

Multi-Objective Evolutionary Optimization for Smart Grid Energy Management

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ABSTRACT

Smart grid energy management is structurally a multi-criteria problem: minimizing generation cost, minimizing emissions, maximizing renewable utilization, and preserving reliability rarely point in the same direction, and collapsing them into a single weighted objective discards the trade-off information an operator actually needs. This article synthesizes the literature on multi-objective evolutionary algorithms (MOEAs) as applied to smart grid and microgrid energy management. We trace the field from foundational Pareto-search frameworks, NSGA-II and its many-objective successor NSGA-III, decomposition-based MOEA/D, strength-Pareto and multi-objective particle swarm methods, through their adaptation for power-system-specific constraint handling, to applied studies spanning microgrid and multi-microgrid dispatch, economic-emission dispatch, optimal power flow, renewable and storage sizing, and demand-side and electric-vehicle-charging scheduling. Reported results across these applications range from modest, single-digit-percentage improvements in dispatch cost and emissions to substantial gains in Pareto-front quality attributable to problem-specific constraint-handling engineering rather than the underlying search paradigm. Read together, the evidence supports Pareto-based evolutionary search as the field's default methodology for exploring cost-emission-reliability trade-offs, while leaving many-objective scalability, the gap between synthetic benchmarks and deployed grids, and computational cost under near-real-time operation as an open research agenda.

Keywords: multi-objective optimization; evolutionary algorithms; smart grid; microgrid energy management; Pareto optimization

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1. Introduction

Electricity grids were built around a simple asymmetry: generation follows demand, and the job of the system operator is to keep that following as cheap, reliable, and (historically, as an afterthought) as clean as possible. The smart grid rearranges that asymmetry. Distributed generation, price-responsive loads, electric vehicles, and grid-scale storage turn what used to be a one-directional dispatch problem into a genuinely bidirectional coordination problem, and the survey literature on smart grid architecture is candid that this shift is as much about information and control as it is about new hardware [1]. An operator managing such a system is rarely optimizing one thing. Minimizing generation cost, minimizing emissions, maximizing renewable utilization, minimizing losses, maintaining voltage and frequency within bounds, and preserving reserve margin for contingencies are all live concerns simultaneously, and they do not point in the same direction. Cutting cost usually means leaning harder on the cheapest, dirtiest generator online; cutting emissions usually means displacing it with something more expensive or less dispatchable. Early smart grid optimization work already flagged this as a structurally multi-objective problem rather than a single-objective one dressed up with constraints [2].

The classical answer to "how do I optimize several conflicting things at once" is to collapse them into one number — a weighted sum of cost and emissions, say — and solve the resulting single-objective problem with whatever solver is convenient. That approach works, but it throws away information the decision-maker actually wants. A single weighted-sum run returns one point on the trade-off surface, chosen by weights the analyst picked in advance, often somewhat arbitrarily. It does not show the operator what is being given up, in cost, to buy a given amount of emissions reduction, or what the shape of that trade-off looks like as either objective is pushed further. Multi-objective evolutionary algorithms (MOEAs) solve a different problem: rather than returning one compromise solution, they evolve a population toward an approximation of the entire Pareto front, the set of solutions for which no objective can be improved without worsening another [3]. A grid operator, or the software layer acting on their behalf, can then pick a point on that front according to the priorities of the moment — a cold snap that pushes reliability above cost, a regulatory reporting deadline that pushes

emissions above everything else — without having to re-run the entire optimization from scratch for every new weighting.

This article synthesizes what the literature has established about applying multi-objective evolutionary optimization specifically to smart grid and microgrid energy management. We are not reporting new experiments; we are pulling together a body of work that spans foundational algorithm design (NSGA-II and its descendants, decomposition-based methods, multi-objective particle swarm variants), applied studies that use these algorithms for microgrid dispatch, economic-emission dispatch, optimal power flow, renewable and storage sizing, and demand-side scheduling, and the recurring practical difficulties that show up once these methods are asked to run on real or realistically-simulated grid problems rather than synthetic test functions. We organize the discussion around five themes: the algorithmic foundations of multi-objective evolutionary optimization; how those algorithms have been adapted specifically for power-system optimization; their application to microgrid and multi-microgrid energy management; their use in economic-emission dispatch and optimal power flow, arguably the most mature application area; and their extension to renewable integration, storage sizing, and demand-side management, where the newest work is concentrated. We close with a frank accounting of open problems — scalability to many objectives, handling of uncertainty, and the gap between benchmark validation and field deployment — that the literature itself has not fully resolved.

It is worth being upfront about the evidentiary character of this field. Most of the numerical results reported in the papers synthesized here come from simulated test systems — standard IEEE bus systems, synthetic microgrid topologies, or benchmark unit-commitment instances — rather than from live grid deployments, and algorithm comparisons are typically made against other evolutionary methods (classical PSO, standard NSGA-II) rather than against the centralized dispatch software actually running in control rooms today. That is a real limitation, and we flag it rather than paper over it. What the literature does support, with reasonable consistency across independent groups working on different sub-problems, is that Pareto-based evolutionary search is now the default methodology for exploring

cost-emission-reliability trade-offs in grid optimization research, and that the specific algorithmic choices — which MOEA variant, which encoding, which constraint-handling mechanism — measurably affect how well that trade-off surface is actually captured.

2. Foundations of Multi-Objective Evolutionary Optimization

The starting point for essentially all of the applied work discussed later in this article is a small set of general-purpose MOEA frameworks developed largely independently of any power-system application, and it is worth understanding what problem each one was actually solving before looking at how the smart-grid literature has bent them toward energy management.

Deb, Pratap, Agarwal, and Meyarivan's NSGA-II is the algorithm most smart-grid papers either use directly or use as their baseline for comparison [3]. Its predecessor, the original NSGA, suffered from high computational complexity in its non-dominated sorting step, a lack of elitism, and a somewhat ad hoc sharing-parameter mechanism for maintaining diversity along the Pareto front. NSGA-II fixed all three: a fast non-dominated sorting procedure that reduced the sorting complexity from a cubic to a quadratic function of population size, an elitist selection strategy that preserves good solutions across generations by combining parent and offspring populations before selection, and a crowding-distance measure that maintains spread along the front without requiring a user-specified sharing radius. The result is a solution concept the authors call an "elitist non-dominated sorting" procedure, and it remains, more than two decades on, the single most cited multi-objective optimizer in the applied energy literature, for reasons that have more to do with its robustness and ease of implementation than with any claim of dominance on every problem class.

NSGA-II's crowding-distance diversity mechanism, however, degrades as the number of objectives grows past three or four — a well-documented weakness of Pareto-dominance-based selection generally, since almost every solution in a random population becomes mutually non-dominated once objective count rises, leaving crowding distance as essentially the only active selection pressure. Deb and Jain's NSGA-III addresses this directly by replacing the crowding-distance mechanism with a reference-point-based niching procedure: a structured set of reference points is

supplied (or generated) spanning the objective space, and selection preserves diversity by associating each candidate solution with its nearest reference point and favoring points that are under-represented in the current population [4]. This reference-point machinery is specifically what lets NSGA-III maintain a well-spread approximation of the Pareto front on problems with substantially more than three objectives — a property that matters for smart grid optimization the moment an operator wants cost, emissions, reliability, and voltage-deviation objectives all optimized jointly rather than folding some of them into constraints.

A structurally different approach to maintaining diversity comes from decomposition rather than dominance. Zhang and Li's MOEA/D reformulates the multi-objective problem as a set of single-objective subproblems, each defined by a different weight vector via a scalarizing function (weighted sum, Tchebycheff, or boundary intersection approaches), and solves them simultaneously using evolutionary operators, with neighboring subproblems (those with similar weight vectors) exchanging information during optimization [5]. Because each subproblem targets a specific region of the Pareto front by construction, MOEA/D sidesteps the "everything is non-dominated" problem that afflicts pure dominance-based selection at higher objective counts, and the original paper reports that it matches or outperforms established methods including NSGA-II and MOGLS on the majority of the continuous multi-objective test instances the authors evaluated. This decomposition idea has proven influential well beyond its original test suite, and several of the smart-grid-specific algorithms discussed later borrow its weight-vector machinery even when they are not pure MOEA/D implementations.

Two further foundational threads deserve mention because applied energy papers cite them almost as often as NSGA-II itself. Zitzler and Thiele's early comparative study introduced the Strength Pareto approach, which assigns each individual a "strength" value proportional to the number of solutions it dominates and derives fitness from the accumulated strength of an individual's dominators, combined with an external archive that preserves non-dominated solutions found so far across generations [6]. That external-archive idea — keep a separate, continuously-updated store of the best non-dominated solutions found, distinct from the

working population — became a standard architectural feature of essentially every MOEA developed afterward, including most of the microgrid- and dispatch-specific algorithms reviewed below. Separately, Coello Coello, Pulido, and Lechuga extended particle swarm optimization, originally a single-objective metaheuristic, to the multi-objective setting by maintaining an external repository of non-dominated solutions and using a hypercube-based adaptive grid to select a global-best guide for each particle from that repository, rather than the single global best a standard PSO would use [7]. Multi-objective PSO (MOPSO) variants of this kind turn out to be especially popular in the economic-emission dispatch literature discussed in a later section, in part because particle swarm's real-valued, gradient-free update rule maps naturally onto continuous generator-output decision variables in a way that binary-encoded genetic operators do not as cleanly.

3. Evolutionary Algorithms for Power System Optimization

Moving from general-purpose MOEA design to power-system-specific adaptation is not a trivial step, and the early literature on applying these ideas to grid structure optimization is explicit that naively bolting an off-the-shelf MOEA onto a power-flow model runs into problems the generic algorithm was never designed to handle: nonlinear AC power-flow equality constraints, discrete decisions (transformer taps, switch states, unit commitment status) mixed with continuous ones (generator output, voltage setpoints), and objective functions that are expensive to evaluate because each candidate solution requires a full power-flow or optimal-power-flow solve just to check feasibility [2]. The practical response across the literature has been less about inventing new MOEA paradigms from scratch and more about adapting the constraint-handling, encoding, and local-search components of NSGA-II-, MOEA/D-, and MOPSO-style algorithms to these grid-specific peculiarities.

A recent and instructive example of this adaptation is Lv, Li, Zhao, and Lei's multi-stage constraint-handling method built on top of NSGA-II for resilient microgrid energy management, which the authors term NSGA-II-MC [8]. Resilience-oriented microgrid dispatch is heavily constrained — load-balance equalities, storage state-of-charge dynamics, ramp-rate limits, islanding feasibility conditions — and the authors report that a

large share of randomly generated candidate solutions in this problem class are infeasible, which starves a standard NSGA-II run of useful genetic material because so much of the population gets discarded or heavily penalized before it can contribute to the search. Their multi-stage constraint-handling procedure instead partitions constraint satisfaction into successive stages during the search rather than applying a single blunt penalty term, and the reported result is substantial: the proposed NSGA-II-MC method achieves a 49.7% improvement in the hypervolume metric — a standard measure of how much of the objective space a Pareto-front approximation dominates, capturing both convergence and spread simultaneously — over classical NSGA-II specifically on the large-scale resilient-microgrid problem instances tested, with the authors reporting the method also outperformed nine other established constrained multi-objective algorithms across their test scenarios. Figure 1 visualizes this result as a relative hypervolume index, with classical NSGA-II normalized to a baseline of 100.

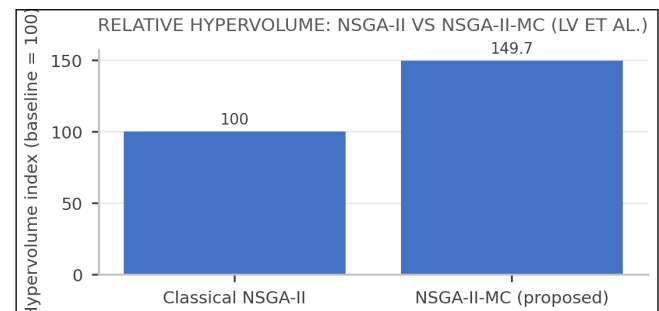


Figure 1: Relative hypervolume index for classical NSGA-II versus Lv et al.'s multi-stage constraint-handling variant (NSGA-II-MC) on large-scale resilient microgrid energy management problems, with classical NSGA-II normalized to a baseline of 100 -- the reported 49.7% hypervolume improvement illustrates how much of the gain attributed to a named MOEA in this literature actually comes from problem-specific constraint-handling engineering rather than the base search mechanism [8].

This finding is worth sitting with, because it illustrates a point that recurs throughout the applied literature: the headline algorithm name (NSGA-II, MOEA/D, MOPSO) explains less of the reported performance than the problem-specific engineering wrapped around it — constraint-handling strategy, encoding scheme, local repair operators, hybridization with problem-specific heuristics. A generic NSGA-II implementation applied naively to a constrained microgrid dispatch problem is a meaningfully weaker algorithm than a constraint-aware variant carrying the same name, and readers comparing reported numbers across papers should keep that

distinction in view rather than treating "NSGA-II" as a single fixed algorithm with a single fixed performance level.

The reference-point machinery in NSGA-III becomes directly relevant once a microgrid or smart-grid dispatch formulation grows past the classical two- or three-objective cost/emission/loss trade-off that dominates the older literature [4]. Modern microgrid energy management formulations increasingly add explicit objectives for renewable curtailment, storage degradation cost, voltage-deviation penalties, and resilience or reliability indices simultaneously, pushing objective counts into the four-to-eight range where dominance-based selection without a structured diversity mechanism tends to lose spread across the front. Decomposition-based approaches inheriting MOEA/D's weight-vector machinery face the same many-objective pressure from a different angle — more objectives require more weight vectors to cover the space adequately, which increases both population size requirements and per-generation computational cost — but the decomposition framing has an advantage specific to grid operations: a system operator with an explicit preference ordering over objectives (say, hard reliability constraints, softer cost preference) can bias the weight-vector distribution toward the region of the front that actually matters operationally, rather than searching for a uniformly-spread front and hoping the operator's preferred region happens to be well represented.

4. Multi-Objective Approaches to Microgrid and Smart Grid Energy Management

Microgrid energy management is where the multi-objective evolutionary literature has produced its densest concentration of applied studies, for a fairly direct reason: a microgrid's energy management system already has to coordinate multiple generation sources, storage, and load simultaneously and continuously, which makes it a natural home for a Pareto-search formulation rather than an occasional planning exercise.

Karimi and Jadid's lexicographic multi-objective approach to multi-microgrid energy management frames the coordination problem across several interconnected microgrids as a hierarchy of objectives solved in a prioritized sequence — operating cost first, then a secondary objective such as emissions or power exchange minimization, each solved subject to not

degrading the previous objective's optimum beyond a specified tolerance [9]. Lexicographic ordering is a comparatively conservative way to handle multiple objectives relative to full Pareto-front generation, because it commits to a strict priority ranking rather than exposing the whole trade-off surface, but the authors argue this maps naturally onto how multi-microgrid coordination actually gets decided in practice, where operating cost genuinely does take precedence over secondary concerns for most operators most of the time.

Table 1: Representative multi-objective evolutionary methods applied to smart grid and microgrid energy management problems, with the problem addressed and the reported effect each cited source gives. [8,15,5,4,18,10].

Method	Source	Problem Addressed	Reported Effect
NSGA-II with multi-stage constraint handling (NSGA-II-MC)	Lv et al. [8]	Resilient microgrid energy management (large-scale)	49.7% higher hypervolume than classical NSGA-II; outperformed nine other constrained MOEAs tested
Elitist multi-objective PSO (NSPSO)	Alshammari et al. [15]	Dynamic economic emission dispatch with wind (10-unit system)	Cost 9.9334e4 vs PSO's 9.9555e4 USD/h (~0.2% lower); emission 1.1158e4 vs 1.1233e4 ton/h (~0.7% lower)
MOEA/D (decomposition-based)	Zhang and Li [5]	General continuous multi-objective benchmark suite	Matched or outperformed NSGA-II and MOGLS on the majority of tested continuous instances
NSGA-III (reference-point based)	Deb and Jain [4]	Many-objective box-constrained benchmark problems	Maintains well-spread Pareto-front approximations as objective count grows past three or four
Forced-initialization differential evolution	Shaheen et al. [18]	Multi-objective optimal power flow (standard IEEE test systems)	Improved convergence speed and Pareto-front quality relative to randomly-initialized DE
Multi-objective multiverse optimization (MVO)	Lagouir et al. [10]	DC microgrid energy management (cost vs. power quality/loss)	Well-distributed Pareto front competitive with established evolutionary alternatives

A larger cluster of recent work targets DC and AC microgrid energy management directly with population-based Pareto-search metaheuristics beyond the classical NSGA family. Lagouir, Badri, and Sayouti applied multi-objective multiverse optimization — a physics-inspired metaheuristic built around an analogy to white-hole/black-hole/wormhole cosmological exchange mechanisms — to DC microgrid energy

management, formulating the problem to jointly minimize operating cost and some measure of power quality or loss, and reporting that their MVO-based approach produces a well-distributed Pareto front competitive with established evolutionary alternatives on their test microgrid [10]. Aeggegn, Nyakoe, and Wekesa extended a similar multi-objective multiverse framework to multi-microgrid energy management explicitly under uncertainty, addressing the reality that renewable generation and load forecasts in a real multi-microgrid deployment are never known with certainty at dispatch time, and their framework incorporates that uncertainty directly into the optimization rather than treating it as a post-hoc sensitivity check [11]. Jani, Karimi, and Jadid pushed the temporal dimension further with a multi-objective two-stage optimization framework for multi-microgrid systems that explicitly accounts for energy storage dynamics across multiple time scales — a longer-horizon scheduling stage coordinated with a shorter-horizon real-time dispatch stage — arguing that treating storage scheduling and real-time dispatch as a single flat optimization horizon, as much of the earlier literature implicitly does, misses interactions between how a battery is scheduled hours ahead and how it actually needs to respond to short-term fluctuations [12].

Sun, Yun, and Chen's robust multi-objective optimization of a multi-energy microgrid incorporating waste treatment is a useful data point for how far the "microgrid" framing has stretched beyond pure electrical dispatch: their formulation jointly optimizes electrical, thermal, and waste-processing objectives within a single multi-energy microgrid model, explicitly building robustness against parameter uncertainty into the multi-objective formulation itself rather than treating robustness as a separate downstream analysis [13]. This kind of multi-energy, multi-service microgrid formulation is, in our reading, where the field is heading — the electrical-only cost/emission/loss trade-off that motivated the earliest applications of NSGA-II to power systems is increasingly just one slice of a broader multi-energy, multi-service optimization problem, and the evolutionary algorithms discussed in this article are being asked to scale accordingly. Kadar's early structural framing of smart grid optimization as inherently multi-objective anticipated exactly this trajectory, treating the grid's evolving structure itself, not just its

dispatch schedule, as something to be optimized across competing criteria [2]. Table 1 summarizes representative reported results from several of the algorithms discussed across this article's applied sections, to make the range of what "multi-objective evolutionary optimization for smart grid energy management" has actually delivered numerically somewhat more concrete than a purely qualitative survey would.

5. Economic-Emission Dispatch and Optimal Power Flow

If microgrid energy management is where the newest applied work concentrates, economic-emission dispatch (EED) and optimal power flow (OPF) are where multi-objective evolutionary optimization has the longest and most methodologically mature track record in the power-systems literature, largely because both problems have well-established single-objective formulations (economic dispatch, optimal power flow) that the multi-objective versions extend in a fairly natural way by adding an emissions or a voltage-stability objective alongside the classical cost objective.

Dynamic economic emission dispatch, scheduling generator output across a time horizon rather than a single snapshot to account for ramp-rate limits and time-varying demand, has attracted particular attention from the particle-swarm side of the MOEA family. Mason, Duggan, and Howley's comparative study of several PSO variants applied to the dynamic economic emission dispatch problem provides a useful methodological benchmark: rather than proposing one new algorithm, the paper systematically compares multiple established PSO variants under a common dynamic EED formulation, exactly the kind of controlled comparison the wider literature, with its tendency for every paper to validate its own preferred variant, needs more of [14]. Alshammari, Ramli, and Mehedi's elitist multi-objective PSO (NSPSO) applied to sustainable dynamic economic emission dispatch integrating wind farms reports concrete, checkable numbers: on their ten-unit test system, NSPSO achieves a minimum cost of 9.9334×10 USD/h against classical PSO's 9.9555×10 USD/h, and a minimum emission of 1.1158×10 ton/h against PSO's 1.1233×10 ton/h, modest but consistent gains on both objectives at once, roughly 0.2% on cost and 0.7% on emissions, with larger absolute figures reported separately on their forty-unit wind-integrated

system [15]. These are not dramatic numbers, and the authors do not present them as such; the value of the comparison is that NSPSO finds solutions that Pareto-dominate the classical PSO baseline on a like-for-like test system, which is precisely what a multi-objective method needs to substantiate.

Xiong, Shuai, and Hu's application of an improved bare-bone multi-objective particle swarm optimizer to combined heat and power economic emission dispatch extends this line of work to the CHP setting, where the heat-power feasible operating region of combined-cycle units is itself non-convex and adds a substantial layer of constraint-handling difficulty [16]. Bare-bone PSO variants dispense with the explicit velocity update of standard PSO in favor of sampling each particle's next position from a distribution centered on its personal-best and global-best positions, which reduces the number of parameters that need tuning, a practical concern when extensive tuning against a target problem is not available.

On the optimal power flow side, differential evolution has emerged as a particularly persistent choice, in part because DE's mutation operator, which perturbs each candidate by a scaled difference between two other population members, adapts its step size implicitly to the current spread of the population without an externally tuned schedule, a useful property on OPF's nonlinear, non-convex feasible region. Varadarajan and Swarup's early application of differential evolution to multi-objective OPF, jointly minimizing fuel cost and a measure of voltage stability or emissions, established DE as methodologically viable for this problem class and provided one of the first systematic comparisons against classical multi-objective methods on standard IEEE test systems [17]. Shaheen, El-Sehiemy, and Farrag's forced-initialization differential evolution algorithm addresses a specific weakness of naive DE initialization, random initial populations disproportionately infeasible or clustered in unhelpful regions of a highly constrained space, by structuring the initial population to more deliberately span the feasible region, which the authors report improves convergence speed and final Pareto-front quality relative to randomly-initialized DE [18]. Lv, Xiong, Fu, Wu, Xu, and Chen's clustering-based multi-objective differential evolution for OPF under stochastic solar power extends this line of work to explicitly handle renewable generation uncertainty

within the OPF formulation itself, using clustering to represent plausible solar-output scenarios rather than optimizing against a single deterministic forecast, a meaningfully more realistic formulation for a grid with substantial photovoltaic penetration [19].

Taken together, this body of EED and OPF work supports a fairly specific and, we think, defensible claim: multi-objective evolutionary methods reliably find Pareto-dominant or near-Pareto-dominant solutions relative to their single-objective or less-sophisticated multi-objective predecessors on standard test systems, with reported improvements that are real but frequently modest in percentage terms on any single objective, and where the genuine value delivered is the shape of the recovered trade-off surface — the menu of cost-emission-loss combinations an operator can choose from — rather than any single headline number.

6. Renewable Integration, Storage Sizing, and Demand-Side Management

The most recent wave of applied work extends multi-objective evolutionary optimization from dispatch — deciding how to operate a fixed set of assets — to planning and demand-side problems: how large should a battery be, how should renewable capacity be sized, and how should flexible loads and EV charging be scheduled, all under multiple competing objectives simultaneously.

On the sizing side, Ibrahim, Jamian, and Rasid's optimal multi-objective sizing of renewable energy sources and battery storage for a multi-microgrid system explicitly incorporates diverse load patterns across the constituent microgrids into the sizing decision, rather than assuming a single representative load profile applies uniformly, a more realistic starting assumption given how differently individual microgrids within a larger interconnected system typically behave [20]. Premadasa, Silva, Chandima, and Karunadasa's multi-objective sizing model for an off-grid hybrid energy microgrid jointly optimizes asset sizing together with the dispatch strategy of a diesel backup generator, treating sizing and operational dispatch as a coupled rather than sequential decision, an important distinction, because a microgrid sized under an assumption of one dispatch strategy can end up meaningfully oversized or undersized once the actual optimal dispatch strategy is worked out separately [21]. Ntube and Li's stochastic multi-objective sizing of a residential battery energy storage system brings this

same joint-optimization logic down to the single-household scale, incorporating stochastic variation in household load into the sizing decision rather than sizing against a single deterministic demand trace [22]. Tito, Lie, and Anderson's earlier work on optimal sizing of a wind-photovoltaic-battery hybrid system considering socio-demographic factors is a reminder that "optimal" sizing here is not purely a technical or economic question: their formulation folds demographic and social factors specific to the deployment context into the sizing objective alongside cost and reliability, which matters for hybrid systems deployed in off-grid and rural-electrification settings where such variation across candidate sites is large [23].

On the demand side, Moon and Lee's multi-residential demand response scheduling framework addresses a scheduling problem that becomes genuinely multi-objective once appliances of different classes — must-run, interruptible, deferrable — are scheduled jointly across many households simultaneously, balancing aggregate cost or peak-demand objectives against individual household comfort or scheduling-flexibility constraints that pull against pure cost minimization [24]. Chen, Chen, He, Liu, Gao, and Zhang's multi-objective residential load scheduling approach for demand response extends this same basic framing with an explicit comfort-versus-cost trade-off formulation, evolving a Pareto front of scheduling solutions rather than committing to a single fixed weighting between the two, on the reasonable premise that different households, or the same household on different days, genuinely place different relative weight on cost savings versus scheduling inconvenience [25].

Electric vehicle charging management sits at the intersection of demand-side scheduling and the broader smart-grid optimization literature, and it has increasingly been approached with methods that combine evolutionary or learning-based multi-objective optimization with priority-aware scheduling logic. Çakıl and Aksoy's reinforcement-learning-based multi-objective smart energy management framework for EV charging stations with priority scheduling is representative of where this sub-area is heading: rather than a pure evolutionary search run once per scheduling horizon, the framework combines a multi-objective formulation, balancing charging cost, grid impact, and user priority or waiting time, with a

reinforcement-learning component that can adapt scheduling decisions online as vehicles arrive and depart, a genuinely different computational paradigm from the population-based evolutionary search that dominates the rest of this article but one that is being explicitly integrated with multi-objective optimization concepts rather than replacing them outright [26]. We read this as an early signal that the field's next methodological wave will likely be hybrid — evolutionary Pareto search combined with learning-based online adaptation — rather than a wholesale replacement of one paradigm by the other, though the evidence base for that combination specifically is still thin relative to the pure-evolutionary literature surveyed elsewhere in this article.

7. Open Challenges

Several limitations recur across the literature synthesized here clearly enough to be worth naming directly rather than leaving implicit. First, scalability to many objectives remains only partially solved for the grid-specific problem formulations that matter operationally. NSGA-III's reference-point mechanism demonstrably helps maintain Pareto-front diversity as objective count grows [4], and MOEA/D's decomposition approach sidesteps the dominance-comparison problem from a different angle [5], but most of the applied microgrid and dispatch studies reviewed here still work with two, three, or occasionally four objectives, even as real deployments increasingly want cost, emissions, reliability, voltage quality, storage degradation, and curtailment all optimized jointly. The genuinely many-objective (five-plus) smart-grid formulation, evaluated with the same rigor as the two- and three-objective literature, is comparatively rare.

Second, the gap between synthetic and realistic evaluation that we flagged in the introduction deserves restating here with more specificity. IEEE test systems (30-bus, 118-bus, and similar) and synthetic microgrid topologies dominate the OPF and dispatch literature [17,18,16], and while these are legitimate, reproducible benchmarks that allow fair algorithm comparison across independent papers, they are not the same as a deployed feeder with real, noisy measurement data, real communication latency between control points, and real operator constraints that never made it into the textbook formulation. The uncertainty-aware formulations that

have started appearing, incorporating stochastic renewable output or load forecasts directly into the optimization [11,19,22], are a meaningful step toward realism, but uncertainty in forecast accuracy is only one of several gaps between benchmark and deployment; measurement noise, communication delay, and asset degradation over the operational lifetime of the system are comparatively under-addressed in the multi-objective evolutionary literature specifically, even where they are well studied elsewhere in the power-systems field.

Third, constraint-handling quality varies enormously across papers claiming to solve "the same" multi-objective dispatch or sizing problem, and this variation is, in our reading, a larger driver of reported performance differences than the choice of underlying MOEA paradigm. Lv et al.'s multi-stage constraint-handling result, a 49.7% hypervolume improvement attributable specifically to better constraint management layered onto an otherwise standard NSGA-II, rather than to a fundamentally different search mechanism, is the clearest single piece of evidence for this in the literature surveyed here [8], and it is a caution against reading "algorithm X beat algorithm Y" headlines in this literature without checking whether the comparison controlled for constraint-handling sophistication.

Fourth, computational cost is a persistent, somewhat under-reported practical constraint. Every candidate solution evaluated by a population-based MOEA applied to OPF or unit-commitment-style dispatch typically requires a full power-flow solve or an equivalent feasibility check, and population sizes in the hundreds evaluated over hundreds of generations translate into tens of thousands of such solves per optimization run. For offline planning problems, sizing a microgrid's storage capacity, say, this cost is usually acceptable; for anything approaching real-time dispatch it is a genuine obstacle, one that the reinforcement-learning hybridization Çakıl and Aksoy's work gestures toward is a plausible response to, though the broader literature has not yet converged on a standard answer [26].

We do not think any of these four gaps undermine the basic case for multi-objective evolutionary optimization as the right methodological family for smart grid energy management's inherently multi-criteria structure — the consistency with which independent groups, working on

microgrid dispatch, economic-emission dispatch, OPF, storage sizing, and demand response, have all converged on Pareto-search evolutionary methods as their tool of choice is itself evidence that the fit between problem and method is sound. But the honest state of the evidence is that this is a maturing applied methodology, not a solved one, and claims of production-grade readiness for any specific algorithm in this literature should be read against the benchmark-heavy, still-thin-on-deployment evidence base described above.

8. Conclusion

The literature reviewed here supports a reasonably specific set of claims about multi-objective evolutionary optimization for smart grid energy management. The foundational algorithms — NSGA-II and its many-objective successor NSGA-III, decomposition-based MOEA/D, strength-Pareto and multi-objective particle swarm approaches — were developed as general-purpose Pareto-search tools and have proven adaptable, with problem-specific constraint-handling and encoding work, to the particular structure of power-system optimization problems [3,4,5,6,7]. Applied to microgrid and multi-microgrid energy management, these methods have been extended to handle multi-energy coupling, forecast uncertainty, and multi-timescale storage coordination [9,10,11,12,13]. Applied to economic-emission dispatch and optimal power flow, they have produced a long track record of reproducible, if often modest, improvements over classical single-objective and less sophisticated multi-objective baselines on standard test systems [14,15,16,17,18,19]. Extended to storage sizing, renewable capacity planning, and demand-side scheduling, they increasingly appear jointly with stochastic and learning-based components rather than as pure evolutionary search in isolation [20,21,22,23,24,25,26].

What ties this body of work together, and what we think is its strongest single contribution to smart grid engineering practice, is the shift away from collapsing cost, emissions, reliability, and the rest into a single arbitrarily-weighted number and toward exposing the actual trade-off surface a decision-maker is operating on. A smart grid structurally invites multi-objective thinking, because its stakeholders — operators, regulators, consumers, and increasingly the climate

itself — do not agree on a single ranking of what matters [1,2]. Multi-objective evolutionary optimization is not a magic solution to that disagreement, and the open problems catalogued in the previous section — many-objective scalability, the synthetic-to-deployed evaluation gap, constraint-handling quality as a confound in algorithm comparisons, and computational cost under real-time pressure — are real and, in several cases, not close to resolved. But the consistent convergence of independent research groups on Pareto-search evolutionary methods as the right tool for this family of problems, across dispatch, sizing, and scheduling sub-domains that developed largely independently of one another, is itself meaningful evidence that this is a durable methodological fit rather than a passing algorithmic fashion, and one that deserves continued development grounded in increasingly realistic evaluation rather than further validation on synthetic benchmarks alone.

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Conflict of Interest

The authors declare that they have no known competing financial or personal interests that could have influenced this work.

Data Availability Statement

This article is a literature synthesis and did not generate new experimental data; all numerical results discussed are drawn from, and attributed to, the cited sources, which readers should consult for underlying data and code availability.

Ethical Approval

Not applicable. This review involved no human participants, animal subjects, or primary data collection.