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REVIEW

Network-Constrained Multi-Objective Optimization for Integrated Microgrids with Renewable and EV Integration: A Systematic Review

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ABSTRACT: The rapid deployment of distributed energy resources (DERs), including photovoltaic (PV) generation, wind turbines (WT), battery energy storage systems (BESS), and electric vehicles (EVs), is transforming modern distribution networks by introducing bidirectional power flows, voltage variations, and increased operational complexity, thereby require enhanced system resilience. This paper presents a systematic review of multi-objective optimization approaches for interconnected multi-microgrid (MMG) systems with explicit consideration of resilience, following the PRISMA 2020 guidelines. A structured literature search and screening process was conducted across major databases, including IEEE Xplore, Scopus, and ScienceDirect, covering publications from 2015 to 2026. The selected studies are synthesised based on modelling frameworks, power flow formulations, resilience metrics, and optimization strategies. The review identifies key trends, including the growing adoption of distributed coordination schemes and advanced optimization techniques to address uncertainty and scalability. However, a critical gap is observed in the integration of resilience objectives with detailed network-constrained modelling, which limits practical applicability in real-world MMG systems. Finally, key research gaps are highlighted, and future research directions are proposed to support the development of unified, scalable, and resilient optimization frameworks for high-DER MMG systems.

KEYWORDS: Distributed energy resources; interconnected multi-microgrids; power flow modelling; resilience; multi-objective optimization; hybrid optimization; distribution networks

1 Introduction

With the ongoing global energy transition, renewable energy penetration in distribution networks is increasing significantly. Distributed energy resources (DERs), including photovoltaic (PV) systems, wind turbines (WT), battery energy storage systems (BESS), and electric vehicle (EV) charging infrastructure, are now widely deployed at the distribution level [1–3]. Traditionally designed for unidirectional power flow, distribution networks now experience bidirectional flows due to excess local generation exported through the point of common coupling (PCC), leading to voltage rise and thermal overloading [4]. Under extreme events such as faults or severe weather, these conditions increase vulnerability to outages and cascading failures. Consequently, modern distribution systems must address not only economic optimality but also resilience, including critical-load supply, adaptive reconfiguration, and rapid post-disturbance recovery [5–7].

Interconnected microgrids have emerged as a promising solution to enhance operational flexibility and local energy utilisation [8,9]. In such systems, multiple microgrids are electrically coupled, and their decisions are interdependent through shared network constraints, influencing voltage profiles, line flows, and power exchange [10]. With increasing renewable penetration and system stress, coordinated operation must simultaneously ensure economic efficiency, electrical feasibility, and resilience objectives, including safe islanding and post-disturbance recovery. This growing interdependence highlights the need for integrated optimization frameworks for coordinated multi-microgrid operation.

Existing studies have explored diverse optimization approaches. Deterministic methods, particularly linear programming (LP) and mixed-integer linear programming (MILP), are widely used for economic dispatch and scheduling [11,12], but often rely on simplified network representations that inadequately capture voltage and reactive power constraints. To address this, optimal power flow (OPF)-based formulations have been adopted to explicitly model nodal balance, voltage magnitudes, and line flows. While nonlinear AC-OPF provides high-fidelity modelling, branch-flow formulations and their linearised variants improve tractability in radial networks. However, linearisation and relaxation may introduce non-negligible errors under heavily loaded, reverse power flow, or islanded conditions.

Metaheuristic algorithms, such as genetic algorithms (GA), particle swarm optimization (PSO), and differential evolution (DE), have been applied to handle nonlinear and nonconvex problems [11,12], but lack guarantees of convergence and global optimality in large-scale systems. More recently, reinforcement learning (RL) approaches have enabled adaptive and data-driven energy management under uncertainty [13,14]. However, their limited ability to explicitly enforce physical network constraints raises concerns regarding voltage violations and operational feasibility.

In parallel, resilience-oriented studies have examined restoration strategies, resilience metrics, and disturbance management [15,16]. However, these are often developed independently of network-constrained optimization frameworks, limiting their ability to ensure both feasibility and resilience performance. Additionally, simplified DER and network models may lead to inaccurate conclusions under extreme or islanded operating conditions.

Despite these advances, the literature remains fragmented across modelling approaches, optimization techniques, and resilience strategies [15–17]. Most studies address economic optimization, network constraints, uncertainty, and resilience in isolation rather than within an integrated framework [10,18,19]. This limits the ability to achieve coordinated multi-microgrid operation that simultaneously satisfies power-flow feasibility, operational security, and resilience objectives [6,7,9]. As highlighted in Table 1, only a limited number of studies jointly consider these aspects. To address this gap, this paper adopts a structured and systematic review approach to synthesise and critically evaluate existing literature [20].

Table 1: Comparative summary of representative review and survey papers on DER-integrated microgrids and distribution networks.

Reference	DER/MG	Network	OPF	Resilience	MMG Coord.	Method	Year
Chen et al. [21]	✓	✓	✓	✓	✓	Mixed	2021
Islam et al. [11]	✓	✓	✓	✓	✓	Mixed	2021
Tobajas et al. [22]	✓	✓	✓	✓	×	MPC	2022
Bordbari and Nasiri [12]	✓	✓	✓	✓	✓	Mixed	2024
De la Cruz et al. [23]	✓	✓	×	✓	✓	Mixed	2024
Yassim et al. [24]	✓	✓	×	×	✓	Mixed	2024
Zia et al. [25]	✓	×	×	×	×	Mixed	2018
Mirhoseini et al. [26]	✓	×	×	×	×	Mixed	2026
Shafiullah et al. [27]	✓	×	×	×	×	Mixed	2022
Ahmethodžić et al. [13]	✓	×	×	×	×	Mixed	2023
Yang et al. [4]	✓	✓	✓	×	×	Mixed	2023
Molzahn and Hiskens [28]	✓	✓	✓	×	×	Deterministic	2020
Nassef et al. [18]	✓	✓	×	×	×	Metaheuristic	2024
Liang et al. [14]	✓	✓	✓	×	×	Mixed	2025

(Continued)

Table 1 (continued)

Reference	DER/MG	Network	OPF	Resilience	MMG Coord.	Method	Year
Mehmood et al. [17]	✓	✓	×	×	×	Mixed	2026
Yang et al. [4]	✓	✓	✓	×	✓	Mixed	2024
Wu et al. [29]	✓	✓	×	×	✓	Learning-based	2023
Roald and Andersson [30]	✓	✓	×	×	✓	Distributed	2019
Gao et al. [31]	✓	✓	×	×	✓	Robust	2023
Zia et al. [32]	✓	×	×	×	✓	Mixed	2020
Lezama et al. [33]	✓	×	×	×	✓	Market-based	2019
Mengelkamp et al. [34]	✓	×	×	×	✓	Market-based	2018
Tan et al. [35]	✓	✓	✓	×	✓	Mixed	2024
This Review	✓	✓	✓	✓	✓	**All**	**2026**

Note: DER/MG denotes modelling of distributed energy resources and microgrids. Network indicates inclusion of electrical constraints (e.g., power flow, voltage, and line limits). OPF refers to optimization or optimal power flow formulations. Resilience denotes the ability to withstand and recover from disturbances. MMG Coord. indicates coordination among interconnected microgrids. A feature is marked (✓) only if explicitly addressed; otherwise (×). Method denotes the primary solution approach (deterministic, metaheuristic, learning-based, robust, distributed, or mixed).

The main contributions of this paper are summarised as follows:

1. This review provides a structured synthesis of optimization approaches for interconnected multi-microgrid systems operating under extreme events, with particular emphasis on distribution-level network-constrained optimal power flow (OPF) modelling and the preservation of electrical feasibility in coordinated operation.
2. It systematically examines resilience-oriented multi-objective optimization frameworks, highlighting the interactions and trade-offs among economic efficiency, operational security, and system resilience.
3. It analyses formulation-level challenges in integrating coordinated multi-microgrid decision-making with explicit distribution power-flow modelling, supported by evidence from existing review studies summarised in Table 1.
4. It establishes a conceptual framework that connects resilience-driven coordination with network-constrained optimization in interconnected distribution systems, and outlines future research directions toward scalable and learning-compatible optimization frameworks.

1.1 Research Questions

To enhance the focus and analytical depth of this review, the study is guided by the following research questions:

1. How do existing optimization frameworks incorporate distribution network constraints in interconnected multi-microgrid systems?
2. How effectively do these frameworks ensure satisfaction of power-flow constraints, voltage limits, and line capacity limits under high DER penetration and bidirectional power flow conditions?
3. How are resilience objectives integrated into network-constrained optimization models under uncertainty and extreme events?
4. What are the key limitations of current approaches, particularly in terms of scalability, constraint enforcement, and real-time applicability?

To systematically address these research questions and enable consistent comparison across the reviewed studies, a set of evaluation criteria is defined as follows.

1.2 Evaluation Criteria for Literature Comparison

Table 1 provides a structured comparison of the reviewed studies based on key evaluation criteria, including DER and microgrid modelling (DER/MG), representation of network constraints (Network), use of optimization and OPF formulations (OPF), consideration of resilience aspects (Resilience), and coordination among interconnected microgrids (MMG Coordination). A checkmark indicates that the feature is explicitly addressed, while a cross denotes its absence.

The remainder of this paper is organized as follows. Section 2 presents the review methodology and study selection process. Section 3 describes the architecture and operational characteristics of interconnected multi-microgrid systems. Section 4 formulates the optimization framework for network-constrained multi-microgrid systems. Section 5 reviews the optimization solution methods. Section 6 provides a comparative discussion and outlines future research directions. Finally, Section 7 concludes the paper.

2 Review Methodology and Study Selection

This review follows the PRISMA 2020 guidelines [20] to ensure a transparent and reproducible study selection process. A systematic search was conducted across IEEE Xplore, Scopus, ScienceDirect, SpringerLink, and the IET Digital Library, with Google Scholar used as a supplementary source. The search used keywords such as ("multi-microgrid" OR "interconnected microgrid" OR "networked microgrids") AND ("energy management" OR "optimal power flow" OR "optimization" OR "resilience"), and was limited to peer-reviewed journal articles published between 2015 and 2026.

The study selection and analysis process were guided by the research questions defined in Section 1.1, ensuring that the inclusion of literature directly supports the structured comparative synthesis of optimization frameworks, network constraints, and resilience strategies.

Studies were included if they: (i) addressed interconnected multi-microgrid systems, (ii) incorporated optimization, control, or resilience-oriented frameworks, and (iii) provided quantitative validation through simulation, case studies, or experimental results. Studies focusing on single microgrids, lacking methodological clarity, or outside the defined scope were excluded.

The selection process involved duplicate removal, title and abstract screening, and full-text assessment. A total of 220 records were identified, with 40 duplicates removed, leaving 180 records for screening. After excluding 50 records, 130 full-text articles were assessed, of which 27 were excluded due to irrelevance (n = 12), insufficient validation (n = 8), or out-of-scope applications (n = 7). As shown in Fig. 1, 103 studies were included in the final synthesis. It should be noted that not all included studies are explicitly cited in the main text; instead, representative and most relevant studies are referenced to support the comparative synthesis.

To ensure the reliability of the reviewed studies, a qualitative assessment was performed based on modelling accuracy, consideration of network constraints, validation methods, and clarity of reported results. Studies with incomplete methodological descriptions or lacking sufficient validation were excluded during the full-text review stage.

Following the selection process, the included studies were systematically analysed and categorised according to optimization methods, network modelling approaches, and resilience strategies, enabling a comparative synthesis aligned with the defined research questions. This structured methodology ensures that the review moves beyond descriptive summarisation toward an evidence-based and comparative synthesis of existing approaches.

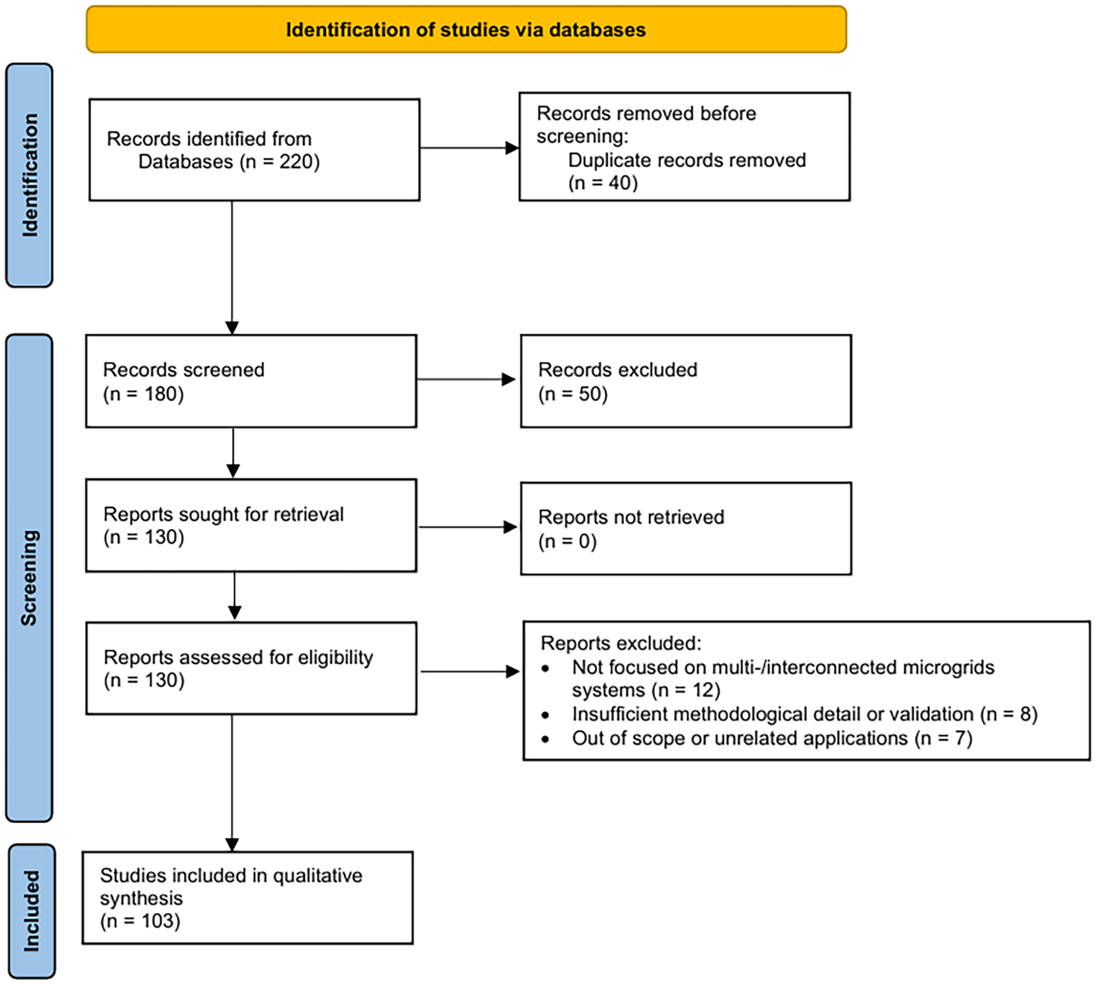

Figure 1: PRISMA 2020 flow diagram of the study selection process for interconnected multi-microgrid systems.

3 Interconnected Microgrid Architecture

Fig. 2 illustrates a conceptual architecture of an interconnected multi-microgrid (MMG) system within a radial distribution network. The system comprises multiple microgrids, denoted as MG_i, $i \in \mathcal{M}$, each integrating local DERs, including renewable generation units, energy storage systems, and loads, coordinated through local control. These microgrids are interconnected through the distribution network, where each connection point is represented as a bus (i.e., a node where generators, loads, and network elements are electrically connected), and are capable of exchanging power with neighbouring microgrids as well as with the upstream grid via tie-lines.

From a system perspective, the interconnection of multiple microgrids introduces strong electrical coupling through shared network constraints, including nodal power balance, voltage limits, and line capacity constraints. As a result, local power injections within an individual microgrid affect network-wide operating conditions, necessitating coordinated and network-constrained operation across the MMG system. This coupling becomes increasingly significant under high penetration of distributed energy resources, where reverse power flows and network congestion may arise [36–38].

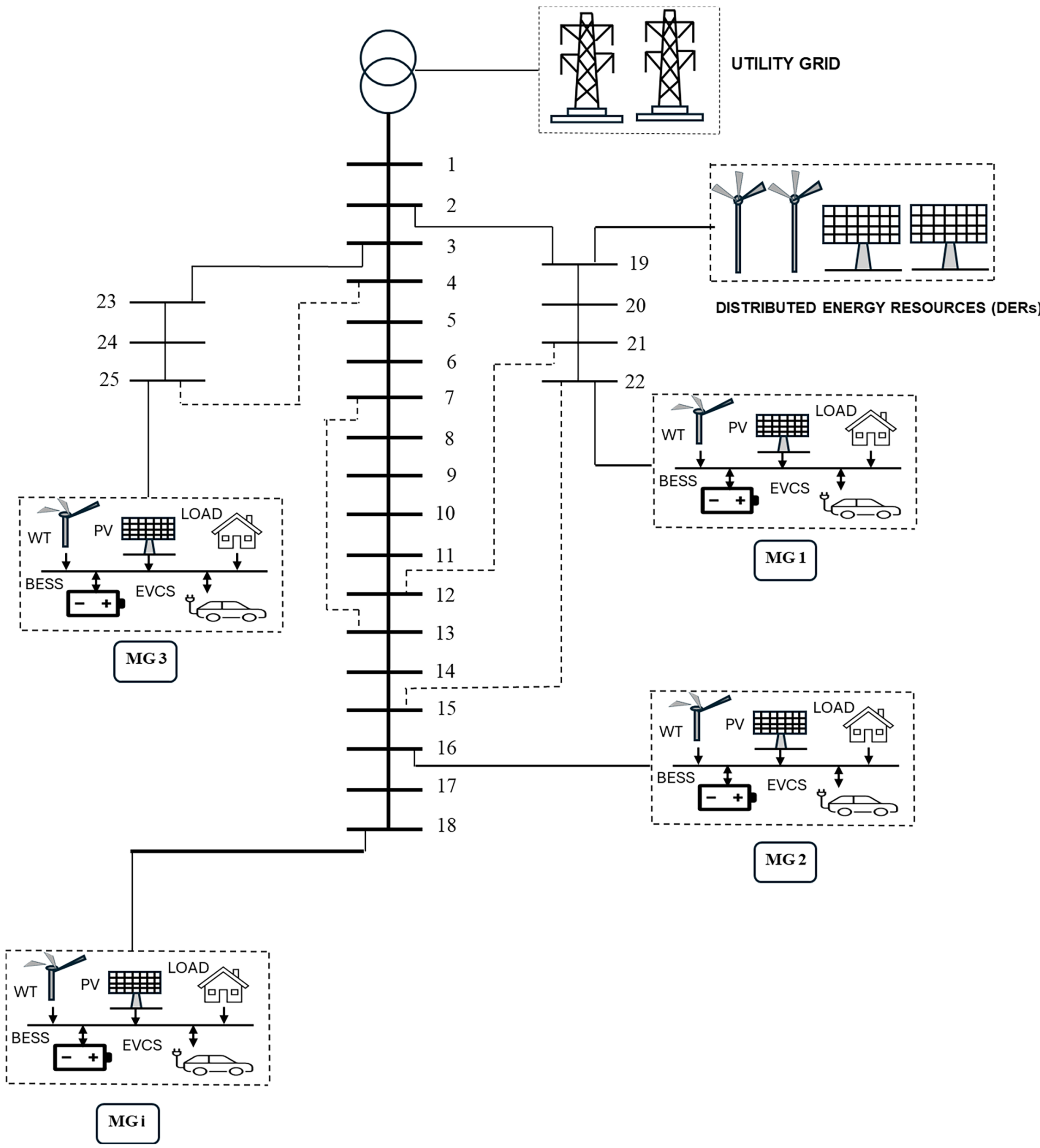

Figure 2: Conceptual architecture of interconnected multi-microgrids within a radial distribution network.

The physical architecture shown in Fig. 2 is systematically characterised in Table 1, where key components, including DER units, interconnecting lines, and tie-lines, are mapped to analytical dimensions such as DER modelling, network constraints, OPF formulation, resilience considerations, and coordination strategies for MMG operation. This mapping establishes a direct link between system-level representation and analytical modelling frameworks.

Despite these developments, a substantial portion of existing studies adopts simplified network representations or decoupled microgrid models, where inter-microgrid interactions are approximated or neglected. While such simplifications improve computational tractability, they may result in infeasible or misleading operational decisions, particularly under islanded operation, extreme events, or highly stressed network conditions. This limitation is especially critical in resilience-oriented studies, where accurate representation of network constraints is required to ensure secure and feasible operation [16,36–38].

The choice of system architecture and modelling assumptions directly influences the effectiveness of subsequent optimization and control strategies. In particular, the level of network modelling fidelity, representation of DER dynamics, and coordination structure determine the feasibility, scalability, and resilience performance of MMG systems. These aspects are examined in the following sections through the formulation of network-constrained optimization problems and the analysis of corresponding solution methodologies.

3.1 Network-Constrained Modelling in Interconnected MMG Systems

Accurate modelling of distribution network constraints is essential in interconnected MMG systems, as electrical coupling among microgrids directly affects voltage profiles, line flows, and power exchange. To capture these interactions, prior studies have employed various power flow formulations, including nonlinear AC-OPF, branch-flow models, DistFlow formulations, and their convex or linearised approximations [28,39–41].

AC-OPF models provide the most physically accurate representation of network behaviour by explicitly capturing voltage magnitudes, phase angles, and reactive power interactions. These models are widely adopted in studies where precise assessment of network feasibility and operational security is required. However, their nonlinear and nonconvex nature leads to high computational complexity, limiting their applicability in large-scale MMG systems and real-time optimization scenarios [28,39].

To improve computational tractability, branch-flow formulations are commonly employed in radial distribution networks. These models simplify the AC power flow equations while preserving key relationships between power flow, voltage magnitude, and line parameters. As a result, they are widely used in optimization-based energy management and scheduling problems for MMG systems. Nevertheless, studies indicate that these formulations rely on simplifying assumptions, such as neglecting line losses or approximating voltage drops, which may introduce inaccuracies under heavily loaded conditions or high DER penetration levels [36,38].

Further simplifications are introduced through linearised OPF models, which are often adopted to enable scalable optimization in large interconnected systems or to facilitate integration with metaheuristic and learning-based approaches. While these models significantly reduce computational burden, they may fail to capture nonlinear network behaviour, particularly under reverse power flow, congestion, or islanded operation conditions. This trade-off between accuracy and computational efficiency is a recurring theme in MMG modelling [16].

Overall, the choice of network modelling approach directly impacts the feasibility, scalability, and reliability of optimization outcomes in interconnected MMG systems. While simplified models enable tractable optimization, they may compromise physical accuracy, whereas detailed models improve fidelity at the expense of computational efficiency. Therefore, selecting an appropriate modelling framework requires careful consideration of system size, operational objectives, and the need to ensure constraint satisfaction under both normal and extreme operating conditions.

3.2 Modelling Approaches for DERs and Loads in MMG Systems

In interconnected MMG systems, DERs and loads are modelled using various approaches that balance accuracy and computational tractability. Across the literature, modelling strategies can be broadly categorised into forecast-based, uncertainty-aware, and detail-enhanced formulations [42–44]. Forecast-based models are widely adopted in optimization-oriented studies, where PV, wind generation, and load demand are represented using predicted profiles. These approaches enable efficient integration into optimization frameworks but rely heavily on forecast accuracy and may not adequately capture variability under uncertain conditions [45,46]. To address variability and uncertainty, many studies employ stochastic, robust, or scenario-based modelling techniques. These uncertainty-aware approaches improve system reliability and robustness, particularly for renewable generation and EV demand, but introduce increased computational complexity [14,47,48].

In addition, modelling approaches differ in the level of detail used to represent system components. Simplified models, such as aggregated EV loads and SOC-based BESS representations, are commonly used to maintain scalability in large MMG systems. In contrast, detailed models, including degradation-aware BESS formulations and individual EV behaviour, provide improved physical realism but significantly increase computational burden [49–51]. Overall, the literature reveals a consistent trade-off between modelling accuracy and computational efficiency. While simplified and forecast-based models are dominant in large-scale optimization studies, their limitations become significant under extreme events, islanded operation, and resilience-oriented scenarios [6,52].

In such conditions, nonlinear system behaviour, voltage instability, and dynamic interactions among DERs become more pronounced, which cannot be accurately captured by simplified formulations. This may lead to underestimation of constraint violations and over-optimistic assessment of system resilience and operational feasibility. These observations highlight the need for modelling frameworks that balance scalability with sufficient physical fidelity, particularly when integrating network constraints, uncertainty, and coordinated multi-microgrid operation within a unified optimization framework [47,53,54].

3.3 Coordination Architectures

Fig. 3 illustrates the internal architecture of a representative microgrid connected to the distribution network at bus i. The microgrid is defined within a boundary, where DERs, including WT, PV arrays, battery energy BESS, and electric vehicle charging stations (EVCS), are interfaced through power electronic converters. Vehicle-to-grid (V2G) capability enables bidirectional power exchange between electric vehicles and the grid [49,55–58]. These components exchange power through a common internal bus and collectively supply local loads. The net active and reactive power exchanged at bus i, denoted by P_i^{inj} and Q_i^{inj}, represent the aggregated contributions of generation, storage, EV charging, and local loads within the microgrid [36,38].

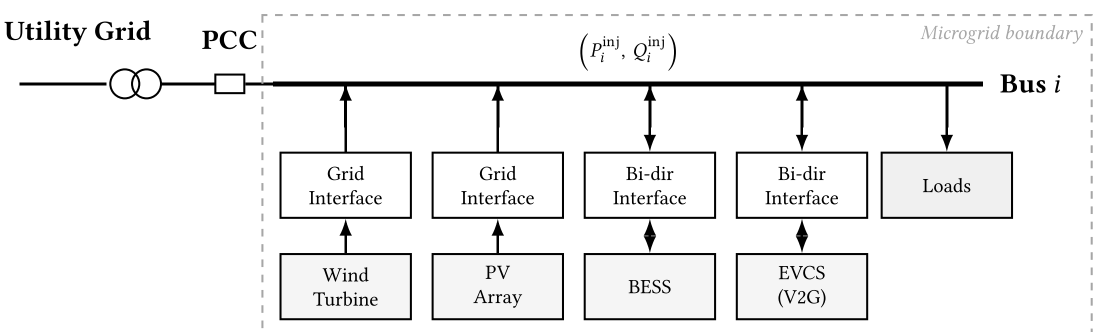

Figure 3: Internal architecture of a representative microgrid.

When multiple such microgrids are interconnected through a shared distribution network, their aggregated power injections become electrically coupled via network constraints. As a result, coordinated operation is required to ensure system-wide power balance, voltage regulation, and secure power exchange.

In the literature, this coordination is typically achieved through centralised, decentralised, and distributed control architectures. Centralised approaches enable globally optimal decision-making but face scalability and communication challenges, whereas decentralised methods improve scalability at the cost of reduced coordination. Distributed frameworks provide a balance by enabling cooperative decision-making among microgrids, although they introduce additional communication and convergence complexities [8,9].

Overall, the choice of coordination architecture directly influences the scalability, robustness, and effectiveness of interconnected MMG operation, particularly under network-constrained and resilience-oriented scenarios.

3.4 Resilience Characteristics of Interconnected Microgrids

Resilience in interconnected multi-microgrid systems is defined as the ability to withstand, adapt to, and recover from disturbances while maintaining acceptable operational performance [12,42,43]. This concept can be structured into three key dimensions: (i) robustness, which reflects the ability to sustain operation during disturbances; (ii) adaptability, referring to the capability to adjust system operation through control and coordination; and (iii) recovery, which involves restoring system functionality following disruptions. These dimensions are commonly represented in the literature through optimization objectives, operational constraints, and coordinated control strategies [59,60].

In practice, these resilience characteristics are realised through operational mechanisms such as islanded operation, coordinated power exchange, and network reconfiguration. However, their effectiveness depends on accurate system modelling and the ability to capture network constraints and dynamic interactions under stressed conditions [8,9]. Interconnected microgrids can enhance system resilience under extreme events such as severe weather disturbances or grid outages. In such conditions, individual microgrids can operate in islanded mode to maintain local power supply using DERs and energy storage systems [59,60]. At the same time, coordinated power exchange among neighbouring microgrids and the upstream utility grid enables load restoration and operational flexibility.

Within interconnected MMG systems, resilience is further supported by the ability to reconfigure power flows and utilise available local resources during disturbances. These capabilities allow the system to maintain critical loads and improve service continuity while satisfying distribution network constraints [61,62]. This limitation can lead to optimistic or misleading assessments of system resilience, highlighting the need for modelling approaches that balance computational tractability with sufficient physical fidelity.

From an optimization perspective, these resilience characteristics are incorporated into operational frameworks through objective functions and constraints that capture system performance under disturbances. Typical formulations include minimisation of unserved energy, maintenance of critical load supply, and enforcement of feasible operation under contingency scenarios. This integration enables a structured representation of resilience within network-constrained optimization of interconnected multi-microgrid systems.

3.5 Comparative Synthesis and Key Insights

Across the reviewed literature, a consistent pattern emerges in the trade-offs between modelling accuracy, computational tractability, and coordination complexity in interconnected MMG systems. Studies employing detailed network-constrained models, such as AC-OPF, demonstrate improved accuracy in ensuring electrical feasibility but face scalability limitations in large systems. In contrast, simplified and linearised models are more widely adopted in large-scale optimization due to their computational efficiency, although they may lead to infeasible or suboptimal solutions under stressed operating conditions [16,36–38].

Similarly, forecast-based DER modelling approaches are predominant in optimization-oriented studies, while uncertainty-aware methods are increasingly adopted to enhance robustness under renewable variability. However, these approaches introduce additional computational burden, limiting their real-time applicability. In terms of coordination, centralised frameworks provide global optimality but suffer from scalability and communication challenges, whereas distributed approaches offer improved scalability at the expense of convergence complexity [8,9,14,45,47,48].

From a resilience perspective, interconnected microgrids enhance system adaptability through islanded operation, coordinated power exchange, and network reconfiguration. Current approaches often adopt idealised representations of the system, which can overlook critical dynamics that emerge during extreme disturbances or heavily loaded conditions. This gap introduces uncertainty in how well resilience evaluations translate to real-world operation [14,42,43]. Overall, the literature indicates that no single modelling or coordination approach simultaneously satisfies scalability, accuracy, and resilience requirements. This highlights a critical research gap in developing integrated frameworks that can ensure network-constrained feasibility while maintaining computational efficiency and robustness under uncertainty.

4 Optimization Framework for Network-Constrained Multi-Microgrid Systems

Building upon the system-level modelling discussed in Section 3, the operation of interconnected MMG systems is commonly formulated as a network-constrained multi-period optimization problem. The objective is to determine feasible power injection schedules $\left(P_i^{\text{inj}}(t), Q_i^{\text{inj}}(t)\right)$ over a scheduling horizon $t \in \mathcal{T}$, subject to network constraints, DER operational limits, and interconnection requirements at the PCC. Fig. 4 presents a conceptual optimization structure adopted in many MMG studies, where forecasted inputs such as renewable generation, load demand, and DER constraints are integrated into a unified decision-making framework [45,63].

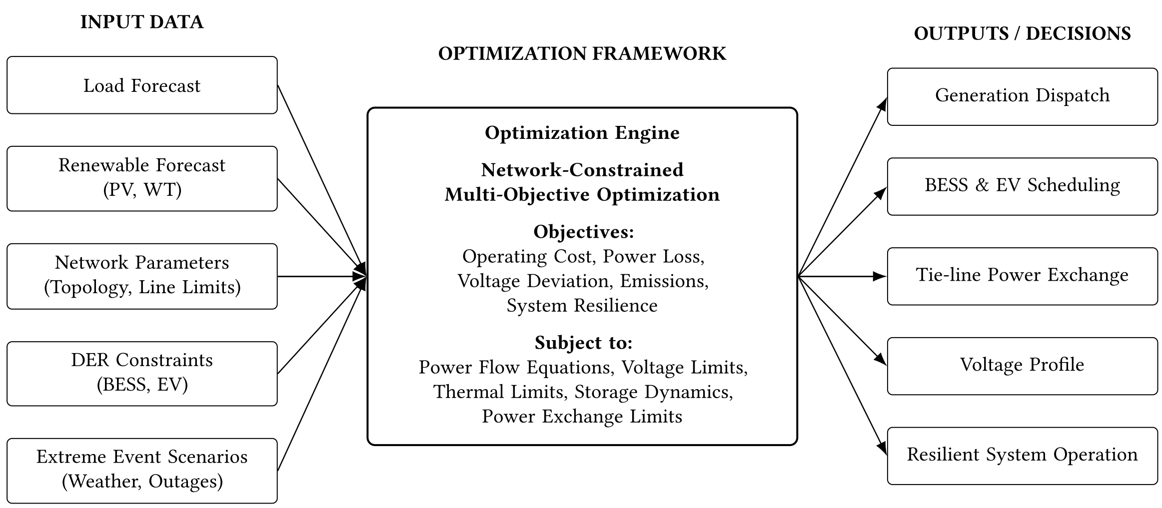

Figure 4: Conceptual optimization framework for network-constrained multi-microgrid operation incorporating power-flow constraints and resilience considerations.

In the literature, these problems are typically formulated as multi-objective optimization models that jointly consider economic performance, network operation, and resilience. Common objectives include minimisation of operational cost, power losses, and voltage deviations, while resilience-oriented studies incorporate metrics such as load restoration capability and operational flexibility under disturbances [11,12,64].

The feasible operating region is defined by network-constrained power-flow relationships and operational limits, ensuring physically consistent and secure system operation. However, incorporating multi-period dynamics and uncertainty significantly increases computational complexity, particularly in large-scale MMG systems. As a result, many studies adopt simplified or linearised formulations to improve tractability, at the expense of modelling accuracy under stressed or highly dynamic conditions [28,30,37,65].

In contrast, data-driven approaches such as RL have been explored to improve adaptability under uncertainty. While these methods enhance flexibility, they do not inherently guarantee constraint satisfaction. Consequently, recent studies integrate constraint-handling mechanisms, including projection-based control and hybrid RL–optimization frameworks, to maintain feasibility within network-constrained environments [66]. Overall, existing frameworks highlight a fundamental trade-off between computational efficiency, physical accuracy, and adaptability, motivating the development of integrated approaches that combine model-based optimization with learning-based methods for scalable and resilient MMG operation [58].

4.1 Objective Functions

The objective function defines the performance criteria used to evaluate and optimise the operation of interconnected multi-microgrid systems over the scheduling horizon $\mathcal{T}$. In the literature, these problems are typically formulated as multi-objective optimization frameworks that balance economic, technical, environmental, and reliability-related criteria, reflecting the diverse operational requirements of MMG systems [4,67].

4.1.1 Economic Objective

Economic objectives are widely adopted in grid-connected MMG operation and are commonly formulated as the minimisation of total operating cost over the scheduling horizon [10]. A representative formulation is

$$\min \sum_{t\in\mathcal{T}} \left[\pi(t)P_{\mathrm{PCC}}(t) + C_{\mathrm{deg},i}\big(P_{BESS,i}(t)\big)\right]\Delta t, \tag{1}$$

where $\pi(t)$ denotes the time-varying electricity price, $P_{\mathrm{PCC}}(t)$ represents the active power exchanged between the multi-microgrid system and the utility grid at the point of common coupling (PCC), and Δt is the duration of each scheduling interval. Positive values of $P_{\mathrm{PCC}}(t)$ indicate power import from the utility grid, while negative values represent export. The function $C_{\mathrm{deg},i}(\cdot)$ models battery degradation cost as a function of charging and discharging power $P_{BESS,i}(t)$ at microgrid i [50]. Such formulations prioritise cost efficiency, although they may require additional constraints or objectives to ensure network security and resilience under dynamic operating conditions.

4.1.2 Network Performance Objectives

Network-oriented objectives are incorporated to ensure that optimization outcomes remain consistent with electrical performance requirements [36,67]. One commonly adopted objective is the minimisation of active power losses in distribution lines:

$$\min \sum_{t\in\mathcal{T}} \sum_{(i,j)\in\mathcal{L}} R_{ij} I_{ij}^2(t), \tag{2}$$

where R_{ij} denotes the resistance of line $(i,j) \in \mathcal{L}$ and $I_{ij}(t)$ is the magnitude of the line current at time t. This objective reflects the electrical efficiency of the distribution network. In addition, voltage regulation objectives are frequently included to maintain acceptable voltage profiles across the network, particularly under high DER penetration.

$$\min \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} \left(V_i(t) - V_i^{\text{ref}} \right)^2, \tag{3}$$

where $V_i(t)$ represents the voltage magnitude at bus i and V_i^{ref} denotes the nominal reference voltage [37]. These objectives are critical in preventing voltage violations and ensuring stable operation of interconnected MMG systems.

4.1.3 Environmental Objective

Environmental objectives are increasingly integrated into MMG optimization frameworks to support low-carbon operation [10]. A common approach is to minimise carbon emissions associated with grid power exchange:

$$\min \sum_{t \in \mathcal{T}} \gamma(t) P_{\text{PCC}}(t) \Delta t, \tag{4}$$

where $\gamma(t)$ represents the emission intensity of grid electricity at time t. This formulation encourages higher utilisation of renewable generation and reduces dependence on carbon-intensive grid supply, although its effectiveness depends on the availability and accuracy of emission intensity data.

4.1.4 Reliability and Service Objectives

Reliability-oriented objectives are incorporated to enhance system robustness, particularly under constrained or islanded operating conditions [47]. For example, load curtailment penalties may be included as

$$\min \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} P_{L,i}^{\text{shed}}(t), \tag{5}$$

where $P_{L,i}^{\text{shed}}(t)$ denotes the curtailed load at bus i during time interval t. Such formulations prioritise service continuity and are particularly important in resilience-oriented MMG studies. When electric vehicles are incorporated, service adequacy can be represented through penalties on unmet charging demand, ensuring that the cumulative energy delivered satisfies required charging levels within specified time windows [51].

4.1.5 Multi-Objective Formulation

In practice, MMG optimization problems are formulated as multi-objective frameworks that require trade-offs among economic efficiency, network performance, environmental sustainability, and reliability. A general weighted aggregation form is expressed as

$$\min F = \sum_{k=1}^{K} w_k f_k(x), \tag{6}$$

where $f_k(x)$ represents each objective function, w_k is its weighting coefficient, and x is the vector of decision variables, including power injections, storage and EV scheduling variables, and network variables [42,43].

While weighted-sum formulations are widely adopted due to their simplicity and ease of implementation, their effectiveness depends on appropriate selection of weighting coefficients and may not fully capture conflicting objectives. As a result, alternative multi-objective techniques, such as Pareto-based approaches, are also explored in the literature to better represent trade-offs among competing criteria.

Overall, the literature indicates that objective function design plays a critical role in shaping optimization outcomes, and no single formulation can simultaneously optimise all performance criteria without trade-offs, particularly in large-scale and resilience-constrained MMG systems.

4.2 Constraints

The optimization problem is subject to electrical network constraints, microgrid resource limits, and grid exchange boundaries, which collectively define the feasible operating region of interconnected MMG systems. These constraints are typically derived from power-flow formulations and device-level operational limits to ensure physically consistent and secure operation across the network. All constraints are enforced for each time interval $t \in \mathcal{T}$ over the scheduling horizon [4,67].

4.2.1 Network Power Flow Constraints

The electrical feasibility of the interconnected multi-microgrid system is governed by the branch-flow equations, which capture the physical relationships between power flows, voltages, and currents in the distribution network [4]. These equations are used to model network-constrained operation in OPF problems, ensuring that power balance, voltage limits, and line capacity constraints are satisfied.

Let $\mathcal{N}$ denote the set of buses and $\mathcal{L}$ the set of distribution lines $(i, j) \in \mathcal{L}$. Here, $i, j, k \in \mathcal{N}$ denote bus indices, where j represents buses connected downstream of bus i through outgoing lines $(i, j) \in \mathcal{L}$, and k represents neighbouring buses connected to bus i through incoming lines $(k, i) \in \mathcal{L}$. The active and reactive power injections at bus i are represented by $P_i^{\text{inj}}(t)$ and $Q_i^{\text{inj}}(t)$, respectively.

Such network-constrained formulations are widely adopted in MMG optimization studies to ensure voltage regulation and line loading limits, although their nonlinear nature introduces significant computational complexity in large-scale systems. In this context, the OPF problem aims to determine optimal power injections and resource scheduling that minimise operational cost or losses while satisfying network constraints. In this context, the OPF problem aims to determine optimal power injections and resource scheduling that minimise operational cost or losses while satisfying network constraints [28,68].

The nodal power balance equations are expressed as

$$P_i^{\text{inj}}(t) = \sum_{j:(i,j)\in\mathcal{L}} P_{ij}(t) - \sum_{k:(k,i)\in\mathcal{L}} P_{ki}(t) \tag{7}$$

$$Q_i^{\text{inj}}(t) = \sum_{j:(i,j)\in\mathcal{L}} Q_{ij}(t) - \sum_{k:(k,i)\in\mathcal{L}} Q_{ki}(t) \tag{8}$$

where $P_{ij}(t)$ and $Q_{ij}(t)$ denote the active and reactive power flows from bus i to bus j along line (i, j). These equations ensure that the net power injection at each bus equals the difference between outgoing and incoming branch flows [67].

Voltage propagation along radial distribution networks is described by

$$V_j^2(t) = V_i^2(t) - 2\left(R_{ij}P_{ij}(t) + X_{ij}Q_{ij}(t)\right) + \left(R_{ij}^2 + X_{ij}^2\right) I_{ij}^2(t), \tag{9}$$

$$P_{ij}^2(t) + Q_{ij}^2(t) = V_i^2(t) I_{ij}^2(t), \tag{10}$$

where $V_i(t)$ denotes the voltage magnitude (typically in per-unit) at bus i, $I_{ij}(t)$ represents the magnitude of the branch current, and R_{ij} and X_{ij} denote the resistance and reactance of line (i, j). These equations capture the nonlinear coupling between bus voltages, branch currents, and power flows in radial distribution networks [4,37].

Operational security is enforced through voltage magnitude limits

$$V_{\min} \leq V_i(t) \leq V_{\max}, \quad \forall i \in \mathcal{N}, \tag{11}$$

where $V_{\min}$ and $V_{\max}$ denote permissible voltage bounds defined by distribution standards [67]. Thermal limits on distribution lines are imposed as

$$P_{ij}^2(t) + Q_{ij}^2(t) \leq \left(S_{ij}^{\max}\right)^2, \quad \forall (i,j) \in \mathcal{L}, \tag{12}$$

where $S_{ij}^{\max}$ denotes the apparent power rating of line (i,j). These constraints ensure voltage regulation and prevent conductor overheating across the distribution network [37].

While these constraints ensure physical feasibility, solving the resulting nonlinear power-flow equations can be computationally demanding, leading many studies to adopt linearised approximations in large-scale MMG optimization problems.

4.2.2 Microgrid Resource Constraints

Within each microgrid connected at bus i, distributed energy resources operate under technical limits. Battery operation is restricted by power and energy limits

$$0 \leq P_{BESS,i}^{ch}(t) \leq P_{BESS,i}^{ch,\max}, \quad 0 \leq P_{BESS,i}^{dis}(t) \leq P_{BESS,i}^{dis,\max}, \tag{13}$$

$$SOC_i^{\min} \leq SOC_i(t) \leq SOC_i^{\max}. \tag{14}$$

where $SOC_i(t)$ denotes the state of charge of the battery at microgrid i at time t.

These constraints are commonly used to model intertemporal flexibility of storage systems, although simplified SOC dynamics may not fully capture degradation effects or nonlinear battery behaviour.

The aggregated electric vehicle charging power at microgrid i is denoted by $P_{EV,i}(t)$. A positive value represents charging demand, whereas a negative value corresponds to vehicle-to-grid power injection [51]. Charging power is limited by installed capacity:

$$-P_{EV,i}^{\max} \leq P_{EV,i}(t) \leq P_{EV,i}^{\max}. \tag{15}$$

Such aggregated EV models improve computational tractability, but may neglect individual vehicle behaviour and uncertainty in user patterns.

4.2.3 PCC Power Exchange Limits

At the point of common coupling (PCC), the active power exchanged between the interconnected multi-microgrid system and the utility grid is denoted by $P_{\mathrm{PCC}}(t)$. Contractual and technical bounds are imposed as

$$P_{\mathrm{PCC}}^{\min} \leq P_{\mathrm{PCC}}(t) \leq P_{\mathrm{PCC}}^{\max}, \tag{16}$$

where $P_{\mathrm{PCC}}^{\min}$ and $P_{\mathrm{PCC}}^{\max}$ denote the minimum and maximum allowable power exchange limits.

These PCC constraints play a critical role in limiting power exchange with the upstream grid and are particularly important in coordinated MMG operation, where excessive tie-line flows may lead to voltage violations or congestion.

These bounds restrict tie-line loading and influence network voltage profiles and branch power flows [36,67].

Overall, the integration of network equations, resource limits, and PCC exchange constraints transforms the optimization problem into a network-constrained optimal power flow framework, where ensuring feasibility, scalability, and computational efficiency remains a key challenge in interconnected MMG systems.

4.3 Multi-Objective Aggregation

The network-constrained optimization problem formulated in this study generally involves multiple and potentially conflicting objectives, including economic cost, distribution network power losses, voltage deviation, emissions, and reliability-related indices [37].

Let $f_k(x)$ denote the k-th objective function, where $k = 1, 2, \ldots, K$, and x represents the vector of optimization variables. The decision vector x may include bus power injections $\left(P_i^{\text{inj}}(t), Q_i^{\text{inj}}(t)\right)$, branch power flows $P_{ij}(t)$ and $Q_{ij}(t)$, bus voltages $V_i(t)$, battery power $P_{BESS,i}(t)$, state of charge $SOC_i(t)$, and electric vehicle charging power $P_{EV,i}(t)$ over the scheduling horizon $t \in \mathcal{T}$. A commonly adopted aggregation strategy is the weighted sum formulation, which converts a multi-objective optimization problem into a single-objective form [69,70].

$$F(x) = \sum_{k=1}^{K} w_k f_k(x), \tag{17}$$

where $F(x)$ denotes the aggregated objective function, $w_k \geq 0$ represents the weighting coefficient assigned to the k-th objective, and $\sum_{k=1}^{K} w_k = 1$ is often imposed for normalisation. The selection of w_k reflects the relative importance assigned to economic, technical, environmental, or reliability criteria. Although computationally efficient and compatible with deterministic solvers such as MILP, SOCP, and convex OPF formulations, the weighted sum approach may not capture non-convex regions of the Pareto front.

An alternative strategy is the ϵ-constraint method [71], in which one objective is selected as the primary optimization target while the remaining objectives are converted into inequality constraints:

$$\min_{x} \; f_1(x), \tag{18}$$

$$f_k(x) \leq \epsilon_k, \quad k = 2, 3, \ldots, K, \tag{19}$$

where ϵ_k denotes a predefined performance bound for the k-th objective. By varying ϵ_k systematically, a set of Pareto-optimal solutions can be generated. This approach is particularly suitable when economic performance is prioritised while maintaining network voltage security, thermal compliance, or emission limits within acceptable ranges [37]. Pareto-based evolutionary methods directly approximate the set of non-dominated solutions without predefined weighting coefficients or hierarchical structure [72]. Let $\mathcal{P}$ denote the Pareto set defined as

$$\mathcal{P} = \left\{x^* \in \mathcal{X} \;\middle|\; \nexists\, x \in \mathcal{X} \text{ such that } f_k(x) \leq f_k(x^*)\ \forall k, \text{ and } f_j(x) < f_j(x^*) \text{ for at least one } j\right\}, \tag{20}$$

where $\mathcal{X}$ represents the feasible set defined by the branch-flow equations, voltage magnitude limits, thermal constraints, resource dynamics, and PCC power exchange bounds. Evolutionary algorithms such as NSGA-II and MOPSO are frequently employed to explore $\mathcal{P}$, particularly when the optimization problem is nonlinear, non-convex, or includes discrete decisions [37].

The choice of aggregation strategy depends on the dimensionality of the network, the level of power-flow modelling detail, computational tractability requirements, and the desired balance between economic and network-level technical performance. In network-constrained multi-microgrid systems, aggregation methods must preserve the feasibility of the branch-flow equations and voltage limits while enabling systematic trade-off analysis among competing operational objectives [37,47].

4.4 Decision Variables and Resource Representation

Decision variables represent controllable quantities that determine power exchange and system operation in interconnected MMG systems. At the network level, the primary decision variables are the active and reactive power injections at each bus, denoted by

$$\left(P_i^{\text{inj}}(t), Q_i^{\text{inj}}(t)\right), \quad \forall i \in \mathcal{N},\ t \in \mathcal{T}. \tag{21}$$

These variables capture the aggregated interaction between each microgrid and the distribution network and are commonly used in OPF-based formulations. Additional network variables, such as branch power flows, currents, and bus voltages, are included to enforce physical feasibility [28,37].

At the microgrid level, decision variables typically include energy storage and flexible demand resources, such as battery power $P_{BESS,i}(t)$, state of charge $SOC_i(t)$, and aggregated electric vehicle charging power $P_{EV,i}(t)$ [49,51,73]. Battery and EV models are often represented using simplified aggregated formulations to maintain computational tractability in large-scale MMG systems, although such representations may not capture detailed operational dynamics [16,49].

At each node, the net power injection is determined by the balance between local renewable generation, storage operation, EV demand, and load consumption, reflecting the aggregated interaction between microgrid resources and the distribution network. Overall, the selection and representation of decision variables directly influence the complexity, scalability, and accuracy of MMG optimization models, particularly when integrating network constraints and uncertainty [36,38].

4.5 Uncertainty Representation

Uncertainty arising from renewable generation variability, load forecast errors, and electricity price fluctuations is a critical challenge in network-constrained MMG optimization [4].

Three main approaches are commonly adopted to address uncertainty: scenario-based stochastic programming, robust optimization, and chance-constrained formulations. Scenario-based methods capture uncertainty through a finite set of representative scenarios, enabling detailed modelling at the expense of increased computational complexity. Robust optimization provides worst-case guarantees under bounded uncertainty but may lead to conservative solutions, while chance-constrained approaches offer a balance by enforcing probabilistic constraint satisfaction [37,47].

These uncertainty modelling techniques are typically integrated with network-constrained power-flow formulations to ensure voltage and thermal limits are satisfied under uncertain operating conditions. However, incorporating uncertainty significantly increases computational burden, particularly in multi-period MMG systems, motivating the use of simplified modelling techniques or decomposition-based approaches in large-scale applications [67].

4.6 Resilience-Oriented Operation under Extreme Events

Extreme weather events such as storms, floods, and equipment failures introduce high-impact disturbances, including line outages and supply interruptions, which significantly challenge the secure operation of distribution networks. Under such disturbances, maintaining reliable electricity supply becomes a critical operational challenge. Interconnected microgrids enhance resilience by enabling local supply through distributed generation, energy storage, and coordinated power exchange among neighbouring microgrids.

In the literature, resilience is incorporated into network-constrained optimization frameworks through additional objectives and constraints that explicitly account for system performance under contingency conditions. A commonly adopted approach is the minimisation of unserved energy or load shedding, which directly quantifies system survivability during disturbances. In this context, the curtailed load at bus i during time interval t is denoted by $P_i^{\text{shed}}(t)$, representing the portion of demand that cannot be supplied due to generation shortages or network limitations [16,37,42,43].

Another widely used approach models contingency scenarios by modifying network constraints to reflect component outages. For example, line outage conditions can be modelled by enforcing branch capacity limits only on available lines:

$$|P_{ij}(t)| \leq \delta_{ij} S_{ij}^{\max}, \tag{22}$$

where $\delta_{ij} \in \{0,1\}$ is a binary parameter indicating the operational status of line (i,j) during an extreme event. A value $\delta_{ij} = 1$ indicates that the line is available, whereas $\delta_{ij} = 0$ represents a line outage condition.

While such formulations improve system resilience by explicitly considering contingency conditions, they significantly increase computational complexity, particularly in multi-period and large-scale MMG systems. Moreover, many existing studies rely on simplified network models, which may not fully capture system behaviour under extreme and highly nonlinear operating conditions.

By incorporating resilience-oriented objectives and contingency constraints together with distribution-level power-flow models, optimization frameworks can support coordinated operation of interconnected microgrids during disturbances [36–38]. Overall, achieving a balance between resilience performance, computational tractability, and physical accuracy remains a key challenge, motivating the development of scalable and network-aware optimization frameworks for extreme-event operation.

4.7 Overall Optimization Formulation

The coordinated operation of interconnected MMG systems is commonly formulated as a network-constrained OPF problem, which integrates decision variables, objective functions, and operational constraints into a unified optimization framework [4,67].

OPF-based formulations enable coordinated scheduling of distributed energy resources, including renewable generation, battery storage, electric vehicles, and power exchange with the utility grid, while ensuring compliance with network constraints. Depending on the modelling approach, these formulations may be implemented using deterministic, stochastic, or robust optimization techniques to account for uncertainty and system variability.

The general optimization problem can be expressed as

$$\min_{x} \; F(x) \tag{23}$$

where x denotes the vector of decision variables, including power injections, storage and EV scheduling variables, and network state variables, and $F(x)$ represents the aggregated objective function defined in Section 4.1.

Subject to network power-flow equations, voltage and line constraints, resource operational limits, and interconnection constraints at the point of common coupling. For resilience-oriented operation, additional contingency constraints and performance metrics, such as load shedding minimisation, are incorporated to enhance system survivability under extreme events [37].

While such unified formulations enable coordinated and physically feasible operation, they also introduce significant computational complexity, particularly in large-scale and multi-period MMG systems. This motivates the development of scalable and efficient solution methods, which are discussed in the following section.

5 Optimization Solution Methods

This section provides a structured and comparative review of optimization solution methods for network-constrained multi-microgrid operation, with emphasis on their ability to balance economic objectives, operational security, and resilience requirements under realistic system conditions [74–76]. The reviewed approaches are categorised into four main groups: deterministic optimization, stochastic and robust optimization, metaheuristic algorithms, and RL-based methods. This classification enables systematic comparison of how different methods address key challenges, including (i) trade-offs among cost, voltage security, and resilience performance, (ii) uncertainty in renewable generation, load demand, and market conditions, and (iii) enforcement of electrical network constraints [77].

For each category, the discussion highlights modelling assumptions, applicability to network-constrained OPF problems, and limitations related to scalability, convergence, and real-time implementation. Particular attention is given to the ability of each method to ensure physically feasible solutions, especially under high DER penetration and extreme operating conditions. Fig. 5 summarises the classification of optimization methods and their application domains in interconnected multi-microgrid systems, providing a conceptual overview to support the comparative analysis presented in this section.

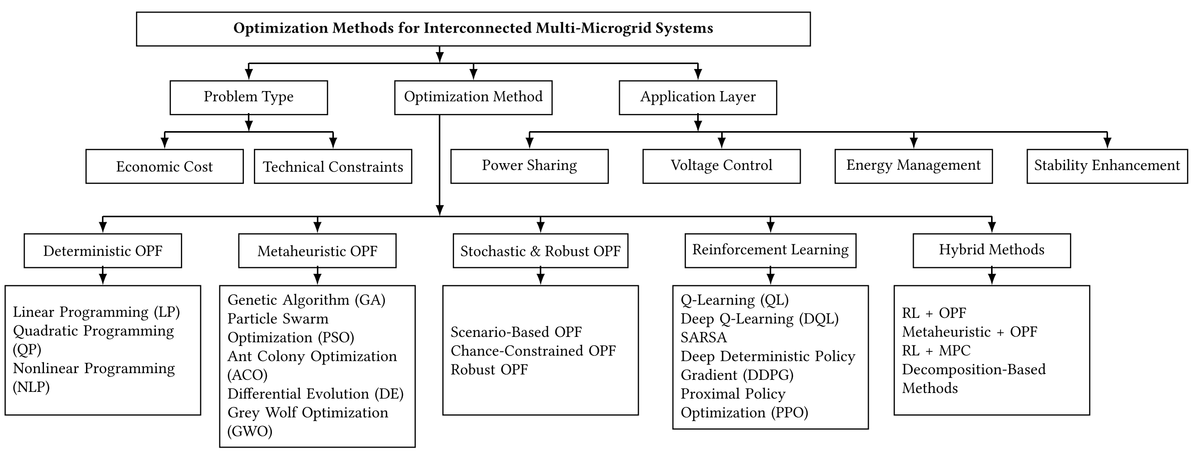

Figure 5: Classification of optimization methods and their application domains in interconnected multi-microgrid systems.

5.1 Deterministic Network-Constrained Optimization

Deterministic optimization forms the foundational approach for solving network-constrained optimal power flow (OPF) problems in interconnected multi-microgrid systems [4,39]. These methods explicitly incorporate power-flow equations, voltage limits, and line constraints, enabling coordinated scheduling of distributed energy resources while ensuring electrical feasibility.

Deterministic OPF formulations are widely applied in planning and day-ahead operational contexts, where system states can be reasonably predicted. Linear, convex, and mixed-integer programming models are commonly adopted to improve computational tractability and represent discrete operational decisions such as unit commitment, network reconfiguration, and scheduling. Multi-objective deterministic formulations are frequently used to capture trade-offs among economic cost, network losses, voltage regulation, and asset degradation, with solution approaches typically based on weighted-sum or Pareto-based optimization techniques [69,70].

Compared with stochastic, robust, and learning-based approaches, deterministic methods provide strong guarantees of constraint satisfaction due to their explicit incorporation of network equations. However, their reliance on point forecasts limits their ability to capture uncertainty in renewable generation and demand variability, which may result in suboptimal or infeasible operation under highly dynamic or extreme conditions. As a result, deterministic optimization is most effective in predictable operating environments, while its performance degrades in scenarios requiring adaptive or uncertainty-aware decision-making, highlighting the need for more flexible solution frameworks discussed in subsequent subsections.

5.2 Metaheuristic Network-Constrained Optimization

Metaheuristic optimization methods are widely applied to network-constrained OPF problems in interconnected multi-microgrid systems, particularly when nonlinear network behaviour, inter-temporal coupling, and discrete decision variables make deterministic formulations difficult to solve [18,78].

These methods employ population-based or stochastic search strategies, such as genetic algorithms, particle swarm optimization, and differential evolution, to explore complex solution spaces. Network constraints are typically incorporated through embedded power-flow calculations, where candidate solutions are evaluated using AC or branch-flow models [39]. Metaheuristic approaches are particularly suitable for multi-objective optimization problems, where Pareto-based techniques are used to balance conflicting criteria such as operational cost, power losses, voltage regulation, and resilience-related metrics. Their flexibility enables application to highly nonlinear and nonconvex problems that are difficult to handle using conventional optimization methods.

However, compared with deterministic OPF methods, constraint enforcement in metaheuristic approaches is typically indirect and relies on penalty functions or repair mechanisms, which do not guarantee strict satisfaction of network constraints. In addition, each candidate solution requires repeated power-flow evaluations, leading to high computational burden and limited scalability for large-scale systems or multi-period optimization problems. The performance of metaheuristic algorithms is highly sensitive to parameter selection, and inappropriate tuning may result in premature convergence or entrapment in local optima, as reported in recent studies on power system optimization [18,78].

5.3 Stochastic and Robust Network-Constrained Optimization

Uncertainty in renewable generation, load demand, and market conditions significantly affects power flows and voltage profiles in interconnected multi-microgrid systems. Stochastic and robust optimization extend deterministic OPF formulations to maintain network feasibility under such uncertain operating conditions. Stochastic optimization represents uncertainty using multiple scenarios and is widely applied in uncertainty-aware scheduling and resilience-oriented studies [38,47]. These approaches enable adaptive decision-making across different operating conditions while preserving network constraints. However, the inclusion of multiple scenarios increases problem size, requiring scenario reduction and decomposition techniques to maintain computational tractability [28,38,48].

Robust optimization addresses uncertainty without relying on probability distributions by enforcing feasibility over predefined uncertainty sets. This ensures system security under worst-case conditions, particularly for voltage regulation and thermal limits. However, studies report that such formulations can be overly conservative, leading to increased operating cost or renewable curtailment. Chance-constrained and distributionally robust variants provide a balance between reliability and economic performance by allowing controlled levels of constraint violation or accounting for ambiguity in uncertainty distributions [30]. These approaches improve flexibility but still require careful modelling of uncertainty.

Across recent studies, stochastic and robust approaches are primarily applied in uncertainty-aware and resilience-oriented operation of multi-microgrid systems. Their effectiveness depends strongly on scenario generation quality and the design of uncertainty sets, which directly influence solution robustness and computational burden. In large-scale systems, the resulting formulations often lead to high-dimensional optimization problems, limiting real-time applicability despite improved security performance. Overall, these approaches enhance the ability of network-constrained OPF to operate under uncertainty, but their practical deployment in large-scale systems remains limited by computational requirements.

5.4 Reinforcement Learning–Based Network-Constrained Methods

RL has emerged as a data-driven approach for control and decision-making in interconnected microgrid and distribution network operation [79]. Unlike conventional optimization methods that rely on explicit system models, RL enables agents to learn control policies through interaction with dynamic environments, making it suitable for systems with high penetration of DERs and uncertain operating conditions.

In network-constrained multi-microgrid systems, RL is applied to determine control actions such as generation dispatch, battery charging/discharging, and electric vehicle scheduling. The problem is commonly formulated as a Markov Decision Process (MDP), where the agent observes system states (e.g., bus voltages, power flows, DER outputs, and state-of-charge), selects actions, and receives rewards that reflect operational objectives such as cost, constraint violations, and resilience performance. The learning objective is to maximise the expected cumulative reward:

$$G_t = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k+1}\right], \tag{24}$$

where G_t represents the expected return from time step t, and $\gamma \in (0, 1)$ is the discount factor that balances immediate and future rewards. This formulation provides a general framework for sequential decision-making, while practical implementation requires careful design of state, action, and reward structures to reflect physical network behaviour.

For large-scale systems with continuous state and action spaces, deep reinforcement learning (DRL) methods, including value-based and actor–critic approaches, are widely adopted to improve scalability and enable coordinated control across interconnected microgrids [57,66,80]. While these methods can capture nonlinear system dynamics through interaction with the environment, they do not inherently guarantee satisfaction of physical network constraints.

This limitation is particularly critical in safety-sensitive power system applications, where infeasible control actions may lead to voltage violations, line congestion, or system instability, especially under unseen or extreme operating conditions. Recent works in microgrid and distribution network operation have proposed several mechanisms to improve constraint compliance in RL-based control. These include action masking to restrict infeasible decisions, projection-based correction of control actions using power-flow models, and constrained RL formulations that incorporate penalty terms or Lagrangian relaxation within the learning process [57,80,81]. In addition, hybrid approaches that integrate RL with OPF-based feasibility checks have been proposed to enhance operational reliability and enforce network constraints during decision-making.

Nevertheless, these approaches do not provide strict feasibility guarantees, and learned policies may still generate infeasible or unsafe actions under unseen conditions. This lack of guaranteed feasibility poses a significant risk in critical infrastructure operation, where even occasional constraint violations may lead to unacceptable reliability and safety consequences. This limitation remains a major barrier to the deployment of RL-based control in safety-critical power system applications, particularly in large-scale interconnected multi-microgrid systems where reliability and operational security are essential.

5.4.1 RL-Based Multi-Microgrid Optimization Framework

As shown in Fig. 6, RL provides a data-driven framework for coordinating interconnected multi-microgrid operation under network constraints by learning control policies through interaction with the system environment [79,80]. In this setting, the agent observes system states—including load demand, renewable generation, battery state-of-charge, and network variables such as bus voltages and line power flows—and determines control actions such as generation dispatch, storage operation, reactive power support, and inter-microgrid power exchange. The reward function is designed to capture multiple operational objectives, including economic cost, power losses, voltage regulation, and resilience performance. Through iterative interaction with the environment, RL enables adaptive and real-time decision-making under dynamic and uncertain operating conditions. For high-dimensional systems, DRL methods are adopted to approximate value functions or policies, enabling scalable control of interconnected microgrids [57,66,80,82].

RL-based approaches are mainly applied in real-time and adaptive control scenarios, where model uncertainty and system variability limit the effectiveness of conventional optimization methods. However, studies report challenges related to convergence stability, sensitivity to reward design, and inconsistent performance under unseen operating conditions. In particular, ensuring compliance with physical network constraints remains a critical limitation without additional constraint-handling mechanisms. Overall, RL provides a flexible framework for adaptive multi-microgrid control, but its deployment in network-constrained and safety-critical applications requires integration with physics-based models or constraint-enforcement strategies.

5.4.2 Types of Reinforcement Learning Methods Used in Microgrid Research

Reinforcement learning methods applied in microgrid optimization can be broadly classified into classical tabular approaches and DRL techniques [79,80,83]. Early studies employed tabular methods such as Q-learning and SARSA, which estimate value functions using discrete state–action mappings [84]. While computationally simple, these approaches are not suitable for large-scale multi-microgrid systems due to the exponential growth of the state space when network variables and distributed resources are included. To address scalability limitations, DRL methods use neural networks to approximate value functions or policies, enabling operation in high-dimensional and continuous control environments. Common approaches include value-based methods for discrete decision-making and actor–critic methods for continuous control tasks [57,66,85].

DRL significantly improves scalability and enables coordinated control across interconnected microgrids; however, it introduces additional challenges related to training instability, hyperparameter sensitivity, and increased computational requirements. Moreover, the lack of inherent mechanisms to enforce network constraints limits its reliability in network-constrained optimization problems without supplementary safety or feasibility layers.

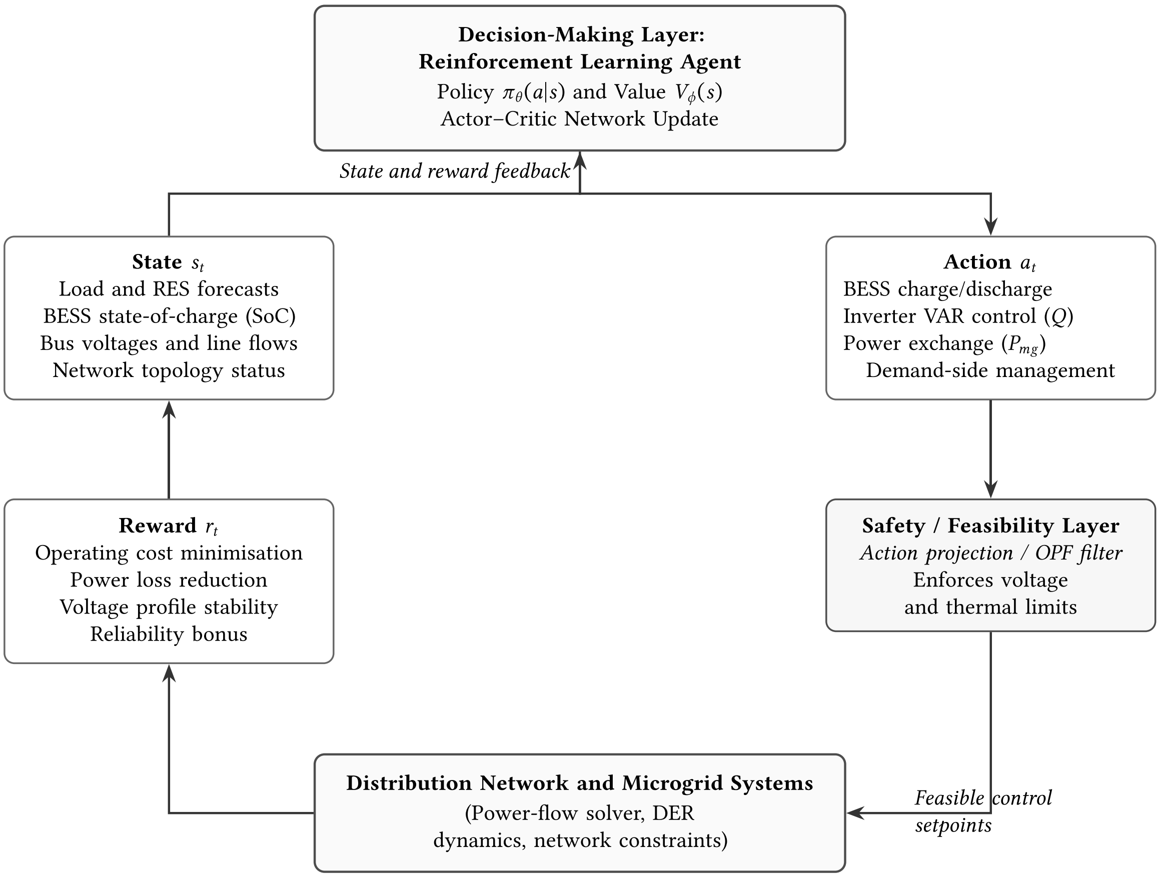

Figure 6: Refined RL framework for microgrid control.

5.4.3 Strength and Limitations of RL in Multi-Microgrid Optimization

RL provides a flexible framework for optimization in interconnected multi-microgrid systems by learning control policies through interaction with the system environment [79,80]. This capability enables adaptive decision-making under time-varying operating conditions, including fluctuations in renewable generation, load demand, and network topology. Once trained, RL policies can generate control actions with low computational latency, making them suitable for real-time operational control in distribution networks [66,80]. DRL further enhances scalability by employing neural networks to approximate value functions or policies, allowing the representation of high-dimensional system states, such as bus voltages, power flows, battery states, and inter-microgrid power exchanges [57,85]. This enables coordinated control in complex and large-scale multi-microgrid systems.

Despite these advantages, several limitations remain in applying RL to network-constrained multi-microgrid optimization. A key challenge is that standard RL formulations do not explicitly enforce power-flow constraints, which may lead to infeasible actions such as voltage violations or line overloading. This issue is particularly critical in safety-sensitive power system operation, where constraint violations can compromise system reliability. In addition, RL methods typically require extensive training data and careful tuning of hyperparameters, and their performance can be sensitive to reward design and training conditions.

Studies also report challenges related to convergence stability and generalisation, where learned policies may perform poorly under unseen or extreme operating scenarios. As a result, although RL offers strong adaptability and real-time capability, its practical deployment in network-constrained multi-microgrid systems remains limited without the integration of constraint-handling mechanisms or hybrid optimization frameworks that ensure physical feasibility and operational security.

5.5 Hybrid optimization Approaches

Hybrid optimization approaches combine multiple techniques to leverage their complementary strengths and mitigate the limitations of individual methods. In interconnected multi-microgrid systems, such approaches are increasingly adopted to address scalability and real-time operational challenges [86,87]. Specifically, scalability is achieved through problem decomposition across multiple microgrids or time horizons, where deterministic OPF handles local or steady-state constraints, while metaheuristic or learning-based methods coordinate global optimization. This reduces the computational burden associated with fully centralised formulations and enables distributed or hierarchical solution strategies [86–88].

For large-scale systems, deterministic optimization methods such as OPF can become computationally expensive, while metaheuristic methods may suffer from slow convergence. Hybrid frameworks address these issues by decomposing complex problems and integrating fast search capabilities with accurate system modelling. For example, hybrid PSO–OPF and GA-based approaches have demonstrated improved convergence and solution quality in distributed energy management problems [89]. In addition, learning-based hybrid approaches, such as reinforcement learning combined with optimization or model predictive control, enable real-time decision-making by shifting computational burden to offline training. These methods can rapidly approximate optimal control policies during operation, making them suitable for dynamic and uncertain environments [90–92]. As a result, real-time operation is facilitated by replacing repetitive online optimization with fast policy inference, significantly reducing computation time while maintaining near-optimal performance.

Furthermore, hierarchical hybrid frameworks separate decision-making across multiple time scales, where optimization techniques handle scheduling and predictive control is used for real-time operation. This structure significantly enhances scalability and responsiveness in interconnected systems [86,87]. This hierarchical coordination aligns with the classification presented in Fig. 5, where deterministic, stochastic, and learning-based methods are integrated across different application layers, enabling scalable and computationally efficient operation in large interconnected systems. Overall, hybrid approaches provide a practical balance between computational efficiency, solution optimality, and adaptability, making them well-suited for large-scale and real-time multi-microgrid applications.

5.6 Comparative Perspective

This section applies the structured evaluation framework defined in Section 2 to compare optimization paradigms based on consistent criteria, including network modelling fidelity, uncertainty representation, constraint enforcement, computational characteristics, scalability, and deployment maturity. Across the reviewed studies, deterministic methods dominate network-constrained optimal power flow (OPF) applications under well-defined conditions, while stochastic and robust methods are used to address uncertainty. Metaheuristic approaches are applied in nonlinear and multi-objective formulations, whereas RL methods are increasingly explored for adaptive and real-time control scenarios [12,14,42,43]. Table 2 presents representative optimization methods applied to renewable–EV–microgrid systems and Table 3 summarises these paradigms using the predefined evaluation dimensions, enabling a systematic comparison of their modelling assumptions, performance characteristics, and application contexts.

Deterministic OPF methods explicitly incorporate network constraints, including power-flow equations, voltage limits, and line capacities, and achieve high computational efficiency through convex or linearised formulations [41,65]. These methods are primarily applied in planning and day-ahead operation, where system conditions are relatively predictable. However, evidence from multiple studies indicates that their performance degrades under high uncertainty and rapidly varying conditions, as deterministic assumptions fail to capture renewable variability and load fluctuations. Stochastic and robust optimization extend deterministic formulations by incorporating uncertainty in renewable generation, load demand, and EV behaviour. These approaches improve operational robustness and are frequently used in resilience-oriented and uncertainty-aware scheduling problems. However, comparative results show that scenario-based methods increase computational burden, while robust formulations may introduce conservative decisions depending on the uncertainty set definition, highlighting a trade-off between robustness and economic performance [47,54]. Metaheuristic algorithms, including PSO and NSGA-II, are applied to nonlinear and multi-objective optimization problems where analytical formulations are difficult. These methods provide flexibility in handling complex objective functions and nonconvex search spaces. Nevertheless, reported results indicate sensitivity to parameter tuning and problem formulation, with feasibility typically verified through repeated power-flow simulations and no guarantee of global optimality or consistent convergence behaviour [18,93]. RL introduces a data-driven paradigm for adaptive control under dynamic and uncertain conditions. RL-based approaches are increasingly investigated for real-time energy management and distributed coordination. However, evidence from recent studies highlights limitations in convergence stability, generalisation under unseen conditions, and the lack of inherent mechanisms to enforce physical network constraints, which is critical for safety-sensitive power system operation [57,80,81].

From a comparative perspective, deterministic and stochastic optimization methods provide stronger guarantees in feasibility and constraint enforcement due to their explicit integration of power-flow models [30,54,94]. In contrast, metaheuristic and RL-based approaches offer greater flexibility in handling nonlinearities and uncertainties but exhibit weaker guarantees in optimality, feasibility, and interpretability [78,85]. Regarding scalability, deterministic and convex OPF formulations are computationally efficient but may face challenges when extended to large-scale stochastic or mixed-integer problems. Stochastic and robust methods further increase computational complexity due to scenario expansion or uncertainty sets [68,94,95]. Metaheuristic approaches suffer from increased computational burden due to repeated power-flow evaluations [96]. RL introduces a data-driven paradigm for adaptive control under dynamic and uncertain conditions. RL-based approaches provide adaptability and fast decision-making capabilities, particularly in real-time energy management and distributed coordination. However, evidence from recent studies highlights limitations in convergence stability, generalisation under unseen conditions, and the lack of inherent mechanisms to enforce physical network constraints, which is critical for safety-sensitive power system operation [57,80,81].

Table 2: Representative optimization methods applied to renewable–EV–microgrid systems.

Reference	Year	Category	Typical Algorithm/Method	Limitation
Meng and Liu [41]	2023	Deterministic OPF	SOCP-relaxed OPF	Relaxation gap
Budiman et al. [46]	2024	Deterministic OPF	Harmonic OPF	High computation
Zhang et al. [48]	2024	Stochastic & Robust OPF	DRO-CVaR	Scenario complexity

(Continued)

Table 2 (continued)

Reference	Year	Category	Typical Algorithm/Method	Limitation
Wan et al. [97]	2023	Deterministic OPF	MISOCP	Poor scalability
Guan et al. [96]	2024	Metaheuristic OPF	Improved PSO	Parameter sensitivity
Elshenawy et al. [98]	2025	Deterministic OPF	Two-stage optimization	High complexity
Vilaisarn et al. [63]	2022	Deterministic OPF	MILP	Limited scalability
Alizadeh et al. [65]	2025	Deterministic OPF	DistFlow + SOCP	Approximation error
Li et al. [74]	2024	Deterministic OPF	MILP sizing	High computation
Poshtyafteh et al. [62]	2024	Deterministic OPF	MMG optimization	Model dependence
Guzmán-Henao et al. [99]	2024	Metaheuristic OPF	Master–slave optimization	High runtime
Ahmed and Mahmoud [100]	2026	Metaheuristic OPF	Multi-objective metaheuristic	Tuning required
Xiao et al. [58]	2025	Metaheuristic OPF	Walrus optimization	Slow convergence
Xiong et al. [80]	2025	Reinforcement Learning	DRL	Data-intensive
Zhu and Li [66]	2025	Reinforcement Learning	Multi-time-scale DRL	Training instability
Liu and Zhao [81]	2025	Reinforcement Learning	Constraint-aware RL	High complexity
Hassan and Khan [101]	2025	Reinforcement Learning	Q-learning	Poor scalability
Wu et al. [57]	2025	Reinforcement Learning	Multi-agent DRL	Comm. overhead
Toquica et al. [85]	2025	Reinforcement Learning	MARL	Non-stationarity
Wu et al. [102]	2026	Reinforcement Learning	MADRL + GRU	Model simplification
Baran and Wu [40]	2015	Deterministic OPF	DistFlow-based OPF	Linear approximation limitations
Khodaei [45]	2015	Stochastic & Robust OPF	Stochastic microgrid scheduling	Scenario dependency

(Continued)

Table 2 (continued)

Reference	Year	Category	Typical Algorithm/Method	Limitation
Olivares et al. [103]	2016	Deterministic OPF	Microgrid control framework	Limited scalability
Conejo et al. [68]	2015	Stochastic & Robust OPF	Stochastic programming	Scenario dependency

Table 3: Comparative evaluation of optimization paradigms for interconnected multi-microgrid operation in distribution networks.

Comparison Criterion	Deterministic OPF	Stochastic/Robust OPF	Metaheuristic OPF	Reinforcement Learning	Hybrid Frameworks
Network modelling (power flow)	Explicit power-flow equations (AC or branch-flow).	Power-flow enforced across scenarios or uncertainty bounds.	Evaluated via repeated power-flow simulations.	Feasibility checked via simulation after each action.	Combines OPF models with learning or heuristic components.
Uncertainty handling	Uses forecast or nominal values.	Models uncertainty via scenarios or bounded sets.	Handled implicitly through population search.	Learns uncertainty through environment interaction.	Combines explicit models with data-driven adaptation.
Constraint enforcement	Explicit mathematical constraints.	Constraints enforced across all scenarios.	Handled via penalties or repair methods.	Handled via reward shaping or external checks.	Combines optimization constraints with learning-based correction.
Optimality guarantee	Strong for convex problems.	Expected or worst-case guarantees.	No guarantee; depends on tuning.	No guarantee; depends on training.	Near-optimal; no strict global guarantee.
Computational characteristics	Solved per scheduling horizon.	Higher cost due to scenarios.	Many simulations required.	Training costly; execution fast.	Offline computation + fast online decisions.
Scalability	High for convex formulations.	Moderate; depends on scenarios.	Limited due to repeated simulations.	Depends on training and system complexity.	High via decomposition and hierarchical structure.
Deployment maturity	Widely used in practice.	Growing research and pilot use.	Mainly academic applications.	Early-stage research.	Emerging for large-scale systems.

Tables 2 and 3 provide a structured comparison of optimization methods and paradigms by linking methodological characteristics to application contexts and reported performance across the reviewed studies. Deterministic OPF methods are predominantly applied in network-constrained scheduling problems with well-defined system conditions, where strong feasibility and optimality guarantees are required. In contrast, stochastic and robust formulations are adopted in studies addressing uncertainty in renewable generation and load demand, particularly in resilience-oriented and uncertainty-aware operation scenarios. Metaheuristic approaches are mainly used in nonlinear and multi-objective optimization problems where analytical formulations are difficult; however, their performance varies depending on parameter tuning and problem structure. Reinforcement learning methods are primarily investigated in real-time control and adaptive energy management contexts, where fast decision-making is required, but their applicability remains limited by the lack of guaranteed feasibility and sensitivity to training conditions. Notably, exceptions exist across all categories: deterministic methods may exhibit degraded performance under high uncertainty, stochastic methods may become computationally intractable for large-scale systems, metaheuristics may yield inconsistent solutions across runs, and RL-based approaches may generate infeasible actions under unseen operating conditions. These observations highlight that the suitability of each optimization paradigm is strongly dependent on the problem context, modelling assumptions, and operational requirements.

6 Discussion and Future Research Directions

Despite significant progress in optimization strategies for interconnected multi-microgrid systems, several key challenges remain in developing network-constrained and resilient operational frameworks. This section highlights critical research gaps related to power-flow integration, resilience modelling, scalability, and practical deployment.

6.1 Integration of Power-Flow Optimization in Multi-Microgrid Coordination

The explicit integration of power-flow models within MMG coordination remains a key challenge. While deterministic and security-constrained OPF methods ensure rigorous enforcement of voltage and thermal constraints [14,19,67] many existing scheduling frameworks prioritise economic objectives without fully incorporating network-constrained power-flow formulations [6]. As a result, ensuring physical feasibility under both normal and disturbed conditions remains limited. Future research should focus on tighter coupling between optimization algorithms and electrical network models, particularly through systematic integration of branch-flow or AC power-flow formulations in coordinated multi-microgrid operation.

6.2 Resilience-Oriented Optimization under Extreme Weather Conditions

Resilience under extreme weather is a critical requirement for modern distribution systems [42]. However, most existing optimization models assume normal operating conditions, while severe events may cause line outages, DER unavailability, and load interruptions. Current studies only partially integrate resilience metrics into network-constrained optimization [22,60]. Future work should explicitly incorporate objectives such as load shedding minimisation, islanded operation, and service restoration within power-flow-based formulations [52]. Despite the recognised role of networked microgrids in enhancing resilience, their integration into coordinated multi-objective optimization remains limited [7,8].

6.3 Modelling Accuracy and System Representation

Network Modelling Detail: Distribution network representations range from simplified models to detailed AC or branch-flow formulations [88]. While simplified models improve tractability, they may not accurately capture voltage behaviour and network constraints. The impact of such modelling simplifications on feasibility and resilience performance remains insufficiently studied [88].

Asset Representation: DERs, including PV, BESS, and EVs, are often modelled using simplified linear approximations. However, neglecting nonlinear characteristics and operational limits may lead to inaccurate assessment of system behaviour, particularly under stressed or extreme conditions [88].

6.4 Validation and Practical Deployment Considerations

Despite extensive simulation-based validation, practical deployment of optimization frameworks for interconnected multi-microgrid systems remains limited.

Benchmark Systems and Performance Metrics: The lack of standardised benchmark systems and unified resilience metrics limits comparability across studies. Establishing consistent evaluation frameworks is essential to improve transparency, reproducibility, and objective performance assessment.

Implementation Challenges: Real-world deployment requires reliable data acquisition, accurate system modelling, robust communication infrastructure, and cybersecurity protection. These practical considerations are often overlooked in optimization-focused studies but are critical for deployment.

Operational Resilience Assessment: Evaluating resilience under extreme conditions is challenging in operational systems due to potential risks to grid stability. Therefore, structured validation methodologies and safe testing strategies are required to enable practical assessment of network-constrained, resilience-oriented optimization frameworks.

7 Conclusion

This paper presents a systematic review of network-constrained multi-objective optimization approaches for interconnected multi-microgrid systems with high penetration of distributed energy resources. A structured comparative framework is developed to evaluate deterministic, stochastic/robust, metaheuristic, and reinforcement learning-based methods in terms of network modelling, uncertainty handling, constraint enforcement, scalability, and operational applicability.

The analysis demonstrates that deterministic and stochastic optimization methods provide strong guarantees in enforcing power-flow constraints and ensuring operational feasibility, while metaheuristic and reinforcement learning approaches offer greater flexibility in handling nonlinearities and dynamic uncertainties. However, the explicit integration of power-flow constraints within multi-objective optimization remains inconsistent across the literature, with many studies prioritising economic objectives over rigorous enforcement of network feasibility. In addition, resilience under extreme conditions is not yet systematically embedded within network-constrained optimization frameworks. Although interconnected microgrids provide operational flexibility, the coordinated integration of resilience metrics with power-flow-constrained models remains limited.

Overall, the findings highlight the need for unified optimization frameworks that simultaneously address network constraints, uncertainty, and resilience. In particular, reinforcement learning-based approaches offer significant potential for adaptive and real-time operation; however, their application in network-constrained MMG systems requires further development to explicitly incorporate power-flow constraints and ensure operational feasibility under realistic conditions.

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