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Review

Networked Microgrids: A Review on Configuration, Operation, and Control Strategies

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Abstract: The increasing impact of climate change and rising occurrences of natural disasters pose substantial threats to power systems. Strengthening resilience against these low-probability, high-impact events is crucial. The proposition of reconfiguring traditional power systems into advanced networked microgrids (NMGs) emerges as a promising solution. Consequently, a growing body of research has focused on NMG-based techniques to achieve a more resilient power system. This paper provides an updated, comprehensive review of the literature, particularly emphasizing two main categories: networked microgrids' configuration and networked microgrids' control. The study explores key facets of NMG configurations, covering formation, power distribution, and operational considerations. Additionally, it delves into NMG control features, examining their architecture, modes, and schemes. Each aspect is reviewed based on problem modeling/formulation, constraints, and objectives. The review examines findings and highlights the research gaps, focusing on key elements such as frequency and voltage stability, reliability, costs associated with remote switches and communication technologies, and the overall resilience of the network. On that basis, a unified problem-solving approach addressing both the configuration and control aspects of stable and reliable NMGs is proposed. The article concludes by outlining potential future trends, offering valuable insights for researchers in the field.

Keywords: networked microgrids; configuration; operation; power flow; communication; control

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1. Introduction

The intensification of climate change poses a threat to power systems, leading to potential challenges like increased electricity demand and adverse impacts on power equipment. This convergence may result in critical issues, such as overloading and overheating, reminiscent of the 2003 blackout incident in the United States. The increasing annual intensity of climate change elevates the likelihood of severe weather events, contributing to a notable uptick in major power outages, as depicted in Figure 1 [1]. Major power outages, exemplified by events in Texas and Quebec, can inflict substantial economic losses, as seen with the USD 130 billion impact in Texas [2], and USD 50 million impact in Quebec [3]. Additionally, such outages pose significant challenges for affected households, enduring prolonged periods without electricity.

The extensive scholarly literature has been dedicated to enhancement of power networks' capability to withstand adverse weather conditions—a practice commonly referred to as enhancement of power system resilience. Researchers suggested diverse strategies for resilience enhancement, such as strategic planning techniques and system hardening methods [4]. A notably promising solution among the various proposed methods involves integrating controllable and smart technologies into the power system and strategically establishing networked microgrids (NMGs). NMGs encompass interconnected microgrids (MGs) capable of exchanging both power and information. This configuration is formed by partitioning distribution systems, linking multiple MGs to create a larger and more resilient power system, as defined in IEEE standard 1547.4 [5]. This interconnected structure enhances resilience in managing energy resources and meeting electricity demand. Findings from [6] underscore the benefits of NMGs in reducing operating costs and improving power supply resilience compared to independent MGs. An illustrative example of the practical significance of this interconnected setup is observed in Adjuntas, Puerto Rico, where the resilience of two microgrids is notably elevated when integrated into a networked microgrid, as detailed in [7]. The versatility of NMGs positions them as a promising means to enhance overall system resilience.

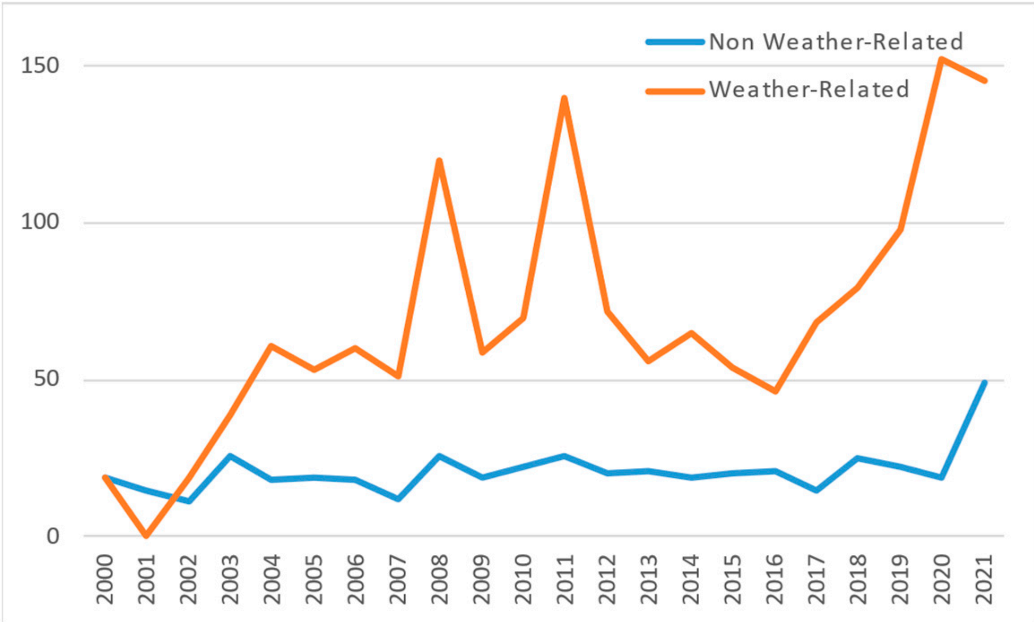

Figure 1. Major power outages in the U.S.

In this context, the present study aims at contributing to this growing research domain by delivering a systematic and contemporary review of the literature on networked microgrids. The main contribution of this article lies in its comprehensive review and categorization of studies within the domain of NMGs. Through meticulous examination, the article classifies the literature into two primary groups: networked microgrids' configuration and networked microgrids' control. In addressing the critical aspects of NMG configurations, the article delves into formation, power distribution, and operational considerations. Furthermore, it explores the control considerations of NMGs, encompassing their communication technologies and protocols, control architecture, modes, and schemes. Each of these components is systematically dissected into multiple subsections, elucidating specific features related to various technologies, methods, and concepts. The distinctive nature of this contribution lies in its detailed exploration of problem modeling, constraints, and objective functions within each subsection. This comparative analysis aids readers in discerning strengths and limitations in NMG configurations and control approaches. In the discussion section, a thorough analysis is conducted on all findings, gaps, and proposed solutions to formulate an optimal response to the challenges faced by NMGs. The discussion underscores the insufficient attention awarded to issues such as NMGs' frequency stability, reliability, recovery and reconfiguration time, expenses linked to remote switches and communication components, as well as the influence of real and transient events and the non-smooth characteristics of DGs and converters. To offer a more realistic and comprehensive viewpoint, a unified problem addressing both the configuration and control aspects of stable and reliable NMGs is suggested. The article also outlines potential future trends, providing valuable insights for researchers in the field.

The paper is structured as follows: Section 2 offers an overview of networked microgrids' configuration aspects, covering formation, power distribution, and operation. Section 3 delves into the literature on networked microgrids' control aspects, including communication technologies, communication protocols, control architecture, control modes, and control schemes. In Section 4, essential findings in both configuration and control are discussed to identify gaps and propose a holistic solution. Potential directions for future research, drawn from the review, are explored in Section 5. The paper concludes with final remarks presented in Section 6.

2. Networked Microgrids' Configuration

The emerging field of networked microgrids holds the potential to revolutionize traditional power grids, offering increased flexibility, sustainability, and resilience. Utilizing advanced configuration techniques, these networked microgrids can transform the way electricity is generated, distributed, and consumed in the future.

The configuration of networked microgrids encompasses three key aspects: formation, power distribution, and operation. Formation involves allocating distributed energy resources (DERs) in each microgrid, establishing boundaries, and determining the physical and operational connections between microgrids to shape the overall structure of the networked microgrids. Power distribution involves conducting power flow analysis, calculating voltage magnitudes, phase angles, and power flows at different points in the system. The integration of power flow analysis, also known as load flow analysis, is crucial for understanding and managing the distribution of electrical power within microgrids, incorporating various elements such as distributed energy resources, energy storage, and loads. Operation defines the behavior of networked microgrids over time under different conditions.

The following sections will explore these concepts in depth, offering a thorough examination of methodologies applied within each domain. Emphasis will be placed on exploring their problem, modeling, objectives, constraints, and comparing the advantages and disadvantages of each method. Although each paper's central idea and contributions will be summarized in a dedicated subsection, it is important to note that a paper may cover more than one aspect.

2.1. Formation

The establishment of NMGs involves restructuring distribution systems into interconnected or independent MGs. NMGs' formation is crucial for ensuring coordinated functionality, control, and resource sharing among microgrids. This adaptation allows them to respond effectively to dynamic conditions, accommodating changes in load demand, generation capacity, and overall system conditions. Several proposed methodologies focus on organizing networked microgrids by determining optimal structures, boundaries, and partitions. The objective is to efficiently allocate resources, ensuring a continuous power supply, even in the face of unexpected disruptions. This section categorizes and examines a range of techniques developed by researchers and practitioners, each offering distinct advantages and considerations.

In the following subsections, a comprehensive review of each of these approaches is conducted to identify their characteristics, and the findings, including both features and limitations, are succinctly summarized in Table 1.

Table 1. Categorization of approaches for forming NMGs.

Methods	Categorizes	Features	Limits	Ref.
Clustering	Partitional, Hierarchical, and Density-Based	Create a straightforward approach with minimal mathematical complexity to support large-scale NMG by focusing on specific MGs.	• Designed for the formation of uncoupled multi-microgrids. • No assurance of finding optimal solutions.	[8–17]
Graph theory	MST, and BFS	Facilitate visualization of distributed-grid problems to find optimal solution rapidly.	• Designed for the formation of uncoupled multi-microgrids. • Efficiency degrades for medium to large systems. • Lacks consideration for transient response. • Fails to address protection concerns.	[18–26]
MIP	MINLP, MILP, and MISOCP	Capable of finding the optimal solution for problems in which decision variables can take on both continuous and discrete values.	• Computationally expensive. • Practically infeasible when the size of the system is large or for real-time decision making. • Less consideration for transient response. • Need for a thorough and accurate mathematical model of the environment • Non-convex characteristics of power flow constraints.	[27–41]
Heuristic	BFS, BSO, Tabu, ABS, and PSO	Discover close-to-optimal solutions within a reasonable timeframe.	• Less consideration for transient response of NMGs • No assurance of an optimal NMGs' formation. • Lacks consideration for transient protection and frequency deviation.	[42–46]
Game theory	Cooperative, and Dart Game	Modeling interactions and strategic interdependence among microgrids.	• Computationally expensive. • Lacks consideration for transient protection and frequency deviation. • Practically infeasible when the size of the NMG is large or for real-time decision making.	[47–52]
DRL	DQN and multi agent DQN	Advanced machine learning techniques with a model-free nature enable dynamic configuration, allowing for their application in an online mode.	• Lack of maturity and reliability in power system applications. • Lacks consideration for transient protection and frequency deviation. • Complex implementation poses challenges in deployment. • Dependence on online and historical data of the network for effective functioning.	[53–61]

2.1.1. Clustering Approaches

The discourse on clustering algorithms concerning the segmentation of distribution networks into multi-microgrids underscores the significance of employing data-driven methodologies to identify nodes or regions with similar attributes such as load demand, geographical proximity, or DER capacity. These methodologies can generally be categorized into partitional clustering, hierarchical clustering, and density-based methods, each serving distinct purposes.

Partitional clustering algorithms play a key role in forming NMGs by pinpointing cluster centers and grouping data points into distinct clusters. The objective is to minimize the squared difference between data points and centroids. These data points represent DERs characterized by features such as power output, energy storage capacity, and geographical location. Typically, K-means and K-medoids algorithms are utilized to cluster DERs based on these features. In K-means, the centroid is the mean of all data points in a cluster, while K-medoids uses actual data points as centroids or medoids. These algorithms initialize random centroids, assign each DER to the closest center, and calculate new centroids iteratively. The iterative refinement process aims to minimize the sum of dissimilarities between data points and cluster representatives. In the context of forming NMGs, the goal of these algorithms is to minimize power loss and maximize load pickup while balancing demand and supply constraints [8–11]. Their advantages include simplicity and scalability, making them well suited for large-scale microgrid systems. However, notable limitations encompass reliance on predefined cluster numbers, sensitivity to initial configurations, challenges with non-convex cluster shapes, and limited consideration of the spatial or geographical factors crucial for microgrid planning [12].

Hierarchical clustering offers an alternative algorithm for organizing data points into clusters, and it involves two primary methods: divisive and agglomerative. In divisive clustering, all DERs are initially grouped into a single cluster, and recursive splitting occurs until each DER forms its own cluster. On the other hand, agglomerative clustering takes a bottom-up approach, starting with each DER in a separate cluster and iteratively merging the most similar pairs until all DERs belong to a unified cluster. This hierarchical structure is employed to form multi-microgrids by allocating DERs and identifying boundaries, taking into account distribution system features such as topology, line impedance, and load distribution. The objective is to maximize the restoration-path availability of critical loads after power outages [13], and minimize maintenance costs [14]. The hierarchical structure enhances microgrid formation by being adaptable to different datasets, allowing the creation of isolated yet dense and large clusters. This adaptability is crucial, especially in sparsely populated and remote locations. However, a significant drawback of hierarchical clustering algorithms is that once objects are linked, they cannot be reconsidered for linkage in another branch of the hierarchical tree. This limitation leads to a lack of robustness and sensitivity to noise and outliers [15].

Density-based clustering algorithms are designed to identify clusters with arbitrary shapes, allowing for the detection of high-load-density clusters and the establishment of microgrid boundaries [16]. These algorithms excel in handling noise in data, offering advantages over hierarchical or partitional methods [17]. However, they may face efficiency challenges when dealing with higher-dimensional data due to their dependence on non-trivial user-defined parameters in the dataset.

2.1.2. Graph Theory Approaches

Graphs, as a specialized data structure, serve as an abstraction for real-world power grids, allowing the visualization and solution of distributed grid problems using graph theory and algorithms. The mapping of electrical networks to graph concepts establishes a connection between network components and vertices, and between connections and edges in the graph. This translation allows for the exploration of intelligent algorithms in solving electrical network problems, proving valuable in the segmentation of distribution networks into multi-microgrids [21]. In power distribution networks, graph-based concepts such as graph partitioning, spanning tree, and spanning forest are utilized to create microgrids, incorporating both loop-based microgrid topology (as in [22,23]), and radial-based microgrid topology (as in [18–20]).

Two key graph-theory-based methods for forming NMGs are minimum spanning tree (MST) algorithms and breadth-first search (BFS) trees. MST algorithms aim to create a tree encompassing all nodes in a network while minimizing total edge weight. In power systems, each DER is represented as a node in a graph, where edges denote potential connections between DERs. The primary goal of MST is to identify the minimum set of edges required to connect all nodes (DERs) efficiently, without forming cycles. In [20,24], this application is used to maximize critical load while adhering to radial topology and operational constraints such as power balance, voltage, and current limits.

Breadth-first search (BFS) is a traversal and search algorithm applied to tree or graph data structures. In the context of forming NMGs' topology, BFS uses a generator bus as the root node, initiating the exploration of adjacent nodes at the present depth before moving on to nodes at the next depth level. This process results in a BFS tree, where each MG extends like a tree by selecting adjacent buses based on their ascending electrical distance from the root. In [19,25,26], this topology is formulated with the aim of maximizing load restoration, taking into account considerations of criticality and operational constraints.

2.1.3. Mixed-Integer Programming Methods

Mixed-integer programming (MIP) serves as a mathematical optimization approach essential for addressing problems wherein decision variables can assume both continuous and discrete values, analogous to the challenges encountered in the formation of NMGs. In the context of NMG formation, the initial step involves creating a mathematical model that comprehensively represents all aspects of the microgrid-formation problems. Typically, graph theory methods, as discussed in references [22,28,30–37], are employed to model the intricate relationships within the microgrid. Subsequently, the optimization objective is established, aiming to determine optimal values for decision variables that either minimize or maximize an objective function, while adhering to a set of constraints. This process enables the formulation of an efficient and effective optimization framework for configuring networked microgrids.

Various types of MIP formulations are applied to address different aspects of forming NMGs. The specific MIP formulation used depends on the characteristics of the microgrid, the objectives, and the constraints of the problem. These methods are generally classified into three classes which include mixed-integer nonlinear programming (MINLP), mixed-integer linear programming (MILP), and mixed-integer second-order cone programming (MISOCP). MINLP extends MIP to handle scenarios where the objective function or constraints include nonlinear relationships, allowing decision variables to take both continuous and integer values. This approach is utilized in [27] to identify a set of viable microgrid clusters, aiming to maximize the restoration of loads within a radial distribution system. While MINLP methods ensure precision without resorting to linearization or convex relaxation that could impact solution accuracy, they suffer from computational inefficiency. Additionally, relaxing integer constraints during the solution process gives rise to nonconvex sub-problems due to the nonconvex nature of power flow equations. To overcome these challenges, MISOCP and MILP methods are introduced. MISOCP, a convex-based mixed-integer formulation, is proposed in [28,39,40] for the dynamic formation of NMGs, aiming to maximize served loads while considering radial and power flow constraints. This formulation strives to offer efficient and accurate solutions, steering clear of the computational inefficiencies and nonconvexity associated with MINLP.

MILP proves to be faster than alternative methods, although it compromises some level of accuracy as its approach involves linearizing the objective function and constraints, along with restricting certain decision variables to integer values. MILP methods find common application in the swift restoration of critical loads in resilience-oriented NMGs' formation problems, as evidenced in various studies [22,29–38]. The linearized consideration of power flow and radial topology constraints is employed in [29,31–38] to reduce problem complexity. While many studies integrate operation constraints related to power balance and limitations on power, voltage, and current, the inclusion of additional constraints, such as frequency limits [22], the count of switching events [32], hardening constraints [37], and the integration of demand-response measures [62], contributes to enhancing problem realism, bringing it closer to real-world conditions.

In summary, according to research findings in [63], concerning NMG formation using MIP methods, MILP stands out for its rapid computational solutions and scalability. In contrast, MISOCP excels in providing superior accuracy, and MINLP ensures exactness despite the longer computational times.

2.1.4. Heuristic Approaches

Heuristic techniques are problem-solving methods that rely on intuitive or rule-based approaches to find approximate solutions in a reasonable amount of time. These techniques, while not guaranteeing optimality, aim to quickly find good solutions meeting specific criteria or objectives. In the context of partitioning distribution networks into multiple microgrids, heuristic-based techniques are commonly used due to the complexity and computational challenges of the problem. Various heuristic methods are mentioned in references [42–46], each addressing optimization problems associated with NMGs' formation. These methods employ algorithms such as Brute Force Search (BFS) [42], Backtracking Search Optimization (BSO) [43], Tabu search [44], Artificial Bee Colony (ABC) [45], and the particle swarm optimization (PSO) method [46]. These investigations have diverse objectives, encompassing the reduction of power losses [42,45], enhancement of reliability [42], mitigation of interactions between microgrids [43], reduction of operational costs [46], and fortification of resilience against uncertain cascading failures [44]. Collaboration among MGs is addressed in [44,46], with a focus beyond radial topologies. AC power flow analysis techniques, such as Backward Forward Sweep [42,43] and modified Newton–Raphson [45,46], are commonly employed in these studies during the configuration of NMGs to enhance solution accuracy.

2.1.5. Game Theory Approaches

In the domain of NMGs, cooperative game theory finds widespread application [47–50], as each microgrid operates autonomously, resembling an independent player. This characteristic renders game theory a valuable tool for modeling interactions and strategic interdependence among microgrids. Within this conceptual framework, each microgrid strives to optimize various objectives, such as minimizing restoration costs [47], reducing power loss [48,49], and minimizing operational costs [50]. However, the actions of one microgrid can have repercussions on others, leading to the emergence of a complex network of interdependencies.

Despite the advantage of game theory in considering all potential combinations among variables, this complexity is heightened. In response to the intricacies associated with game theory methods, the concept of the Darts game is introduced in [51,52]. This strategy is designed to discover the optimal configuration of NMGs with a central focus on minimizing the costs linked to restoration. The approach involves nonlinear AC power flow analysis to assess power distribution among MGs, and it accounts for radial topology constraints, emergency-demand-response-program constraints, and electrical constraints.

2.1.6. Deep Reinforcement Learning-Based Approaches

Deep reinforcement learning (DRL) has emerged as a potent method across various domains, demonstrating its efficacy in reconfiguring distribution networks into NMGs [53–60]. DRL utilizes advanced machine learning techniques to dynamically configure and optimize microgrid compositions within larger networks. This involves modeling the system as a Markov Decision Process (MDP), where the formation of microgrids is determined through a sequence of decision-making steps. An agent, representing the microgrid's controller or distribution system operator, interacts with the environment and learns an optimal policy through trial and error, taking actions like selecting energy sources, adjusting network connections, and optimizing parameters to maximize cumulative rewards. These rewards align with objectives such as load pickup [55,58,59] and topology feasibility [53,54]. DRL empowers microgrids to autonomously adapt, integrate renewable energy, and optimize configurations in real time, making them more adaptive, resilient, and efficient contributors to the broader power infrastructure [64]. The crucial aspect of DRL methods lies in their model-free nature, allowing for their application in an online mode. This capability facilitates swift decision making through straightforward numerical calculations, eliminating the necessity for actual power system modeling or the formulation of complex power flow equations.

DRL-based methods commonly employed in the formation of NMGs encompass Deep Q-Networks (DQN) and multi-agent DQN. DQN employs an artificial neural network to functionally approximate state–action pairs, with Q values trained to derive optimal decisions. In works such as [53–57], DQN is applied to dynamically configure NMGs, aiming to enhance system resilience by accommodating all loads while considering operational constraints, power flow constraints, and radial topology assumptions. Achieving Dynamic NMGs through DQN hinges on enabling the Q-network to learn appropriate responses within the MDP. Numerous techniques have been explored to enhance the efficiency of DQN learning. Notably, experience replay is employed to avoid overwriting experiences, Epsilon-greedy-based exploration facilitates early-stage convergence, and the utilization of a Double Q-Network proves to be highly effective in mitigating overestimation [53,54].

DQNs are executed in a centralized fashion, involving a single centralized agent interacting with the environment at each time step. Consequently, training the centralized DRL on extensive power systems with thousands of nodes would demand an impractically lengthy duration to train a vast number of neural network parameters. To tackle this issue in the context of NMGs, a multi-agent DQN method is introduced in [58–60], where agents collaborate to expedite prey capture compared to a single agent through the sharing of acquired knowledge.

During extreme events such as natural disasters or cyber-attacks, the data from the power system encounters challenges related to scarcity and accuracy. These issues can have detrimental effects on DRL training processes, potentially leading to incorrect decisions during the configuration of NMGs. To overcome this challenge, ref. [54] employs Generative Adversarial Networks, GANs, an unsupervised and model-free method capable of automatically extracting data features without the need for labeling. This approach enhances the robustness of the training process by addressing data scarcity and accuracy concerns in challenging scenarios.

2.2. Power Distribution

The configuration of NMGs is significantly reliant on power flow (PF) calculations. Analyzing the power flow or voltage profile is crucial for understanding the distribution of power within the network. This information plays a key role in dispatching microgrids optimally, ensuring their stable and reliable operation. Additionally, it aids in identifying areas with high load concentration and interconnected DERs, which are deemed as promising candidates for microgrid formation. According to Table 2, researchers used different PF techniques in configuring NMGs.

PF calculations frequently employ various numerical techniques to linearize nonlinear equations and solve them within electrical power systems. The PF calculation typically consumes a significant amount of execution time and involves complexities, mainly because it necessitates updating the voltage magnitude and angle in each iterative process [65]. These challenges become particularly pronounced in NMGs due to their dependency on various factors, including the operational mode, types of microgrids, and network topologies. The detailed discussions on these factors will be presented in the subsequent subsections.

Table 2. PF techniques employed for configuration of NMGs.

PF Techniques	Ref.
AC PF	[33,34,51,53,55,58–60,64]
Linear DistFlow	[31,39–41,44,61,63,66]
NR	[8–10,16,20,57]
BFS	[27,32,42,43]
Kirchhoff's law	[19,25,30,56]
Gauss-Seidel	[26]

2.2.1. Operational Modes

The operational modes of networked microgrids, including both grid-connected and islanded modes, require distinct methodologies for power flow analysis. In the grid-connected mode, the voltage and frequency of microgrids are determined by the main grid. On the other hand, in the islanded mode, control units of DGs take charge, managing both active and reactive power to regulate frequency and voltage.

In grid-connected mode, power flow in NMGs follows traditional distribution network analysis, assuming constant voltage at the slack bus and microgrid frequency. Therefore, conventional AC power flow techniques, such as Gauss-Seidel, Newton–Raphson (NR), and backward/forward sweep (BFS), can be applied for PF analysis in grid-connected NMGs. These established computer-aided algorithms have a long history of successful applications in AC power systems dating back to the 1950s. While AC power flow techniques provide accuracy and are well-suited for capturing the complexities of real-world power systems characterized by diverse loads, generation sources, and network configurations, they also come with drawbacks. These techniques introduce complexities and computational burdens, which can impact the efficiency of power flow analysis. To overcome these challenges, alternative methods such as the DC power flow model (as used in [66]) and linearized DistFlow (employed in [39–41,61,67]) are employed for analyzing the power flow in grid-connected NMGs.

In isolated NMGs lacking a slack bus, assuming a constant steady-state frequency is not viable, leading to the need for its calculation as a variable in power flow analysis. To tackle this challenge, there is a requirement for the development of a method to correct the frequency and reference bus voltage magnitude. Several studies, documented in references [68–74], have devised power flow models for islanded networked microgrids, incorporating considerations of power sharing, voltage regulation, and interface power exchange.

2.2.2. Microgrid Types

The diverse array of microgrid configurations, encompassing DC, AC, and hybrid systems within NMGs, significantly influences power flow analysis. In DC microgrids, the study involves the calculation of electrical power distribution primarily operating on direct current, allowing bidirectional power flow and integration of distributed energy resources, and energy storage systems. Voltage regulation is crucial for stability and efficiency in these systems. The absence of reactive power and the focus on controlling voltage levels distinguishes power flow analysis in DC microgrids from traditional AC power systems, presenting unique challenges and opportunities for innovative PFA strategies such as those proposed in [74–76].

Power flow analysis in AC microgrids involves the assessment and calculation of the steady-state distribution of electrical power within the network. This analysis focuses on maintaining voltage and frequency parameters within acceptable limits, ensuring the stability and reliability of the microgrid. Traditional power flow methods, such as the NR algorithms, are commonly employed to solve the system's nonlinear equations and determine the flow of active and reactive power. Challenges in AC microgrid power flow arise from factors such as varying loads, intermittent renewable energy sources, and the presence of synchronous generators. The researchers proposed various power flow calculation methods, as seen in [77–82], to enhance accuracy and efficiency, especially in AC microgrids

Future power systems are envisioned as NMGs in which many hybrid microgrids, including AC and DC microgrids, are interconnected to exchange power in a controlled manner. Power flow analysis in hybrid microgrids involves the examination of electrical power distribution within a network that integrates both AC and DC components. Hybrid microgrids combine diverse energy sources and storage systems, presenting unique challenges in interoperability and coordinated control. Efficient power flow analysis in these systems requires sophisticated modeling techniques to address the complexities arising from the integration of different grid types. Researchers proposed various PFA methods, discussed in [83–86], to analyze power flow within hybrid microgrids.

2.2.3. Network Topologies

The choice of network topology, such as radial grids, meshed types, and ring grids, plays a crucial role in power flow analysis for networked microgrids. Radial grids, characterized by a simple tree-like structure, make power flow analysis straightforward. Meshed grids, featuring multiple interconnected paths for enhanced fault tolerance, necessitate advanced algorithms for power flow analysis due to the presence of multiple routes. Ring grids, allowing bidirectional power flow for increased redundancy and reliability, introduce complexity in power flow analysis as injected power may cause voltage variations. In [87], existing methods addressing power flow problems considering different topologies are comprehensively reviewed.

2.3. Operation

There are two primary types of networked microgrids based on their operational characteristics: predetermined networked microgrids (PNMGs) and dynamic networked microgrids (DNMGs). A predefined networked microgrid maintains a consistent switching status and network configuration regardless of the system's operating conditions and customer priorities. The boundaries of the microgrid are determined based on factors such as supply adequacy, reliability indices, and maximum coverage. These predetermined networked microgrids operate according to established rules and agreements. For example, grid-tied microgrids are connected to the main grid and coordinate their operation with the utility grid, following predetermined agreements and regulations for power sharing and exchange. Virtual power plants integrate various distributed energy resources and function as a single controllable entity, with power generation and sharing predetermined based on the capabilities and capacities of the distributed energy resources [88]. Community microgrids, designed to serve specific communities or areas, also fall into the category of predetermined networked microgrids [89]. They have predefined connections, power sharing arrangements, and operational strategies tailored to meet the specific needs of the community.

On the other hand, DNMGs, an evolved form of networked microgrids, have gained popularity due to their advanced structure. As per [90–92], dynamic microgrids can be described as microgrids with adaptable boundaries that dynamically adjust to maintain a balance between generation and load. This flexibility enables dynamic microgrids to optimize their operations in real time, ensuring efficient utilization of resources and meeting the evolving demands of the system. DNMGs exhibit real-time adaptability and flexibility, utilizing advanced control algorithms, communication technologies, and intelligent decision-making capabilities to optimize resource utilization and ensure reliable operation. DNMGs are capable of self-healing, automatically detecting and responding to faults or disruptions, and reconfiguring their operations to restore power supply [91,93,94]. Additionally, demand-responsive microgrids dynamically adjust power consumption and load profiles based on grid conditions and user preferences, enabling efficient utilization of energy resources. Multi-agent systems are also a type of dynamic networked microgrid that facilitate real-time coordination and cooperation among interconnected components, optimizing power sharing and load balancing [95,96].

Dynamic networked microgrids offer distinct advantages when compared to predetermined networked microgrids. Their flexible boundaries, which expand or shrink based on the real-time generation and load conditions, enable superior adaptability to changing energy demands and resource availability. This flexibility enhances the overall resilience of the system, as dynamic networked microgrids can reconfigure themselves in response to disruptions or faults, isolating affected sections and ensuring uninterrupted operation. Moreover, dynamic networked microgrids optimize the utilization of distributed energy resources by dynamically adjusting connections and allocations, leading to improved energy efficiency and cost-effectiveness [97]. The scalability of dynamic networked microgrids allows for seamless integration of new microgrids and DERs, accommodating the growing demand for renewable energy sources. Additionally, their ability to balance loads and manage voltage and frequency fluctuations enhances grid stability. Overall, dynamic networked microgrids offer increased flexibility, resilience, optimal resource utilization, scalability, and grid stability, making them a promising solution for efficient and sustainable power distribution in the evolving energy landscape. While the benefits of DNMGs are evidently greater than those of PDNMGs, Table 3 indicates that over 40 percent of studies focus on configuring PNMGs.

Table 3. List of key studies in DNMGs and PNMGs.

Operation	Ref.
DNMGs	[9,11,24,26–28,31,33,46,53,55–60]
PNMGs	[8,10,13,16,19,20,25,30,32,34,42–44,51,63,64]

3. Networked Microgrids' Control

Effective monitoring and control techniques play a crucial role in optimizing performance and bolstering the overall resilience of networked microgrids. These techniques aid in the efficient distribution of energy, reducing power losses, and enabling adaptive operation. They ensure that networked microgrids can swiftly adjust to changing conditions and optimize their functioning in response to disruptions. To implement advanced and real-time control techniques, a robust and reliable communication structure is necessary. Therefore, in the upcoming sections, we will initially review various communication techniques and then delve into the control approaches and aspects of NMGs in depth.

3.1. Communication

In the context of networked microgrids, effective communication infrastructure plays a crucial role in ensuring the smooth management of energy and coordination among various components. These communication tools facilitate the exchange of information not only between microgrids but also with the central energy management system and end users [98]. They enable the implementation of advanced functionalities, including load balancing, demand response, and fault detection, which rely on continuous and reliable communication [99]. Communication technologies, protocols, and their impacts on the control and management of NMGs are reviewed.

3.1.1. Technologies

The technologies involved can be broadly classified into wired, wireless, and hybrid options. Wired solutions encompass Power Line Communication, Fiber Optic Communication, and Ethernet, taking advantage of existing infrastructure to deliver high reliability, speed, security, and ample bandwidth [100].

On the other hand, wireless technologies, such as Wi-Fi, Zigbee, Wireless Sensor Networks, Bluetooth, Near Field Communication, Cellular, and satellite communication, offer flexibility for both short- and long-range communication needs. They are utilized for real-time data collection, monitoring and control of power generation, load management, and power supply planning [100].

Hybrid approaches often blend wired and wireless elements or employ mesh networks, capitalizing on the strengths of both to create resilient and adaptable communication networks. The selection of a specific technology depends on factors like deployment cost, reliability, scalability, and the unique requirements of the microgrid in question.

3.1.2. Protocols

In the context of a networked microgrid system, effective and reliable operation relies on adherence to specific rules and conventions collectively known as communication protocols. These protocols play a crucial role in facilitating the exchange of information by establishing a common language and structure for communication. Three fundamental elements characterize communication protocols: syntax, semantics, and timing. Syntax pertains to the format and structure of exchanged data, including details such as data encoding, bit order, and framing. Semantics involves interpreting the meaning of exchanged data, encompassing control signals, commands, or responses conveying specific actions. Timing governs synchronization and coordination, addressing factors like communication rates and data transmission sequencing. These elements collectively define the rules and conventions necessary for accurate and reliable data exchange in diverse domains. Various communication protocols, including Modbus, MQTT, DNP3, and the IEC 61850 series standards [101], are utilized in networked microgrids [100]. However, a standardized protocol is currently lacking across the communication system of networked microgrids [102].

3.1.3. Challenges

While the progress of the communication network contributes to improving the reliability and scalability of NMGs to a certain extent, they are vulnerable to communication limitations such as bandwidth constraints, time delays, traffic congestion, and packet losses, which can significantly impact overall system responses [100]. To address these challenges and ensure the performance of NMGs, various methods, including predictive controllers [103–105], lead–lag compensation controller [106], and adaptive controllers [107,108], are proposed. However, a thorough assessment is necessary to minimize their potential adverse effects on NMGs as much as possible.

3.2. Control

The control of NMGs involves overseeing and managing network functions to achieve goals such as energy trading, optimizing operational costs, maximizing power stability, ensuring reliability, enhancing user comfort, and achieving a resilience index. The control capabilities of networked microgrids are analyzed and evaluated through various perspectives, including the control architecture, control modes, and control schemes. The control architecture and control modes illustrate the framework for NMGs' control, while the control scheme delineates the approach to managing interconnection and interchange among MGs. All these capabilities, along with their features and limitations, are succinctly presented in Table 4 and systematically and thoroughly examined, considering their formulation models, objectives, and features, in the subsequent subsections.

Table 4. Categorization of control techniques for NMGs.

Control Features	Categories	Features	Limits	Ref.
Architecture	Centralized	Effective in situations requiring precise coordination and centralized controller.	• Single-point communication. • Reliability issues. • Struggle with a large number of agents.	[109–119]
	Decentralized	Enhance privacy protection of MGs, facilitates communication among MGs in different points.	• Difficulty in achieving system-wide objectives • Increased vulnerability to communication failures. • Limited scalability with a growing number of agents.	[120–126]
	Distributed	Ensure regular operation of NMGs by adjusting voltage and frequency, even without communication with master controllers.	• Privacy concern. • Increased vulnerability to communication failures.	[127–148]
Modes	Master–Slave	Enable centralized coordination among MGs and DS.	• Single-point communication. • Reliability issues.	[109–113,149]
	P2P	Allow decentralized decision making and mutual collaboration among MGs and DS.	• Increased communication complexity in large-scale systems. • Limited scalability with a growing number of peers.	[138,140,143,148, 150–160]
Scheme	Hierarchical	Provide a structured approach with levels of decision making, facilitating coordination between MGs and DS.	• Potential delays in decision making due to multi-level hierarchy. • Increased vulnerability to failures in higher-level controllers. • Complexity in ensuring alignment between local and global objectives.	[114,161–170]
	Droop-Based	Aid in load sharing and maintain voltage and frequency stability amidst variations with less reliance on communication systems.	• Less able to manage all dynamic behaviors of NMGs. • Less applicable in large-scale networks.	[171–184]
	Optimization	Assist in determining optimal setpoints for various operational parameters of NMGs.	• Less applicable in large-scale networks. • Model-based and centralized structure.	[109,110,112,113, 137–142,185–192]
	AI	Allow NMGs to dynamically adapt and respond to changing conditions in real time.	• Complexity in implementation. • Less maturity in power systems. • Dependent on historical and real-time data.	[124,131,193–196]

3.2.1. Control Architecture

Control architecture, in a broader sense, refers to the overarching design and arrangement of control systems that govern and manage the behavior of complex systems [197]. In the context of networked microgrids, control architecture plays a pivotal role in dictating how various system components, such as generators, energy storage units, loads, and controllers, interact and communicate to ensure the smooth and dependable operation of the networked microgrids. It delineates the process of data acquisition, analysis, and utilization for making informed control decisions. Three primary control architecture options exist for networked microgrids: centralized, decentralized, and distributed. Within centralized control architecture, all decision-making processes and control actions are orchestrated and overseen by a central processing unit or controller [119]. The central entity gathers data and measurements from various microgrid components and coordinates their operation. It takes a comprehensive view of the entire networked microgrid and implements actions to optimize overall performance, as highlighted in [109,110]. This control architecture is applied in the management of energy for both grid-connected [111] and islanded NMGs [112–114]. Centralized control is effective in situations requiring precise coordination and centralized optimization, but it often faces criticism for the potential single-point communication failure problem and reliability issues [115–117]. Additionally, it struggles to effectively manage a system with a large number of agents [118].

Conversely, decentralized control hinges on local decision-making processes at the level of individual microgrid components. Every component within the microgrid operates autonomously, utilizing predefined algorithms grounded in local measurements to optimize its local operation, whether functioning as a distributed energy resource or a load. This methodology reduces complexity and improves privacy protection by requiring only a restricted exchange of information, as highlighted in [120]. Decentralized control assumes a more distributed character, potentially enhancing the microgrid's resilience by diminishing reliance on a central controller [121–124]. Decentralized controls are used for networked MGs systems and grid-connected MGs with a mix of fast-changing distributed generators owned by different parties [125,126].

Distributed control represents a hybrid approach amalgamating elements from both centralized and decentralized control paradigms. In this architecture, each local controller communicates and cooperates with neighboring controllers within the microgrid. This intercommunication allows for a degree of centralized decision making while preserving a measure of autonomy at the local level. Distributed control aims to combine the benefits of centralized coordination with the resilience and adaptability afforded by local decision making. This method ensures the regular operation of NMGs by adjusting voltage and frequency, even without communication with master controllers [127–131]. While information sharing among neighboring agents is crucial for certain control functions in distributed control, it raises privacy concerns due to the potential exposure of sensitive data. To mitigate this issue and uphold privacy in NMGs, various methods are proposed in [132–142]. The distributed control of networked microgrids involves a sophisticated information network, where each DG incorporates remote sensing and control actuation with its microgrid center controller. However, this complexity introduces susceptibility to cyberattacks on communication links for inter-microgrid data sharing. Addressing this concern, refs. [143–148] introduce a cyber-resilient distributed control framework.

3.2.2. Control Modes

Control modes in the realm of networked microgrids encompass two fundamental approaches: master–slave and peer-to-peer control modes. In the master–slave control mode, a central controller, known as the master controller, takes charge of managing and making decisions for the entire networked microgrid. The other components or nodes, referred to as slaves, obediently execute the commands and instructions issued by the master controller. This mode is frequently utilized in situations involving NMGs that necessitate centralized control, encompassing both islanding scenarios [109,112,113,149] and grid-connected setups [110,111].

Conversely, the peer-to-peer (P2P) control mode empowers diverse microgrid components or nodes to engage in direct communication and collaboration. In this setup, each node possesses the autonomy to make independent decisions and can seamlessly exchange information with other nodes as the situation demands. This mode is particularly well suited for dynamic and adaptable microgrid configurations, facilitating enhanced flexibility and responsiveness. A P2P control architecture is proposed for NMGs in studies [138,140,143,148,150–156], integrating multiple layers and facilitating interactions among different agents such as utility, MGs, and smart parking lots. The outcomes presented in paper [158] indicate that the P2P control architecture can reduce the annual energy cost of trading energy among microgrids by 0.75% while ensuring the maintenance of system reliability. P2P control relies on bidirectional network communication, rendering the system vulnerable to various attacks, including private data leakage, data breaches, collusion, distributed denial of service, and man-in-the-middle attacks [159,160]. To tackle these challenges, several solutions, such as blockchain-based methods [143,157], are proposed.

3.2.3. Control Schemes

Control schemes within the context of networked microgrids can be categorized into several main types: hierarchical control schemes, droop-based control, optimization-based techniques, and artificial intelligence-based methods. Hierarchical control schemes are organized systems that divide control responsibilities into three layers—primary, secondary, and tertiary. This structuring aims to standardize the operation of microgrids, enhancing their overall resilience [169]. While the primary goal of hierarchical control is to effectively manage network frequency and voltage by fostering collaboration among distributed energy sources, it has introduced several challenges within power control systems. These challenges are particularly associated with the integration of power electronics, telecommunications, fault monitoring, and security considerations. The primary control level is responsible for ensuring the reliable operation of networked microgrid components in real time. It primarily deals with tasks like maintaining voltage and frequency within acceptable limits [164], load sharing among microgrid components [163], power transactions between microgrids [114,162], and responding to immediate disturbances [165]. Primary control operates at a fast timescale, typically in the range of milliseconds to seconds, and focuses on maintaining the microgrid's stability. Secondary control operates at a slower timescale, often in the range of minutes to hours. It aims to synchronize the interconnecting microgrids by regulating the voltage and frequency in response to variations in load and energy supply [114,162,166]. This level of control is responsible for optimizing the operation of microgrid components and ensuring efficient energy distribution. The tertiary control level deals with the long-term planning and optimization of networked microgrids. It focuses on coordinating the flow of power between the microgrid and the main grid [167], optimizing resource allocation [170], and ensuring cost effectiveness [161]. Tertiary control operates at timescales ranging from hours to days and even weeks.

Droop-based control, primarily implemented at the secondary control layer, involves setting droop characteristics for components like generators and inverters. These characteristics aid in load sharing and maintain voltage and frequency stability amidst variations. The dynamic model for the droop controller is applied across the entire microgrid, discussed in both small-scale [171,175] and large-scale [172–174] scenarios. This control strategy simplifies structures and reduces reliance on communication systems, as demonstrated in references [176–178]. However, in islanded microgrids using droop-based control, a challenge arises in ensuring voltage and frequency stability without a main grid [179]. This is due to the absence of slack buses, changing control modes of DERs, dynamic microgrid structures, and stringent data privacy requirements. Various approaches, like the adaptive droop-based controllers [180–182], predictive model [104,183], and enhancements to the droop-based primary controller through a secondary controller [184], are proposed to address this challenge.

Optimization-based control strategies in NMGs often leverage optimization methods to enhance the efficiency, reliability, and economic viability of the DERs within the interconnected microgrid system. These optimization-based control schemes utilize mathematical algorithms such as MILP [112,113,137,141,185,192], MISOCP [186], two-stage robust MIP [109,142], heuristic algorithm [123,140,187], optimal power flow [110,138,139], and game theory [188–191] to determine the optimal setpoints for various operational parameters, including bus voltage [137,138,186], feeder power loss [137,138,185], risk index [140,192], resilience level [109], thermal rates of distribution lines [112], power sharing [113,139], active and reactive power [110], and the coordination of demand response [141,142]. By considering factors such as operation cost [109,110,112,113,137–142], energy loss [186], restoring loads [192], load of congested line [112], and energy not supplied [140], environmental sustainability, and grid constraints, optimization methods allow NMGs to dynamically adapt to changing conditions in real time. These advanced control strategies enable NMGs to operate with increased efficiency, optimize the utilization of renewable resources, and respond dynamically to fluctuations in energy demand and supply. Additionally, optimization-based control contributes to the resilience and adaptability of NMGs, making them well-suited for addressing the challenges associated with distributed energy generation and variable loads in a networked environment.

Artificial intelligence-based techniques are increasingly recognized for their role in advancing microgrid control and management. These AI-driven methods can dynamically adjust to changing conditions, predict system behavior, optimize resource allocation, and enhance fault detection and response capabilities. In pursuit of these advancements, certain studies concentrate on developing AI-based controllers, such as the artificial neural network-based controller [124,196], DNQ-based controller [131,193–195] and the data-driven distributed secondary frequency controller. The objective functions of these methods vary, encompassing optimizing energy sharing among MGs [124,131,196], optimizing the pricing policy [193,194], as well as minimizing operation cost [195].

4. Discussion and Analysis

This paper extensively examined two key facets of NMGs: configuration and control. Based on the reviewed literature, this section provides a discussion on challenges, gaps, and proposed solutions accordingly. Finally, a comparative analysis is conducted aiming to unveil a solutions approach considering the identified challenges associated with NMGs.

4.1. NMGs' Configuration

The challenges associated with the configuration of NMGs are multifaceted, covering formation, power distribution, and operational aspects. Formation involves defining boundaries by determining switch statuses, allocating DERs among MGs, specifying the type of interconnected MGs, and establishing the topology of these networks. In addition, power distribution within NMGs entails the analysis of power flow within the network. Furthermore, the operational dimension involves defining the behavior of NMGs over time, considering various conditions and scenarios.

Formation in NMGs can be achieved through rapid methods like minimum spanning tree and k-means clustering. While these approaches are quick, they fall short in finding optimal solutions, especially when dealing with numerous DERs and components. To attain optimal solutions, researchers often turn to optimization methods such as MIP, heuristic approaches, game theory, or methods based on deep learning.

Graph theory plays a crucial role in formulating the NMGs formation as a mathematical optimization problem by providing a mathematical abstraction of the distribution system. Most researchers in the field focus on defining the objective function as maximizing the restoration of all loads or critical loads to enhance resilience. However, it is noteworthy that enhancing resilience goes beyond simply maximizing the restored load; factors like the time of restoration and minimizing damages are integral components of resilience but are often overlooked in the literature.

Constraints in the optimization problem typically revolve around operational factors, including power balance, power, current, voltage limits, the number of switch actions, and topology constraints, encompassing limitations on lines between components, the number of DGs in microgrids, radiality, and limits on interconnected MGs. Notably, frequency limits and transient switching protection are infrequently considered in the optimization problem, with only rare instances, such as in [22].

The primary objective of the formation process is to adjust the status of switches. However, this switching can lead to frequency deviations, causing imbalances that have severe consequences for the system. For example, opening switches on lines connecting large non-critical loads may trigger significant power imbalances, potentially damaging critical load equipment due to frequency deviation. Protective relays are designed to operate during frequency instability, leading to service interruptions or even a collapse of the microgrid.

While many studies consider the radiality constraint, some overlook its importance. Maintaining a radial structure simplifies operational issues like synchronization and load sharing among microgrids. However, it is crucial to recognize that NMGs may not adhere strictly to a radial topology; they may include ring- and meshed-type topologies. Considering distribution systems with energy sources at consumer premises, where the flow direction is not predetermined, becomes essential. This non-radial network approach acknowledges the reversible relationship between parent–child nodes, allowing for the potential existence of multiple root nodes. Moreover, the stochasticity of unintentional islanding in networked microgrids' configuration must be considered. Given that a fundamental feature of microgrids is to seamlessly separate from the distribution system during outages and continue supplying its islanded portion, accounting for this stochastic element becomes critical in the configuration of networked microgrids.

Many studies have focused on utilizing model-based optimization approaches to tackle uncertainties in the configuration of NMGs. However, the practical applications of these approaches face challenges due to the lack of operational models in the literature that consider technical parameters of MGs and are applied to real cases. In addressing these challenges, model-free methods such as DRL emerge as viable solutions, as indicated in [53–57]. DRL methods offer alternative approaches which do not rely on explicit models and technical parameters. However, they are not without their own set of challenges. DRL methods encounter complexities related to coordination, management, and the accuracy of data. Single-agent DRL approaches may face limitations in communication, while multi-agent systems introduce complexity and time-consuming processes. Moreover, DRL methods rely on learning from trial and error, and under extreme events, the data may be scarce and less accurate, potentially impacting the training processes negatively. The trade-off between the benefits of model-free methods like DRL and the challenges they present underscores the need for careful consideration and evaluation in the context of NMGs' formation.

The configuration problem of NMGs, given the inclusion of hybrid AC/DC MGs, demands more than conventional PFA techniques. The amalgamation of AC and DC introduces unique challenges, particularly non-smooth characteristics resulting from DGs and converters. Traditional power flow algorithms prove inadequate in addressing such challenges, leading to distributed power flow calculation results that significantly deviate from the actual model constraints.

DNMGs are envisioned as the future of NMGs, behaving akin to smart grids with capabilities for dynamic forecasting, responsive actions, and adaptive behavior. They not only react to changes in demand but also possess the capability to alter their configuration in diverse conditions, showcasing efficiency in response and adaptation. While many acknowledge the potential of DNMGs, the lack of real-world testing is noticeable in most works. Furthermore, to attain optimal control and flexibility in DNMGs, it is imperative to deploy remotely controlled automatic switches and control agents at each node and line. However, this requirement introduces complexities in the formation of DNMGs and may present economic challenges, potentially leading to a more delayed restoration process.

4.2. NMGs' Control

Before delving into control aspects, it is essential to review communication, since the communication infrastructure plays a crucial role in monitoring and controlling NMGs. This infrastructure facilitates the exchange of information not only among microgrids but also with the central energy management system and end users. However, communication limitations, including bandwidth constraints, time delays, traffic congestion, and packet losses, can significantly impact overall system responses, especially in scenarios focusing on resilience, where response time and cooperation among network components are crucial. Additionally, NMGs are susceptible to cyberattacks. The cost of implementing advanced communication in NMGs poses another challenge. Therefore, when designing state-of-the-art control for NMGs, it is imperative to consider these challenges in the problem.

The control of NMGs involves overseeing and managing network functions with the goals of energy trading, optimizing operational costs, maximizing power stability, ensuring reliability, enhancing user comfort, and achieving a resilience index. The assessment of networked microgrid control capabilities involves a multifaceted examination, encompassing perspectives such as control architecture, control modes, and control schemes. The control architecture and control modes provide insights into the structure of NMGs' control, while the control scheme outlines the strategy for overseeing interconnection and interchange among MGs.

Centralized control architectures, while straightforward, suffer from low reliability due to single-point communication. On the other hand, decentralized controls, although reliable, become complex in large-scale systems. Distributed architectures, combining the advantages of both centralized and decentralized approaches, offer a promising solution. Despite potential privacy concerns in information exchange, optimizing information sharing can mitigate risks. In this control architecture, the P2P control mode is utilized to accelerate communication and cooperation among MGs.

While hierarchical or droop control schemes are straightforward, they may struggle with scenarios involving changing control modes of DERs, dynamic microgrid structures, plug-and-play integration of neighboring microgrids, and stringent data privacy requirements, especially in islanded NMGs without slack buses. Addressing these challenges necessitates the use of optimization methods, with MIP being a commonly utilized approach. However, challenges persist, including the accuracy of uncertain parameters, time consumption, reliance on central controllers, and handling vast data in large power systems. To overcome these challenges, AI methods, particularly DQN [131,193–195], present a promising solution. These methods are capable of managing extensive data, forecasting, learning, and reinforcing. However, it is important to note that these emerging methods are not yet fully mature in the context of power systems.

4.3. NMGs' Configuration and Control

Recently, the predominant focus of researchers has been on managing NMGs, often assuming that the NMGs are already configured. Additionally, many of these studies primarily consider operational costs as the key objective function. However, challenges persist in the reconfiguration of DS into NMGs. Notably, there is a relative scarcity of recent studies on the configuration of NMGs compared to control aspects. Existing works often overlook critical challenges related to NMGs' stability and reliability, relying on assumptions such as radial topology. Furthermore, the emphasis is frequently on maximizing restored loads.

Integrating these two aspects into a unified problem and addressing real challenges in both configuration and control can yield a more realistic and comprehensive perspective. This approach has the potential to provide a promising solution to configure and control NMGs effectively.

5. Future Research Direction

This section lists all of problems that require further exploration and innovation, considering the continuously changing landscape of energy systems and operational paradigms. The following outlines key areas for prospective research in the domain of networked microgrids.

- Cyber-Physical Security: As digital technologies and the Internet of Things (IoT) become more integrated into NMGs' research, particularly in studies such as [53,55,57,64,131,193–195], it is imperative for future research to prioritize robust cybersecurity measures. Ensuring the security of NMGs against cyber threats, including concerns such as hacking and data breaches, should be a central focus.
- Energy Market Participation: While dynamic networked microgrids proposed in [9,53,55–57,60] offer enhanced resilience compared to predetermined ones, the substantial costs associated with high-tech components, network reconfiguration, installation, and maintenance present a considerable investment challenge. Hence, future research could delve into cost analysis for these methods and investigate regulatory and market frameworks needed to enable the active participation of dynamic networked microgrids in energy trading and demand-response programs.
- Environmental Sustainability: In the pursuit of minimizing the carbon footprint, researchers can investigate inventive strategies to improve the environmental sustainability of networked microgrids, as suggested in certain studies such as [46,64]. This involves optimizing the use of renewable energy resources and energy storage technologies, coupled with integrating environmental metrics into proposed frameworks.
- Demand Response: While some studies [30,46,51] incorporate demand response in their approaches, there is a need for further research to delve deeper into understanding load demand variations during large-scale disturbances. It is crucial to thoughtfully integrate these variations into models, placing emphasis on developing efficient responses.
- Exploration of Resilience Indices: In resilience metrics, all aspects of resiliency, including energy not supplied, load shedding, cost, and recovery time, are considered. Despite numerous proposed resilience indices for power systems, only a few studies, such as [51,64], incorporate them into their NMGs' configuration approaches. Given that the primary goal of establishing NMGs is to enhance power system resilience, it might be essential for research to include resilience indices in creating NMGs.
- Accidental Outage Consideration: Given the inherent unpredictability of power systems and the impossibility of foreseeing all events or guaranteeing their current state, it is crucial for the research to evaluate proposed models, such as those outlined in [25,26,28,53,56,57,60,63,64,112,113,137,141,185,192–194], in the context of accidental events like switching faults, component losses, losing data, and short-circuit faults. These events have the potential to disrupt power systems during the formation and control of NMGs.
- Switching Delay: Researchers should include mechanical component delays, telecommunication lags, and reliability-oriented delays as constraints in their methods, particularly in dynamic approaches like those discussed in [11,26,53,55,57,64]. These approaches involve operating numerous switches, resulting in a more intricate and delayed restoration process. Additionally, it is essential to note that the assumed rapid on-and-off switching in proposed methods may not align with the practical constraints and feasibility in real-world scenarios.
- Real Conditions Analysis: The absence of evaluations under real-world natural disasters and severe conditions in numerous studies, such as those outlined in [19,24,25,28,29,42,43,46,53,56,57,60,64,149,190], may render the proposed methods universally inapplicable. Subsequent research endeavors should prioritize the collection of real data from natural disasters and conduct analyses to assess the effectiveness of formation methods across diverse real-world scenarios.

6. Conclusions

In conclusion, this research significantly contributed to shaping the trajectory of networked microgrids as a pivotal strategy for enhancing the resilience of modern power systems. The meticulous examination led to the classification of the literature into two primary categories: networked microgrids' configuration and networked microgrids control. The study thoroughly addressed critical aspects of NMG configurations, including formation, power distribution, and operational considerations. Likewise, it delved into the control considerations of NMGs, covering communication technologies and protocols, control architecture, modes, and schemes. This contribution's distinctiveness lies in its detailed exploration of problem modeling, constraints, and objective functions within each subsection. Tables facilitated a concise comparison of merits and demerits, aiding readers in discerning strengths and limitations in NMGs' configurations and control approaches. In the discussion section, all findings, gaps, and solutions were succinctly analyzed to derive an optimal solution for NMGs' challenges. Persistent challenges in reconfiguring distribution systems into NMGs were identified, with a relative scarcity of recent studies on NMG configuration compared to control aspects. The inadequate consideration of challenges related to NMGs' frequency stability, reliability, recovery and reconfiguration time, costs associated with remote switches and communication components, as well as the impact of real and transient events and the non-smooth characteristics of DGs and converters, was highlighted. This lack of attention was often rooted in assumptions such as radial topology, fast and flawless switches, stable DGs and converters, stable and predefined configuration, and flawless communication in NMGs' problems. The existing research also tended to prioritize maximizing restored loads in configuration works and focusing on operational costs in control aspects. Integrating these factors into a unified problem that addresses both the configuration and control of stable and reliable NMGs provides a more realistic and comprehensive perspective. The article further outlined potential future trends, offering valuable insights for researchers in the field.

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