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Review

Artificial Intelligence and Optimization for Distributed Generation Planning in Unbalanced Distribution Networks: A Systematic Critical Review of Engineering Transferability and Validation

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Abstract

Distributed-generation (DG) planning is shaped by two complementary methodological streams: artificial-intelligence (AI) methods that search or learn efficiently in difficult non-convex spaces, and mathematical-optimization methods that expose structure, bounds, recourse, and constraint logic. Reported objective improvements cannot be compared directly when studies differ in feeder physics, uncertainty models, protection assumptions, or validation settings. This review critically examines peer-reviewed DG-planning evidence published from 2016 to March 2026 using PRISMA 2020 reporting guidance, with review-specific deviations disclosed explicitly. The historical search ledger contains 122 records. Following decision-variable re-audit and source verification, the harmonized planning matrix contains 26 studies; sixteen previously scored records provide contextual evidence, and thirteen post-closure sources update the narrative only. The synthesis separates computational-intelligence and learning-assisted AI from convex, mixed-integer, decomposition, stochastic, and robust optimization, then evaluates the strength of the planning claim supported by each study. Of the 26 planning studies, 10 use explicit unbalanced or multiphase models, eight treat uncertainty non-deterministically, and two embed protection centrally. The heterogeneous evidence does not support a statistically adjusted ranking of solver families, and reported objective improvements should not be read as proof of general superiority. Credible DG-planning conclusions require objective design, phase-aware network physics, uncertainty treatment, protection feasibility, and validation to be aligned with the decision being supported.

Keywords: artificial intelligence; mathematical optimization; distributed generation; unbalanced distribution networks; evolutionary computation; surrogate-assisted optimization; uncertainty; protection coordination; transferability

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1. Introduction

Distributed-generation (DG) planning is a constrained mathematical program whose feasible set is defined by nonlinear power-flow equations, discrete siting decisions, and operating limits that are often phase dependent. Rooftop photovoltaic (PV) systems, battery energy storage systems (BESS), electric vehicles (EVs), flexible demand, and inverter-based resources change both the magnitude and the direction of power flow, frequently at locations that were not observable when the feeder was designed. In low- and medium-voltage networks, single-phase laterals, unequal customer loading, regulator actions, and neutral coupling make the admissible region itself phase dependent. A model that suppresses those effects can still return a numerically optimal point, but that point may cease to be optimal, or even feasible, when it is evaluated on the feeder that the investment is meant to serve [1–4]. Reported optimizer performance cannot be separated from the feasible set, constraint logic, and validation model on which the optimum is claimed.

The literature has responded with a wide range of formulations. Early DG-allocation studies were dominated by loss reduction, voltage-profile improvement, and simple siting/sizing objectives; later work added annualized cost, hosting capacity, storage, network reconfiguration, reliability, uncertainty, and multi-period operation [5–8]. That progression is important, but it also makes headline results progressively less comparable. A 5% loss reduction on a balanced 33-bus benchmark is not commensurate with a 5% increase in hosting capacity on a measured three-phase feeder. Nor can a weighted multi-objective score be compared meaningfully with annualized cost unless normalization, weights, time aggregation, and feasibility constraints are stated. The review literature has catalogued these objectives and algorithms effectively, yet the field still lacks a disciplined way to ask whether two reported "improvements" represent the same planning claim, or whether one is supported by a materially stronger model and validation setting.

A second source of ambiguity is the growing use of artificial-intelligence terminology. In power-system optimization, evolutionary and swarm algorithms are frequently grouped under computational intelligence, while more recent work introduces Bayesian search, learned power-flow surrogates, graph-based models, and physics-informed learning. These approaches solve different problems. A metaheuristic can explore mixed discrete–continuous decisions without an exact convex reformulation; a surrogate can reduce expensive feeder evaluations; a learned model can approximate a mapping that would otherwise require repeated simulation. None of those functions, by itself, certifies electrical feasibility. Conversely, convex relaxations, mixed-integer formulations, decomposition, stochastic programming, and robust optimization can expose lower bounds, recourse, or explicit uncertainty sets, but their guarantees are conditional on the network model, relaxation tightness, and assumptions used to obtain tractability [9–13]. Accordingly, AI is not treated as a synonym for "advanced optimizer". AI-enabled methods and mathematical optimization are separated by function, and hybrid methods are judged by the layer that actually enforces feeder physics and constraints. In the taxonomy, PSO, GA, and HHO are labeled classical computational-intelligence (CI) search methods, not learning-based AI. The learning-based category is reserved for methods that infer a model, policy, representation, or surrogate from data; this distinction is maintained in the method tables and interpretation.

This distinction exposes a weakness in a common comparison practice. Papers often benchmark optimizers by the best objective value reached on one or two IEEE feeders. Such comparisons are useful for algorithm development, but they do not establish deployment superiority when constraint handling, stopping rules, repeated-run statistics, phase modeling, uncertainty, or protection differ across studies. A method may appear stronger because infeasible candidates are repaired after the search, because voltage unbalance is absent

from the model, or because the benchmark contains none of the operational limits that bind on the target network. The opposite problem also occurs: a mathematically structured formulation can appear conservative because it models recourse, uncertainty, or network limits that a simpler benchmark formulation omits. The relevant comparison is therefore not "Which optimizer wins?" but "Which planning claim remains valid after the assumptions behind that result are made explicit?"

Existing reviews provide strong foundations but leave this question only partially resolved. Foundational surveys organize DG allocation by objectives, constraints, analytical techniques, and algorithms [5,6,8]. Uncertainty-focused reviews clarify probabilistic and planning risks [7,14]; more recent work broadens the discussion toward distribution expansion, DER integration, network reconfiguration, unbalanced DG siting, digital twins, and data-driven operation [15–20]. These perspectives are complementary rather than redundant. Their limitation for the present question is that they do not jointly audit objective comparability, phase-aware feeder fidelity, uncertainty treatment, protection feasibility, and validation depth under one evidence rubric. Table 1 makes that distinction explicit. The gap is therefore not the absence of another optimizer taxonomy; it is the absence of a common test for the strength of the engineering claim attached to an optimization result.

Four recurring failure modes motivate that test. First, objective functions are not commensurate: electrical loss, voltage deviation, annualized cost, reliability, hosting capacity, and weighted composites are reported with different units and aggregation rules, so cross-paper ranking is fragile. Second, the feasible set is not held fixed: balanced equivalents, single-period models, and simplified AC constraints can enlarge or reshape the admissible region relative to an explicit three-phase unbalanced formulation. Third, risk and protection are often omitted: deterministic planning can understate load and renewable uncertainty, while voltage and thermal limits alone can miss fault-current, relay-selectivity, or coordination constraints that become binding after DG is connected [21–24]. Fourth, validation settings answer different questions: a benchmark feeder demonstrates algorithmic behavior, whereas a measured or utility-anchored feeder tests whether the recommendation survives data quality, operating rules, export limits, phase asymmetry, and local control. Each of these choices can change the preferred site, size, dispatch, or admissible penetration level.

The term transferability is used here for the degree to which a published planning result remains technically credible when it is moved from its study environment toward deployment conditions. Transferability is deliberately narrower than generalizability. It does not assume that one feeder's numerical solution should transfer to another feeder. Instead, it asks whether the claim is supported by enough formulation fidelity and validation evidence to inform a comparable real decision. A benchmark study can be methodologically sound and still provide only benchmark-level evidence. A measured-feeder case can be practically informative and still be weak if uncertainty or protection is omitted. The review therefore treats model fidelity, uncertainty, protection, and validation as separate evidence dimensions rather than collapsing them into a single notion of realism.

AI-enabled search and computational-intelligence methods are increasingly relevant to difficult DG-planning problems, especially when discrete siting, nonlinear power flow, scenario growth, or repeated simulation create computational bottlenecks. Mathematical optimization addresses a complementary question: how search, approximation, relaxation, decomposition, and uncertainty modeling interact with the underlying feasible set. For distribution-system planning, the useful boundary is not between "old" and "new" algorithms. It is between methods that merely propose candidate decisions and methods or verification layers that establish what those decisions mean under network constraints. That boundary is particularly important for hybrid AI–optimization workflows, where a

fast outer model can be valuable only if approximation error and final AC feasibility are checked explicitly.

The review addresses five linked research questions. First, which objective families are meaningfully comparable, and what normalization and reporting are required for cross-study interpretation? Second, how does explicit three-phase or unbalanced network fidelity alter the feasible set and the credibility of DG-planning conclusions? Third, what distinct roles do AI-enabled and mathematical-optimization methods play in search, approximation, guarantees, constraints, and uncertainty? Fourth, which uncertainty, protection, validation, and implementation conditions separate benchmark evidence from transferable planning guidance? Fifth, what minimum evidence should support claims of algorithm superiority, hosting-capacity improvement, economic benefit, or deployment readiness? The review makes four contributions. First, it reconstructs objective functions into comparable electrical, economic, reliability, hosting-capacity, and phase-quality families and states the units, aggregation rules, and constraints required for comparison. Second, it separates computational-intelligence and learning-assisted AI from convex, mixed-integer, decomposition, stochastic, and robust optimization so that search flexibility is not confused with mathematical assurance. Third, it audits the literature through four transferability dimensions (network fidelity, uncertainty, protection, and validation) using conservative coding rules that penalize missing reporting rather than filling gaps by inference. Fourth, it converts the synthesis into claim-level guidance on what evidence supports a benchmark statement, a planning statement, or a utility-facing recommendation. The intended readers are distribution-system planners, power-system researchers, and researchers developing AI and optimization methods who must judge whether a reported optimum is stronger than the formulation permits.

The remainder of the paper follows the same logic. Section 2 defines the evidence base, positions the review against adjacent surveys, and documents the screening and coding rules. Section 3 examines objective construction, network equations, storage, and protection constraints. Section 4 compares AI-enabled, mathematical, hybrid, and uncertainty-aware solution strategies by function rather than by novelty label. Section 5 then tests how validation setting and evidence structure alter claim strength. The Discussion converts those findings into minimum-evidence rules and research priorities, and the concluding section states what the literature currently justifies and what it does not. Figure 1 states the comparison taxonomy used throughout the paper.

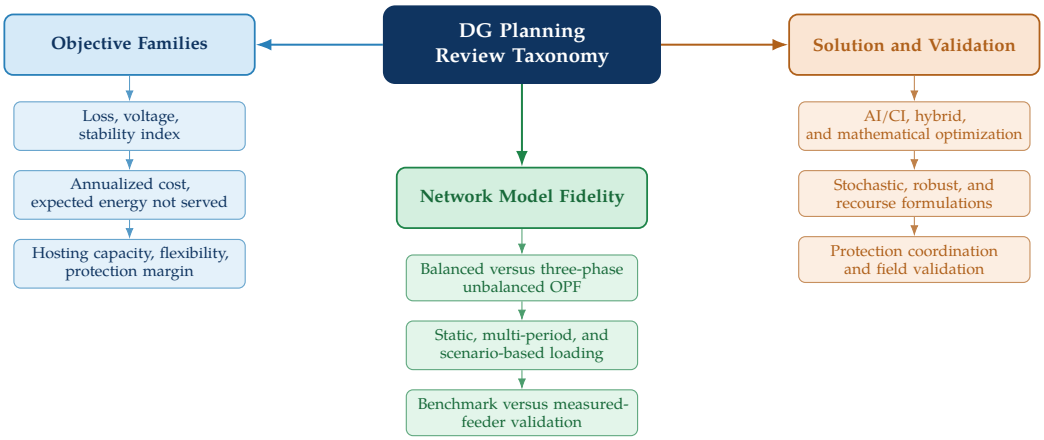


Figure 1. DG-planning evidence taxonomy for cross-study comparison across objectives, feeder fidelity, optimization, uncertainty, and validation. Blue, green, and orange identify the objective, network-model, and solution/validation branches, respectively; arrows indicate the direction of the taxonomy from each parent category to its subcategories.

2. Review Scope and Corpus Coverage

The historical search ledger contains 122 records relevant to DG planning and its engineering boundary conditions. The decision-variable re-audit reassigned 16 of the previously coded 42 records to contextual evidence. Subsequent source verification removed one unverified planning record and corrected the identity and coding of another. An already-cited, independently eligible PV/reactive-device planning study was then admitted under the same five tests, yielding a final 26-study matrix. Supplementary File S3 preserves the original 42-row trail and the separately identified addition. The historical search totals are not a new count of verified bibliographic identities; no revised exhaustive corpus partition is inferred from this targeted correction. Thirteen post-closure sources remain narrative-only. The final matrix is a deliberately selected, auditable subset, not a representative sample of the wider literature.

Prior reviews form four complementary streams rather than a single sequence of increasingly complete surveys. One stream classifies DG objectives, constraints, and allocation algorithms [5,6,8,25]; a second concentrates on uncertainty and active-distribution planning [7,14,15]; a third examines specific network or operational problems such as voltage regulation, reconfiguration, power quality, and unbalanced siting [17–19,26–28]; and a fourth extends toward data-driven operation, digital twins, and distribution-operator integration [16,20,29]. The synthesis does not supersede these streams; it asks whether the planning claims reported across them survive a common audit of objective comparability, phase-aware physics, uncertainty, protection, and validation. Table 1 compares the closest 2024–2026 reviews selected for direct overlap with the five audit dimensions; it is a focused positioning set rather than an exhaustive bibliography. This boundary makes the residual gap visible without relying on a generic statement that "few reviews exist". Supporting 2025–2026 studies are then used only where they test one of those evidence dimensions directly; for example, behind-the-meter visibility changes what can be inferred about available DG capacity [30], while protection-coordinated reconfiguration changes the admissible hosting envelope [31]. This architecture keeps the novelty claim falsifiable: if an adjacent review already performs the same five-dimensional evidence audit, the claimed gap would disappear.

Table 1. Positioning against the closest recent DG-planning reviews.

Review	Primary Focus	Unresolved Engineering Gap Addressed Here
[15]	Distribution-network expansion planning and emerging challenges	Does not jointly audit unbalanced-model fidelity, protection integration, and bounded transferability of DG-planning claims.
[14]	Uncertainty management for active distribution-system planning	Strong uncertainty coverage, but limited joint treatment of objective comparability, protection-aware feasibility, and validation depth.
[17]	DG siting and sizing in unbalanced distribution systems	Closest unbalanced-DG scope, but remains allocation-centered rather than evidence-centered across uncertainty, protection, and validation.
[16]	DER integration and operation in distribution networks	Operator-facing synthesis, but not a formulation-level audit of DG siting/sizing transferability.

Table 1. *Cont.*

Review	Primary Focus	Unresolved Engineering Gap Addressed Here
[20]	Digital-twin technologies for active distribution networks	Emphasizes digitally updated network representation rather than DG siting, sizing, and cross-study claim comparability.
[19]	Coupled DG and network-reconfiguration optimization	Focuses on optimization strategies; evidence strength across fidelity, uncertainty, protection, and validation remains unresolved.
[32]	Hosting-capacity analysis in DER-rich systems	Strong hosting-capacity framing, but limited audit of DG siting/sizing protection feasibility and cross-study transferability.

Review Methodology and PRISMA 2020 Reporting Protocol

This critical review is reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement insofar as its items apply to a qualitative engineering evidence synthesis. Review-specific deviations, including single-reviewer primary screening, subsequent supervisory verification without a prospectively designed inter-rater statistic, and incomplete reason-level archival counts for records removed before title-and-abstract screening, are disclosed rather than imputed. The protocol was not prospectively registered, and no registration identifier exists. The screening procedure identifies studies that provide sufficient mathematical, operational, and validation detail to support cross-study comparison in DG planning under unbalanced distribution-network conditions. Figure 2 reports the complete available record flow, and Supplementary File S1 provides the full PRISMA 2020 checklist with item-level reporting locations.

Literature published between 2016 and March 2026 was searched across IEEE Xplore, Scopus, ScienceDirect, SpringerLink, and Web of Science (WoS) using three mandatory concept blocks: DG or DER terminology, a distribution-network context, and a planning/optimization decision. Unbalanced, protection, hosting-capacity, real-feeder, measured-data, and EV terms were used only in supplementary sensitivity searches and prioritization, never as mandatory eligibility conditions. Records retrieved by the three core blocks remained eligible when none of the realism terms appeared, and backward/forward citation checking was used to reduce dependence on indexing vocabulary. EV-only operational papers were screened out by EX1–EX4 whenever they lacked an explicit DG-planning formulation. Supplementary File S2 reports database-specific reproducible query strings and the archived timing information. The search ledger records March 2026 as the final closed-search month but does not preserve day-level timestamps for individual databases; this limitation is now disclosed rather than replaced by reconstructed dates.

AI terminology was not used as a stand-alone inclusion gate because that would bias the evidence base toward papers whose titles foreground a method label and against mathematically equivalent planning studies. Instead, method-family classification was applied after DG-planning eligibility had been established. During extraction, solution methods were coded into four analytical groups: (i) computational-intelligence methods, including evolutionary and swarm search; (ii) learning- or surrogate-assisted AI methods; (iii) mathematical-optimization methods, including convex, mixed-integer, decomposition, stochastic, and robust formulations; and (iv) hybrid AI–mathematical workflows. This post-eligibility coding preserves one common planning corpus for comparison while allowing direct assessment of whether AI changes computational tractability, feasibility enforcement, or transferability rather than merely adding a method label.

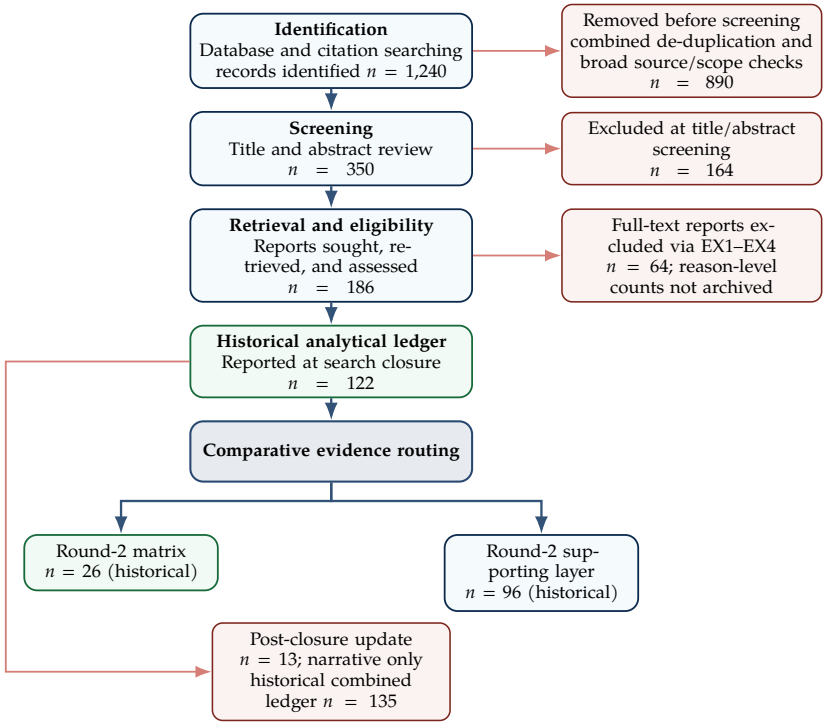


Figure 2. PRISMA 2020 record-flow diagram used to construct the closed analytical corpus and harmonized comparison matrix.

Critical appraisal followed claim-level guardrails before any cross-study conclusion was written. Best objective value was not treated as evidence of algorithm superiority when feeder, objective, constraint set, or stopping rule differed. A benchmark-feeder result was not promoted to field-transferable evidence without an explicit validation bridge. Mathematical optimality or relaxation claims were interpreted only within the stated network model and formulation assumptions. Likewise, AI or surrogate acceleration was recorded separately from final AC-feasibility verification. Missing phase, uncertainty, protection, or validation information was coded conservatively as missing or lower-fidelity evidence rather than reconstructed from author intent. These rules are used again in Section 6 to state the minimum evidence needed for common DG-planning claims.

Primary screening and initial coding were performed by the lead reviewer, followed by record-level verification by senior coauthors. This was not prospectively blinded duplicate screening, and no inter-rater statistic is claimed. The present revision additionally re-audits every row of the previous 42-study coding sheet against the explicit planning-decision test. The resulting eligibility decisions and retained four-component scores are provided in Supplementary File S3; all final totals and figures are calculated from the 26 source-verified planning rows, including the separately documented replacement.

The archived search ledger records 1240 gross database and citation-search records. A combined 890 records were removed before title-and-abstract screening through de-duplication and broad source, document-type, and obvious scope checks; separate pre-screening reason counts were not preserved. Of 350 screened records, 164 were excluded, and 186 reports underwent full-text assessment. Sixty-four were excluded under EX1–EX4, yielding 122 analytical records; the historical ledger does not preserve a reason-by-reason allocation of those 64 exclusions. The 26-study harmonized matrix is a selective quantitative subset and is not claimed to be representative of the wider literature.

Matrix admission was rechecked with five observable tests: (i) the article reports an explicit DG/PV siting, sizing, allocation, generation-hosting-limit, or investment decision directly coupled to DG integration; (ii) the objective and central network constraints are identifiable; (iii) network physics can be coded without inference; (iv) uncertainty, protection, and validation can each be coded, including a zero-level code when absent; and (v) the decision and every coded field are traceable to the source. A paper describing an enabling method or operating constraint without such a planning decision belongs to the supporting layer even if it has strong three-phase modelling. The re-audit found that the earlier 42-row matrix had mixed direct-planning and enabling-method studies under the previous broad admission description. Sixteen records were therefore reassigned, including voltage control [33,34], power-flow model comparison [35], voltage-sensitivity analysis [36], and distribution locational pricing [37]. Their technical insights remain in the narrative but not in planning-study counts. Supplementary File S3 reports the article-level decision basis for every re-audited row; the historical ledger still lacks failed-test vectors for the 80 records already in the supporting layer before this re-audit.

Source verification is distinguished from the original retrieval process. The final matrix replaces the unverified joint transformer/DG record with the already-cited PV/reactive-device planning study by Cortés-Caicedo et al. [38]. Its explicit siting and capacity variables, coupled three-phase model, deterministic profiles, absence of embedded protection, and benchmark-feeder tests give $F/U/P/V = 2/0/0/0$. The archived Khomarudin et al. study [39] is dated 2021 and coded $0/0/0/1$: its phase-equivalent formulation does not retain coupled phase physics, while the named Yogyakarta feeder supports case-level evidence. These source corrections do not constitute a search rerun or establish membership of the replacement in the original closed ledger. Table 2 summarizes the search architecture and implementation rules. Appendix A reports the final 26 scored rows; Supplementary File S3 records the 43-row reconciliation, including the excluded historical record and separately admitted replacement.

Table 2. Search architecture and implementation rules used for the PRISMA 2020-reported evidence search.

Block	Representative Terms and Implementation Rule
DG planning	(“distributed generation” OR “distributed energy resources” OR PV OR photovoltaic OR storage) AND (planning OR siting OR sizing OR allocation OR hosting capacity).
Distribution-network context	(distribution network OR distribution system OR active distribution network OR feeder OR microgrid), with network-level planning relevance required.
Optimization/uncertainty	(optimization OR metaheuristic OR evolutionary OR swarm OR convex OR mixed-integer OR stochastic OR robust OR uncertainty OR surrogate OR machine learning).
Realism filters	Terms related to unbalanced OR three-phase OR protection OR relay OR hosting capacity OR real feeder OR measured feeder were used to prioritize high-fidelity records; absence was not an automatic exclusion when the planning formulation remained eligible.
Databases and limits	IEEE Xplore, Scopus, ScienceDirect, SpringerLink, and Web of Science; peer-reviewed English-language literature; 2016–March 2026 for the closed search, followed by a separately coded post-closure currency check. Database syntax was adapted while preserving the four conceptual blocks.

The search architecture establishes how records were found, whereas Table 3 specifies how the resulting evidence was screened, coded, and separated into quantitative and

narrative layers. Keeping these functions distinct prevents database retrieval rules from being mistaken for eligibility or appraisal criteria.

Table 3. PRISMA 2020 reporting and review protocol used for structured engineering evidence synthesis.

Protocol Element	Implementation
Databases and window	IEEE Xplore, Scopus, ScienceDirect, SpringerLink, and Web of Science; 2016–March 2026.
Record distillation	Gross records 1240; records removed before screening 890 (combined de-duplication and broad source/scope checks); title/abstract screening 350; full-text reports sought and assessed 186; full-text exclusions 64; historical analytical ledger 122; final source-verified planning matrix 26; source amendments reconciled separately in S3.
Post-closure currency check	Thirteen later studies were retained for narrative currency only and excluded from all 122-record and 26-study quantitative counts.
Matrix admission rule	Five mandatory tests: explicit planning decision; identifiable objective and network constraints; codable physics; codable uncertainty, protection, and validation (including explicit zero-level codes); and traceable source evidence. Failure of any test routed the record to the supporting layer.
Comparative guardrail	Objective values were not ranked across non-equivalent feeders, constraints, baselines, time horizons, or validation settings.

The protocol defines the evidence layers, but reproducibility also requires explicit rejection rules. Table 4 therefore states the four exclusion codes applied at full-text assessment and clarifies which studies lacked a planning objective, an AC network model, a network-level decision, or transparent constraint enforcement.

Table 4. Exclusion criteria applied during PRISMA 2020-reported screening.

Code	Exclusion Rule
EX1: no explicit mathematical objective	Narrative, policy, or regulatory discussions without a reproducible mathematical planning formulation.
EX2: no AC network constraint model	Idealized single-bus or lossless copper-plate formulations without AC power-flow constraints.
EX3: component-level control only	Converter, Volt/Var, or relay-analysis studies without a network-level planning decision.
EX4: opaque constraint handling	Optimization results reported without a stated mechanism for enforcing central network constraints.

Figure 2 preserves the archived retrieval counts and the Round-2 allocation before final source verification. The final matrix additionally incorporates the separately documented source correction described above and reconciled in Supplementary File S3. Historical ledger counts should therefore not be read as a newly verified bibliographic inventory.

Figure 3 reports only the publication-year composition of the 26-study planning matrix. No study published before 2021 appears in this selected subset; this does not establish that older planning work was absent or ineligible in the wider 122-record corpus. The chart

must not be interpreted as a field-wide publication trend, and the 13 post-closure sources are not plotted.

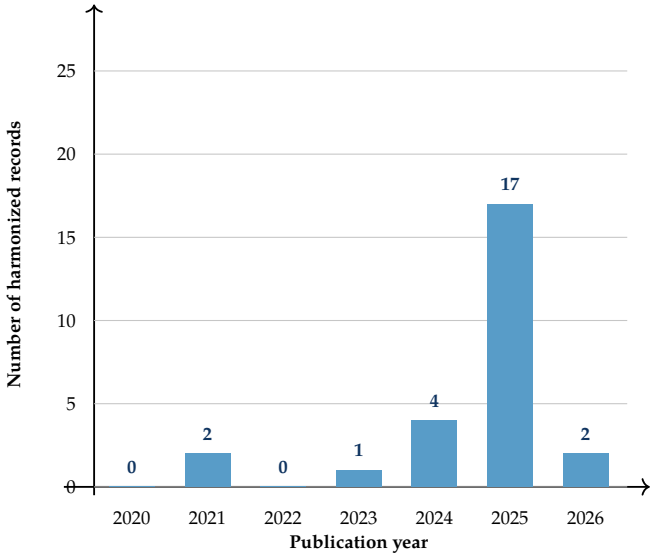


Figure 3. Source-verified publication-year composition of the selected 26-study harmonized planning matrix (2021–2026). The chart is not a bibliometric trend for the wider literature; post-closure studies are excluded from the quantitative analysis.

3. Problem Formulation and Mathematical Fidelity

This section defines formulation in the strict planning sense used throughout the review: the objective stack, the decision-variable set, and the feasibility constraints that determine whether a reported optimum remains technically meaningful. Apparent solver differences are often driven instead by network physics, uncertainty treatment, or admissibility checks. DG planning has therefore moved beyond loss-minimization screening on single-phase equivalent networks toward multi-objective, mixed-integer nonlinear programming (MINLP) structures in asymmetric, strongly coupled multiphase settings.

3.1. Objective Function Complexity and Normalization

Early studies relied mainly on active-power-loss minimization via standard DistFlow branch models. Modern active distribution networks operate closer to steady-state security boundaries, so the objective space now includes voltage stability indices (VSI), voltage unbalance factors (VUF), and expected energy not served (ENS) under probabilistic contingencies. The main mathematical gap is still ad-hoc scalarization of disparate metrics: many studies aggregate annualized capital expenditure (CAPEX), operational expenditure (OPEX), losses (kW), and squared voltage deviations (pu^2) into a single scalar f_{multi}. The strongest formulations avoid arbitrary weighting through the ε-constraint method, exact Pareto tracing, or monetized risk penalties such as Value of Lost Load or curtailment cost [22,40]. Table 5 organizes these objective families by natural unit, physical interpretation, and formulation complexity; the emphasis is comparability of claims rather than frequency ranking.

Multi-objective DG planning requires explicit normalization or monetization when combining incommensurate units such as kW losses, pu^2 voltage error, and annualized investment cost [3,22,40,41]. Objective-family incidence is therefore interpreted as overlapping evidence rather than as mutually exclusive bins; the critical requirement is that each reported objective retain its units, normalization rule, time basis, and feasibility context.

Table 5. Objective-function taxonomy reported across the comparative DG-planning evidence base.

Objective Class	Representative Form	Natural Unit	Interpretation	Typical Use in Literature
Active power loss	$\sum R_{ij} I_{ij}^2$ or equivalent quadratic loss form	kW or MWh/year	Penalizes Joule losses and feeder inefficiency	Nearly universal; often the primary screening objective in radial feeders
Reactive loss/burden	$\sum X_{ij} I_{ij}^2$ or reactive-flow penalty	kVAr or MVArh/year	Tracks reactive transport and voltage-support burden	Common in co-optimization with reactive compensation, less often standalone
Voltage deviation	$\sum_i (V_i - V_{ref})^2$	pu^2	Measures departure from desired voltage profile	Used with loss minimization to avoid technically poor low-loss solutions
Voltage unbalance	phase-voltage spread, VUF, or negative-sequence metric	% or pu	Captures phase asymmetry and LV quality issues	More visible in three-phase and low-voltage studies than in benchmark single-phase papers
Voltage stability	VSI, L-index, or margin-to-collapse measure	index	Approximates steady-state security margin	Often added as a secondary objective or threshold constraint
Economic cost	CAPEX + OPEX + curtailment + maintenance + penalties	USD/year, NPV, or annualized cost	Converts planning alternatives into comparable financial decisions	Standard in planning papers with explicit horizons and tariff assumptions
Reliability/ENS	expected unserved energy, interruption cost, SAIFI/SAIDI proxies	kWh/year, MWh/year, or monetary penalty	Reflects service continuity and outage exposure	Common in expansion, restoration, and resilience-aware formulations
Emissions	CO_2-equivalent or pollutant penalty term	kg/year or tCO_2/year	Internalizes environmental burden	More frequent in integrated-energy studies than in feeder-only DG siting work
Hosting capacity	maximum admissible DG under constraints	kW, MW, or % penetration	Measures DER accommodation without violating network constraints	Widely used in PV-rich and low-voltage studies; often maximized under voltage and thermal limits
Protection security	fault-current margin, relay selectivity, or miscoordination penalty	A, pu, or dimensionless margin	Prevents technically infeasible solutions under altered fault current patterns	Still rare in optimization despite high practical importance
Flexibility use	procured flexibility, curtailed flexibility, or activation cost	kW, kWh, or monetary cost	Represents non-wire alternatives and demand-side support	Emerging in regulation- and flexibility-oriented planning literature

Note: The natural unit reported here follows the quadratic voltage form. Some source papers instead report performance in pu after applying the square root.

The issue sharpens in unbalanced studies because phase-voltage spread, VUF, regulator operation, curtailment, and phase-specific loading often sit beside classical loss and voltage objectives [10,21,33,34,42]. Adjacent EV, storage, flexibility, and hosting-capacity studies show the same expansion [31,43–46]. Credible comparison therefore requires distinguishing

direct electrical objectives from monetized terms and feasibility targets, together with explicit reporting of units, normalization, time basis, and constraint treatment.

Key findings from the formulation analysis:

- Loss minimization alone is insufficient; many classifiable core studies employ multi-objective formulations or explicit feasibility-constrained variants [40,41,47].
- Reliability (ENS) and emissions objectives remain underrepresented relative to their field importance [3,48].
- The ε-constraint method can avoid an arbitrary weighted sum, but its usefulness still depends on explicit objective units and feasible-set definitions.
- Protection coordination (CTI) constraints appear in only a small minority of core studies despite documented field relevance [23,24,49].
- BESS SOC dynamics convert single-period problems into time-coupled formulations, adding computational complexity [21,50,51].

3.2. Network Constraints and Three-Phase Modeling

Feasibility is determined by power-flow equations, voltage and thermal limits, and, increasingly, protection constraints. Here, $|V_i|$ denotes the bus-voltage magnitude in pu, $v_i = |V_i|^2$ the squared voltage magnitude used in DistFlow-type relaxations, and $V_i^{(\phi)}$ the phase-specific voltage variable in the multiphase model. Branch parameters are written consistently as r_{ij} and x_{ij}.

Another fidelity layer that remains underreported in the DG-planning literature is voltage-dependent demand modeling. Many benchmark studies still treat demand as constant power, even though practical feeder loading often follows mixed ZIP behavior in which active and reactive demand vary with local voltage magnitude. A standard active-power ZIP representation can be written as:

$$P_{L,i}(V_i) = P_{L,i}^0 \left[a_p \left(\frac{|V_i|}{V_0} \right)^2 + b_p \left(\frac{|V_i|}{V_0} \right) + c_p \right], \quad a_p + b_p + c_p = 1, \tag{1}$$

with an analogous expression for reactive demand. When this dependence is omitted, planners effectively assume that nodal demand is insensitive to voltage regulation, which can bias hosting-capacity, loss, and siting conclusions in feeders where load composition is not close to constant power [52,53]. In transferability terms, the omission matters because a study may appear physically detailed at the network level while still relying on a demand model that suppresses one of the main voltage-coupled mechanisms seen in practice.

The fundamental AC power-flow balance equations, which must be satisfied for each bus i and each phase $\phi \in \{a, b, c\}$ in an unbalanced feeder, can be written in phase-coupled form as [4,35,54]:

$$\begin{aligned} P_{DG,i}^{(\phi)} - P_{Di}^{(\phi)} &= \sum_{j=1}^{N_b} \sum_{\psi \in \{a,b,c\}} |V_i^{(\phi)}||V_j^{(\psi)}| \cdot \left(G_{ij}^{(\phi\psi)} \cos \delta_{ij}^{(\phi\psi)} + B_{ij}^{(\phi\psi)} \sin \delta_{ij}^{(\phi\psi)} \right), \\ Q_{DG,i}^{(\phi)} - Q_{Di}^{(\phi)} &= \sum_{j=1}^{N_b} \sum_{\psi \in \{a,b,c\}} |V_i^{(\phi)}||V_j^{(\psi)}| \cdot \left(G_{ij}^{(\phi\psi)} \sin \delta_{ij}^{(\phi\psi)} - B_{ij}^{(\phi\psi)} \cos \delta_{ij}^{(\phi\psi)} \right), \end{aligned} \tag{2}$$

where N_b is the number of buses, $\delta_{ij}^{(\phi\psi)} = \delta_i^{(\phi)} - \delta_j^{(\psi)}$, and the mutual-coupling terms $G_{ij}^{(\phi\psi)}$ and $B_{ij}^{(\phi\psi)}$ come from the full three-phase admittance representation. A branch-level relation that makes phase coupling and the neutral conductor explicit is

$$\begin{bmatrix} \Delta V_{ij}^{(a)} \\ \Delta V_{ij}^{(b)} \\ \Delta V_{ij}^{(c)} \\ \Delta V_{ij}^{(n)} \end{bmatrix} = \mathbf{Z}_{ij}^{abcn} \begin{bmatrix} I_{ij}^{(a)} \\ I_{ij}^{(b)} \\ I_{ij}^{(c)} \\ I_{ij}^{(n)} \end{bmatrix}, \tag{3}$$

where the off-diagonal entries of $\mathbf{Z}_{ij}^{abcn}$ carry phase-to-phase and phase-to-neutral mutual impedances. Per-phase simplifications can omit neutral-return effects that are material in asymmetric feeders. In four-wire low-voltage networks, neutral current is a physical state variable; omitting it can suppress phase-specific voltage violations and distort hosting-capacity conclusions [35,54].

Three-phase unbalanced modeling is essential for low-voltage planning where phase-wise loads, single-phase DG, and neutral return effects are significant. The synthesis therefore distinguishes conventional three-phase three-wire representations from four-wire multi-conductor models: neutral and earth-return effects are often critical in low-voltage feeders, yet they are still omitted or left unstated in many planning papers. Full multi-conductor models capture neutral currents directly, whereas per-phase unbalanced formulations at minimum preserve phase-specific voltage and power-flow asymmetries that single-phase approximations systematically underestimate [4,35]. Against that background, inequality constraints enforce the main operational limits [21,22]:

$$V_{\min} \le |V_i| \le V_{\max} \tag{4}$$

$$|I_{ij}| \le I_{ij,\max} \tag{5}$$

$$P_{DG}^{\min} \le P_{DG,i} \le P_{DG}^{\max} \tag{6}$$

$$Q_{DG}^{\min} \le Q_{DG,i} \le Q_{DG}^{\max} \tag{7}$$

where $V_{\min}$ and $V_{\max}$ are the lower and upper voltage limits, $I_{ij,\max}$ is the branch-current limit, and $P_{DG}^{\min}$, $P_{DG}^{\max}$, $Q_{DG}^{\min}$, and $Q_{DG}^{\max}$ are the admissible DG capability bounds.

3.3. Protection Coordination and Feasibility Constraints

Protection coordination remains one of the most frequently neglected feasibility layers in optimization-based DG planning. Renewable DG alters fault-current magnitudes and directionality, which can compromise the coordination time interval (CTI) between primary and backup relays. While earlier benchmark studies treated protection as a post hoc validation check, higher-fidelity planning studies indicate that non-linear inverse-time overcurrent relay characteristics often need to be represented directly in the optimization space:

$$t_{\text{op}} = \frac{A}{\left(\frac{I_f}{I_p}\right)^B - 1} \times \text{TDS}, \tag{8}$$

where t_{op} is the relay operating time, I_f is the fault current, I_p is the pickup current, TDS is the time-dial setting, and A, B are standard curve constants. The fundamental protection constraint enforces selectivity:

$$t_{\text{backup}} - t_{\text{primary}} \ge \text{CTI}. \tag{9}$$

Embedding protection coordination in a planning model is mathematically demanding because fault currents and relay operating times change with DG location, size, network topology, and directional current paths. Joint DG–protection formulations therefore add discrete coordination logic or nonlinear relay constraints to an already non-convex planning problem, increasing computational burden and making the protection model itself part of the feasible-set definition [23,24,31]. The relevant engineering test is not whether a particular linearization or metaheuristic is used, but whether the final siting and sizing decision is checked against explicit fault-current and selectivity requirements under the network states claimed by the study.

Formulations that internalize these protection thresholds generally report lower admissible DG capacities than loss-only models, showing that selectivity and fault-current behavior can become binding limits alongside steady-state voltage or thermal constraints [23,24].

The same formulation choices also govern candidate screening before final optimization. Some studies rely on voltage-sensitivity factors, loss-sensitivity indices, or phase-aware screening metrics to reduce the candidate set, whereas others search all admissible buses directly through particle swarm optimization, Harris Hawks optimization, or hybrid mixed-integer formulations [22,36,42,55]. Reported siting quality therefore depends not only on the optimizer, but also on whether the screening stage preserves weak-node, high-value, or protection-critical buses.

4. Artificial Intelligence, Mathematical Optimization, Co-Optimization, and Uncertainty Handling

The solution-method evidence is organized around a functional distinction rather than a novelty ranking. Computational-intelligence and learning-assisted AI methods are evaluated for search flexibility, sample efficiency, and their dependence on the power-flow model used for feasibility checks. Mathematical-optimization methods are evaluated for relaxation tightness, decomposition structure, explicit uncertainty representation, and the conditions under which bounds or optimality statements remain valid. Hybrid workflows are treated as a third case because their credibility depends on whether the AI layer proposes candidates while a physics-constrained mathematical layer certifies feasibility, or whether infeasible decisions are repaired only after the search. This distinction is used consistently in the method comparison and in the transferability interpretation that follows.

The non-convex, mixed-integer nature of distribution planning calls for diverse solution strategies. The appropriate solver depends on problem scale, objective complexity, and operating uncertainty. Deterministic, scenario-based, probabilistic, stochastic, robust, and risk-aware treatments are therefore compared by the planning question they answer rather than by methodological complexity alone.

4.1. Artificial Intelligence and Computational-Intelligence Methods

Metaheuristics remain dominant for joint siting and sizing because they naturally handle discrete topology decisions, off-the-shelf nonlinear power-flow engines such as OpenDSS or MATPOWER, and multiobjective Pareto evaluations without exact mathematical relaxations [5]. Particle Swarm Optimization (PSO), Harris Hawks Optimization (HHO), and Genetic Algorithms (GA) remain widely reported [5,17,55,56], but their practical performance depends more on candidate-bus screening, feasibility repair, and population initialization than on canonical update rules. Studies that map continuous particles directly to feeder buses by simple rounding without an explicit repair or ranking layer should therefore be read cautiously, because apparent algorithmic gains may reflect undocumented feasibility filtering rather than the search rule itself. The main bottleneck is still the cost of repeated AC power-flow evaluation, which is why recent work increasingly turns to sample-efficient search, adaptive population methods, reinforcement learning, and learned surrogates. Noise-aware Bayesian optimization and learned three-phase power-flow emulators show how expensive feeder evaluations can be reduced or redirected [11,12]. Recent applied studies add game-theoretic DG/EVCS planning, improved metaheuristic scheduling, DER-aware virtual-power-plant control, and operational optimization of renewable-rich networks [57–60]. These developments strengthen the evidence for algorithmic flexibility, but they do not remove the need to report feasibility repair, repeated-run behavior, network-model fidelity, and deployment-facing validation. A recent distributed-PV configuration study likewise illustrates that engineering usefulness depends on where capacity is connected and how voltage and loss effects are represented, not only on the optimization label [61]. Additional 2024–2026 papers expand the optimizer catalog, but

mostly reinforce a method-family trend rather than stronger transferability evidence on feeder realism, protection, or validation depth [22,24,40,62–66].

Reported optimizer comparisons should still be read cautiously when papers do not disclose repeated-run behavior, feasibility-repair logic, or a stable benchmark protocol in enough detail to separate search performance from encoding advantages. Data-driven surrogates and Bayesian search are relevant mainly as computational accelerators in the present corpus, not yet as standalone planning evidence, because feasibility and transferability still depend on the underlying feeder model and constraint enforcement [11–13,29,65].

4.2. Convex Relaxation and Mathematical Programming

Second-Order Cone Programming (SOCP) and semidefinite programming (SDP) relax the non-convex AC power-flow model, enabling branch-and-bound or cutting-plane methods. These relaxations sit inside a broader OPF approximation literature that includes semidefinite duality results, exact radial relaxations, and systematic surveys of convexification quality [67–69]. Convex SOCP/SDP relaxations can provide globally optimal solutions to the relaxed formulation and useful lower bounds for the original non-convex problem; mixed-integer convex variants preserve those guarantees only with respect to the stated relaxed model and assumptions [69]. SOCP relaxations of the single-phase or per-phase DistFlow equations are well suited for radial feeders [9]:

$$\left\| \begin{bmatrix} 2P_{ij} \\ 2Q_{ij} \\ \ell_{ij} - v_i \end{bmatrix} \right\|_2 \leq \ell_{ij} + v_i \tag{10}$$

where $v_i = |V_i|^2$ and $\ell_{ij} = |I_{ij}|^2$ are the squared voltage and current magnitudes, respectively.

Because v_i and ℓ_{ij} represent squared voltage and squared current magnitudes, they are nonnegative in the physical feeder model, which is what permits this second-order cone form. This cone inequality is the convex relaxation of the original DistFlow relation $P_{ij}^2 + Q_{ij}^2 = \ell_{ij} v_i$. For radial networks under the usual branch-flow assumptions, the relaxation can be exact under standard conditions (for example, monotone loads and no binding upper bounds on active generation) [9]; however, exactness should not be assumed once the feeder becomes meshed or the three-phase coupling is strong. The unbalanced case is materially harder than the balanced radial case because phase coupling, mutual impedances, regulator asymmetry, and neutral-return effects weaken the separability that makes single-phase branch-flow relaxations attractive in the first place. In strongly coupled multiphase feeders, phase interaction, neutral effects, reverse power flow, and inverter limits can weaken the conditions that make single-phase radial relaxations tight. SOCP/SDP results should therefore be reported together with relaxation tightness or AC-feasibility recovery rather than treated as automatic substitutes for full three-phase feeder validation [10,69].

A second practical difficulty is scale: once unbalanced OPF is coupled to hourly or sub-hourly storage dynamics, the decision space expands across buses, phases, devices, and time, so even mathematically cleaner convex subproblems can become computationally burdensome over long horizons. In practice, convex relaxations serve best as lower bounds and warm-starts for hybrid solvers rather than standalone methods.

4.3. Co-Optimization and Storage Constraints

Planning isolated DG placement neglects substantial gains available through coordinated asset deployment, as recent unbalanced-feeder studies show that joint planning of DG, BESS, and D-STATCOM resources can materially improve both losses and voltage quality relative to DG-only strategies; when battery energy storage systems (BESS) are

co-planned with DG, the optimization must therefore enforce storage-energy dynamics and capacity limits [21,50,70,71]:

$$E_{i,t+1} = E_{i,t} + \eta_c P_{c,i,t} \Delta t - \frac{P_{d,i,t} \Delta t}{\eta_d}, \tag{11}$$

$$E_{\min} \le E_{i,t} \le E_{\max}, \qquad 0 \le P_{c,i,t}, P_{d,i,t} \le P_{\text{rated}}, \tag{12}$$

where $P_{c,i,t}$ and $P_{d,i,t}$ are the charging and discharging power, η_c and η_d are the respective efficiencies, $E_{\min}$ and $E_{\max}$ are the lower and upper energy bounds, and P_{rated} is the inverter power rating. If a paper instead reports normalized state of charge, then $\text{SOC}_{i,t} = E_{i,t}/E_{\max}$. Written in this energy form, every additive term in the state-update equation has units of energy. These intertemporal coupling constraints convert the planning problem from a static snapshot into a time-coupled optimization, which is one reason why storage-inclusive studies require multi-period or scenario-based solution strategies.

EV charging and flexible resources add a clear recourse dimension to network planning. Two-stage formulations first select infrastructure or DG decisions, then optimize network topology and DER dispatch across scenarios. Recent work also coordinates heterogeneous flexibility through virtual-power-plant control, DG/EVCS co-planning, and multi-year feeder–storage planning, showing that aggregation and operational coupling can change the feasible operating region before a siting decision is finalized [57,59,72]. In DG planning, two-stage scenario-based recourse can change the preferred investment relative to deterministic screening because hosting and loss outcomes depend on EV charging and renewable uncertainty [22]. Operational stochastic dispatch studies provide complementary evidence about the recourse layer but do not themselves optimize DG investment [66].

4.4. Uncertainty Quantification and Stochastic Methods

Renewable generation and demand are probabilistic, so planning must represent variability across time horizons and contingency states. Monte Carlo, probabilistic hosting-capacity, and data-driven PV studies show that direct uncertainty modeling can change admissible DG envelopes, while scenario reduction lowers computational burden without discarding tail behavior [73–76]. Two-stage stochastic DG planning separates first-stage investment decisions from second-stage recourse [22]:

Recent evidence makes the interaction between uncertainty, forecasting, storage, and network constraints more explicit. Nazih et al. [77] jointly optimize PV and wind hosting capacity, loss reduction, and voltage-unbalance reduction under renewable and load uncertainty on the IEEE 13- and 123-node unbalanced feeders. Ma et al. [78] use a polynomial-chaos Kriging surrogate to estimate probabilistic PV-hosting limits while retaining voltage-magnitude and voltage-unbalance constraints. Recent applied formulations also couple robust multi-year feeder planning, storage investment, and renewable-rich network operation with explicit security or uncertainty considerations [60,72,79]. These studies answer different questions: allocation under reduced scenarios, accelerated probabilistic assessment, and forecast-informed recourse are not interchangeable evidence. Where validation remains benchmark- or simulation-based, their numerical gains should therefore be interpreted as method evidence rather than direct utility limits.

$$\min_{x} \; c^{\top} x \; + \; \mathbb{E}_{\xi}\Big[\min_{y \ge 0} \; q^{\top} y \;\Big|\; \mathbf{W}_{\text{rec}} y = h(\xi) - \mathbf{T}_{\text{rec}} x \Big], \tag{13}$$

where x collects investment variables, y collects operational recourse, ξ is the random load-generation vector, and c, q, $\mathbf{W}_{\text{rec}}$, $\mathbf{T}_{\text{rec}}$, $h(\xi)$ define costs and coupling. The comparative point is that scenario design, recourse variables, and penalty placement can change the

investment decision, especially in EV-coupled planning [22]. Robust optimization instead replaces distributional assumptions with a bounded uncertainty set $\mathcal{U}$ [21,80]:

$$\min_{x} \max_{\xi \in \mathcal{U}} f(x, \xi) \quad \text{s.t.} \quad g(x, \xi) \leq 0 \ \ \forall \xi \in \mathcal{U}, \tag{14}$$

Robust formulations guard against worst-case realizations without scenario probabilities, but they can be conservative if $\mathcal{U}$ is too large. Distributionally robust chance constraints (DRCC) occupy the middle ground by enforcing voltage feasibility over an ambiguity set [10]:

$$\inf_{\mathbb{P} \in \mathcal{D}} \mathbb{P}\{V_{\min} \leq V_i(\xi) \leq V_{\max}\} \geq 1 - \epsilon, \tag{15}$$

where $\mathcal{D}$ is the ambiguity set and ϵ is the admissible violation probability. DRCC reduces both robust over-conservatism and the distributional specificity of classical chance constraints.

SDP relaxations, when applied to three-phase unbalanced OPF, take a matrix-variable form [67,69]:

$$\min \ \operatorname{tr}(C\mathbf{X}) \quad \text{s.t.} \quad \operatorname{tr}(A_k \mathbf{X}) = b_k, \ \ k = 1, \ldots, K, \quad \mathbf{X} \succeq 0, \tag{16}$$

where $\mathbf{X}$ lifts the voltage variables and C, A_k, and b_k encode the objective and constraints. The rank-1 recovery condition can fail under strong phase coupling and neutral effects, motivating decomposition or regularization [10,69].

Recent unbalanced-network work also uses stochastic model predictive control (MPC) to preserve phase-aware limits under receding-horizon updates [34]. The combined literature confirms that uncertainty models answer different planning questions; Monte Carlo, robust, DRCC, and stochastic-recourse choices should follow the planner's information structure rather than algorithmic convenience. Solver-family comparisons are interpreted cautiously because many studies use mixed workflows, embedded OPF layers, or decomposition rather than a single identifiable outer solver.

4.5. Validation Evidence and Methodological Credibility

Validation depth determines whether an optimized DG plan is evidence of algorithmic behavior or a credible basis for feeder planning. Standard IEEE feeders remain valuable for reproducible screening, but balanced equivalents and stylized multiphase cases do not reproduce the full combination of phase asymmetry, conductor data, transformer limits, export rules, protection settings, and time-varying demand encountered in operating networks. Utility-anchored and real-feeder studies show that local conditions can alter admissible hosting capacity, preferred sites, and the value of storage or flexibility [81–84]. The PV investment scenarios of Hariadi et al. [85] provide contextual penetration-limit evidence, not a scored optimization result. Accordingly, benchmark results are interpreted here as transferable only when the claimed conclusion is checked on an explicit three-phase model or connected to a measured, real-feeder, regional, or utility operating context. A larger test system alone does not constitute stronger validation if its physical assumptions remain simplified or incompletely reported.

Methodological credibility was screened at the level of the claim rather than assigned from the optimizer label. A study could support direct comparison only when its planning objective, network constraints, decision variables, uncertainty treatment, protection role, and validation setting were reported without unsupported reconstruction. For stochastic or learning-assisted methods, credibility also depends on scenario construction, out-of-sample assessment, and final verification using the physical feeder model; for population-based search, repeated-run reporting and transparent feasibility handling are needed before small objective differences can be interpreted as algorithm superiority. Studies reporting only the

best heuristic run, omitting scalarization weights or units, or enforcing central constraints through undocumented repair were retained only for bounded contextual interpretation when appropriate. These rules do not form a clinical risk-of-bias instrument; they are engineering guardrails that prevent model simplification, selective reporting, or opaque constraint handling from being mistaken for deployment-ready evidence [5,9,11,12,24].

4.6. Reproducibility and Reporting Standards

One of the clearer reproducibility weaknesses in the literature is the absence of standardized formulations, test data, and benchmarking protocols. IEEE test feeders remain useful reference cases, but no single benchmark captures present-day load diversity, EV uptake, demand response, rooftop PV, and utility operating constraints. OpenDSS, GridLAB-D, MATPOWER, and synthetic-data generators exist, yet they still do not provide a common planning benchmark with fixed objectives, constraints, and validation rules. Recent work on AMI-based impact assessment, phase identification, voltage-device support, and learned three-phase power-flow surrogates suggests that data quality and model definition can influence conclusions as much as optimizer choice itself [12,82,86,87].

Stronger reporting should therefore include canonical multi-objective formulations, benchmark problems with reported Pareto frontiers, anonymized real-feeder repositories, relative solution quality against lower bounds such as second-order cone programming (SOCP) or semidefinite programming (SDP) relaxations, computational cost, out-of-sample robustness, and physical feasibility checks such as protection coordination or transient-stability verification. Reproducible comparison also requires explicit reporting of temporal basis and validation class, because static peak-load studies, dispatch-aware studies, and year-long scenario studies do not test the same planning question. For unbalanced planning, informative contextual evidence also comes from low-voltage and multiphase studies with asymmetric loading, single-phase interconnections, or real-feeder data [4,35,85]; balanced IEEE benchmark studies remain more useful for screening and algorithm development than for final transferability claims [33,73,74,88].

4.7. Digital Twins, AI-Assisted Planning, and Protection-Aware Updating

A distribution-network digital twin can connect AI-based search with planning only when it is treated as a maintained engineering model rather than as a visualization layer. The physical feeder model supplies phase topology, impedances, transformer and regulator states, customer-phase assignments, protection settings, and operating limits; supervisory control and data acquisition, advanced metering infrastructure, phasor measurements, weather data, and asset records update the twin's state and parameter estimates. AI or surrogate models can then screen siting and sizing alternatives, identify informative scenarios, or accelerate repeated three-phase simulations, while a mathematical optimization layer retains explicit investment, recourse, and feasibility constraints. Candidate plans must finally be replayed in the calibrated three-phase model across operating and contingency scenarios. This division of labor prevents prediction speed from being confused with electrical admissibility and turns the digital twin into a validation bridge between offline planning and observed feeder behavior [20,89–91].

Protection must be represented in the same update loop. Changes in topology, inverter controls, fault-current contribution, relay settings, and islanding logic can invalidate a DG plan even when its steady-state voltage profile remains acceptable. A protection-aware twin should therefore maintain versioned device settings and topology, calculate fault currents for credible operating states, test pickup sensitivity and primary–backup selectivity, and feed violated margins back to the planning optimizer as constraints or corrective investment options. Real-time data do not convert a long-horizon planning problem into real-time

control; instead, they support periodic recalibration, model-discrepancy detection, and validation of the scenarios used in planning. The IEA and IRENA reports provide system-level evidence for digital, interoperable, and flexible grids, while the Horizon Europe TwinEU project illustrates the move toward federated electricity-system twins. These reports and project materials are retained as implementation context rather than counted as peer-reviewed records in the 122-record analytical corpus [23,24,89–92].

5. Algorithmic Comparison and Evidence Structure

Table 6 compares solution families by the evidence they can support rather than by reported objective improvement alone. Evolutionary and swarm methods provide flexible search over mixed siting–sizing spaces, but they do not by themselves certify feasibility or global optimality. Learning-assisted surrogates can reduce expensive feeder evaluations, yet their planning value depends on out-of-sample fidelity and on final verification with the physical network model. Convex relaxations, mixed-integer formulations, decomposition, stochastic programming, and robust optimization provide different forms of mathematical structure, bounds, or recourse, with guarantees that remain conditional on model assumptions, relaxation tightness, and tractability. Hybrid strategies are strongest when the search layer and the feasibility layer are reported separately. The comparison therefore asks which combination of artificial-intelligence search or learning and mathematical optimization supports a specific planning claim, at what computational cost, and with what level of physical assurance.

Table 6. Comparative characteristics of DG-planning method families.

Method Family	AI/Math Class	Disc.	What It Does Well	Main Caveat in DG Planning	Best Evidence Role	Key Studies
PSO (particle swarm optimization)	CI	Yes	Flexible non-convex search with minimal modeling overhead	No certificate; reported gains depend strongly on encoding, repair logic, and repeated PF burden.	screening/siting	[5,93]
HHO (Harris Hawks optimization)	CI	Yes	Strong exploration for rugged search spaces and recent benchmark studies	Similar to PSO in guarantee level; parameter tuning and PF burden still dominate practical performance.	screening/planning	[55]
GA (genetic algorithm)	CI	Yes	Natural fit for mixed siting-sizing encodings and chromosome-level repair	Solution quality is highly representation-dependent and still lacks certifiable bounds.	planning/siting	[5,17]
SOCP relaxation	Math	No	Produces explicit feasible envelopes, lower bounds, and warm starts under stated assumptions	Discrete siting still requires mixed-integer second-order cone programming (MISOCP); tightness is conditional on topology and model fidelity.	bound/warm start	[9,10]
SDP relaxation	Math	No	Stronger convex envelope when rank recovery remains credible	Cone size and rank failure can make practical large-scale unbalanced use difficult.	bound analysis	[10]

Table 6. *Cont.*

Method Family	AI/Math Class	Disc.	What It Does Well	Main Caveat in DG Planning	Best Evidence Role	Key Studies
ADMM decomposition	Math	Partial	Scales multiphase or decomposed OPF layers better than monolithic heavy formulations	Convergence speed, coordination logic, and final solution quality of alternating direction method of multipliers (ADMM) remain model-dependent.	scalable OPF layer	[4,10]
Surrogate/emulator	AI/ML	No	Accelerates repeated PF or recourse evaluation once trained on credible high-fidelity data	No intrinsic feasibility guarantee; out-of-sample error can distort siting conclusions.	fast screening	[11,12]
Hybrid (metaheuristic + convex screening)	Hybrid	Partial	Separates discrete search from inner physics-constrained feasibility checking	Final assurance still inherits the heuristic outer layer unless the discrete problem is solved exactly.	mixed discrete-continuous planning	[5,9]

More broadly, reported algorithmic performance often depends as much on formulation structure, candidate screening, and network-model fidelity as on optimizer family. Differences attributed to PSO, GA, HHO, or hybrid methods are often partly driven by distinct feasibility-repair mechanisms, scenario definitions, or power-flow approximations rather than by search logic itself. A paper that screens candidate buses aggressively, relaxes three-phase coupling, or repairs infeasible particles ex post is not directly comparable with one that embeds AC or unbalanced feasibility inside the search loop, even if both are nominally classified under the same optimizer family. Figure 4 is a conceptual tradeoff diagram rather than an empirical scatter plot. Horizontal placement reflects the explicitness of feasibility enforcement, bounds or certificates, and final physical-model verification; vertical placement reflects formulation size, repeated power-flow burden, decomposition communication, and training or scenario cost. Positions are ordinal judgments synthesized from the method characteristics in Table 6; distances between boxes have no numerical meaning. The diagram shows why surrogate workflows sit low on assurance unless they are anchored to higher-fidelity power-flow layers, while hybrid and decomposition-based approaches gain credibility only when their feasibility logic is explicit.

Appendix A Table A3 reports the retained study-level coding used to reconstruct the headline counts and transferability scores. Across the 26-study planning matrix, 10 studies use explicit three-phase or unbalanced feeder representations, eight use non-deterministic uncertainty treatment, and two embed protection as a central feasibility layer. These counts are not nested subsets and can be audited directly from the Physics, Uncert., and Prot. columns; Table A2 states the operational counting rules.

The six entries retained under the physics-not-stated classification were re-audited against bibliography metadata, Crossref abstracts, and repository extraction notes before finalization. They remain in the matrix because their objective design, planning role, and feeder or validation context are still comparably informative, whereas the archived evidence does not justify reclassifying them as either reduced-fidelity or explicit unbalanced-physics studies without unsupported inference. Additional 2024–2026 studies were retained only when they extended methodological coverage beyond the core comparative matrix and met the same traceability standard used in the quantitative synthesis. The supporting layer therefore emphasizes source-verified studies with clear methods, feeder definitions, and

deployment-relevant outcomes for DG planning in unbalanced or constrained distribution systems [24,30,31,81,83,94]. DOI-verified corroborative studies lacking a sufficiently harmonized field set remain part of the supporting analytical layer but are excluded from the scored comparative core.

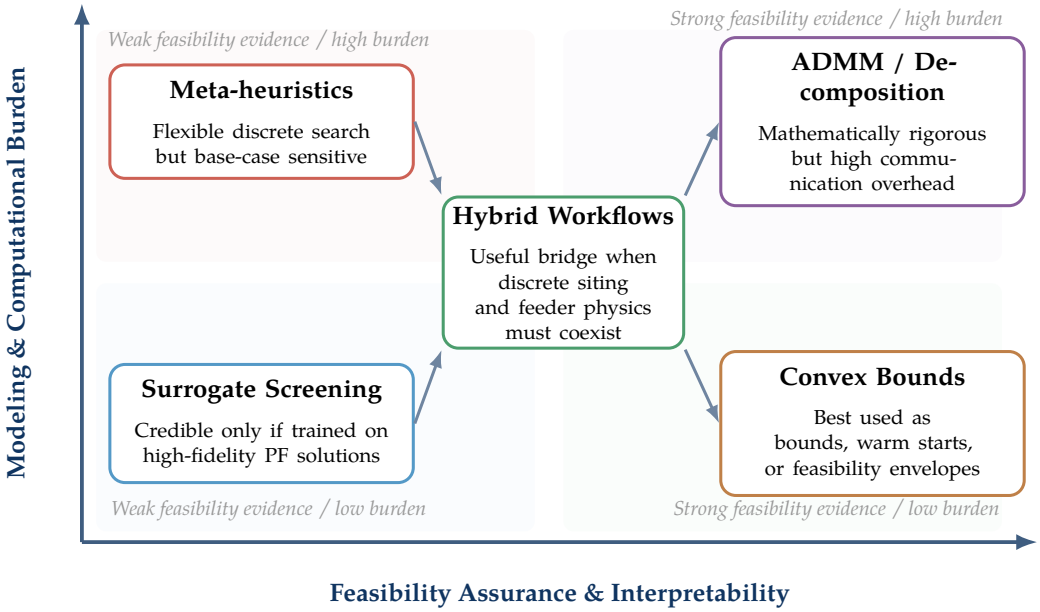


Figure 4. Conceptual solver-tradeoff diagram for DG planning. Placements are ordinal judgments based on feasibility enforcement, validation, and computational burden; distances are not measured quantities.

Recent directly aligned studies extend the contextual layer in three directions: they tighten hosting conclusions under unbalanced low-voltage sensitivity [17,84,95], shift admissible DG envelopes under export limits and protection-device co-allocation [24,81,96], and show that EV-coupled recourse changes preferred DG sites once charging demand interacts with voltage-security limits and multi-agent operations [22,31,83,97]. Table 7 concentrates the most decision-relevant 2025–2026 evidence by evidentiary function rather than optimizer label, while additional complements are cited directly in the surrounding synthesis.

Table 7. Recent evidence clusters relevant to DG-planning transferability.

Evidence Cluster	Selected 2024–2026 Studies *	Engineering Relevance to Planning Transferability
Reliability and resilience	[48,96,98,99]	Shows limits of loss-voltage-only planning by showing that multi-stage reliability, microgrid formation, islanded operability, and resilience penalties now materially reshape admissible DG plans.
Protection-feasible planning	[24,31,100,101]	Supplies a rare but high-value line of evidence that relay coordination, protection adaptation, and EV-rich protection-constrained hosting can bind DG planning more tightly than steady-state voltage criteria alone.
Operator-facing flexibility and hosting	[81,83,94,102,103]	Identifies operator-facing planning conditions in which hosting limits, diversified flexible resources, storage, EV smart charging, and regional operating rules are treated as planning variables rather than as after-the-fact scenario checks.

Table 7. *Cont.*

Evidence Cluster	Selected 2024–2026 Studies *	Engineering Relevance to Planning Transferability
Unbalanced exactness and computational tractability	[13,38,104,105]	Links exact unbalanced MINLP, credible unbalanced OPF structure, and physics-informed graph neural network (GNN) acceleration to the question of which DG-planning models remain both solvable and physically defensible.
Observability and phase-aware credibility	[30,86,106]	Shows that behind-the-meter uncertainty, phase identification, and voltage-state estimation constrain whether high-fidelity planning results can be trusted outside benchmark feeders.

* These studies illustrate contextual evidence clusters; only those also listed in Table A3 enter the 26-study harmonized planning matrix and its quantitative summaries.

Table 8 presents selected, illustrative evidence examples rather than method-family-level findings. Each row is bounded to the cited study or small evidence cluster and its stated baseline; the entries are not pooled estimates, an exhaustive family summary, or evidence of general superiority. Most papers in the wider 122-record evidence base do not expose reusable numeric fields on a sufficiently harmonized basis to support defensible formal statistical analysis, and the table is not part of the 26-study planning count.

Table 8. Illustrative evidence examples linking selected planning strategies to interpretation limits; the rows are not method-family-level findings.

Strategy	Evidence Setting	Illustrative Reported Signal	Bounded Interpretation
Metaheuristics (PSO/GA/HHO)	IEEE benchmark feeders	Strong nominal loss/voltage gains are common but baseline-sensitive [55].	Most credible as screening evidence unless feeder physics, protection, and repeated-run feasibility are controlled.
SOCP/SDP relaxations	Constrained three-phase settings	Explicit electrical constraints produce tighter feasible envelopes [10].	Stronger for feasibility claims when relaxation assumptions and recovery quality are reported.
Two-stage stochastic planning	DG–EV feeder planning	Scenario design and recourse can change the preferred DG plan [22].	Illustrates why deterministic screening can mis-rank alternatives when uncertainty changes the investment decision.
BESS co-optimization	Active MV/LV unbalanced grids	Hosting and loss outcomes depend on storage placement and phase-aware coordination [21].	Stronger when temporal operation and phase-voltage quality are inside the planning problem, not post-checked.
Exact unbalanced MINLP	Three-phase PV/reactive-device planning	Exact coupled-network feasibility reduces the admissible portfolio [38].	High formulation credibility, but computational scalability remains case-size dependent.
Protection-constrained planning	Relay-sensitive feeders	Admissible DG capacity falls when selectivity and coordination are embedded [23].	Converts attractive steady-state optima into smaller but more field-credible feasible envelopes.
Utility/export-limit planning	Regional or utility-validated cases	Export rules and operating envelopes materially shift hosting limits [81].	Strong transferability because the result is conditioned on actual operator rules.

Table 8. *Cont.*

Strategy	Evidence Setting	Illustrative Reported Signal	Bounded Interpretation
PV penetration-policy scenarios	Feeder-specific scenario analysis	Tested investment levels yield different PV penetration limits [85].	Contextual planning evidence; not a scored optimization study.
EV-coupled recourse	EV-integrated two-stage planning	Charging uncertainty changes preferred DG siting and penetration envelopes [22].	Shows that uncertainty and electrification affect the planning decision, not only operating cost.

Figure 5 shows the transferability-score distribution for the 26 retained planning studies. Each total equals the sum of the four subscores in Appendix A Table A3. Sixteen studies fall in the benchmark band and ten in the partial band; none reaches the field-oriented or high-transfer bands. The maximum is 4/8. Annual means are descriptive of this selected subset only (2021: 2.50; 2023: 3.00; 2024: 2.00; 2025: 2.18; 2026: 3.00), with very small cohorts outside 2025. Neither the chart nor the bands supports a field-wide temporal trend or an empirically validated decision threshold.

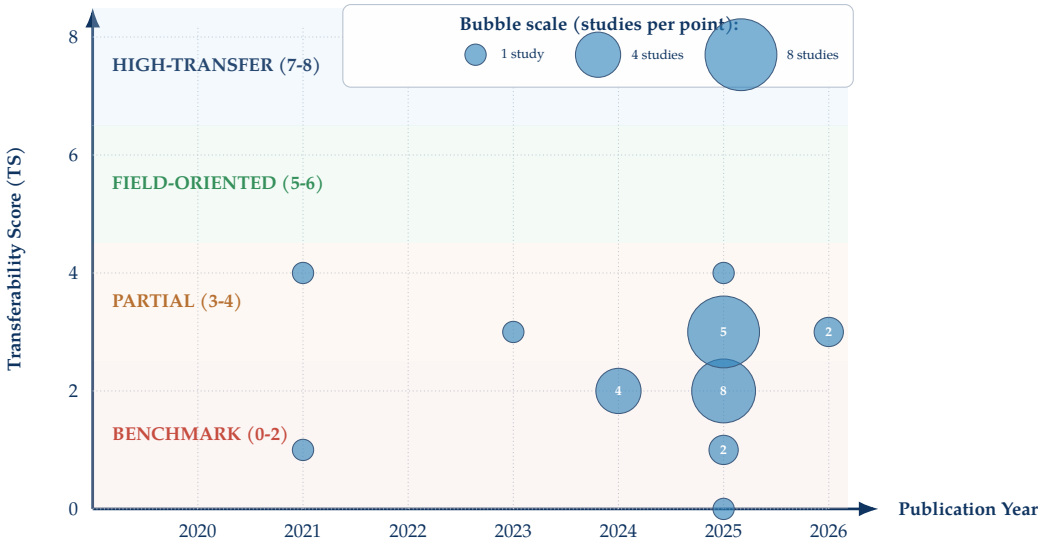


Figure 5. Source-verified transferability-score distribution by publication year within the selected 26-study harmonized planning matrix. Bubble labels give the number of planning studies at each coordinate; the plot is descriptive of the selected matrix and is not a field-wide temporal trend.

Figure 6 conceptualizes how the transferability requirements align with a three-layer architecture linking unbalanced feeder physics, protection-feasibility enforcement, and upper-level stochastic or robust search. Credible planning emerges only when these layers are solved as a coupled chain rather than treated as isolated checks.

The architecture in Figure 6 does not imply that the evidence dimensions form nested subsets. Figure 7 therefore returns to the audited matrix and reports phase-aware physics, non-deterministic uncertainty treatment, and embedded protection separately against the common 26-study denominator, preserving the distinction between a proposed planning architecture and the prevalence actually observed in the literature.

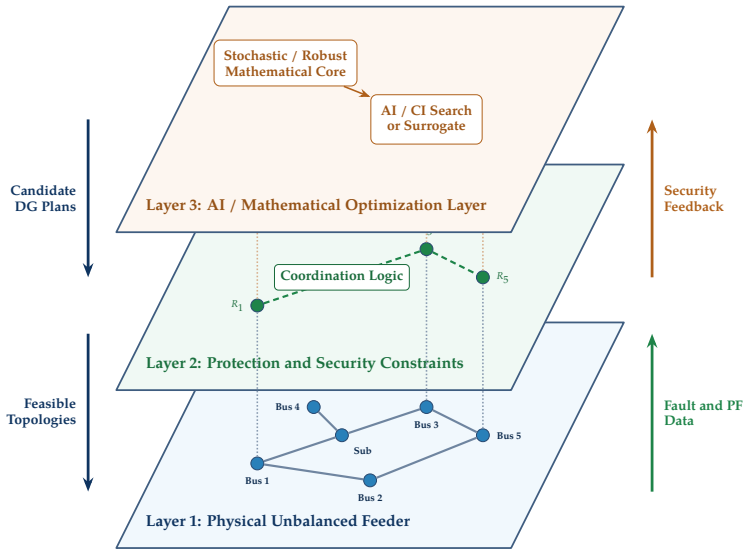


Figure 6. Three-layer DG-planning architecture linking feeder physics, protection feasibility, and stochastic or robust search.

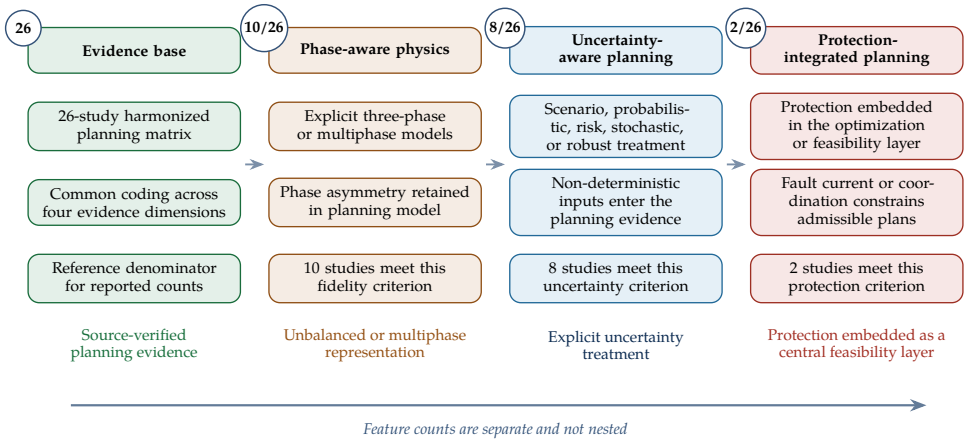


Figure 7. Source-verified evidence-feature prevalence in the 26-study harmonized planning matrix. Counts refer to distinct coding dimensions and should not be interpreted as nested subsets unless a study satisfies multiple criteria simultaneously.

6. Discussion

The synthesis does not support a universal ranking of DG-planning algorithms, and that negative result is important. Reported objective improvements are generated under feeder models, objectives, constraint sets, time horizons, and validation settings that are too heterogeneous for a defensible league table. What the evidence does support is a ranking of *claim strength*. Read with Table 7 and Figure 7, three changes consistently make a planning claim harder but more informative. Coordinated asset models replace isolated DG placement as reactive support, EV charging, switching, and storage enter the decision space [21,22,70]. Explicit uncertainty and protection reduce the set of apparently attractive solutions by adding recourse, risk, fault-current, or coordination conditions [22–24]. Finally, measured or utility-anchored validation exposes local asymmetry, export rules, data limitations, and operating controls that benchmark feeders are not designed to represent [81,84,85]. The consequence is not that benchmark optimization is unimportant; it is that benchmark evidence answers a narrower question than a deployment-facing study.

The distinction can be made operational by matching the strength of a claim to the minimum evidence needed to support it. Table 9 is intentionally conservative: it does

not prescribe one solver, but it identifies what a reviewer or planner should expect before accepting a stronger conclusion.

Table 9. Minimum evidence required for common DG-planning claims.

Claim	Minimum Persuasive Evidence	What Weakens the Claim
Algorithmic superiority	Same mathematical problem and feeder; identical constraints; feasible final solutions; repeated-run statistics for stochastic methods; runtime/evaluation budget; stopping rule.	Comparing best values across different feeders or objectives, omitting feasibility repair, or reporting one stochastic run.
AI/surrogate acceleration	Out-of-sample error or calibration; evaluation-budget comparison; explicit physical-model verification; failure or out-of-distribution behavior.	Treating prediction accuracy as planning feasibility, or reporting speedup without final AC/three-phase verification.
Mathematical optimality or bound	Complete formulation; relaxation/decomposition assumptions; optimality gap or tightness evidence where applicable; final feasibility in the stated network model.	Extending guarantees beyond the modeled assumptions or treating a relaxed optimum as physically exact without recovery/tightness checks.
Hosting-capacity improvement	Voltage and thermal limits; time-varying or uncertainty treatment when material; phase/unbalance representation where relevant; explicit curtailment/control assumptions.	Static balanced screening used to support a feeder-wide deployment limit without phase, time, or control sensitivity.
Deployment or utility readiness	Measured or utility-anchored feeder, or a documented validation bridge; protection and operating-envelope checks; export/control rules; data-quality assumptions.	Benchmark-only evidence presented as an interconnection, reinforcement, tariff, or investment recommendation.

The evidence supports a division of labor between artificial-intelligence methods and mathematical optimization rather than a universal solver hierarchy. Evolutionary and swarm intelligence are useful when siting variables, discrete topology choices, and non-convex power-flow evaluations make a monolithic exact model difficult; learning-assisted surrogates can reduce the number of expensive feeder simulations; and mathematical programming is strongest when bounds, explicit recourse, or constraint certificates are needed. None of these advantages is transferable by itself. An AI-generated candidate remains only as credible as the feeder model and feasibility layer used to assess it, while

a mathematically elegant relaxation can overstate assurance if the relaxation is loose or the network model suppresses phase coupling. The most defensible hybrid architecture therefore uses AI for exploration or acceleration and an explicit physics-constrained layer for feasibility, uncertainty, and protection checks [9–13].

Uncertainty, model fidelity, and validation settings reinforce this pattern. Explicit uncertainty modeling (two-stage recourse, DRCC, or noise-aware planning) changes admissible DG penetration, annualized cost, and voltage quality [10,11,34,66], particularly under unbalanced modeling where phase-aware storage placement, three-phase OPF fidelity, and learned three-phase surrogates expose effects that balanced screening suppresses [12,21,35]. Validation and transferability separate academically interesting formulations from utility-relevant evidence: real-feeder and contextual studies show that measured load diversity, export rules, and local protection constraints can shift preferred DG plans away from IEEE-style screening results [31,81,84,85], while economic OPF reveals that transformer degradation and locational value signals can reorder feasible investments [3]. Protection studies sharpen the point that admissible DG capacity is not determined by voltage and losses alone: selectivity and fault-current behavior can redefine the feasible envelope after a steady-state optimum has been found [23,24,49].

The newest operator-facing evidence also broadens what counts as validation. Mahairi et al. [107] combine time-series nodal hosting capacity, Monte Carlo uncertainty, sequence-voltage and neutral-current limits, coordinated EV charging, and an interactive decision tool validated on a real European low-voltage network. Zhou et al. [108] show that DG planning should also account for portfolios of extreme-weather conditions rather than one hazard in isolation. At the network boundary, Miah et al. [109] identify decentralized transmission–active-distribution coordination as an enabling route for procuring services from distributed renewable resources. Together, these studies support a wider transferability test: credible renewable-integration plans must survive local phase constraints, time-varying flexibility, resilience stress, and upstream coordination requirements.

Six weaknesses recur: weak protection integration, scarce utility-scale demonstrations, limited device-specific protection modeling, incomplete behind-the-meter observability, underdeveloped regulatory-technical co-optimization, and immature digital models [13,24,30,83,86,101,103,106,110]. These limit whether a published optimum can be read as a credible recommendation for an operating feeder. The gap appears at implementation, where plans must survive protection review, operating-envelope checks, asset-management constraints, and incomplete visibility. Stronger transferability claims should therefore be anchored in measured-feeder validation, explicit uncertainty treatment, phase-aware modeling where relevant, and protection-aware feasibility checks [24,81,83–85,103,111,112]. For utilities, the practical sequence is to improve feeder models and time-series measurements, raise fidelity where unbalance or protection margins bind, and cross-check candidate plans on at least one measured feeder. For researchers, the priority is disciplined comparison across common feeders, units, and constraint sets, clearly reporting where benchmark evidence ends and field-relevant guidance begins. Platform choice also matters: OpenDSS, GridLAB-D, PowerFactory, and PowerModelsDistribution.jl align better with explicit three-phase feeder behavior, whereas MATPOWER-style workflows are more suitable for screening unless phase-coupled effects are preserved.

6.1. Policy, Economic, and Regulatory Implications

The transferability results have direct implications for distribution-system policy and investment. When hosting-capacity studies rely on reduced feeder models, simplified protection assumptions, or benchmark-only validation, DG limits can understate deploy-

ment constraints and distort interconnection, reinforcement, and non-wires decisions. Two stakeholder-facing implications follow:

- **For Regulators and Policymakers:** Interconnection and non-wires assessments are more credible when major DER planning cases are supported by high-fidelity, protection-aware modeling and are bounded by local operating rules, export limits, and feeder-specific data assumptions.
- **For Utility Operators and DSOs:** The reviewed evidence favors moving beyond static hosting-capacity maps toward more dynamic, protection-constrained planning workflows. Investments in advanced metering infrastructure (AMI) and phase-identification tools can reduce the visibility gaps that limit planning fidelity.

This is especially relevant where flexibility markets, dynamic export rules, EV growth, and customer-sited resources interact on constrained feeders. The rubric is not a regulatory instrument, but it helps separate exploratory results from evidence strong enough for tariff design, connection policy, hosting-capacity publication, or staged investment decisions. Higher-fidelity planning can reduce avoidable capital misallocation by clarifying when reinforcement, reactive support, observability upgrades, protection changes, or flexibility contracts are substitutable.

6.2. Implications for Decarbonization, Decentralization, and Digitization

The evidence connects the three transition forces through one planning chain. Decarbonization sets the need to accommodate more renewable electricity and electrified demand; decentralization moves generation, storage, and controllable demand to phase-sensitive distribution feeders; and digitization supplies the measurements, models, communications, and optimization interfaces needed to coordinate those assets. Treating these forces separately can produce misleading investment signals. For example, a nominal increase in PV hosting capacity is not a transferable decarbonization benefit if it depends on unobserved phase allocation, ignores protection selectivity, or assumes flexibility that cannot be dispatched under local connection rules.

Recent 2025 evidence reinforces this chain from complementary angles: uncertainty-aware PV and wind allocation quantifies phase-sensitive renewable limits [77,78]; a real-network software framework turns monitoring and flexible charging into operator-usable hosting-capacity decisions [107]; resilience-oriented planning tests DG portfolios against multiple weather hazards [108]; and transmission–distribution coordination exposes the market and operational interfaces needed to use decentralized renewable services at system level [109]. None removes the need for protection-aware field validation, but together they demonstrate the value of linking physical fidelity, digital decision support, and institutional coordination.

For integrated renewable systems, the practical pathway is therefore staged rather than technology-specific. First, utilities need auditable phase-aware feeder models and time-series data. Second, planners should co-optimize renewable DG with storage, reactive support, EV charging, demand flexibility, and reinforcement alternatives under common economic units. Third, candidate portfolios should be tested against uncertainty, protection, communications, and operating-envelope constraints before market or tariff conclusions are drawn. This sequence clarifies where digital investment creates system value: not as an end in itself, but by converting decentralized flexibility into dependable renewable-hosting capability and by revealing when conventional reinforcement or protection upgrades remain necessary.

7. Research Gaps and Future Directions

Figure 8 is a conceptual research-priority map. Urgency is judged from the combination of a recurring evidence deficit and the severity of its deployment consequence, such as infeasible protection settings or unsupported investment decisions. Maturity is judged from the availability of explicit formulations, repeated demonstrations, and measured- or utility-anchored validation. The axes are ordinal, the node coordinates are not estimated data, and distances between nodes have no quantitative interpretation.

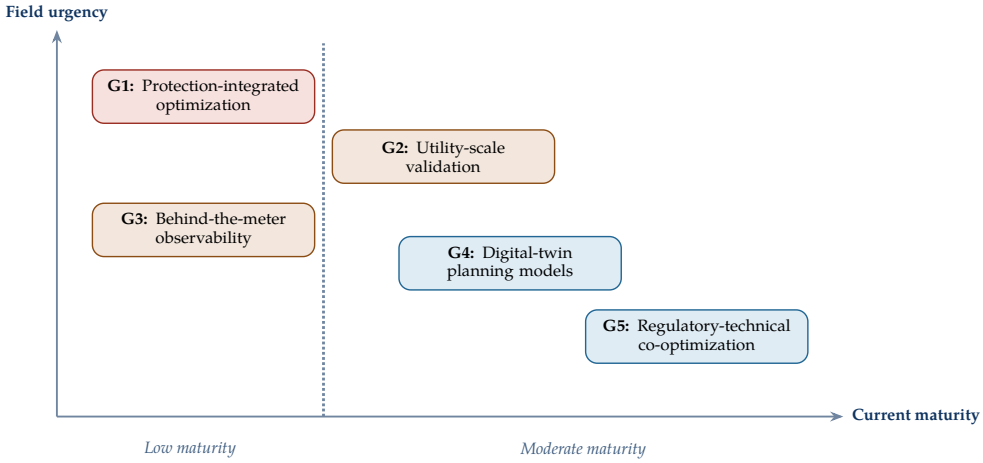


Figure 8. Conceptual research-priority map for transferability-oriented DG planning. Maturity and urgency are ordinal judgments based on formulation availability, validation depth, repeated evidence deficits, and deployment consequences. The dotted vertical line separates the illustrative low- and moderate-maturity regions; it is not a measured threshold.

The gap analysis is derived from repeated evidence deficits in the harmonized matrix rather than from topic popularity. It identifies five near-term priorities plus one adjacent direction. Protection-integrated optimization is first because protection is often a binding feasibility condition, yet few studies model it centrally rather than as a post-optimization check [23,24,49,92]. Utility-scale validation follows because benchmark evidence remains richer than measured-feeder studies that combine time-series operation and deployment constraints [31,81,83–85]. A third priority is observability of behind-the-meter and phase-specific resources, especially in low-voltage networks with rooftop PV, flexible demand, and customer storage [30,82,86,87,106]. Advanced metering, phase identification, state estimation, and open-data feeder reconstruction therefore become enabling tools [113]. The final priorities are digitally updated planning models [20,114] and deployment-aware co-optimization that treats congestion sequencing, operator constraints, implementation timing, and risk exposure explicitly [115].

A sixth, emerging priority is trustworthy and physics-informed AI for strategic DG planning. Reinforcement-learning and data-driven planning remain underrepresented in the harmonized set because current evidence is stronger for operational Volt/Var control than for long-horizon siting and sizing [29]. Future AI contributions should therefore report out-of-distribution error, physical-feasibility enforcement, uncertainty calibration, repeated-run behavior, and the point at which a learned or surrogate model is checked against a three-phase feeder model. Physics-informed graph models and learned power-flow emulators are promising computational complements, but the present evidence does not yet justify treating them as substitutes for deployment-facing validation [12,13]. Climate adaptation and resilience add urgency: temperature, storm, electrification, and recovery uncertainty can shift loading, fault exposure, restoration constraints, and asset aging away from benchmark assumptions. Thus, protection integration, utility validation, observability,

digital models, and regulatory-technical co-optimization are also prerequisites for credible low-carbon planning. Transferability gaps translate into interconnection delay, avoidable capital misallocation, and weaker evidence for non-wires alternatives.

8. Conclusions

The synthesis addresses a narrower and more defensible question than "which DG optimizer is best?": what is the published evidence strong enough to support? Across the 2016–March 2026 analytical corpus, objective values become comparable only when units, normalization, time aggregation, and constraints are explicit; network-model fidelity changes the feasible set on phase-asymmetric feeders; and validation depth changes whether a result should be read as an algorithmic demonstration or as planning evidence. In the 26-study harmonized planning matrix, 10 studies use unbalanced or multiphase models and only two treat protection as a central feasibility layer, which explains why strong numerical results are more common than high-transferability claims.

Across the reviewed evidence, the available heterogeneous studies do not support a formal ranking of AI and mathematical-optimization families across realistic distribution-system settings. Computational-intelligence methods offer flexible mixed-variable search, and learning-assisted AI can reduce repeated feeder evaluations, but neither provides a feasibility certificate by itself. Convex, mixed-integer, stochastic, robust, and decomposition methods can provide stronger mathematical structure or bounds, yet those guarantees remain conditional on model fidelity and formulation assumptions. Hybrid workflows are therefore most credible when AI is used for exploration or acceleration while an explicit physics-constrained layer enforces network, uncertainty, and protection feasibility. The strongest transferability claims are not those with the largest numerical improvement, but those that align objective design, three-phase feeder representation, uncertainty treatment, protection feasibility, and measured or utility-anchored validation.

For policy and utility practice, the proposed framework provides a renewable-integration lens for judging whether DG-planning evidence is mature enough to support hosting-capacity, resilience, flexibility-market, and non-wires decisions. The review indicates that planning evidence is more credible when final recommendations are tested beyond stylized benchmarks and when protection limits, operating assumptions, export rules, observability gaps, and implementation constraints are reported before investment conclusions are drawn. In this way, phase-aware digital models and coordinated planning of PV, storage, EV charging, and flexible demand become enabling infrastructure for decentralized decarbonization rather than optional modeling refinements.

The review is limited by its English-language indexed scope, primary screening by one reviewer followed by non-blinded supervisory verification rather than prospective duplicate screening, missing day-level timestamps for the five named databases, absence of retained study-level failed-test vectors for the original 80 supporting records, and selective harmonized matrix, which prioritizes formulation-level comparability and validation depth over exhaustive cataloging. Geographic representation is uneven, the March 2026 cutoff may underrepresent preprint-heavy subfields, and some papers lack the fields needed for disciplined harmonization. Narrowing the gap between published optima and utility-anchored planning guidance will require stronger comparative evidence, more real-feeder validation, and fuller integration of protection, observability, and regulatory feasibility; additional heuristic variants alone are unlikely to close it.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/en19215031/s1, File S1: PRISMA 2020 checklist with item-level manuscript locations; File S2: database-specific search strings and transferability-score sensitivity

analysis; File S3: machine-readable eligibility and coding sheet for the historical 42-row audit and the separately admitted replacement.

Author Contributions: A.M.G., Conceptualization, methodology, software, formal analysis, investigation, data curation, visualization, writing, original draft preparation. A.S.Z., Conceptualization, methodology, validation, supervision, project administration, funding acquisition, writing, review and editing. R.M., Formal analysis, investigation, validation, writing, review and editing. M.M., Validation, supervision, funding acquisition, writing, review and editing. S.A., Validation, writing, review and editing. A.A.-S., Validation, supervision, resources, funding acquisition, writing, review and editing. H.A.A.E.-G., Methodology, validation, supervision, writing, review and editing. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Appendix A contains the 26-study planning matrix. Supplementary File S3 supplies its subscores together with the eligibility decisions and reasons for the historical 42 records and the separately admitted replacement. Supplementary File S2 contains the database-specific reproducible search strings and score-sensitivity analysis. The historical ledger did not retain study-level failed-test vectors for the 80 records originally in the supporting layer; their evidentiary functions are reported in Appendix B. No new experimental or confidential dataset was generated.

Conflicts of Interest: The authors declare no conflicts of interest.

Symbols and Abbreviations

Symbols

$P_{L,i}^{0}$	Nominal active demand at bus i	TDS	Relay time-dial setting
V_0	Nominal voltage used in the ZIP load model	t_{op}	Relay operating time
a_p, b_p, c_p	ZIP active-power coefficients, with $a_p + b_p + c_p = 1$	t_{primary}, t_{backup}	Primary and backup relay operating times
r_{ij}, x_{ij}	Resistance and reactance of branch (i, j)	CTI	Coordination time interval
$P_{ij,t}$, $Q_{ij,t}$	Active and reactive branch power at time t	$E_{i,t}$	Energy stored in unit i at time t
v_i, ℓ_{ij}	Squared voltage and squared current variables in DistFlow relaxations	$P_{c,i,t}$, $P_{d,i,t}$	Storage charging and discharging power
$V_i^{(\phi)}$	Phase-specific voltage at bus i	η_c, η_d	Charging and discharging efficiencies
$P_{DG,i}^{(\phi)}$, $Q_{DG,i}^{(\phi)}$	Phase-specific active and reactive DG output	Δt	Time-step duration
$P_{Di}^{(\phi)}$, $Q_{Di}^{(\phi)}$	Phase-specific active and reactive demand	$E_{\min}$, $E_{\max}$	Lower and upper storage-energy bounds
N_b	Number of buses in the network model	P_{rated}	Rated inverter or storage power
$\delta_i^{(\phi)}$	Voltage angle at bus i, phase ϕ	$\text{SOC}_{i,t}$	Normalized state of charge
$\delta_{ij}^{(\phi\psi)}$	Phase-angle difference between bus-phase pairs	x, y	First-stage investment and second-stage recourse variables
$G_{ij}^{(\phi\psi)}$, $B_{ij}^{(\phi\psi)}$	Mutual conductance and susceptance terms	c, q	Investment and operating cost vectors
$\mathbf{Z}_{ij}^{abcn}$	Three-phase four-wire branch-impedance matrix	ξ	Uncertainty realization
$I_{ij}^{(\phi)}$	Phase current on branch (i, j)	$\mathbf{W}_{\text{rec}}$, $\mathbf{T}_{\text{rec}}$	Recourse-constraint coefficient matrices

ϕ, n	Phase index and neutral-conductor index	$\mathcal{U}$	Bounded uncertainty set for robust optimization
$V_{\min}$, $V_{\max}$	Lower and upper admissible voltage limits	$\mathcal{P}$	Ambiguity set of probability distributions
$I_{ij,\max}$	Thermal current limit of branch (i,j)	ϵ	Admissible chance-constraint violation probability
$P_{DG}^{\min/\max}$ $Q_{DG}^{\min/\max}$	Active and reactive DG capability bounds	$\mathbf{X}$	Positive-semidefinite voltage lifting used in SDP
A, B	Inverse-time relay-curve constants	C, A_k, b_k	SDP objective and constraint coefficients
I_f, I_p	Fault current and relay pickup current	TS	Aggregate transferability score
Abbreviations			
AC	Alternating current	MISOCP	Mixed-integer second-order cone programming
ADMM	Alternating direction method of multipliers	MPC	Model predictive control
AI	Artificial intelligence	MV	Medium voltage
AMI	Advanced metering infrastructure	NPV	Net present value
BESS	Battery energy storage system	OPF	Optimal power flow
CAPEX	Capital expenditure	OPEX	Operational expenditure
CTI	Coordination time interval	PF	Power flow
DER	Distributed energy resource	PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
DG	Distributed generation	PSO	Particle swarm optimization
DRCC	Distributionally robust chance constraint	PV	Photovoltaic
D-STATCOM	Distribution static compensator	SAIDI	System average interruption duration index
ENS	Expected energy not served	SAIFI	System average interruption frequency index
EV	Electric vehicle	SDP	Semidefinite programming
GA	Genetic algorithm	SOC	State of charge
GNN	Graph neural network	SOCP	Second-order cone programming
HHO	Harris Hawks optimization	STATCOM	Static synchronous compensator
LV	Low voltage	VSI	Voltage stability index
ML	Machine learning	VUF	Voltage unbalance factor
MINLP	Mixed-integer nonlinear programming	WoS	Web of Science

Appendix A. Harmonized Study-Level Audit Matrix and Transferability Scoring

The appendix is part of the article and contains the minimum row-level evidence needed to reconstruct the main quantitative claims without relying on external files. Table A3 reports all 26 harmonized planning records using the same fixed coding fields applied throughout the synthesis. Tables A1 and A2 define the score and the three headline count rules. Supporting records and the 13 post-closure studies do not enter these quantitative calculations; source-verification amendments are reconciled separately in S3.

Table A1. Operational scoring key used for the transferability assessment.

Dimension	Score 0	Score 1	Score 2
Fidelity (F)	Physics = N/S or balanced/phase-equivalent (0)	Physics = Red. (1)	Physics = 3ϕ/U (2)
Uncertainty (U)	Det. (0)	Scen., Prob., or Risk (1)	Rob. or Stoch. with formal decision coupling (2)
Protection (P)	None (0)	Post (1)	Emb. (2)
Validation (V)	Bench. (0)	Case (1)	Meas. or Util. (2)

For every row, $TS = F + U + P + V$. The unweighted sum gives TS $\in [0, 8]$: benchmark = 0–2, partial = 3–4, field-oriented = 5–6, and high-transfer = 7–8. Equal weighting is used only as an auditable baseline, not as a utility-specific preference model.

The transferability-score bands are diagnostic categories for structured comparison, not empirically validated decision thresholds. Equal weighting is used as a transparent diagnostic baseline because the review has no defensible empirical basis for assigning universal utility preferences to fidelity, uncertainty, protection, or validation. The score bands partition the 0–8 scale for interpretation and are not calibrated risk thresholds. A one-at-a-time sensitivity analysis changed each dimension weight from 1.00 to 0.75 and 1.25, renormalizing the maximum weighted score to eight. Spearman rank correlations with the baseline ranged from 0.942 to 0.978, and no weighting case produced a high-transfer study. Class membership was less stable near the fixed boundaries: benchmark counts ranged from 17 to 23 and partial counts from 3 to 9; no case reached a field-oriented band. The score is therefore suitable for transparent ordering and gap diagnosis, but individual band labels near a boundary should not be treated as robust utility decisions. Full results and formulas are reported in Supplementary File S2.

Table A1 defines the four scored dimensions and makes the deliberately unweighted baseline transparent. Table A2 then states the operational inclusion rule for each headline count, allowing readers to reproduce the reported 10, 8, and 2 study totals without interpreting narrative descriptions.

Table A2. Audit trail for the headline count claims used in the synthesis. Badge colors distinguish coding categories; the printed labels define the counting rules.

Claim	Operational Rule	Count	Audit Path
Unbalanced or multiphase formulations	Physics code = 3ϕ / Unb..	10/26	Table A3, Physics column.
Non-deterministic uncertainty treatment	Uncertainty code = Scenario, Prob., Robust, Stoch., or Risk rather than Det..	8/26	Table A3, Uncert. column.
Protection as a central feasibility layer	Protection code = Emb.; Post is not counted as embedded planning.	2/26	Table A3, Prot. column.

The coding rules in Tables A1 and A2 are applied record by record in Table A3. Presenting the complete matrix here exposes every classification and score to inspection, rather than asking readers to accept aggregate counts that cannot be traced to individual studies.

Table A3. Study-level audit matrix used to reconstruct the headline counts and transferability scores.

Study	Yr.	Physics (F)	Uncert. (U)	Prot. (P)	Evidence (V)	TS	Class
[24]	2025	N/S (0)	Det. (0)	Emb. (2)	Bench. (0)	**2**	benchmark
[21]	2021	3ϕ/U (2)	Rob. (2)	None (0)	Bench. (0)	**4**	partial
[50]	2023	3ϕ/U (2)	Det. (0)	Post (1)	Bench. (0)	**3**	partial
[116]	2024	Red. (1)	Scen. (1)	None (0)	Bench. (0)	**2**	benchmark
[117]	2024	3ϕ/U (2)	Det. (0)	None (0)	Bench. (0)	**2**	benchmark
[118]	2024	3ϕ/U (2)	Det. (0)	None (0)	Bench. (0)	**2**	benchmark
[38]	2025	3ϕ/U (2)	Det. (0)	None (0)	Bench. (0)	**2**	benchmark
[119]	2025	3ϕ/U (2)	Det. (0)	None (0)	Bench. (0)	**2**	benchmark
[120]	2025	3ϕ/U (2)	Det. (0)	None (0)	Bench. (0)	**2**	benchmark
[121]	2025	Red. (1)	Scen. (1)	None (0)	Bench. (0)	**2**	benchmark
[122]	2025	Red. (1)	Det. (0)	None (0)	Case (1)	**2**	benchmark
[123]	2025	Red. (1)	Rob. (2)	None (0)	Bench. (0)	**3**	partial
[81]	2026	N/S (0)	Scen. (1)	None (0)	Util. (2)	**3**	partial
[22]	2024	N/S (0)	Stoch. (2)	None (0)	Bench. (0)	**2**	benchmark
[70]	2025	3ϕ/U (2)	Det. (0)	None (0)	Case (1)	**3**	partial
[94]	2025	3ϕ/U (2)	Risk (1)	None (0)	Bench. (0)	**3**	partial
[39]	2021	Bal./Eq. (0)	Det. (0)	None (0)	Case (1)	**1**	benchmark
[84]	2026	3ϕ/U (2)	Det. (0)	None (0)	Case (1)	**3**	partial
[124]	2025	N/S (0)	Det. (0)	None (0)	Bench. (0)	**0**	benchmark
[125]	2025	Red. (1)	Stoch. (2)	None (0)	Bench. (0)	**3**	partial
[102]	2025	Red. (1)	Det. (0)	None (0)	Bench. (0)	**1**	benchmark
[126]	2025	Red. (1)	Det. (0)	None (0)	Bench. (0)	**1**	benchmark
[127]	2025	Red. (1)	Det. (0)	Post (1)	Case (1)	**3**	partial
[128]	2025	N/S (0)	Det. (0)	None (0)	Util. (2)	**2**	benchmark
[101]	2025	N/S (0)	Det. (0)	Emb. (2)	Util. (2)	**4**	partial
[129]	2025	Red. (1)	Det. (0)	None (0)	Case (1)	**2**	benchmark

Each coded cell reports its subscore in parentheses, and $TS = F + U + P + V$. Codes: Physics = 3ϕ/U (explicit three-phase/unbalanced), Red. (reduced fidelity), N/S (not stated). Uncertainty = Det., Scen., Prob., Rob., Stoch., Risk. Protection = Emb., Post, None. Evidence = Bench., Case, Meas., Util. TS is defined in Table A1.

Appendix B. Supporting Evidence Map for the Closed Analytical Corpus

The 26-study matrix is the only layer used for scored comparison of planning studies. The 16 reassigned studies are documented with row-level reasons in Supplementary File S3 and remain available as contextual evidence for voltage control, phase-aware power flow, sensitivity analysis, pricing, EV hosting, and reconfiguration [3,31,33–37,42,66,85,95,114,130–133]. The grouped citations below illustrate the evidentiary functions of supporting records; they are not a complete row-level inventory of the historical supporting layer and do not enter the scored matrix.

The supporting evidence on planning frameworks, review taxonomies, and system-level decision structure helps distinguish allocation, expansion, voltage-control, hosting-capacity, and joint DG–switch planning questions from narrower optimizer comparisons [134–141].

A second evidence stream addresses unbalanced-network physics, feeder fidelity, and power quality. Soltani et al. [142] explicitly model untransposed lines, transformers, and DERs in current–voltage unbalanced AC OPF, with comparison against OpenDSS and testing on a utility feeder. This provides a direct modelling basis for interpreting phase-aware feasibility, without treating an operational model as a DG-allocation study. Complementary evidence addresses voltage stability, regulator action, asset health, and power-quality effects [143–153].

Evidence on EV, storage, reactive-support, and flexibility co-planning shows how electrification, storage, DSTATCOM, local trading, and flexible operation enlarge the decision

space beyond isolated DG siting and can change preferred locations, capacities, and feasible hosting envelopes [154–168].

Studies addressing protection, reliability, resilience, and operating security are not uniformly harmonizable, but they demonstrate that reconfiguration, reliability, fault behavior, resilience, and high-penetration stress can become binding planning considerations rather than secondary checks [169–173].

AI, computational-intelligence, and recent method-led studies broaden the search-method evidence around evolutionary, swarm, hybrid, and neural-assisted optimization. They are retained as computational comparators but are not promoted to stronger transferability evidence unless their feeder physics, uncertainty, protection, and validation layers support that claim [174–190].

Finally, feeder-specific evidence from rural, long-medium-voltage, and utility distribution settings is retained to test whether benchmark-derived conclusions remain plausible when actual network length, reinforcement needs, and local voltage behavior become material [191–193]. The supporting layer is interpretive by design, and none of these grouped citations changes the 26-study denominator, transferability scores, or headline counts reported in the main synthesis.

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