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Review

Exploring the Potential of Microgrids in the Effective Utilisation of Renewable Energy: A Comprehensive Analysis of Evolving Themes and Future Priorities Using Main Path Analysis

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Abstract: Microgrids are energy systems that can operate independently or in conjunction with the main electricity grid. Their purpose is to link different energy sources, enhance customer participation in energy markets, and improve energy system efficiency and flexibility. However, regulatory, technical, and financial obstacles hinder their deployment. To comprehend the current state of the field, this study utilized citation network analysis (CNA) methodology to examine over 1500 scholarly publications on microgrid research and development (R&D). The study employed modularity-based clustering analysis, which identified seven distinct research clusters, each related to a specific area of study. Cluster 1, focused on control strategies for microgrids, had the highest proportion of publications (23%) and the maximum citation link count (151), while Cluster 4, which examined microgrid stability, had the lowest proportion of papers (10%). On average, each publication within each cluster had four citation links. The citation network of microgrid research was partitioned using cluster analysis, which aided in identifying the main evolutionary paths of each subfield. This allowed for the precise tracing of their evolution, ultimately pinpointing emerging fronts and challenges. The identification of key pathways led to the discovery of significant studies and emerging patterns, highlighting research priorities in the field of microgrids. The study also revealed several research gaps and concerns, such as the need for further investigation into technical and economic feasibility, legislation, and standardization of microgrid technology. Overall, this study provides a comprehensive understanding of the evolution of microgrid research and identifies potential directions for future research.

Keywords: microgrid; carbon emissions; renewable energy; electric vehicles

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1. Introduction

Microgrids, which are local networks of energy sources and consumers, often work in tandem with the central power grid, but they can disconnect and operate autonomously if necessary, as shown in Figure 1. These systems can supply electricity to a single building, campus, or small community using a combination of decentralized energy resources, such as renewable sources and energy storage, as well as traditional electricity generation [1]. With the increased reliance on renewable sources such as solar and wind, microgrids are becoming increasingly popular as a means of efficiently integrating these sources into the power grid. Turbines in microgrids can offer a dependable source of electricity generation that can function separately from the larger utility grid. Depending on the requirements of the system, turbines, including wind and microturbines, can be used in microgrids in a variety of ways. They also improve power reliability and resilience by allowing for isolation or disconnection during outages and continuing to supply essential loads. Microgrids have the potential to enhance grid efficiency and flexibility by integrating decentralized energy resources, demand response, and energy storage, as well as promoting customer involvement in energy markets through advanced metering and control systems [2].

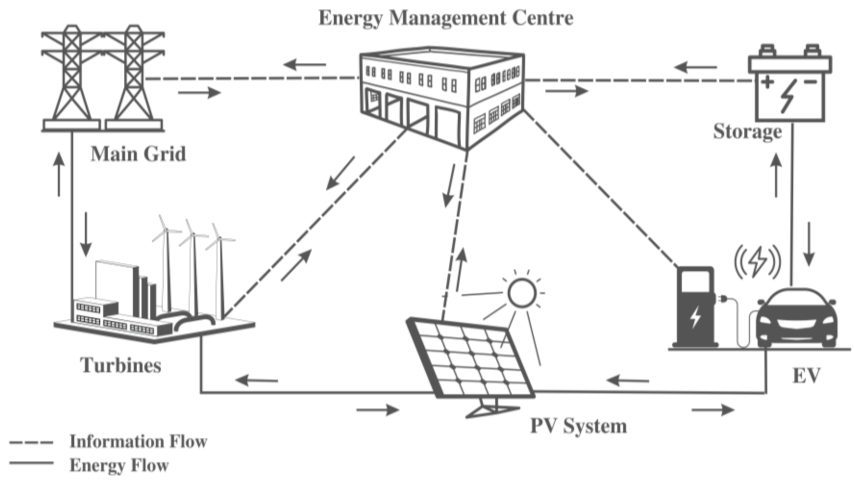

Figure 1. A typical schematic of a microgrid system.

However, the widespread adoption of microgrids faces challenges, including regulatory barriers, technical limitations, and financial considerations.

Despite these obstacles, the global microgrid market is anticipated to expand rapidly over the next few years, driven by the need to modernize and upgrade outdated power infrastructure as well as the rising need for reliable and sustainable power. This expansion is anticipated to be notably rapid. Microgrids offer a hopeful solution for integrating renewable energy sources into the power grid, enhancing the reliability and robustness of energy systems, as well as improving overall efficiency and flexibility. However, it is essential to recognize the obstacles and constraints that must be overcome for the wider application of microgrids and the maturation of this technology through continued R&D. Research on microgrids is dispersed throughout numerous subdomains, including control and regulation optimization, storage, and cyber security, among others. There are a number of reviews on microgrids, but they are generally limited to a single topic, such as control studies, microgrids with converter-interfaced generations [3], protection strategies of AC/Dc microgrids [4], market participation [5], industrial microgrids [6], cyber-security [7], sustainability of microgrids [8], and microgrid architectures [9]. The objective of this study is to examine the evolution of research and development (R&D) within various subfields of microgrids by conducting a social network analysis (SNA) on a corpus of research publications. Citation network analysis (CNA) has emerged as a methodical and scientific way of analysing research literature to uncover changes in techniques, future trends, and research frontiers. 'The information landscape of an area's evolution towards research frontiers is complex and shaped by citations, making CNA a valuable tool for technology forecasting and an alternative to expert-based methods that draw on SNA techniques [10]. This paper employs cluster analysis to segment the citation network of research on microgrids, highlighting the key evolutionary paths of each subfield and tracing the evolution to identify challenges and emerging fronts. In addition to tracing the existing technological advances in this sector and identifying the restrictions that impeded expansion of microgrid technology, the key routes of the evolution of each cluster indicate the future paths and emerging research fronts.

2. Methodology

In this study, we conduct a main path analysis of a citation network of microgrid (MG)-based research articles. As shown in Figure 2, the MG citation network was constructed by collecting citation information via Web of Science (WoS).

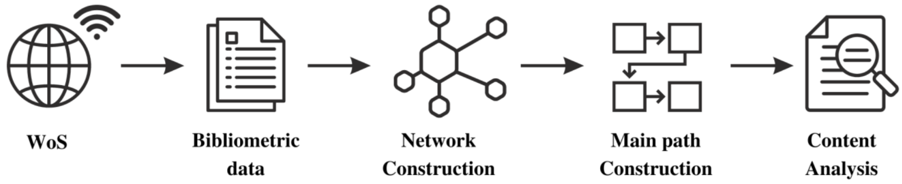

Figure 2. Schematic representation of main path analysis.

Assigning a weight to every directed link between two nodes is the initial step in preparing a main path [10]. Three key measures [11] are used to assess a link's weight: Node Pair Projection Count (NPPC), Search Path Node Pair (SPNP), and Search Path Link Count (SPLC). Of these three, the SPLC of a given link indicates the number of search paths by which the network traversed through the link; therefore, it is believed to be the most significant to traversal weight. If the SPLC value is large, more search paths traverse the link [12]. At a source node, citation networks construct their major paths by connecting the links carrying the heaviest load until they reach a sink node. Each relationship in a primary path supports the dissemination of knowledge to later publications, and these relationships are often used to trace the progress of science by matching historical facts and citation links. The major path nodes denote milestones in the study domain [13]. Although the priority search method selects connections of a primary path directly, the total number of network traversals may not be the highest. The first step of main path analysis is to identify the connections with the highest travel count that emerge from all resources. The first node of a global main path is called the initial node, and the subsequent three links are produced by repeating the operation until a sink node is reached. Here, we developed the software package GEPHI's global main path [14]. By tracking down the relevant MG technology papers, we built the global main path analysis. We obtained bibliometric information from the Web of Science by utilizing the keyword "microgrid", which we then utilized to build the citation network [15]. This citation network consisted of 1000 nodes, including cited papers. To identify the predominant research themes, we performed a modularity-based clustering analysis on the citation network [16], which resulted in seven major clusters, each representing a distinct research theme. Each cluster was extracted as a separate network and identified the key route of evolution. These key routes are given as supplementary figures (Figures S1–S7). Each key route traces the evolution of its domain, depicting milestone papers. The leaf nodes indicate the emerging trends and immediate future agenda, as shown in Figure 3.

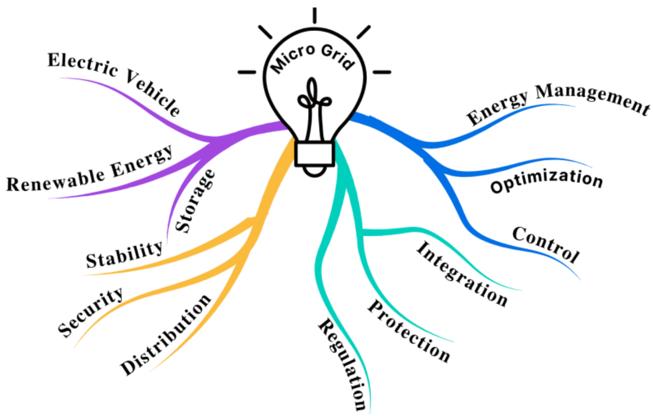

Figure 3. Streams of microgrid research and development.

3. Evolution of Microgrid Technology

There are numerous subdomains of microgrid technology research (Figure 3), each of which focuses on a distinct component of microgrid design, operation, and management. Energy storage, control, power electronics and power quality, renewable energy integration, stability, storage, protection and cybersecurity, regulation and distribution, and economic and business models are some of the major areas of microgrid technology study. The following is a discussion of the viewpoints, limitations, and future possibilities for each of these diverse subdomains identified through main path analysis.

3.1. Control Strategies for Microgrids

The largest discovered cluster was examined first in the citation network study. The content of the research articles of the important nodes along the evolutionary path was studied to monitor the evolution, constraints, and future research potential. One of the central nodes focuses in particular on the design and assessment of controllers, which integrates synchronization algorithms to insure a seamless and secure reconnection of the utility and microgrids after the fault is rectified [17,18]. Incorporating an inverter-based microgrid [19] with parallel inverters [20–23] into a distribution network has made it easier to use distributed generation, storage, and renewable energy sources. It has also improved power quality and reduced losses, increasing the system's dependability and efficiency. The actual and reactive power requirements for the microgrid must be distributed among the inverters in line with their ratings, and the grid voltage must be controlled in Figure 4. In small grids with substantial nonlinear and unbalanced load proportions, the waveform quality in terms of balance, transient disturbances, and harmonics needs to be actively regulated [24]. Additionally, a method for handling inverters connected in parallel in a standalone AC supply system [25] and control strategies for flexible microgrids composed of parallel connections between numerous line-interactive UPS systems using droop approach [20,26–32] to prevent vital interactions among UPS units were also discussed [33]. Numerous control techniques based on active power flow [34–38], line impedance [21,32,39–44], voltage quality [30,32,38,45–49], stability [28,37,41,42,50–55], load sharing [56], frequency quality [46,47,49,53,57], current quality [19,38,48,58], system dynamics (DOF) [59], synchronization [60], reliability [61], operating cost [61,62], hierarchy [42,63–66], reactive power [32,37,38,52,67,68], communication time delay [66], etc., were reported in the literature for enhancing the overall performance of the microgrid, as shown in Figure 4.

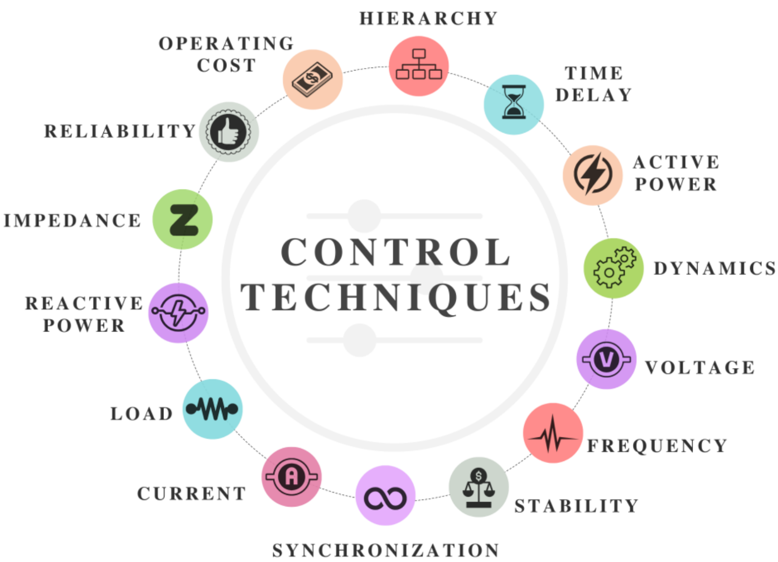

Figure 4. Microgrid control techniques.

This cluster studies microgrid control strategies. The research has focused on designing and testing controllers with synchronization algorithms to allow a smooth and secure reconnection of the utility and microgrids following a fault. Due to multiple distributed energy resources (DERs) and demands, microgrids are hard to manage. Microgrid control and monitoring require communication networks and data management systems, which are prone to failure. The unpredictability of distributed energy resources (DERs) and demand in a microgrid makes system management difficult. An inverter-based microgrid with parallel inverters in a distribution network makes distributed generation, storage, and renewable energy easier and more reliable and efficient. Active power flow, line impedance, voltage quality, stability, load sharing, frequency quality, and reactive power have all been used to improve microgrid performance. To increase microgrid performance and dependability, this research may continue to explore new control mechanisms.

3.2. Optimization and Management of Microgrid Systems

The following cluster (Figure S2) of the citation network regards the different optimization methods for microgrids. "The expert multi-objective AMPSO (Adaptive Modified Particle Swarm Optimization) algorithm [69] has been compared to other evolutionary algorithms such as GA (genetic algorithms) and PSO (Particle Swarm Optimization) in a study of optimization methods for microgrid with renewable energy sources, including tidal energy [70], and a backup Micro-Turbine/Fuel Cell/Battery hybrid power source". Incorporating cutting-edge distributed energy resources can greatly enhance the performance of power systems, particularly distribution networks. However, it is important to note that excessive use of renewable energy under certain conditions could result in negative effects on the system's performance. It has been shown through simulations utilising a bi-level operational framework based on the energy band that adding a microgrid to a DN increases the system's capabilities as a whole. Bi-level cooperation problems were solved using enhanced non-dominated sorting genetic algorithms, which integrate the optimisation of the distribution networks and the profit maximisation of the microgrid [71]. SystemC-AMS-based modelling and simulation frameworks for cyber-physical electrical energy systems (CPEES) were also developed for optimization [72].

To ensure the dependability and stability of a distribution network (DN) with many microgrids, various frameworks for operation management [73,74], market management [75,76], and security and risk management [77–79] (as shown in Figure 5) and algorithms for efficient energy [80–84] were also developed. Energy management is shown in Figure 6. Algorithms based on demand-side response [85–88], voltage stability [89], price elasticity [90], consumer comfort [91,92], multi-carriers [93], distributed generation (DG) [94], customer response [95], operating costs [79,92,95–100], hybrid renewable energy sources [101–105], interconnected microgrids [106,107] environmental pollution [108], emissions [109,110], cooperative participation [111], and storage [97,112,113] were found to be the key routes in this network. Reverse power flows, local oscillations, and frequency fluctuations are the key uncertainties [114] of microgrids, which challenge their stability, reliability, and protection. Smart modelling of microgrids using Petri nets (PNs) aids in handling these kinds of encounters, which are extensively employed to illustrate and research the operations of industrial systems in both discrete and continuous-time occurrences. Time-based pricing networks are seen as more reliable options for grid integration strategies in the context of unpredictable loads and renewable energy sources. Electric-vehicle-based microgrids have the potential to utilize energy storage systems, with the vehicles being able to aid the microgrid in satisfying load demands and maintaining voltage and power quality.

Figure 5. Microgrid management.

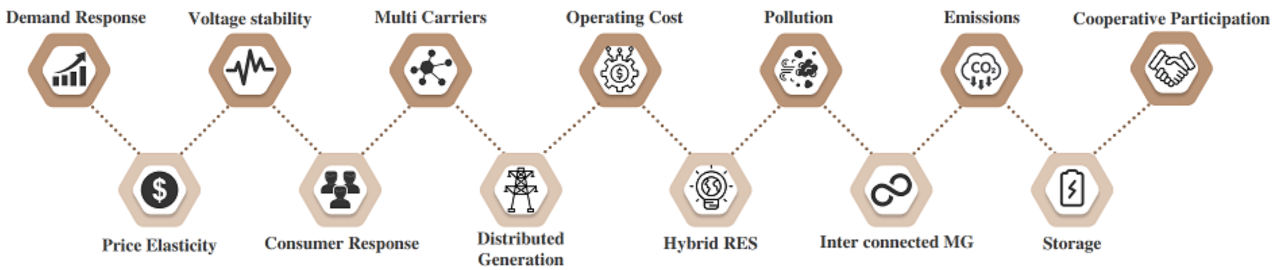

Figure 6. Microgrid energy management.

However, during periods of high EV usage, the microgrid may experience increased load. Implementing EV power scheduling can address the profit and cost profile as well as support demand-related issues faced by microgrids.

Microgrid optimization and management now includes advanced PSO algorithms, dynamic demand response (DR), hierarchical models, and smart consumer behaviour. Hierarchical decentralized frameworks were created to manage MEMGs and smart consumers. Deep-learning-based forecasters and risk-averse information gap decision theory (IGDT) scheduling risk controlling were applied to predict uncertain parameters. A prediction-based approach for designing dynamic demand response (DR) systems that match smart consumers' behaviour reduced peak energy and heat costs by 17.5% and 8.78%, respectively [115]. Hierarchical models were constructed for generation scheduling, mobile unit allocation, distribution feeder reconfiguration (DFR), and maintenance crew scheduling to improve DC-MG resilience. Simulations indicated that DFR and proactive interventions cut ENS by 19,124 kWh and 4101 kWh, respectively, when considering load demand, wind speed, and solar radiation uncertainty. Information exchange between microgrids boosted the supply service level to key loads by 48.16%, boosting resilience by 3.47% [116]. Enhanced mixed binary–continuous PSO employed V-shaped QPSO to handle binary variables for six scenarios, taking market price, supply, and demand volatility into account, to tackle unit commitment (UC) problems in microgrids. This quadratic PSO outperformed classical PSO with SPSO and HPSO in several instances [117]. PSO was used to handle dynamic economic load dispatch (DELD) in grid-connected MGs with integrated demand response programs. The two-point estimate method (TPEM) addressed demand, renewable-energy generation, and market price uncertainties. The simulations showed that demand response integration reduced the study microgrid's running costs by 21.77% [118]. Fast-start distributed generators and fast-responding needs were studied to boost microgrid flexibility and affordability. Fast-responding needs can work with a scenario-based scheduling, but slow-responding demands cannot. If switched off at the DA stage, a slow-start generator cannot be restarted [119]. A bi-level bidding system was created to manage energy exchange between networked microgrids with traditional and smart users. Load demand and renewable generation uncertainty were managed using the CVAR approach. Simulations show that risk-taker scheduling lowers the market-clearing price and increases smart customers' comfort index [120]. Finally, CCHP MGs with battery-charging stations received an information gap decision theory (IGDT)-based energy management system [121]. Considering the ON/OFF history of power/heat/cooling units, least up-time and least down-time constraints, start-up and shut-down ramp rate limits, and other risk factors, battery energy storage (BES) and thermal energy storage (TES) reduced MG operating expenses by 7.4% and 1.82%, respectively [122]. The battery-charging station (BCS) raised the MG operation cost by 20.19%, and taking into account uncertainties, it increased by 8.22% [123].

The discussion in this session focuses on managing and optimizing microgrid systems. The integration of renewable energy sources has the potential to improve power systems; however, excessive reliance on such sources may have adverse effects on system performance. Microgrid optimization has been facilitated through the utilization of optimization algorithms such as AMPSO, GA, and PSO. Various management frameworks have been devised for the purpose of managing operations, marketing, security, and risk management. The significance of energy management algorithms in the management of microgrids has been established, encompassing demand-side response, voltage stability, price elasticity, and consumer comfort. Microgrid stability, reliability, and protection are impacted by various uncertainties, including but not limited to reverse power flows, local oscillations, and frequency fluctuations. Several solutions were proposed, including intelligent modelling using Petri nets, time-based pricing networks, and microgrids based on electric vehicles with scheduling. The study concludes by emphasizing that microgrid optimization and management now incorporate sophisticated PSO algorithms, dynamic demand response, hierarchical models, and intelligent consumer behaviour. More research is required to develop and test novel optimization and management methods and frameworks for microgrid systems, which is the research gap. Prospective paths for research encompass the advancement of novel algorithms, frameworks, and systems with the aim of augmenting the efficiency, dependability, and cost-effectiveness of microgrid systems.

3.3. Microgrid Regulation

The third largest cluster (Figure S3) in term of number of papers in the citation network examines microgrid regulation, shown in Figure 7. Multi-agent system (MAS) technology manages a microgrid to optimize energy exchange between producing units, local loads, and the main grid using a classic distributed algorithm based on the symmetrical assignment problem [124]. Using interconnected microgrids and lumped loads, these systems arrange energy resources for island power systems. Energy resource scheduling comprises three phases. First, each microgrid's internal demand is scheduled. The next step is to search for the best wholesale energy deals coming from a network's electricity export providers. Finally, each microgrid is rescheduled to match demand from the wholesale energy market simulation and internal needs [125]. Multi-agent systems manage multiple microgrid-distributed energy resources in a two-level configuration. The symmetrical assignment problem with a naive auction algorithm matches energy market buyers and sellers. Market participants include generation, load, auction, grid, and storage organisations [126]. DSC regulates frequency, voltage, and power in microgrids using local unit controllers. Microgrid situations with more distributed generators (DGs) require this technique. Secondary control's narrow traffic pattern allows local-controller, local-area communication. The voltage restoration separates the voltage and frequency control design by employing a distributed finite-time control strategy to converge all distributed generations (DGs) to the set point in constrained time [127]. Consensus-based distributed frequency control with control input limitations restores frequency [128]. A novel coordinated power controller design architecture optimises scattered generator active power output. Distributed generating systems have DED and CC function modules for each bus.

Distributed consensus-theory-based DED calculates each generator's optimal active power generation references [129]. Distributed cooperative VUC control is used for islanded microgrids. Each distributed generator (DG) may balance sensitive load bus (SLB) voltage. Each local DG's contribution level (CL) is proposed to demonstrate compensation ability. Each local DG features a supplementary compensation architecture and communication layer [130,131]. Control strategies are necessary for isolated microgrids with inconsistent communication in order to regulate frequency and voltage of each distributed generator (DG) and share active/reactive power. Droop-based secondary and tertiary control strategies are established using iterative learning mechanics. The DGs only need to communicate sporadically and in a low-bandwidth manner with their neighbours, as control inputs are updated at the end of each iteration. Periodic communication can be costly and inefficient in microgrid control [132]. In isolated microgrids, secondary frequency and voltage are managed through event-triggered distributed control.

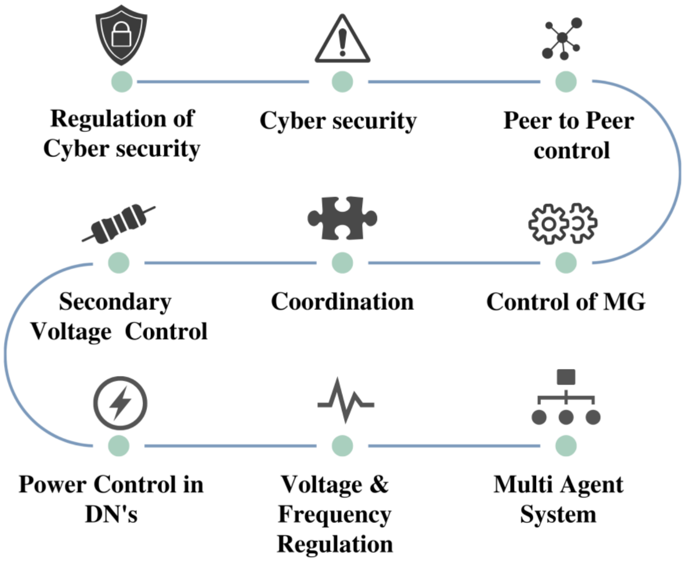

Figure 7. The evolution of R&D of microgrid regulation.

The proposed control strategies aim to restore frequency and voltage, accurately share active power, and minimize communication among the secondary controllers. Feedback control laws are replaced with estimator outputs, which are only updated during event-triggered times [133].

A new master–slave-organised DC microgrid network control technique with distributed iterative-event triggers and constrained communication capacity can synchronise DER voltages. Low-bandwidth communication networks can optimise load sharing for economic operation [134]. Broadcast gossip distributes peer-to-peer control entirely. To govern voltage and reactive power sharing, DER units need local voltage and current readings from their neighbours. The broadcast gossip communication protocol's scalability and reliability allow control inputs to precisely share reactive power across each DER by restoring voltage levels at the shared coupling. Distributed controllers replace the central hierarchy in local DERs. Line switches' peer-to-peer requirements ensure microgrid system stability, allowing DERs to plug-and-play and survive topology changes [135,136]. For DC cyber-physical microgrids, resilient neighbour-based distributed cooperative control involves slow-switching topologies and communication delays. The proposed robust control method can synchronize a DC microgrid's voltages by achieving optimal load sharing for DERs' generation cost reductions to improve economic operation at the same layer through a sparse communication network, taking communication delays and slow-switching topologies into account [136,137]. In an isolated AC microgrid, a two-layer distributed control technique may regulate the output power of huge DERs such as PVs and BESSs to achieve self-consistent proportional power sharing with time delay [138,139].

A distributed dynamic event-triggered control rule for each distributed generator handles secondary frequency restoration and active power distribution in an AC microgrid system with constrained varying time delays. Dynamic event-triggered approaches reduce communication costs. Lyapunov function analysis provides stability, active power sharing, and asymptotic frequency restoration. The adequate condition limits time delays [139]. DoS attacks are mitigated using a secondary-control-layer-distributed resilient control technique. Even during DoS attacks, the control technique maintains bus voltage and optimises current sharing by tertiary layer. A new secondary-layer robust sampling approach protects against DoS assaults. Most secondary control methods sample at a predetermined pace. The easy-to-implement distributed robust controller may maintain DC microgrid system stability despite DoS attacks, according to theoretical research [140]. The sample control architecture uses a time-varying sampling period and enhanced communication to prevent sophisticated attackers from collecting it. Resilient secondary controllers depend on sample period and communication. According to theory, the offered technique can restore bus voltage and share current even during DoS assaults and heterogeneous communication delays. A controller-hardware in-the-loop DC microgrid test system tests our method against communication delays and DoS attacks [141,142]. Attacks on the voltage and frequency control-loop inverter input channels that are unknown and unbounded could have a negative impact on microgrid stability and its cooperative performance. “Stability analysis with Lyapunov techniques combined with an entirely distributed attack-resilient control framework retains the uniformly bounded consensus for voltage containment and frequency regulation” [143].

In conclusion, managing and connecting a variety of systems and components is necessary for microgrids. For regulators, this makes microgrid operation and construction complicated. Regulations governing microgrid connectivity vary by country. Regulators struggle to develop guidelines for utility and microgrid collaboration. System security and dependability must be balanced with innovation and the incorporation of renewable energy sources in microgrid control. Microgrid management makes sure that microgrids integrate well with the main power grid. Regulations for consumer protection, grid management, and interconnection are mentioned. The laws strike a compromise between customers, utilities, and microgrid operators. Future microgrid regulation is anticipated to support the integration of renewable energy, enhance system stability and reliability, and protect consumers. New regulations may be necessary for distributed energy sources, energy storage technologies, and electric automobiles. International standards and harmonized regulations are required to facilitate the development and implementation of microgrids throughout the world due to the rising demand for them and their potential to increase energy security and decrease reliance on conventional grid systems. Lastly, microgrid regulation is expected to support the integration of renewable energy, system dependability, and stakeholder interests.

3.4. Stability of Microgrids

Microgrid stability is the major concern addressed in the fourth cluster (Figure S4) in the citation network. Intelligent controller systems estimate system variables and adjust to operational changes to outperform the traditional controllers [144]. A mathematical model shows how modest rooftop photovoltaic (PV) power plants affect a larger power system’s economic and performance characteristics. PV electricity generation had a high break-even cost below 10% [145]. Battery storage stabilises PV system power output (Figure 8), but it is expensive and wasteful. This study proposes altering MPPT control parameters to smooth short-term power output changes in PV systems without additional equipment. The proposed measure restricts PV system power output growth by moving the MPPT control operating point to a position where maximum power is not created with current insolation when insolation increases rapidly [146]. PV/battery cuts peak demand by 7% [147]. The benefit of PV and emergency storage when used together is greater than when these two technologies are used separately, and distributed PV and storage may enhance grid security [148]. A new energy-storage-modelling software links wind turbines, solar PV arrays, and variable electrical loads. The model calculates the filling and emptying of the energy store and anticipates power curtailment or unfulfilled demand. This unique modelling strategy outperforms previous methodologies [149]. The output of a PV system is optimized using MPPT, but it converges to a local maximum instead of the maximum of the curve. A two-stage MPPT control is suggested for non-uniform insolation [150]. A Photovoltaic Energy Capacitor System (PV-ECS) power-generating system using solar energy estimation has been described, and energy capacitor systems coupled to power electronics devices can control power [151,152]. Fuzzy logic and PSO are used to optimize the most prevalent proportional–integral (PI)-based frequency controllers in AC microgrid systems [153], and Kriging-based surrogate modelling reduces assessment costs [154]. A microgrid test platform evaluates the performance and robustness of synthesized controllers under disturbances and uncertainties [155]. A marine vessel equipped with a portable islanded microgrid comprising PV, wind turbine, SWE, and ESS employs a fuzzy PD + I load frequency controller (LFC). Electric vehicles manage load frequency in islanded microgrids [156]. Alternative power-balancing technologies are being investigated because battery energy storage systems (BESS) are expensive and degrade quickly. Low-frequency EV BESSs with vehicle-to-grid capability are popular.

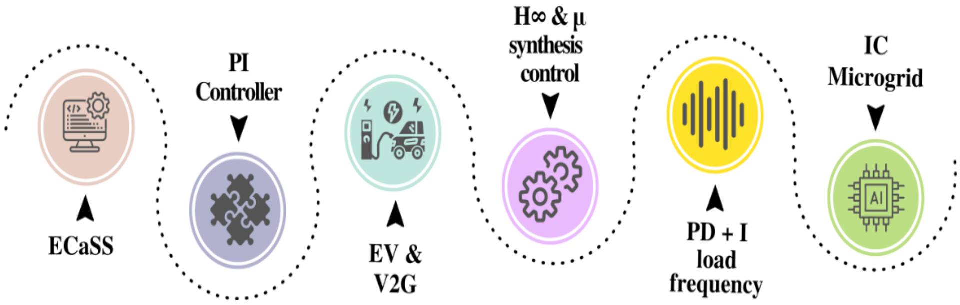

Figure 8. The methods of enhancing stability of microgrids.

When employed in V2G scenarios, a novel multi-objective fractional order control approach for EVs optimizes the V2G controller under a variety of operating conditions caused by intermittent renewable energy sources [157]. An efficient two-area interconnected microgrid (ICG), based on renewable energy sources without batteries, uses dish Stirling solar power generation, wind power generation, plug-in hybrid electric vehicles, a diesel engine driven generator, heat pumps, and freezers [158]. For load frequency analysis in hybrid microgrids with wind, micro-hydro, biogas, and biodiesel generators, one study linearizes a medium-sized linear-Fresnel-reflector solar-thermal power unit. The model simulates workable DR approaches for isolated and interconnected modes [159]. Optimization-based FO controller tuning uses GOA, GSA, GA, and PSO [160]. The stability boundary locus (SBL) method finds the FOPI controller's stable parameters space or fuel-cell microgrid stability boundary curves. The system's characteristic equation determines the SBL's stable zones. Electrolysers and fuel cells are sustainable [161,162]. Hydrogen Fuel Cells (HFCs) connected to microgrid control frameworks are studied for their efficiency and environmental friendliness. Power restrictions with high demand or transient events fluctuate HFCs. This study improves virtual synchronous generator (VSG) control for power production systems that combine HFCs and supercapacitors (SCs) [163]. Two-stage photovoltaic power generation has DC-link voltage management difficulties. Using DC-side synchronised active power regulation, two-stage photovoltaic (PV) power generation without energy storage was developed [164].

Microgrid stability study ensures safe and reliable operation. This involves studying how microgrids affect electricity system stability during disruptions and creating new control algorithms to improve voltage and frequency stability. Research uses machine learning and artificial intelligence to improve microgrid performance. Control algorithms, distributed energy resources (DERs), and photovoltaic (PV) and energy storage power output are improved to improve microgrid stability.

Future research on the topic of microgrid stability will focus on enhancing the stability of these systems through the creation of new and improved control algorithms. These algorithms will use machine learning and artificial intelligence to optimize microgrid performance and stability in real time. There will be research undertaken to evaluate the effect of microgrids on the stability of the electrical grid during outages and to regulate the voltage and frequency levels in microgrids to preserve system stability. Microgrid stability is crucial, since these systems are vital to the electrical system's safety and reliability.

3.5. Microgrid—Energy Storage

Energy storage (Figure 9) is a major issue in microgrid construction and is discussed in the fifth cluster (Figure S5) of the citation network. Thermal energy stores use thermal inputs and outputs to connect to the system, while electrical energy stores use electrical inputs and outputs, and the efficiency and reliability of these electrical energy systems (EES) need to be monitored consistently [165]. Electrical energy is stored in flywheels, pumped hydro, compressed air, and electrochemical devices. Ice storage, custom thermal storage medium, and phase transition materials use material, sensible, and latent heat capacities [166]. All solar electric systems need batteries. Their efficiencies and lifespans affect PV system performance and economics. Batteries made specifically for photovoltaic systems need to have a high cycle stability and a very low discharge rate. An algorithm for large battery storage systems measures electrolyte-specific gravity and voltage at a predetermined temperature to establish a battery's state of charge [167]. The life cycle costs of a rural energy-storage electromechanical flywheel battery and a lead-acid-battery storage system were compared. Flywheels were cheaper than lead batteries over time. Based on the foregoing, small-scale flywheel energy storage could boost rural electricity in sub-Saharan Africa. Electromechanical flywheel battery storage reduces lead-acid-battery disposal environmental impacts. Examining the separation of Cd and Ni from Ni-Cd batteries using an aqueous two-phase system (ATPS) made of water, copolymer L35, and Li_2SO_4 is crucial when taking environmental considerations into account. The amount of additional extractant (potassium iodide), the mass ratio between the phases of the ATPS, leaching, the tie-line length (TLL), and the dilution factor of the battery samples all affect how these metals are extracted from bottom stage (BP) to the upper stage (UP) of the ATPS [168]. Online impedance spectroscopy was used to solve battery lifespan and isolated maintenance issues. Battery impedance spectroscopy is integrated into static converter control [169]. A micro-hydraulic technology was used to partially replace battery storage in a standalone photovoltaic facility. The micro-hydraulic system has a water pump, water turbine, DC generator, and two identical water reservoirs. The photovoltaic generator leverages an inverter to directly supply demand during the day, and any excess energy pumps water from the lower reservoir to the higher reservoir. The lower-reservoir water turbine powers the load at night [170]. Wind power and energy storage technologies were integrated to solve power system issues caused by wind's intermittent nature. Wind–hydro pumped storage is one example.

Wind and hydro solutions fulfil local electricity needs, reducing the reliance on fossil fuels and imports compared to the wind–light complementary pumped storage power system. This system employs solar, wind, and complementary energy sources to generate clean electricity and store backup power [171–173]. It has the potential to grow, with a low-cost wind–hydropower system being analysed from both an investment perspective (to maximize returns) and a system perspective (to increase renewable energy penetration and reduce costs). Genetic algorithms are used to optimize the system [174]. To address the issue of resource volatility causing electricity demand to exceed generation, pumped storage can replace batteries in wind–solar hybrid power systems [175]. The combination of wind, solar, and hybrid technologies creates and stores electricity at low cost [176]. In Cameroon, hybrid systems combining pico-hydro and photovoltaic with biogas generators reduce electricity costs [177]. Deep-cycle batteries are superior for standalone renewable power systems, but pumped storage with a battery bank is 55% cheaper than deep-cycle batteries and more economical with a hydraulic controller. Increasing storage autonomy and capacity would make pumped storage more cost-competitive. Pumped storage with batteries is the best option for reliability, energy efficiency, and technology implementation [178]. Microwave-induced CO_2 gasification of carbon compounds could store energy. Charcoal used the least energy in a study that studied four materials. Activated carbon and charcoal reacted well with CO_2, while anthracite and coke did not. Charcoal was the most energy-efficient, especially at high volumetric hourly space velocities (VHSVs). The multimode microwave oven was more energy-efficient than the single-mode oven. Initial studies demonstrated that this method could reach energy efficiency of roughly 50% at laboratory scale. To compete with energy storage technologies, these performances can be improved. Since particle size improves process power, it affects energy consumption. Thus, a pressure drop–energy consumption compromise is needed. Comparing multimode vs. single-mode microwave heating, multimode heating is more energy-efficient. This paper proposes an energy-efficient technique that outperforms H_2-based fuel cells and batteries. Water reservoirs and flywheels are more energy-efficient yet cause environmental and socio-economic issues. Only supercapacitors outperform microwave-induced charcoal CO_2 gasification [179].

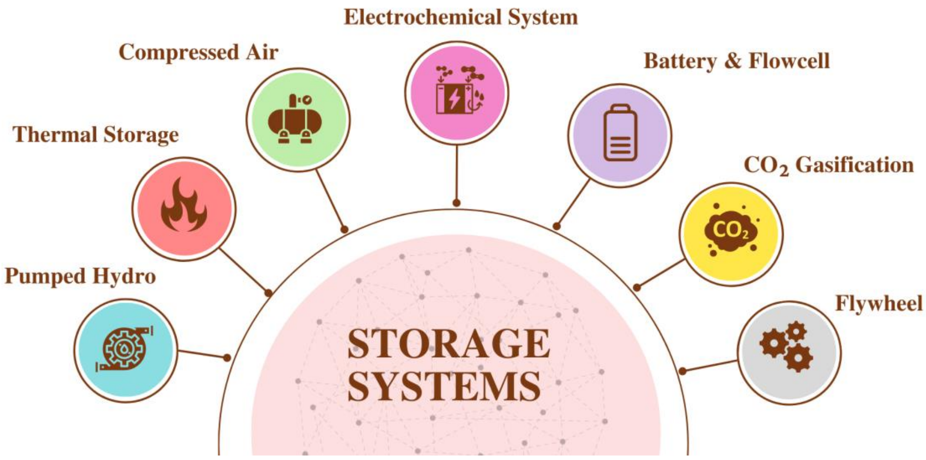

Figure 9. Microgrid energy storage Systems.

Remote communities can improve energy security and living circumstances by using renewable energy, especially solar and wind power linked with microgrid technology. Solar, wind, and energy storage allow isolated communities to generate sustainable electricity at cheaper costs than fuel. Renewable energy technologies benefit isolated microgrids. In the best instance, PV panels reduce LCOE by 19% compared to diesel engine systems. Using biomass as the major energy source reduces costs by twice as much, and gasifier-based and ORC-based systems create roughly 95% renewable electricity. However, usage of biomass in huge amounts will increase environmental pollution. By combining conventional power with local renewable energy in a remote place, the hybrid microgrid energy system is controlled accurately. The concept shows pumped storage of hydroelectricity's efficacy in irrigation and power restitution. Fuel savings and CO_2 reduction are demonstrated by the proposed technology [180–182]. Hybrid microgrid architecture using an Equilibrium Optimizer (EO) is proposed. The microgrid system is designed using EO because it quickly finds the best option. EO selects the best system design to reduce cost, increase stability, and cover load in varied climates. PV, WT, battery, and diesel generator constitute a microgrid. This study minimises net present cost (NPC) while preserving reliability, availability, and renewable percentage [183,184]. For optimal convergence, efficacy tools are needed for microgrid design. Stochastic metaheuristic algorithms solve complex problems best. The Gradient Artificial Hummingbird Algorithm (GAHA) reduces microgrid system energy cost (EC) by combining a gradient-based optimizer (GBO) with Artificial Hummingbird Algorithm (AIHA) [185–187]. The hybrid Harris Hawks Optimizer Arithmetic Optimization Algorithm (HHHOAOA) is a new metaheuristic algorithm for sizing and designing autonomous microgrids, which increases solution variety during optimization to improve solution accuracy [188]. EV-load scheduling reduces standalone microgrid costs, and the artificial hummingbird algorithm outperforms mainstream metaheuristics in off-grid microgrid size. Load demand affects off-grid microgrid cost more than meteorological data. Battery storage reduces overbuilt and excessive curtailment hazards [189].

Energy storage technologies are too expensive for microgrids to justify. Energy storage for isolated or low-income microgrids may be found difficult. Integrating storage devices into microgrids is difficult because they must match the microgrid's load and generation profile. This includes coordinating storage-system charging and discharging with microgrid generators and loads. Energy storage devices need regular replacement and maintenance. Remote or inaccessible microgrids may struggle with this. Energy storage is essential to a microgrid, but its cost, technical challenges, safety concerns, durability concerns, and regulations make it difficult to adopt. Energy storage research tries to overcome these challenges. To improve microgrid stability and reliability, energy storage solutions are being integrated. Alternative power-balancing methods are being studied because BESS are expensive and degrade quickly. Vehicle-to-grid low-frequency electric vehicle battery energy storage devices are common. Machine learning and AI are improving control algorithms and microgrid stability. Researchers are using energy-storage-modelling software to link wind turbines, solar PV arrays, and variable electrical loads to optimize microgrid efficiency. Future research will likely focus on developing more efficient and cost-effective energy storage systems for microgrids and increasing their stability and performance through enhanced control algorithms. The utilisation of cutting-edge battery technologies is one area of future development in energy storage for microgrids. The most popular battery type in microgrids right now is lithium-ion, but there are many other battery types that are being developed that have higher energy densities, longer cycle lives, and better safety. Microgrids will be able to store energy more effectively and reliably thanks to these new battery technologies, which will also increase their affordability and renewability. Integration of energy storage with other energy management technologies, such as demand response and energy efficiency, is another area of future development. Microgrids can optimise their energy use, lessen their reliance on the grid, and increase their resilience and sustainability by combining energy storage with these technologies.

The creation of new energy storage business models is another aspect of the future potential of energy storage in microgrids. New business models that use energy storage as a resource that generates income are emerging as the cost of energy storage continues to fall. Energy storage, for instance, can be utilised to offer grid services such as frequency management or participation in the capacity market, bringing in more money for microgrid operators. Last but not least, integrating energy storage with EV charging infrastructure is a part of the future scope of energy storage in microgrids. Energy storage can be crucial in regulating this demand and lessening the burden on the grid as more EVs are deployed and the need for charging infrastructure grows.

3.6. Microgrid Protection

Microgrids can combine numerous distributed renewable energy sources with distribution networks, but creating a sufficient protection mechanism is a hurdle for microgrid installation, as shown in Figure 10 and addressed in the respective cluster (Figure S6) of the citation network. Digital relays and a communication network were suggested to defend the microgrid system instead of conventional methods, which are inefficient [190]. Distributed generators (DGs) can improve power system dependability and quality through intentional islanding or microgrid operation. Controlling and protecting voltage and frequency are the biggest challenges for microgrids. Protection plans for lines and DGs during islanded operation, control methods for inverter-based DGs to manage voltage and frequency [191], and microprocessor-controlled relay-based protection methods for low-voltage microgrids were also created [192,193]. Microprocessor-controlled relays also protected looping or meshed microgrids [194]. Intelligent protection methods such as wavelet transforms and decision trees [195] can effectively protect the microgrid from problematic circumstances related to such substantial operational condition swings. A superimposed reactive energy protection strategy uses directional features and a threshold to identify the microgrid's problematic phase and section. The Hilbert transform calculates superimposed reactive energy (SRE) and sequence components of superimposed current in this protection technique. This protects looping and radial microgrids against solid and high-impedance faults [196].

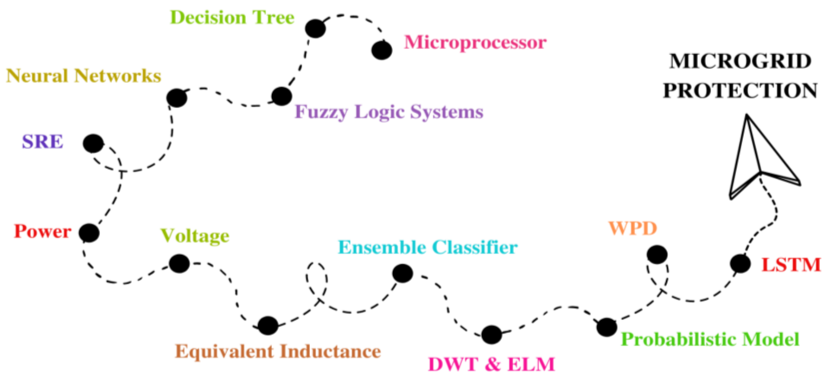

Figure 10. Various methods and algorithms used for Microgrid Protection.

Apart from this, a protection approach for microgrids employing interval type-2 fuzzy logic [197], using two separate fuzzy systems to detect, classify, and locate microgrid faults while taking into account the numerous uncertainties involved with faults, was also discussed. "After a single-phase tripping event, these fuzzy systems employ the phase angle between superimposed modal voltage and modal current to identify the fault direction, helping to secure the microgrid and acting as a fall back in case the primary protection fails" [198]. PV-integrated microgrids use power electronic converters due to photovoltaic (PV) source operation's intermittent load demand. A convolutional neural network (ConvNet)-based protection technique was used to distinguish between PV system inverter failures and distribution line symmetrical and asymmetric faults, as well as to detect, classify, and identify the defective section [199]. Most fault detection methods use a communication mechanism to convey information between protection units, which could compromise the entire protection system given the vulnerability of power electronic converters in DC microgrids. In contrast, an equivalent inductance-based fault detection system employing a simplified fault current equation was found to be more effective at performing the task [200]. Despite DC microgrids' many advantages and features, protecting them is difficult due to factors including photovoltaic (PV) systems' self-limited current, wind energy systems' long time constants, and communication systems' dependence, among others. A protection system for DC microgrids was also developed that uses the rate of power (dP) and rate of voltage (dV) and maps them as a dP-dV profile [201] suitable for all RES and energy storage systems, regardless of the DC microgrid's power rating and design. In addition to this, to guarantee the adaptability of DC microgrids to system reconfiguration and weather sporadicity, an ensemble-classifier-based protection technique has also been published [202], where the ensemble-based method is insensitive to individual classifier bias and dataset dimension/size [203]. A fault detection/classification, mode detection, and section identification approach based on Discrete Wavelet Transform (DWT) and Extreme Learning Machine (ELM) has been developed for grid-connected and island-mode microgrids to tolerate nonlinear wind-speed fluctuation. Similarly, a joint probabilistic model for understanding the variations in wind speed and solar irradiance was also developed [204]. Due to the growing number of distributed energy resources, demand in the network, and the cost of communication infrastructure, sensors in every bus are sometimes too expensive to monitor and preserve. To reduce transmission delay, a communication network needs significant bandwidth to transmit sensor data. An ensemble classifier and Wavelet Packet Decomposition (WPD)-based low-cost protection approach for hybrid microgrids with optimum sensor location and converter failure immunity was also evaluated [205]. Due to low fault current and non-linear dynamics, hybrid microgrids have trouble detecting high-impedance faults (HIF). Network reconfiguration caused by N-1 contingency and weather-induced stochastic variation in PV-based distributed energy resources (DERs) make HIF identification more difficult. A long short-term memory (LSTM)-based protection strategy with improved weather sporadicity and N-1 adaptation was also proposed for higher HIF sensitivity [206].

Microgrids frequently consist of a variety of generators, storage devices, and loads, making it challenging to ensure that all components can communicate and work together efficiently. The remote control and monitoring of microgrids raises concerns regarding cybersecurity and the possibility of malicious attacks on the system. To safeguard data exchanges between microgrid components and control systems, secure communication protocols will be necessary. This will prevent hackers from intercepting and modifying data as well as interfering with communications between microgrid components. In the future, cyber-physical systems (CPS) will play an increasingly vital role in microgrid operations. CPS merge physical and cyber technologies to build a system that is more efficient and resilient. Nonetheless, safeguarding CPS will be essential to ensuring that they are not susceptible to assault. Critical to minimising the impact of any cyberattack on the microgrid will be the development of an incident response strategy that includes methods for detecting, responding to, and recovering from cyberattacks. This research will likely focus on developing intelligent protection systems that can adapt to changing conditions and respond in real time to protect the microgrid against disturbances. However, like any power system, microgrids are susceptible to a variety of risks that must be managed to ensure their safe and efficient operation. These risks include equipment failure, cybersecurity threats, natural disasters, and regulatory compliance. To mitigate risks associated with microgrid operations, operators can adopt diverse strategies, including but not limited to regular equipment maintenance, cybersecurity measures, disaster preparedness plans, and compliance monitoring. Adequate risk management is crucial for ensuring the dependability, safety, and financial sustainability of microgrid systems. The application of advanced analytics and machine-learning methodologies for the detection and anticipation of potential hazards represents a promising avenue for the advancement of microgrid risk management. The utilization of various techniques can facilitate the detection of potential hazards prior to their manifestation through the assessment of extensive amounts of information from diverse origins, thereby enabling preventive management and alleviation of risks.

The integration of cybersecurity protocols within the framework of microgrid risk management represents an exciting prospect for future exploration. The employment of digital technologies and the Internet of Things (IoT) in microgrids has led to an increase in cybersecurity risks, posing a significant threat to the operation and management of these systems. The integration of cybersecurity measures into the risk management framework is imperative to ensure the protection of microgrids from potential online threats. The future risk management scope of microgrids includes the advancement of novel frameworks and techniques for managing risks. As microgrids continue to evolve and diversify, it will be necessary to create novel risk management frameworks and methodologies that are tailored to the specific risks associated with different types of microgrids, including off-grid or islanded microgrids. Future microgrid risk management will include energy management, grid integration, and renewable energy integration. The establishment of a comprehensive approach to microgrid management can ensure optimal performance and risk mitigation. This can be achieved by integrating risk management with other aspects of microgrid operation and management. The study of risk management in microgrids has emerged as a significant field of investigation, owing to the escalating implementation of microgrids on a global scale. Current research involves risk assessment frameworks, risk scenario modelling, and risk management tactics. Despite advancements, research on renewable energy integration, climate change implications, and cost-effective and dependable risk management methods is still lacking. Further investigation is imperative in these domains to guarantee secure and enduring functioning and endorse the extensive implementation of microgrids as a fundamental element of the energy shift.

3.7. Microgrid and EV Charging

The primary theme that emerged in the next cluster (Figure S7) relates to the modelling, optimising, controlling, and maintenance procedures for microgrid EV charging stations and their storage (Figure 11). Microgrids with PV and energy storage systems (ESS) for charging stations have been developed, since the number of electric cars (EV) in cities has expanded quickly [207]. Traditional sizing methods cannot examine large-scale situations using nonlinear optimization models to ensure design economy and dependability.

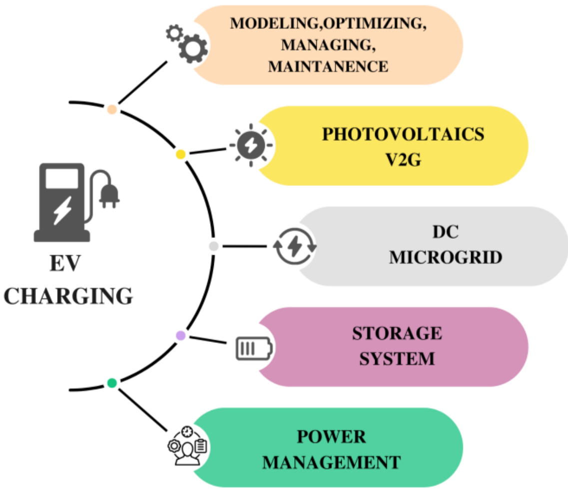

Figure 11. Microgrid and electric vehicle charging.

Many physical–economic model (PEM) and data-driven model (DDM) techniques have been developed to manage nonlinear battery degradation and optimal power distribution under varied EV charging profiles [208]. A concise tree-based machine learning (ML) model that was tested on a public dataset of data from domestic EV charge points and trained on each charge station based on the behaviour of its users revealed that the forecasting error can be reduced by up to 4 times, which in turn results in a progress of up to 50% in a combined aging–quality of service metric [209]. Microgrids based on PV panels put on rooftops or car parking shades, electrochemical stationary storage, EV charging stations, and public grid connection reduce power grid overload and increase renewable energy [210,211]. PV-powered electric vehicle charging stations with V2G power management were also included [212]. Real-time mixed-integer linear programming problems were created to minimize energy expenditure while taking into account EV arrival and departure [213].

Fast charging and EV storage systems are further topics covered in this cluster. According to the optimization results for EV fast charging using continuous differentiable charging (CDC) and multi-stage constant current (MCC), the CDC method can reduce the charging time by roughly 33.5% without compromising battery health [214], which is also supported by simulation results using the SMC method [215]. Through the definition of a SystemC-AMS framework, which simultaneously models the physical and mechanical evolution, together with environmental characteristics and energy flows, an EV power consumption model that considers the characteristics of the vehicle and the driving route, along with accurate models for all power components, renewable power sources, and batteries, has also been developed [216]. “The impact of battery ageing models on energy management of microgrids” [217], “DCM based on fuzzy logic systems” [218], "Virtual-battery based droop control for ESS" [219], and "EV drivers' behaviour based power management strategies" [220] are the other concepts covered in this cluster.

The futures of electric vehicle (EV) charging and microgrids are deeply linked, since both play a vital part in the transition to a cleaner, more sustainable energy system. Integration of microgrids with EV charging infrastructure has the potential to minimize reliance on fossil fuels by allowing EV owners to charge their vehicles using renewable energy generated locally. It also helps balance energy demand and supply, reducing strain on grid infrastructure and encouraging the use of renewable energy sources for EV charging. As the market for electric vehicles (EVs) continues to expand, advancements in microgrids and EV charging will be required to facilitate this transition to a more sustainable energy system. By offering a localised supply of renewable energy and grid services, microgrids can play a significant role in the smart charging of electric cars (EVs). Smart charging is the process of optimising EV charging based on variables including power costs, the availability of renewable energy sources, and grid stability.

Microgrids can facilitate smart charging by combining EV charging stations with renewable-energy generators such as solar or wind turbines. Both the carbon footprint of EV charging and the expense of maintaining charging stations can be decreased as a result. Moreover, microgrids can act as platforms for the application of sophisticated algorithms and management techniques for EV smart charging. These algorithms can optimise EV charging schedules and lower charging costs for EV users by utilising real-time information on power pricing, the availability of renewable energy sources, and system conditions.

4. Exploring AI-Based Research Methodologies for Microgrid Control

This section discusses AI-based microgrid research methodologies. Microgrid control points include DERs, loads, weather forecasts, energy markets, and the main grid [221]. In microgrids, a hierarchical classical control system is employed to manage primary and secondary Maximum Power Point Tracking (MPPT), voltage and frequency regulation, power sharing, protection, fault recovery, and rapid communication, as explained in [221]. Meanwhile, a high-level tertiary control system oversees energy management, power flow management within the microgrid and the larger power grid, prosumer market participation, customer segmentation, load and generation forecasting, and market price prediction [221–226]. Most control approaches use neural-network-based algorithms. Convolution neural network and K-Nearest Neighbour have classified and clustered in several studies. Reinforcement learning may be applied in power-sharing and energy marketing decisions.

In AI-enhanced microgrid primary control, the principal control layer prioritizes real-time power-sharing, MPPT, and inertia control. Traditional microgrid droop control lacks precision, speed, and robustness. However, AI can enhance these aspects of control [227]. AI can track the MPP with a 0.1% error [228]. Most of the control layers use neural network (NN)-based solutions, and ANN-based droop control improves active and reactive power sharing and voltage and frequency management [229]. Virtual energy-based droop control [219] and bus-signalling primary control [230] allow grid–PV–ESS integrated system coordination. SoC-based power-sharing solutions [231] use fuzzy logic to fine-tune local controller droop coefficients to maintain SoC level across all storage devices [232–234]. This enables the controllers to respond dynamically to changes in the microgrid and maintain a stable and balanced distribution of power. By using SoC-based power-sharing solutions with fuzzy logic, microgrid operators can optimize the use of renewable energy sources and ensure reliable and efficient power delivery [235].

Traditional secondary control methods have delayed response, imprecise control, and expensive communication infrastructure requirements, which can compromise system reliability [236]. At this control layer, microgrid stability during faults faces difficulties [237]. These difficulties demand intelligent control methods. The secondary layer (Figure 12) keeps uncontrolled variations within acceptable limits for load or generation changes [26]. Several techniques have been introduced to manage voltage and frequency deviation at this level, including the Multilayer Perceptron (MLP) model [238], the use of Artificial Neural Networks (ANN) and genetic algorithms (GA) [239], the reinforcement learning (RL) approach [240], the Interval Type 2 (IT2) fuzzy system based on deep reinforcement learning (DRL) [241], the distributed machine learning (ML) method [242], and the Extreme Learning Machine (ELM) technique [243]. These methods have pros and cons, depending on the microgrid scenario.

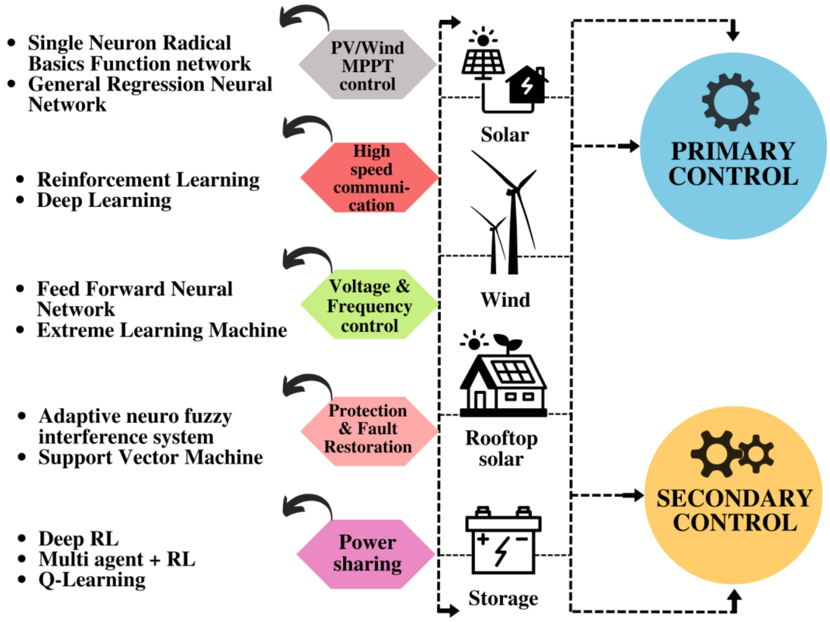

Figure 12. An outline of AI techniques in primary and secondary control and functionality of microgrids.

Communication delay is crucial in hierarchical control systems. Communication compensation blocks address network and time delays [244]. Delay minimization Q-Learning [245] reduces communication latency by 66% and 33% compared to other algorithms. A regression model has been developed to compensate for communication issues, ensuring swift and efficient voltage restoration, even under conditions of communication impairment [244].

As described in [246], a secured communication network based on deep-learning technology has been implemented to identify and categorize anomalous signals, safeguarding the microgrid against false signals. Low-inertia microgrids must maintain stability during faults. Controlling active and reactive power dispatch from DERs and maintaining load margin requires Corrective Voltage Control (CVC). An ML-based secondary-layer CVC framework [247] predicts optimal active and reactive power from each DER to restore voltage. In another approach, SVM-based fault detection [248] measures voltage and current at each selected point to accurately locate the fault section. Another tree-based ML model [249] has been proposed to measure voltage and current signals at each feeder to identify faulty events and alert the control system. In [250], NN-based adaptive microgrid protection combines ANN and SVM fault identification features also a multi-agent-based ML model [251] protects grid-tied and islanded AC microgrids.

The tertiary control layer (Figure 13) is responsible for optimizing the microgrid's power flow and managing grid import/export [252], ensuring that distributed energy resources (DERs) are dispatched efficiently to reduce costs. This layer also enables DER units to participate in energy markets and provide support to other microgrids or external grids. Artificial intelligence (AI) can enhance the control capabilities of this layer. The Optimal Power Flow (OPF) method, which considers network power quality requirements and operational limitations on assets, is used to determine the optimal objective function value for an electrical network [253].

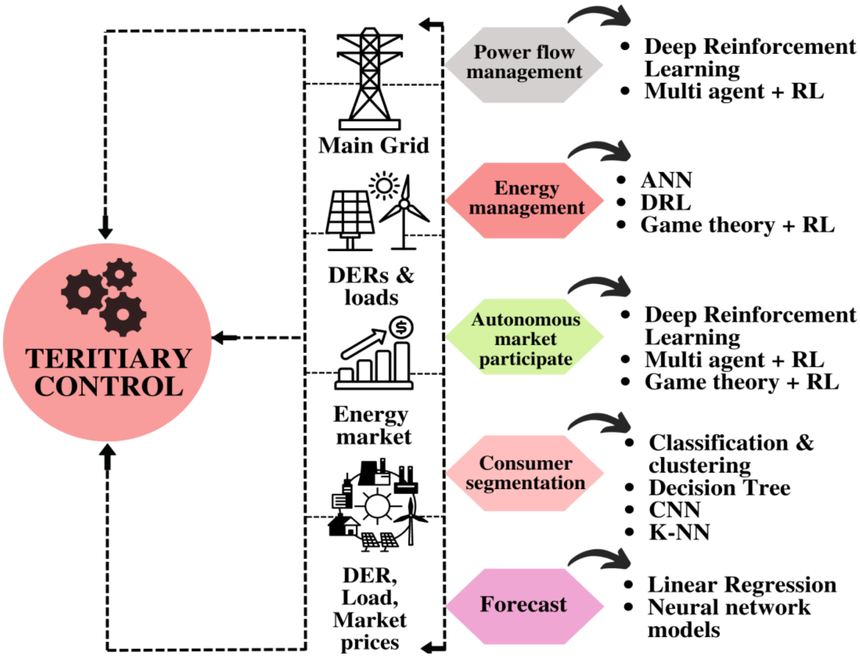

Figure 13. An outline of AI techniques in tertiary control and functionality of microgrids.

When Energy Storage Systems (ESS) are present within a microgrid, a Dynamic Optimal Power Flow (DOPF) approach [254] can be utilized to optimize DER output over a specified time horizon. Predictive control based on dynamic programming is recommended for peak shaving and maximizing owner profitability in grid-connected PV systems with ES [255,256]. In addition, an isolated microgrid consisting of diesel generators, wind turbines, and energy storage presents a multi-objective optimization challenge [257]. As noted in References [258,259], machine-learning (ML) power flow methods based on data analysis are proposed for such scenarios. Moreover, cooperative reinforcement learning (RL) is employed to optimize the economic dispatch of distributed energy resources (DERs), as described in Reference [260]. A multi-agent neural network (NN)-based energy management system (EMS) is employed in grid-connected microgrids to coordinate and minimize grid power imports [261].

Even though AI-based control systems have demonstrated promising results in enhancing the performance of microgrids, there are still limitations. The absence of standardization and compatibility across various microgrid components and systems is a major barrier to the implementation of AI in microgrids. Nevertheless, there are numerous opportunities for advancing the application of AI in microgrids in the future. Among these are the development of common communication protocols and data formats for microgrid components, as well as the enhancement of data gathering and sharing procedures. In addition, additional research can be conducted to develop more robust and precise artificial intelligence models for microgrid control, such as those based on deep-learning or reinforcement-learning algorithms. There is also the possibility of integrating AI with other developing technologies, such as blockchain, to improve the usefulness and security of microgrids. Nevertheless, the future of artificial intelligence in microgrids appears positive, with further developments anticipated in the coming years. While research into AI-enhanced hierarchical control of MGs is necessary, it is also crucial to have a broad understanding of microgrid research. Energy management, demand response, and grid integration are just a few of the microgrid research fields that could gain from using AI technologies. The social, economic, and environmental effects of microgrid deployment and use should also be considered, as well as how AI might be utilised to improve these effects. In conclusion, while the field of AI-enhanced hierarchical control of MGs is one that shows promise, it is crucial to have a broad understanding of microgrid research to fully explore the potential of AI in microgrid operation and administration.

5. Comparison of Recent Reviews with the Proposed Methodology

Table 1 presents a comparison of the proposed methodology with the latest reviews on microgrid research. The proposed study employs citation network analysis and modularity-based clustering analysis, which helped identify the main evolutionary paths and emerging fronts and challenges of the subfields. The study comprehensively presents the evolution of microgrid research and identifies potential directions for future research. The other studies use a systematic review methodology to discuss various aspects of microgrid planning, operation, and control, including the use of renewable energy sources, control tactics, and control strategies. One study also emphasizes the need for a consensus procedure to monitor voltage and frequency for stability and reliability in microgrids with intermittent renewable energy sources.

Table 1. Comparison of latest reviews with the proposed methodology.

Study	Year	Methodology	Number of Papers Reviewed	Research Clusters Identified	Key Findings
Proposed Study	2023	citation network analysis (CNA) methodology and modularity-based clustering analysis	349	7	The study used CNA and cluster analysis to partition the citation network of microgrid research and identify the main evolutionary paths of each sub-field. The main paths were traced to pinpoint emerging fronts and challenges, providing a comprehensive understanding of the evolution of microgrid research. The study also identified potential directions for future research in microgrids.
[262] F. S. Al-Ismail	2021	systematic review methodology	131	N/A	The paper discussed the evolution of DC microgrids and their characteristics, advantages over AC microgrids, and various aspects of DC microgrid planning, operation, and control, including DC sources, energy storage systems, DC distribution systems, and load management strategies.
[263] Shahgholian, G	2021	systematic review methodology	280	2	The study described microgrids' applications and types and their control goals, including coordinated control and local control. It also tackled microgrid load frequency control and tiny signal stability improvement, concluding that microgrid technology could improve power system sustainability and resilience.
[264] S. P. Bihari et al.	2021	systematic review methodology	69	2	The paper discussed hybrid microgrids that use renewable energy sources including solar photovoltaic, wind, and biomass and the necessity for a consensus mechanism to monitor voltage and frequency for stability and reliability. It also examined microgrid economics and proposed hybrid biomass–solar photovoltaic–wind turbine microgrid systems that prioritize power quality, real-time monitoring, and economic analysis.
[265] N. Altin and S. E. Eyimaya	2021	systematic review methodology	164	2	This paper outlined central and decentralized control strategies and analysed their advantages, disadvantages, and applications. The paper also noted that different architectures can improve reliability depending on the application or resource category.
[266] Ishaq S et al.	2022	systematic review methodology	92	6	The article suggested several control topologies depending on integrated source, connected loads, and MG ratings. It also studied MG control strategies, the infrastructure's major issues, and microgrid optimization methods and their benefits and downsides.

6. Conclusions

Microgrids are energy systems that can operate independently or in conjunction with the main electricity grid. They have the potential to integrate renewable energy sources, enhance customer participation in energy markets, and improve energy system efficiency and flexibility. However, the deployment of microgrids faces several obstacles, such as regulatory, technical, and financial challenges. To better understand the current state of the field, a study was conducted using citation network analysis (CNA) methodology to examine over 1500 scholarly publications on microgrid research and development. The study employed modularity-based clustering analysis, which identified seven distinct research clusters, each related to a specific area of study. Cluster 1, focused on control strategies for microgrids, had the highest proportion of publications (23%) and the maximum citation link count (151), while Cluster 4, which examined microgrid stability, had the lowest proportion of papers (10%). On average, each publication within each cluster had four citation links. The citation network of microgrid research was partitioned using cluster analysis, which aided in identifying the main evolutionary paths of each subfield. This allowed for the precise tracing of their evolution, ultimately pinpointing emerging fronts and challenges. The study revealed several research gaps and concerns, such as the need for further investigation into technical and economic feasibility, legislation, and standardization of microgrid technology. For example, one potential direction for future research is the application of artificial intelligence and machine learning to regulate and enhance the performance of microgrid systems. Another area of interest is the development of methods for optimally integrating microgrids with major grids and the optimized charging and discharging of contemporary loads such as electric vehicles connected to these grids. These systems are increasingly vulnerable to cyberattacks that compromise the security and stability of the grid. Hence, development of secure communication protocols is a crucial research area for the future. Similarly, the development of advanced control systems and high-tech power electronics components to ensure their stability, dependability, and safety constitutes another research direction. Overall, the study provides a comprehensive understanding of the evolution of microgrid research and identifies potential directions for future research. With the advances in integrated technologies, microgrids have the potential to play a significant role in realizing the UN Sustainable Development Goal 7 (SDG7), which calls for "affordable, reliable, sustainable and modern energy for all". By investing in research and development initiatives in the areas identified by the study, we can accelerate the deployment and adoption of microgrid systems and create a more sustainable and secure energy future for all.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/designs7030058/s1, Figure S1: Control Strategies for Microgrids; Figure S2: Optimization and Management of Microgrid Systems; Figure S3: Microgrid Regulation; Figure S4: Stability of Microgrids; Figure S5: Microgrid-Energy Storage; Figure S6: Microgrid–Protection; Figure S7: Microgrid and EV Charging.

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References

1. Schwaegerl, C.; Tao, L. The microgrids concept. In *Microgrids: Architectures and Control*; Wiley: Hoboken, NJ, USA, 2013; pp. 1–24.
2. De Matos, J.G.; e Silva, F.S.; Ribeiro, L.A.D.S. Power control in ac isolated microgrids with renewable energy sources and energy storage systems. *IEEE Trans. Ind. Electron.* **2014**, *62*, 3490–3498. [CrossRef]
3. Hossain, M.A.; Pota, H.R.; Hossain, M.J.; Blaabjerg, F. Evolution of microgrids with converter-interfaced generations: Challenges and opportunities. *Int. J. Electr. Power Energy Syst.* **2019**, *109*, 160–186. [CrossRef]
4. Mirsaeidi, S.; Dong, X.; Said, D.M. Towards hybrid AC/DC microgrids: Critical analysis and classification of protection strategies. *Renew. Sustain. Energy Rev.* **2018**, *90*, 97–103. [CrossRef]
5. Villanueva-Rosario, J.A.; Santos-García, F.; Aybar-Mejía, M.E.; Mendoza-Araya, P.; Molina-García, A. Coordinated ancillary services, market participation and communication of multi-microgrids: A review. *Appl. Energy* **2022**, *308*, 118332. [CrossRef]
6. Guti, D.; Colmenar-Santos, A.; Rosales-Asensio, E. A review of the state of the art of industrial microgrids based on renewable energy. *Electronics* **2022**, *11*, 1002.
7. Nejabatkhah, F.; Li, Y.W.; Liang, H.; Ahrabi, R.R. Cyber-Security of Smart Microgrids: A Survey. *Energies* **2020**, *14*, 27. [CrossRef]
8. Boche, A.; Foucher, C.; Villa, L.F.L. Understanding microgrid sustainability: A systemic and comprehensive review. *Energies* **2022**, *15*, 2906. [CrossRef]
9. Ahmed, M.; Meegahapola, L.; Vahidnia, A.; Datta, M. Stability and Control Aspects of Microgrid Architectures–A Comprehensive Review. *IEEE Access* **2020**, *8*, 144730–144766. [CrossRef]
10. Bindu, N.; Sankar, C.P.; Kumar, K.S. From conventional governance to e-democracy: Tracing the evolution of e-governance research trends using network analysis tools. *Gov. Inf. Q.* **2019**, *36*, 385–399. [CrossRef]
11. Hummon, N.P.; Dereian, P. Connectivity in a citation network: The development of DNA theory. *Soc. Netw.* **1989**, *11*, 39–63. [CrossRef]
12. Batagelj, V. Efficient algorithms for citation network analysis. *arXiv* **2003**, arXiv:Cs/0309023.
13. Garfield, E.; Sher, I.H.; Torpie, R.J. *The Use of Citation Data in Writing the History of Science*; Technical Report; Institute for Scientific Information Inc.: Philadelphia, PA, USA, 1964.
14. Sivaprasad, A.; Beevi, N.S.; Manojkumar, T. Dengue and Early Warning Systems: A review based on Social Network Analysis. *Procedia Comput. Sci.* **2020**, *171*, 253–262. [CrossRef]
15. Gustafsson, H.; Hancock, D.J.; Côté, J. Describing citation structures in sport burnout literature: A citation network analysis. *Psychol. Sport Exerc.* **2014**, *15*, 620–626. [CrossRef]
16. Mclean, C.; He, X.; Simpson, I.T.; Armstrong, D.J. Armstrong, Improved functional enrichment analysis of biological networks using scalable modularity based clustering. *J. Proteom. Bioinform.* **2016**, *9*, 9–18. [CrossRef]
17. Li, Y.; Vilathgamuwa, D.; Loh, P.C. Design, Analysis, and Real-Time Testing of a Controller for Multibus Microgrid System. *IEEE Trans. Power Electron.* **2004**, *19*, 1195–1204. [CrossRef]
18. Lasseter, R.H. Microgrids. In Proceedings of the 2002 IEEE Power Engineering Society Winter Meeting, Conference Proceedings (Cat. No.02CH37309), New York, NY, USA, 27–31 January 2002; Volume 1, pp. 305–308.
19. Pogaku, N.; Prodanovic, M.; Green, T.C. Modeling, Analysis and Testing of Autonomous Operation of an Inverter-Based Microgrid. *IEEE Trans. Power Electron.* **2007**, *22*, 613–625. [CrossRef]
20. Mohamed, Y.A.-R.I.; El-Saadany, E.F. Adaptive Decentralized Droop Controller to Preserve Power Sharing Stability of Paralleled Inverters in Distributed Generation Microgrids. *IEEE Trans. Power Electron.* **2008**, *23*, 2806–2816. [CrossRef]
21. Li, Y.W.; Kao, C.-N. An accurate power control strategy for power electronics-interfaced distributed generation units operating in a low-voltage multibus microgrid. *IEEE Trans. Power Electron.* **2009**, *24*, 2977–2988.
22. Chen, C.-L.; Wang, Y.; Lai, J.-S.; Lee, Y.-S.; Martin, D. Design of Parallel Inverters for Smooth Mode Transfer Microgrid Applications. *IEEE Trans. Power Electron.* **2009**, *25*, 6–15. [CrossRef]
23. De, D.; Ramanarayanan, V. Decentralized Parallel Operation of Inverters Sharing Unbalanced and Nonlinear Loads. *IEEE Trans. Power Electron.* **2010**, *25*, 3015–3025. [CrossRef]
24. Prodanovic, M.; Green, T. High-Quality Power Generation Through Distributed Control of a Power Park Microgrid. *IEEE Trans. Ind. Electron.* **2006**, *53*, 1471–1482. [CrossRef]
25. Chandorkar, M.; Divan, D.; Adapa, R. Control of parallel connected inverters in standalone AC supply systems. *IEEE Trans. Ind. Appl.* **1993**, *29*, 136–143. [CrossRef]
26. Guerrero, J.M.; Vasquez, J.C.; Matas, J.; De Vicuna, L.G.; Castilla, M. Hierarchical control of droop-controlled AC and DC microgrids—A general approach toward standardization. *IEEE Trans. Ind. Electron.* **2010**, *58*, 158–172. [CrossRef]
27. Kim, J.; Guerrero, J.M.; Rodriguez, P.; Teodorescu, R.; Nam, K. Mode Adaptive Droop Control With Virtual Output Impedances for an Inverter-Based Flexible AC Microgrid. *IEEE Trans. Power Electron.* **2011**, *26*, 689–701. [CrossRef]
28. Majumder, R.; Chaudhuri, B.; Ghosh, A.; Majumder, R.; Ledwich, G.; Zare, F. Improvement of Stability and Load Sharing in an Autonomous Microgrid Using Supplementary Droop Control Loop. *IEEE Trans. Power Syst.* **2010**, *25*, 796–808. [CrossRef]
29. Delghavi, M.B.; Yazdani, A. An Adaptive Feedforward Compensation for Stability Enhancement in Droop-Controlled Inverter-Based Microgrids. *IEEE Trans. Power Deliv.* **2011**, *26*, 1764–1773. [CrossRef]
30. de Souza, A.C.Z.; Santos, M.; Castilla, M.; Miret, J.; de Vicuña, L.G.; Marujo, D. Voltage security in AC microgrids: A power flow-based approach considering droop-controlled inverters. *IET Renew. Power Gener.* **2015**, *9*, 954–960. [CrossRef]

31. Eskandari, M.; Li, L.; Moradi, M.H.; Siano, P. A nodal approach based state-space model of droop-based autonomous networked microgrids. *Sustain. Energy Grids Netw.* **2019**, *18*, 100216. [CrossRef]
32. Eskandari, M.; Li, L.; Moradi, M.H.; Siano, P.; Blaabjerg, F. Simultaneous reactive power sharing and voltage regulation in an autonomous networked microgrid. *IET Gener. Transm. Distrib.* **2020**, *14*, 1366–1377. [CrossRef]
33. Guerrero, J.M.; Vasquez, J.C.; Matas, J.; Castilla, M.; de Vicuña, L.G. Control strategy for flexible microgrid based on parallel line-interactive ups systems. *IEEE Trans. Ind. Electron.* **2008**, *56*, 726–736. [CrossRef]
34. Dasgupta, S.; Sahoo, S.K.; Panda, S.K. Single-Phase Inverter Control Techniques for Interfacing Renewable Energy Sources With Microgrid—Part I: Parallel-Connected Inverter Topology With Active and Reactive Power Flow Control Along With Grid Current Shaping. *IEEE Trans. Power Electron.* **2010**, *26*, 717–731. [CrossRef]
35. Rowe, C.N.; Summers, T.J.; Betz, R.E.; Cornforth, D.J.; Moore, T.G. Arctan Power–Frequency Droop for Improved Microgrid Stability. *IEEE Trans. Power Electron.* **2012**, *28*, 3747–3759. [CrossRef]
36. Mumtaz, F.; Syed, M.H.; Al Hosani, M.; Zeineldin, H.H. A Novel Approach to Solve Power Flow for Islanded Microgrids Using Modified Newton Raphson With Droop Control of DG. *IEEE Trans. Sustain. Energy* **2015**, *7*, 493–503. [CrossRef]
37. Eskandari, M.; Li, L. Microgrid operation improvement by adaptive virtual impedance. *IET Renew. Power Gener.* **2018**, *13*, 296–307. [CrossRef]
38. Pérez-Ibacache, R.; Cedeño, A.L.; Silva, C.A.; Carvajal, G.; Agüero, J.C.; Yazdani, A. Decentralized model-based predictive control for DER units integration in AC microgrids subject to operational and safety constraints. *IEEE Trans. Power Deliv.* **2020**, *36*, 2479–2489. [CrossRef]
39. Roslan, A.M.; Ahmed, K.H.; Finney, S.J.; Williams, B.W. Improved Instantaneous Average Current-Sharing Control Scheme for Parallel-Connected Inverter Considering Line Impedance Impact in Microgrid Networks. *IEEE Trans. Power Electron.* **2010**, *26*, 702–716. [CrossRef]
40. Rokrok, E.; Golshan, M. Adaptive voltage droop scheme for voltage source converters in an islanded multibus microgrid. *IET Gener. Transm. Distrib.* **2010**, *4*, 562–578. [CrossRef]
41. He, J.; Li, Y.W. Analysis, Design, and Implementation of Virtual Impedance for Power Electronics Interfaced Distributed Generation. *IEEE Trans. Ind. Appl.* **2011**, *47*, 2525–2538. [CrossRef]
42. Baghaee, H.R.; Mirsalim, M.; Gharehpetian, G.B.; Talebi, H.A. A Decentralized Power Management and Sliding Mode Control Strategy for Hybrid AC/DC Microgrids including Renewable Energy Resources. *IEEE Trans. Ind. Inform.* **2017**, 1. [CrossRef]
43. Baghaee, H.R.; Mirsalim, M.; Gharehpetian, G.B.; Talebi, H.A. Unbalanced harmonic power sharing and voltage compensation of microgrids using radial basis function neural network-based harmonic power-flow calculations for distributed and decentralised control structures. *IET Gener. Transm. Distrib.* **2018**, *12*, 1518–1530. [CrossRef]
44. Eskandari, M.; Li, L.; Moradi, M.H.; Siano, P.; Blaabjerg, F. Optimal Voltage Regulator for Inverter Interfaced Distributed Generation Units Part I: Control System. *IEEE Trans. Sustain. Energy* **2020**, *11*, 2813–2824. [CrossRef]
45. Wang, F.; Duarte, J.L.; Hendrix, M.A.M. Grid-Interfacing Converter Systems With Enhanced Voltage Quality for Microgrid Application—Concept and Implementation. *IEEE Trans. Power Electron.* **2011**, *26*, 3501–3513. [CrossRef]
46. Chung, I.-Y.; Liu, W.; Cartes, D.A.; Collins, E.G.; Moon, S.-I. Control Methods of Inverter-Interfaced Distributed Generators in a Microgrid System. *IEEE Trans. Ind. Appl.* **2010**, *46*, 1078–1088. [CrossRef]
47. Li, Y.; Li, Y.W. Power management of inverter interfaced autonomous microgrid based on virtual frequency-voltage frame. *IEEE Trans. Smart Grid* **2011**, *2*, 30–40. [CrossRef]
48. He, J.; Li, Y.W.; Munir, S. A Flexible Harmonic Control Approach Through Voltage-Controlled DG–Grid Interfacing Converters. *IEEE Trans. Ind. Electron.* **2011**, *59*, 444–455. [CrossRef]
49. Kim, J.-Y.; Jeon, J.-H.; Kim, S.-K.; Cho, C.; Park, J.H.; Kim, H.-M.; Nam, K.-Y. Cooperative Control Strategy of Energy Storage System and Microsources for Stabilizing the Microgrid during Islanded Operation. *IEEE Trans. Power Electron.* **2010**, *25*, 3037–3048. [CrossRef]
50. Barklund, E.; Pogaku, N.; Prodanovic, M.; Hernandez-Aramburo, C.; Green, T.C. Energy Management in Autonomous Microgrid Using Stability-Constrained Droop Control of Inverters. *IEEE Trans. Power Electron.* **2008**, *23*, 2346–2352. [CrossRef]
51. Iyer, S.V.; Belur, M.N.; Chandorkar, M.C. A Generalized Computational Method to Determine Stability of a Multi-inverter Microgrid. *IEEE Trans. Power Electron.* **2010**, *25*, 2420–2432. [CrossRef]
52. Elrayyah, A.; Sozer, Y.; Elbuluk, M.E. A novel load-flow analysis for stable and optimized microgrid operation. *IEEE Trans. Power Deliv.* **2014**, *29*, 1709–1717. [CrossRef]
53. Eskandari, M.; Li, L.; Moradi, M.H.; Siano, P.; Blaabjerg, F. Active Power Sharing and Frequency Restoration in an Autonomous Networked Microgrid. *IEEE Trans. Power Syst.* **2019**, *34*, 4706–4717. [CrossRef]
54. CAragon, A.; Guzman, R.; de Vicu, L.G.; Miret, J.; Castilla, M. Constrained predictive control based on a large-signal model for a three-phase inverter connected to a microgrid. *IEEE Trans. Ind. Electron.* **2021**, *69*, 6497–6507. [CrossRef]
55. Baghaee, H.R.; Mirsalim, M.; Gharehpetian, G.B.; Talebi, H.A. A generalized descriptor-system robust H∞ control of autonomous microgrids to improve small and large signal stability considering communication delays and load nonlinearities. *Int. J. Electr. Power Energy Syst.* **2017**, *92*, 63–82. [CrossRef]
56. Majumder, R.; Ghosh, A.; Ledwich, G.; Zare, F. Load sharing and power quality enhanced operation of a distributed microgrid. *IET Renew. Power Gener.* **2009**, *3*, 109–119. [CrossRef]

57. Serban, E.; Serban, H. A Control Strategy for a Distributed Power Generation Microgrid Application With Voltage- and Current-Controlled Source Converter. *IEEE Trans. Power Electron.* **2010**, *25*, 2981–2992. [CrossRef]
58. Rocabert, J.; Azevedo, G.M.; Luna, A.; Guerrero, J.M.; Candela, J.I.; Rodr, P. Intelligent connection agent for three-phase grid-connected microgrids. *IEEE Trans. Power Electron.* **2011**, *26*, 2993–3005. [CrossRef]
59. Babazadeh, M.; Karimi, H. A Robust Two-Degree-of-Freedom Control Strategy for an Islanded Microgrid. *IEEE Trans. Power Deliv.* **2013**, *28*, 1339–1347. [CrossRef]
60. Cho, C.; Jeon, J.-H.; Kim, J.-Y.; Kwon, S.; Park, K.; Kim, S. Active synchronizing control of a microgrid. *IEEE Trans. Power Electron.* **2011**, *26*, 3707–3719. [CrossRef]
61. Rocabert, J.; Luna, A.; Blaabjerg, F.; Rodriguez, P. Control of power converters in ac microgrids. *IEEE Trans. Power Electron.* **2012**, *27*, 4734–4749. [CrossRef]
62. Nutkani, U.; Loh, P.C.; Blaabjerg, F. Droop scheme with consideration of operating costs. *IEEE Trans. Power Electron.* **2013**, *29*, 1047–1052. [CrossRef]
63. Baghaee, H.R.; Mirsalim, M.; Gharehpetian, G.B. Performance improvement of multi-der microgrid for small and large-signal disturbances and nonlinear loads: Novel complementary control loop and fuzzy controller in a hierarchical droop-based control scheme. *IEEE Syst. J.* **2016**, *12*, 444–451. [CrossRef]
64. Xin, H.; Zhao, R.; Zhang, L.; Wang, Z.; Wong, K.P.; Wei, W. A Decentralized Hierarchical Control Structure and Self-Optimizing Control Strategy for F-P Type DGs in Islanded Microgrids. *IEEE Trans. Smart Grid* **2015**, *7*, 3–5. [CrossRef]
65. Baghaee, H.R.; Mirsalim, M.; Gharehpetian, G.B. Power Calculation Using RBF Neural Networks to Improve Power Sharing of Hierarchical Control Scheme in Multi-DER Microgrids. *IEEE J. Emerg. Sel. Top. Power Electron.* **2016**, *4*, 1217–1225. [CrossRef]
66. Baghaee, H.R.; Mirsalim, M.; Gharehpetian, G.B.; Talebi, H.A. Eigenvalue, Robustness and Time Delay Analysis of Hierarchical Control Scheme in Multi-DER Microgrid to Enhance Small/Large-Signal Stability Using Complementary Loop and Fuzzy Logic Controller. *J. Circuits Syst. Comput.* **2017**, *26*, 1750099. [CrossRef]
67. He, J.; Li, Y.W. An enhanced microgrid load demand sharing strategy. *IEEE Trans. Power Electron.* **2012**, *27*, 3984–3995. [CrossRef]
68. Shabbir, N.S.K.; Liang, X.; Li, W.; Imtiaz, S.; Quaicoe, J. A Novel Model Predictive Controller for Distributed Generation in Isolated Microgrids—Part II: Model Predictive Controller Implementation. *IEEE Trans. Ind. Appl.* **2022**, *58*, 5860–5870. [CrossRef]
69. Moghaddam, A.A.; Seifi, A.; Niknam, T.; Pahlavani, M.R.A. Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source. *Energy* **2011**, *36*, 6490–6507. [CrossRef]
70. Javidsharifi, M.; Niknam, T.; Aghaei, J.; Mokryani, G. Multi-objective short-term scheduling of a renewable-based microgrid in the presence of tidal resources and storage devices. *Appl. Energy* **2018**, *216*, 367–381. [CrossRef]
71. Kim, H.-Y.; Kim, M.-K.; Kim, H.-J. Optimal operational scheduling of distribution network with microgrid via bilevel optimization model with energy band. *Appl. Sci.* **2019**, *9*, 4219. [CrossRef]
72. Chen, Y.; Vinco, S.; Pagliari, D.J.; Montuschi, P.; Macii, E.; Poncino, M. Modeling and simulation of cyber-physical electrical energy systems with SystemC-AMS. *IEEE Trans. Sustain. Comput.* **2020**, *5*, 552–567. [CrossRef]
73. Bazmohammadi, N.; Tahsiri, A.; Anvari-Moghaddam, A.; Guerrero, J.M. Optimal operation management of a regional network of microgrids based on chance-constrained model predictive control. *IET Gener. Transm. Distrib.* **2018**, *12*, 3772–3779. [CrossRef]
74. Bazmohammadi, N.; Tahsiri, A.; Anvari-Moghaddam, A.; Guerrero, J.M. Stochastic predictive control of multi-microgrid systems. *IEEE Trans. Ind. Appl.* **2019**, *55*, 5311–5319. [CrossRef]
75. Tong, X.; Hu, C.; Zheng, C.; Rui, T.; Wang, B.; Shen, W. Energy Market Management for Distribution Network with a Multi-Microgrid System: A Dynamic Game Approach. *Appl. Sci.* **2019**, *9*, 5436. [CrossRef]
76. Bahmani, R.; Karimi, H.; Jadid, S. Stochastic electricity market model in networked microgrids considering demand response programs and renewable energy sources. *Int. J. Electr. Power Energy Syst.* **2019**, *117*, 105606. [CrossRef]
77. Vahedipour-Dahraie, M.; Rashidizadeh-Kermani, H.; Najafi, H.R.; Anvari-Moghaddam, A.; Guerrero, J.M. Stochastic security and risk-constrained scheduling for an autonomous microgrid with demand response and renewable energy resources. *IET Renew. Power Gener.* **2017**, *11*, 1812–1821. [CrossRef]
78. Vahedipour-Dahraie, M.; Anvari-Moghaddam, A.; Guerrero, J.M. Evaluation of reliability in risk-constrained scheduling of autonomous microgrids with demand response and renewable resources. *IET Renew. Power Gener.* **2018**, *12*, 657–667. [CrossRef]
79. Karimi, H.; Jadid, S. Optimal microgrid operation scheduling by a novel hybrid multi-objective and multi-attribute decision-making framework. *Energy* **2019**, *186*, 115912. [CrossRef]
80. Dong, Y.; Liu, F.; Lu, X.; Lou, Y.; Ma, Y.; Eghbalian, N. Multi-objective economic environmental energy management microgrid using hybrid energy storage implementing and developed Manta Ray Foraging Optimization Algorithm. *Electr. Power Syst. Res.* **2022**, *211*, 108181. [CrossRef]
81. Li, N.; Su, Z.; Jerbi, H.; Abbassi, R.; Latifi, M.; Furukawa, N. Energy management and optimized operation of renewable sources and electric vehicles based on microgrid using hybrid gravitational search and pattern search algorithm. *Sustain. Cities Soc.* **2021**, *75*, 103279. [CrossRef]
82. Rezaei, N.; Kalantar, M. Stochastic frequency-security constrained energy and reserve management of an inverter interfaced islanded microgrid considering demand response programs. *Int. J. Electr. Power Energy Syst.* **2015**, *69*, 273–286. [CrossRef]
83. Rezaei, N.; Kalantar, M. Economic–environmental hierarchical frequency management of a droop-controlled islanded microgrid. *Energy Convers. Manag.* **2014**, *88*, 498–515. [CrossRef]

84. Raghav, L.P.; Kumar, R.S.; Raju, D.K.; Singh, A.R. Optimal Energy Management of Microgrids Using Quantum Teaching Learning Based Algorithm. *IEEE Trans. Smart Grid* **2021**, *12*, 4834–4842. [CrossRef]
85. Kumar, R.S.; Raghav, L.P.; Raju, D.K.; Singh, A.R. Impact of multiple demand side management programs on the optimal operation of grid-connected microgrids. *Appl. Energy* **2021**, *301*, 117466. [CrossRef]
86. Singh, A.R.; Ding, L.; Raju, D.K.; Raghav, L.P.; Kumar, R.S. A swarm intelligence approach for energy management of grid-connected microgrids with flexible load demand response. *Int. J. Energy Res.* **2021**, *46*, 4301–4319. [CrossRef]
87. Raghav, L.P.; Kumar, R.S.; Raju, D.K.; Singh, A.R. Optimal day ahead energy consumption management in grid-connected microgrids. *Int. J. Energy Res.* **2021**, *46*, 1864–1881. [CrossRef]
88. Dashtdar, M.; Flah, A.; Hosseinimoghadam, S.M.S.; Kotb, H.; Jasi, E.; Gono, R.; Leonowicz, Z.; Jasi, M. Optimal operation of microgrids with demand-side management based on a combination of genetic algorithm and artificial bee colony. *Sustainability* **2022**, *14*, 6759. [CrossRef]
89. Raju, D.K.; Kumar, R.S.; Raghav, L.P.; Singh, A.R. Enhancement of loadability and voltage stability in grid-connected microgrid network. *J. Clean. Prod.* **2022**, *374*, 133881. [CrossRef]
90. Raghav, L.P.; Kumar, R.S.; Raju, D.K.; Singh, A.R. Analytic Hierarchy Process (AHP)–Swarm intelligence based flexible demand response management of grid-connected microgrid. *Appl. Energy* **2021**, *306*, 118058. [CrossRef]
91. Khosravi, M.; Azarinfar, H.; Nejati, S.A. Microgrids energy management in automated distribution networks by considering consumers' comfort index. *Int. J. Electr. Power Energy Syst.* **2022**, *139*, 108013. [CrossRef]
92. Mansouri, S.A.; Ahmarinejad, A.; Nematbakhsh, E.; Javadi, M.S.; Nezhad, A.E.; Catal, J.P. A sustainable framework for multi-microgrids energy management in automated distribution network by considering smart homes and high penetration of renewable energy resources. *Energy* **2022**, *245*, 123228. [CrossRef]
93. Jiang, W.; Wang, X.; Huang, H.; Zhang, D.; Ghadimi, N. Optimal economic scheduling of microgrids considering renewable energy sources based on energy hub model using demand response and improved water wave optimization algorithm. *J. Energy Storage* **2022**, *55*, 105311. [CrossRef]
94. Kumar, R.S.; Raghav, L.P.; Raju, D.K.; Singh, A.R. Customer-oriented energy demand management of grid connected microgrids. *Int. J. Energy Res.* **2021**, *45*, 18695–18712. [CrossRef]
95. Kumar, R.S.; Raghav, L.P.; Raju, D.K.; Singh, A.R. Intelligent demand side management for optimal energy scheduling of grid connected microgrids. *Appl. Energy* **2021**, *285*, 116435. [CrossRef]
96. Shams, M.H.; Shahabi, M.; MansourLakouraj, M.; Shafie-khah, M.; Catal, J.P. Adjustable robust optimization approach for two-stage operation of energy hub-based microgrids. *Energy* **2021**, *222*, 119894. [CrossRef]
97. Yin, N.; Abbassi, R.; Jerbi, H.; Rezvani, A.; Müller, M. A day-ahead joint energy management and battery sizing framework based on θ-modified krill herd algorithm for a renewable energy-integrated microgrid. *J. Clean. Prod.* **2021**, *282*, 124435. [CrossRef]
98. Majidi, M.; Mohammadi-Ivatloo, B.; Anvari-Moghaddam, A. Optimal robust operation of combined heat and power systems with demand response programs. *Appl. Therm. Eng.* **2018**, *149*, 1359–1369. [CrossRef]
99. Zhu, J.; Huang, S.; Liu, Y.; Lei, H.; Sang, B. Optimal energy management for grid-connected microgrids via expected-scenario-oriented robust optimization. *Energy* **2021**, *216*, 119224. [CrossRef]
100. NKoltsaklis, E.; Giannakakis, M.; Georgiadis, M.C. Optimal energy planning and scheduling of microgrids. *Chem. Eng. Res. Des.* **2018**, *131*, 318–332. [CrossRef]
101. Murty, V.V.S.N.; Kumar, A. RETRACTED ARTICLE: Multi-objective energy management in microgrids with hybrid energy sources and battery energy storage systems. *Prot. Control. Mod. Power Syst.* **2020**, *5*, 1–20. [CrossRef]
102. Luo, L.; Abdulkareem, S.S.; Rezvani, A.; Miveh, M.R.; Samad, S.; Aljojo, N.; Pazhoohesh, M. Optimal scheduling of a renewable based microgrid considering photovoltaic system and battery energy storage under uncertainty. *J. Energy Storage* **2020**, *28*, 101306. [CrossRef]
103. Wang, C.; Liu, Y.; Li, X.; Guo, L.; Qiao, L.; Lu, H. Energy management system for stand-alone diesel-wind-biomass microgrid with energy storage system. *Energy* **2016**, *97*, 90–104.29. [CrossRef]
104. Zheng, Y.; Jenkins, B.; Kornbluth, K.; Kendall, A.; Træholt, C. Optimization of a biomass-integrated renewable energy microgrid with demand side management under uncertainty. *Appl. Energy* **2018**, *230*, 836–844. [CrossRef]
105. Mobasseri, A.; Tostado-Véliz, M.; Ghadimi, A.A.; Miveh, M.R.; Jurado, F. Multi-energy microgrid optimal operation with integrated power to gas technology considering uncertainties. *J. Clean. Prod.* **2022**, *333*, 130174. [CrossRef]
106. Bazmohammadi, N.; Tahsiri, A.; Anvari-Moghaddam, A.; Guerrero, J.M. A hierarchical energy management strategy for interconnected microgrids considering uncertainty. *Int. J. Electr. Power Energy Syst.* **2019**, *109*, 597–608. [CrossRef]
107. Ahmadi, S.E.; Rezaei, N. A new isolated renewable based multi microgrid optimal energy management system considering uncertainty and demand response. *Int. J. Electr. Power Energy Syst.* **2019**, *118*, 105760. [CrossRef]
108. Shahryari, E.; Shayeghi, H.; Mohammadi-Ivatloo, B.; Moradzadeh, M. A copula-based method to consider uncertainties for multi-objective energy management of microgrid in presence of demand response. *Energy* **2019**, *175*, 879–890. [CrossRef]
109. Karimi, H.; Jadid, S. Optimal energy management for multi-microgrid considering demand response programs: A stochastic multi-objective framework. *Energy* **2020**, *195*, 116992. [CrossRef]
110. Pourghasem, P.; Sohrabi, F.; Abapour, M.; Mohammadi-Ivatloo, B. Stochastic multi-objective dynamic dispatch of renewable and CHP-based islanded microgrids. *Electr. Power Syst. Res.* **2019**, *173*, 193–201. [CrossRef]

111. Garcia-Torres, F.; Báez-Gonzalez, P.; Tobajas, J.; Vazquez, F.; Nieto, E. Cooperative optimization of networked microgrids for supporting grid flexibility services using model predictive control. *IEEE Trans. Smart Grid* **2020**, *12*, 1893–1903. [CrossRef]
112. Nojavan, S.; Majidi, M.; Esfetanaj, N.N. An efficient cost-reliability optimization model for optimal siting and sizing of energy storage system in a microgrid in the presence of responsible load management. *Energy* **2017**, *139*, 89–97. [CrossRef]
113. El-Bidairi, K.S.; Nguyen, H.D.; Jayasinghe, S.; Mahmoud, T.S.; Penesis, I. A hybrid energy management and battery size optimization for standalone microgrids: A case study for Flinders Island, Australia. *Energy Convers. Manag.* **2018**, *175*, 192–212. [CrossRef]
114. Elgamal, M.; Korovkin, N.; Menaem, A.A.; Elmitwally, A. Day-ahead complex power scheduling in a reconfigurable hybrid-energy islanded microgrid with responsive demand considering uncertainty and different load models. *Appl. Energy* **2021**, *309*, 118416. [CrossRef]
115. Mansouri, S.A.; Jordehi, A.R.; Marzband, M.; Tostado-Véliz, M.; Jurado, F.; Aguado, J.A. An IoT-enabled hierarchical decentralized framework for multi-energy microgrids market management in the presence of smart prosumers using a deep learning-based forecaster. *Appl. Energy* **2023**, *333*, 120560. [CrossRef]
116. Mansouri, S.A.; Nematbakhsh, E.; Ahmarinejad, A.; Jordehi, A.R.; Javadi, M.S.; Marzband, M. A hierarchical scheduling framework for resilience enhancement of decentralized renewable-based microgrids considering proactive actions and mobile units. *Renew. Sustain. Energy Rev.* **2022**, *168*, 112854. [CrossRef]
117. Rezaee Jordehi, A. A mixed binary-continuous particle swarm optimisation algorithm for unit commitment in microgrids considering uncertainties and emissions. *Int. Trans. Electr. Energy Syst.* **2020**, *30*, e12581. [CrossRef]
118. Rezaee Jordehi, A. Dynamic environmental-economic load dispatch in grid-connected microgrids with demand response programs considering the uncertainties of demand, renewable generation and market price. *Int. J. Numer. Model. Electron. Netw. Devices Fields* **2021**, *34*, e2798. [CrossRef]
119. Jordehi, A.R.; Tabar, V.S.; Mansouri, S.; Sheidaei, F.; Ahmarinejad, A.; Pirouzi, S. Two-stage stochastic programming for scheduling microgrids with high wind penetration including fast demand response providers and fast-start generators. *Sustain. Energy Grids Netw.* **2022**, *31*, 100694. [CrossRef]
120. Mansouri, S.A.; Nematbakhsh, E.; Jordehi, A.R.; Tostado-Véliz, M.; Jurado, F.; Leonowicz, Z. A risk-based bi-level bidding system to manage day-ahead electricity market and scheduling of interconnected microgrids in the presence of smart homes. In Proceedings of the 2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Prague, Czech Republic, 28 June–1 July 2022; pp. 1–6.
121. Jordehi, A.R. Information gap decision theory for operation of combined cooling, heat and power microgrids with battery charging stations. *Sustain. Cities Soc.* **2021**, *74*, 103164. [CrossRef]
122. Jordehi, A.R. Scheduling heat and power microgrids with storage systems, photovoltaic, wind, geothermal power units and solar heaters. *J. Energy Storage* **2021**, *41*, 102996. [CrossRef]
123. Rezaee Jordehi, A. An improved particle swarm optimisation for unit commitment in microgrids with battery energy storage systems considering battery degradation and uncertainties. *Int. J. Energy Res.* **2021**, *45*, 727–744. [CrossRef]
124. Dimeas, A.; Hatziargyriou, N. Operation of a Multiagent System for Microgrid Control. *IEEE Trans. Power Syst.* **2005**, *20*, 1447–1455. [CrossRef]
125. Logenthiran, T.; Srinivasan, D.; Khambadkone, A.M. Multi-agent system for energy resource scheduling of integrated microgrids in a distributed system. *Electr. Power Syst. Res.* **2011**, *81*, 138–148. [CrossRef]
126. Kumar Nunna, H.S.V.S.; Doolla, S. Multiagent-Based Distributed-Energy-Resource Management for Intelligent Microgrids. *IEEE Trans. Ind. Electron.* **2012**, *60*, 1678–1687. [CrossRef]
127. Shafiee, Q.; Stefanović, Č.; Dragičević, T.; Popovski, P.; Vasquez, J.C.; Guerrero, J.M. Robust networked control scheme for distributed secondary control of islanded microgrids. *IEEE Trans. Ind. Electron.* **2013**, *61*, 5363–5374. [CrossRef]
128. Guo, F.; Wen, C.; Mao, J.; Song, Y.-D. Distributed Secondary Voltage and Frequency Restoration Control of Droop-Controlled Inverter-Based Microgrids. *IEEE Trans. Ind. Electron.* **2014**, *62*, 4355–4364. [CrossRef]
129. Chen, G.; Lewis, F.L.; Feng, E.N.; Song, Y. Distributed Optimal Active Power Control of Multiple Generation Systems. *IEEE Trans. Ind. Electron.* **2015**, *62*, 7079–7090. [CrossRef]
130. Guo, F.; Wen, C.; Mao, J.; Chen, J.; Song, Y.-D. Distributed Cooperative Secondary Control for Voltage Unbalance Compensation in an Islanded Microgrid. *IEEE Trans. Ind. Inform.* **2015**, *11*, 1078–1088. [CrossRef]
131. Lu, X.; Yu, X.; Lai, J.; Guerrero, J.M.; Zhou, H. Distributed Secondary Voltage and Frequency Control for Islanded Microgrids With Uncertain Communication Links. *IEEE Trans. Ind. Inform.* **2016**, *13*, 448–460. [CrossRef]
132. Lu, X.; Lai, J.; Yu, X.; Wang, Y.; Guerrero, J.M. Distributed Coordination of Islanded Microgrid Clusters Using a Two-Layer Intermittent Communication Network. *IEEE Trans. Ind. Inform.* **2017**, *14*, 3956–3969. [CrossRef]
133. Chen, M.; Xiao, X.; Guerrero, J.M. Secondary Restoration Control of Islanded Microgrids With a Decentralized Event-Triggered Strategy. *IEEE Trans. Ind. Inform.* **2017**, *14*, 3870–3880. [CrossRef]
134. Lai, J.; Lu, X.; Yu, X.; Yao, W.; Wen, J.; Cheng, S. Distributed multi-DER cooperative control for master-slave-organized microgrid networks with limited communication bandwidth. *IEEE Trans. Ind. Inform.* **2018**, *15*, 3443–3456. [CrossRef]
135. Lai, J.; Lu, X.; Wang, F.; Dehghanian, P.; Tang, R. Broadcast Gossip Algorithms for Distributed Peer-to-Peer Control in AC Microgrids. *IEEE Trans. Ind. Appl.* **2019**, *55*, 2241–2251. [CrossRef]

136. Lai, J.; Lu, X.; Monti, A. Distributed secondary voltage control for autonomous microgrids under additive measurement noises and time delays. *IET Gener. Transm. Distrib.* **2019**, *13*, 2976–2985. [CrossRef]
137. Lai, J.; Lu, X.; Yu, X.; Monti, A. Stochastic Distributed Secondary Control for AC Microgrids via Event-Triggered Communication. *IEEE Trans. Smart Grid* **2020**, *11*, 2746–2759. [CrossRef]
138. Lai, J.; Lu, X. Robust self-consistent control of PV-battery-based microgrids without continuous communication. *Int. J. Electr. Power Energy Syst.* **2020**, *119*, 105900. [CrossRef]
139. Lian, Z.; Deng, C.; Wen, C.; Guo, F.; Lin, P.; Jiang, W. Distributed Event-Triggered Control for Frequency Restoration and Active Power Allocation in Microgrids With Varying Communication Time Delays. *IEEE Trans. Ind. Electron.* **2020**, *68*, 8367–8378. [CrossRef]
140. Lian, Z.; Guo, F.; Wen, C.; Deng, C.; Lin, P. Distributed Resilient Optimal Current Sharing Control for an Islanded DC Microgrid Under DoS Attacks. *IEEE Trans. Smart Grid* **2021**, *12*, 4494–4505. [CrossRef]
141. Deng, C.; Guo, F.; Wen, C.; Yue, D.; Wang, Y. Distributed Resilient Secondary Control for DC Microgrids Against Heterogeneous Communication Delays and DoS Attacks. *IEEE Trans. Ind. Electron.* **2021**, *69*, 11560–11568. [CrossRef]
142. Lu, J.; Zhang, X.; Hou, X.; Wang, P. Generalized Extended State Observer-Based Distributed Attack-Resilient Control for DC Microgrids. *IEEE Trans. Sustain. Energy* **2022**, *13*, 1469–1480. [CrossRef]
143. Zuo, Y.; Zhang, Y.; Wang, Y. Adaptive resilient control of ac microgrids under unbounded actuator attacks. *Energies* **2022**, *15*, 7458. [CrossRef]
144. Hosseini, E.; Shahgholian, G. Partial- or full-power production in WECS: A survey of control and structural strategies. *EPE J.* **2017**, *27*, 125–142. [CrossRef]
145. Asano, H.; Yajima, K.; Kaya, Y. Influence of photovoltaic power generation on required capacity for load frequency control. *IEEE Trans. Energy Convers.* **1996**, *11*, 188–193. [CrossRef]
146. Ina, N.; Yanagawa, S.; Kato, T.; Suzuoki, Y. Smoothing of PV system output by tuning MPPT control. *Electr. Eng. Jpn.* **2005**, *152*, 10–17. [CrossRef]
147. Nagayoshi, H.; Kurokawa, K.; Ohashi, Y.; Nishida, K.; Deguchi, T. Peak-power reduction with 100 kW PV and battery combined system at Shonan institute of technology. *Sol. Energy Mater. Sol. Cells* **2001**, *67*, 601–609. [CrossRef]
148. Hoff, T.E.; Perez, R.; Margolis, R.M. Maximizing the value of customer-sited PV systems using storage and controls. *Sol. Energy* **2007**, *81*, 940–945. [CrossRef]
149. Barton, J.P.; Infield, D.G. A probabilistic method for calculating the usefulness of a store with finite energy capacity for smoothing electricity generation from wind and solar power. *J. Power Sources* **2006**, *162*, 943–948. [CrossRef]
150. Kobayashi, K.; Takano, I.; Sawada, Y. A study of a two stage maximum power point tracking control of a photovoltaic system under partially shaded insolation conditions. *Sol. Energy Mater. Sol. Cells* **2006**, *90*, 2975–2988. [CrossRef]
151. Rahman, H.; Yamashiro, S.; Nakamura, K. Development of an Advanced Grid-Connected PV-ECS System Considering Solar Energy Estimation. *IEEJ Trans. Power Energy* **2005**, *125*, 399–407. [CrossRef]
152. Kinjo, T.; Senjyu, T.; Urasaki, N.; Fujita, H. Output Levelling of Renewable Energy by Electric Double-Layer Capacitor Applied for Energy Storage System. *IEEE Trans. Energy Convers.* **2006**, *21*, 221–227. [CrossRef]
153. Bevrani, H.; Habibi, F.; Babahajyani, P.; Watanabe, M.; Mitani, Y. Intelligent Frequency Control in an AC Microgrid: Online PSO-Based Fuzzy Tuning Approach. *IEEE Trans. Smart Grid* **2012**, *3*, 1935–1944. [CrossRef]
154. Pan, I.; Das, S. Kriging based surrogate modeling for fractional order control of microgrids. *IEEE Trans. Smart Grid* **2014**, *6*, 36–44. [CrossRef]
155. Bevrani, H.; Feizi, M.R.; Ataee, S. Robust frequency control in an islanded microgrid: $H\infty$ and $\mu-$synthesis approaches. *IEEE Trans. Smart Grid* **2015**, *7*, 706–717. [CrossRef]
156. Khooban, M.H.; Dragicevic, T.; Blaabjerg, F.; Delimar, M. Shipboard microgrids: A novel approach to load frequency control. *IEEE Trans. Sustain. Energy* **2017**, *9*, 843–852. [CrossRef]
157. Khooban, M.-H.; Niknam, T.; Shasadeghi, M.; Dragicevic, T.; Blaabjerg, F. Load Frequency Control in Microgrids Based on a Stochastic Noninteger Controller. *IEEE Trans. Sustain. Energy* **2017**, *9*, 853–861. [CrossRef]
158. Latif, A.; Das, D.C.; Ranjan, S.; Barik, A.K. Comparative performance evaluation of WCA-optimised non-integer controller employed with WPG–DSPG–PHEV based isolated two-area interconnected microgrid system. *IET Renew. Power Gener.* **2019**, *13*, 725–736. [CrossRef]
159. Latif, A.; Chandra Das, D.; Kumar Barik, A.; Ranjan, S. Illustration of demand response supported co-ordinated system performance evaluation of YSGA optimized dual stage PIFOD-(1 + PI) controller employed with wind-tidal-biodiesel based independent two-area interconnected microgrid system. *IET Renew. Power Gener.* **2020**, *14*, 1074–1086. [CrossRef]
160. Zaheeruddin; Singh, K. Intelligent fractional order-based centralized frequency controller for microgrid. *IETE J. Res.* **2020**, *68*, 2848–2862. [CrossRef]
161. Özdemir, M.T. The effects of the FOPI controller and time delay on stability region of the fuel cell microgrid. *Int. J. Hydrogen Energy* **2020**, *45*, 35064–35072. [CrossRef]
162. Yildirim, B. Advanced controller design based on gain and phase margin for microgrid containing PV/WTG/fuel cell/electrolyzer/BESS. *Int. J. Hydrogen Energy* **2021**, *46*, 16481–16493. [CrossRef]
163. Zhu, Y.; Wang, H.; Zhu, Z. Improved VSG control strategy based on the combined power generation system with hydrogen fuel cells and super capacitors. *Energy Rep.* **2021**, *7*, 6820–6832. [CrossRef]

164. Zhong, C.; Zhou, Y.; Chen, J.; Liu, Z. DC-side synchronous active power control of two-stage photovoltaic generation for frequency support in Islanded microgrids. *Energy Rep.* **2022**, *8*, 8361–8371. [CrossRef]
165. Chen, Y.; Vinco, S.; Baek, D.; Quer, S.; Macii, E.; Poncino, M. Cost-Aware Design and Simulation of Electrical Energy Systems. *Energies* **2020**, *13*, 2949. [CrossRef]
166. Baker, J. New technology and possible advances in energy storage. *Energy Policy* **2008**, *36*, 4368–4373. [CrossRef]
167. Mahmoud, M. On the storage batteries used in solar electric power systems and development of an algorithm for determining their ampere–hour capacity. *Electr. Power Syst. Res.* **2004**, *71*, 85–89. [CrossRef]
168. Lacerda, V.G.; Mageste, A.B.; Santos, I.J.B.; Da Silva, L.H.M.; Da Silva, M.D.C.H. Separation of cd and ni from ni–cd batteries by an environmentally safe methodology employing aqueous two-phase systems. *J. Power Sources* **2009**, *193*, 908–913. [CrossRef]
169. Depernet, D.; Ba, O.; Berthon, A. Online impedance spectroscopy of lead acid batteries for storage management of a standalone power plant. *J. Power Sources* **2012**, *219*, 65–74. [CrossRef]
170. Manolakos, D.; Papadakis, G.; Papantonis, D.; Kyritsis, S. A stand-alone photovoltaic power system for remote villages using pumped water energy storage. *Energy* **2004**, *29*, 57–69. [CrossRef]
171. Dursun, B.; Alboyaci, B. The contribution of wind-hydro pumped storage systems in meeting Turkey's electric energy demand. *Renew. Sustain. Energy Rev.* **2010**, *14*, 1979–1988. [CrossRef]
172. Li, Y.Q.; Yang, M.M.; Zhao, L.; Wang, F.J. The research of wind-light complementary based on pumped storage power system. In *Advanced Materials Research*; Trans Tech Publ: Zurich, Switzerland, 2012; Volume 354, pp. 1132–1136.
173. Bakos, G.C. Feasibility study of a hybrid wind/hydro power-system for low-cost electricity production. *Appl. Energy* **2002**, *72*, 599–608. [CrossRef]
174. Papaefthymiou, S.V.; Papathanassiou, S.A. Optimum sizing of wind-pumped-storage hybrid power stations in island systems. *Renew. Energy* **2014**, *64*, 187–196. [CrossRef]
175. Li, R.; Wu, B.; Li, X.; Zhou, F.; Li, Y. Design of wind-solar and pumped-storage hybrid power supply system. In Proceedings of the 2010 3rd International Conference on Computer Science and Information Technology, Chengdu, China, 9–11 July 2010; Volume 5, pp. 402–405.
176. Ma, T.; Yang, H.; Lu, L.; Peng, J. Technical feasibility study on a standalone hybrid solar-wind system with pumped hydro storage for a remote island in Hong Kong. *Renew. Energy* **2014**, *69*, 7–15. [CrossRef]
177. Nfah, E.; Ngundam, J. Feasibility of pico-hydro and photovoltaic hybrid power systems for remote villages in Cameroon. *Renew. Energy* **2009**, *34*, 1445–1450. [CrossRef]
178. Ma, T.; Yang, H.; Lu, L. Feasibility study and economic analysis of pumped hydro storage and battery storage for a renewable energy powered island. *Energy Convers. Manag.* **2014**, *79*, 387–397. [CrossRef]
179. Bermudez, E.; Ruisanchez, A.; Arenillas, A.; Moreno, J.; Menendez. Energy convers. *Manag* **2014**, *78*, 559–564.35.
180. Otsuka, J.; Hayama, S.; Ohashi, Y. Present and future technologies of precision and ultraprecision positioning. *J.-Jpn. Soc. Precis. Eng.* **2001**, *67*, 173–178. [CrossRef]
181. Djelailia, O.; Kelaiaia, M.S.; Labar, H.; Necaibia, S.; Merad, F. Energy hybridization photovoltaic/diesel generator/pump storage hydroelectric management based on online optimal fuel consumption per kWh. *Sustain. Cities Soc.* **2018**, *44*, 1–15. [CrossRef]
182. Fodhil, F.; Hamidat, A.; Nadjemi, O. Potential, optimization and sensitivity analysis of photovoltaic-diesel-battery hybrid energy system for rural electrification in algeria. *Energy* **2019**, *169*, 613–624. [CrossRef]
183. Kharrich, M.; Kamel, S.; Abdeen, M.; Mohammed, O.H.; Akherraz, M.; Khurshaid, T.; Rhee, S.-B. Developed Approach Based on Equilibrium Optimizer for Optimal Design of Hybrid PV/Wind/Diesel/Battery Microgrid in Dakhla, Morocco. *IEEE Access* **2021**, *9*, 13655–13670. [CrossRef]
184. Kharrich, M.; Kamel, S.; Alghamdi, A.S.; Eid, A.; Mosaad, M.I.; Akherraz, M.; Abdel-Akher, M. Optimal Design of an Isolated Hybrid Microgrid for Enhanced Deployment of Renewable Energy Sources in Saudi Arabia. *Sustainability* **2021**, *13*, 4708. [CrossRef]
185. Kharrich, M.; Abualigah, L.; Kamel, S.; AbdEl-Sattar, H.; Tostado-Véliz, M. An improved arithmetic optimization algorithm for design of a microgrid with energy storage system: Case study of el kharga oasis, egypt. *J. Energy Storage* **2022**, *51*, 104343. [CrossRef]
186. Kharrich, M.; Kamel, S.; Abdel-Akher, M.; Eid, A.; Zawbaa, H.M.; Kim, J. Optimization based on movable damped wave algorithm for design of photovoltaic/ wind/ diesel/ biomass/ battery hybrid energy systems. *Energy Rep.* **2022**, *8*, 11478–11491. [CrossRef]
187. El-Sattar, H.A.; Kamel, S.; Hassan, M.H.; Jurado, F. An effective optimization strategy for design of standalone hybrid renewable energy systems. *Energy* **2022**, *260*, 124901. [CrossRef]
188. Çetınbaş, İ.; Tamyürek, B.; Demırtaş, M. The hybrid harris hawks optimizer-arithmetic optimization algorithm: A new hybrid algorithm for sizing optimization and design of microgrids. *IEEE Access* **2022**, *10*, 19254–19283. [CrossRef]
189. Mohseni, S.; Khalid, R.; Brent, A.C. Metaheuristic-based isolated microgrid sizing and uncertainty quantification considering EVs as shiftable loads. *Energy Rep.* **2022**, *8*, 11288–11308. [CrossRef]
190. Sortomme, E.; Venkata, S.S.; Mitra, J. Microgrid Protection Using Communication-Assisted Digital Relays. *IEEE Trans. Power Deliv.* **2009**, *25*, 2789–2796. [CrossRef]

191. Zeineldin, H.H.; El-Saadany, E.F.; Salama, M.M.A. Distributed Generation Micro-Grid Operation: Control and Protection. In Proceedings of the 2006 Power Systems Conference: Advanced Metering, Protection, Control, Communication, and Distributed Resources, Clemson, SC, USA, 14–17 March 2006; pp. 105–111. [CrossRef]
192. Zamani, M.A.; Sidhu, T.S.; Yazdani, A. A Protection Strategy and Microprocessor-Based Relay for Low-Voltage Microgrids. *IEEE Trans. Power Deliv.* **2011**, *26*, 1873–1883. [CrossRef]
193. Zamani, M.A.; Yazdani, A.; Sidhu, T.S. A Communication-Assisted Protection Strategy for Inverter-Based Medium-Voltage Microgrids. *IEEE Trans. Smart Grid* **2012**, *3*, 2088–2099. [CrossRef]
194. Zamani, M.A.; Sidhu, T.S.; Yazdani, A. A communication-based strategy for protection of microgrids with looped configuration. *Electr. Power Syst. Res.* **2013**, *104*, 52–61. [CrossRef]
195. Mishra, D.P.; Samantaray, S.R.; Joos, G. A Combined Wavelet and Data-Mining Based Intelligent Protection Scheme for Microgrid. *IEEE Trans. Smart Grid* **2015**, *7*, 2295–2304. [CrossRef]
196. Bukhari, S.B.A.; Zaman, M.S.U.; Haider, R.; Oh, Y.-S.; Kim, C.-H. A protection scheme for microgrid with multiple distributed generations using superimposed reactive energy. *Int. J. Electr. Power Energy Syst.* **2017**, *92*, 156–166. [CrossRef]
197. Singh, M.; Basak, P. Q and frequency component-based fault and nature detection for hybrid microgrid. *Sustain. Energy Grids Netw.* **2021**, *28*, 100552. [CrossRef]
198. Bukhari, S.B.A.; Haider, R.; Zaman, M.S.U.; Oh, Y.S.; Cho, G.J.; Kim, C.H. An interval type-2 fuzzy logic based strategy for microgrid protection. *Int. J. Electr. Power Energy Syst.* **2018**, *98*, 209–218. [CrossRef]
199. Manohar, M.; Koley, E.; Ghosh, S. Enhancing resilience of PV-fed microgrid by improved relaying and differentiating between inverter faults and distribution line faults. *Int. J. Electr. Power Energy Syst.* **2019**, *108*, 271–279. [CrossRef]
200. Shamsoddini, M.; Vahidi, B.; Razani, R.; Mohamed, Y.A.-R.I. A novel protection scheme for low voltage DC microgrid using inductance estimation. *Int. J. Electr. Power Energy Syst.* **2020**, *120*, 105992. [CrossRef]
201. Nahas, E.W.; Mansour, D.E.A.; Abd el-Ghany, H.A.; Eissa, M.M. Developing a smart power-voltage relay (*SPV-Relay*) with no communication system for Dc microgrids. *Electr. Power Syst. Res.* **2020**, *187*, 106432. [CrossRef]
202. Tiwari, S.P.; Koley, E.; Ghosh, S. Communication-less ensemble classifier-based protection scheme for DC microgrid with adaptiveness to network reconfiguration and weather intermittency. *Sustain. Energy Grids Netw.* **2021**, *26*, 100460. [CrossRef]
203. Manohar, M.; Koley, E.; Ghosh, S. Reliable protection scheme for PV integrated microgrid using an ensemble classifier approach with real-time validation. *IET Sci. Meas. Technol.* **2018**, *12*, 200–208. [CrossRef]
204. Manohar, M.; Koley, E.; Ghosh, S. Stochastic Weather Modeling-Based Protection Scheme for Hybrid PV–Wind System With Immunity Against Solar Irradiance and Wind Speed. *IEEE Syst. J.* **2020**, *14*, 3430–3439. [CrossRef]
205. Rameshrao, A.G.; Koley, E.; Ghosh, S. An optimal sensor location based protection scheme for DER-integrated hybrid AC/DC microgrid with reduced communication delay. *Sustain. Energy Grids Netw.* **2022**, *30*, 100680. [CrossRef]
206. Rameshrao, A.G.; Koley, E.; Ghosh, S. A LSTM-based approach for detection of high impedance faults in hybrid microgrid with immunity against weather intermittency and N-1 contingency. *Renew. Energy* **2022**, *198*, 75–90. [CrossRef]
207. Van Roy, J.; Leemput, N.; Geth, F.; Büscher, J.; Salenbien, R.; Driesen, J. Electric vehicle charging in an office building microgrid with distributed energy resources. *IEEE Trans. Sustain. Energy* **2014**, *5*, 1389–1396. [CrossRef]
208. Wei, Y.; Han, T.; Wang, S.; Qin, Y.; Lu, L.; Han, X.; Ouyang, M. An efficient data-driven optimal sizing framework for photovoltaics-battery-based electric vehicle charging microgrid. *J. Energy Storage* **2022**, *55*, 105670. [CrossRef]
209. Chen, Y.; Alamin, K.S.S.; Pagliari, D.J.; Vinco, S.; Macii, E.; Poncino, M. Electric Vehicles Plug-In Duration Forecasting Using Machine Learning for Battery Optimization. *Energies* **2020**, *13*, 4208. [CrossRef]
210. Cheikh-Mohamad, S.; Sechilariu, M.; Locment, F.; Krim, Y. PV-Powered Electric Vehicle Charging Stations: Preliminary Requirements and Feasibility Conditions. *Appl. Sci.* **2021**, *11*, 1770. [CrossRef]
211. Krim, Y.; Sechilariu, M.; Locment, F. PV Benefits Assessment for PV-Powered Charging Stations for Electric Vehicles. *Appl. Sci.* **2021**, *11*, 4127. [CrossRef]
212. Wang, D.; Sechilariu, M.; Locment, F. PV-Powered Charging Station for Electric Vehicles: Power Management with Integrated V2G. *Appl. Sci.* **2020**, *10*, 6500. [CrossRef]
213. Cheikh-Mohamad, S.; Sechilariu, M.; Locment, F. Real-Time Power Management Including an Optimization Problem for PV-Powered Electric Vehicle Charging Stations. *Appl. Sci.* **2022**, *12*, 4323. [CrossRef]
214. Wang, S.; Kuang, K.; Han, X.; Chu, Z.; Lu, L.; Ouyang, M. A model-based continuous differentiable current charging approach for electric vehicles in direct current microgrids. *J. Power Sources* **2021**, *482*, 229019. [CrossRef]
215. Mohammed, A.M.; Alalwan, S.N.H.; Taşcıkaraoğlu, A.; Catalão, J.P. Sliding mode-based control of an electric vehicle fast charging station in a dc microgrid. *Sustain. Energy Grids Netw.* **2022**, *32*, 100820. [CrossRef]
216. Chen, Y.; Baek, D.; Kim, J.; Di Cataldo, S.; Chang, N.; Macii, E.; Vinco, S.; Poncino, M. A systemC-AMS framework for the design and simulation of energy management in electric vehicles. *IEEE Access* **2019**, *7*, 25779–25791. [CrossRef]
217. Wang, S.; Guo, D.; Han, X.; Lu, L.; Sun, K.; Li, W.; Sauer, D.U.; Ouyang, M. Impact of battery degradation models on energy management of a grid-connected DC microgrid. *Energy* **2020**, *207*, 118228. [CrossRef]
218. Garcia-Trivino, P.; Torreglosa, J.P.; Fernandez-Ramirez, L.M.; Jurado, F. Decentralized Fuzzy Logic Control of Microgrid for Electric Vehicle Charging Station. *IEEE J. Emerg. Sel. Top. Power Electron.* **2018**, *6*, 726–737. [CrossRef]
219. Wang, S.; Lu, L.; Han, X.; Ouyang, M.; Feng, X. Virtual-battery based droop control and energy storage system size optimization of a DC microgrid for electric vehicle fast charging station. *Appl. Energy* **2019**, *259*, 114146. [CrossRef]

220. Wang, D.; Locment, F.; Sechilariu, M. Modelling, Simulation, and Management Strategy of an Electric Vehicle Charging Station Based on a DC Microgrid. *Appl. Sci.* **2020**, *10*, 2053. [CrossRef]
221. Trivedi, R.; Khadem, S. Implementation of artificial intelligence techniques in microgrid control environment: Current progress and future scopes. *Energy AI* **2022**, *8*, 100147. [CrossRef]
222. Nti, I.K.; Teimeh, M.; Nyarko-Boateng, O.; Adekoya, A.F. Electricity load forecasting: A systematic review. *J. Electr. Syst. Inf. Technol.* **2020**, *7*, 13. [CrossRef]
223. Kuster, C.; Rezgui, Y.; Mourshed, M. Electrical load forecasting models: A critical systematic review. *Sustain. Cities Soc.* **2017**, *35*, 257–270. [CrossRef]
224. Wang, H.; Lei, Z.; Zhang, X.; Zhou, B.; Peng, J. A review of deep learning for renewable energy forecasting. *Energy Convers. Manag.* **2019**, *198*, 111799. [CrossRef]
225. Akhter, M.N.; Mekhilef, S.; Mokhlis, H.; Shah, N.M. Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. *IET Renew. Power Gener.* **2019**, *13*, 1009–1023. [CrossRef]
226. Aggarwal, S.K.; Saini, L.M.; Kumar, A. Electricity price forecasting in deregulated markets: A review and evaluation. *Int. J. Electr. Power Energy Syst.* **2009**, *31*, 13–22. [CrossRef]
227. Wu, T.; Wang, J. Artificial intelligence for operation and control: The case of microgrids. *Electr. J.* **2020**, *34*, 106890. [CrossRef]
228. Ko, J.-S.; Huh, J.-H.; Kim, J.-C. Overview of Maximum Power Point Tracking Methods for PV System in Micro Grid. *Electronics* **2020**, *9*, 816. [CrossRef]
229. Vigneysh, T.; Kumarappan, N. Artificial Neural Network Based Droop-Control Technique for Accurate Power Sharing in an Islanded Microgrid. *Int. J. Comput. Intell. Syst.* **2016**, *9*, 827–838. [CrossRef]
230. Jayamaha, D.K.J.S.; Lidula, N.W.A.; Rajapakse, A.D. Bus Voltage Signalling Based Coordinated Control of DC Microgrids. In Proceedings of the 2018 Australasian Universities Power Engineering Conference (AUPEC), Auckland, New Zealand, 27–30 November 2018; pp. 1–6.
231. Lu, X.; Sun, K.; Guerrero, J.M.; Vasquez, J.C.; Huang, L. State-of-Charge Balance Using Adaptive Droop Control for Distributed Energy Storage Systems in DC Microgrid Applications. *IEEE Trans. Ind. Electron.* **2014**, *61*, 2804–2815. [CrossRef]
232. Diaz, N.L.; Dragičevi´c, T.; Vasquez, J.C.; Guerrero, J.M. Fuzzy-logic-based gain-scheduling control for state-of-charge balance of distributed energy storage systems for DC microgrids. In Proceedings of the 2014 IEEE Applied Power Electronics Conference and Exposition-APEC 2014, Fort Worth, TX, USA, 16–20 March 2014; pp. 2171–2176.
233. Diaz, N.L.; Wu, D.; Dragicevic, T.; Vasquez, J.C.; Guerrero, J.M. Fuzzy droop control loops adjustment for stored energy balance in distributed energy storage system. In Proceedings of the 2015 9th International Conference on Power Electronics and ECCE Asia (ICPE-ECCE Asia), Seoul, Korea, 1–5 June 2015; pp. 728–735.
234. Diaz, N.L.; Wu, D.; Dragičević, T.; Vasquez, J.C.; Guerrero, J.M. Stored energy balance for distributed PV-based active generators in an AC microgrid. In Proceedings of the 2015 IEEE Power & Energy Society General Meeting, Denver, CO, USA, 26–30 July 2015.
235. Abhishek, A.; Ranjan, A.; Devassy, S.; Verma, B.K.; Ram, S.K.; Dhakar, A.K. Review of hierarchical control strategies for DC microgrid. *IET Renew. Power Gener.* **2020**, *14*, 1631–1640. [CrossRef]
236. Gao, F.; Kang, R.; Cao, J.; Yang, T. Primary and secondary control in DC microgrids: A review. *J. Mod. Power Syst. Clean Energy* **2019**, *7*, 227–242. [CrossRef]
237. Keshavarztalebi, M. Microgrid Control and Protection: Stability and Security. Ph.D. Thesis, University of Central Florida, Orlando, FL, USA, 23 August 2016.
238. Jafari, M.; Sarfi, V.; Ghasemkhani, A.; Livani, H.; Yang, L.; Xu, H.; Koosha, R. Adaptive neural network based intelligent secondary control for microgrids. In Proceedings of the 2018 IEEE Texas Power and Energy Conference (TPEC), College Station, TX, USA, 8–9 February 2018; pp. 1–6.
239. Shokoohi, S.; Golshannavaz, S.; Khezri, R.; Bevrani, H. Intelligent secondary control in smart microgrids: An on-line approach for islanded operations. *Optim. Eng.* **2018**, *19*, 917–936. [CrossRef]
240. Bagheri, M.; Nurmanova, V.; Abedinia, O.; Naderi, M.S. Enhancing Power Quality in Microgrids With a New Online Control Strategy for DSTATCOM Using Reinforcement Learning Algorithm. *IEEE Access* **2018**, *6*, 38986–38996. [CrossRef]
241. Khooban, M.H.; Gheisarnejad, M. A novel deep reinforcement learning controller based type-II fuzzy system: Frequency regulation in microgrids. *IEEE Trans. Emerg. Top. Comput. Intell.* **2020**, *5*, 689–699. [CrossRef]
242. Al Karim, M.; Currie, J.; Lie, T.T. A distributed machine learning approach for the secondary voltage control of an Islanded micro-grid. In Proceedings of the 2016 IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia), Melbourne, VIC, Australia, 28 November–1 December 2016.
243. Huang, G.B.; Zhu, Q.Y.; Siew, C.K. Extreme learning machine: A new learning scheme of feedforward neural networks. In Proceedings of the 2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No.04CH37541), Budapest, Hungary, 25–29 July 2004; Volume 2, pp. 985–990.
244. Heydari, R.; Khayat, Y.; Amiri, A.; Dragicevic, T.; Shafiee, Q.; Popovski, P.; Blaabjerg, F. Robust High-Rate Secondary Control of Microgrids With Mitigation of Communication Impairments. *IEEE Trans. Power Electron.* **2020**, *35*, 12486–12496. [CrossRef]
245. Elsayed, M.; Erol-Kantarci, M.; Kantarci, B.; Wu, L.; Li, J. Low-Latency Communications for Community Resilience Microgrids: A Reinforcement Learning Approach. *IEEE Trans. Smart Grid* **2020**, *11*, 1091–1099. [CrossRef]
246. Chang, Q.; Ma, X.; Chen, M.; Gao, X.; Dehghani, M. A deep learning based secured energy management framework within a smart island. *Sustain. Cities Soc.* **2021**, *70*, 102938. [CrossRef]

247. Al Karim, M.; Currie, J.; Lie, T.T. A feature based distributed machine learning for post fault restoration of a microgrid under different stochastic scenarios. In Proceedings of the 2017 IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia), Auckland, New Zealand, 4–7 December 2017; pp. 1–6.
248. Arunan, A.; Ravishankar, J.; Ambikairajah, E. Differential Fault Detection Scheme for Islanded AC Microgrids Using Digital Signal Processing and Machine Learning Techniques. In Proceedings of the 2019 9th International Conference on Power and Energy Systems (ICPES), Perth, WA, Australia, 10–12 December 2019; pp. 1–6. [CrossRef]
249. Kar, S.; Samantaray, S.R.; Zadeh, M.D. Data-Mining Model Based Intelligent Differential Microgrid Protection Scheme. *IEEE Syst. J.* **2015**, *11*, 1161–1169. [CrossRef]
250. Lin, H.; Sun, K.; Tan, Z.; Liu, C.; Guerrero, J.M.; Vasquez, J.C. Adaptive protection combined with machine learning for microgrids. *IET Gener. Transm. Distrib.* **2019**, *13*, 770–779. [CrossRef]
251. Uzair, M.; Li, L.; Zhu, J.G.; Eskandari, M. A protection scheme for AC microgrids based on multi-agent system combined with machine learning. In Proceedings of the 2019 29th Australasian Universities Power Engineering Conference (AUPEC), Nadi, Fiji, 26–29 November 2019; pp. 1–6. [CrossRef]
252. Moayedi, S.; Davoudi, A. Distributed Tertiary Control of DC Microgrid Clusters. *IEEE Trans. Power Electron.* **2016**, *31*, 1717–1733. [CrossRef]
253. Lavaei, J.; Low, S.H. Zero Duality Gap in Optimal Power Flow Problem. *IEEE Trans. Power Syst.* **2011**, *27*, 92–107. [CrossRef]
254. Levron, Y.; Guerrero, J.M.; Beck, Y. Optimal Power Flow in Microgrids With Energy Storage. *IEEE Trans. Power Syst.* **2013**, *28*, 3226–3234. [CrossRef]
255. Riffonneau, Y.; Bacha, S.; Barruel, F.; Ploix, S. Optimal Power Flow Management for Grid Connected PV Systems With Batteries. *IEEE Trans. Sustain. Energy* **2011**, *2*, 309–320. [CrossRef]
256. Perez, E.; Beltran, H.; Aparicio, N.; Rodriguez, P. Predictive Power Control for PV Plants With Energy Storage. *IEEE Trans. Sustain. Energy* **2013**, *4*, 482–490. [CrossRef]
257. Mayhorn, E.; Kalsi, K.; Elizondo, M.; Zhang, W.; Lu, S.; Samaan, N.; Butler-Purry, K. Optimal control of distributed energy resources using model predictive control. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; pp. 1–8. [CrossRef]
258. Karagiannopoulos, S.; Aristidou, P.; Hug, G. Data-Driven Local Control Design for Active Distribution Grids Using Off-Line Optimal Power Flow and Machine Learning Techniques. *IEEE Trans. Smart Grid* **2018**, *10*, 6461–6471. [CrossRef]
259. Bellizio, F.; Karagiannopoulos, S.; Aristidou, P.; Hug, G. Optimized Local Control for Active Distribution Grids using Machine Learning Techniques. In Proceedings of the 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR, USA, 5–10 August 2018.
260. Liu, W.; Zhuang, P.; Liang, H.; Peng, J. Distributed Economic Dispatch in Microgrids Based on Cooperative Reinforcement Learning. *IEEE Trans. Neural Netw. Learn. Syst.* **2018**, *29*, 2192–2203. [CrossRef]
261. Elamine, D.O.; Nfaoui, E.H.; Jaouad, B. Multi-agent system based on fuzzy control and prediction using NN for smart microgrid energy management. In Proceedings of the 2015 Intelligent Systems and Computer Vision (ISCV), Fez, Morocco, 25–26 March 2015; pp. 1–6. [CrossRef]
262. Al-Ismail, F.S. DC Microgrid Planning, Operation, and Control: A Comprehensive Review. *IEEE Access* **2021**, *9*, 36154–36172. [CrossRef]
263. Shahgholian, G. A brief review on microgrids: Operation, applications, modeling, and control. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e12885. [CrossRef]
264. Bihari, S.P.; Sadhu, P.K.; Sarita, K.; Khan, B.; Arya, L.D.; Saket, R.K.; Kothari, D.P. A Comprehensive Review of Microgrid Control Mechanism and Impact Assessment for Hybrid Renewable Energy Integration. *IEEE Access* **2021**, *9*, 88942–88958. [CrossRef]
265. Altin, N.; Eyimaya, S.E. A Review of Microgrid Control Strategies. In Proceedings of the 2021 10th International Conference on Renewable Energy Research and Application (ICRERA), Istanbul, Turkey, 26–29 September 2021; pp. 412–417. [CrossRef]
266. Ishaq, S.; Khan, I.; Rahman, S.; Hussain, T.; Iqbal, A.; Elavarasan, R.M. A review on recent developments in control and optimization of micro grids. *Energy Rep.* **2022**, *8*, 4085–4103. [CrossRef]