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Optimization of Hybrid Renewable Energy Systems: Classical Optimization Methods, Artificial Intelligence, Recent Trend, and Software Tools

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Abstract: This article synthesizes the state of the art in the optimization of Hybrid Renewable Energy Systems (HRES), emphasizing that robust HRES planning is inherently an integrated sizing-and-dispatch problem constrained by techno-economic, environmental, and reliability requirements. The review first consolidates classical optimization methods, highlighting the continued relevance of deterministic programming (LP/MILP/MINLP) for transparent and reproducible co-optimization of capacity investment and operational dispatch, alongside analytical, graphical, iterative, and probabilistic approaches for feasibility screening and baseline benchmarking. It then evaluates artificial intelligence–based optimization techniques, including evolutionary computation, swarm intelligence, and multi-objective evolutionary frameworks, noting their effectiveness in nonconvex, mixed-variable, and simulation-driven sizing problems while underscoring the need for rigorous constraint handling, statistical validation, and transparent reporting of computational budgets. The article further examines hybrid optimization strategies that integrate global search with exact dispatch solvers, surrogate-assisted learning, decomposition schemes, and control–co-design paradigms, identifying these as mature approaches that enhance feasibility, scalability, and operational realism. Recent trends in newly proposed AI optimizers are critically discussed, with emphasis on reproducibility, sensitivity analysis, and fair benchmarking against strong baselines. Finally, the article outlines the role of software tools in enabling practical HRES optimization, spanning packaged techno-economic platforms, solver-based modeling environments, and co-simulation workflows for network-constrained planning. Overall, the findings indicate a clear progression toward multi-objective, uncertainty-aware, degradation-informed formulations implemented through integrated toolchains and hybrid solver–AI architectures, with future work warranted on uncertainty quantification, network and resilience constraints, and reproducible evaluation protocols.

Keywords: Hybrid Renewable Energy Systems, Classical optimization methods, Artificial intelligence, Multi-objective optimization.

1.Introduction

Fossil fuel resources remain geographically concentrated in a limited set of jurisdictions, a structural characteristic that confers disproportionate leverage over global energy supply security and price formation [1,2]. By contrast, renewable energy resources are broadly distributed but intrinsically variable, with generation profiles governed by meteorological and seasonal conditions. This asymmetry amplifies systemic vulnerability: geopolitical instability and conflict in fossil-fuel–rich regions can propagate supply shocks, heighten price volatility, and undermine macroeconomic stability [4-6].

Concurrently, escalating climate-risk concerns and decarbonization imperatives have accelerated the global transition toward low-carbon energy systems [7-9]. Within this context, hybrid renewable energy systems (HRES), particularly configurations integrating biomass, hydropower, wind, and solar technologies, have become pivotal enablers of energy sustainability by improving supply adequacy, flexibility, and resilience through portfolio diversification. Recent assessments report rapid expansion in renewable deployment, with 2023 figures indicating installed capacities exceeding approximately 405.5 GW (solar PV), 150.3 GW (bioenergy), 123.1 GW (wind), and ~24.0 GW (hydropower). In parallel, grid-scale energy storage remains dominated by pumped hydro storage (PHS), which accounts for roughly 97% of global storage capacity in many widely cited assessments, underscoring its continuing centrality to large-scale flexibility provision [10-13].

The optimization of Hybrid Renewable Energy Systems (HRES) has historically been grounded in classical optimization methods, which remain essential for transparent model formulation and benchmarking. Deterministic numerical approaches, such as linear programming (LP), mixed-integer linear programming (MILP), and mixed-integer nonlinear programming (MINLP), enable rigorous co-optimization of component sizing and operational dispatch under explicit technical constraints (e.g., power balance, state-of-charge dynamics, converter limits) and reliability indices (e.g., LPSP, EENS) [14-18]. Complementary classical strategies, including analytical and graphical constructions as well as iterative search, have been widely used for preliminary design and feasibility screening, particularly where simplified energy-balance representations and autonomy constraints provide engineering insight. Although these methods can deliver reproducible and, in some cases, provably optimal solutions, their performance may degrade when confronted with strong nonconvexities, discontinuities, high-dimensional design spaces, and high-resolution time-series operation, conditions that characterize modern HRES planning, especially with degradation-aware storage and hydrogen subsystems [19-22].

To address these complexities, artificial intelligence (AI)–based optimization has become a dominant paradigm in contemporary HRES sizing research, with evolutionary computation and swarm intelligence methods (e.g., GA/DE/ES, PSO variants) widely adopted for their ability to search nonconvex spaces and accommodate mixed discrete, continuous variables [23-25]. Multi-objective AI frameworks (e.g., NSGA-II/III, MOEA/D) are particularly valuable because HRES planning is inherently multi-criteria, requiring explicit trade-off analysis across cost, emissions, and reliability. More recently, learning-enabled strategies, such as surrogate-assisted optimization (Gaussian processes, neural networks, gradient boosting) and reinforcement learning, have been introduced to reduce computational cost and to better capture sequential decision-making under uncertainty [23-26]. The recent trend is a clear shift toward hybrid and uncertainty-aware formulations: coupling global AI search with exact dispatch solvers (MILP/MINLP), embedding stochastic/robust optimization to internalize resource and demand uncertainty, and incorporating high-fidelity component models (battery aging, electrolyzer part-load behavior) via surrogate modeling or decomposition [27,28].

In parallel, software tools have become central enablers of HRES optimization by providing integrated environments for simulation, dispatch, economic assessment, and constraint verification. Packaged techno-economic platforms support rapid feasibility analysis and scenario comparison, while optimization-centric planning tools and algebraic modeling frameworks (e.g., Python/Julia-based modeling with commercial or open solvers) enable fully customized objective functions and constraint sets suitable for publication-grade formulations [29,30]. Where electrical network realism is required, distribution-system simulators and co-simulation workflows are commonly coupled to external optimizers to enforce voltage and thermal limits, quantify losses, and ensure implementable designs at feeder level. Current best practice increasingly favors toolchains rather than single tools: a structured workflow in which data pipelines, time-series simulation, solver-based dispatch, and decision analysis are integrated to produce robust sizing recommendations that are technically feasible, economically defensible, and aligned with resilience and decarbonization targets [31-33].

Numerous studies have investigated the optimization of hybrid renewable energy systems (HRES), reflecting their growing importance for achieving cost-effective, reliable, and low-carbon energy supply in both grid-connected and off-grid contexts. Study [34] presents an optimized HRES sizing framework based on the Lotus Effect Optimization Algorithm (LEOA), a recently developed nature-inspired metaheuristic reported to exhibit strong capability in addressing multi-objective, nonlinear optimization problems. The proposed methodology targets the simultaneous minimization of the levelized cost of energy (LCOE), enhancement of system reliability, and mitigation of environmental impacts. Validation is performed through a real-world case study in Qassim, Saudi Arabia. The reported results indicate that LEOA provides superior performance relative to benchmark algorithms, including PSO, GA, simulated annealing (SA), and MOPSO, demonstrated through improved convergence behavior, higher solution accuracy, and reduced computational effort. Specifically, the optimized design achieves an LCOE of USD 0.275/kWh, attains an 85% renewable energy penetration level, and delivers an emissions reduction of approximately 40%. Collectively, these outcomes suggest that LEOA constitutes a viable optimization engine for deriving economically attractive, reliable, and environmentally sustainable HRES designs, with potential applicability in future smart-grid planning and operation.

In [35], the proposed HRES sizing model is demonstrated through a case study in Dunhuang City, China, and its effectiveness is assessed via comparative evaluation against alternative optimization techniques. The results indicate that the Modified Al-Biruni Earth Radius (MBER) algorithm yields the most cost-effective and dependable configuration, reporting a total system cost of approximately 4.23 million (in the stated currency). Relative to competing approaches, MBER is reported to achieve favorable techno-economic and reliability performance, including an overall cost on the order of 4.1 million USD, a low loss of power supply probability (LPSP), and an annual unmet-load duration of approximately 356 h. In the broader analysis, a representative baseline solution is also noted with an overall cost of 5.26 million (in the stated currency) at 0.5% LPSP, underscoring the direct influence of reliability targets on total cost and system dependability.

Study [36] investigated the techno-economic optimization of a grid-connected hybrid renewable energy system (HRES) for the Moroccan context, employing a suite of metaheuristic optimizers, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimization (GWO), and Artificial Bee Colony (ABC), as well as hybrid variants that couple these algorithms with a Modified Marquardt Gradient Descent (MGD) scheme to enhance convergence and solution refinement. The principal design criterion is the minimization of the levelized cost of electricity (LCOE) while maintaining satisfactory energy adequacy and renewable contribution. The optimized configurations are reported to deliver annual electricity generation exceeding 5000 kWh for system capacities up to 20 kWp, which supports a daily demand of 17.12 kWh (approximately 6248.8 kWh annually), while ensuring a renewable energy fraction (REF) of no less than 80%.

This article contributes a unified synthesis of Hybrid Renewable Energy System (HRES) optimization by framing the problem explicitly as an integrated sizing-and-dispatch task governed by techno-economic objectives (e.g., NPC/LCOE), environmental targets, and reliability requirements (e.g., LPSP/EENS), and by providing a structured taxonomy that comparatively organizes classical methods (numerical, analytical, graphical, iterative, probabilistic), artificial intelligence–based techniques (evolutionary, swarm, surrogate-assisted, and reinforcement learning), and hybrid optimization frameworks. It further advances the discussion by critically positioning hybrid architectures, particularly global-search sizing coupled with exact MILP/MINLP dispatch, as well as surrogate- and decomposition-assisted variants, as a best-practice direction for achieving feasible, scalable, and operationally realistic designs. In addition, it evaluates recent trends in newly proposed AI optimizers and articulates methodological standards required for credible adoption, including standardized benchmarking, parameter sensitivity analysis, operator ablation, and transparent reporting of computational budgets. Finally, the article offers practical guidance on software tool usage by distinguishing packaged techno-economic platforms, solver-based modeling environments, and network-constrained co-simulation workflows, and it outlines a forward-looking research agenda emphasizing uncertainty quantification, degradation-aware modeling, resilience and network constraints, and reproducible evaluation protocols to strengthen the rigor and real-world impact of future HRES optimization studies.

2. Classical Optimization Methods

The optimal sizing of hybrid renewable energy systems (HRES) constitutes a critical planning problem that directly influences system techno-economic viability, operational reliability, and environmental performance [36-38]. An HRES typically integrates multiple energy sources, such as photovoltaic (PV) arrays, wind turbines, energy storage systems, and auxiliary conventional generators, to supply electrical demand under variable resource availability and load conditions. In this context, optimal sizing refers to the systematic determination of the installed capacities of system components such that predefined objectives, while satisfying technical and operational constraints [39-42].

Before the widespread adoption of modern metaheuristic, artificial intelligence, and hybrid optimization frameworks, a broad class of classical optimization methods formed the foundation of HRES sizing studies [43-45]. These methods, which include numerical, graphical, iterative, probabilistic, and analytical approaches, are characterized by their deterministic formulations, mathematical transparency, and strong physical interpretability [46-49]. Figure 1 demonstrates classical optimization methods.

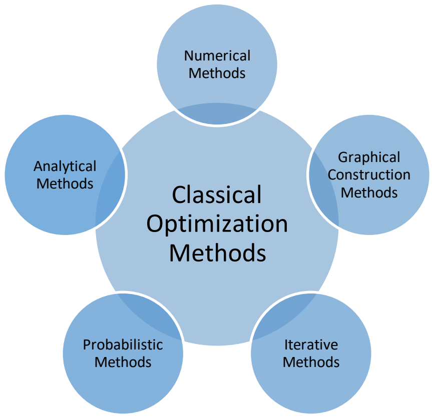

Figure 1. Classical Optimization Methods.

Classical optimization methods have been extensively applied in off-grid, grid-connected, and remote microgrid HRES planning, often relying on simplified yet insightful representations of energy balance, storage dynamics, and reliability indices. Each method category offers distinct advantages and limitations in terms of modeling accuracy, scalability, treatment of uncertainty, and computational burden. Table 1 illustrates classical optimization methods for optimal sizing of hybrid renewable energy systems (HRES).

Table 1. Classical optimization methods for optimal sizing of HRES [50-61]

Method Class	Core Principle	Typical Sizing Variables	Objective Functions	Constraints / Performance Metrics	Strengths
Numerical Methods	Formulate sizing as deterministic optimization and solve using numerical solvers (LP, MILP, MINLP).	PV, wind, battery (kWh/kW), inverter, diesel generator, electrolyzer, hydrogen tank capacities.	NPC, LCOE, TAC, fuel cost, emissions.	Power balance, SOC limits, reliability (LPSP, EENS), operational limits.	High accuracy; reproducible; global optimum for convex models.
Graphical Construction Methods	Use visual trade-off curves and feasibility regions to determine suitable system sizes.	Typically, two main variables (e.g., PV vs battery, PV vs wind).	Cost–reliability trade-off, minimum capacity for autonomy.	Autonomy hours, energy sufficiency, renewable fraction.	Simple, intuitive, useful for preliminary design.

Iterative Methods	Enumerate candidate sizes and simulate performance iteratively until objectives are met.	Discrete PV, wind, battery, diesel sizes.	NPC or LCOE minimization with reliability satisfaction.	LPSP, unmet load, SOC feasibility.	Flexible; handles nonlinear component models.
Probabilistic Methods	Incorporate uncertainty using probability distributions and reliability theory.	Same as numerical methods but under uncertainty.	Expected cost minimization under reliability probability constraints.	LOLP, LOLE, EENS, confidence levels.	Realistic treatment of uncertainty; risk-aware sizing.
Analytical Methods	Closed-form or simplified equations based on energy balance and autonomy.	PV, wind, battery sizes using average values.	Minimum capacity for energy sufficiency.	Energy neutrality, autonomy duration.	Very fast; useful for first-order estimates.

A. Numerical Optimization Methods

Numerical optimization methods constitute one of the most widely adopted classical approaches for optimal HRES sizing. In these methods, the sizing problem is formulated as a deterministic mathematical optimization model, typically expressed as linear programming (LP), mixed-integer linear programming (MILP), or mixed-integer nonlinear programming (MINLP). Decision variables represent the installed capacities of system components, while objective functions commonly aim to minimize net present cost (NPC), levelized cost of energy (LCOE), or total annualized cost (TAC). Numerical methods enable rigorous handling of operational constraints such as power balance, battery state-of-charge dynamics, component capacity limits, and reliability indices (e.g., LPSP or EENS). Their main strength lies in their reproducibility and, for convex formulations, their ability to guarantee global optimality [62-65]. However, their applicability may be constrained by the need for linearization or simplification of inherently nonlinear component models, and computational complexity can increase significantly with long-term, high-resolution simulations.

B. Graphical Construction Methods

Graphical construction methods rely on visual representations of energy balance, reliability constraints, and cost–capacity trade-offs to determine feasible and near-optimal system sizes. Typical examples include capacity–reliability curves, iso-cost lines, and autonomy-based sizing charts. These methods are particularly common in early-stage HRES feasibility studies and educational contexts. Graphical methods generally focus on a limited number of dominant sizing variables, such as PV capacity versus battery storage or PV–wind capacity combinations. Their main advantage lies in their intuitive nature and ease of interpretation [65-69]. However, due to their limited scalability and low resolution, they are unsuitable for complex multi-component HRES configurations and cannot adequately capture time-coupled operational constraints.

C. Iterative Methods

operation. For each candidate configuration, system performance is evaluated against predefined objectives and constraints, and the optimal solution is selected based on Iterative methods employ systematic enumeration or stepwise adjustment of candidate system sizes combined with chronological simulation of HRES comparative performance. Iterative approaches are highly flexible and capable of incorporating nonlinear and black-box component models, including detailed battery and generator behaviors [70-74].

D. Probabilistic Methods

Probabilistic optimization methods explicitly account for uncertainties in renewable resource availability, load demand, and other stochastic inputs. These methods employ probability distributions, reliability theory, or scenario-based modeling to ensure that the HRES satisfies reliability criteria with a specified confidence level. Probabilistic methods typically minimize expected cost subject to probabilistic reliability constraints such as LOLP, LOLE, or EENS. Their key advantage is their ability to produce risk-aware and more realistic sizing decisions, especially for systems exposed to high variability [75-77]. However, they require extensive data and careful statistical modeling, and their results can be sensitive to distribution assumptions and correlation structures.

E. Analytical Methods

Analytical methods derive closed-form or semi-analytical expressions for HRES sizing based on simplified energy balance equations and storage autonomy considerations. These methods often rely on average or representative values of renewable generation and load demand. Analytical approaches are computationally efficient and provide valuable insight into the fundamental relationships between system components [79-81]. They are particularly useful for first-order feasibility assessment and derivation of design guidelines. However, their reliance on simplifying assumptions limits their accuracy, as they typically neglect temporal variability, extreme events, and detailed operational constraints.

In summary, classical optimization methods continue to play a fundamental role in HRES sizing research and practice. While each method category exhibits inherent limitations, their transparency, physical interpretability, and methodological rigor make them indispensable for preliminary design, comparative analysis, and validation of advanced optimization techniques.

3. Artificial Intelligence–Based Optimization Techniques

The optimal sizing of hybrid renewable energy systems (HRES) has evolved into a highly complex and multidimensional optimization problem due to the increasing penetration of variable renewable energy sources, the integration of advanced storage technologies, and the growing emphasis on techno-economic efficiency, environmental sustainability, and system reliability. Unlike conventional power systems, HRES planning must simultaneously address nonlinear component characteristics, time-coupled operational dynamics, stochastic renewable resources, and conflicting design objectives such as cost minimization, emission reduction, and reliability maximization [82,83].

Classical optimization techniques, while foundational, often encounter limitations when dealing with large-scale, nonconvex, and uncertainty-driven HRES sizing problems. In response, artificial intelligence (AI)–based optimization techniques have gained significant traction in recent years. These techniques leverage learning, adaptation, and population-based search mechanisms to efficiently explore complex solution spaces without requiring strict mathematical assumptions such as convexity or linearity [84,85]. As a result, AI-based methods have become particularly attractive for HRES applications involving high-resolution time-series simulations, nonlinear storage degradation models, hydrogen subsystems, and multi-objective planning requirements. Figure 2 shows artificial intelligence–based optimization techniques.

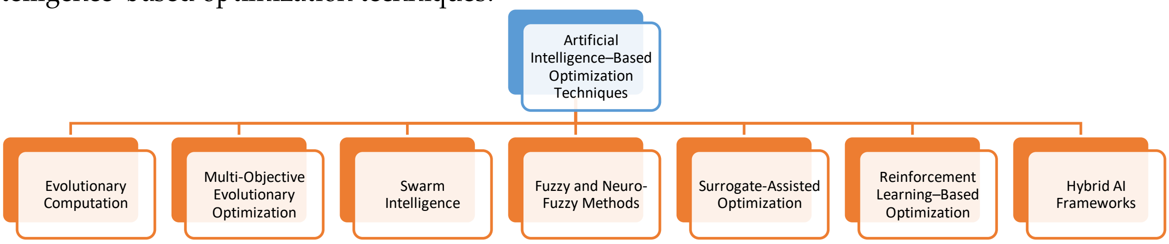

Figure 2. Artificial Intelligence–Based Optimization Techniques.

AI-based optimization approaches encompass a broad spectrum of techniques, including evolutionary computation, swarm intelligence, fuzzy and neuro-fuzzy systems, surrogate-assisted learning, deep learning–guided optimization, reinforcement learning, and hybrid AI frameworks. Each category offers distinct advantages in terms of global search capability, uncertainty handling, computational efficiency, and adaptability. Table 2 provides a structured classification of these methods, highlighting their applications and strengths.

Table 2. Artificial Intelligence–Based Optimization Techniques Applied to Optimal Sizing of HRES [82-88].

AI-Based Optimization Class	Representative Techniques	Application in HRES Sizing	Typical Decision Variables	Objective Functions	Strengths
Evolutionary Computation	GA, DE, ES, CMA-ES	Population-based global search over capacity combinations coupled with time-series simulation.	PV, wind, battery energy/power, inverter, diesel generator, electrolyzer, H_2 storage.	NPC, LCOE, TAC, emissions minimization.	Strong global exploration; handles discrete and continuous variables.
Multi-Objective Evolutionary Optimization	NSGA-II, NSGA-III, SPEA2, MOEA/D	Simultaneous optimization of conflicting objectives and generation of Pareto fronts.	Same as evolutionary computation.	Cost–emission–reliability trade-offs.	Explicit trade-off analysis; suitable for planning studies.
Swarm Intelligence	PSO, MOPSO, ACO, ABC	Collective agent-based search for optimal component capacities.	PV, wind, storage, DG capacities.	NPC/LCOE minimization; renewable fraction maximization.	Simple structure; fast convergence.
Fuzzy and Neuro-Fuzzy Methods	Fuzzy logic, ANFIS, fuzzy MCDM	Incorporates linguistic and uncertain preferences in sizing decisions.	Capacity ratios and candidate configurations.	Multi-criteria satisfaction (cost, reliability, emissions).	Handles uncertainty and qualitative criteria.
Surrogate-Assisted Optimization	ANN, GP (Kriging), SVR, XGBoost, Bayesian optimization	Uses ML surrogates to approximate simulation-based performance metrics.	All HRES component capacities.	NPC/LCOE minimization with reduced evaluations.	Major computational speed-up; supports high-fidelity models.
Reinforcement Learning–Based Optimization	DQN, PPO, SAC, DDPG	Learns operational policies; sizing evaluated.	Capacities and control policy parameters.	Long-term cost and reliability optimization.	Adaptive and suitable for uncertainty.
Hybrid AI Frameworks	GA + MILP, PSO + MPC, EA + surrogate	Combines AI global search with exact or predictive dispatch optimization.	Full set of HRES sizing variables.	Multi-objective techno-economic optimization.	High solution quality and robustness.

A. Evolutionary Computation Techniques

Evolutionary computation (EC) techniques, such as Genetic Algorithms (GA), Differential Evolution (DE), and Evolution Strategies (ES), are among the most widely used AI-based methods for optimal HRES sizing. These algorithms emulate biological evolution through selection, crossover, and mutation operators to iteratively improve a population of candidate solutions. In HRES applications, each individual typically represents a vector of system capacities, including PV arrays, wind turbines, battery energy and power ratings, inverters, and auxiliary generators. EC techniques are particularly effective for handling mixed discrete–continuous decision variables and highly nonlinear objective functions.

They are frequently coupled with chronological simulation models to evaluate system performance in terms of cost, reliability indices (e.g., LPSP or EENS), and emissions [89-92]. However, their main drawback lies in high computational demand, especially when long-term, high-resolution simulations are required, and in their sensitivity to algorithm parameter tuning.

B. Multi-Objective Evolutionary Optimization

Multi-objective evolutionary algorithms (MOEAs), such as NSGA-II, NSGA-III, SPEA2, and MOEA/D, extend evolutionary computation to explicitly address conflicting objectives inherent in HRES sizing. Instead of producing a single optimal solution, these algorithms generate a Pareto front that represents trade-offs among objectives such as net present cost, carbon emissions, and reliability. MOEAs are particularly valuable for planning and policy-oriented studies, where decision-makers must balance economic, environmental, and technical criteria. Their ability to visualize trade-offs enhances transparency and supports informed decision-making. Nevertheless, MOEAs typically incur higher computational costs than single-objective approaches, and the quality of the Pareto front depends on diversity preservation and constraint-handling strategies [93-96].

C. Swarm Intelligence Techniques

Swarm intelligence methods, including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC), are inspired by collective behavior observed in natural systems. In HRES sizing, these methods explore the solution space through coordinated movements of agents influenced by individual and collective experience. Swarm intelligence techniques are relatively simple to implement and often exhibit fast convergence in continuous search spaces. They have been extensively applied to off-grid and microgrid HRES sizing problems [97-100]. However, premature convergence and limited constraint-handling capability can compromise solution quality, particularly in problems involving discrete sizing decisions and strict reliability requirements.

D. Fuzzy and Neuro-Fuzzy Approaches

Fuzzy logic and neuro-fuzzy systems introduce human-like reasoning into the HRES sizing process by representing objectives and constraints using linguistic variables and membership functions. These methods are especially useful when design criteria such as “high reliability” or “low cost” are inherently imprecise or subjective. Fuzzy-based approaches are often employed as decision-support tools or integrated with other optimization methods to rank candidate system configurations [101-103].

E. Surrogate-Assisted and Machine Learning–Based Optimization

Surrogate-assisted optimization combines machine learning models, such as artificial neural networks, Gaussian process regression, or gradient-boosting methods, with optimization algorithms to reduce computational burden. In HRES sizing, surrogates are trained to approximate expensive simulation outputs, such as long-term cost or reliability metrics, enabling faster evaluation of candidate solutions [104-106]. This approach significantly accelerates optimization and enables the inclusion of high-fidelity component models, such as battery aging or hydrogen system dynamics. However, surrogate accuracy and generalization must be carefully validated, as model errors can mislead the optimization process if extrapolation occurs beyond the training domain.

F. Reinforcement Learning–Based Optimization

Reinforcement learning (RL) techniques, including DQN, PPO, SAC, and DDPG, represent a paradigm shift by framing HRES sizing and operation as a sequential decision-making problem. RL agents learn optimal policies through interaction with the system environment, receiving rewards based on long-term performance. RL is particularly suitable for co-design problems that couple sizing with operational control under uncertainty. Despite its adaptability and learning capability, RL faces challenges related to training stability, reproducibility, and safety assurance, making it less mature for planning-level sizing without additional constraint-enforcement mechanisms [107-111].

G. Hybrid AI Frameworks

Hybrid AI frameworks integrate complementary optimization paradigms to exploit their respective strengths. Common examples include combining evolutionary algorithms with MILP-based dispatch optimization or integrating AI-based global search with model predictive control (MPC). Hybrid approaches often achieve superior solution quality and robustness by ensuring both global exploration and rigorous constraint satisfaction. Although they introduce additional implementation complexity, such frameworks are increasingly recognized as state-of-the-art solutions for practical HRES sizing problems [112-117].

Artificial intelligence–based optimization techniques have emerged as powerful and flexible tools for addressing the optimal sizing problem of hybrid renewable energy systems (HRES), particularly in scenarios characterized by nonlinear component behavior, high-dimensional decision spaces, multiple conflicting objectives, and significant uncertainty in renewable resources and load demand. As summarized in the table on AI-based optimization techniques applied to HRES sizing, evolutionary computation and swarm intelligence methods provide strong global search capabilities and are widely used for techno-economic optimization of system capacities. Multi-objective evolutionary algorithms further enhance planning analysis by explicitly capturing trade-offs among cost, reliability, and environmental performance. Fuzzy and neuro-fuzzy approaches contribute interpretability and facilitate decision-making under vague or qualitative requirements, while surrogate-assisted and machine learning–based optimization significantly reduce computational burden and enable the inclusion of high-fidelity component models. Reinforcement learning introduces adaptive and sequential decision-making capabilities, particularly valuable for co-design of sizing and operation, although its practical application requires careful safety and constraint management. Hybrid AI frameworks, which integrate complementary techniques, represent a mature and effective direction for achieving robust and high-quality solutions.

4. Hybrid optimization techniques applied to optimal sizing of HRES

The optimal sizing of hybrid renewable energy systems (HRES) is inherently a complex planning problem that involves the simultaneous determination of multiple interdependent component capacities under technical, economic, environmental, and reliability constraints. As HRES configurations increasingly incorporate diverse generation technologies, advanced energy storage systems, power electronic interfaces, and, in some cases, hydrogen-based subsystems, the resulting optimization problem becomes highly nonlinear, nonconvex, and computationally demanding. Moreover, the presence of uncertainty in renewable resource availability, load demand, and market conditions further complicates the sizing process.

While classical and standalone artificial intelligence–based optimization techniques have demonstrated effectiveness in addressing certain aspects of HRES sizing, each class exhibits intrinsic limitations. Mathematical programming approaches may struggle with nonlinearity and scalability, whereas pure AI or metaheuristic methods often lack rigorous constraint enforcement and can be computationally inefficient when high-fidelity operational models are employed. To overcome these challenges, hybrid optimization techniques have emerged as a powerful and pragmatic solution that combines complementary strengths of multiple optimization paradigms within a unified framework.

Hybrid optimization techniques integrate global search capabilities, local refinement, exact mathematical solvers, learning-based surrogates, and advanced operational control methods to achieve robust, high-quality sizing solutions. These approaches are particularly well suited for modern HRES planning, where accuracy, feasibility, uncertainty awareness, and computational efficiency must be balanced. Table 3 categorizes and compares the main hybrid methodologies.

Table 3. Hybrid optimization techniques applied to optimal sizing of HRES.

Hybrid Technique Class	Typical Hybrid Combinations	Decision Variables	Objective Functions	Constraints / Performance Indices	Strengths
Metaheuristic + Mathematical Programming	GA/PSO/NSGA-II + MILP/MINLP	PV, wind, battery energy/power, inverter, DG, electrolyzer, H_2 tank.	NPC, LCOE, TAC, emissions, multi-objective Pareto.	Power balance, SOC limits, LPSP, EENS, ramping.	High solution quality; rigorous constraint satisfaction.

Metaheuristic + Local Search (Memetic)	GA + hill climbing, PSO + Nelder–Mead	Continuous and discrete component capacities.	Cost minimization with reliability constraints.	SOC feasibility, loss-of-load limits.	Improved convergence and precision.
Multi-Stage Hybrid Optimization	Analytical/graphical pre-sizing + GA/PSO	Bounded PV, wind, storage capacities.	NPC/LCOE minimization.	Reliability and renewable fraction targets.	Reduced search space; faster computation.
Surrogate-Assisted Hybrid Optimization	ANN/GP/XGBoost + GA/PSO/BO	All HRES sizing variables.	Cost and reliability optimization.	Learned feasibility constraints.	Significant computational speed-up.
Decomposition-Based Hybrid Methods	Benders/Lagrangian + heuristics	Investment and dispatch variables.	NPC/TAC minimization.	Operational feasibility, reliability indices.	Scalable for large systems.
Stochastic / Robust Hybrid Optimization	Scenario-based MILP + NSGA-II	Capacities with scenario-dependent dispatch.	Expected cost, CVaR, emissions.	LOLP, LOLE, chance constraints.	Risk-aware and reliable designs.
Control–Co-Design Hybrid Optimization	GA/NSGA-II + MPC/RL	Capacities and controller parameters.	Long-term cost and reliability.	SOC safety, unmet load penalties.	Operationally robust solutions.
Optimization + MCDM Hybrid	NSGA-II + TOPSIS/VIKOR/AHP	Pareto-optimal capacity sets.	Multi-objective trade-offs.	Policy and reliability constraints.	Transparent final decision-making.

A. Metaheuristic + Mathematical Programming Hybrid Methods

One of the most prominent hybrid frameworks combines metaheuristic algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), or NSGA-II, with mathematical programming techniques, typically mixed-integer linear or nonlinear programming (MILP/MINLP). In this architecture, the metaheuristic operates as an outer loop that explores the space of candidate system capacities, while the mathematical programming model serves as an inner loop that determines the optimal operational dispatch for each candidate sizing. This approach ensures rigorous satisfaction of operational constraints, including power balance, state-of-charge dynamics, unit commitment, and reliability indices, while retaining strong global exploration capabilities. Consequently, it is widely regarded as a benchmark-quality method for HRES sizing. However, the requirement to solve numerous MILP/MINLP problems results in substantial computational overhead and increased implementation complexity.

B. Metaheuristic + Local Search (Memetic Optimization)

Memetic optimization techniques enhance standard metaheuristics by incorporating local search methods, such as hill climbing or gradient-free simplex algorithms, to refine promising candidate solutions. In the context of HRES sizing, global exploration identifies promising regions of the solution space, after which local optimization improves solution precision and convergence speed. This hybrid strategy can significantly improve solution quality compared to standalone metaheuristics. Nevertheless, careful balancing between global and local search phases is essential to avoid premature convergence or entrapment in local optima, particularly in highly multimodal sizing landscapes.

C. Multi-Stage Hybrid Optimization Approaches

Multi-stage hybrid optimization frameworks decompose the HRES sizing problem into sequential phases. Typically, an initial analytical or graphical pre-sizing stage is employed to identify feasible capacity bounds based on energy balance or autonomy requirements. This reduced search space is then explored using more advanced AI-based or metaheuristic optimization methods. This approach offers notable computational efficiency by eliminating infeasible or noncompetitive regions early in the process. However, its effectiveness depends strongly on the quality of the pre-sizing assumptions, and overly restrictive bounds may inadvertently exclude the global optimum.

D. Surrogate-Assisted Hybrid Optimization

Surrogate-assisted hybrid optimization integrates machine learning models, such as artificial neural networks, Gaussian process regression, or gradient-boosted trees, with optimization algorithms to approximate expensive objective and constraint evaluations. In HRES sizing, surrogates are trained on simulation or dispatch results and subsequently used to accelerate the optimization process. This hybrid approach enables the inclusion of high-fidelity models, such as battery degradation or hydrogen system thermodynamics, which would otherwise be computationally prohibitive. The principal limitation lies in surrogate accuracy and generalization, necessitating rigorous validation and adaptive sampling strategies.

E. Decomposition-Based Hybrid Methods

Decomposition-based hybrid techniques apply mathematical decomposition principles, such as Benders decomposition or Lagrangian relaxation, to separate long-term investment decisions from short-term operational optimization. Heuristic or AI-based methods are often employed to accelerate convergence or manage integrality in the investment problem. This structure enhances scalability and interpretability for large-scale or long-horizon HRES planning problems. However, formulation complexity and the need for careful coordination between subproblems present significant implementation challenges.

F. Stochastic and Robust Hybrid Optimization

Hybrid stochastic and robust optimization frameworks combine AI-based search with uncertainty-aware mathematical programming. Scenario-based stochastic MILP models or robust optimization formulations are embedded within metaheuristic or evolutionary search processes to produce risk-aware sizing solutions. These approaches explicitly address variability in renewable generation, load demand, and economic parameters, leading to more reliable and resilient HRES designs. The main drawback is the substantial computational burden associated with scenario explosion and the need for scenario reduction or uncertainty set calibration.

G. Control–Co-Design Hybrid Optimization

Control–co-design hybrid methods integrate sizing optimization with advanced operational control strategies, such as model predictive control (MPC) or reinforcement learning (RL). Candidate system sizes are evaluated under realistic, closed-loop operational policies, ensuring that the selected design performs well under real-time constraints and forecast errors. this hybrid paradigm yields operationally robust designs but requires extensive simulation or training effort and raises challenges related to reproducibility and fair benchmarking.

H. Optimization + Multi-Criteria Decision-Making (MCDM) Hybrids

In optimization-MCDM hybrid approaches, multi-objective optimization techniques (e.g., NSGA-II) are first used to generate a Pareto-optimal set of HRES designs. Subsequently, decision-making tools such as TOPSIS, VIKOR, or AHP are applied to select a final design based on stakeholder preferences or policy priorities.

As summarized in the table on hybrid optimization techniques applied to HRES sizing, frameworks that combine global search algorithms with exact dispatch optimization ensure both solution optimality and rigorous constraint satisfaction. Memetic and multi-stage hybrid methods enhance convergence speed and computational efficiency, while surrogate-assisted and decomposition-based approaches enable scalable optimization with high-fidelity system models. Stochastic and robust hybrid techniques further improve design reliability by explicitly accounting for uncertainty, and control–co-design hybrids ensure that sizing decisions remain valid under realistic operational conditions.

5. Recent trend on Artificial Intelligence–Based Optimization Algorithms

In recent years, a substantial body of work has introduced new population-based optimization algorithms inspired by biological, physical, and socio-political processes. These methods are typically designed to enhance global search capability, mitigate premature convergence, and improve the exploration–exploitation trade-off in highly nonlinear, nonconvex, and multimodal optimization landscapes as presented in Figure 3. Nevertheless, the practical value of newly proposed optimizers depends not only on conceptual novelty but also on rigorous benchmarking, robust parameter sensitivity analysis, and validation on application-driven problems (e.g., HRES sizing, controller tuning, and constrained engineering design). The following subsections summarize a set of recently developed algorithms and their reported applications.

Figure 3. Recent trend on AI.

A. Black Widow Optimization Algorithm

Black Widow Optimization (BWO) is a population-based metaheuristic inspired by the lifecycle and mating behavior of black widow spiders, particularly the procreation–cannibalism dynamics observed among spiderlings. The algorithm is commonly governed by three principal control parameters: (i) procreation (reproduction) rate, (ii) cannibalism rate, and (iii) mutation rate. The procreation percentage (PP) determines the fraction of individuals permitted to reproduce, thereby improving population diversity and increasing the likelihood of exploring the search space effectively. Cannibalism is typically modeled in multiple stages to eliminate inferior individuals early, which can accelerate convergence. Mutation is then used to preserve a balance between exploration and exploitation by introducing controlled perturbations into candidate solutions. Appropriate tuning of these parameters is essential to avoid stagnation and to sustain search diversity, particularly in complex, high-dimensional problems. In terms of applications, BWO has been reported for controller design in standalone hybrid renewable energy systems integrating wind, tidal, and wave sources.

B. Sailfish Optimizer

The Sailfish Optimizer (SFO) is inspired by the cooperative hunting strategy of sailfish, where predator–prey interactions are modeled through two populations: predators (sailfish) and prey (sardines). In the algorithmic formulation, sailfish represent candidate solutions (positions in the search space), while sardines contribute to diversification by modeling prey dynamics and collective defense behaviors. The method alternates attack strategies to disrupt prey formations, updates prey movements across the search space, and allows predators to “capture” prey by relocating toward fitter positions.

Typically, the best sailfish solution and the most “injured” sardine (a proxy for vulnerable solutions) are retained to guide exploitation, implying that the elite solutions can significantly influence convergence behavior and overall performance. SFO is often reported to offer rapid convergence and competitive global search performance, especially for large-scale problems, due to its structured balance between intensification (predators) and diversification (prey). To strengthen exploitation, a hybrid adaptive hill-climbing Binary Sailfish Optimizer has been proposed and applied to feature selection problems using standard UCI datasets, with comparative evaluation against multiple AI-based feature selection techniques.

C. Deer Hunting Algorithm

The Deer Hunting Algorithm (DHA) is a human-inspired optimization method that emulates hunting strategies by considering factors such as wind direction and prey positioning. The algorithm initializes a population of hunters and designates a leader, while the remaining hunters (successors) are positioned relative to the leader and iteratively updated using coefficient vectors designed to move the population toward promising regions of the search space. The method may incorporate angular updates that relate the wind angle to the prey visualization angle, supporting exploration by enabling successors to adjust their search trajectories.

DHA has been validated on benchmark suites and constrained engineering design problems, demonstrating competitive performance against established optimizers. However, a commonly noted limitation is its susceptibility to convergence issues due to reliance on multiple random parameters, which can increase variability across runs and complicate parameter tuning. In an applied study, an improved deer hunting approach was used to analyze the economic performance of a combined solar chimney power plant integrated with SOEC, SOFC, and HRSG for residential power supply in Yazd, Iran, with comparative results reported against GA and PSO.

D. Tunicate Swarm Algorithm

The Tunicate Swarm Algorithm (TSA) is a bio-inspired optimizer motivated by the swarming behaviors of marine tunicates and their jet propulsion mechanisms. In the mathematical model, candidate solutions (search agents) evolve under three key behavioral conditions: (i) avoiding collisions/conflicts with neighboring agents through a position update vector that may account for social and environmental forces, (ii) moving toward the best neighboring solution to promote exploitation, and (iii) converging toward the globally best search agent to enhance intensification. Typically, elite solutions are preserved to emulate collective swarm intelligence, with remaining agents updating positions toward the best-performing candidates. An improved TSA has been introduced for simultaneous allocation and control of capacitor banks (CBs), distributed generators (DGs), and distribution network reconfiguration (DNR) to reduce power losses and enhance service quality [256]. The method was tested on standard 33-bus, 69-bus, and large-scale 119-bus radial distribution networks under varying demand scenarios and compared against conventional TSA and other approaches such as PSO, GA, EA, WCA, BFOA, and CSA.

E. Artificial Electric Field Algorithm

The Artificial Electric Field Algorithm (AEFA) is grounded in Coulomb's law of electrostatic attraction and repulsion. In AEFA, candidate solutions are treated as charged particles whose interactions are driven by electrostatic forces. The "best" particle (with the highest charge, corresponding to the best fitness) tends to move more conservatively, while other particles update their positions and velocities based on personal best and global best histories, rendering AEFA a memory-based optimizer akin to velocity-position update schemes. AEFA has been evaluated on real-parameter, single-objective optimization benchmarks, with reported competitive performance relative to several state-of-the-art algorithms. Furthermore, stability and convergence behavior have been examined through theoretical analysis to identify conditions under which particle motion remains stable and convergent.

F. Water Strider Algorithm

The Water Strider Algorithm (WSA) models the lifecycle and behavior of water strider insects, incorporating territoriality, mating dynamics, ripple-based communication, foraging behavior, and succession mechanisms. The algorithm begins by initializing a population over a conceptual lake surface and evaluating fitness. The population is then partitioned into territories, typically assigning stronger individuals to more advantageous regions. A keystone male's position is updated through signals influenced by female response dynamics. Because mating can be energy-intensive, the keystone then transitions to a foraging phase to locate food resources; failure to locate food leads to replacement by a new larva whose position is randomly initialized within the territory. WSA has been assessed on numerical benchmark functions and engineering design problems, with reported results indicating improved performance over several comparator algorithms. The inclusion of territorial structuring and replacement dynamics is intended to preserve diversity while supporting localized intensification.

G. Political Optimizer

The Political Optimizer (PO) is a socio-inspired metaheuristic that maps a multi-stage political process into an optimization framework. The algorithm typically models five phases: constituency allocation, party formation, election campaign, inter-party election, and parliamentary affairs. During initialization, the population is partitioned into political parties and constituencies. In the campaign phase, position update rules are formulated to reflect learning from previous elections, where party members and candidates adjust their positions relative to party leaders and constituency winners, respectively. Inter-party elections are simulated per constituency to select winners, and the parliamentary phase aggregates winners across parties to form a governing coalition. A distinctive feature of PO is that each solution may assume dual roles (party member and candidate), and position updates are guided by two elite references (party leader and constituency winner), rather than a single global best. This dual-elite interaction aims to diversify guidance signals and improve convergence robustness. The method has been evaluated on multiple optimization problems against a broad set of benchmark algorithms, reporting competitive performance.

6. Software Tools

The optimal sizing of hybrid renewable energy systems (HRES) is a multidisciplinary problem that requires the integrated consideration of techno-economic performance, system reliability, environmental impact, and operational feasibility under variable renewable resources and load demand. As HRES configurations become more complex, incorporating diverse generation technologies, energy storage systems, power electronic interfaces, and, in some cases, hydrogen-based subsystems, the reliance on analytical or purely theoretical approaches alone becomes insufficient. Consequently, software tools have become indispensable in HRES sizing studies, providing structured environments for modeling, simulation, optimization, and decision support as highlighted in Figure 4.

Figure 4. Software tools applied to optimal sizing of HRES.

Software tools applied to HRES sizing range from commercial techno-economic platforms and optimization-driven planning tools to power-system simulation environments and algebraic modeling frameworks. These tools differ significantly in terms of modeling depth, optimization capability, treatment of uncertainty, and ability to incorporate electrical network constraints. Their adoption has enabled researchers and practitioners to evaluate a wide range of design scenarios, perform sensitivity and uncertainty analyses, and derive practical, implementable system configurations.

A. Commercial techno-economic sizing platforms

Commercial platforms are frequently used for rapid techno-economic assessment and optimal sizing of HRES configurations by combining component libraries (PV, wind, batteries, diesel generators, converters, and grid interaction) with built-in dispatch simulation and economic evaluation. HOMER / HOMER Pro is the most common example, widely adopted for least-cost sizing and feasibility analysis of off-grid and grid-connected microgrids, enabling comparative scenario studies across technology mixes and financial assumptions.

B. Optimization-driven microgrid planning tools

Optimization-centric planning tools perform HRES sizing by explicitly solving an optimization model (often MILP-based) that co-optimizes system capacities and dispatch to minimize cost and/or achieve resilience and emissions targets. NREL's REopt® is a prominent example: it is designed to optimize DER system sizes and dispatch for buildings, campuses, and microgrids, and it explicitly supports resilience analysis such as sustaining critical loads during outages. DER-CAM (LBNL) is another well-established decision-support tool for determining optimal DER investments in buildings and multi-energy microgrids, with extensive documentation and tutorials supporting structured workflows.

C. Power-system simulation environments coupled with external optimizers

When HRES sizing must reflect electrical network constraints (e.g., voltage limits, feeder losses, phase imbalance, hosting capacity, protection constraints), researchers commonly rely on detailed distribution-system simulators and then couple them with external optimization routines (MILP/MINLP or metaheuristics). OpenDSS is widely used as an open-source distribution simulator for DER and microgrid studies, and it is often paired with MATLAB or Python-based optimization to perform network-constrained planning and sizing. In this workflow, the optimizer proposes candidate HRES capacities, while the simulator validates feasibility and computes network performance metrics (losses, voltage profiles, constraint violations), enabling sizing decisions that are electrically realistic rather than purely energy-balance-based.

D. Algebraic modeling languages and optimization libraries

For publication-grade or project-specific sizing studies requiring full flexibility in objectives and constraints (e.g., explicit LPSP/EENS limits, degradation-aware storage modeling, emissions caps, market participation, hydrogen subsystem coupling), HRES sizing is frequently implemented in algebraic modeling frameworks. In these settings, the system is formulated using an optimization modeling language (e.g., in GAMS-style workflows for DER-CAM implementations and related research) and solved using mathematical programming solvers; this approach supports transparent reporting of decision variables, constraints, and optimality gaps and is particularly effective for MILP/MINLP formulations in co-optimized sizing and dispatch.

Software tools play a central role in the optimal sizing of hybrid renewable energy systems by bridging the gap between theoretical optimization models and practical system implementation. Commercial techno-economic platforms facilitate rapid feasibility assessment and comparative analysis, while optimization-centric tools enable rigorous co-optimization of system capacities and dispatch under economic, reliability, and resilience objectives. Power-system simulation environments further enhance realism by incorporating network-level constraints, and algebraic modeling frameworks provide maximum flexibility for custom, publication-grade HRES formulations. No single software tool is universally optimal for all HRES sizing problems. Instead, tool selection should be guided by system scale, required modeling fidelity, uncertainty considerations, and the specific objectives of the study. In many advanced applications, hybrid workflows that combine multiple software tools, such as optimization solvers with power-system simulators, offer the most robust and credible solutions. As HRES planning continues to evolve toward higher renewable penetration and increased system intelligence, the strategic use of appropriate software tools can remain a key enabler of reliable, cost-effective, and sustainable energy system design.

7. Conclusion

This article reviewed the optimization of Hybrid Renewable Energy Systems (HRES) from a unified planning perspective, emphasizing that credible HRES design is fundamentally an integrated sizing-and-dispatch problem conducted under techno-economic, environmental, and reliability constraints. The discussion established the motivation for HRES optimization in the context of renewable intermittency, decarbonization requirements, and the need for resilient energy supply, and it framed optimization as the principal mechanism for balancing competing objectives such as minimizing lifecycle cost (e.g., NPC/LCOE), reducing emissions, and ensuring adequacy metrics (e.g., LPSP/EENS). Across the reviewed literature, it is evident that the choice of optimization paradigm must be matched to model fidelity, uncertainty level, and decision context (off-grid versus grid-connected, resilience-driven versus cost-driven design), rather than selected solely based on algorithmic novelty.

With respect to classical optimization methods, the review highlighted their continuing importance due to transparency, reproducibility, and rigorous constraint representation. Numerical programming approaches (LP/MILP/MINLP) remain indispensable for co-optimizing capacity investment and operational dispatch when the system can be formulated with sufficient tractability, while analytical, graphical, iterative, and probabilistic methods provide valuable first-cut feasibility assessment, sensitivity insights, and baseline benchmarks. Nonetheless, classical methods can become restrictive under strong nonconvexities, detailed component physics (e.g., electrolyzer part-load efficiency, battery degradation), and long-horizon high-resolution time series, motivating the adoption of more flexible solution strategies.

The article then examined AI-based optimization techniques, which have become prevalent because they can navigate nonconvex and mixed-integer design spaces and readily integrate simulation-based evaluations. Evolutionary computation and swarm intelligence methods are widely used for single- and multi-objective sizing, and multi-objective evolutionary algorithms provide explicit Pareto fronts that support decision-making across cost–emissions, reliability trade-offs. However, the review emphasized that AI-based methods require disciplined constraint handling, statistical validation, and transparent reporting of computational budgets to avoid misleading conclusions. Building on this, hybrid optimization techniques were identified as a mature and practically effective direction, particularly frameworks that couple global metaheuristic search with exact dispatch solvers (MILP/MINLP), surrogate-assisted learning for computational acceleration, decomposition strategies for scalability, and control–co-design approaches that evaluate designs under realistic closed-loop operation. These hybrid structures frequently deliver superior feasibility, robustness, and solution quality compared with standalone approaches, albeit with higher implementation complexity.

Recent advances were further characterized by the rapid emergence of new AI optimizers and their variants, often motivated by specific exploration–exploitation mechanisms. While many of these algorithms report promising benchmark performance, the review underscored that their research value in HRES sizing depends on standardized comparisons against strong baselines, sensitivity analysis of algorithmic parameters, ablation of proposed operators, and evaluation under uncertainty and realistic operational constraints. Finally, the article demonstrated that software tools are central enablers of HRES optimization, ranging from packaged techno-economic sizing platforms to solver-centric modeling environments and power-system simulators coupled with external optimizers for network-constrained planning. Best practice increasingly favors integrated toolchains that combine data processing, high-fidelity simulation, solver-based dispatch, and decision analysis, ensuring that optimized designs are both technically implementable and economically defensible.

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