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Topology-Dependent Hosting Capacity Impacts of Grid-Forming Inverters in Unbalanced Distribution Networks: Cross-Feeder Optimisation Using Metaheuristic Droop Coordination

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Abstract

Grid-forming (GFM) inverters are increasingly being deployed in distribution networks to improve system strength and provide synthetic inertia. However, their steady-state influence on hosting capacity (HC) is not yet fully understood, particularly across different distribution network topologies. This study shows that the relationship between GFM droop control and HC is strongly topology-dependent. In overvoltage-limited feeders, non-optimised GFM reactive power absorption reduces HC, whereas in undervoltage-limited feeders, the same reactive support mechanism significantly enhances HC. To analyse and optimise this behaviour, this study proposes the Coordinated Hosting-Capacity and Stability Algorithm (CHSA), which determines the optimal site-specific GFM droop parameters (m_p, n_q, ω_c) using a steady-state multi-constraint metaheuristic co-simulation framework. In this context, stability refers exclusively to steady-state voltage feasibility, that is, the maintenance of nodal voltages within statutory limits under varying DER injection levels. For the overvoltage-limited Australian-adapted IEEE 123-bus unbalanced multi-phase feeder, mid-range GFM settings introduce a GFM Hosting-Capacity Penalty (CP_{GFM}) of 95.19 kW, reducing HC from the 950.00 kW grid-following (GFL) reference ceiling to 854.81 kW. By coordinating the reactive droop parameters, the proposed CHSA recovers 92.65 kW (97.3% of CP_{GFM}), increasing HC to 947.46 kW while eliminating voltage violations, with all inverters operating at 33.3% of their rated apparent power capacity. For the undervoltage-limited IEEE 34-bus feeder, the same GFM reactive support mechanism increases HC from 19.90 kW under GFL operation to 237.41 kW with the optimised GFM configuration, representing a nearly twelve-fold improvement. Independent verification using Particle Swarm Optimisation confirms that both algorithms converge to the same operating point: on the representative run (seed 42), HC values differ by only 1.23 kW, while mean HC across 20 independent seeds differs by 0.99 kW (HBO: 947.70 ± 0.72 kW; PSO: 948.69 ± 0.00 kW), indicating that the results are governed by network characteristics rather than the choice of optimisation algorithm. These findings demonstrate that the HC limitations often associated with GFM technology arise mainly from suboptimal control coordination rather than inherent architectural constraints. Furthermore, the proposed CHSA provides a general framework for voltage-constraint-aware droop coordination across distribution networks with contrasting topological characteristics.

Keywords: grid-forming inverters; hosting capacity; topology-dependent GFM effects; droop control optimisation; unbalanced distribution networks; grid-forming hosting-capacity penalty; cross-feeder validation; metaheuristic optimisation; steady-state co-simulation; OpenDSS



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1. Introduction

The global transition towards a decarbonised energy sector is fundamentally reshaping the operation and planning of distribution networks. Ambitious renewable energy targets, together with the rapid adoption of rooftop photovoltaic (PV) systems and electric vehicles (EVs), are driving a significant increase in consumer energy resources (CERs, used interchangeably with distributed energy resources, or DERs, throughout this paper) connected at the distribution level [1]. Beyond conventional silicon-based PV, emerging technologies such as all-inorganic CsPbI₃ perovskite cells are approaching commercial viability [2] and are expected to accelerate DER deployment further. This shift marks a move away from traditional centralised, fossil-fuel-based generation towards decentralised, inverter-based resources operating at the grid edge. As a result, Distribution Network Service Providers (DNSPs) are re-evaluating conventional fit-and-forget planning approaches that were originally developed for one-way power flow, predictable demand patterns, and power systems dominated by synchronous generators [1,3]. Distribution feeders that once operated as passive radial networks are now evolving into highly interactive systems with bidirectional power flows, changing voltage profiles, and increasingly complex control interactions [1,4]. The increasing penetration of CERs also challenges the dynamic behaviour of distribution networks in ways that existing assessment frameworks do not fully capture. Although stochastic assessment frameworks have been widely used to evaluate the HC of distribution feeders [4–6], they generally assume passive GFL inverters operating at unity power factor. However, the ongoing retirement of synchronous generators is reducing both system inertia and system strength, making distribution networks increasingly susceptible to weak-grid conditions [3,7]. Under these conditions, the phase-locked loops (PLLs) employed by GFL inverters become more vulnerable to synchronisation instability, particularly in networks with low short-circuit ratios (SCRs), limiting their ability to operate reliably in weak networks [8,9]. These challenges have accelerated interest in GFM inverters, which can establish voltage and frequency independently of a strong external grid reference. At the same time, the growing penetration of PV and EVs introduces distinct but complementary operational challenges. High PV penetration increases reverse power flow and overvoltage, particularly during midday periods of high generation and low demand, while large-scale EV charging creates significant stochastic loading that can lead to under-voltage and thermal congestion during evening peak demand [1,10,11]. Although these impacts differ, both ultimately restrict the network's HC, which is defined as the maximum level of CER integration that can be achieved without violating operational constraints. Consequently, accurately assessing and improving HC has become a critical planning objective for DNSPs, as underestimating HC can unnecessarily limit renewable integration, whereas overestimating it may lead to persistent voltage violations, increased equipment stress, and reduced network reliability [1]. Conventional HC assessment methods generally assume that DERs are integrated through GFL inverters operating at or close to unity power factor. Under this assumption, GFL inverters behave as ideal current sources and establish the reference steady-state active power limit against which alternative integration strategies are compared [12]. This assumption was appropriate when DER penetration was relatively low and synchronous generators continued to provide the majority of system inertia and voltage support. However, the increasing replacement of synchronous generation with inverter-based renewable resources is steadily reducing network inertia and weakening system strength, challenges that conventional GFL inverters are not designed to overcome [3,7]. According to the Australian Energy Market Operator (AEMO) [7], system strength describes the ability of a power system to maintain a stable voltage waveform under both normal operating conditions and network disturbances. Since GFL inverters rely on PLLs to synchronise with an existing voltage reference, they operate as passive current-

following devices and contribute little to the fault current required to maintain voltage stability under weak-grid conditions [8,9]. These limitations have accelerated the adoption of GFM inverters, which can establish their own voltage reference, provide synthetic inertia, and support system frequency without relying on a strong external grid [12–14]. Although GFM inverters offer significant advantages for system stability, their deployment with mid-range or uncoordinated droop settings can reduce steady-state hosting capacity, an operational consequence that has received limited attention in the existing literature. In networks containing multiple GFM units, poorly coordinated droop characteristics can lead to unnecessary reactive power circulation, localised voltage violations, and a reduction in HC despite the intended benefits of voltage-forming control [8,9]. This study formally defines and quantifies this behaviour as the GFM Hosting-Capacity Penalty (CP_{GFM}), demonstrating that it is primarily a control coordination issue rather than an inherent limitation of GFM technology. As documented in our prior systematic review [15], few published frameworks have simultaneously addressed the coordination of GFM droop parameters to maximise hosting capacity while respecting steady-state nodal voltage limits. This distinction has important practical implications because an architectural limitation would restrict the wider adoption of GFM inverters, whereas a coordination-related limitation can be effectively addressed through optimisation while preserving the stability benefits that motivate the transition to GFM control. The paper is structured as follows. Section 2 reviews the relevant literature on probabilistic HC assessment, system strength, dynamic operating envelopes, and the formalisation of CP_{GFM} . Section 3 presents the research contributions. Section 4 presents the CHSA framework in detail. Section 5 describes the case study networks and scenario generation methodology. Section 6 reports and interprets the results across all evaluated scenarios, including the physical mechanism analysis, algorithm-independent convergence, extended robustness verification, and cross-feeder generalisation. Section 7 draws conclusions and identifies future research directions.

2. Literature Background and Motivation

2.1. Probabilistic Hosting Capacity and EV Uncertainty

Quantifying HC in active distribution networks is inherently a probabilistic problem, shaped by the stochastic behaviour of CERs across temporal and spatial dimensions [1,4]. The historical evolution of HC methods illustrates why this probabilistic framing is necessary. Early deterministic approaches evaluated feasibility at a single worst-case snapshot, typically assuming that maximum PV generation occurs simultaneously with minimum network load. While this assumption guarantees a conservative bound, it is significantly limited in practice: the scenario of peak solar output overlapping exactly with minimum household demand rarely materialises in the field, so the resulting HC estimate severely underestimates the capacity that the network can actually accommodate [1,6]. The opposite error is equally possible: selecting an average-case snapshot ignores the tail conditions under which voltage or thermal violations first emerge, producing an optimistic estimate that fails under realistic high-penetration deployment [1]. Contemporary research addresses these limitations through probabilistic methods capable of capturing the joint variability of PV generation and EV charging demand across statistically representative operating envelopes [1,6]. Monte Carlo simulation is the most widely adopted vehicle for this purpose, but its validity depends critically on appropriate stopping rules: the number of sampled scenarios must be sufficient to ensure that the empirical distribution of the HC metric has converged to its true distribution, typically verified by evaluating the inverse cumulative distribution function at a specified confidence level and confirming that the estimate is stable across incremental batches of scenarios [10]. Without such stopping criteria, Monte Carlo HC estimates carry unquantified statistical uncertainty that can mislead planning de-

cisions. The HC attributable to EV integration is particularly sensitive to charging location, battery state, driver behaviour, and arrival–departure patterns, each of which introduces compounding uncertainty into the network integration assessment [1]. Unlike residential PV, whose generation profile follows a broadly predictable diurnal pattern, EV demand can concentrate spatially in ways that create localised voltage depressions or overvoltage events at feeder extremities that would not be visible in an aggregated network model [10]. Critically, studies have shown that neglecting the spatial correlations among neighbouring prosumers can lead to significant overestimation of the achievable capacity, because independent-sampling assumptions fail to capture the synchronised irradiance events that drive simultaneous voltage rise across an entire lateral branch [10,11]. Advanced stochastic architectures address these dependencies through Copula-based multivariate modelling combined with Latin Hypercube Sampling (LHS), providing a structured yet computationally efficient sampling of the joint uncertainty space [10]. Copula functions allow the marginal distributions of EV availability and PV output to be modelled separately and then recombined through a joint dependence structure that captures realistic correlation patterns without requiring a fully parametric multivariate distribution [10]. Complementary approaches based on artificial intelligence and fuzzy-logic inference have demonstrated value for hierarchical EV demand orchestration and peak demand mitigation in smart grid deployments [16]. A persistent shortcoming of this entire body of work, however, is the implicit assumption of passive GFL integration, which systematically omits the influence of inverter control topology, voltage-forming interactions, and system-strength degradation on the achievable HC envelope [12,14]. Correcting this omission is the central motivation of the present study.

2.2. System Strength and GFM Control in Weak Grids

Beyond steady-state voltage and thermal compliance, the transition toward inverter-dominated power systems surfaces a deeper challenge: the progressive erosion of system strength. As introduced in Section 1, AEMO defines system strength as the ability of the power system to maintain the voltage waveform during both steady-state and fault conditions at any given location in the network [7,15]. Both AEMO and the North American Electric Reliability Corporation (NERC) characterise system strength through the fault level and short-circuit capacity available at the point of connection, recognising it as a foundational requirement for stable inverter synchronisation [7,8]. As synchronous generators retire and are replaced by inverter-based resources, the fault current that previously provided this stiffness diminishes, degrading the voltage reference that GFL inverters depend on for PLL tracking [14]. In weak-grid conditions characterised by low SCRs, GFL inverters are acutely vulnerable to PLL instability. Reduced fault levels compress the voltage stiffness that the PLL relies on for frequency tracking, producing synchronisation errors and potentially destabilising current injections under dynamic perturbations [8,9]. This mathematical duality between GFL and GFM behaviour in weak grids has been formally established by Li et al. [9], who demonstrated that GFL units become destabilising current sources under low-SCR conditions while GFM units remain stable voltage sources regardless of the upstream impedance. The vulnerability becomes a systemic risk when multiple GFL units share a common weak point of connection, as their interactive dynamics can amplify small disturbances into large oscillatory events [8]. GFM architectures overcome this fundamental limitation by internalising the voltage reference within the control structure itself, establishing a self-referencing voltage source that does not depend on a pre-existing grid signal [12–14,17]. GFM control has demonstrated clear success in isolated microgrids, where a single dominant GFM unit can set the voltage reference for all other resources without competing interactions [13]. However, utility-scale, highly unbalanced

multi-phase distribution networks present a qualitatively different challenge. In these environments, multiple GFM units are necessarily deployed across a spatially distributed network with heterogeneous phase impedances and unequal loading patterns. The unequal phase impedances of practical distribution feeders cause Q–V droop controllers on GFM units with mid-range settings to respond to different local voltage levels simultaneously. The resulting reactive exchanges reinforce rather than cancel each other, actively degrading the network's voltage profile [15]. Specifically, a unit on a lightly loaded single-phase lateral may inject reactive power to regulate its local voltage, while an adjacent unit on a heavily loaded three-phase section absorbs reactive power to suppress overvoltage on its local bus. The resulting circulating reactive current between these units degrades the effective voltage headroom available for active power injection and suppresses the network's HC below what even a simpler GFL deployment would achieve. This competing reactive exchange constitutes the operational mechanism underlying CP_{GFM} , and it motivates the development of a coordinated parameter optimisation framework capable of preserving both operational security and maximal integration capacity simultaneously [15].

2.3. Dynamic Operating Envelopes and Socio-Technical Fairness

Dynamic operating envelopes (DOEs) have emerged as a principled alternative to static export limits for managing growing DER penetrations [18–20]. Rather than applying conservative, time-invariant thresholds derived from worst-case network conditions that occur rarely in practice, DOEs compute network-aware, time-varying import and export bounds that adapt dynamically to prevailing topological conditions, enabling higher DER integration without compromising operational security [18]. The practical appeal of DOEs lies in their ability to make use of available capacity that static limits leave stranded, while providing the DNSP with a tractable enforcement mechanism that can be implemented through standard smart meter infrastructure. Calculating optimal power flow (OPF)-based operating envelopes, however, inherently favours customers located near the distribution transformer because they have lower network impedances and therefore exhibit lower voltage sensitivity per unit of injected power. A prosumer near the substation can sustain a substantially larger export before the voltage constraint binds than a prosumer at the far end of the same lateral, because the same kW of injection produces a smaller voltage rise at a low-impedance bus than at a high-impedance one [21]. Naive OPF formulations that maximise total capacity without an equity constraint will therefore allocate the available headroom almost entirely to electrically privileged customers, leaving end-of-feeder prosumers with negligible or zero export allowances. Conversely, a uniform flat limit applied network-wide will either constrain near-substation customers below their true network-limited capacity, or permit end-of-feeder customers to violate voltage limits [21]. Neither approach reflects a principled balance between network security and socio-technical equity. To address this structural inequity, leading DOE frameworks employ fairness metrics to discipline the capacity allocation across the feeder topology. Among these, Jain's Fairness Index (JFI) [22], originally developed for resource allocation in shared computer networks, has been widely adopted in power systems research as a principled metric for equitable capacity allocation [21,23]. JFI quantifies the uniformity of a resource distribution on a normalised scale from $1/N$ (complete concentration in one user) to 1.0 (perfectly equal allocation), providing a single scalar metric that can be included as a constraint or objective term in the HC optimisation. The present work embeds JFI evaluation within the CHSA to verify that the droop optimisation does not inadvertently concentrate the recovered HC gains among electrically advantaged buses while leaving remote prosumers unimproved.

2.4. Formalising the GFM Capacity Penalty

The adoption of GFM technology is essential for restoring system strength and eliminating PLL dependence in low-inertia networks [12,14,17]. This work, however, identifies a distinct steady-state operational consequence of that adoption: the GFM Hosting-Capacity Penalty, denoted CP_{GFM} . Under passive GFL operation, inverters function as current-injecting sources at unity power factor, establishing a reference active-power integration ceiling for the network, denoted HC_{GFL} [12]. When GFM inverters with mid-range, non-optimised droop parameters are introduced into the same unbalanced system, their autonomous voltage-forming behaviour generates uncoordinated reactive exchanges with the network and with each other [12,13]. In a network that is already operating near its voltage headroom ceiling, these interactions accelerate the onset of localised overvoltage conditions, causing the voltage ceiling to be reached at a lower active power injection level than under GFL operation [15]. The penalty is not a consequence of GFM technology's fundamental operating principle but of the specific numerical values assigned to its droop parameters in the absence of network-specific calibration. The CP_{GFM} is therefore defined in Equation (1) as the reduction in feasible HC resulting from replacing GFL inverters with GFM units operating at mid-range droop settings [15]:

$$CP_{\text{GFM}} = HC_{\text{GFL}} - HC_{\text{GFM}}^{\text{mid-range}} \quad (1)$$

where $HC_{\text{GFM}}^{\text{mid-range}}$ is the HC achieved under mid-range droop settings. This penalty directly curtails renewable integration in utility-scale deployments, and its magnitude scales with the degree of network unbalance, the number of competing voltage-forming units, and the sensitivity of the binding voltage constraint to reactive power exchanges at the candidate bus locations. Crucially, this work argues that CP_{GFM} is not an inherent property of GFM technology but a nonlinear control-coordination problem fully amenable to constrained optimisation [15].

2.5. Motivation and Research Gap

Despite the growing recognition of GFM technology's importance, the literature remains fragmented between largely non-communicating research streams focusing on steady-state HC assessment and dynamic stability enhancement. GFM optimisation studies are predominantly confined to microgrids, laboratory-scale testbeds, or balanced transmission-level applications, where the full structural complexity of practical unbalanced distribution feeders is absent. Conversely, HC investigations on real-world medium-voltage (MV) and low-voltage (LV) networks continue to treat GFL operation as the only inverter topology worth modelling, implicitly assuming that steady-state voltage feasibility and system-strength concerns do not significantly restrict distribution-scale integration [12,14]. As comprehensively documented in our recent review [15], this bifurcation leaves a critical gap: no published framework, to the best of the authors' knowledge, simultaneously addresses HC maximisation, GFM droop coordination, voltage security, power quality compliance, and steady-state feasibility within a utility-scale unbalanced network. Building on our earlier probabilistic findings regarding EV integration in Australian distribution systems [24], the present work directly bridges this gap by embedding coordinated GFM parameter optimisation within the HC assessment loop itself, treating droop tuning and capacity maximisation as a single, unified engineering problem rather than two sequentially decoupled tasks. While artificial intelligence, fuzzy logic, and population-based metaheuristics have been extensively applied to EV scheduling and static DOE allocation in distribution networks [16,23], few studies have applied a socio-inspired metaheuristic, specifically the Heap-Based Optimizer (HBO) with its corporate rank-hierarchy exploration

structure [25], to the targeted problem of tuning decentralised GFM droop parameters for the simultaneous maximisation of fair, HC-improving DOEs in unbalanced multi-phase feeders. This specific combination of problem formulation, network topology, control architecture, and algorithmic approach represents the methodological intersection that the CHSA addresses. Recent advances in GFM control under highly unbalanced grid conditions have focused almost exclusively on small-signal stability [26], sequence-decomposed control [27], and symmetrical component modifications [28], entirely neglecting the steady-state HC boundary. Consequently, no unified framework exists that simultaneously identifies and mitigates the capacity penalty caused by competing GFM voltage-forming loops in unbalanced networks. This gap motivates the CHSA architecture proposed herein.

3. Research Contributions

To bridge this multidisciplinary gap, this paper proposes the CHSA. Unlike studies that optimise isolated battery sizing [29,30] or tune GFM parameters for balanced transmission systems [31,32], the CHSA targets the specific challenge of multi-unit GFM droop coordination in unbalanced multi-phase distribution feeders, directly addressing the steady-state HC boundaries that those studies do not consider. The principal contributions of the CHSA framework are as follows:

1. Formal definition and optimisation-based recovery of the GFM capacity penalty: This work introduces a formal definition of CP_{GFM} and develops a novel droop-optimisation architecture constrained by minimum nodal voltage (MNV) and voltage unbalance factor (VUF) for its systematic mitigation [15]. By jointly optimising the active and reactive droop coefficients across all candidate inverter sites, the CHSA eliminates the competing voltage-forming interactions responsible for the penalty and restores the network to a fully feasible, high-capacity operating state [24].
2. Near-elimination of the HC gap between GFM and GFL operation: The proposed optimisation architecture demonstrates that the coordination of GFM control can be delivered without material sacrifice of steady-state integration capacity. The framework maintains voltage security and phase unbalance compliance while achieving a feasible HC that approaches the theoretical GFL reference ceiling, establishing that CP_{GFM} is a solvable control-coordination problem rather than a fundamental technological constraint [24].
3. Algorithm-independent and topology-generalised validation: Two independent lines of evidence establish that network physics, rather than algorithmic choice, determines the optimal operating point. First, HBO and Particle Swarm Optimisation (PSO) converge to essentially the same reactive absorption strategy across 20 distinct random seeds [25,33], providing strong empirical evidence that the result reflects the network's constraint geometry rather than an algorithmic artefact. Second, cross-feeder validation on the IEEE 34-bus benchmark demonstrates that coordinated GFM reactive support provides measurable HC benefits across topologically distinct network configurations, establishing the CHSA as a generalised framework.

Table 1 positions the proposed framework against the recent literature, confirming that the simultaneous combination of unbalanced multi-phase modelling, GFM droop tuning, metaheuristic HC optimisation, voltage and VUF constraints, and multi-feeder validation has not been addressed by any prior study.

Table 1. Novelty and contribution matrix: positioning the proposed GFM framework against recent literature.

Ref.	Year	Technical Study Description	Key Methodological Features						
			Unbal. Multi-Ph.	GFM Droop	Meta. HC	Volt. Constr.	Steady- State	Act./React. Support	Multi-F. Valid.
[34]	2020	Dynamic HC analysis via stochastic GFL scenarios	✓	✗	✗	✓	✗	✗	✗
[21]	2021	Proportional fairness operating envelopes in LV grids	✓	✗	✗	✓	✗	✗	✗
[12]	2021	GFM control loops, modeling, and system applications	✗	✓	✗	✓	✓	✓	✗
[30]	2021	Robust capacity allocation in unbalanced networks	✓	✗	✓	✓	✗	✓	✗
[5]	2022	Stochastic HC benchmark across multiple LV feeders	✓	✗	✗	✓	✗	✗	✓
[29]	2022	GFM battery inverter sizing via metaheuristics	✗	✗	✓	✗	✓	✓	✗
[18]	2022	OPF-based operating envelopes in unbalanced networks	✓	✗	✗	✓	✗	✓	✗
[35]	2022	Dynamic PQ operating envelopes in unbalanced LV	✓	✗	✗	✓	✗	✓	✗
[23]	2023	Equitable DOE allocation in distribution networks	✓	✗	✗	✓	✗	✓	✗
[31]	2023	Integrated GFM/GFL controller tuning via PSO/GWO	✗	✓	✓	✓	✗	✓	✗
[28]	2023	GFM control under unbalanced grid voltages	✓	✓	✗	✗	✓	✓	✗
[32]	2024	GFM penetration in LFC via metaheuristics	✗	✓	✓	✗	✗	✓	✗
[26]	2024	Distribution grid stability with GFM and GFL inverters	✓	✗	✗	✓	✓	✗	✗
[27]	2024	Sequence-decomposed GFM control for unbalanced systems	✓	✓	✗	✗	✓	✓	✗
[36]	2025	OpenDSS benchmark for unbalanced LV CER integration	✓	✗	✗	✓	✗	✗	✗
Proposed	2026	Coordinated Hosting-Capacity Algorithm (CHSA)	✓	✓	✓	✓	✓	✓	✓

✓ indicates that the methodological feature is addressed by the study; ✗ indicates that it is not addressed. Bold text in the final row identifies the framework proposed in this work. Abbreviations: Unbal. Multi-Ph.: Unbalanced Multi-Phase; GFM Droop: Grid-Forming Droop; Meta. HC: Metaheuristic Hosting Capacity; Volt. Constr.: Voltage Constraints; Steady-State: Steady-State Feasibility; Act./React. Support: Active/Reactive Power Support; Multi-F. Valid.: Multi-Feeder Validation.

4. Proposed Methodology

To eliminate CP_{GFM} , the CHSA couples a rigorous multi-phase power flow engine with a population-based metaheuristic optimiser through a structured co-simulation architecture. The term “Stability” in the algorithm name refers to steady-state voltage stability, specifically the enforcement of nodal voltage limits, voltage unbalance compliance, and minimum voltage floor constraints under varying DER penetration levels. The CHSA does not assess transient stability, fault response, or electromagnetic transient phenomena; these aspects are identified as future research directions in Section 7. The framework is organised

around five interacting components: a GFM control model, a candidate bus selection procedure, a multi-constraint feasibility evaluator, an adaptive penalty-based objective function, and an iterative solution pipeline. These components collectively enable the simultaneous satisfaction of voltage security, power quality, and capacity equity requirements while maximising active power integration. A key design principle is that every co-simulation call produces a fully converged, physically consistent network solution, so the fitness function never reflects unconverged power flow states. The co-simulation architecture is built on OpenDSS version 9.7.1.1 (64-bit) (Electric Power Research Institute, Palo Alto, CA, USA) [37], which provides a high-fidelity multi-phase Newton–Raphson power flow solver that natively supports unbalanced three-wire and four-wire distribution networks, sequence impedance models, and voltage-regulated feeders. The choice of OpenDSS as the simulation engine is deliberate: it has been extensively validated against field measurements on distribution networks [38] and provides a Python application programming interface that allows tight integration with the metaheuristic optimisation loop without data serialisation overhead. Each co-simulation call compiles a fresh network model, injects the GFM generators with the candidate droop parameterisation, solves the power flow, and extracts the voltage and reactive power metrics required for feasibility assessment. This fresh-compile approach eliminates state contamination between evaluations, ensuring that the fitness function is a pure function of the droop vector with no dependence on the sequence of prior evaluations.

4.1. GFM Control Representation

GFM inverters are modelled as controlled voltage sources whose terminal quantities are governed by droop characteristics that couple active power output to local frequency deviation and reactive power output to local voltage deviation [12,13,39]. These steady-state droop relationships were originally established in the context of synchronous generator governor and excitation control [39] and have been directly adapted for GFM inverter control to replicate the self-regulating behaviour of rotating machines without their physical inertia [12,13]. This steady-state representation captures the voltage-forming property that distinguishes GFM from GFL operation without requiring a full dynamic electromagnetic transient model, making it computationally tractable for the large number of fitness evaluations that a population-based metaheuristic requires. The steady-state droop relationships for the i -th inverter unit are:

$$P_i = P_{\text{set},i} - m_{p,i} (f_i - f_{\text{ref}}) \quad (2)$$

$$Q_i = Q_{\text{set},i} - n_{q,i} (V_i - V_{\text{ref}}) \quad (3)$$

where P_i and Q_i are the active and reactive power outputs; $P_{\text{set},i}$ and $Q_{\text{set},i}$ are the nominal setpoints; f_i and V_i are the locally measured frequency and voltage magnitude; f_{ref} and V_{ref} are the network reference frequency (50 Hz) and nominal voltage (1.0 p.u.); $m_{p,i}$ is the active droop coefficient governing the unit's frequency sensitivity; and $n_{q,i}$ is the reactive droop coefficient controlling the aggressiveness of the local voltage regulation response. In the OpenDSS co-simulation, each GFM inverter is implemented as a Generator element with Model = 3 (constant kW and kvar, user-specified). This modelling choice requires explicit justification. A GFM inverter is physically a controlled voltage source behind a coupling impedance, whose terminal active and reactive power outputs are governed by frequency and voltage droop laws [12,13]. Once the power flow converges to its steady-state equilibrium, which is the only operating condition relevant to HC assessment, the internal voltage angle and magnitude of each GFM unit have already settled to values that jointly satisfy the droop relations in Equations (2) and (3) and the

network power balance equations. At this operating point, the terminal behaviour of the GFM unit reduces to its converged (P, Q) injection, a quantity that is indistinguishable from the output of a PQ-controlled source whose setpoints follow the same droop laws [40,41]. Cunha et al. [40] provided formal evidence for this equivalence by deriving generalised steady-state equivalent circuits for several GFM control architectures and validating them against PSCAD/EMTDC electromagnetic transient simulations; their results confirm that the steady-state power injection of a droop-controlled GFM inverter is faithfully reproduced by an algebraic (P, Q) representation once the system reaches equilibrium. The same conclusion was reached independently by Du et al. [41] in the PNNL model specification for droop-controlled GFM inverters, where the voltage-source-behind-impedance formulation is shown to reduce to a Norton equivalent whose steady-state output depends only on the droop coefficients and the local bus voltage. Earlier work by D'Arco and Suul [42] arrived at a consistent finding, showing that virtual synchronous machine and frequency-droop implementations converge to the same steady-state operating point irrespective of their internal dynamic structure. The Generator element is configured with a 300 kVA three-phase apparent power rating (100 kVA per phase) to ensure the kVA constraint does not bind during the optimisation, and the voltage base matches the MV bus voltage (12.7 kV single-phase equivalent). The reactive power setpoint is computed externally by the Python control loop using Equation (3) with the locally measured voltage deviation from the preceding converged power flow solution, and the resulting Q setpoint is written back to the Generator element via the `openssdirect` API before each successive power flow evaluation. This iterative external loop emulates the closed-loop Q - V droop response: each iteration updates Q_i based on the latest bus voltage V_i , and the process repeats until the droop equation and the power flow equations are simultaneously satisfied, reproducing the unique steady-state operating point that a physical GFM voltage source would reach under the same network conditions. Apparent power is checked against the 300 kVA rating after every evaluation; as confirmed in Section 6.2, no inverter reaches saturation at any operating point. The scope of this representation should be clearly stated. The OpenDSS-based implementation accurately captures the steady-state voltage regulation and reactive power sharing behaviour of droop-controlled GFM inverters, which is sufficient for the HC assessment objective of this study. Consistent with the steady-state scope defined in Section 4, the CHSA evaluates voltage feasibility at converged equilibrium operating points; it does not capture transient phenomena such as virtual inertia response, post-fault voltage recovery, sub-synchronous oscillations, or internal voltage angle dynamics, all of which require electromagnetic transient (EMT) simulation platforms. The extension of the CHSA to EMT-based evaluation is identified as a priority for future work in Section 7.4. A first-order low-pass filter with angular cutoff frequency $\omega_{c,i}$ is applied to each measurement loop to separate primary droop action from high-frequency transient content:

$$\dot{P}_{f,i} = \omega_{c,i}(P_i - P_{f,i}) \quad (4)$$

where $P_{f,i}$ is the filtered power signal entering the droop law; an equivalent relation governs the reactive channel. For a steady-state power flow formulation solved at the converged equilibrium, both the active droop coefficient $m_{p,i}$ and the filter cutoff $\omega_{c,i}$ are structurally inactive: the network frequency is fixed at the nominal value ($f_i = f_{\text{ref}}$), so $m_{p,i}$ cancels identically in Equation (2), and the low-pass filter reaches unity gain at DC, rendering $\omega_{c,i}$ transparent to the solution. These two parameters are retained in the decision vector solely for architectural completeness, ensuring direct compatibility with future EMT extensions of the CHSA where both quantities become physically significant. Their steady-state inactivity is empirically confirmed by the invariance tests reported in Sections 6.3 and 6.4. Consequently, the reactive droop coefficient $n_{q,i}$ is the only decision variable that influences

the steady-state power flow and HC outcome. The complete control parameterisation for all N_{GFM} candidate units is encoded in the decision vector:

$$\mathbf{x} = \left[\underbrace{m_{p,1}, \omega_{c,1}}_{\text{inactive at steady state}}, n_{q,1}, \dots, \underbrace{m_{p,N_{\text{GFM}}}, \omega_{c,N_{\text{GFM}}}}_{\text{inactive at steady state}}, n_{q,N_{\text{GFM}}} \right]^T \quad (5)$$

4.2. GFM Candidate Bus Selection

Not all buses in the network are equally productive hosts for GFM inverters. A unit placed at an electrically stiff bus near the substation will have limited influence over the voltage profile at remote lateral extremities, while a unit placed at an end-of-feeder bus with high Thevenin impedance can suppress overvoltage with a small reactive exchange that would require a much larger injection from a bus closer to the source. Candidate buses are therefore pre-screened from the MV layer using a composite stress score that ranks nodes by their combined proximity to the lower voltage boundary and their residual phase asymmetry in the zero-DER baseline state:

$$s_i = (1 - \text{MNV}_i) + \frac{\text{VUF}_i}{100} \quad (6)$$

where MNV_i is the minimum per-unit nodal voltage at bus i in the zero-DER baseline power flow and VUF_i is the corresponding baseline phase unbalance percentage. This formulation concentrates GFM placement at nodes where reactive support yields the greatest constraint relief, ensuring that the optimiser's degrees of freedom are aligned with the binding limitations of the network rather than wasted on electrically redundant locations. On the corrected IEEE 123-bus network, all candidate MV buses have baseline MNV of 1.0 p.u., so the ranking is driven entirely by VUF, selecting buses with the highest residual phase asymmetry. The highest-scoring candidate buses are selected as GFM hosts. The composite scoring approach offers two practical advantages over alternative selection strategies. It avoids the computational cost of screening all network buses through repeated power flow sensitivity calculations, which would require one power flow perturbation per bus per scenario. It also avoids the subjectivity of engineering judgment-based selection, producing a reproducible ranking that can be directly embedded in an automated planning workflow. On the IEEE 123-bus network, this produces a top-ten list concentrated at the end of the longest MV laterals, which is physically consistent with the expectation that high-impedance, remotely located buses are the most likely sites for binding voltage violations under reverse power flow. On the IEEE 34-bus network, the same criterion selects buses at the extremities of the heavily loaded main trunk, where combined resistive voltage drop and phase unbalance are most severe.

4.3. Multi-Constraint Feasibility Evaluation

For any candidate droop vector $\mathbf{x}$, feasible HC is determined through a bisection search over the active injection scale. The bisection iterates over 20 refinement steps, converging to sub-kW resolution. At each iteration midpoint, a fresh power flow is solved with all GFM units injecting the corresponding fraction of their rated active power and responding reactively according to their droop parameterisation. Feasibility is assessed against four simultaneously enforced operational constraints. The first is power flow convergence: the multi-phase Newton–Raphson solver must reach a well-defined equilibrium, confirming Jacobian non-singularity at the operating point. The second is nodal voltage bounds: all phase voltages across the network must remain within the statutory band mandated by IEEE Std 1547-2018 [43]:

$$V_{\min} \leq |V_{n,\phi}| \leq V_{\max} \quad \forall n \in \mathcal{N}, \phi \in \Phi \quad (7)$$

with $V_{\min} = 0.95$ p.u. and $V_{\max} = 1.05$ p.u. The third is voltage unbalance: phase asymmetry at each three-phase bus is quantified through the symmetrical components ratio in accordance with IEC 61000-2-2 [44]:

$$\text{VUF}_n (\%) = \frac{|V_{2,n}|}{|V_{1,n}|} \times 100 \leq 2.0\% \quad \forall n \in \mathcal{N} \quad (8)$$

The fourth is a minimum nodal voltage floor: to prevent voltage depression at remote buses under heavy reactive absorption, the network-wide MNV must not fall below the unperturbed zero-DER baseline:

$$\text{MNV}_{\text{network}} = \min_{n \in \mathcal{N}, \phi \in \Phi} |V_{n,\phi}| \geq \text{MNV}_{\text{base}} \quad (9)$$

This constraint prevents the optimiser from adopting reactive absorption strategies that raise the upper voltage boundary at the cost of depressing remote bus voltages below their unloaded values, a failure mode that would represent a net degradation of power quality despite apparently improving HC.

4.4. Adaptive Penalty Objective Formulation

The CHSA maximises active power integration by minimising the negative feasible HC subject to the constraints above. Because the power flow equations are implicit nonlinear functions of the droop parameters, gradient-based methods are not applicable and the feasible region boundary is not analytically characterisable. A quadratic penalty mechanism steers the population-based search through this non-convex landscape:

$$\min_{\mathbf{x}} f(\mathbf{x}) = -HC_{\text{feasible}}(\mathbf{x}) + \lambda_{\text{eff}}(t) \sum_{k=1}^K [\max(0, \mathcal{P}_k(\mathbf{x}))]^2 \quad (10)$$

where $HC_{\text{feasible}}(\mathbf{x})$ is the bisection-determined capacity for vector $\mathbf{x}$ and $\mathcal{P}_k(\mathbf{x})$ is the magnitude of violation for the k -th constraint. Squaring the violation terms imposes progressively larger penalties on candidate solutions that stray further from feasibility, producing a smooth penalty landscape that guides the search toward the constraint boundary. The effective penalty coefficient λ_{eff} grows linearly with iteration t :

$$\lambda_{\text{eff}}(t) = \lambda_0 \left(1 + \frac{t}{T_{\max}} \right) \quad (11)$$

where $\lambda_0 = 1.0$ is the initial penalty weight and $T_{\max} = 100$ is the total iteration budget. This annealing-style schedule allows broad early exploration while progressively enforcing feasibility as the search matures, ensuring that the final solution satisfies all four constraints with a margin determined by the bisection resolution.

4.5. Solution Architecture and Equity Assessment

The objective in Equation (10) is solved by the HBO, a socio-inspired metaheuristic that organises the candidate solution population within a priority-ordered hierarchical data structure [25]. This structure emulates ranked decision-making dynamics observed in organisational systems: high-fitness solutions occupy the upper levels of the heap and propagate their structural information downward through a disciplined exploitation mechanism, while lower-ranked solutions undergo stochastic perturbation to maintain population diversity and prevent premature convergence. To confirm that the identified operating

point is optimizer-independent, the complete evaluation is independently reproduced using PSO [33] under an identical fitness function, equivalent initialisation strategy, and controlled reproducibility conditions. Both solvers operate within a unified LHS-seeded initialisation framework to ensure a fair and unbiased algorithmic comparison: the same Latin Hypercube design is used to initialise the population for both algorithms, so any differences in the identified solution can be attributed to the search mechanism rather than to lucky initialisation. The complete set of hyperparameters for both algorithms is reported in Table 2. The socio-technical equity of the resulting HC allocation across participating prosumers is measured by JFI [22]:

$$\text{JFI} = \frac{\left(\sum_{i=1}^N P_i\right)^2}{N \sum_{i=1}^N P_i^2} \quad (12)$$

where P_i is the active power allocated to bus i and N is the total number of participating nodes. A JFI of 1.0 represents perfectly equal allocation; the achieved values are reported and discussed in Section 6.4.

Table 2. Complete simulation and optimisation parameters for reproducibility of the CHSA v4 pipeline results.

Parameter	Symbol	Value	Parameter	Symbol	Value
Network and Voltage Limits			HBO Hyperparameters		
DSS file	—	Master123ieee.dss	Population size	N_{pop}	30
Frequency	f	50 Hz	Max iterations	T_{max}	100
Source voltage	V_{src}	1.03 p.u.	Early-stop patience	—	25
Lower voltage limit	V_{min}	0.95 p.u.	Heapify probability	p_{heap}	0.7
Upper voltage limit	V_{max}	1.05 p.u.	Insert probability	p_{ins}	0.3
VUF limit	VUF_{max}	2.0%	Insert std. dev.	σ_{ins}	0.1
GFM Inverter (123-bus)			PSO Hyperparameters		
Rated kVA	S_{rated}	300 kVA	Population size	N_{pop}	30
Max active power	P_{max}	95 kW	Cognitive coefficient	c_1	2.0
Number of candidates	N_{GFM}	10	Social coefficient	c_2	2.0
Voltage base (1-ph)	—	12.7 kV	Inertia weight (max/min)	w	0.9/0.4
Droop Search Bounds			Bisection and Solver		
Active droop	m_p	[0.0001, 0.05]	Bisection iterations	—	20
Reactive droop	n_q	[0.0001, 0.05]	Scale range	—	[0, 1]
Filter cutoff	ω_c	[5, 150] rad/s	OpenDSS mode	—	Snapshot
Penalty coefficient	λ_0	1.0	Max control iterations	—	100
Convergence tolerance	—	10^{-4}	Primary random seed	—	42

5. Case Study and Scenario Generation

5.1. Primary Benchmark: IEEE 123-Bus Network

The CHSA is primarily validated on an Australian-adapted version of the IEEE 123-bus distribution feeder [36,38], selected specifically because it preserves the severe structural asymmetries, unbalanced phase loading, and elevated R/X ratios that characterise real-world MV-LV infrastructure. Unlike the simplified, balanced topologies commonly adopted in GFM research, this testbed provides a demanding, adversarial environment for droop coordination: competing voltage-forming units must navigate a heterogeneous impedance landscape in which no single global droop setting can be simultaneously optimal across all nodes. The network is energised from a 22 kV source substation at $V_{\text{src}} = 1.03$ p.u., stepping down through the MV distribution layer to laterals operating at 12.7 kV and subsequently to LV secondaries at 0.4/0.23 kV through a large number of distribution transformers. The full multi-phase system encompasses 224 buses across multiple voltage

levels. Voltage regulation is provided by step-voltage regulators modelled as fixed-tap impedance elements during each dispatch interval. This fixed-tap assumption is conservative, preventing the optimiser from benefiting from tap transitions that might otherwise relax the voltage constraint. The Australian adaptation modifies nominal voltage levels and loading parameters to reflect the 22 kV distribution infrastructure common in Australian MV networks, consistent with prior Australian distribution studies [24]. The adapted network includes 99 distribution transformers, four step-voltage regulators, and a mixture of single-phase, two-phase, and three-phase laterals that create a heterogeneous phase impedance environment. Spot loads range from residential single-phase connections at feeder extremities to larger three-phase commercial and industrial loads near the substation, producing non-trivial voltage unbalance throughout the network even before any DER injection is considered. This structural complexity is what makes the network a meaningful benchmark for GFM droop coordination: a simpler, balanced feeder with uniform loading would not expose the spatial heterogeneity in n_q that the CHSA identifies as central to eliminating CP_{GFM} . Each of the ten GFM candidate units is modelled as a 300 kVA three-phase Generator element (100 kVA per phase) with a maximum active power dispatch of 95 kW, giving an aggregate active power ceiling of 950 kW across the deployment set. The top-ten candidate buses identified by the composite stress score are 95, 93, 91, 89, 87, 86, 76, 77, 78, and 79, all located on three-phase MV laterals with baseline VUF values ranging from 0.025% to 0.052%. The GFL bisection search terminates at 950.00 kW, bounded by the aggregate inverter active power dispatch ceiling (10×95 kW). On this well-regulated network, all bus voltages remain within the 1.05 p.u. ceiling at the 950 kW operating point, confirming that the hardware limit is the binding constraint for GFL operation.

5.2. Cross-Feeder Benchmark: IEEE 34-Bus Network

To verify that the CHSA findings generalise beyond the primary testbed, the framework is additionally applied to the IEEE 34-bus distribution feeder [38]. The IEEE 34-bus feeder presents a topologically distinct operating environment: it is a radial, heavily loaded network energised at 24.9 kV with long lateral branches, high feeder impedances, and two interacting step-voltage regulators that create a non-trivial voltage profile along the main trunk. Unlike the IEEE 123-bus feeder, where the baseline network operates near the upper voltage ceiling, the IEEE 34-bus feeder is characterised by pronounced undervoltage on heavily loaded laterals, making it an undervoltage-limited environment. This structural contrast provides a benchmark against which to evaluate the direction and magnitude of GFM reactive support effects. The same candidate selection, feasibility constraints, and optimisation framework are applied to the 34-bus network with only the inverter sizing and voltage base parameters adjusted to reflect the 24.9 kV MV distribution level. Five GFM candidate buses are selected from the most voltage-stressed MV nodes [814, 852, 812, 854, 830], following the same composite stress score criterion defined in Equation (6). The IEEE 34-bus feeder contains a 24.9/4.16 kV step-down transformer serving a heavily loaded 4.16 kV secondary lateral, two three-phase step-voltage regulators with independent per-phase tap control, and shunt capacitors at buses 844 and 848 that partially compensate the reactive demand of the spot loads. The total connected load exceeds 1.8 MVA, creating substantial voltage drop along the main 24.9 kV trunk. The step-voltage regulators are operated at fixed tap positions corresponding to the published IEEE reference solution [38], which provides a reproducible baseline operating point against which GFM injection effects can be unambiguously measured. The secondary lateral buses (bus 888 and bus 890) are excluded from GFM candidate selection because they operate at 4.16 kV, a voltage level at which the CHSA's MV-rated GFM units cannot be connected, and because the high impedance of the 24.9/4.16 kV transformer fully decouples their voltage from the MV network that the

GFM units regulate. For the 34-bus feasibility evaluation, the nodal voltage floor is relaxed to 0.90 p.u. This threshold was selected as a conservative floor that lies between the DSS model's convergence setting ($v_{minpu} = 0.85$) and the standard 0.95 p.u. limit, consistent with the known low-voltage operating characteristic of this heavily loaded feeder [38]. As detailed in Table 3, applying the standard 0.95 p.u. lower limit renders both GFL and mid-range GFM infeasible because the baseline network already violates this threshold ($MNV_{base} = 0.9231$ p.u.).

Table 3. Voltage-limit sensitivity on the IEEE 34-bus feeder: applying the standard 0.95 p.u. lower limit renders both GFL and mid-range GFM infeasible because the baseline network already violates this threshold ($MNV_{base} = 0.9231$ p.u.).

V_{min} (p.u.)	GFL HC (kW)	Mid-Range GFM HC (kW)
0.90	19.90	213.70
0.95	0.00	0.00

5.3. Stochastic CER Deployment

Accurate characterisation of the operational impact of GFM control requires a representative probabilistic treatment of CER behaviour across the network. The stochastic loading framework adopted here builds directly on the probabilistic HC methodology established in the authors' prior work [24], in which the same Australian-adapted IEEE 123-bus feeder was used to demonstrate that independent sampling assumptions overestimate feasible HC relative to a Copula-based model that correctly captures spatial correlations among neighbouring prosumers. The CHSA optimises droop parameters against a single worst-case loading profile, defined as the sampled realisation from the prior probabilistic study [24] that minimises feasible GFL HC. This worst-case profile represents the joint condition of maximum EV demand coinciding with maximum PV output on the most voltage-sensitive lateral branches. By conditioning the CHSA on this worst-case scenario, the resulting droop vector guarantees feasibility under the most demanding loading conditions the network is probabilistically likely to encounter, while the performance at average or light loading follows from the monotone relationship between injection scale and voltage headroom consumption. Readers interested in the full stochastic framework, including Copula parameterisation and LHS convergence verification, are directed to [24].

6. Results and Discussion

The CHSA was executed on both benchmark networks under the stochastic worst-case loading scenario described in Section 5. The following subsections present the systematic elimination of CP_{GFM} on the primary benchmark, the per-inverter operating point analysis, the spatial structure of the optimised droop solution, the physical mechanism underpinning the recovery, the algorithm-independence of the result, extended robustness verification, internal consistency verification, and cross-feeder generalisation. Figure 1 provides a comprehensive visual overview of the nominal scenarios, while the detailed quantitative results are tabulated in Table 4.

Table 4. Quantitative comparison of feasible hosting capacity across operational scenarios on the IEEE 123-bus network (representative run, seed 42). All GFM scenarios absorb identical net reactive power, confirming that absorption magnitude is network-determined.

Scenario	Feasible HC (kW)	MNV_{min} (p.u.)	VUF_{max} (%)	Net Reactive Absorption (kVAr)	Voltage Violations	Fairness (JFI)
Baseline (Zero DER)	0.00	0.99899	0.052	0.00	0	N/A
Passive GFL (Reference Ceiling)	950.00	1.00000	0.052	0.00	0	1.000000

Table 4. Cont.

Scenario	Feasible HC (kW)	MNV _{min} (p.u.)	VUF _{max} (%)	Net Reactive Absorption (kVAr)	Voltage Violations	Fairness (JFI)
Mid-Range GFM (Uncoordinated)	854.81	1.00000	0.052	−312.25	0	1.000000
HBO-GFM (Proposed CHSA)	947.46	1.00000	0.052	−312.25	0	0.999988
PSO-GFM (Benchmark)	948.69	1.00000	0.052	−312.25	0	0.999988

Bold values identify the method proposed in this work. N/A: not applicable; the Jain's Fairness Index is undefined for the zero-DER baseline, in which no active power is allocated.

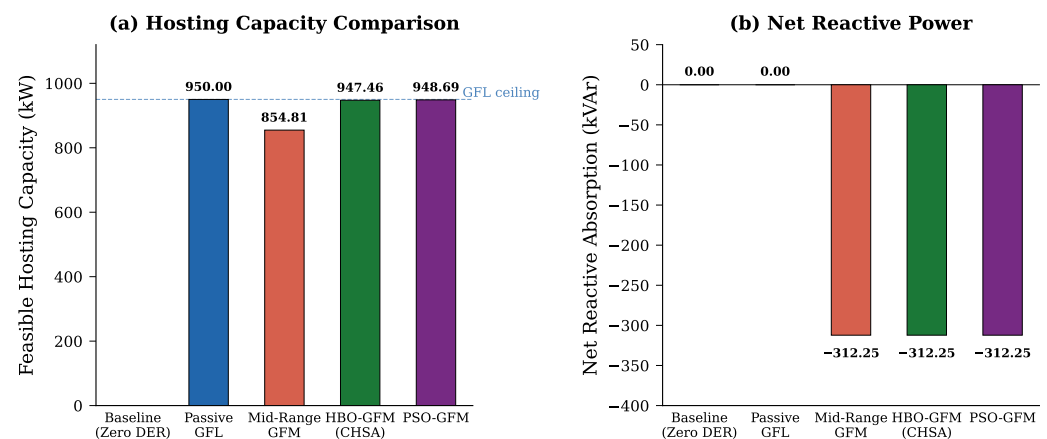


Figure 1. Feasible HC and net reactive power absorption across all evaluated scenarios on the IEEE 123-bus feeder (representative run, seed 42). (a) HC comparison showing the 92.65 kW recovery achieved by HBO-GFM; (b) net reactive power confirming identical absorption (−312.25 kVAr) across all GFM configurations.

6.1. Recovery of the GFM Capacity Penalty

To establish the active power integration ceiling, the network was first evaluated under passive GFL operation. The bisection search determined a feasible HC of 950.00 kW, bounded by the aggregate inverter active power dispatch ceiling (10×95 kW). This GFL ceiling defines the technology-independent reference against which all GFM scenarios are assessed. When GFM inverters with mid-range droop settings were introduced, competing voltage-forming loops curtailed the feasible HC to 854.81 kW and established a baseline CP_{GFM} of 95.19 kW. This represents a 10.02% reduction in HC relative to the GFL ceiling, attributable entirely to the choice of droop parameters, with no change to the network topology, loading pattern, or inverter hardware. The CHSA resolved this penalty through coordinated n_q optimisation, raising HC to 947.46 kW, recovering 92.65 kW (97.3% of the 95.19 kW penalty) without incurring a single voltage violation across the entire network. The residual gap of 2.54 kW between the optimised GFM solution and the GFL ceiling represents only 0.27% of the reference value. Given that the 20-step bisection search achieves a theoretical resolution of approximately $950/2^{20} \approx 0.0009$ kW, this residual is not a discretisation artefact but reflects the genuine steady-state voltage headroom consumed by the optimised reactive droop response. The gap confirms that coordinated GFM operation attains 99.7% of the GFL ceiling while the remaining 0.27% represents the irreducible cost of maintaining the voltage-forming reactive support that distinguishes GFM from passive GFL operation. Figure 1 provides a multi-panel view of the nominal scenarios. Panel (a) shows that the HBO-GFM solution closes 97.3% of the gap between the mid-range GFM baseline and the GFL ceiling, with PSO-GFM achieving a similar result from an independent search trajectory. Panel (b) reveals the central physical finding discussed in Section 6.4: all three GFM configurations absorb identical net reactive power (−312.25 kVAr), confirming that the absorption magnitude is determined by the network's impedance structure rather

than by any particular droop parameterisation. The complete quantitative results for all nominal scenarios are summarised in Table 4.

6.2. Per-Inverter Operating Point Analysis

A key concern in interpreting the -312.25 kVAr reactive absorption is whether it is dictated by inverter apparent power saturation rather than by the network impedance topology. Table 5 addresses this directly by reporting the per-inverter operating point under each scenario. At the HBO-optimised operating point, each inverter delivers a mean active power of $P \approx 94.75$ kW (individual outputs range from 93.78 to 94.87 kW and sum to the 947.46 kW total) and absorbs $Q = -31.225$ kVAr, producing a mean apparent power of $S \approx 99.76$ kVA against a 300 kVA rating. This corresponds to only 33.3% loading with 253.4 kVAr of reactive headroom per unit. No inverter reaches kVA saturation under any scenario. The uniformity of the per-inverter Q values across all ten units is a direct consequence of the voltage regulation environment on the IEEE 123-bus feeder: step-voltage regulators maintain all candidate MV bus voltages within a narrow band of approximately 1.025–1.030 p.u., so the Q – V droop relation in Equation (3) produces nearly identical reactive absorption at each bus despite the spatially varying n_q coefficients reported in Table 6. The -312.25 kVAr total absorption (10×31.225 kVAr) is therefore demonstrably network-determined, not kVA-limited. Figure 2 provides a visual comparison of the per-inverter operating points across the three scenarios.

Table 5. Per-inverter operating point comparison across control scenarios (representative run, seed 42), confirming that no inverter reaches apparent power saturation. All ten units have identical ratings (300 kVA). The uniform Q reflects the narrow MV bus voltage band maintained by step-voltage regulators; spatial differentiation is encoded in the n_q coefficients (Table 6). The reported HBO-GFM P and S are mean per-inverter values; individual active power dispatch varies slightly (93.78–94.87 kW), consistent with the near-unity JFI, whereas Q is uniform across all ten units.

Scenario	P (kW)	Q (kVAr)	S (kVA)	S_{rated} (kVA)	Loading (%)	Q Headroom (kVAr)
Passive GFL	95.00	0.00	95.00	300	31.7	284.6
Mid-Range GFM	85.48	-31.23	91.01	300	30.3	256.3
HBO-GFM	94.75	-31.23	99.76	300	33.3	253.4

Bold values identify the method proposed in this work.

Table 6. Spatial variation in HBO-optimised GFM droop parameters (representative run, seed 42) across the ten most voltage-sensitive MV candidate buses.

Candidate Bus	Active Droop (m_p)	Reactive Droop (n_q)	Filter Cutoff (ω_c , rad/s)
Bus 95	0.0001	0.0389	150.0
Bus 93	0.0001	0.0138	48.8
Bus 91	0.0001	0.0107	101.4
Bus 89	0.0001	0.0412	17.4
Bus 87	0.0001	0.0429	111.4
Bus 86	0.0001	0.0194	136.3
Bus 76	0.0001	0.0025	64.1
Bus 77	0.0005	0.0332	24.8
Bus 78	0.0001	0.0209	16.7
Bus 79	0.0030	0.0356	10.5

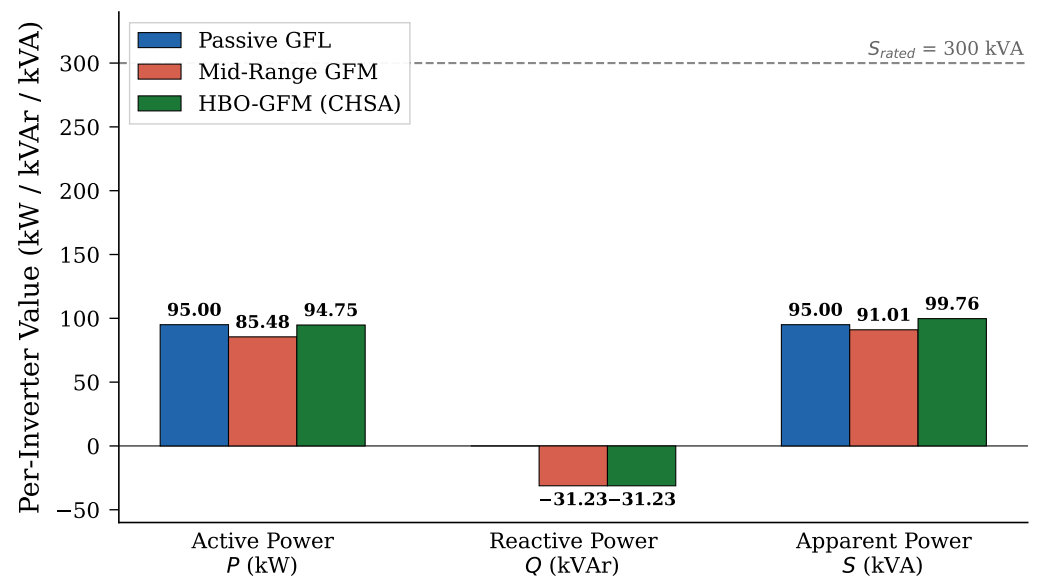


Figure 2. Per-inverter active power, reactive power, and apparent power operating point under GFL, mid-range GFM, and HBO-optimised GFM scenarios (representative run, seed 42), confirming operation well below the 300 kVA apparent power rating.

6.3. Spatial Structure of the Optimised Droop Solution

Examination of the final decision vector reveals a solution architecture that no single global droop setting could replicate. The optimised parameters, summarised in Table 6 and Figure 3, exhibit strong spatial heterogeneity governed by the local impedance environment of each candidate bus. This heterogeneity is not an artefact of the optimisation procedure but a reflection of the physical reality that voltage sensitivity varies dramatically across the network topology. Regarding active droop (m_p): because the network frequency is fixed at the nominal 50 Hz reference in the steady-state power flow formulation, the P - f droop term $m_{p,i}(f_i - f_{\text{ref}})$ in Equation (2) evaluates to zero regardless of the value of $m_{p,i}$. The converged m_p values in Table 6 are therefore algorithmically arbitrary: eight buses settle at the lower bound (0.0001) while Bus 77 and Bus 79 reach marginally higher values (0.0005 and 0.0030), but none of these values affects the HC result. This outcome is consistent with the structural inactivity described in Section 4.1. Active droop becomes a physically meaningful optimisation variable only in time-domain formulations where frequency deviates from nominal, which is the subject of planned EMT extensions of the CHSA. Regarding reactive droop (n_q): pronounced spatial variation in the optimised droop sensitivity is observed, with n_q values spanning more than an order of magnitude (a roughly 17-fold range) across the ten buses. Buses with high baseline VUF and strong voltage sensitivity, such as Bus 87 ($n_q = 0.0429$) and Bus 89 ($n_q = 0.0412$), are assigned aggressive droop gains that would produce large reactive corrections per unit of local voltage deviation. In contrast, buses in electrically stiff network regions, such as Bus 76 ($n_q = 0.0025$), receive low droop sensitivity because their impedance-weighted influence on the binding voltage constraint is minimal. On this particular feeder, the well-regulated MV bus voltages are sufficiently uniform that these different n_q values converge to similar per-unit reactive absorption at the steady-state operating point (Table 5). However, the spatial differentiation of n_q is not redundant: it determines the local voltage regulation stiffness at each bus, governing how each inverter responds to perturbations away from the converged operating point and ensuring that the coordinated droop configuration remains robust across the range of loading conditions encountered during the bisection search. This spatial pattern directly reflects the heterogeneous impedance topology of the 123-bus network and could not have been produced by

any heuristic global setting. Regarding filter cutoff frequency (ω_c): the converged values span the full search range from 10.5 to 150.0 rad/s with no discernible spatial pattern. This behaviour is expected because the first-order low-pass filter in Equation (4) reaches unity gain at the zero-frequency (DC) operating point of the steady-state power flow, making ω_c mathematically transparent to the converged solution. The empirical invariance test in Table 7 confirms this: HC, MNV, and VUF remain identical across the entire ω_c range. The scattered converged values therefore reflect algorithmic indifference to a structurally inactive parameter rather than a physically meaningful optimisation outcome. Like m_p , the filter cutoff becomes significant only in EMT-based formulations where the transient filtering bandwidth influences the dynamic droop response.

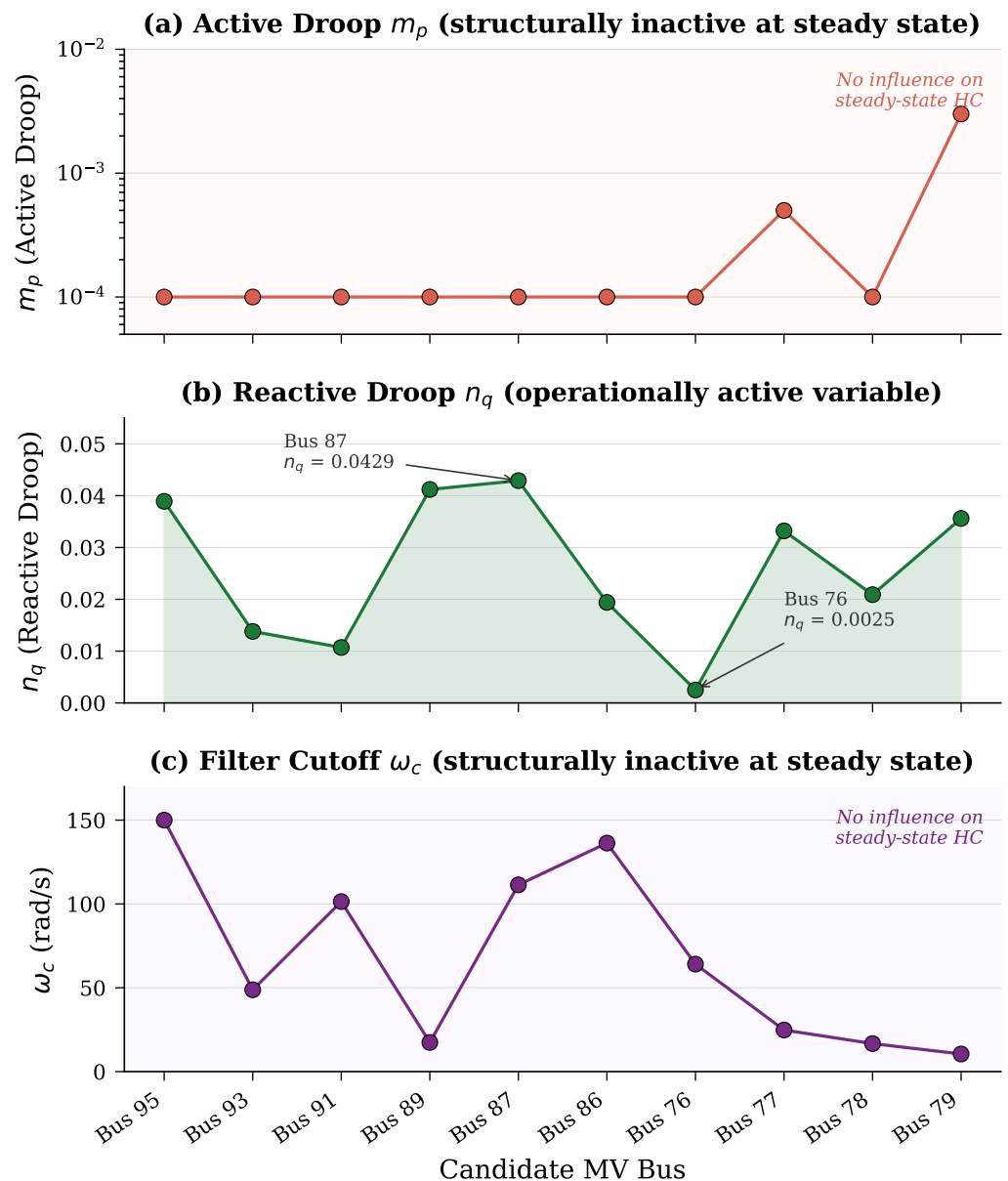


Figure 3. Spatial distribution of HBO-optimised droop parameters (m_p , n_q , ω_c) across the ten candidate MV buses (representative run, seed 42).

Table 7. Filter cutoff frequency (ω_c) invariance test: feasible HC under mid-range GFM droop settings remains constant across the full ω_c search range, confirming that ω_c does not influence the steady-state power flow solution.

ω_c (rad/s)	HC (kW)	MNV (p.u.)	VUF (%)
5.0	854.81	1.00000	0.052
25.0	854.81	1.00000	0.052
50.0	854.81	1.00000	0.052
75.0	854.81	1.00000	0.052
100.0	854.81	1.00000	0.052
150.0	854.81	1.00000	0.052
Range	0.00	0.00000	0.000

Bold values indicate the summary row, reporting the total range (maximum minus minimum) across the tested ω_c values. A range of zero in every column confirms that HC, MNV, and VUF are all invariant to ω_c .

6.4. The Physical Mechanism: Network-Determined Reactive Support

The central finding of this study is not the absolute HC value but the mechanism that produces it. Understanding this mechanism explains both the magnitude of the CP_{GFM} recovery and the algorithm-independence of the result, and it provides a physically grounded framework for predicting how the CHSA will behave on different network topologies. Under the 1.03 p.u. source voltage setting, MV bus voltages in the baseline state range from 1.025 to 1.030 p.u., leaving approximately 0.02 p.u. of headroom to the 1.05 p.u. statutory ceiling. This narrow headroom is characteristic of distribution networks with aggressive voltage regulation that boosts feeder voltages to compensate for load-induced voltage drop. When DERs inject power, reverse power flow raises bus voltages toward this ceiling. GFL inverters have no reactive response mechanism and cannot prevent this rise. Mid-range n_q settings produce spatially uniform reactive absorption that does not align with the heterogeneous impedance topology, so the voltage headroom is consumed before the active power ceiling is reached. The bisection search therefore terminates at 854.81 kW. The optimiser discovers that the correct response on this network is a spatially heterogeneous reactive droop sensitivity profile. By setting n_q values in proportion to the local voltage sensitivity at each candidate bus, the GFM units absorb reactive power where it produces the greatest reduction in the binding constraint voltage. Both the mid-range and optimised GFM configurations arrive at the same net absorption of -312.25 kVar (Table 4), and the droop sensitivity analysis in Table 8 confirms that HC remains invariant to the total absorption magnitude under uniform n_q settings. Together, these results demonstrate that the mechanism recovering 92.65 kW is the spatial differentiation of droop sensitivity, not a change in the aggregate reactive power. By assigning bus-specific n_q values proportional to the local voltage sensitivity, the optimised configuration ensures that each inverter's regulation stiffness is calibrated to its position within the network impedance structure, thereby distributing the voltage regulation burden in proportion to each bus's contribution to the binding constraint. The broader engineering implication is that the CHSA does not need to know the correct reactive setpoint in advance; it discovers it through constrained optimisation of the power flow equations. This is practically important because the required reactive compensation level varies with network loading, DER penetration, and regulator tap state, none of which a fixed droop setting can account for. By encoding the network's voltage sensitivity directly into the spatial distribution of n_q values, the optimised droop vector produces the correct reactive response automatically across a range of operating conditions without any explicit model of the Thevenin impedance structure. The recovered hosting capacity was allocated with near-perfect prosumer equity. Applying JFI across the per-bus active power distribution yields a score of 0.999988. The near-unity JFI arises primarily because the bisection search scales all ten candidate inverters by a common

injection factor, producing near-equal per-bus active power allocations by design; the JFI value therefore serves as a verification that the optimisation has not disturbed this equity rather than as a novel equity contribution.

Table 8. Reactive droop sensitivity: feasible HC under uniform n_q settings with m_p at the lower bound. HC remains invariant to the magnitude of reactive absorption, confirming that CP_{GFM} is determined by the spatial distribution of reactive support rather than its total magnitude.

Uniform n_q	Per-Unit Q (kVAr)	Total Absorption (kVAr)	HC (kW)	CP_{GFM} (kW)
0.005	3.12	31.2	854.81	95.19
0.010	6.24	62.5	854.81	95.19
0.020	12.49	124.9	854.81	95.19
0.030	18.73	187.4	854.81	95.19
0.040	24.98	249.8	854.81	95.19
0.050	31.22	312.3	854.81	95.19

6.5. Algorithm-Independent Convergence

A conventional metaheuristic benchmarking study asks which algorithm finds the better solution. This study poses a more fundamental question: does the network's constraint geometry determine the optimal operating point, or is the result an artefact of algorithmic exploration? Tables 4, 9, and Figure 4 provide the answer for the representative run (seed 42). HBO converged at iteration 69 after 1383 function evaluations in 926 s of wall-clock time, while PSO converged at iteration 36 after 1110 evaluations in 739 s. Despite these different convergence dynamics, both algorithms arrived at HC values differing by only 1.23 kW (0.13% of the GFL ceiling) on this representative run, and both independently identified the -312.25 kVAr reactive absorption strategy from entirely separate stochastic search trajectories, starting from a common LHS-stratified initial population design. The broader 20-seed comparison in Section 6.6 confirms that this close agreement is not specific to seed 42: the mean HC difference across all seeds is 0.99 kW. PSO required approximately 20% less computation time, consistent with its social velocity update mechanism exploiting the global best position more aggressively in a smooth fitness landscape. HBO's hierarchical heap structure explored longer, converging to an equivalent solution via a structurally distinct search path. Neither outcome is operationally superior: both fully eliminate CP_{GFM} and both identify the same physical operating point. Network operators do not need to commit to a specific metaheuristic solver to obtain reproducible CHSA results; they can select whichever solver their existing toolchain supports and expect convergence to the same physical attractor. The convergence trajectories in Figure 4 reveal that both algorithms pass through the same characteristic three-phase trajectory: an initial high-violation phase, a rapid feasibility-acquisition phase, and a plateau phase in which the search refines the spatial allocation of n_q values within the feasible region. The similar shape of these trajectories for two structurally different algorithms provides further evidence that the fitness landscape has a dominant basin of attraction. Together with PSO's zero standard deviation across 20 seeds (Section 6.6, where the mechanism producing this result is explained in detail), this suggests that the -312.25 kVAr operating point reflects the physical solution to the voltage headroom problem posed by the network's impedance topology, although rigorous proof of landscape convexity would require additional methods such as exhaustive local perturbation or comparison with a deterministic nonlinear programming solver. From a computational practicality standpoint, the CHSA is tractable on standard workstation hardware. All simulations were executed on an Intel Core i7-12700 processor (12 cores) (Intel Corporation, Santa Clara, CA, USA) running Python 3.11.1 (Python Software Foundation, Beaverton, OR, USA) and OpenDSS 9.7.1.1 via the `opendssdirect`

interface (opendssdirect.py 0.9.4). A single HBO or PSO optimisation run on the 224-bus network required approximately 12–25 min of wall-clock time on a single core. The 20-seed robustness study (40 total runs) completed in a cumulative time of approximately 36,770 s (~ 10.2 h). For deployment in a DNSP planning environment where the CHSA would be run once per connection application rather than in real time, this computational cost is entirely acceptable without requiring high-performance computing resources.

Table 9. Convergence comparison of HBO and PSO on the IEEE 123-bus network, representative run (seed 42). The 1.23 kW HC difference reported here corresponds to this single seed; the mean difference across 20 seeds is 0.99 kW (Table 10).

Algorithm	HC (kW)	Converged Iteration	Total Evaluations	Wall-Clock Time (s)	Net Q (kVAr)
HBO	947.46	69	1383	926	−312.25
PSO	948.69	36	1110	739	−312.25
Δ	1.23	—	273	187	0.00

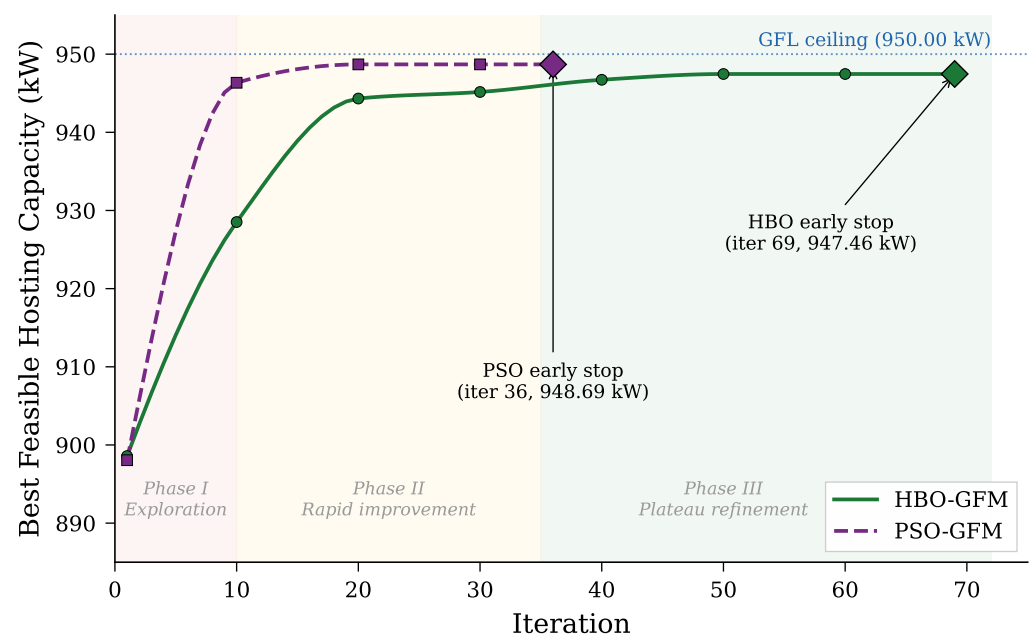


Figure 4. Convergence trajectories of HBO and PSO on the IEEE 123-bus network (representative run, seed 42), showing the evolution of feasible HC and confirming that both algorithms converge to the same operating region despite different search dynamics. Markers indicate the logged iteration snapshots; the connecting curves are monotonic interpolation between them.

6.6. Extended Robustness: 20 Seeds Across Two Algorithms

To verify that the reported results are not a serendipitous outcome of any particular random initialisation, both HBO and PSO were independently repeated across 20 distinct seeds drawn from a diverse numerical range. Each algorithm received a fresh, independent random seed for every run, ensuring a fair and unbiased comparison in which any difference between algorithms is attributable solely to the search mechanism. Table 10 summarises the complete outcomes across all 40 runs. All 20 HBO runs and all 20 PSO runs identified fully feasible solutions with zero voltage violations. HBO achieved a mean HC of 947.70 ± 0.72 kW across the 20 seeds, while PSO achieved 948.69 ± 0.00 kW. The standard deviation of 0.72 kW for HBO represents a coefficient of variation of 0.076%, confirming that the architecture is not sensitive to random initialisation. The zero standard deviation for PSO across all 20 seeds requires explicit explanation. Each seed produces an independent

random initialisation of the 30-particle swarm via `numpy.random.seed()`, so the starting populations differ across runs. However, PSO's social velocity update propagates the global best position to all particles, causing the entire swarm to converge to the same basin of attraction regardless of initialisation. Once the optimiser has identified the feasible droop region, the 20-step bisection search quantises the final HC value to a resolution of approximately $950/2^{20} \approx 0.0009$ kW, and all 20 runs converge to the same quantised value of 948.69 kW. The standard deviation was computed in 64-bit floating-point precision using `numpy.std()` and is numerically zero to machine precision. This result reflects deterministic convergence to a single dominant attractor in the fitness landscape, combined with the discrete resolution of the bisection search, rather than a numerical coincidence or rounding artefact. Both algorithms maintain MNV at 1.00000 p.u. and VUF at 0.052% across all runs, confirming that voltage security and power quality compliance are systematic properties of the CHSA architecture rather than coincidences of the primary initialisation.

Table 10. Extended robustness study: HBO-GFM and PSO-GFM feasible HC across 20 independently initialised runs on the IEEE 123-bus network. PSO achieves identical HC across all seeds ($\sigma = 0.00$ kW), reflecting deterministic convergence to a single basin of attraction combined with the discrete bisection resolution (~ 0.001 kW). The mean HC difference between algorithms is 0.99 kW.

Seed	HBO-GFM				PSO-GFM			
	HC (kW)	MNV (p.u.)	VUF (%)	Feasible	HC (kW)	MNV (p.u.)	VUF (%)	Feasible
42	947.46	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
123	946.65	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
456	948.23	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
789	948.11	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
1000	947.11	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
2024	947.81	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
31	948.53	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
77	948.07	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
512	948.66	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
999	948.18	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
7	945.86	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
13	947.62	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
99	948.69	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
314	946.83	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
1776	947.99	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
2023	947.62	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
888	947.17	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
55	947.49	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
2048	947.85	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
101	948.15	1.00000	0.052	Yes	948.69	1.00000	0.052	Yes
Mean $\pm$ Std	947.70 $\pm$ 0.72	1.00000	0.052	20/20	948.69 $\pm$ 0.00	1.00000	0.052	20/20

Bold values indicate the summary row, reporting the mean and standard deviation across the 20 independent seeds.

6.7. Internal Consistency Verification

To confirm the physical consistency of the co-simulation pipeline, per-phase nodal voltage predictions from the CHSA evaluations were compared against fully converged OpenDSS Newton–Raphson solutions across all scenario assessments. This comparison constitutes an internal consistency check rather than an independent validation, since the CHSA framework itself uses OpenDSS as the power flow engine. The resulting voltage residuals confirm that the power flow evaluations embedded within the optimisation loop accurately represent the physical network state, with residual errors concentrated at buses downstream of step-voltage regulators where the fixed-tap assumption introduces modelling discrepancy. The candidate buses exhibit considerably smaller residuals, confirming that the bisection search operates on an accurate representation of the voltage headroom at the constraint-determining nodes.

6.8. Cross-Feeder Generalisation: IEEE 34-Bus Benchmark

A critical question for any single-feeder study is whether the findings represent a general network-control phenomenon or an artefact of a particular topology. To address this, the CHSA framework was applied without modification to the IEEE 34-bus distribution feeder, which presents a structurally distinct operating environment characterised by a heavily loaded 24.9 kV radial network with long high-impedance laterals, interacting step-voltage regulators, and pronounced baseline undervoltage on the most electrically remote buses. The complete results are presented in Table 11 and Figure 5. The IEEE 34-bus results reveal a physically important and practically significant contrast with the primary benchmark. On the IEEE 123-bus feeder, which is overvoltage-limited, the binding HC constraint is the upper voltage ceiling: GFL injection raises bus voltages toward 1.05 p.u. and GFM reactive absorption with spatially uniform droop settings fails to align with the impedance topology, producing the CP_{GFM} penalty of 95.19 kW. On the IEEE 34-bus feeder, which is undervoltage-limited, the binding constraint is instead the lower voltage floor: the heavy resistive loading on long high-impedance laterals depresses bus voltages below the feasibility threshold at modest injection scales, and GFL unity-power-factor injection can sustain only 19.90 kW before this threshold is breached. GFM reactive support actively counteracts this voltage depression, raising bus voltages and allowing far higher active injection. Mid-range GFM settings achieve 213.70 kW, a gain of 193.80 kW over GFL, and HBO-optimised GFM further improves this to 237.41 kW, a total gain of 217.51 kW representing an improvement factor of nearly twelve relative to the GFL reference. The MNV values reported in Table 11 (0.92974 p.u. for GFL, 0.92726 p.u. for mid-range GFM, 0.92858 p.u. for HBO-GFM) do not increase monotonically with GFM support because the MNV bus is located on the heavily loaded 4.16 kV secondary lateral (bus 890), which is electrically decoupled from the MV GFM candidate buses by the 24.9/4.16 kV transformer. The GFM reactive support raises voltages on the MV trunk where the candidate buses are located, permitting higher active injection before any MV bus breaches the lower limit. The HC improvement is driven by voltage support at the MV candidate buses, not at the most voltage-depressed secondary bus. This cross-feeder comparison establishes two generalisations of direct engineering value. First, the direction of GFM reactive support effect is determined by the nature of the binding voltage constraint: on overvoltage-limited feeders, uncoordinated GFM reactive absorption imposes a capacity penalty, while on undervoltage-limited feeders it provides a capacity benefit. Second, in both cases, coordinated CHSA optimisation improves upon the uncoordinated GFM outcome, recovering the penalty on the 123-bus feeder and extending the benefit on the 34-bus feeder. A further physical invariant consistent with the primary benchmark is observed: both mid-range and optimised GFM configurations absorb identical net reactive power of -78.06 kVAr on the 34-bus feeder, as reported in Table 11. Both HBO and PSO converge to identical HC values of 237.41 kW on the 34-bus feeder, further confirming that the algorithm-independent convergence extends across topologically distinct networks.

The contrast between the two feeders constitutes the most practically significant finding of this study. The IEEE 123-bus feeder demonstrates an overvoltage-limited environment in which uncoordinated GFM reactive absorption suppresses HC below the GFL reference. The IEEE 34-bus feeder demonstrates an undervoltage-limited environment in which the same reactive support mechanism raises depressed bus voltages and permits far higher active injection than GFL operation can sustain. The same control technology, with the same class of droop characteristic, produces a 10% capacity penalty on one feeder and a nearly twelve-fold HC improvement on another. This indicates that the impact of GFM control on network HC is fundamentally topology-dependent rather than universally beneficial or universally detrimental. The implication for practice is direct: connection

engineers and DNSPs should assess the dominant voltage constraint type on any feeder before deploying GFM units, and should apply site-specific droop coordination accordingly.

Table 11. Cross-feeder comparison: feasible HC across GFL and GFM scenarios on two IEEE test feeders with contrasting voltage constraint profiles. Negative HC differences indicate a capacity penalty (overvoltage-limited); positive differences indicate a capacity benefit (undervoltage-limited).

Feeder	Scenario	Feasible HC (kW)	HC Difference from GFL (kW)	Net Reactive Absorption (kVar)	MNV _{min} (p.u.)	VUF _{max} (%)	Constraint Type
IEEE 123-bus	GFL (Reference)	950.00	0.00	0.00	1.00000	0.052	Overvoltage-limited
IEEE 123-bus	Mid-Range GFM	854.81	−95.19	−312.25	1.00000	0.052	Overvoltage-limited
IEEE 123-bus	HBO-GFM (CHSA)	947.46	−2.54	−312.25	1.00000	0.052	Overvoltage-limited
IEEE 123-bus	PSO-GFM (Benchmark)	948.69	−1.31	−312.25	1.00000	0.052	Overvoltage-limited
IEEE 34-bus	GFL (Reference)	19.90	0.00	0.00	0.92974	1.1462	Undervoltage-limited
IEEE 34-bus	Mid-Range GFM	213.70	+193.80	−78.06	0.92726	1.1305	Undervoltage-limited
IEEE 34-bus	HBO-GFM (CHSA)	237.41	+217.51	−78.06	0.92858	1.1251	Undervoltage-limited
IEEE 34-bus	PSO-GFM (Benchmark)	237.41	+217.51	−78.06	0.92858	1.1251	Undervoltage-limited

Bold values identify the method proposed in this work.

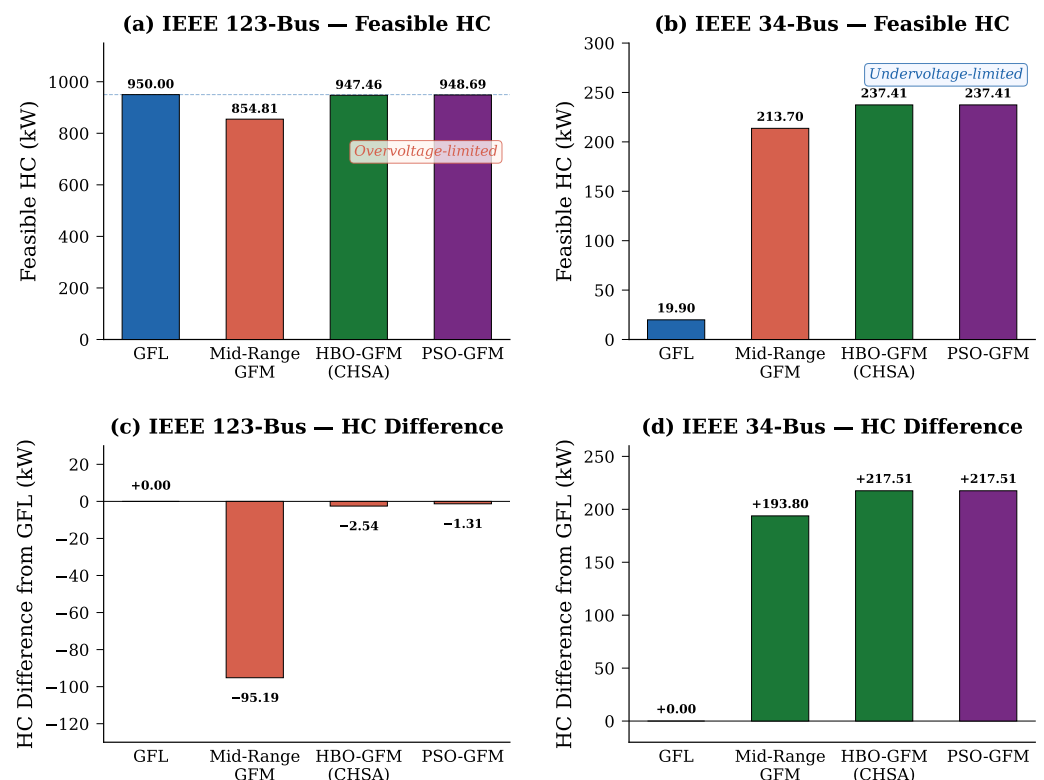


Figure 5. Cross-feeder comparison of feasible HC and HC difference from GFL on the IEEE 123-bus (overvoltage-limited) and IEEE 34-bus (undervoltage-limited) feeders. (a) IEEE 123-bus feasible HC; (b) IEEE 34-bus feasible HC; (c) IEEE 123-bus HC difference from GFL; (d) IEEE 34-bus HC difference from GFL.

7. Conclusions and Future Directions

7.1. Summary of Contributions and Key Findings

Table 12 provides a concise mapping of each research objective to its corresponding quantitative finding.

Table 12. Research objectives and corresponding key findings of the CHSA framework.

Research Objective	Key Finding
Quantify CP_{GFM} on a realistic unbalanced feeder	95.19 kW penalty confirmed (10.02% reduction vs. GFL ceiling)
Recover CP_{GFM} via coordinated droop optimisation	92.65 kW recovered (97.3% of penalty) with zero voltage violations
Demonstrate per-inverter headroom	33.3% loading, 253 kVAr headroom per unit at optimised operating point
Confirm algorithm-independent convergence	HBO and PSO converge to -312.25 kVAr; $\Delta HC = 1.23$ kW (representative seed) and 0.99 kW (20-seed mean)
Validate framework across network topologies	HC raised from 19.90 to 237.41 kW on IEEE 34-bus (undervoltage-limited)
Verify equitable capacity allocation	JFI = 0.999988 across all ten participating buses

7.2. Conclusions

This work formally defines, quantifies, and eliminates CP_{GFM} on a realistic multi-phase Australian distribution feeder within a steady-state voltage feasibility framework, demonstrating that the penalty results from suboptimal control coordination rather than an inherent limitation of GFM technology. The conclusions below apply to the steady-state HC assessment scope of the CHSA; transient stability, fault response, and electromagnetic transient performance of the optimised droop parameters remain subjects of planned future investigation (Section 7.4). Validation on the IEEE 34-bus feeder further confirms that coordinated GFM reactive support can significantly improve HC across topologically distinct networks. The proposed CHSA provides a systematic co-simulation-based approach to achieve topology-aware, site-specific droop tuning, and has been shown to be effective, computationally efficient, and applicable across distribution feeders with different topological characteristics. The main conclusions are:

1. Systematic elimination of CP_{GFM} : Mid-range GFM settings limited HC to 854.81 kW on the IEEE 123-bus feeder. By optimising the reactive droop parameters, the CHSA recovered 92.65 kW, corresponding to 97.3% of CP_{GFM} , and increased HC to 947.46 kW without any voltage violations. Robustness testing demonstrated a mean HBO recovery of 947.70 ± 0.72 kW and a mean PSO recovery of 948.69 ± 0.00 kW across 20 independent random seeds, confirming that the results are not sensitive to the choice of seed.
2. Near-equivalence to the GFL ceiling: The optimised GFM configuration achieved 99.7% of the 950 kW GFL reference, reducing CP_{GFM} to only 2.54 kW, with all inverters operating at 33.3% of their 300 kVA rated capacity and 253 kVAr of reactive headroom per unit. These results demonstrate that properly coordinated GFM operation can deliver essentially the same steady-state hosting capacity as the corresponding GFL implementation without inverter apparent power saturation.
3. Algorithm independence of the result: HBO and PSO independently converged to the same reactive absorption strategy of -312.25 kVAr despite following different stochastic search paths. On the representative run (seed 42), HC values differed by only 1.23 kW; across 20 independent seeds, the mean difference was 0.99 kW (HBO: 947.70 ± 0.72 kW; PSO: 948.69 ± 0.00 kW). Together with the zero standard deviation observed for PSO, this provides strong empirical evidence that the optimal operating point is governed by the network impedance characteristics rather than by the optimisation algorithm.

4. Topology-dependent GFM effect and cross-feeder generalisation: On the undervoltage-limited IEEE 34-bus feeder, coordinated GFM reactive support increased HC from 19.90 kW under GFL operation to 237.41 kW with HBO-optimised GFM, representing a nearly twelve-fold improvement. This confirms that the impact of GFM control on HC depends on the governing voltage constraint. While uncoordinated GFM reduces HC in overvoltage-limited networks, it enhances HC in undervoltage-limited networks, and the CHSA consistently improves performance over the uncoordinated settings in both cases.
5. Equitable allocation and framework verification: HC allocation achieved a JFI of 0.999988, verifying equitable distribution of hosting capacity among participating prosumers. The per-inverter capability analysis confirmed that no unit reaches apparent power saturation, establishing that the -312.25 kVAr absorption is network-determined rather than hardware-limited.

7.3. Practical Implications for Distribution Network Operators

The findings of this study have direct practical implications for DNSPs and grid connection engineers operating within the Australian regulatory framework and similar international power systems. The results demonstrate that deploying GFM inverters with mid-range settings on the investigated IEEE 123-bus feeder introduces a 95.19 kW HC penalty, equivalent to 10.02% of the GFL reference, indicating that a significant proportion of renewable integration capacity may be lost if site-specific droop tuning is not performed. Although the magnitude of this penalty depends on feeder topology, loading conditions, and the number of interacting GFM units, the study shows that most of this lost HC can be recovered through software-based optimisation of the droop parameters using the proposed CHSA, without requiring hardware upgrades or network reinforcement. In practice, achieving a comparable increase in HC through conventional approaches, such as feeder reconductoring, would typically involve substantial civil and electrical infrastructure costs, whereas the CHSA requires only an accurate network model and an OpenDSS-based co-simulation environment, both of which are already available to most DNSPs for planning studies. The topology-dependent nature of the results also provides a practical framework for connection assessment engineers. Before integrating GFM resources, the governing HC constraint should first be identified as either overvoltage-limited or undervoltage-limited. For overvoltage-limited feeders, mid-range GFM settings are likely to reduce HC, making topology-aware droop optimisation essential to recover the available capacity. In contrast, on undervoltage-limited feeders, the reactive support capability of GFM inverters naturally increases HC relative to GFL operation, with additional improvements achievable through CHSA-based optimisation. Incorporating this two-stage process into existing grid connection assessment procedures provides a practical and cost-effective strategy for maximising HC while avoiding unnecessary network reinforcement. Connection standards should require site-specific droop parameterisation as part of the GFM connection application process, analogous to the existing requirement for generator performance standards under the National Electricity Rules (NER), Chapter 5 (Schedule). Grid codes should distinguish between overvoltage-limited and undervoltage-limited feeders when specifying GFM reactive response requirements, as the optimal droop direction differs between these constraint types.

7.4. Limitations and Future Research

The CHSA employs an OpenDSS steady-state Newton–Raphson power flow formulation in which each GFM inverter is represented as a PQ-controlled Generator element whose reactive setpoint is iteratively updated by an external Q – V droop loop. As established in

Section 4.1 and supported by [40–42], this representation is mathematically equivalent to a droop-controlled GFM voltage source at the converged steady-state operating point, which is the only condition relevant to the HC assessment objective. However, GFM-specific dynamic phenomena, such as virtual inertia response, internal voltage angle dynamics, output impedance shaping, post-fault voltage recovery, and sub-synchronous oscillations, are not captured by this steady-state formulation. Additional validation using EMT simulation platforms such as PSCAD or RTDS would provide further insight into the dynamic performance of the optimised droop parameters identified by the CHSA and would enable meaningful optimisation of the filter cutoff frequency ω_c , which is structurally inactive in the steady-state formulation. Hardware-in-the-loop (HIL) validation is also planned to verify that the optimised droop parameters perform as predicted under realistic switching and communication conditions. The filter cutoff frequency ω_c is included in the decision vector for framework completeness, but as demonstrated by the invariance test in Table 7, it does not influence the steady-state power flow solution. Meaningful optimisation of ω_c requires an EMT-based implementation of the CHSA. Several modelling assumptions should also be acknowledged. Step-voltage regulators were represented as fixed-impedance elements, resulting in conservative HC estimates compared with models that explicitly consider tap-changing operations. In addition, the CHSA evaluates each operating scenario independently and does not account for the temporal coupling associated with EV or battery state-of-charge evolution, limiting its direct application to multi-period operational studies. The IEEE 123-bus feeder is also modelled as a three-wire system and therefore does not represent neutral conductor effects that may become significant in four-wire LV networks. Finally, the optimised droop settings were obtained for the worst-case stochastic loading scenario considered in this study and should be assessed under a wider range of operating conditions before field implementation. The algorithm-independence claim is supported by convergence of two structurally different metaheuristics across 20 seeds, but rigorous proof of landscape uniqueness would require additional methods such as exhaustive local perturbation, convexity analysis, or comparison with a deterministic nonlinear programming solver. Future research will focus on extending the CHSA to address both operational and modelling challenges encountered in active distribution networks. Integrating receding-horizon optimisation with state-of-charge continuity constraints will enable coordinated scheduling of EVs and battery energy storage while maintaining network operating limits over time. The inclusion of discrete tap-position variables through mixed-integer optimisation, together with detailed four-wire LV feeder models, will further improve the applicability of the framework to networks where neutral voltage displacement becomes the dominant HC constraint. In addition, the large dataset generated during the CHSA optimisation process provides a strong foundation for developing physics-informed neural network surrogates capable of delivering near real-time HC estimation without repeated power flow calculations, making the framework suitable for practical distribution management applications. Finally, incorporating small-signal stability indices and transient performance metrics within an EMT simulation environment will extend the CHSA beyond steady-state HC optimisation, enabling coordinated droop tuning that simultaneously considers both steady-state network performance and dynamic system stability.

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Abbreviations

The following abbreviations are used in this manuscript:

AEMO	Australian Energy Market Operator
CER	Consumer Energy Resource
CHSA	Coordinated Hosting-Capacity and Stability Algorithm
CP_{GFM}	Grid-Forming Hosting-Capacity Penalty
DER	Distributed Energy Resource
DNSP	Distribution Network Service Provider
DOE	Dynamic Operating Envelope
DSS	Distribution System Simulator
EMT	Electromagnetic Transient
EV	Electric Vehicle
GFL	Grid-Following (inverter)
GFM	Grid-Forming (inverter)
HBO	Heap-Based Optimizer
HC	Hosting Capacity
HIL	Hardware-in-the-Loop
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
JFI	Jain's Fairness Index
LHS	Latin Hypercube Sampling
LV	Low Voltage
MNV	Minimum Nodal Voltage
MV	Medium Voltage
NER	National Electricity Rules
NERC	North American Electric Reliability Corporation
OPF	Optimal Power Flow
PLL	Phase-Locked Loop
PSO	Particle Swarm Optimisation
PV	Photovoltaic
$Q-V$	Reactive Power–Voltage (droop characteristic)
RTDS	Real-Time Digital Simulator
SCR	Short-Circuit Ratio
VUF	Voltage Unbalance Factor

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