demand the ESS is discharged into the network to fulfil the peak energy demands that cannot be met by the generation baseload. And during the low demand, the energy storage gets charged. It can be seen that the storage maintains frequency and voltage by balancing supply and demand, especially during the day with uncertainty in generation from renewable sources. Normally, for a generation without storage, peaking plants have to be run for periods. An MG with a storage system will command a control strategy that can manage and control the ESS in optimally boosting stable energy requirements.

Ref. [128] proposed a system value assessment for grid-integrated ESSs to quantify the total system value and understand the generation revenue across the power system. The main purpose of the study was to investigate planning, proper operational guidance and regulations when introducing ESS into the grid. In addition, a co-optimization strategy in the BESS was encouraged for peak shaving and regulating the frequency. Further assessment on the same still needs to be conducted for ESS integration for stand-alone MG systems. Efficient energy storage management optimizes power sharing in MG applications. The optimization must consider a design that minimizes the overall system cost and power losses. The control of the state of charge (SoC) is important in achieving efficient supply from storage to demand while ensuring that there is enough energy reserved for the future. Nowadays, hybrid ESSs have better performance in MG applications because of their reliable operation. Further research must be conducted to overcome the complexities in the synchronization of energy storage into MGs [51, 129, 130].

2.7 | In-depth analysis of the MG control strategies

Many studies have demonstrated how hybrid sources in MGs complement each other to ensure a reliable and resilient system. Some challenges that hinder the implementation of various RERs in hybrid MG systems are frequency and voltage control, intelligent energy management system (IEMS), operational cost, power converter control systems that connect generation

TABLE 3 Main features of some MG control strategies.

Ref.	Control strategy
[131]	The strategy used a *DSM-based optimal EMS* with a hybrid honey badger optimization and dwarf mongoose optimization algorithms.
[132]	The MILP model was proposed to optimally *coordinate the active distribution* networks HESs.
[133]	A heuristic-modified particle swarm optimization (PSO) algorithm was used to determine *optimal BESS controls* in a real-time EMS for a community MG.
[134]	A *finite control set-model predictive control strategy* for enhanced single inverter performance in RESs was developed. The study also developed a *theoretical framework* in addition to experimental evaluation and hardware development.
[135]	Optimal *management of controllable shiftable loads* in a system with DERs was implemented using a glowworm swarm optimization technique.
[136]	A control method for harmonic suppression in wind power plants in a multi-bus MG system was developed in DigSilent software. A *droop-based harmonic current sharing* strategy had better performance with the proposed hierarchical harmonic control architecture.
[137]	A *distributed model-free adaptive control strategy* with an event-triggered mechanism was proposed to achieve optimal power sharing with reduced communication burden. The strategy operated in a *unified control framework*.
[138]	A *variable neighbourhood search with a differential evolutionary PSO algorithm* was considered in smart MG operations with multiple DERs. The multi-objective *stochastic control models* were applied to solve the DER control problems to maximize profits.
[139]	*DSM-based* household appliance *scheduling and controlling techniques* are implemented in a smart grid system. The electricity cost and peak-to-average ratio demand were reduced.
[140]	*PSO-based power management and load scheduling* methods to reduce operating costs by shifting the demand to avoid peak hours were developed and evaluated for an MG with HESs.
[141]	A combined imitative learning and deep reinforcement learning in a *digital twin*-based data-driven strategy for MGs.
[142]	A coordinated preventive and emergency dispatch method for enhancing MG system resilience and reduced losses using a robust *optimal dispatching model*.
[143]	Optimal allocation of hybrid WT DG and BESS using a *multi-dimensional EMS* in a flexible interconnected distribution network considering seasonal uncertainties.
[144]	A *MAS* that had several IoT devices and energy consumption was optimized using *genetic algorithm (GA)*. Energy flow was modelled based on communication and processing system, sensing data acquisition, ESS and power manager.
[145]	A *MAS-based* decentralized control scheme used a *loop droop controller* for MG stabilization and to improve security. There was coordinated switching between strategies in a central agent.
[146]	A centralized MG control with a *coordinated decentralized control* strategy of the distributed RESs and integrated BESSs using an *adaptive robust* approach.
[147]	Optimal control of an MG with DERs and BESS. A *PI controller* was designed using a *differential evolution optimization* method for energy storage. To restore the frequency and voltage in the system, *ANN* was used for training the patterns that were obtained from the controller parameters.
[148]	An optimal control framework called *Oxtimal* which relied on a reduced order model for supervisory control of PVs connected to the grid was presented. It aimed to minimize storage device usage and deviate from dispatching loads from desired usage.

units, and socio-economics-related issues. Table 3 features more studies on MG control strategies that were reviewed. This sub-section provides an in-depth analysis of some related studies that employed control strategies on various challenges experienced in HESs, MG systems, and EMS applications.

Javaid et al. [149] presented three evolutionary algorithm-based methods for a DSM model for an intelligent load management system. The appliance scheduling model aimed to achieve a cost-efficient method to manage the operating time and schedules of electrical appliances using binary PSO, GA, and cuckoo search optimization methods. The main contribution of the study was a model that catered for different loads and user types to reduce peak demand and electricity costs. The three algorithms were used to solve a centralized optimization problem with control parameters that could determine optimal solutions within an acceptable processing time. To optimize energy consumption, the time of use (ToU) pricing scheme was proposed with an automated system for load monitoring and management. The problem formulation was based on the scheduling of different appliances, which were grouped depending on the amount of energy they consumed. The developed objective for minimizing electricity cost is given in Equation (1):

$$min\left(\sum_{i=1}^{24}\sum_{j=1}^{n}E_{cost_{aj},i}\right) \tag{1}$$

$$s.t\ :\ \sum_{j=1}^{n}\sum_{i=1}^{24}E_{cost_{aj},} = E_{grid} \tag{1a}$$

$$\sum_{j=1}^{n}\sum_{i=1}^{24}E_t = E_{grid,j} + E_{RES,i} \tag{1b}$$

$$\zeta_{max,aj} \leq 24 - \beta_{aj}, \tag{1c}$$

$$\sigma_{i,aj} \epsilon \{0, 1\} \tag{1d}$$

where $\zeta_{max,aj}$ is the appliance's maximum waiting time, $\sigma_{i,aj}$ is for ON and OFF in appliances, a is the appliance for a given set A, and $E_{cost_{aj},i}$ is the cost of electricity.

It can be concluded that the application of various optimization tools performs differently from the cases that were conducted. Further investigation of other techniques, must be

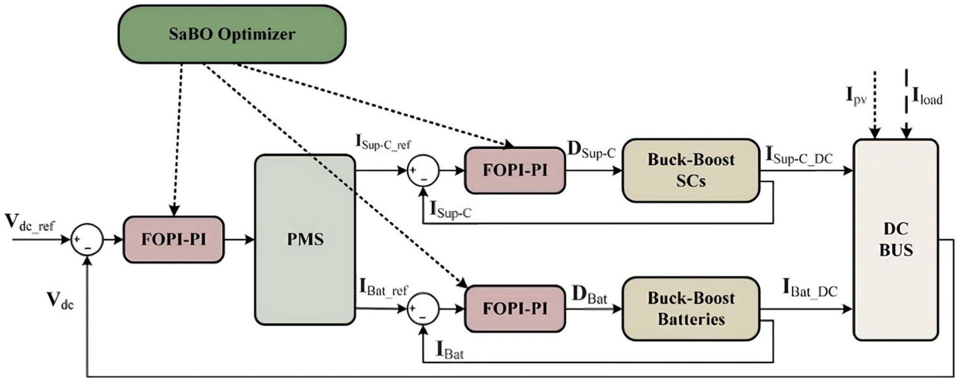

FIGURE 10 Proposed control strategy for DC bus [149].

conducted to determine the most optimal method to further reduce the electricity costs for the consumer.

Khairalla et al. [150] proposed a robust hybrid controller for managing current in a DC bus voltage using a supercapacitor and a battery to stabilize power flows. A novel power management strategy (PMS) was developed using a self-adaptive bonobo optimizer (SaBO) for optimization of the objective function problem. Figure 10 shows the block diagram of the proposed DC bus control strategy. The interaction among the following components in the proposed controllers, that is, the PMS, current control loops, and hybrid fractional order proportional integral (FOPI)-PI controllers, resulted in a novel control strategy that gave the best results. The FOPI-PI controllers enhanced the control performance by capturing accurate precise dynamic controls with increased stability and less system disturbances. The combination of the FOPI and PI controllers increased its robustness and stability, giving it the ability to minimize overshoot and reduce settling time. It also became less sensitive to process parameter changes. Equation (2) expresses the transfer function of the FOFP-PI controller.

$$G_c\ (s) = \left(K_{p1} + \frac{Ki1}{s^{\gamma}}\right)\left(K_{p2} + \frac{Ki2}{s}\right) \tag{2}$$

where K_{p1} is proportional gain, K_{i1} *is* integral gain and γ is value for the integrator order of the FOPI controller whilst K_{p2} and K_{i2} are the proportional gain and integral gain of the PI regulator, respectively.

The proposed control strategy utilized batteries to handle the power surge changes whereas superconductors handled the rapid power changes, to overcome the slow time response by the batteries.

The main aim was to achieve an optimally coordinated utilization among the batteries and superconductors. The proposed SaBO technique was introduced for the first time in DC-based MG systems, and it performed extraordinarily well, giving an improved BESS life span and steady-state performance.

Kermani et al. [151] investigated the performance of a PV-BESS-based MG system using a rule-based energy management optimization technique that considered the cost function as the objective problem. The EMS optimally scheduled the available resource utilization for a grid-connected MG system. The considered model of the hybrid generation MG system is shown in Figure 11. Equation (3) defines the objective function used in the study as follows:

$$\min\,(CF) = \min\left(\sum_{t_0}^{T} CR\,(t) + CP\,(t)\right) \tag{3}$$

where CF is the cost function, CR is the cost received, and CP is the cost paid with time *(t)*.

The rule-based EMS strategy is based on predefined rules from MG constraints. Limitations of the MG system had to be noted to make an accurate strategy that follows the guidelines. The Bellman algorithm was used to determine the minimum value of the cost function. This system enabled FiT for surplus power to be sold to the main grid. The iteration-based method met the study objectives by achieving energy cost reduction and increasing PV efficiency. However, the study lacks comparative analysis with other optimization techniques for similar systems to prove the superiority of the proposed method.

Moghaddam et al. [152] proposed multiple MG management operations using a fuzzy self-adaptive (FSA) PSO algorithm. The developed objective function had a multi-objective optimization problem to minimize the total operating cost while considering emissions. The developed multi-objective optimization model is expressed as follows:

(1) Minimize the total operating cost:

$$\min\, f_1\,(X) = \sum_{t=1}^{T} cost^t \tag{4}$$

(2) Minimize total pollutant emissions:

$$\min\, f_2\,(X) = \sum_{t=1}^{T} emission^t \tag{5}$$

where cost includes any cost of operation in the system, for example, fuel cost, utility cost, battery cost, and emissions including CO_2, SO_2, and NO_2 with time (*t*).

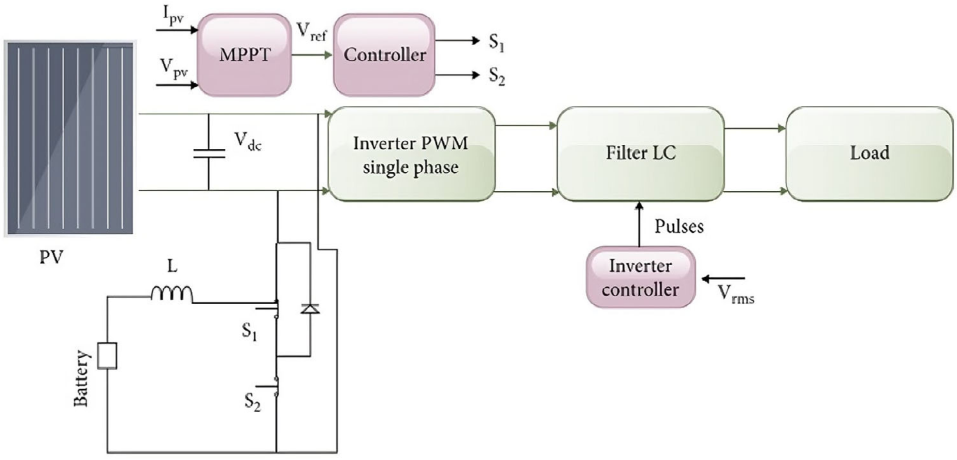

FIGURE 11 Hybrid generation MG system structure [151].

The FSA approach was introduced to overcome the inertia weight and learning factor challenges experienced in the conventional PSO algorithm. The main contribution of this study lies in the modification of the proposed optimization approach. A suitable provision of power exchange in a grid-connected MG benefited both the objectives by reducing emissions and cost with some acceptable precision in results.

Song et al. [153] proposed a switched integral reinforcement learning model to solve frequency control challenges in a grid with EVs. The scheme had an ANN structure to train the proposed model for the dynamic asymmetric problem frequency regulation capacity problem. This study introduced a novel scheme that enabled cooperation between vehicle-to-grid (V2G) systems and grid power plants with a primary focus on controlling the frequency regulation schedules. Figure 12a depicts the V2G integrated grid model with RESs, EVs, generators, and controllers. The proposed ANN used a modified switched NN structure that was specifically for V2G frequency regulation control, as depicted in Figure 12b. Unlike the classical ANN structure, the switched NN structure had two similar subnetworks, giving the V2G system more flexibility in controlling the total cost. The superiority of the proposed switched integral reinforcement learning technique in improving the performance of frequency regulation and control cost was compared with other controllers on an IEEE-14 bus test system. The proposed method achieved better frequency regulation performance and a smaller control cost. Further research in the frequency regulation controllers coordinated to save costs in MGs was recommended.

Hai et al. [104] proposed a voltage control method to perform effective multiple coordinated controls in PV units, converters, and BESSs in low voltage (LV) distribution systems. Accurate control commands were determined by the scheme to maintain normal line voltage ranges. A hierarchical control architecture with a MAS, shown in Figure 13, was developed and designed for the Gochang LV distributed system. It had a master and local agent at the supervisory control units. The local agents' control algorithms were embedded into a remote unit with automated metering infrastructure (AMI) devices using 32-bit microcontroller hardware. The voltage control method aimed to improve the utilization of DERs, prioritize the source that can produce more power, and to reduce energy losses in the networks. The BESS's rated size had to be reduced to minimize the energy discharge for voltage control. The proposed voltage control strategy was implemented and analysed for several cases to evaluate its performance. It was noted that the implementation of affordable microcontrollers worked best in low and medium voltage distribution networks, whereas in large complex networks, there would be a computational burden and a delay in the system communication. The control system also relied on accurate data to be provided for best performance.

Ref. [154] conducted a comparative study using the Grey Wolf Optimizer (GWO) technique and Homer Pro to optimize the HES components. This was to achieve a reduction in the cost of energy (COE), net present cost (NPC), and CO_2 emissions. The study targeted HESs in a remote rural area in India, which required careful planning and design to maximize utilization of available resources efficiently. The main contribution of the study was to address the coordination strategies experienced in decentralized HESs. The study also identified the best combination of the HES for the given MG system. An assessment of how annual wind speed and solar energy affected COE and annual electricity output was analysed. It was noted that the GWO algorithm gave better results with a fast convergence rate compared to using Homer Pro for optimization on COE and NPC. The three combinations of HES were modelled using PV, WT, BESS, and biogas generators. A socioeconomic impact assessment was an important aspect to conduct when implementing remote MGs with HES to benefit local communities.

Alvarez et al. [155] developed a fast response optimization technique for active power dispatching in distributed MGs. The objective function problem was to minimize fuel consumption and reduce emissions. The development and design of low-cost programmable microcontrollers and simple software tools have been gaining more attention in solving MG operations. The

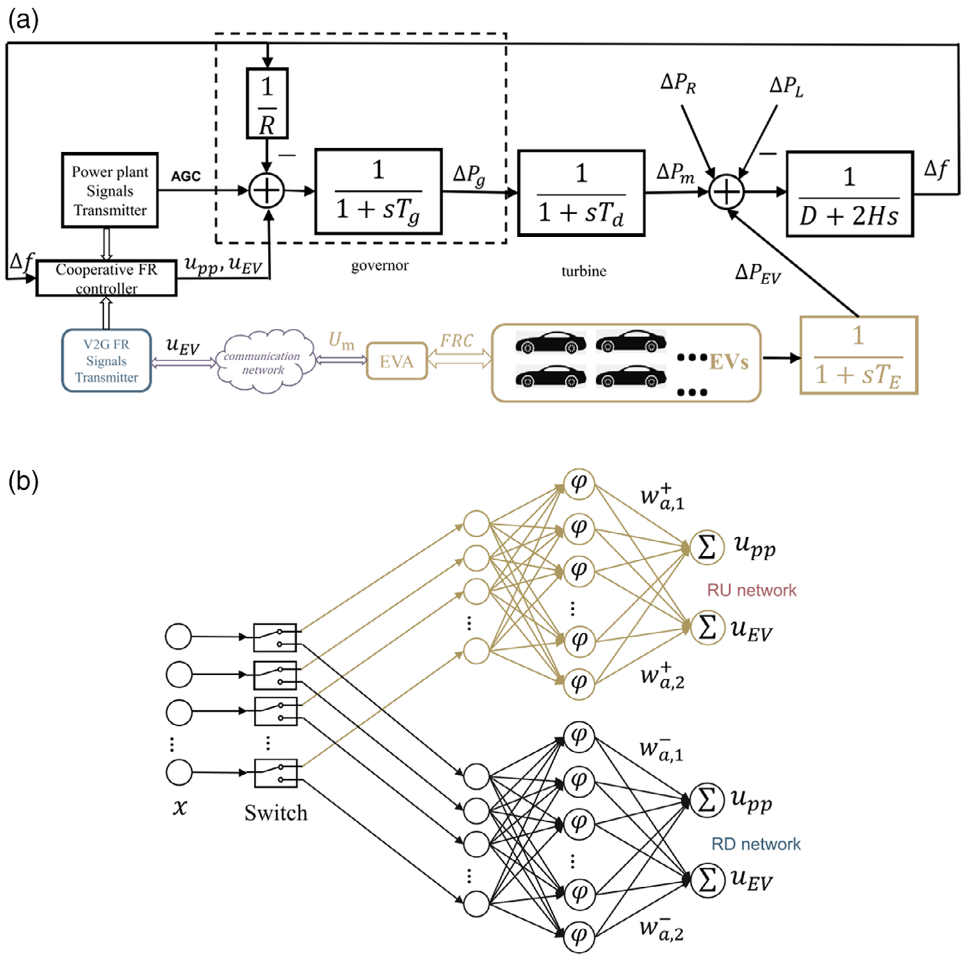

FIGURE 12 (a) Power system model with V2G [153]. (b) Switched neural network (NN) structure [153].

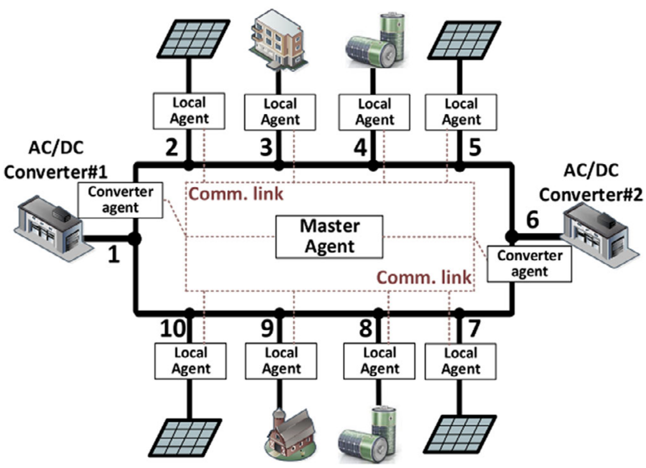

FIGURE 13 MAS configuration for the LV distribution system [104].

study focussed on the implementation of controllers for micro sources to be able to adjust the grid-connected MG generation to load online using a low-cost developed controller. A power dispatch algorithm (PDA) and a cost function algorithm with a heuristic approach were developed. PDA was implemented in the central controller and tested in comparison with other algorithms. The proposed methods allowed for seamless integration of the entire system and were able to achieve the expected objective functions. However, the study must consider looking into more comparative analysis with other existing controllers on overall performance, especially when it comes to practical system implementation.

In [156], a rule-based energy management strategy for port cranes was developed and investigated to confirm the suitability of a hybrid energy storage system comprising grid-connected batteries and supercapacitors. The system models were developed from graphical energetic macroscopic representations, which included local control and physical systems. The modelling had to follow the following principles: (1) integral causality of the energetic system, (2) interaction between subsystems and (3) inversion applied to the local control scheme. MATLAB/Simulink software was used to model the proposed method with the port crane model for a system in Cape Town, South Africa. The EMS had three reference currents used to control the power from the three sources. The PSO algorithm was used to optimize battery usage. The proposed method achieved a reduction in energy consumption from the grid and demand peak shaving.

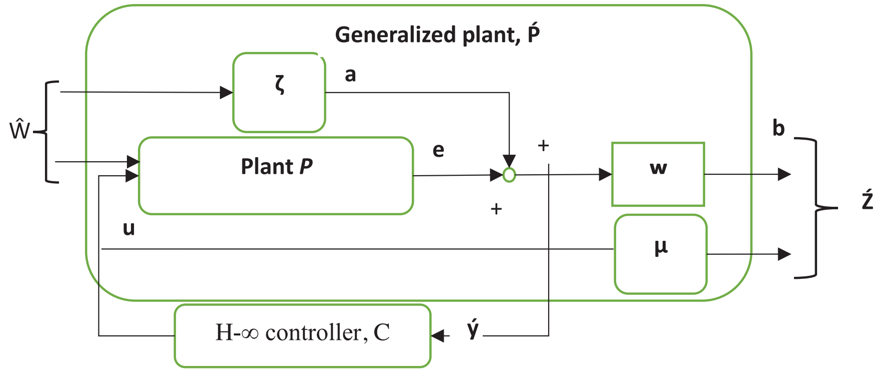

FIGURE 14 Structure diagram of the one stage H-∞ control method [157].

Ref. [157] presented a comparative study between H-infinity (H-∞) and model predictive control methods for MGs that ensured seamless transitions from grid-connected to island mode and vice-versa. The proposed methods focused on improving the performance of droop control and a comparison was made based on integral time-weighted absolute error, integral of absolute error and integral of square error. We focus on discussing the advanced intelligent control method based on H-∞ robust control from this study. H-∞ control uses a linear matrix inequality (LMI) tool to handle control problems to determine feasible and optimal solutions. It reduces the effect of uncertainties and disturbances during transitions in grid-connected MGs. Figure 14 illustrates the formulation of a one-stage H-∞ control method. The generalized plant, $\acute{P}$ with a plant nominal transfer function $P(s)$ and feedback control $C(s)$. The control method was able to adapt the voltage, current and power control loops which improved the power quality of the system. The generation-load mismatch in island mode MGs was also reduced. The simulation results show how the H-∞ based controller had more reduced error in the load voltage and frequency compared to the model predictive control method. H-∞ also gave a robust controller in weak MG systems where parameters are not constant.

Similar studies that considered H-∞ have been summed up: Ref. [158] highlighted how there are many challenges associated with DERs when connecting to the distribution networks causing power quality issues. The authors proposed a two-layer hybrid control scheme with PV sources using H-∞ for adjusting the BESSs to suppress the voltage unbalances and an fuzzy logic (FL) controller for the correct selection of the transformer on the load tap changer. The two controls worked hand in hand with H-∞ controller parameter adjusted by the FL controller to determine the optimal current required in the batteries. A self-tuning H-∞ controller was designed to use an FL controller for dynamic parameter adjusting. The output from the H-∞ controller determined the battery inverters' reference voltages. Figure 15 illustrates the proposed primary control level with H-∞ controller and FL controller which solves the challenges in the system under abnormal or unexpected conditions. The primary control level is intended to operate optimally within desirable conditions. The control system was tested on the distribution model with PV and BESS system in MATLAB.

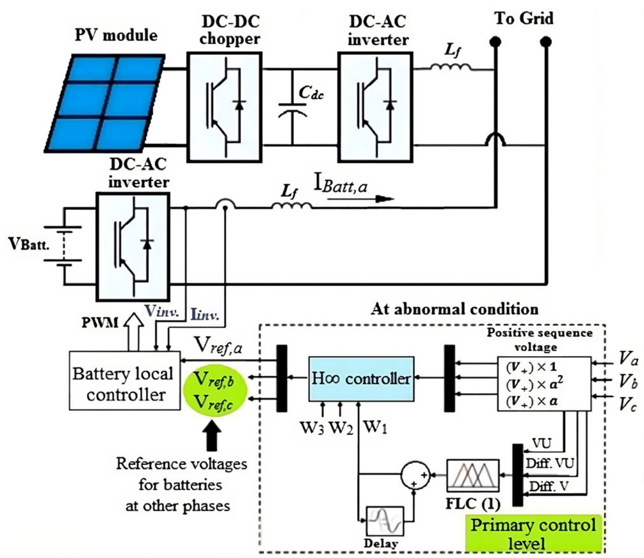

FIGURE 15 Proposed primary control level [158].

Ref. [159] also proposed a robust inertial controller for converter-based DGs that are employed in low inertia MG systems using an linear matrix inequality (LMI)-based H2/H-∞ method. The H2/H-∞ method gave support in fast frequency restoration and improved the inertial features. An optimal H2/H-∞ controller was provided by following a linear fractional transformation that employs a convex solution procedure. There was no need for online computations, thus computational time and design complexity were reduced. The novel mixed robust H2/H-∞ controller was established to improve on the performance requirements other than just satisfying robust Mg stability. In [160], H-∞ and μ-control techniques were proposed to address robust frequency control in islanded MGs. Fluctuations from intermittent sources and dynamic perturbations have a great influence on the system frequency which requires robust controllers to reduce these challenges. H-∞ and μ-control techniques have proved to be robust control methods more suitable for stability analysis and control synthesis problems in MG systems. However, extensive research still needs to be done in optimizing MG control systems since there are a few applications in MGs [161].

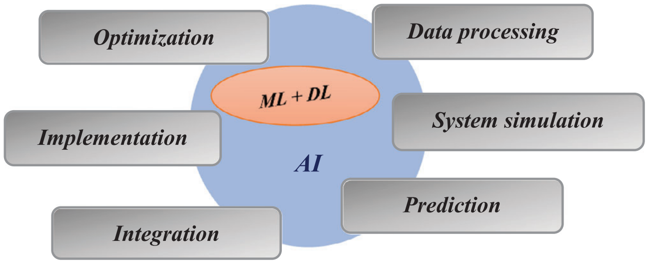

FIGURE 16 Workflow. DL, deep learning; ML, machine learning.

3 | APPLICATION OF AI AND OPTIMIZATION TECHNIQUES IN MG CONTROL STRATEGIES

The advancement in AI-based technology has seen more smarter and complex systems offering better results. AI-based methods have gained momentum in solving MG problems and their control strategies. The various challenges of MG systems such as intermittent RERs, generation and load forecasting, estimation, control and monitoring, can be solved by developing control strategies that are system-specific with the help of AI and optimization techniques [34, 35, 162–165]. AI encompasses anything that has a form of intelligence in machines and/or systems [166–169]. It still depends on human expertise to derive the knowledge and optimization problem for a specific application. Figure 16 depicts a simplified workflow of how AI is used to leverage data to improve performance in certain tasks within systems. The breakdown of the steps is as follows:

1. Data processing: The initial step involves collecting and preparing the data that will be used to train the AI model. This may involve cleaning, removing duplicates, and formatting the data into a usable state.
2. System simulation: A simplified model of system is then created to represent the real system. It is used to test and refine the AI model before it is deployed in the real world.
3. ML ± DL: Machine learning (ML) and deep learning (DL) techniques are applied to the data, and allow the AI model to learn from the data and identify patterns.
4. AI prediction: Once the AI model has been trained, it can be used to make predictions about the system. These predictions can be used to improve the performance of the system in a number of ways, such as by identifying and preventing errors or optimizing resource allocation.
5. Integration and implementation: The AI model is then integrated into the real system. This may involve developing an application programming interface (API) that allows the system to communicate with the AI model.
6. Optimization: Once the AI model is integrated into the system, its performance can be monitored and optimized. This may involve retraining the model with new data or adjusting the way that the model is used.

As the AI model is exposed to more data and is further refined, it can become more accurate in its predictions and lead to even greater improvements in system performance. With ML methods, accessed data can be analysed and used with DL models, which are then tested and deployed in a real-life environment [170]. We have seen how ML and DL have been used in solving complex problems in MGs and data manipulation by learning from experience and being able to make informed decisions in the future [92]. Looking at most of the recent literature, it can be noted that several researchers have been considering the use of AI in MG control strategy applications.

3.1 | A brief overview of some of the emerging MG technologies

The growth of hybrid energy resource penetration in MG systems has led to the development of several control techniques, such as state estimation substantival to system operations [34]. Due to intermittent renewable generation, MG conditions tend to vary temporally and spatially. State forecasting has become crucial for grid operators when dispatching controllable resources, preparing for changing grid conditions, and reducing operational costs [171]. It has been noted that forecasted system states enable grid operators to have improved coordinated control efforts and prioritized control needs, thus improving system resilience, efficiency, and reliability [64, 109, 172, 173]. Conventional control methods in MGs, are primarily used to regulate voltage and frequency, such as proportional-integral (PI) control, and they require accurate mathematical models of the system, despite non-linearity challenges. On the other hand, AI-based control strategies such as fuzzy logic (FL) control and artificial neural network (ANN) based methods can handle non-linear system dynamics with less accurate mathematical models [42]. Researchers are developing ML-based methods that can predict system states for the short- and long-term future using neural networks (NNs), ensemble learning and decision tree-based approaches [85].

Masoomi et al. [174] investigated the impact of Industry 5.0 (I5.0) in achieving sustainable development in RESs and its supply chain. I5.0 has a strong responsibility to achieve sustainable energy solutions through human–machine collaboration and to improve the economy whilst overcoming environmental and social challenges. The human-centric approach puts value on people in a socio-technological environment. Thus, ensuring efficient use of energy resources with the social and environmental impact in mind. However, studies on MGs regarding EMSs that are considered I5.0 are underexplored and researchers have paid limited attention to the context of the renewable energy sector.

DT technology already explores Industry 4.0 with AI and cloud computing to virtually monitor physical systems. Mostly DT technology is based on data-driven methods with ML. Recently, we have seen huge volumes of data being available in MG systems such as energy consumption data, energy generation data, and O&M among others. This has promoted further research to be from a data-guided viewpoint. Power dispatching strategies tend to be event-driven using different control strategies, with hierarchical stages that have various control tasks in each stage [77, 117, 175, 176]. Ref. [177] proposed an online MG optimization method that used imitation learning improved by a data-driven approach. Imitation learning uses an ML approach that learns from experience by imitating the behaviour of experts to handle decision-making problems. Historical data was explored to learn the optimal ESS strategy schedules.

Physics-informed neural networks (PINNs) are a recent advancement showing promise in MG prediction and control [178]. Several studies have demonstrated PINNs' effectiveness. Paruthiyil et al. [179] used a PINN-based ML algorithm for fault detection in DC MGs. This method achieved greater accuracy in fault location even with limited training data. Antonelo et al. [180] developed a framework using a novel and adaptable PINN architecture for control problems with extended time horizons. Their approach offered faster simulations, making it computationally more efficient than traditional numerical methods. Another study [181] employed a PINN algorithm to address challenges in determining the Lyapunov function for transient stability assessment in MGs. Rai et al. [182] proposed a PINN-based modelling approach for fast frequency support in MGs using energy storage. Their method achieved excellent data fitting by incorporating the system's physical information into the training process. This led to improved performance and adaptability of the neural network models while significantly reducing data requirements. Additionally, a PINN learning scheme was devised in [183] to discover control policies and certificates for uncertain networked MGs, explicitly guaranteeing safety, stability, and robustness. Another approach combined physics-informed reinforcement learning (PIRL) with model-based analysis to control inverter-based PQ controllers with trajectory tracking capabilities in MGs [184]. This method addressed the issue of parameter uncertainty and accelerated learning. Overall, physics-informed implementations can enhance the safety of data-driven methods for MGs and prevent hardware damage among other issues.

Hailu et al. [185] introduced a data-driven fuzzy inference system (FIS) tuned by hybrid genetic-simulated annealing (HGSA)-FIS for quick static security assessment when there was a component failure in a multi-area power system with RE. An effective data-driven short-term load forecast approach that utilized DL was proposed in [186] to improve energy utilization in MGs. Xinhe et al. [187] presented a data-driven VPP in a real-time electricity market for enhanced stability and reduction in dispatching costs. The market operator had a virtual auction process in real time with the VPP bidding package model which had to exchange power and information in between to make accurate decisions in favour of the customer and the supplier. The data-driven method considered the dispatching capability and dispatching cost characteristics. Some of the limitations in data-driven systems that need to be addressed are as follows:

1. Lack of prediction confidence due to ambiguities and irregularities in the provided data.
2. Load data can be vulnerable to threats and attacks that fool models into giving incorrect predictions.
3. Electrical load data tend to vary from one source to another, environment conditions as a result may bring limitations when the data is trained and managed from multiple sites.
4. A wide variety of noise and uncertainties can have a negative impact on the prediction performance.

The advancement in technologies discussed above also brings an important concept of self-healing and resiliency in MG systems. Among other benefits of various control strategies, they enhance the resilience of MGs. For example, a study in [188], looked at enhancing the resiliency of DC MGs using a model predictive control. RERs and loads tend to fluctuate with unexpected system failures which result in severe voltage and frequency instability causing damage to equipment and power interruption. A resilient MG system is required to be able to withstand any disruptions through the application of control strategies. Armaghan et al. [189] proposed a resiliency enhancement strategy for smart distribution operations with DERs that considered uncertainty in weather conditions. A Monte-Carlo simulation (MCS) for modelling uncertainties was devised with possible management programs that included DR, network reconfiguration of EVs and energy management. Currently, there is no universally accepted definition of resilience in MGs or power systems. However, most existing resilience-related research work is on the survivability of critical loads and intermittent weather [50], defence from cyber-attacks in cyber-physical systems [190], and penetration of hybrid energy resources [176].

In [191], a self-healing technique in an MG with HESs was also proposed. The model used DR with controllable loads when the line capacity limits were reached or if the generated capacity was low. This happened in critical cases to control some loads within shedding zones. The authors contributed a novel mathematical model that assisted in optimally clearing faults by changing the topology of the grid and determining the generation. The consideration of a smart grid concept and communication infrastructure enabled the realization of a centralized healing procedure at the distribution level with a cost-based objective. We have seen how MGs with MASs can also have agents perform autonomous actions which respond to the collective behaviour of the system as a whole in fulfilling. Such a self-organizing system especially during emergencies and faults in energy systems ensures that the MG remains resilient in a self-healing setup that is adaptive with a nature-driven perspective. The subsection below briefly introduces and compares some computational intelligence methods employed in MG control strategies with a focus on optimization methods.

3.2 | Optimization techniques

An optimization method is defined as an attempt to determine the best possible outcome from all available possibilities [45, 192]. It normally involves finding a minimum or maximum in an objective function relative to a set of available choices in

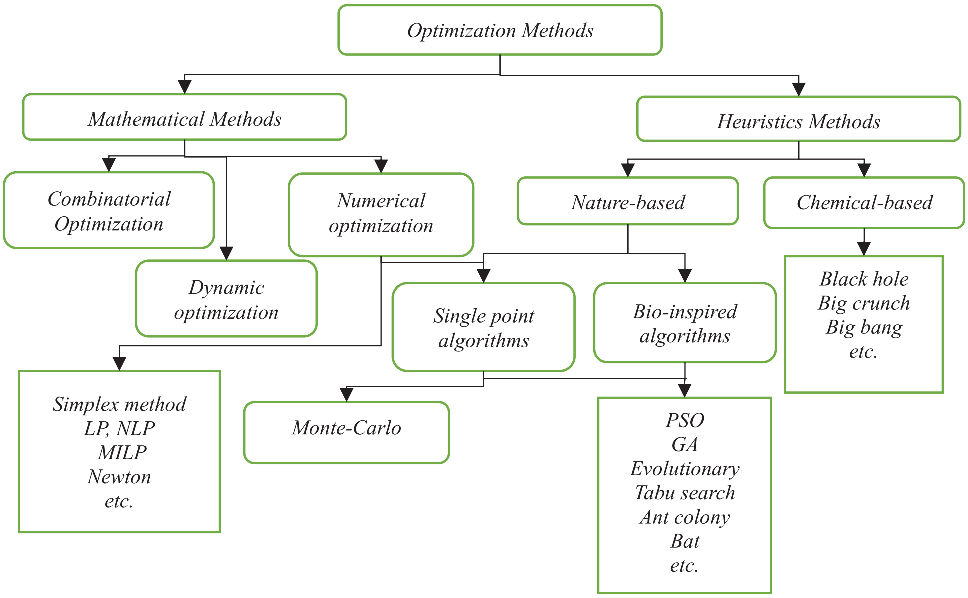

FIGURE 17 Taxonomy of the optimization methods [195].

a situation. Two optimization approaches commonly applied to problems are mathematical and heuristic. Figure 17 depicts an overview of the optimization approaches divided into two main groups. Heuristic methods use simple strategies that are inspired by nature and produce fast and adequate results for problems that are too complex to solve using numerical optimization methods. They have a greedy approach that makes them easy to implement for high searching efficiency, but difficult to converge to a global solution depending on the problem's complexity. The mathematical approaches use deterministic methods that consider concepts. Some examples include the simplex approach, quasi-Newton, and steepest descent methods [193]. Mixed integer linear programming (MILP) is another optimization method for solving complex mathematical programming problems [194]. The MG energy scheduling problem is a good example that can be defined by accurate mathematical solution algorithms and solved with less computing effort while significantly raising the probability of suboptimality [34].

There are many optimization methods, and an appropriate method for managing and controlling MGs should be selected according to the nature of the problem, the type of information and data available, and other factors. Therefore, the approach of each optimization method can be evaluated by considering its properties, strengths, and limitations. It can be seen that there is no single best method for dealing with optimization strategies in MGs. Each technique is suitable for some specific situation. A summary of some commonly adopted optimization techniques, and their merits and shortfalls are presented in Table 4.

3.2.1 | Mixed integer linear programming (MILP)

MILP algorithms are used to solve linear problems that have a linear objective function with linear constraints and restrictions. MILP is a classical mathematical optimization method that provides mathematically proven and guaranteed optimal solutions. It finds solutions with high precision and accuracy. Ref. [196] highlights how MILP is a powerful and flexible method for solving complex, large problems in engineering. MILP paradigms have been applied to several problems, including in MG systems. Typical applications involve factors with unknown certainty before deciding an outcome. Some applications include MG design and operations, planning and scheduling, energy optimization, and system analysis. A general approach to the MILP can be expressed using the following mathematical formula [198]:

$$\min f^T x subject\ to \begin{cases} A.x \leq b \\ Aeq.x = beq \\ lb \leq x \leq ub. \end{cases} \tag{6}$$

where x is an integer, A and Aeq are matrices, B and Beq are vectors, lb and ub represent the boundaries of the constraints.

Ref. [101] presented a prediction-based optimization strategy for energy balance in an MG system. A detailed scheme with a multi-objective function was constructed using MILP to determine optimal solutions that were easier to solve in the CPLEX optimizer. Ref. [197] discussed MILP methods for polygeneration optimization problems in energy systems. There were a few limitations noted which were addressed by complementing with other methods such as clustering algorithms, piecewise linearization, and rolling horizon approaches. Ref. [99] proposed a price-based DR strategy that considered the trading and frequency regulation ancillary services in dispatching energy. A three-stage MILP optimization model was used for determining the day-ahead energy planning and trading for three-time scales.

TABLE 4 Comparison overview of some of the common optimization strategy methods.

Method	Remark(s)	Merits	Drawbacks
MILP	Tackled using CPLEX, MATLAB solvers, etc.	a. Provides accurate solutions for well-defined problems b. Easy to find optimal dispatch c. Guaranteed convergence of solutions	a. Constraints are complex to specify b. Risk of high dimensionality of the problem c. Non-linear functions cannot be taken into account
PSO	Commonly used in continuous non-linear functions, population-based, follows speed & velocity in a search space among a swarm	a. Easy and simple to implement b. Has faster speed in decision-making c. Able to escape the local optimal solution d. Low computational time e. Ability to run parallel simulations	a. Not easy to obtain global optimal in less optimal solutions b. Impossible to look at discrete optimization functions c. Premature convergence
ANN	Non-linear mapping architecture, ability to learn & adapt, used for prediction	a. Strong adaptability and learning capability b. Networks process information and training data with ease giving the best outcome c. Easily handles non-linear problems d. Can handle noisy data	a. Black box in nature b. Flawed inputs give false results c. Requires lots of data d. Computationally expensive e. May consume time to develop f. Can be difficult to interpret results
Fuzzy logic	Used in the decision support domain, it uses a set of linguistic rules to determine action rather than numbers	a. Easy to interpret b. Can accommodate several inputs c. Does not require precise inputs d. Has lower hardware requirements	a. Dependant on human expertise & knowledge b. Fuzzy algorithms require broad validation and verification c. Accuracy compromised due to inaccurate d. Does not have the learning ability of new knowledge
GA	Uses a random process of mutation, crossover & natural selection; it is an adaptive and versatile algorithm	a. Easy and simple to implement b. Efficient to search large solution space without getting trapped c. Less exhaustive search d. Has simple operators that can solve complex computations	a. Not easy to find an optimal solution b. Slow to converge c. Requires a greater number of runs
Monte Carlo	Applied in prediction and forecasting models with uncertainty. Uses probability distribution functions	a. Reduces uncertainties for time-varying and seasonal problems b. Flexible, can model a range of possible outcomes c. Able to vary risk assumptions d. Can be used in both deterministic and stochastic problems	a. Expensive b. Time-consuming c. Complex and difficult to understand d. Requires large computing power e. Requires many computations and times for large volumes of variables

A home energy management framework that was solved using MILP was proposed in [198] to optimize energy utilization and energy payment to benefit the end user. An multi-criteria decision making (MCDM) approach was used to determine a suitable balance in a multi-objective with the MILP scheduling problem. The approach also contributed to the overall improvement in electrical network upstream flexibility and advancements in smart grid technology with sustainable energy management. The end-user attitudes towards home energy management problems can be complex and require more research to be looked at for future research. The proposed framework in [199] was formulated as a MILP problem for sustainable energy infrastructures for future cyber-physical homes. The authors had to investigate the investment and operational cost of using PV and BESS, optimal sizing of RERs and the effect of DR from EV. The MILP framework was used to draw comparisons from various supply structures. It can be noted that MILP formulations have been effectively applied. However, the major drawbacks such as not taking non-linear effects into account are normally tackled by combining MILP with other methods.

3.2.2 | Particle swarm optimization (PSO)

The PSO algorithm is a bio-inspired meta-heuristic intelligent algorithm that imitates the behaviour of a swarm of animals [4]. The swarm normally moves in a certain direction in a collective search for food. When one member locates food, the rest of the population will follow learning from the behaviour of members close by in search of the same food. Thus, the population learns from each individual's experiences and communication as they search for food, cooperatively. PSO considers a solution through a search space, for example, a swarm of birds/fish can be taken to be particles that explore the whole search space with each particle evaluated by the fitness function. The position and velocity movement of the particle will play an essential role guided by the following general equations [200]:

$$v_i^{k+1} = v_i^k + \alpha rand_1 \left[g^* - x_i^k\right] + \beta rand_2 \left[x_i^* - x_i^k\right], \tag{7}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{8}$$

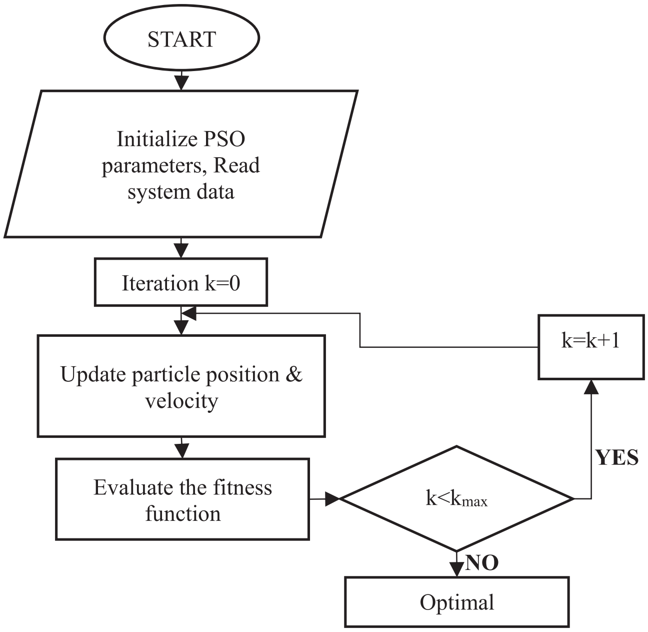

FIGURE 18 Optimization procedure of the PSO algorithm.

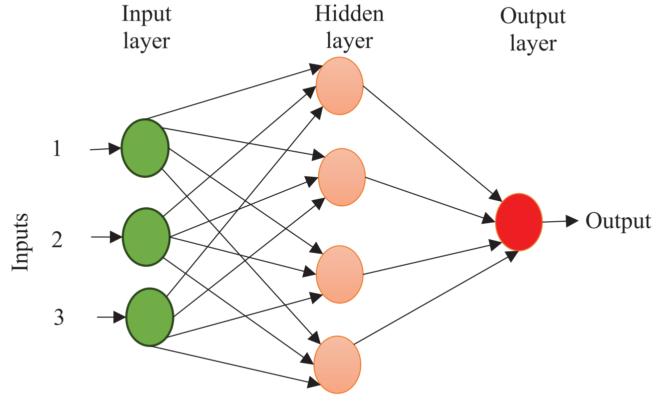

FIGURE 19 Basic architecture of an ANN.

where x_i is the position of the particle, v_i is the velocity of the particle, α and β are learning parameters (acceleration constants) and $rand_1$ and $rand_2$ are two random vectors range [0–1] and g^* is the current global best whilst x_i^* is the current individual local best.

Figure 18 shows the basic optimization procedure for finding optimal solutions using the PSO algorithm. The PSO algorithm is based on three basic steps: (1) initial generation of particles' positions and velocities, (2) velocity update, and (3) position update [201]. In the initialization stage, a population of initial solutions is randomly generated for an optimization problem in a feasible search area. A source (prey) represents the optimal solution whilst the quality of the solution is represented by the latest position.

The literature has established various studies that used different variations of the PSO algorithm to suit the applied problem needs in achieving optimal solutions. Cingoz et al. [67] introduced a PSO-based optimization procedure that determined the optimal parameters for an effective droop mechanism in MG operations. The study was conducted in a simulated MATLAB/Simulink environment and experimentally using a DC MG test bench for validation. The proposed method achieved enhanced current sharing and improved voltage degradation with accuracy in both the simulated and experimental environments, proving the effectiveness of the PSO algorithm. Ref. [202] considered a hybrid optimization algorithm with PSO to solve a forecasting problem in wind power production for RESs. A combination of data filtering techniques was based on soft computing that used ANNs optimized using PSO for the developed prediction model. Ref. [203] presented an intelligent scheduling of RESs for maximum utilization in a cyber-physical energy system. The PSO algorithm was employed in the designed study models to optimize the cost and emissions in a system with grid-able EVs. In [204], a control strategy that used a modified binary PSO algorithm and Tabu search approach to reduce power losses and improve voltage profiles in networks with large DG penetration was presented. The introduction of the double fitness approach in considering the constraints improved the computational time, which ameliorated the impact of load variation on the losses. Despite the fast calculation time, the loads at the same stage were strictly limited by the method.

3.2.3 | Artificial neural network (ANN)

ANN models were developed to imitate the biological nervous system. ANN is connected by basic units that form direct links with numeric weights. The units are referred to as nodes, where each unit calculates linear combinations passed through the activation function to derive the outputs [85]. ANNs have been utilized in pattern recognition, prediction clustering and classification applications [205]. The two main ANN architectures are Feedforward and Recurrent, and the general structure consists of three layers; (1) an input layer, (2) a hidden layer, and (3) an output layer. Figure 19 shows the basic structure of an ANN architecture.

In [206], a battery degradation cost model was integrated into an energy management strategy with an ANN-based method. ANN was able to provide a reliable set of stochastic scenarios for the generation methodology with different scheduling schemes. The main objective was to reduce the household electricity consumption cost via smart coordination of the BESS and the EV in a home setup. The value of the stochastic solution was then computed to prove the efficiency of the proposed method. The cooperative scheduling of the BESS had the most profitable scheme whilst the uncoordinated scheme risked the highest electricity cost in procurement. Ladjouzi et al. [207] proposed an ANN-based scheme for maximum power point tracking (MPPT) in wind turbines. An ANN with a multi-layer perceptron (MLP) architecture was considered to train the provided datasets to achieve an optimal electromagnetic torque in a turbine within the system. The method managed to give better results on the influential variables used in wind turbine power generation. Ref. [208] implemented an ANN model to solve short-term forecasting at the load side. Estimations of load profiles within 24 h were generated from historical data that looked at time, weather, and load demand. They were integrated with other DSM schemes to improve matching the load with available supply. ANN was the most suitable method because of its ability to learn from both linear and non-linear relationships of the modelled data.

The deep reinforcement learning (DRL) method is one of the most promising learning-based EMS methods that use ANN as a function approximator capable of continuously learning state-action transitions under uncertainty. Agents are also able to learn the dynamics of MG by interacting with various components in MGs. Ref. [209] proposed a novel MG model for energy management with flexible demand. The EMS coordinated various flexible sources by prioritising the available sources, DSM and pricing. Several DL algorithms in the study were implemented in the MG model and empirically compared. DRL algorithms were studied in [100] to solve energy scheduling problems in MGs. The study showed that all three DRL algorithms that were developed, were improved from the basics of ANN architecture and modified for best performance in MG energy control coordination. Ref. [210] critically reviewed various studies that focussed on short-term wind power prediction using ANN models. ANN has proved to be a robust tool for dealing with non-linear problems that have even superior performance when hybridized with other algorithms. It can be seen that the maturity of prediction tools in providing more accurate results with speed has improved over the years.

3.2.4 | Fuzzy logic (FL)

FL system is based on deterministic and inference rules that determine the outcome from the given inputs. It mimics the human mind in reasoning and depends on linguistic variables. The three main components in an FL controller are: (1) fuzzification–which is responsible for converting input values to linguistic, (2) inference system–which determines the expected output from the given linguistic variables in a knowledge base, and (3) defuzzification–which converts the linguistic variables back to output crisp values. The FL control method has been employed in various problems that require strategic coordination in systems or machines [211, 212]. In MG systems, it is applicable in problems such as forecasting, controlling PV systems, load prioritization, power balancing, and system stabilization. It has been noted that FL has mostly been combined with other optimization techniques to take advantage of AI algorithms for better performance [213, 214]. An overview of the FL control block diagram is shown in Figure 20.

Irmak et al. [215] designed an FL-based EMS for an event-triggered secondary control of the BESS controller to manage overall power flow regulation and voltage stability based on power generation from the sources. The controller was able to prevent deep discharge and overcharging in BESS. Mamdani inference model was used to determine the output values whilst the defuzzification process used the *centre of gravity* method to

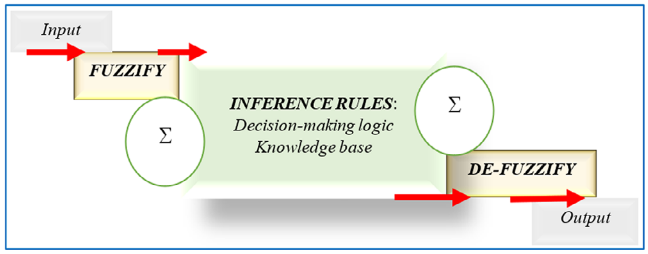

FIGURE 20 Fuzzy logic control block diagram.

determine the power values of the battery charge ratio and the RESs. This enabled for effective management of all the sources that were available in the system. The controller ensured that the MG operated safely due to the power regulation and sharing. The proposed study was tested in a MATLAB/Simulink environment.

An FL controller for DR with a focus on thermostats to manage air-conditioning and household thermal comfort in an MG system was proposed [216]. The considered input parameters were radiation from solar, electricity price and the presence of the household occupants. The EMS had to use time-shiftable operations that were controlled using the thermostat, and power shiftable loads such as EVs and BESS. The FL approach used the Mamdani FIS to fuzzify the input parameters into linguistic *IF-THEN* rules, whilst the *centre of the area* was used in the defuzzification method. A daily total cost reduction was realised with the proposed controller under the Turkish ToU and FiT rates.

3.2.5 | Genetic algorithm (GA)

GA is a bio-inspired algorithm that follows the principles of evolutionary biology to search for solutions to a given problem. It is a single point-based algorithm that uses an iterative process to identify a fitness function from the following components: (1) natural selection, (2) mutation, (3) crossover, and (4) replication. GA is stochastic and does a random search by mutation and crossover among the population. It can solve constrained, unconstrained and multi-criteria optimization problems, and can address mixed integer programming problems with components that have integer value restrictions. However, it should be noted that GA takes many function evaluations which may or may not converge to a local or global minimum. Figure 21 shows how a GA algorithm works.

Ref. [20] discussed how GA is applied in optimization strategies with multi-objective function problems. A well-coordinated optimization model was determined by the characteristics and requirements for the given problem to achieve the most reliable and accurate simulation results. GA was also implemented in [208] for DSM applications to manage load shedding and load shifting, and identify optimal strategies that give the best results in the system. GA searched for the optimum shiftable loads and prioritized loads for load shedding. GA was chosen

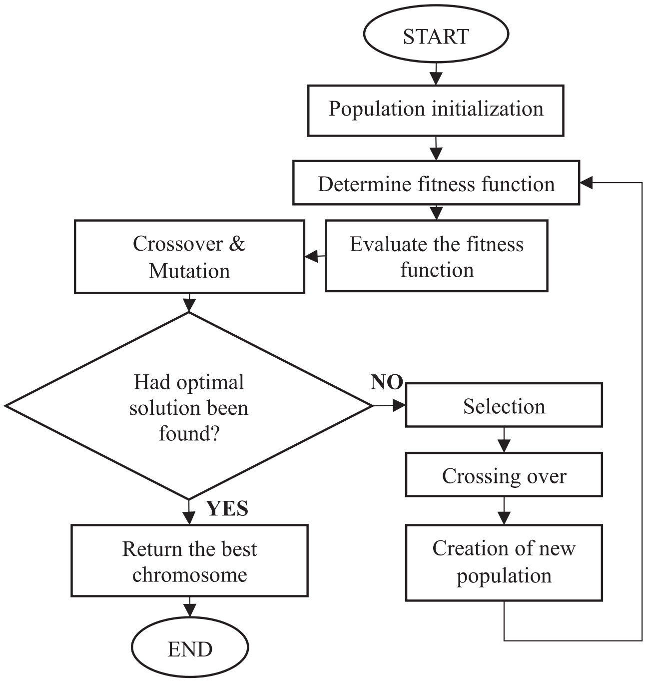

FIGURE 21 Optimization procedure of the GA algorithm.

because of its simplicity and ability to solve many constrained problems with ease, supported by the results obtained from the conducted study.

In [217], a study on the optimization of DG operations using AI techniques was presented with GA being of main interest. The algorithm was applied to reduce the total operating cost in a 24 h time frame and determine the optimal cost of operation. This positively affected the efficiency curve and constraints of individual units when optimal settings of the DGs were realized. Awais et al. [218] proposed a DSM strategy that focussed on minimising the peak-to-average ratio and increasing MG efficiency by making more use of the spinning reserve. GA was used to solve the load scheduling problem by determining the proper loads that can be shifted and controlled during peak load demand, which resulted in total cost reduction. The strategy was beneficial to the MG operator and consumer, especially at the distribution level.

3.2.6 | Monte-Carlo

Monte Carlo simulations (MCS) are used to solve problems with uncertainties by evaluating the behaviour of physical systems and mathematical models using a set of random input numbers. It is characterized as a stochastic, non-deterministic sampling method because of its use and capability of generating random numbers. The study case in [219] used MCS to evaluate the loss of load probability (LOLP) values at different PV ratings and PV-BESS combinations. The authors recommended considering the hardware components when modelling the system components to achieve a more accurate measure of the system's reliability in both simulated and hardware experimental results. Yu et al. [220] developed a hybrid fuzzy-stochastic technique that addressed the peak demand issue under various uncertainties. MCS was used to determine peak-load probability distribution data, which was projected into a matrix of various parameters related to uncertainties. However, the method was limited to single-objective problems. The authors recommended that more studies on energy trade and supply needed to be conducted. In [221], a techno-economic framework was developed to model and assess multi-energy MGs. The proposed stochastic approach for reliable dynamic energy market price used sequential MCSs. It was based on MG operations during various conditions and contingencies. It was found that reliability services had little or moderate costs when adjustments were made in the MG operations to maximise the benefits.

Several researchers have conducted studies on control strategies and energy management operations in MGs for single and/or multi-objective optimization problems [222–228]. Multi-objective function optimization problems are normally used to consider more than one objective problem and require complex mathematical programming to solve them. Table 5 presents an overview of some of the optimization strategies employed in MG control applications. It can be noted how PV and BESS components appear in almost all the studies with PV and WT supplying power from intermittent sources. There were very few studies that considered predictive or forecasting model analysis. Operational cost stood out the most in most studies as one of the objectives that was achieved, followed by energy utilization and system stability. Various modifications of the PSO algorithm were noted in most studies, whilst fuzzy control and neural network methods had a fair share of application in MG control from the studied literature. Most strategies seemed to have employed heuristic methods as compared to mathematical optimization methods, with some strategies using more than one optimization method. The complexity of some problems demanded a multi-objective function solution to ensure all parameters were optimally considered at the same time to achieve a robust MG control strategy. However, in some cases, a single objective solution approach for each interested parameter yields better results. It may be concluded that most studies tabulated in Table 5 approached the problems as single objective functions.

4 | CONCLUSION

The study reviewed more than 228 research articles on methods and strategies employed to solve various MG control problems, ranging from 2010 to 2024. The review highlighted the growing importance of optimization methods and some of the emerging technologies in addressing the MG challenges with and/or without HESs. The study also identified several key findings and concerns on the application of optimization techniques in MG operations pertaining to control strategies. Case studies on control strategy implementation in MGs have provided valuable insights into the practical application of different strategies. The strategies aim to achieve various specific objectives with most MGs pre-eminenting to deliver resilient and self-healing systems

TABLE 5 Overview of optimization methods for MG control applications.

Ref.	Year	Solution approach	Hybrid optimization methods	Single objective	Multi-objective	MG components	Predictive analysis model	Remarks
[178]	2023	XGBoost-based imitation learning (IL)	–	Operational cost Trading cost Power output curtailment	–	WT, PV, ESS, grid	Considered	The method outperformed MILP and DRL methods. IL had training efficiency with enhanced accuracy of online scheduling
[78]	2023	Ensemble empirical-mode decomposition method	Fuzzy control algorithm	Reduce operating cost Improve operation stability Applicability to different wind speeds.	–	Supercapacitors, power to hydrogen system, WT and grid	–	"Source–load" turbulence suppression Method is used to stabilize the system from a wind farm. The synergy control between the supercapacitors and the power of hydrogen system is considered
[39]	2022	Sparrow search algorithm	–	Operating cost Total emission	Operating cost and total emission, simultaneously	PV, WT, fuel cell, BESS, micro-turbine (MT), grid	–	BESS lifecycle constraints were not considered: frequent charging/discharging cycles affect the BESS lifecycle
[217]	2023	Fuzzy logic control	–	Prevent overcharging and discharging in BESS	Improve power-sharing	WT, PV, ESS, DC load	–	Event-triggered distributed secondary control was verified using Lyapunov's stability criteria. Communication burden was reduced and the RES was successfully optimally supplied to the demand
[107]	2021	Recurrent neural network (RNN) + Adaptive whale optimization algorithm	Tabu search	–	Operation and maintenance cost utilization of sources	PV, WT, MT, BESS	Recurrent neural network (RNN)	Technique had fast time execution. RNN suffers from a vanishing gradient
[38]	2022	Artificial hummingbird algorithm (AHA)	–	MG Operational cost	–	PV, WT, DiG, grid	Point estimation method	MG system state was described using the variable uncertainties
[41]	2020	Binary PSO	PSO	Energy cost	Energy cost Peak-to-average ratio	PV, BESS, grid	–	Real-time data usage will help improve the proposed system
[42]	2023	Genetic algorithm (GA)	ANFIS	Accurate converter outputs	–	PV, BESS, WT	–	Transfer function MG model was limited to the small-signal-based pole-zero cancellation to simulate a nearly linear MG
[26]	2022	Non-linear optimization method	–	Fuel cost Energy utilization	–	PV, WT, DiG, BESS	–	Lacks clarity on the optimization tool used
[227]	2015	Power limitation algorithm	–	Utilization of storage elements Smooth power supply	–	PV, BESS, ultra-capacitors	Considered	Various control strategies realized the electrical references (frequency and voltage)

(Continues)

TABLE 5 (Continued)

Ref.	Year	Solution approach	Hybrid optimization methods	Single objective	Multi-objective	MG components	Predictive analysis model	Remarks
[109]	2021	Two-stage fuzzy Logic (FL)	–	Operation of poly-generation	–	PV, EVs, grid BESS	–	Need to combine management with poly-generation sizing for further improvement
[111]	2020	Model predictive control	–	Electricity cost Power flow Generation-load balance	–	PV, BESS, grid	Weather forecast model	Control scheme implemented to predict the SoC in the PV/Bess system
[81]	2018	Agent-based control algorithm	–	Load consumption	–	PV, BESS	–	Model a DR-based system
[10]	2022	DSM strategy using ANN	–	Load shifting Peak clipping	–	PV, BESS	–	Lowers power consumption and improved grid stability
[101]	2020	Prediction-based strategy	MILP MINP	Load shifting	Fuel consumption Energy utilization	DiG, BESS, grid	Softmax regression	Collaborative scheduling of multiple DGs
[67]	2017	Particle swarm optimization (PSO)	–	Operational cost	–	PV, WT, fuel cell, BESS, EVs	Load stochastic model	Inherent limitations of the droop control technique were reduced for DC MGs.
[228]	2016	Branch-and-bound search tree	Fuzzy predictive filter	Operation cost	–	Grid	–	Control Scheme was not examined on controller stability and robustness
[40]	2020	Artificial Bee Colony (ABC) algorithm	–	Power losses Load shading	–	PV, WT, main grid	–	Focused on the performance of synchronization of MG to the grid
[103]	2019	Self-adaptive PSO (SAPSO) algorithm	–	–	Daily load variance Customer satisfaction Operating cost Power balancing	IEEE33-bus distribution system	–	Improvement of cooperation among electricity market agents in the distribution system was not considered
[45]	2017	Modified PSO	–	Operation and maintenance cost Overall system income	–	PV, WT, fuel cell, CHP system, solar collector, grid	–	The technique did not consider forecasting the load and generation

during operation considering technical, cost, socio-economics and environment among others. This can serve as a reference for researchers interested in studying MG control strategies, especially on MG management operations.

Strong interlinks in most emerging technological applications such as DT, MAS, advancements in IoT, embedded systems, ML and optimization techniques in relation were observed. AI was somehow involved in all aspects of MG system applications, such as control and monitoring. There is still more interest and ongoing research towards control strategies, intelligent control systems, EMS, and the application of AI in the MG domain. Among the optimization methods mentioned in this study, the PSO algorithm has been significantly applied in many optimal operation management problems. This is mainly due to its simplicity, population-based search capability, robustness, and convergence speed. However, it is worth noting that the performance of a conventional PSO algorithm greatly depends upon its learning and weighting factors which may get trapped in local optima.

It can be seen from this article that there are limited studies on DSM in SSA, and more research is encouraged to be conducted. Individual DG applications can create more problems than they may solve if not carefully considered in the initial system approach modelling. Exploitation of aggregated RESs and off-grid MG systems must be studied with care so that appropriate decisions can be made for better-performing operations. The complex interactions among various energy domains require comprehensive research on energy management and control strategies in MGs. There is also a high demand for dealing with multi-objective function problems in MGs due to conflicting goals. It is essential to continue exploring MG control strategies that support the incorporation of AI and emerging technologies, with a broader look at other factors that affect MGs.

AUTHOR CONTRIBUTIONS

Shaibu Ali Juma: Conceptualization; formal analysis; investigation; methodology; validation; visualization; writing—original draft. **Sarah Paul Ayeng'o**: Supervision; validation; writing—review and editing. **Cuthbert Z. M. Kimambo**: Resources; supervision; validation; writing—review and editing.

ACKNOWLEDGEMENTS

The authors acknowledge Mzuzu University and the Department of Mechanical and Industrial Engineering under the College of Engineering, University of Dar es Salaam for supporting this study by providing finance and resources, respectively.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The research has no data available.

ORCID

Shaibu Ali Juma https://orcid.org/0000-0001-5112-1054

REFERENCES

1. Alam, M.S., Chowdhury, T.A., Dhar, A., Al-Ismail, F.S., et al.: Solar and wind energy integrated system frequency control: A critical review on recent developments. Energies 812(16), 1–31 (2023). https://doi.org/10.3390/en16020812
2. Nale, R., Biswal, M., Kishor, N., Merino, J., Perez-Basante, A., Rodriguez-Seco, J.E.: Real-time analysis of islanding detection scheme developed for AC microgrid system. Electr. Power Syst. Res. 226, 109926 (2023). https://doi.org/10.1016/j.epsr.2023.109926
3. Ruta, W., Saulo, M., Odero, N.A., Juma, S.A.: Combined economic and emissions dispatch with valve point effect using a novel moth flame optimization and bat hybrid algorithm. Int. J. Sci. Res. Publ. 9(3), 8728 (2019). https://doi.org/10.29322/ijsrp.9.03.2019.p8728
4. Philipo, G.H., Kakande, J.N., Krauter, S.: Demand-side-management for optimal dispatch of an isolated solar microgrid. In: Proceedings of the 2023 IEEE AFRICON, pp. 1–6. IEEE, Piscataway, NJ (2023). https://doi.org/10.1109/AFRICON55910.2023.10293343
5. Zalengera, C., et al.: Decentralization: the key to accelerating access to distributed energy services in sub-Saharan Africa? J. Environ. Stud. Sci. 10(3), 270–289 (2020). https://doi.org/10.1007/s13412-020-00608-7
6. Raymond, J., Kihedu, J.H., Kimambo, C.Z.M.: A model for sustainable adoption of solar photovoltaic technology in Tanzania. Tanzania J. Eng. Technol. 41(2), 16–34 (2022). https://doi.org/10.52339/tjet.v41i2.776
7. Juma, S.A., Mtonga, T., Mharakurwa, E.T., Nyachionjeka, K.: Optimal switching sequence using an improved metaheuristic technique in a distribution network system with fixed DG units. In: Proceedings of the 2023 IEEE AFRICON, pp. 1–6. IEEE, Piscataway, NJ (2023). https://doi.org/10.1109/AFRICON55910.2023.10293322
8. Xing, X., Jia, L.: Energy management in microgrid and multi-microgrid. IET Renewable Power Gener. 1–29 (2023). https://doi.org/10.1049/rpg2.12816
9. Vaish, J., Tiwari, A.K., Siddiqui, K.M.: Optimization of micro grid with distributed energy resources using physics based meta heuristic techniques. IET Renew. Power Gener. 1–17 (2023). https://doi.org/10.1049/rpg2.12699
10. Philipo, G.H., Kakande, J.N., Krauter, S.: Neural network-based demand-side management in a stand-alone solar PV-battery microgrid using load-shifting and peak-clipping. Energies 15(14), 5215 (2022). https://doi.org/10.3390/en15145215
11. Hettiarachchi, D., Shing Choi, S., Rajakaruna, S., Ghosh, A.: Development of control strategy for community battery energy storage system in grid-connected microgrid of high photovoltaic penetration level. Int. J. Electr. Power Energy Syst. 155, 109527 (2023). https://doi.org/10.1016/j.ijepes.2023.109527
12. Mbungu, N.T., Naidoo, R.M., Bansal, R.C., Vahidinasab, V.: Overview of the optimal smart energy coordination for microgrid applications. IEEE Access 7, 163063–163084 (2019). https://doi.org/10.1109/ACCESS.2019.2951459
13. Nikam, V., Kalkhambkar, V.: A review on control strategies for microgrids with distributed energy resources, energy storage systems, and electric vehicles. Int. Trans. Electr. Energy Syst. 31(1), 1–26 (2021). https://doi.org/10.1002/2050-7038.12607
14. Alam, M.S., Al-Ismail, F.S., Rahman, S.M., Shafiullah, M., Hossain, M.A.: Planning and protection of DC microgrid: A critical review on recent developments. Eng. Sci. Technol. 41, 101404 (2023). https://doi.org/10.1016/j.jestch.2023.101404
15. Salehi, N., Martinez-Garcia, H., Velasco-Quesada, G., Guerrero, J.M.: A comprehensive review of control strategies and optimization methods for individual and community microgrids. IEEE Access 10, 15935–15955 (2022). https://doi.org/10.1109/ACCESS.2022.3142810
16. Philipo, G.H., Chande Jande, Y.A., Kivevele, T.: Clustering and fuzzy logic-based demand-side management for solar microgrid operation: Case study of Ngurudoto microgrid, Arusha, Tanzania. Hindawi Adv. Fuzzy Syst. 2021(13), (2021). https://doi.org/10.1155/2021/6614129
17. Lorenzoni, L., Cherubini, P., Fioriti, D., Poli, D., Micangeli, A., Giglioli, R.: Classification and modeling of load profiles of isolated mini-grids in

developing countries: A data-driven approach. Energy Sustainable Dev. 59, 208–225 (2020). https://doi.org/10.1016/j.esd.2020.10.001
18. Philipo, G.H., Abeid, Y., Jande, Y.A.C., Kivevele, T.: Demand-side management of solar microgrid operation: Effect of time-of-use pricing and incentives. Hindawi J. Renewable Energy 2020(12), (2020). https://doi.org/10.1155/2020/6956214
19. Lu, S., et al.: Control strategies for distributed energy resources to maximize the use of wind power in rural microgrids. In: Proceedings of the 2011 IEEE Power and Energy Society General Meeting, pp. 1–8. IEEE, Piscataway, NJ (2011). https://doi.org/10.1109/PES.2011.6039787
20. Hong, B., Miao, W., Liu, Z., Wang, L.: Architecture and functions of micro-grid energy management system for the smart distribution network application. Energy Procedia 45(2018), 478–483 (2018). https://doi.org/10.1016/j.egypro.2018.04.095
21. Ma, J., Zhang, N., Wen, Q., Wang, Y.: An efficient local multi-energy systems planning method with long-term storage. IET Renewable Power Gener. 18(3), 426–441 (2023). https://doi.org/10.1049/rpg2.12726
22. Syed, D., Zainab, A., Ghrayeb, A., Refaat, S.S., Abu-Rub, H., Bouhali, O.: Smart grid big data analytics: Survey of technologies, techniques, and applications. IEEE Access 9, 59564–59585 (2021). https://doi.org/10.1109/ACCESS.2020.3041178
23. Espina, E., Llanos, J., Burgos-Mellado, C., Cárdenas-Dobson, R., Martínez-Gómez, M., Sáez, D.: Distributed control strategies for microgrids: An overview. IEEE Access 8, 193412–193448 (2020). https://doi.org/10.1109/ACCESS.2020.3032378
24. Agajie, T.F., Lele, A.F., Ali, A., Amoussou, I., Khan, B., Elsisi, M.: Optimal sizing and power system control of hybrid solar PV-biogas generator with energy storage system power plant. Sustainablity 15(7), 5739 (2023). https://doi.org/10.3390/su15075739
25. Shahgholian, G.: A brief review on microgrids: Operation, applications, modeling, and control. Int. Trans. Electr. Energy Syst. 31(6), 1–28 (2021). https://doi.org/10.1002/2050-7038.12885
26. Suwi, O.M., Justo, J.J.: Optimal energy management for off-grid hybrid renewable energy. In: Proceedings of the Seventh International Conference on Mechanical and Industrial Engineering (MIE), pp. 72–78. IEEE, Piscataway, NJ (2023). https://doi.org/10.52339/tjet.v42i1.889
27. Chikumbanje, M., Frame, D., Galloway, S.: Minigrid integration planning (MGIP) for loss reduction and voltage profile improvement beyond energy access in developing countries. Energy Strategy Rev. 44, 100974 (2022). https://doi.org/10.1016/j.esr.2022.100974
28. Manbachi, M.: Energy management systems for hybrid AC/DC microgrids: Challenges and opportunities. In: Operation of Distributed Energy Resources in Smart Distribution Networks. pp. 303–348. Academic Press, Cambridge, MA (2018). https://doi.org/10.1016/B978-0-12-814891-4.00013-8
29. Tazi, K., Abbou, F.M., Abdi, F.: Multi-agent system for microgrids: design, optimization and performance. Artif. Intell. Rev. 53(2), 1233–1292 (2019). https://doi.org/10.1007/s10462-019-09695-7
30. Babatunde, O.M., Munda, J.L., Hamam, Y.: Renewable energy technologies for generation expansion planning: A fuzzy modified similarity-based approach. In: Proceedings of the 2019 IEEE 2nd International Conference on Renewable Energy and Power Engineering, pp. 216–220. IEEE, Piscataway, NJ (2019). https://doi.org/10.1109/REPE48501.2019.9025160
31. Responding to climate change. https://www.unenvironment.org/regions/africa/regional-initiatives/responding-climate-change/. Accessed 24 Nov 2023
32. Eko, J.O., Paul, M.C.: Integrated sustainable energy for sub-saharan africa: A case study of machinga boma in Malawi. Energies 14(19), 6330 (2021). https://doi.org/10.3390/en14196330
33. Ravikumar, S., Vennila, H.: Hybrid wind solar system for efficient power generation. In: Proceedings of the International Conference on Electronics, Communication and Aerospace Technology, pp. 73–79. IEEE, Piscataway, NJ (2017)
34. Elweddad, M., Güneşer, M., Yusupov, Z.: Designing an energy management system for household consumptions with an off-grid hybrid power system. AIMS Energy 10(4), 801–830 (2022). https://doi.org/10.3934/energy.2022036
35. Nehrir, M.H., et al.: A review of hybrid renewable/alternative energy systems for electric power generation: Configurations, control, and applications. IEEE Trans. Sustainable Energy 2(4), 392–403 (2011). https://doi.org/10.1109/TSTE.2011.2157540
36. McCauley, D., Grant, R., Mwathunga, E.: Achieving energy justice in Malawi: From key challenges to policy recommendations. Clim. Chang. 170(28), 1–22 (2022). https://doi.org/10.1007/s10584-022-03314-1
37. El Mezdi, K., et al.: Performance improvement through nonlinear control design and power management of a grid-connected wind-battery hybrid energy storage system. Results Eng. 20, 101491 (2023). https://doi.org/10.1016/j.rineng.2023.101491
38. Alamir, N., Kamel, S., Megahed, T.F., Hori, M.: Developing an artificial hummingbird algorithm for probabilistic energy management of microgrids considering demand response. Front. Energy Res. 10, 1–17 (2022). https://doi.org/10.3389/fenrg.2022.905788
39. Fathy, A., Alanazi, T.M., Rezk, H., Yousri, D.: Optimal energy management of micro-grid using sparrow search algorithm. Energy Rep. 8, 758–773 (2022). https://doi.org/10.1016/j.egyr.2021.12.022
40. Mogaka, L.O., Nyakoe, G.N., Saulo, M.J.: Power prioritization and load shedding in an island with RESs using ABC algorithm. Hindawi J. Eng. 2020, 10 (2020). https://doi.org/10.1155/2020/8131952
41. Dinh, H.T., Yun, J., Kim, D.M., Lee, K.H., Kim, D.: A home energy management system with renewable energy and energy storage utilizing main grid and electricity selling. IEEE Access 8, 49436–49450 (2020). https://doi.org/10.1109/ACCESS.2020.2979189
42. Aloo, L.A., Kihato, P.K., Kamau, S.I., Orenge, R.S.: Modeling and control of a photovoltaic-wind hybrid microgrid system using GA-ANFIS. Heliyon 9(4), e14678 (2023). https://doi.org/10.1016/j.heliyon.2023.e14678
43. Kini, R., et al.: Control-centric living laboratory for management of distributed energy resources. IEEE Open Access J. Power Energy 10, 48–60 (2022). https://doi.org/10.1109/OAJPE.2022.3223656
44. Van, L.P., Hoang, L., Do, K., Takano, H.: An improved state machine-based energy management strategy for renewable energy microgrid with hydrogen storage system. Energy Rep. 9, 194–201 (2023). https://doi.org/10.1016/j.egyr.2022.10.385
45. Maleki, A., Rosen, M.A., Pourfayaz, F.: Optimal operation of a grid-connected hybrid renewable energy system for residential applications. Sustainability 9(8), 1–20 (2017). https://doi.org/10.3390/su9081314
46. Mirsaeidi, S., Muttaqi, K.M., He, J., Dong, X.: A coordinated power flow control strategy to enhance the reliability of hybrid AC/DC power grids during cascading faults. Int. J. Electr. Power Energy Syst. 155, 109651 (2023). https://doi.org/10.1016/j.ijepes.2023.109651
47. Yegon, P., Singh, M.: Frequency stability enhancement of microgrid using optimization techniques-based adaptive virtual inertia control. Int. Trans. Electr. Energy Syst. 2023, 19 (2023). https://doi.org/10.1155/2023/2121721
48. Jia, H., Zhang, C., Du, J., Kuang, N.: A data-driven approach for reactive power optimization incorporating interval values for renewable power generation. Int. Trans. Electr. Energy Syst. 2023, 14 (2023). https://doi.org/10.1155/2023/6678942
49. Rama, S.T., Rajini, V.: Optimization of switching control and microgrid energy management system with alternate arm converter based on bacterial foraging algorithm. Int. Trans. Electr. Energy Syst. 2023, 35 (2023). https://doi.org/10.1155/2023/5585420
50. Jasim, A.M., Jasim, B.H., Alhasnawi, B.N., Flah, A., Kraiem, H.: Coordinated control and load shifting-based demand management of a smart microgrid adopting energy internet. Int. Trans. Electr. Energy Syst. 2023, 33 (2023). https://doi.org/10.1155/2023/6615150
51. Ashokkumar, V., Venkatramanan, C.B.: PSO-ANFIS-based energy management in hybrid AC/DC microgrid along with plugin electric vehicle. Int. J. Photoenergy 2023, 24 (2023). https://doi.org/10.1155/2023/2852972
52. Yan, M., et al.: Energy management considering multiple power markets and microgrid storage. Front. Energy Res. 11, 1–12 (2023). https://doi.org/10.3389/fenrg.2023.1285270
53. Kadi, S., Benbouhenni, H., Abdelkarim, E., Imarazene, K., Berkouk, E.M.: Implementation of third-order sliding mode for power control and

maximum power point tracking in DFIG-based wind energy systems. Energy Rep. 10, 3561–3579 (2023). https://doi.org/10.1016/j.egyr.2023.09.187

54. Leitloff, V., Chen, H., Chen, D., et al.: Towards a standardisation for digital inputs and outputs of protection functions in IEC 60255 series. Prot. Control Mod. Power Syst. 7, 26 (2022). https://doi.org/10.1186/s41601-022-00246-x
55. Zolfaghari, M., Gharehpetian, G.B., Blaabjerg, F., Anvari-Moghaddam, A.: A new robust nonlinear control strategy for UIPC in isolated hybrid microgrids. Int. J. Electr. Power Energy Syst. 155(PB), 109569 (2023). https://doi.org/10.1016/j.ijepes.2023.109569
56. El-Fergany, A.A.: Reviews, challenges and insights on computational methods for network reconfigurations in smart electricity distribution networks. Arch. Comput. Methods Eng. 31, 1233–1253 (2024). https://doi.org/10.1007/s11831-023-10007-0
57. Miroshnyk, O., Moroz, O., Shchur, T., Chepizhnyi, A., Qawaqzeh, M., Kocira, S.: Investigation of smart grid operation modes with electrical energy storage system. Energies 16(6), 2638 (2023). https://doi.org/10.3390/en16062638
58. Sen, S., Kumar, V.: Microgrid modelling: A comprehensive survey. Annu. Rev. Control 46, 216–250 (2018). https://doi.org/10.1016/j.arcontrol.2018.10.010
59. Zia, M.F., Elbouchikhi, E., Benbouzid, M.E.H.: An energy management system for hybrid energy sources-based stand-alone marine microgrid. IOP Conf. Ser.: Earth Environ. Sci. 322, 012001 (2019). https://doi.org/10.1088/1755-1315/322/1/012001
60. Raghavendran, C.R., Preetha Roselyn, J., Devaraj, D.: Development and performance analysis of intelligent fault ride through control scheme in the dynamic behaviour of grid connected DFIG based wind systems. Energy Rep. 6, 2560–2576 (2020). https://doi.org/10.1016/j.egyr.2020.07.015
61. Madiba, T., Bansal, R.C., Mbungu, N.T., Bettayeb, M., Naidoo, R.M., Siti, M.W.: Under-frequency load shedding of microgrid systems: A review. Int. J. Model. Simul. 42(4), 653–679 (2021). https://doi.org/10.1080/02286203.2021.1964061
62. Zafari, P., Zangeneh, A., Moradzadeh, M., Ghafouri, A., Parazdeh, M.A.: Various droop control strategies in microgrids. In: Tabatabaei, M.N., et al. (eds.) Power Systems, pp. 527–554. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-23723-3_22
63. Subramanian, V., Vairavasundaram, I., Aljafari, B.: Analysis of optimal load management using a stand-alone hybrid AC/DC microgrid system. Int. Trans. Electr. Energy Syst. 2023, 14 (2023). https://doi.org/10.1155/2023/7519436
64. Salehimehr, S., Taheri, B., Sedighizadeh, M.: Short-term load forecasting in smart grids using artificial intelligence methods: A survey. J. Eng. 2022(12), 1133–1142 (2022). https://doi.org/10.1049/tje2.12183
65. Tepe, I.F., Irmak, E.: A review of control strategies and metaheuristic algorithms used in DC microgrids. Int. J. Renewable Energy Res. 12(2), 799–818 (2022). https://doi.org/10.20508/ijrer.v12i2.12854.g8466
66. Tabatabaee, S., Karshenas, H.R., Bakhshai, A., Jain, P.: Investigation of droop characteristics and X/R ratio on small-signal stability of autonomous microgrid. In: Proceedings of the 2011 2nd Power Electronics, Drive Systems and Technologies Conference, pp. 223–228. IEEE, Piscataway, NJ (2011). https://doi.org/10.1109/PEDSTC.2011.5742422
67. Cingoz, F., Elrayyah, A., Sozer, Y.: Optimized settings of droop parameters using stochastic load modeling for effective DC microgrids operation. IEEE Trans. Ind. Appl. 53(2), 1358–1371 (2017). https://doi.org/10.1109/ECCE.2015.7309732
68. Tuladhar, A.: Power management of an off-grid PV inverter system with generators and battery banks. In: Proceedings of the 2011 IEEE Power and Energy Society General Meeting, pp. 1–5. IEEE, Piscataway, NJ (2011). https://doi.org/10.1109/PES.2011.6039261
69. Brahmendra Kumar, G.V., Palanisamy, K.: A review on microgrids with distributed energy resources. In: Proceedings of the 2019 Innovations in Power and Advanced Computing Technologies, pp. 1–6. IEEE, Piscataway, NJ (2019). https://doi.org/10.1109/i-PACT44901.2019.8960189
70. Eajal, A.A., Abdelwahed, M.A., Ponnambalam, K.: Power flow analysis of AC/DC hybrid microgrids. In: Proceedings of the 2016 IEEE Electrical Power and Energy Conference (EPEC), pp. 2–7. IEEE, Piscataway, NJ (2016)
71. Stanev, R.: A primary power control of small hydro power plants operating in autonomous, micro and minigrids. In: Proceedings of the 2014 18th International Symposium on Electrical Apparatus and Technologies, IEEE, Piscataway, NJ (2014). https://doi.org/10.1109/SIELA.2014.6871891
72. Acharya, S., El Moursi, M.S., Al-Hinai, A.: Coordinated frequency control strategy for an islanded microgrid with demand side management capability. IEEE Trans. Energy Convers. 33(2), 639–651 (2018). https://doi.org/10.1109/TEC.2017.2763186
73. Lopes, L.A.C., Katiraei, F., Mauch, L., Vandenbergh, K., Arribas, M.: PV Hybrid Mini-Grids: Applicable Control Methods for Various Situations. International Energy Agency, Paris (2012)
74. Azim, M.I., et al.: A proportional power sharing method through a local control for a low-voltage islanded microgrid. Energy Rep. 8(14), 51–59 (2022). https://doi.org/10.1016/j.egyr.2022.10.119
75. Seane, T.B., Samikannu, R., Bader, T.: A review of modeling and simulation tools for microgrids based on solar photovoltaics. Front. Energy Res. 10, 1–20 (2022). https://doi.org/10.3389/fenrg.2022.772561
76. Fahad, M., Elbouchikhi, E., Benbouzid, M.: Microgrids energy management systems: A critical review on methods, solutions, and prospects. Appl. Energy 222, 1033–1055 (2018). https://doi.org/10.1016/j.apenergy.2018.04.103
77. Raju, L., Milton, R.S., Mahadevan, S.: Multiagent systems based modeling and smart microgrid using MACSimJX. Sci. World J. 2016, 14 (2016). https://doi.org/10.1155/2016/9858101
78. Charbonnier, F., Morstyn, T., McCulloch, M.D.: Scalable multi-agent reinforcement learning for distributed control of residential energy flexibility. Appl. Energy 314(2), 118825 (2022). https://doi.org/10.1016/j.apenergy.2022.118825
79. Kim, S.H., Shin, Y.J.: Optimize the operating range for improving the cycle life of battery energy storage systems under uncertainty by managing the depth of discharge. J. Energy Storage 73, 109144 (2023). https://doi.org/10.1016/j.est.2023.109144
80. Faia, R., Ribeiro, B., Goncalves, C., Gomes, L., Vale, Z.: Multi-agent based energy community cost optimization considering high electric vehicles penetration. Sustainable Energy Technol. Assess. 59(3), 103402 (2023). https://doi.org/10.1016/j.seta.2023.103402
81. Rwegasira, D., Mvungi, N., Tenhunen, H.: Agent based system for improved control and monitoring of a solar driven DC microgrid. In: Proceedings of the 2018 IEEE PES/IAS PowerAfrica, pp. 890–894. IEEE, Piscataway, NJ (2018)
82. Jiang, T., Hua, T., Xiao, H., Fu, L., Pei, W., Ma, T.: P2P transaction method for distributed energy prosumers based on reputation value. Glob. Energy Interconnect. 6(3), 308–323 (2023). https://doi.org/10.1016/j.gloei.2023.06.005
83. Janko, S., Johnson, N.G.: Reputation-based competitive pricing negotiation and power trading for grid-connected microgrid networks. Appl. Energy 277(8), 115598 (2020). https://doi.org/10.1016/j.apenergy.2020.115598
84. Chen, W., Xiang, Y., Liu, J.: Optimal operation of virtual power plants with shared energy storage. IET Smart Grid 6(2), 147–157 (2023). https://doi.org/10.1049/stg2.12084
85. Antonopoulos, I., et al.: Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renewable Sustainable Energy Rev. 130, 109899 (2022). https://doi.org/10.1016/j.rser.2020.109899
86. Zhang, Y., Huang, T., Bompard, E.F.: Big data analytics in smart grids: A review. Energy Inf. 1(8), 1–24 (2018). https://doi.org/10.1186/s42162-018-0007-5
87. Guzhov, S., Krolin, A.: Use of big data technologies for the implementation of energy-saving measures and renewable energy sources in buildings. In: Proceedings of the 3rd Renewable Energies, Power Systems and Green Inclusive Economy, pp. 1–5. IEEE, Piscataway, NJ (2018). https://doi.org/10.1109/REPSGIE.2018.8488861

88. Feng, S., Yang, D., Zhou, B., Luo, Y., Li, G.: Real-time active power dispatch of virtual power plant based on distributed model predictive control. Electron. Lett. 58(23), 872–875 (2022). https://doi.org/10.1049/ell2.12640
89. Basu, M., Jena, C., Khan, B.: Dynamic optimal power flow for multi-operator renewable energy-based virtual power plants. IET Renewable Power Gener. 17(10), 2625–2637 (2023). https://doi.org/10.1049/rpg2.12775
90. Zhang, H., Xu, T., Wu, H., Liu, B., Nazif Faqiry, M.: Risk-based stochastic day-ahead operation for data centre virtual power plants. IET Renewable Power Gener. 13(10), 1660–1669 (2019). https://doi.org/10.1049/iet-rpg.2018.5736
91. Alahyari, A., Ehsan, M., Pozo, D., Farrokhifar, M.: Hybrid uncertainty-based offering strategy for virtual power plants. IET Renewable Power Gener. 14(13), 2359–2366 (2020). https://doi.org/10.1049/iet-rpg.2020.0249
92. Lopez, J.R., Camacho, J., Ponce, P., MacCleery, B., Molino, A.: A real-time digital twin and neural net cluster-based framework for faults identification in power converters of microgrids, self organized map neural network. Energies 15(19), 7306 (2022). https://doi.org/10.3390/en15197306
93. Espin-Sarzosa, D., Palma-behnke, R., Valencia-Arroyave, F.: Towards digital twins of small productive processes in microgrids. Energies 16(11), 4324 (2023). https://doi.org/10.3390/en16114324
94. Bazmohammadi, N., et al.: Microgrid digital twins: Concepts, applications, and future trends. IEEE Access 10, 2284–2302 (2022). https://doi.org/10.1109/ACCESS.2021.3138990
95. Yu, P., et al.: Framework design and application perspectives of digital twin microgrid. In: Proceedings of the 2022 3rd International Conference on Power Engineering (ICPE 2022), pp. 669–678. Elsevier, Amsterdam (2023). https://doi.org/10.1016/j.egyr.2023.04.253
96. Park, H.A., Byeon, G., Son, W., Jo, H.C., Kim, J., Kim, S.: Digital twin for operation of microgrid: Optimal scheduling in virtual space of digital twin. Energies 13(20), 1–15 (2020). https://doi.org/10.3390/en13205504
97. Kumari, N., Sharma, A., Tran, B., Chilamkurti, N., Alahakoon, D.: A comprehensive review of digital twin technology for grid-connected microgrid systems: State of the art, potential and challenges faced. Energies 16(14), 5525 (2023). https://doi.org/10.3390/en16145525
98. Yang, L., Song, G., Wenhui, S., Guoqing, H., ZhengPing, W.: Integrated control strategy for smooth switching of the PV and battery-storage micro-grid based on operation state tracking. IET J. Eng. 2019(16), 1062–1067 (2019). https://doi.org/10.1049/joe.2018.8877
99. Zhang, F., Yu, J., Yao, S., Yang, Y., Zhao, Z.: Price-based response strategy of micro-energy-grid in energy-ancillary service markets. Energy Rep. 8, 1–13 (2022). https://doi.org/10.1016/j.egyr.2022.09.084
100. Jin, X., Lin, F., Wang, Y.: Research on energy management of microgrid in power supply system using deep reinforcement learning. IOP Conf. Ser.: Earth Environ. Sci. 804, 032042 (2021). https://doi.org/10.1088/1755-1315/804/3/032042
101. Liu, Z., Zhang, H., Dong, J., Yu, H.: A prediction-based optimization strategy to balance the use of diesel generator and emergency battery in the microgrid. Int. J. Energy Res. 44(7), 5425–5440 (2020). https://doi.org/10.1002/er.5292
102. Logenthiran, T., Srinivasan, D., Shun, T.Z.: Demand side management in smart grid using heuristic optimization. IEEE Trans. Smart Grid 3(3), 1244–1252 (2012). https://doi.org/10.1109/TSG.2012.2195686
103. Wu, H., Dong, P., Liu, M.: Optimization of network-load interaction with multi-time period flexible random fuzzy uncertain demand response. IEEE Access 7, 161630–161640 (2019). https://doi.org/10.1109/ACCESS.2019.2940721
104. Hai, T.P., Chung, I.-Y., Kim, T., Kim, J.: Coordinated voltage control scheme for multi-terminal low-voltage DC distribution system. J. Electr. Eng. Technol. 13(4), 1921–9718 (2018). https://doi.org/10.5370/JEET.2018.13.4.1459
105. Singh, B., Bishnoi, S.K., Sharma, M., Singh, P., Dhundhara, S.: An application of nature inspired algorithm based dual-stage frequency control strategy for multi micro-grid system. Ain Shams Eng. J. 14, 102125 (2023). https://doi.org/10.1016/j.asej.2023.102125
106. Nagaraja, Y., Devaraju, T., Vijaykumar, M.: Optimal distributed control of renewable energy-based microgrid–An energy management approach. Int. J. Ambient Energy 42(14), 1635–1642 (2019). https://doi.org/10.1080/01430750.2019.1611660
107. Suresh, M., Meenakumari, R.: Optimum utilization of grid connected hybrid renewable energy sources using hybrid algorithm. Trans. Inst. Meas. Control 43(1), 21–33 (2021). https://doi.org/10.1177/0142331220913740
108. Ali, Z., Christofides, N., Hadjidemetriou, L., Kyriakides, E.: Multi-functional distributed generation control scheme for improving the grid power quality. IET Power Electron. 12(1), 30–43 (2019). https://doi.org/10.1049/iet-pel.2018.5177
109. Ramadhani, F., Hussain, M.A., Mokhlis, H., Illias, H.A.: Two-stage fuzzy-logic-based for optimal energy management strategy for SOFC/PV/TEG hybrid polygeneration system with electric charging and hydrogen fueling stations. J. Renewable Sustainable Energy 13(2), 024301 (2021). https://doi.org/10.1063/5.0010832
110. Perera, M.K., et al.: Multi agent based energy management system for microgrids. In: Proceedings of the PIICON 2020 - 9th IEEE Power India International Conference, pp. 6–11. IEEE, Piscataway, NJ (2020). https://doi.org/10.1109/PIICON49524.2020.9113021
111. Lupangu, C., Justo, J.J., Bansal, R.C.: Model predictive for reactive power scheduling control strategy for PV–battery hybrid system in competitive energy market. IEEE Syst. J. 14(3), 1–8 (2020)
112. Justo, J.J.: Intelligent energy management strategy considering power distribution networks with nanogrids, microgrids, and VPP concepts. In: Bansal, R.C. (ed.) Handbook of Distributed Generation, pp. 791–815. Springer International Publishing, Berlin (2017). https://doi.org/10.1007/978-3-319-51343-0
113. Yang, Z., Liu, H., Ni, M.: Day-ahead operation strategy for multiple data centre prosumers: A cooperative game approach. IET Renew. Power Gener. 1–15 (2023). https://doi.org/10.1049/rpg2.12797
114. Jindal, A., Singh, M., Kumar, N.: Consumption-aware data analytical demand response scheme for peak load reduction in smart grid. IEEE Trans. Ind. Electron. 65(11), 8993–9004 (2018). https://doi.org/10.1109/TIE.2018.2813990
115. Sechilariu, M.: Intelligent energy management of electrical power systems. Appl. Sci. 10(8), 10–13 (2020). https://doi.org/10.3390/APP10082951
116. Stewart, E., Stadler, M., Roberts, C., Reilly, J., Arnold, D., Joo, J.: Data-driven approach for monitoring, protection, and control of distribution system assets using micro-PMU technology. In: Proceedings of the 24th International Conference & Exhibition on Electricity Distribution (CIRED), pp. 1011–1014. IET, Savoy Place, London (2017). https://doi.org/10.1049/oap-cired.2017.0416
117. Shen, J., Jiang, C., Li, B.: Controllable load management approaches in smart grids. MDPI Energies 8, 11187–11202 (2015). https://doi.org/10.3390/en81011187
118. Lawi, L., Kalinga, E.A.: User-centred scalable big data visualizer for power consumption data in the electrical secondary distribution network. Tanzania J. Eng. Technol. 39(2), 177–197 (2020)
119. Zhu, Y., Wang, J., Bi, K., Sun, Q., Zong, Y., Zong, C.: Energy optimal dispatch of the data center microgrid based on stochastic model predictive control. Front. Energy Res. 10(863292), 1–9 (2022). https://doi.org/10.3389/fenrg.2022.863292
120. Yin, R., Ghatikar, G., Piette, M.A.: Big-data analytics for electric grid and demand-side management energy analysis and environmental impacts division. https://escholarship.org/uc/item/4hv8s32t/ (2019). Accessed 4 Nov 2023
121. Nur, F., Ramli, M.A.M., Bouchekara, H.R., Milyani, A.H.: Optimal scheduling of a microgrid with power quality constraints based on demand side management under grid-connected and islanding operations. Int. J. Electr. Power Energy Syst. 155, 109650 (2023). https://doi.org/10.1016/j.ijepes.2023.109650
122. Mahmood, A., et al.: A new scheme for demand side management in future smart grid networks. Procedia Comput. Sci. 32, 477–484 (2014). https://doi.org/10.1016/j.procs.2014.05.450

123. Will, A.L.E.: Optimal allocation of phase-switching devices for dynamic load balancing. Springer J. Electr. Eng. 102, 163–173 (2022). https://doi.org/10.1007/s00202-022-01656-8
124. Razzaq, S., Zafar, R., Khan, N.A., Butt, A.R.: A novel prosumer-based energy sharing and management (PESM) approach for cooperative demand side management (DSM) in smart grid. MDPI Appl. Sci. 6(10), 275 (2016). https://doi.org/10.3390/app6100275
125. Faisal, M., Hannan, M.A., Ker, P.J., Hussain, A., Bin Mansor, M., Blaabjerg, F.: Review of energy storage system technologies in microgrid applications: Issues and challenges. IEEE Access 6, 35143–35164 (2018). https://doi.org/10.1109/ACCESS.2018.2841407
126. Kumar, A., Priyalakshmi, K., Rangnekar, S.: An overview of energy storage and its importance in Indian renewable energy sector Part I–Technologies and comparison. J. Energy Storage 13, 10–23 (2017). https://doi.org/10.1016/j.est.2017.06.005
127. Zhang, Q., et al.: Coordinated control of distributed energy storage systems for DC microgrids coupling photovoltaics and batteries. MDPI Energies 16(2), 665 (2023). https://doi.org/10.3390/en16020665
128. Yang, Y., et al.: System value assessment method of energy storage system for multi-services of power system considering battery degradation. IET Energy Syst. Integr. 5(3), 355–364 (2023). https://doi.org/10.1049/esi2.12109
129. Ren, X., Zeng, Y., Sun, Z., Wang, J.: A novel day optimal scheduling strategy for integrated energy system including electric vehicle and multisource energy storage. Int. Trans. Electr. Energy Syst. 2023, 3880254 (2023). https://doi.org/10.1155/2023/3880254
130. Zhang, Z., Huang, J., Zhou, N., Yang, H., Zhou, R.: Two-stage optimization model of centralized energy storage participating in peak shaving with maximum reserve capacity and minimum carbon emission of the system. Int. Trans. Electr. Energy Syst. 2023, 13 (2023). https://doi.org/10.1155/2023/6694078
131. Balavignesh, S., Kumar, C., Ueda, S., Senjyu, T.: Optimization-based optimal energy management system for smart home in smart grid. Energy Rep. 10, 3733–3756 (2023). https://doi.org/10.1016/j.egyr.2023.10.037
132. Qiao, X., et al.: Optimal scheduling of distribution network incorporating topology reconfiguration, battery energy system and load response. CSEE J. Power Energy Syst. 8(3), 743–756 (2022). https://doi.org/10.17775/CSEEJPES.2019.02300
133. Hossain, M.A., Pota, H.R., Squartini, S., Abdou, A.F.: Modified PSO algorithm for real-time energy management in grid-connected microgrids. Renew. Energy 136, 746–757 (2019). https://doi.org/10.1016/j.renene.2019.01.005
134. Lin, C.H., Farooqui, S.A., Liu, H.D., Huang, J.J., Fahad, M.: Finite control set model predictive control (FCS-MPC) for enhancing the performance of a single-phase inverter in a renewable energy system (RES). Mathematics 11(21), 4553 (2023). https://doi.org/10.3390/math11214553
135. Graditi, G., Di Silvestre, M.L., Gallea, R., Sanseverino, E.R.: Heuristic-based shiftable loads optimal management in smart micro-grids. IEEE Trans. Ind. Inf. 11(1), 271–280 (2015). https://doi.org/10.1109/TII.2014.2331000
136. Li, S., Wu, J., Agundis-Tinajero, G.D., Chaudhary, S., Vasquez, J.C., Guerrero, J.M.: A hierarchical harmonic control method for wind power plants in microgrids. In: Proceedings of the 49th Annual Conference of the IEEE Industrial Electronics Society (IES), pp. 1–6. IEEE, Piscataway, NJ (2023). https://doi.org/10.1109/iecon51785.2023.10312706
137. Yang, C., Zheng, T., Bu, M., Li, P., Guerrero, J.M.: Distributed model-free adaptive control strategy for hybrid AC/DC microgrid with event-triggered mechanism. IEEE Trans. Ind. Electron. 71(8), 1–10 (2023). https://doi.org/10.1109/TIE.2023.3331158
138. Garcia-Guarin, J., et al.: Smart microgrids operation considering a variable neighborhood search: The differential evolutionary particle swarm optimization algorithm. Energies 12(16), 1–13 (2019). https://doi.org/10.3390/en12163149
139. Ullah, M.N., Javaid, N., Khan, I., Mahmood, A., Farooq, M.U.: Residential energy consumption controlling techniques to enable autonomous demand side management in future smart grid communications. In: Proceedings of the 2013 Eighth International Conference on Broadband and Wireless Computing, Communication and Applications, pp. 545–550 (2013). https://doi.org/10.1109/BWCCA.2013.94
140. Kerboua, A., Boukli-Hacene, F., Mourad, K.A.: Particle swarm optimization for micro-grid power management and load scheduling. Int. J. Energy Econ. Policy 10(2), 71–80 (2020). https://doi.org/10.32479/ijeep.8568
141. Sun, H., Liu, N., Tan, L., Du, P., Zhang, B.: Digital twin-based online resilience scheduling for microgrids: An approach combining imitative learning and deep reinforcement. IET Renewable Power Gener. 18(1), 1–13 (2023). https://doi.org/10.1049/rpg2.12887
142. Junjie, R., Ming, Z., Zhi, Z., Gengyin, L.: Coordination of preventive and emergency dispatch in renewable energy integrated power systems under extreme weather. IET Renewable Power Gener. 18(7), 1164–1176 (2023). https://doi.org/10.1049/rpg2.12893
143. Belbachir, N., Zellagui, M., Kamel, S.: Multi-dimensional energy management based on an optimal allocation of hybrid wind turbine distributed generation and battery energy storage system in a flexible interconnected distribution network considering seasonal uncertainties. In: Proceedings of the 4th International Electronic Conference on Applied Sciences, pp. 1–6. MDPI, Basel (2023). https://doi.org/10.3390/ASEC2023-16292
144. Raval, M., Bhardwaj, S., Aravelli, A., Dofe, J., Gohel, H.: Smart energy optimization for massive IoT using artificial intelligence. Internet of Things 13, 100354 (2021). https://doi.org/10.1016/j.iot.2020.100354
145. Dou, C., Lv, M., Zhao, T., Ji, Y., Li, H.: Decentralised coordinated control of microgrid based on multi-agent system. IET Gener. Transm. Distrib. 9(16), 2474–2484 (2015). https://doi.org/10.1049/iet-gtd.2015.0397
146. Ngamroo, I., Surinkaew, T.: Coordinated decentralized and centralized microgrid control for distributed renewable energy sources with integrated batteries. IET Renewable Power Gener. 16(15), 3251–3266 (2022). https://doi.org/10.1049/rpg2.12576
147. Alshehri, J., Alzahrani, A., Khalid, M., Alismail, F.: Optimal control of a microgrid with distributed renewable generation and battery energy storage. In: Proceedings of the 2020 IEEE Power and Energy Society Innovative Smart Grid Technologies Conference, pp. 1–5. IEEE, Piscataway, NJ (2020). https://doi.org/10.1109/ISGT45199.2020.9087685
148. Young, J., Wilson, D.G., Weaver, W., Robinett, R.D.: Supervisory optimal control for photovoltaics connected to an electric power grid. In: Proceedings of the 11th Solar & Storage Power System Integration Workshop (SIW 2021), pp. 115–122. IET, Savoy Place, London (2021). https://doi.org/10.1049/icp.2021.2490
149. Javaid, N., et al.: An intelligent load management system with renewable energy integration for smart homes. IEEE Access 5, 13587–13600 (2017). https://doi.org/10.1109/ACCESS.2017.2715225
150. Khairalla, A.G., et al.: Enhanced control strategy and energy management for a photovoltaic system with hybrid energy storage based on self-adaptive. Front. Energy Res. 11, 1283348 (2023). https://doi.org/10.3389/fenrg.2023.1283348
151. Kermani, A., et al.: Energy management system for smart grid in the presence of energy storage and photovoltaic systems. Hindawi Int. J. Photoenergy 2023, 15 (2023). https://doi.org/10.1155/2023/5749756
152. Moghaddam, A.A., Seifi, A., Niknam, T.: Multi-operation management of a typical micro-grids using particle swarm optimization: A comparative study. Renewable Sustainable Energy Rev. 16(2), 1268–1281 (2012). https://doi.org/10.1016/j.rser.2011.10.002
153. Song, X., Sun, J., Tan, S., Ling, R., Chai, Y., Guerrero, J.M.: Cooperative grid frequency control under asymmetric V2G capacity via switched integral reinforcement learning. Int. J. Electr. Power Energy Syst. 155, 109679 (2023). https://doi.org/10.1016/j.ijepes.2023.109679
154. Faisal, A., Anwer, N.: Optimization and techno-economic analysis of hybrid renewable energy systems for the electrification of remote areas. Wind Eng. 10, 1–19 (2023). https://doi.org/10.1177/0309524%D7231210266
155. Alvarez, E., Campos, A.M., Arboleya, P., Gutiérrez, A.J.: Microgrid management with a quick response optimization algorithm for active power dispatch. Int. J. Electr. Power Energy Syst. 43(1), 465–473 (2012). https://doi.org/10.1016/j.ijepes.2012.06.015
156. Takalani, R., Masisi, L.: Development of an energy management strategy for port cranes. In: Proceedings of the IECON 2021– 47th Annual Conference of the IEEE Industrial Electronics Society, pp. 1–6.

IEEE, Piscataway, NJ (2021). https://doi.org/10.1109/IECON48115.2021.9589271
157. Sedhom, B.E., El-Saadawi, M.M., Hatata, A.Y., Abd-Raboh, E.H.E.: H-Infinity versus model predictive control methods for seamless transition between islanded- and grid-connected modes of microgrids. IET Renewable Power Gener. 14(5), 856–870 (2020). https://doi.org/10.1049/iet-rpg.2019.0018
158. Alghassab, M.A., Nour, A.M.M., Hatata, A.Y., Sedhom, B.E.: Two-layer hybrid control scheme for distribution network integrated with photovoltaic sources based self-tuning H-infinity and fuzzy logic controller. IET Renew. Power Gener. 1–20 (2023). https://doi.org/10.1049/rpg2.12709
159. Maleki, S., Nikoukar, J., Tousifian, M.H.: Robust frequency control of microgrids: A mixed H2/H∞ virtual inertia emulation. Int. Trans. Electr. Energy Syst. 2023, 14 (2023). https://doi.org/10.1155/2023/6872765
160. Bevrani, H., Feizi, M.R., Ataee, S.: Robust frequency control in an islanded microgrid: H-∞ and μ-synthesis approaches. IEEE Trans. Smart Grid 7(2), 706–717 (2016). https://doi.org/10.1109/TSG.2015.2446984
161. Bevrani, H.: Robust Power System Frequency Control. Springer International Publishing, Berlin (2014). https://doi.org/10.1007/978-0-387-84878-5
162. Sawle, Y., Gupta, S.C., Bohre, A.K., Meng, W.: PV-wind hybrid system: A review with case study. Cogent Eng. 3(1), 1–31 (2016). https://doi.org/10.1080/23311916.2016.1189305
163. Falchetta, G., Kasamba, C., Parkinson, S.C.: Monitoring hydropower reliability in Malawi with satellite data and machine learning. Environ. Res. Lett. 15(1), 14011 (2020). https://doi.org/10.1088/1748-9326/ab6562
164. Rahman, H.A., Majid, M.S., Rezaee Jordehi, A., Chin Kim, G., Hassan, M.Y., Fadhl, S.O.: Operation and control strategies of integrated distributed energy resources: A review. Renewable Sustainable Energy Rev. 51, 1412–1420 (2015). https://doi.org/10.1016/j.rser.2015.07.055
165. Kamarposhti, M.A., Colak, I., Shokouhandeh, H., Iwendi, C., Padmanaban, S., Band, S.S.: Optimum operation management of microgrids with cost and environment pollution reduction approach considering uncertainty using multi-objective NSGAII algorithm. IET Renewable Power Gener. 1–13 (2022). https://doi.org/10.1049/rpg2.12579
166. Bozorg-Haddad, O.: Advanced Optimization by Nature-Inspired Algorithms. Studies in Computational Intelligence, vol. 720. Springer Nature, Singapore (2018). https://doi.org/10.1007/978-981-10-5221-7
167. Kumar, S., et al.: Chaotic marine predators algorithm for global optimization of real-world engineering problems. Knowledge-Based Syst. 261, 110192 (2022). https://doi.org/10.1016/j.knosys.2022.110192
168. Mharakurwa, E.T., Juma, S.A.: A weighting factor-fuzzy logic based transformer residual life estimation model. In: Proceedings of the 2021 IEEE PES/IAS PowerAfrica, pp. 1–4. IEEE, Piscataway, NJ (2021). https://doi.org/10.1109/PowerAfrica52236.2021.9543460
169. Shivam, K., Tzou, J.C., Wu, S.C.: A multi-objective predictive energy management strategy for residential grid-connected PV-battery hybrid systems based on machine learning technique. Energy Convers. Manage. 237(195), 114103 (2021). https://doi.org/10.1016/j.enconman.2021.114103
170. Forootan, M.M., Larki, I., Zahedi, R., Ahmadi, A.: Machine learning and deep learning in energy systems–A review. Sustainability 14(8), 4832 (2022). https://doi.org/10.3390/su14084832
171. Olivella-Rosell, P., et al.: Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources. Appl. Energy 210, 881–895 (2018). https://doi.org/10.1016/j.apenergy.2017.08.136
172. Kondaiah, V.Y., Saravanan, B., Sanjeevikumar, P., Khan, B.: A review on short-term load forecasting models for micro-grid application. J. Eng. 2022(7), 665–689 (2022). https://doi.org/10.1049/tje2.12151
173. Souhe, F.G.Y., Mbey, C.F., Boum, A.T., Ele, P., Kakeu, V.J.F.: A hybrid model for forecasting the consumption of electrical energy in a smart grid. J. Eng. 2022(6), 629–643 (2022). https://doi.org/10.1049/tje2.12146
174. Masoomi, B., Sahebi, I.G., Ghobakhloo, M., Mosayebi, A.: Do industry 5.0 advantages address the sustainable development challenges of the renewable energy supply chain? Sustainable Prod. Consumption 43(4), 94–112 (2023). https://doi.org/10.1016/j.spc.2023.10.018
175. Olatomiwa, L., et al.: Optimal planning and deployment of hybrid renewable energy to rural healthcare facilities in Nigeria. MDPI Energies 16(21), 7259 (2023). https://doi.org/10.3390/en16217259
176. Konara, K.M.S.Y., Kolhe, M.L., Sharma, A.: Power dispatching techniques as a finite state machine for a standalone photovoltaic system with a hybrid energy storage. AIMS Energy 8, 214–230 (2020). https://doi.org/10.3934/energy.2020.2.214
177. Sun, H., Zhang, B., Liu, N.: Imitation learning-based online optimal scheduling for microgrids: An approach integrating input clustering and output classification. IET Renewable Power Gener. 11, 1–12 (2023). https://doi.org/10.1049/rpg2.12909
178. Bertozzi, O., et al.: Application of data-driven methods in power systems analysis and control. IET Energy Syst. Integr. 1–16 (2023). https://doi.org/10.1049/esi2.12122
179. Paruthiyil, S.K., Bidram, A., Reno, M.J.: A physics-informed learning technique for fault location of DC microgrids using traveling waves. IET Gener. Transm. Distrib. 16(23), 4791–4805 (2022). https://doi.org/10.1049/gtd2.12642
180. Antonelo, E.A., Camponogara, E., Seman, L.O., Jordanou, J.P., de Souza, E.R., Hübner, J.F.: Physics-informed neural nets for control of dynamical systems. Neurocomputing 579, 127419 (2024). https://doi.org/10.1016/j.neucom.2024.127419
181. Mishra, P., Zhang, P.: Physics-informed transient stability assessment of microgrids. IEnergy 2(3), 231–239 (2023). https://doi.org/10.23919/ien.2023.0022
182. Rai, A., Bhujel, N., Dhiman, V., Hummels, D., Tamrakar, U., Byrne, R.H., Tonkoski, R.: A physics-informed neural network modeling approach for energy storage-based fast frequency support in microgrids. In: Proceedings of the 2024 IEEE Electrical Energy Storage Application and Technologies Conference, IEEE, Piscataway, NJ (2024). https://doi.org/10.1109/EESAT59125.2024.10471220
183. Wang, L., Zhang, S., Zhou, Y., Fan, C., Zhang, P., Shamash, Y.A.: Physics-informed, safety and stability certified neural control for uncertain networked microgrids. IEEE Trans. Smart Grid 15(1), 1184–1187 (2024). https://doi.org/10.1109/TSG.2023.3309534
184. She, B., Li, F., Cui, H., Shuai, H., Oboreh-Snapps, O., Bo, R., et al.: Inverter PQ control with trajectory tracking capability for microgrids based on physics-informed reinforcement learning. IEEE Trans. Smart Grid 15(1), 99–112 (2024). https://doi.org/10.1109/TSG.2023.3277330
185. Hailu, E.A., Nyakoe, G.N., Muriithi, C.M.: Data-driven approach to fuzzy inference system tuning for static security assessment of multi-area power systems with renewable energy. Ain Shams Eng. J. 15(2), 102369 (2023). https://doi.org/10.1016/j.asej.2023.102369
186. Abdel-Basset, M., Hawash, H., Sallam, K., Askar, S.S., Abouhawwash, M.: STLF-Net: Two-stream deep network for short-term load forecasting in residential buildings. J. King Saud Univ. Comput. Inf. Sci. 34(7), 4296–4311 (2022). https://doi.org/10.1016/j.jksuci.2022.04.016
187. Xinhe, C., Wei, P., Wei, D., Hao, X.: Data-driven virtual power plant bidding package model and its application to virtual VCG auction-based real-time power market. IET Smart Grid 3(5), 614–625 (2020). https://doi.org/10.1049/iet-stg.2020.0038
188. Ni, F., Zheng, Z., Xie, Q., Xiao, X., Zong, Y., Huang, C.: Enhancing resilience of DC microgrids with model predictive control based hybrid energy storage system. Int. J. Electr. Power Energy Syst. 128(9), 106738 (2021). https://doi.org/10.1016/j.ijepes.2020.106738
189. Armaghan, S.M., Asgharzadeh, F., Yousef-khanghah, B., Ashraf, H.R.: Resilient operation of electric vehicles considering grid resiliency and uncertainties. Int. Trans. Electr. Energy Syst. 2023, 15 (2023). https://doi.org/10.1155/2023/5320002
190. Ju, J., Wang, Q., Wang, W., Ni, M.: Resilience enhancement strategy for cyber–physical distribution systems that considers cross-space propagation of information risk. IET Renewable Power Gener. 5, 1–11 (2023). https://doi.org/10.1049/rpg2.12767
191. Vazinram, F., Hedayati, M., Effatnejad, R., Hajihosseini, P.: Self-healing model for gas-electricity distribution network with consideration of various types of generation units and demand response capability.

Energy Convers. Manage. 206, 112487 (2020). https://doi.org/10.1016/j.enconman.2020.112487
192. Juma, S.A., Ngoo, L.M., Muriithi, C.M.: A review on optimal network reconfiguration in the radial distribution system using optimization techniques. In: Proceedings of Sustainable Research and Innovation Conference, pp. 34–40. SRI, Nairobi (2018)
193. Twaisan, K., Barışçı, N.: Integrated distributed energy resources (DER) and microgrids: Modeling and optimization of DERs. Electronics 11(18), 2816 (2022). https://doi.org/10.3390/electronics11182816
194. Chikumbanje, M.: Planning the Grid Integration of Minigrids in Developing Countries. University of Strathclyde Glasgow. https://doi.org/10.48730/nq1y-4f07/ (2022). Accessed 01 Nov 2023
195. Olorunfemi, T.R., Nwulu, N.: Optimization applications in distributed energy resources: Review and limitations. In: Proceedings of the International Conference on Computational Techniques, Electronics and Mechanical Systems, pp. 446–450. IEEE, Piscataway, NJ (2018). https://doi.org/10.1109/CTEMS.2018.8769319
196. Kantor, I., Robineau, J.L., Bütün, H., Maréchal, F.: A mixed-integer linear programming formulation for optimizing multi-scale material and energy integration. Front. Energy Res. 8, 00049 (2020). https://doi.org/10.3389/fenrg.2020.00049
197. Urbanucci, L.: Limits and potentials of mixed integer linear programming methods for optimization of polygeneration energy systems. In: Proceedings of the 73rd Conference of the Italian Thermal Machines Engineering Association, pp. 1199–1205. Elsevier B.V., Pisa (2018). https://doi.org/10.1016/j.egypro.2018.08.021
198. Dorahaki, S., MollahassaniPour, M., Rashidinejad, M.: Optimizing energy payment, user satisfaction, and self-sufficiency in flexibility-constrained smart home energy management: A multi-objective optimization approach. e-Prime Adv. Electr. Eng. Electron. Energy 6(12), 100385 (2023). https://doi.org/10.1016/j.prime.2023.100385
199. Ardalan, C., Vahidinasab, V., Safdarian, A., Shafie-khah, M., Catalão, J.P.S.: Pave the way for sustainable smart homes: A reliable hybrid AC/DC electricity infrastructure. Electr. Power Syst. Res. 210, 108128 (2022). https://doi.org/10.1016/j.epsr.2022.108128
200. Sadek, M., Ameur, B., Sakly, A.: FPGA implementation of parallel particle swarm optimization algorithm and compared with genetic algorithm. Int. J. Adv. Comput. Sci. Appl. 7(8), 070809 (2016). https://doi.org/10.14569/IJACSA.2016.070809
201. Gad, A.G.: Particle swarm optimization algorithm and its applications: A systematic review. Arch. Comput. Methods Eng. 29(5), 2531–2561 (2022). https://doi.org/10.1007/s11831-021-09694-4
202. Mandal, P., Zareipour, H., Rosehart, W.D.: Forecasting aggregated wind power production of multiple wind farms using hybrid wavelet-PSO-NNs. Int. J. Energy Res. 38, 1654–1666 (2014). https://doi.org/10.1002/er.3171
203. Saber, A.Y., Venayagamoorthy, G.K.: Efficient utilization of renewable energy sources by gridable vehicles in cyber-physical energy systems. IEEE Syst. J. 4(3), 285–294 (2010). https://doi.org/10.1109/JSYST.2010.2059212
204. Liu, C., Lv, X., Guo, L., Cai, L., Su, K.: Control strategy for power loss reduction considering load variation with large penetration of distributed generation. Hindawi Adv. Electr. Eng. 2017, 1–6 (2017). https://doi.org/10.1155/2017/5764054
205. Yang, Y., Tan, Z., Yang, H., Ruan, G., Zhong, H., Liu, F.: Short-term electricity price forecasting based on graph convolution network and attention mechanism. IET Renewable Power Gener. 16(12), 2481–2492 (2022). https://doi.org/10.1049/rpg2.12413
206. Zeynali, S., Rostami, N., Ahmadian, A., Elkamel, A.: Two-stage stochastic home energy management strategy considering electric vehicle and battery energy storage system: An ANN-based scenario generation methodology. Sustainable Energy Technol. Assess. 39, 100722 (2020). https://doi.org/10.1016/j.seta.2020.100722
207. Ladjouzi, S., Grouni, S., Djebiri, M., Soufi, Y.: A neural MPPT approach for a wind turbine. In: Proceedings of the 2017 6th International Conference on Systems and Control (ICSC), pp. 210–214. IEEE, Piscataway, NJ (2017). https://doi.org/10.1109/ICoSC.2017.7958689
208. Morgan, M.Y., El Sobki, M.S., Osman, Z.H.: Matching demand with renewable resources using artificial intelligence techniques. In: Proceedings of the EuroCon 2013, pp. 1011–1019. IEEE, Piscataway, NJ (2013). https://doi.org/10.1109/EUROCON.2013.6625105
209. Nakabi, T.A., Toivanen, P.: Deep reinforcement learning for energy management in a microgrid with flexible demand. Sustainable Energy, Grids Networks 25, 100413 (2021). https://doi.org/10.1016/j.segan.2020.100413
210. Mathenge, J.N., Murage, D.K., Nderu, J.N., Muriithi, C.M.: A review on artificial neural network models for short term wind power prediction. In: Proceedings of the Sustainable Research and Innovation Conference, pp. 54–58. SRI, Nairobi (2018)
211. Youssef, A., El-Telbany, M., Zekry, A.: The role of artificial intelligence in photo-voltaic systems design and control: A review. Renewable Sustainable Energy Rev. 78, 72–79 (2017). https://doi.org/10.1016/j.rser.2017.04.046
212. Luca, R., Whiteley, M., Neville, T., Shearing, P.R., Brett, D.J.L.: Comparative study of energy management systems for a hybrid fuel cell electric vehicle: A novel mutative fuzzy logic controller to prolong fuel cell lifetime. Int. J. Hydrogen Energy 47(57), 24042–24058 (2022). https://doi.org/10.1016/j.ijhydene.2022.05.192
213. Heydari, A., et al.: A combined fuzzy GMDH neural network and grey wolf forecasting considering SCADA data. MDPI Energies 14(12), 3459 (2021). https://doi.org/10.3390/en14123459
214. Galgali, V.S., Vaidya, G.A., Ramachandran, M.: Selection of distributed generation system using multicriteria decision making fuzzy TOPSIS optimization. In: Proceedings of the 2016 5th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), pp. 86–89. IEEE, Piscataway, NJ (2016). https://doi.org/10.1109/ICRITO.2016.7784931
215. Irmak, E., Kabalcı, E., Calpbinici, A.: Event-triggered distributed secondary control for enhancing efficiency, reliability and communication in island mode DC microgrids. IET Renewable Power Gener. 18, 78–94 (2023). https://doi.org/10.1049/rpg2.12897
216. Duman, A.C., Erden, H.S., Gönül, Ö., Güler, Ö.: A home energy management system with an integrated smart thermostat for demand response in smart grids. Sustainable Cities Soc. 65, 102639 (2021). https://doi.org/10.1016/j.scs.2020.102639
217. Elkazaz, M.H., Hoballah, A.A., Azmy, A.M.: Operation optimization of distributed generation using artificial intelligent techniques. Ain Shams Eng. J. 7(2), 855–866 (2016). https://doi.org/10.1016/j.asej.2016.01.008
218. Awais, M., et al.: An efficient genetic algorithm based demand side management scheme for smart grid. In: Proceedings-2015 18th International Conference on Network-Based Information Systems, pp. 351–356. IEEE, Piscataway, NJ (2015). https://doi.org/10.1109/NBiS.2015.54
219. Singh, S.S., Fernandez, E.: Reliability evaluation of a solar photovoltaic system with and without battery storage. In: Proceedings of the 2015 Annual IEEE India Conference (INDICON), pp. 1–6. IEEE, Piscataway, NJ (2015). https://doi.org/10.1109/INDICON.2015.7443379
220. Yu, L., Li, Y.P., Huang, G.H., Shan, B.G.: A hybrid fuzzy-stochastic technique for planning peak electricity management under multiple uncertainties. Eng. Appl. Artif. Intell. 62, 252–264 (2017). https://doi.org/10.1016/j.engappai.2017.04.014
221. Martínez Ceseña, E.A., Good, N., Syrri, A.L.A., Mancarella, P.: Techno-economic and business case assessment of multi-energy microgrids with co-optimization of energy, reserve and reliability services. Appl. Energy 210, 896–913 (2018). https://doi.org/10.1016/j.apenergy.2017.08.131
222. Ridha, H.M., et al.: Multi-objective optimization and multi-criteria decision making aided by numerical method: Framework and a case study of Malaysia and South Africa. Energy Convers. Manage. 274, 116468 (2022). https://doi.org/10.1016/j.enconman.2022.116468
223. Hao, J., Yang, Y., Xu, C., Du, X.: A comprehensive review of planning, modeling, optimization, and control of distributed energy systems. Carbon Neutrality 1(1), 1–29 (2022). https://doi.org/10.1007/s43979-022-00029-1
224. Assad, U., et al.: Smartgrid, demand response and optimization: A critical review of computational methods. Energies 15(6), 1–36 (2022). https://doi.org/10.3390/en15062003

225. Abdmouleh, Z., Gastli, A., Ben-Brahim, L., Haouari, M., Al-Emadi, N.A.: Review of optimization techniques applied for the integration of distributed generation from renewable energy sources. Renewable Energy 113, 266–280 (2017). https://doi.org/10.1016/j.renene.2017.05.087
226. Choudar, A., Boukhetala, D., Barkat, S., Brucker, J.M.: A local energy management of a hybrid PV-storage based distributed generation for microgrids. Energy Convers. Manage. 90, 21–33 (2015). https://doi.org/10.1016/j.enconman.2014.10.067
227. Santos, R.M., Zong, Y., Sousa, M.C., Mihet-Popa, L.: Fuzzy predictive filtering in nonlinear economic model predictive control for demand response. In: Proceedings of the 2016 IEEE Electrical Power and Energy Conference (EPEC), pp. 1–6. IEEE, Piscataway, NJ (2016). https://doi.org/10.1109/EPEC.2016.7771725
228. Trinh, P., Chung, I.: Optimal control strategy for distributed energy resources in a DC microgrid for energy cost reduction and voltage regulation. MDPI Energies 14(4), 992 (2021). https://doi.org/10.3390/en14040992

How to cite this article: Juma, S.A., Ayeng'o, S.P., Kimambo, C.Z.M.: A review of control strategies for optimized microgrid operations. IET Renew. Power Gener. 1–34 (2024). https://doi.org/10.1049/rpg2.13056