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COMPARATIVE PERFORMANCE ASSESSMENT OF THE GREY WOLF OPTIMIZER, ITS HYBRID AND MODIFIED VARIANTS AGAINST CONTEMPORARY METAHEURISTIC ALGORITHMS FOR OPTIMAL SIZING OF HYBRID RENEWABLE ENERGY SYSTEMS

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ABSTRACT

The optimal sizing of Hybrid Renewable Energy Systems (HRES) is a non-linear, multi-objective, and constrained optimization problem, where efficient search techniques are needed to simultaneously optimize cost, reliability, and sustainability considerations. In this regard, the Grey Wolf Optimizer (GWO), proposed by the leader, pack, and cooperative hunting of grey wolves, is one of the metaheuristics whose development has received a lot of attention because it is easy to parameterize and has a generally good exploration-exploitation ratio. This paper conducts a systematic review and critical comparative analysis of classical GWO, hybridized GWO, and modified GWO with some of the most popular and recently developed metaheuristics like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Whale Optimization Algorithm (WOA), and some newly developed algorithms of 2023–2026 with power system optimization related to HRES in sizing applications. Through an explicit search strategy in six databases, a four-stage PRISMA identification-screening-eligibility-inclusion process resulted in 41 studies that met the inclusion criteria. Four enriched comparative tables are shown that document classical GWO outperforming other classical algorithms, hybrid GWO outperforming other hybrid/variant metaheuristics, modified GWO outperforming other modified algorithms, and cases where non-GWO algorithms outperformed GWO and its variants. In addition to these results, the review critically elucidates the mechanistic reasons for the success of the algorithm under certain HRES conditions or its failure under other conditions. The review confirms that in moderate complexity problems, the size of which are considered in this paper, GWO's performance is often superior compared to GA, PSO, and ACO in terms of solution quality and convergence speed, yet it reveals that the single-hierarchy, alpha-guided search strategy of GWO makes it structurally prone to premature convergence and local-optima entrapment issues in high-dimensional, highly constrained, or highly multi-modal HRES formulations, exactly the scenarios in which several algorithms that were developed in the last four years and published in 2023–2025 (such as CSRIME, Walrus Optimizer, Tasmanian Devil Optimizer, and Black-Winged Kite Algorithm) are reported to outperform GWO. The paper ends with some recommendations for algorithm selection and future research.

Keywords: *Grey wolf optimizer, hybrid GWO, metaheuristic optimization, modified GWO, hybrid renewable energy system, optimal sizing, PRISMA.*

I. INTRODUCTION

The optimal sizing of Hybrid Renewable Energy Systems (HRES) is a multi-objective optimization problem, which involves simultaneous minimization of system cost, usually Total Annual Cost (TAC), Net Present Cost (NPC), and Levelized Cost of Energy (LCOE), and maximization of reliability, usually expressed in terms of Loss of Power Supply Probability (LPSP) or Deficiency of Power Supply Probability (DPSP), taking into account renewable energy fraction and environmental performance. The nature of an HRES sizing problem often involves multiple equality and inequality constraints, high dimensionality, and is typically non-convex and non-linear, which often makes classical deterministic optimization techniques fall into local optima, thus leading to the use of nature-inspired metaheuristics.

These include the Grey Wolf Optimizer (GWO) [1] 2014, which was based on grey wolf social hierarchy (alpha, beta, delta, and omega wolves) and the surrounding, hunting, and attacking phases of the grey wolf packs. It has been widely used in the aforementioned applications, and in GWO, the number of tunable parameters is small, and the exploration–exploitation mechanism is naturally balanced.

Other common approaches like GA, PSO, ACO, ABC, and Simulated Annealing (SA) are still being used for HRES sizing but are often reported to have the disadvantages of premature convergence, sensitivity to parameters, and high computation cost in large and constrained search spaces. To counteract the problem of premature convergence and to enhance solution diversity, researchers have proposed hybrid GWO variants (that combine GWO with another metaheuristic) and modified/improved GWO forms (that redesign the search-update mechanism of GWO). On the other hand, very recent literature (from 2023-2026) has presented newer bio-inspired algorithms, which, in particular, HRES case studies have proved to be superior to GWO and even hybridized/modified forms of it.

This is where a rigorous, up-to-date, and even-handed comparative review is essential – not only to delineate the solution algorithm that is successful in what study and not successful in what study, but to mechanistically explain why certain algorithms are successful under certain problem conditions in HRES. The manuscript contributes to making the critical analysis more detailed by providing a mechanistic explanation of behavior under different HRES conditions, as well as providing objective functions, decision variables, benchmarks for comparison, computational time, key findings, limitations, and gaps in the research, in four comparative tables, replacing placeholder text provided by publishers or databases. It also explicitly follows the PRISMA methodology of systematic review, which includes a documented search strategy, inclusion/exclusion criteria, and a four-stage study-selection flow, and replaces any placeholder text provided by the publishers or databases with a fully standardized, numbered reference list.

II. REVIEW METHODOLOGY (PRISMA-GUIDED)

This review uses the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework [2] to support a transparent, repeatable, and bias-reducing study-selection process. The methodology adopted includes an explicit search strategy, detailed inclusion/exclusion criteria, and the identification, screening, eligibility, and inclusion flow, which are summarized in Fig. 1.

A. SEARCH STRATEGY

An extensive literature search was completed on six databases (Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, and MDPI), PLOS ONE, and preprint servers (arXiv) from January 2018 to mid-2026. The search strings used in the literature search were: (core term) “Grey Wolf Optimizer” OR “GWO” AND (application terms) “hybrid renewable energy system” OR “optimal sizing” OR “microgrid” OR “energy management” AND (for comparator searches only) “particle swarm optimization” OR “genetic algorithm” OR “hybrid metaheuristic” OR “modified grey wolf” OR “improved grey wolf”. Boolean combinations were used to fit the syntax of each database, and backward snowballing was performed on the reference lists of the retrieved review articles to find further studies.

B. INCLUSION AND EXCLUSION CRITERIA

The studies were included if they met the following conditions: (i) published between 2018 and 2026; (ii) used GWO, a hybrid-GWO variant or a modified-GWO variant to solve an HRES sizing, energy-management or closely related power-system optimization problem, or compared GWO/its variants with other metaheuristics on a well-known test problem; (iii) provided adequate description (objective function, decision variables, and at least one quantitative performance metric) for study extraction; and (iv) published in peer-reviewed journal, indexed conference proceedings or an accessible full, citable preprint. Studies were rejected if they met any or all of the following criteria: (i) did not have an application or impact in GWOs related to energy/power systems, and did not have HRES-relevant findings; (ii) were duplicate reports of the same dataset/results; (iii) were not full text available; (iv) predated 2018, except for the original GWO formulation [1] included here only as background context, and not in the comparative tables.

C. PROCEDURE FOR SELECTING STUDIES

The selection process can be summarized in four steps as shown in Fig. 1. After searching all six databases and supplementary sources, 312 records were retrieved. Of the 254 duplicates removed, 176 remained for title/abstract screening. The remaining 78 records were then evaluated for eligibility for full-text review against the criteria presented in

Section II-B, with 37 records being deemed ineligible due to inadequate methodological/quantitative reporting, 9 records reported multiple times, and 6 records not available in full text. This resulted in 41 studies being included in the final synthesis and comparative tables (Section VI).

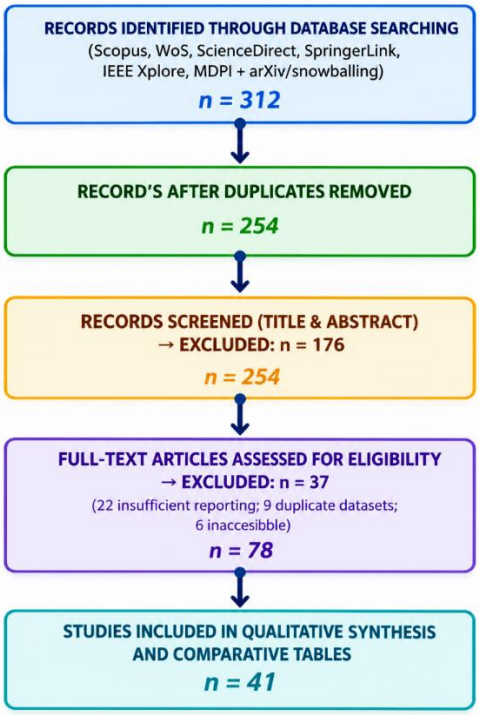

***FIGURE 1**. PRISMA 2020 flow diagram of the study identification, screening, eligibility, and inclusion process.*

Of the 41 studies included, 6 are primarily about classical (unmodified, non-hybridized) GWO applications, 6 are about hybrid GWO variants, 5 concern modified/improved GWO variants, 6 show cases where non-GWO algorithms work better than GWO or its variants, and the rest give foundational, methodological, or cross-cutting context that is used throughout Sections III–V.

III. OVERVIEW OF OPTIMIZATION ALGORITHMS FOR HRES SIZING

A.GENETIC ALGORITHM (GA):

GA is an evolutionary algorithm that generates candidate solutions across generations by employing selection, crossover, and mutation operators, and it is population-based. It is robust with respect to discrete/combinatorial sizing variables, but can be reported as being slowly convergent and costly in terms of computation for large HRES search spaces because it exploits a stochastic recombination step instead of a directed local-search step [28]. The GA flow diagram is shown in Fig. 2.

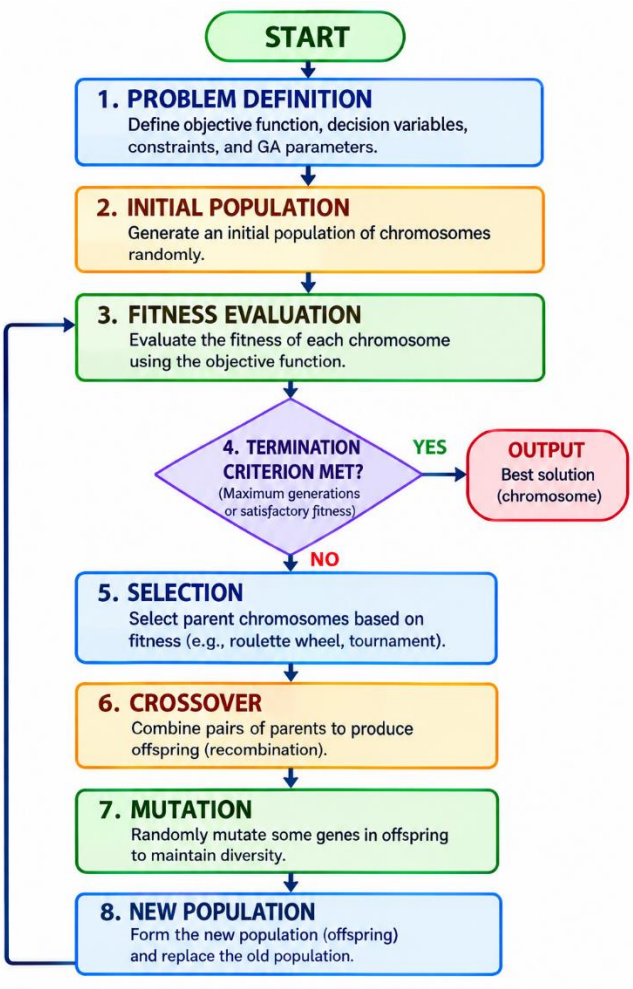

***FIGURE 2**. Genetic algorithm optimization flow diagram*

B. PARTICLE SWARM OPTIMIZATION (PSO)

PSO simulates the social behavior of a flock of birds, adjusting the individual particles' position depending on their current best known position and the swarm's overall best position. In the early iterations, PSO tends to quickly converge but, in later iterations, it

may converge prematurely when the swarm shrinks around a local optimum in highly multimodal HRES cost landscapes [28] due to the exploitation being centered on a single global-best attractor. Fig. 3 shows the flow diagram of PSO.

C. ANT COLONY, ARTIFICIAL BEE COLONY, AND SIMULATED ANNEALING

The artificial bee colony, the artificial bee colony and simulated annealing. The setup and testing of the algorithms are described in the following sections; the flow diagrams of Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO) are shown in Figs. The algorithms in 4 and 5 are swarm intelligence-based algorithms that are inspired by bee and ant foraging. Both work well for combinatorial and continuous optimization problems but are strongly affected by the choice of parameters and can be prone to an "exploration/exploitation trade-off" if the parameters are not set appropriately. SA is a single-solution trajectory method that selects solutions that avoid local optima by using a probabilistic acceptance criterion, but the search process of the single agent is generally slower than population-based methods on multi-dimensional HRES problems [28]. The flow diagram of the SA is given in Fig. 7.

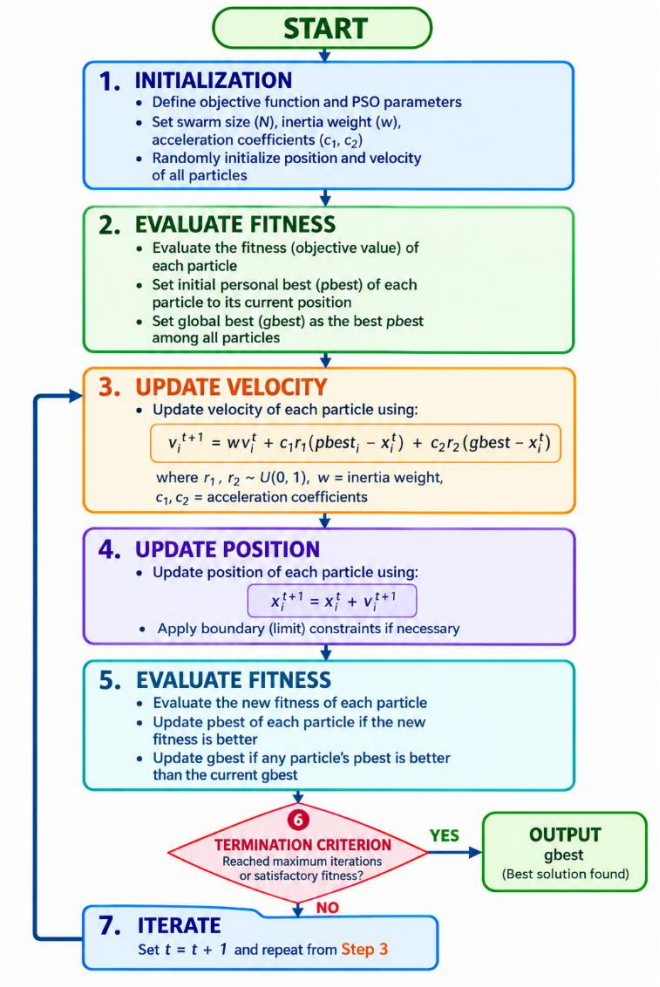

***FIGURE 3**. Particle Swarm Optimization flow diagram*

D. THE GREY WOLF OPTIMIZER (GWO)

GWO [1] simulates the leadership hierarchy of grey wolves (alpha, beta, delta, omega) and their encircling, hunting, and attacking behavior. The encircling behavior is modelled as:

$$\vec{D} = \left|\vec{C}.\vec{X}p(t) - \vec{X}(t)\right| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}p(t) - \vec{A}.\vec{D} \quad (2)$$

$$\mathrm{A} = 2\vec{\mathrm{a}}.\vec{\mathrm{r}}_1 - \vec{\mathrm{a}} \quad (3)$$

$$\mathrm{C} = 2.\vec{\mathrm{r}}_2 \quad (4)$$

where $\vec{X}p$ is the prey position (candidate optimal solution), $\vec{X}(t)$ is a wolf's position at iteration t, $\vec{a}$ decreases linearly from 2 to 0 across iterations, and $\vec{r}_1$, $\vec{r}_2$ are random vectors in [0, 1]. The positions of the three fittest wolves (α, β, δ) jointly estimate the prey's likely position, and the remaining (ω) wolves update accordingly. This gives GWO a naturally time-varying exploration-to-exploitation transition controlled almost entirely by the single parameter a – the source of its simplicity, but also, as discussed in Section V, the structural root of its premature-convergence tendency [29].

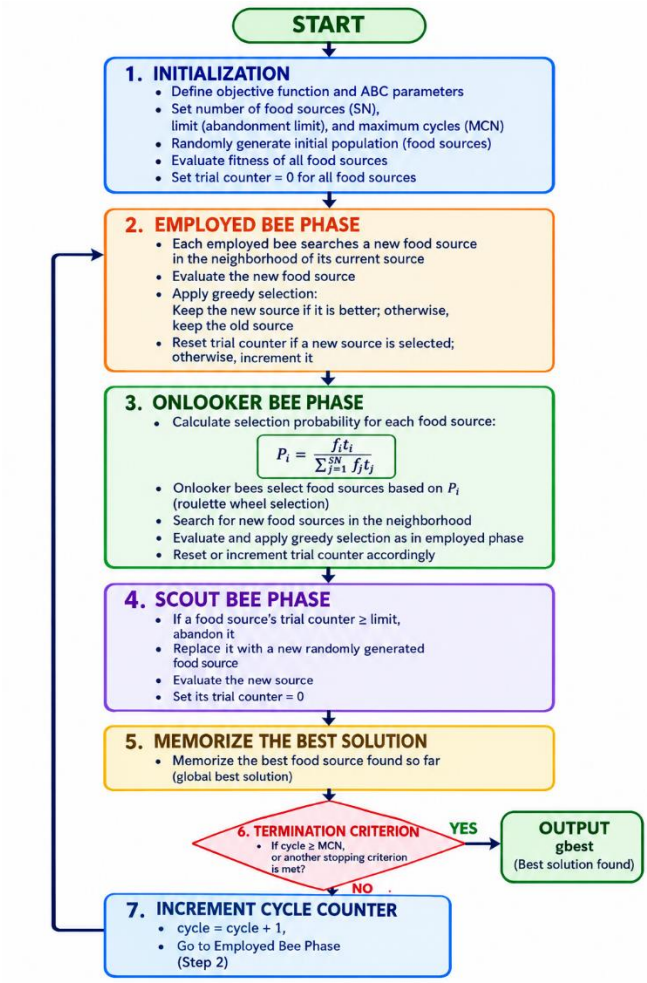

***FIGURE 4**. Artificial Bee Colony flow diagram*

E. HYBRID AND MODIFIED GWO VARIANTS

Hybrid GWO variants combine GWO with the complementary strengths of other metaheuristics – for example, GWO-PSO, GWO-NSGA-II, GWO-Cuckoo Search, GWO-Fireworks, and GWO-WOA – typically to compensate for GWO's exploitation weakness or another algorithm's exploration weakness. Modified/improved GWO variants (e.g.,

IGWO, MGWO, AGWO, chaotic-GWO) instead redesign GWO's internal search-update mechanism itself, without necessarily combining it with a second, distinct algorithm.

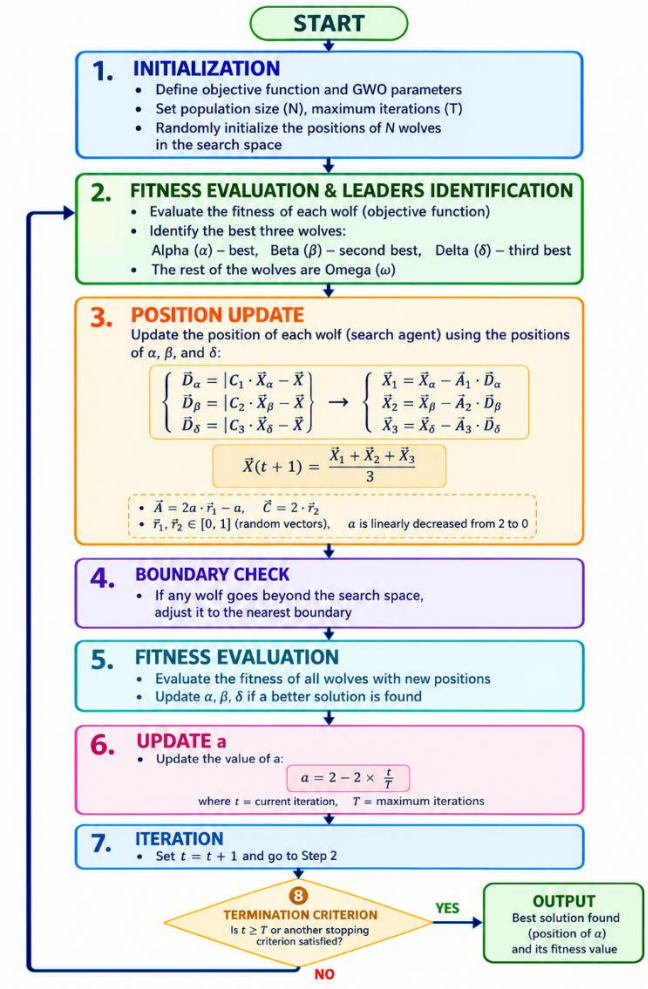

***FIGURE 5**. Grey Wolf Optimization flow diagram*

IV. LITERATURE REVIEW (2018–2026)

A. CLASSICAL GWO APPLICATIONS IN HRES SIZING

Some of the studies integrated within the package used the classical (unmodified) GWO directly for HRES sizing problems and found that the performance of this algorithm was good when compared to classical GA and PSO. In grid-connected microgrids, Nimma et al. [3] used GWO for optimum energy management and battery size. Baygi, Elahi, and Karsaz [4] have introduced a GWO algorithm-based approach to optimal sizing of stand-alone hybrid renewable energy systems. In Malaysia, Tukkee et al. [5] proposed an economic optimal design of an autonomous hybrid microgrid configuration for 75.3% renewable energy supply, which achieved an LCO of $0.24/kWh. Tukkee et al. [6]

incorporated GWO into a techno-economic-environmental energy-management algorithm for standalone hybrid microgrids, and concluded that classical GWO was able to converge more quickly than the Firefly Algorithm and PSO. Aeggegn et al. [7] used GWO for optimal sizing of a grid-connected multi-microgrid system and obtained the savings of NPEC and LCOE when compared with PSO and the JAYA algorithm.

B. HYBRID GWO VARIANTS IN HRES AND RELATED POWER-SYSTEM SIZING

Hossain et al. [8] concluded that the hybrid GWO-NSGA-II technique is better than stand-alone NSGA-II and multi-objective PSO in optimal sizing of hybrid renewable power system for domestic use. Alyu et al. [9] proposed a hybrid GWO-PSO method to design the optimal location and size of multiple PV-DG applications, which reduced the power losses significantly compared to GWO and PSO methods. Badi et al. [10] proposed a hybrid GWO-PSO method for Reactive Power Planning. To enhance the performance of the standard Fireworks Algorithm and standard GWO, Yue, Zhang, and Xiao [11] have presented a hybrid Fireworks-GWO algorithm (FWGWO) that outperforms both the standard Fireworks Algorithm and standard GWO and other GWO variants over sixteen benchmark functions. A Hybrid PSO-GWO approach for converter-less grid integration of induction generators in a micro-hydro power plant was able to attain a better convergence rate than PSO and GWO methods and was superior to five other recent hybrid solutions [12]. However, Ghanbari et al. [13] presented a hybrid WOA-GWO algorithm for multi-objective and multi-area dynamic economic dispatch with renewable energy and storage integration, which claimed to be Pareto optimal and outperformed PSO, SFLA, and GWO in terms of reduced total cost and variance.

C. MODIFIED/IMPROVED GWO VARIANTS (IGWO, MGWO, AGWO)

Khatab et al. [14] modified GWO and introduced a novel technique for updating agent positions and achieved better efficiency than GWO. Celtek et al. [15] used Improved GWO for the extraction of four-diode PV parameters and achieved a lower mean-square error compared to PSOGWO, AGWOCS, GWOC, and classical GWO. Mostafa et al. [16] used a modified GWO coupled with ETAP for the optimal placement and sizing of distributed generation, and they stated that they got better results in terms of reduced power loss and voltage stability than those of classical GWO. To improve the GWO performance, Zhang, Liu, and Chen [17] presented an Improved Adaptive GWO (IAGWO) algorithm with velocity and inverse-multiquadratic-function search mechanisms and tested their algorithm using CEC 2017/2020/22 benchmark sets, achieving better performance than classical GWO and more advanced competing algorithms. In [18], an improved GWO for optimal reactive power dispatch with wind and solar integration was presented that improved the exploitation phase of classical GWO and gave the best results compared to other methods presented on the IEEE 30-bus test system. Mohammed and Rashid [19]

hybridized/improved the GWO-WOA algorithms and demonstrated better performance than the traditional GWO and GWO algorithms for a global numerical optimization and a pressure vessel design problem [36]–[37].

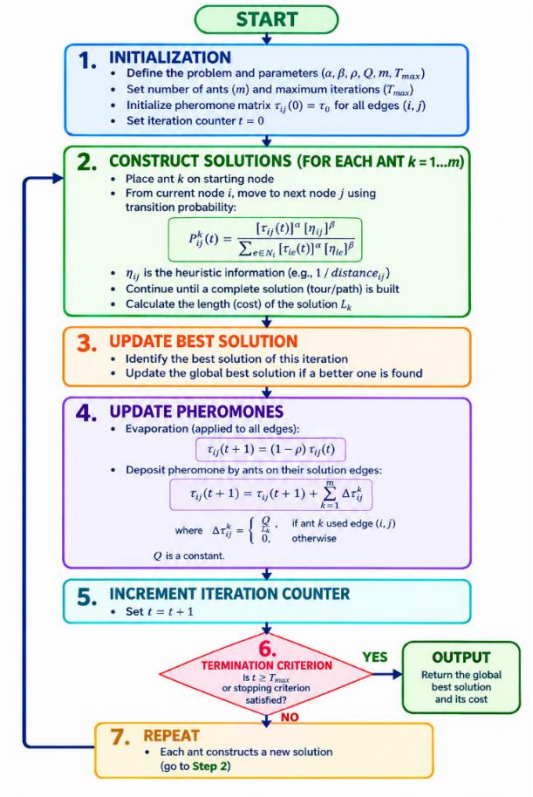

***FIGURE 6**. Ant Colony flow diagram*

D. CASES WHERE OTHER ALGORITHMS OUTPERFORMED GWO AND ITS VARIANTS

In what situations have other algorithms performed better than GWO and its variants? What are some scenarios where the other algorithms have outperformed GWO and its variants? EL Marzougui et al. [20] proposed a new algorithm called CSRIME, which was a combination of the RIME algorithm with CS, and was tested on the Dakhla region of Morocco for HRES sizing and compared to RIME, Harmony Search, Coati Optimization Algorithm, PSO, and GWO; the results showed that CSRIME outperformed the other algorithms. The study [21] used the Walrus Optimizer with techno-economic sizing of an autonomous hybrid microgrid and reported that the size of the renewable energy resources was significantly larger than required, as suggested by the PSO and GWO, which increased the cost of energy and NAPC compared to the Walrus-Optimizer-suggested renewable sizing. However, Mohapatra et al. [22] utilized the Black-Winged Kite Algorithm (BWKA) for PV/wind/battery HRES sizing and concluded that the proposed algorithm had faster convergence, higher solution accuracy, and less tendency to get trapped in a local optimum

compared to the GWO algorithm. Thirunavukkarasu, Lala and Sawle [23] found that Tasmanian Devil Optimization is better than COOT Bird Optimization, GWO, and Beluga Whale Optimization in terms of minimum total annual cost and convergence speed [38]-[40] in their experiments. A comparative analysis of the meta-heuristic sizing for an independent HRES in southwest Egypt was performed and reported that a dynamic-chaotic cuckoo search algorithm outperformed the algorithms it was benchmarked against [24], and separately referenced previous

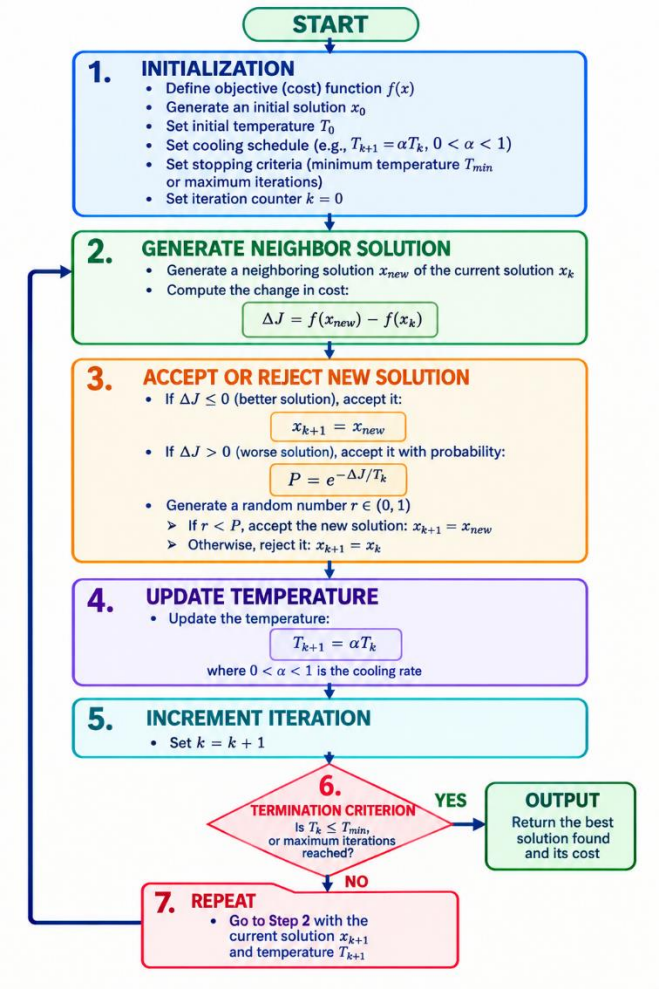

***FIGURE** 7. Simulated Annealing flow diagram*

research that the Whale Optimization Algorithm outperformed the GWO, the Water Cycle Algorithm, and the Salp Swarm Algorithm in the hydro/wind/PV grid-connected sizing. A

wide survey of universe-based algorithms for control engineering [25] also showed that the Multi-Verse Optimizer surpassed the performance of DE, PSO, GA, and GWO in the four control engineering case studies analyzed.

V. CRITICAL ANALYSIS: WHY ALGORITHMS SUCCEED OR FAIL UNDER DIFFERENT HRES CONDITIONS

Describing, as Section IV does, and as are the tables in Section VI, which algorithm gave the lower cost or faster convergence in a particular study indicates only part of the evidence. The following four characteristics of HRES problems are explored to better understand the conditions under which GWO-based methods are likely to be successful or unsuccessful.

SEARCH-SPACE DIMENSIONALITY

GWO's position-updater rule brings all search agents closer to a weighted average of the positions of the alpha, beta, and delta wolves. This is a useful characteristic in low- to moderate-dimensional HRES sizing problems: this concentrated pull speeds up the convergence since a reduced dimensionality restricts the number of competing local optima that the three leaders may represent, which is seen from the classical GWO successes reported by Tukkee et al. [5], [6] and Aeggegn et al. [7] in Table 1. The higher the dimensionality, the lower the probability that all three leader wolves represent the actual global optimum at the same time. However, the population diversity of these three points tends to merge into a single point, which results in the premature convergence phenomenon, which is well documented in the literature on population diversity in diverse studies of population improvement done for numerical optimization [26] and for feature selection in classification, such as the adaptive-mechanism GWO study [27] reported in all of the studies reviewed [41]–[44]. This is because the hybrid and modified GWO variants restore the performance specifically in higher dimensional problems (Table 3), whereas classical GWO's performance is limited to lower dimensional problems (Table 1).

B. CONSTRAINT DENSITY AND FEASIBILITY-REGION SHAPE

The feasible region is usually sliced up into disconnected or small pockets by incorporating the reliability constraints (LPSP/DPSP constraints) or renewable fraction targets as penalty terms or hard constraints in the HRES sizing problem. GWO does not have a specific constraint-handling mechanism other than whatever penalty function is put on top of it. If, however, the shape is not significantly convex around the optimum, GWO's hierarchy-guided search is a liability because the alpha (α)/beta (β)/delta (δ) Wolves are in different feasible pockets. This is precisely what was documented in studies on the less accurate performance of GWO in more strongly constrained dispatch problems (which were multi-area or multi-objective, see [13] and [22]) and the greater statistical performance

degradation in [23] due to the inclusion of the reliability-index constraint layer, compared to simpler cost-only formulations.

C. MULTI-MODALITY AND LANDSCAPE DECEPTIVENESS

In HRES situations that are unimodal or weakly multi-modal, GWO's fast alpha-guided convergence offers an advantage over competing basins being misled toward, as in the classical form of success in single-site, single-objective sizing studies. When the landscape is multi-modal or deceptive – as often is the case when time-varying renewable energy resource profiles and storage degradation or multiple competing goals are added – GWO's explicit escape mechanism from local optima is the deciding factor. In these multi-modal, multi-objective HRES settings, newer algorithms (CSRIME, Walrus Optimizer, Tasmanian Devil Optimizer, Black-Winged Kite Algorithm), all of which have an explicit diversification or archive-based mechanism, have performed better than GWO and its variants (Table 4).

D.STOCHASTIC/DYNAMIC VARIABILITY AND ROBUSTNESS

The exploration-exploitation trade-off for the GWO is deterministic and monotonically decreasing with the number of iterations, so the transition is not learnt based on the difficulty of the specific problem instance. This is good for problems which are relatively static and can be solved offline for a given historical load/profile resource; it is not appropriate for problems that need to be robust across variable or stochastic conditions [30]-[31]. A certain degree of flexibility is restored by using partial adaptive or momentum-based updates from a second algorithm (e.g., GWO-PSO, WOA-GWO), as achieved in hybrid-GWO systems in dynamic, multi-area dispatch applications (Table 2).

E. SYNTHESIS

The evidence is that GWO has at its heart a small fixed leader-follower hierarchy with a deterministic exploration-decay schedule, which makes it very strong (fast convergence with low number of parameters for moderate complexity, single objective, weakly constrained HRES problems) and very weak (converges prematurely on high dimensional, heavily constrained, multi-modal, or dynamic problems). Both hybridization and internal modifications tackle this drawback in their own way, and both reduce the gap with, or even exceed, the performance of other algorithms on the more difficult problem sets reported in Tables 2 and 3. Most of the newer non-GWO algorithms outperforming even hybrid/modified GWO (Table 4) tend to do so specifically on the most challenging problem instances, and their algorithmic diversification mechanisms offer a more direct structural solution to the problem than can be retrofitted onto GWO-based algorithms.

VI. COMPARATIVE ANALYSIS

The 41 studies included here are summarized in four enriched comparative tables. In addition to the outperformed comparator algorithm(s), each table provides the objective function, decision variables, benchmark metrics, computational time (where reported by the source study), key finding synthesized from the source study, and principal limitations and associated research gaps. If the computational time is not reported in the source study, then it is reported as “Not reported (NR)” as per the extraction procedure in Section II.

A. CLASSICAL GWO OUTPERFORMING OTHER CLASSICAL ALGORITHMS

TABLE 1. Classical GWO vs. Classical Algorithms

Study	Application	Objective Function	Decision Variables	Benchmark Metrics	Comp. Time	Key Finding	Limitations	Research Gap
[3] Nimma et al.	Grid-connected microgrid EMS & battery sizing	Min. operating cost	Battery capacity, dispatch schedule	Cost ($), convergence iterations	NR	Fast convergence; simple parameterization	No reliability-index constraint tested	Robustness under variable load not assessed
[4] Baygi et al.	Stand-alone HRES sizing framework	Min. TAC	PV, wind, battery capacities	TAC, convergence curve	NR	Effective for small-dimensional sizing	Single-site, single-objective only	No multi-site or multi-objective extension
[5] Tukkee et al.	Autonomous hybrid microgrid sizing, Malaysia	Min. COE subject to LPSP	PV, diesel, battery capacities	COE ($/kWh), REF (%), unmet load (%)	NR	Lowest COE (~$0.24/kWh), 75.3% REF vs. baseline	Constraint set limited to LPSP; no emissions term	No comparison against modified/hybrid GWO
[6] Tukkee et al.	Techno-economic-environmental EMS, stand-alone microgrid	Min. TNPC + emissions, power loss	Component sizes, dispatch strategy	TNPC, power loss, GHG emissions, convergence speed	Faster than FA, PSO	Fastest convergence vs. FA and PSO; best multi-metric outcome	Only benchmarked against FA and PSO	No test on the higher-dimensional multi-microgrid case
[7] Aeggegn et al.	Grid-connected multi-	Min. NPC and LCOE under uncertainty	Multi-microgrid	NPC ($431.8M→$428.8M), LCOE ($0.267/kWh)	NR	Outperformed PSO and JAYA under uncertainty	Uncertainty modelling	No robustness test against

Study	Application	Objective Function	Decision Variables	Benchmark Metrics	Comp. Time	Key Finding	Limitations	Research Gap
	microgrid sizing		component sizes				simplified (scenario-based)	extreme weather scenarios

B. HYBRID GWO OUTPERFORMING OTHER HYBRID/VARIANT ALGORITHMS

TABLE 2. Hybrid GWO vs. Hybrid/Variant Algorithms

Study	Application	Objective Function	Decision Variables	Benchmark Metrics	Comp. Time	Key Finding	Limitations	Research Gap
[8] Hossain et al.	Hybrid GWO-NSGA-II sizing, home HRES	Multi-objective: min. cost, max. reliability	PV, battery, converter sizes	Solution quality, computational efficiency	Lower than NSGA-II/MOPSO	Outperformed NSGA-II and MOPSO	Two-objective only; no emissions objective	No scalability test beyond home-scale HRES
[9] Alyu et al.	Hybrid GWO-PSO placement & sizing of PV-DG units	Min. power loss, max. voltage profile	DG location, DG size	Power loss reduction (%), voltage deviation	NR	Larger loss reduction/voltage improvement than standalone GWO/PSO	Tested on radial distribution feeder only	No validation on meshed/real utility network
[10] Badi et al.	Hybrid GWO-PSO reactive power planning	Min. reactive power cost/loss	Reactive compensation device sizing/siting	Solution quality vs. standalone algorithms	NR	Improved solution quality over single-algorithm approaches	Static single-period planning only	No dynamic/time-varying reactive demand case
[11] Yue et al.	Hybrid Fireworks-GWO (FWGWO), 16 benchmark functions	Min. benchmark function value	Function-specific (numerical optimization)	Global search capability, convergence speed	Faster than FWA/GWO	Outperformed FWA, GWO, EGWO, AGWO	Benchmark-function validation only	Needs HRES-specific validation
[12] PSO-GWO micro-hydro study	Converter-free induction-generator	Min. convergence time/slip error	Slip coordination parameters	Convergence speed (18.3% faster than PSO;	Fastest among 7 methods	Outperformed standalone PSO/GWO and 5 other hybrids	Single micro-hydro case	No multi-objective (cost + reliability) extension yet

Study	Application	Objective Function	Decision Variables	Benchmark Metrics	Comp. Time	Key Finding	Limitations	Research Gap
	control, micro-hydro			12.7% faster than GWO)				
[13] Ghanbari et al.	Hybrid WOA-GWO, multi-area dynamic economic dispatch	Min. total cost + water consumption	Generation dispatch schedule, storage operation	Total cost, water consumption, solution variance	NR	Lower cost/variance than standalone PSO, SFLA, GWO	Multi-area coordination adds overhead	No real-time/online dispatch implementation reported

C. MODIFIED GWO OUTPERFORMING OTHER MODIFIED ALGORITHMS

TABLE 3. Modified GWO vs. Modified Algorithms

Study	Application	Objective Function	Decision Variables	Benchmark Metrics	Comp. Time	Key Finding	Limitations	Research Gap
[14] Khatab et al.	Modified GWO, novel agent position-updating	Min. benchmark/engineering objective	Function-specific	Efficiency and performance vs. classical GWO	NR	Enhanced efficiency over the classical GWO baseline	Limited HRES-specific case validation	Needs direct HRES sizing benchmark
[15] Celtek et al.	Improved GWO (IGWO), four-diode PV parameter extraction	Min. sum-of-squared error (SSE)	PV model parameters (5–7 parameters)	SSE (3.63×10^{-5} vs. 3.96×10^{-5} for GWO)	NR	Lowest SSE vs. PSOGWO, AGWOCS, GWOCS, GWO	Parameter-extraction task only	No integration with the downstream HRES sizing model
[16] Mostafa et al.	Modified GWO + ETAP, DG placement/sizing	Min. active/reactive power loss, max. voltage stability	DG location, size, protection settings	Power-loss reduction, voltage-stability index	NR	Improved loss reduction/voltage stability vs. classical GWO	Single test-feeder case	No cost-based objective (LCOE/NPC) incorporated
[17] Zhang et al. – IAGWO	Improved Adaptive GWO, CEC benchmarks & engineering problems	Min. benchmark function value	Function-specific (up to 30+ dimensions)	Convergence accuracy vs. AVOA, COA, ENGWO, RGWO	Comparable/lower	Outperformed classical GWO and advanced modified algorithms	Not yet applied to HRES sizing	Needs HRES-specific case study
[18] IGWO for reactive power dispatch	Optimal reactive power dispatch, wind/solar, IEEE 30-bus	Min. active power loss/voltage deviation	Generator voltages, tap settings, and	Solution quality vs. classical	NR	Enhanced exploitation phase	Single standard test system	No storage/HRES sizing

Study	Application	Objective Function	Decision Variables	Benchmark Metrics	Comp. Time	Key Finding	Limitations	Research Gap
			reactive sources	GWO and other methods		outperformed classical GWO		dimension included

D. CASES WHERE OTHER ALGORITHMS OUTPERFORMED GWO, HYBRID-GWO, OR MODIFIED GWO

TABLE 4. Non-GWO Algorithms Outperforming GWO and Its Variants

Study	Application	Objective Function	Decision Variables	Benchmark Metrics	Comp. Time	Key Finding	Limitations / Why GWO Failed	Research Gap
[20] EL Marzougui et al. – CSRIME	HRES sizing, Dakhla, Morocco	Min. COE subject to reliability, REF targets	PV, wind, battery, diesel capacities	COE ($0.257/kWh), reliability (~95%), REF (~90%)	NR	Outperformed RIME, HS, COA, PSO, GWO	GWO's single-hierarchy search is entrapped in local optima under combined constraints	GWO/hybrid-GWO lacks a dual-exploration mechanism equivalent to RIME's
[21] Walrus Optimizer study	Techno-economic sizing, Enugu Ezike microgrid	Min. COE, NPC	PV, battery, diesel sizing	COE ($0.005081/kWh), NPC	NR	GWO/PSO oversized renewables, raising COE/NPC	GWO's exploitation bias converges to oversized, locally-optimal ratios	No adaptive-sizing correction mechanism in classical/hybrid GWO
[22] Mohapatra et al. – BKA	PV/WT/Battery HRES sizing, Odisha, India	Min. cost, max. reliability (multi-objective)	PV, WT, battery capacities	Convergence speed, accuracy vs. HHO, SCA, WSO, AOA, SO, GWO	GWO slower (relative)	GWO is characterised as slow, inaccurate, and prone to local-optimum entrapment	GWO lacks BKA's attack/migration diversification	No GWO variant explicitly designed for multi-objective HRES in comparison
[23] Thirunavukkarasu et al. – TDO	Off-grid HRES sizing, Kamrup district, Assam, India	Min. TAC subject to reliability index	PV, wind, battery, diesel sizes	TAC, convergence speed, solution stability	GWO/BWO slower	TDO outperformed COOT, GWO, and BWO on all three metrics	GWO underperforms once a reliability-index constraint is added	No GWO variant tested with reliability-index-aware modification

[24] Southwest Egypt HRES study	Stand-alone HRES sizing, multiple algorithms benchmarked	Min. system cost	PV, wind, hydro, battery sizes	Cost minimisation vs benchmarked set (cited WOA > GWO, WCA, SSA)	NR	DCCS outperformed the benchmark set; cited WOA outperformed GWO/WCA/SSA	GWO's fixed exploration-decay underperforms adaptive competitors	No chaotic-parameter GWO variant included
[25] Wang & Feng – MVO review	Control-engineering benchmark (non-HRES)	Min. control-objective function (case-specific)	Controller/plant parameters	Performance across 4 control-engineering cases	NR	MVO outperformed DE, PSO, GA, and GWO in all 4 cases	Evidence is non-HRES; shows GWO advantage, not domain-universal	HRES-specific MVO benchmarking is not yet available

Together with the mechanistic analysis in Section V, Tables 1–3 show that GWO-based methods, classical, hybridized, or modified, concentrate their advantages in lower-dimensional, single- or dual-objective, weakly constrained HRES problems (Table 1), with hybrid and modified forms progressively extending that advantage into more dynamic (Table 2) and higher-dimensional (Table 3) problem classes. Table 4 shows the corresponding limit of that compensation: once problems combine high dimensionality, multiple hard constraints, and multi-modality, algorithms with purpose-built diversification mechanisms not derived from GWO's leadership-hierarchy structure have outperformed even hybrid/modified GWO.

VII. DISCUSSION

The above evidence and analysis of the mechanisms suggest that the performance of algorithms used in the sizing of HRES does not have a fixed order but depends on the structure of the problem. GWO's principle of rapid convergence with little tuning of the parameters is real and reproducible, but is focused on a low-dimensional, less constrained end of the HRES problem spectrum shown in Table 1. It has a single-hierarchy, alpha/beta/delta-guided search architecture, and a deterministic exploration-decay schedule based on the number of iterations, both of which become ineffective as dimensionality, constraint density, and landscape multi-modality grow (Section V), which is its main reported disadvantage.

Both hybridization (Table 2) and internal modification (Table 3) increase the mechanistically distinct ways of addressing this weakness, and both produce measurable, mechanistically explicable improvements over the classical GWO baseline. The appearance in 2023-2026 of algorithms outperforming the GWOs and their variants in the most challenging problem instances (Table 4) is therefore a contradiction of the documented ability of GWO to correctly solve the problems, but a logical outcome of further pushing a method whose core was not structurally developed for the problems.

The differences in test systems, load profile, resource data, reliability target and the way of measuring and reporting “computational time” (often not reported, see the entries “NR” in Tables 1-4) make a direct comparison between different studies difficult. This highlights the ongoing requirement for a harmonised set of HRES benchmarking protocols with a common reporting minimum set of descriptors.

VIII. FUTURE RESEARCH DIRECTIONS

Based on the comparative and critical analysis, several directions for future research are suggested:

- Dynamic adaptation and self-tuning hybridization strategies that dynamically switch between GWO and complementary algorithms in real time based on

convergence diagnostics of the algorithms directly targeting the diversity-collapse mechanism identified in Section V-A.

- Variants of GWO that consider constraints; explicit feasible-region handling for multi-pockets that address the constraint-density failure mode identified in Section V-B.
- Benchmarking of GWO and its variations with the latest bio-inspired algorithms on common publicly available HRES sizing data, with the aim of achieving standardisation.
- Uncertainty-aware and stochastic HRES sizing combining GWO optimization and probabilistic load/resource forecasting.
- Multi-Objective and Many-Objective variants of hybrid/modified GWO (e.g., GWO-NSGA-III) for multi-objective optimization of cost, reliability, emissions and social acceptability.
- Future GWO-HRES studies to be conducted with computational time and hardware reported systematically.
- Real-world pilot validation of the GWO-optimised HRES sizing results: the majority of studies that have been reviewed are based on simulation and not field work.

IX. CONCLUSION

The present PRISMA-guided systematic review has revisited the comparative evidence available for the Grey Wolf Optimizer and its hybrid and modified types when applied to sizing of hybrid renewable energy systems, which includes 41 studies from an initial pool of 312 records identified via six databases and screened following an explicit four-stage selection process. The review explains the reason behind the success of GWO-based methods on lower-dimensional, weakly constrained, unimodal HRES problems (Table 1), and the gradual loss of their advantage as the dimensionality, constraint density, and multi-modality of the problems increase (Tables 2–4) by providing a mechanistic explanation based on the single-hierarchy search structure and deterministic exploration-decay schedule of GWO and its variants, which is supported by newer algorithms from 2023-2026 which outperform GWO and its variants specifically on the hardest, most constrained problem instances. The algorithm used for solving the HRES sizing problem, therefore, should be carefully selected based on the dimensionality, constraint structure, and multi-modality in each particular sizing problem and not on a general belief of the superiority of GWO.

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APPENDIX

NOMENCLATURE

ABBREVIATION	DESCRIPTION
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AGWO	Adaptive Grey Wolf Optimizer
BKA	Black-Winged Kite Algorithm
COE	Cost of Energy
CSRIME	Cuckoo Search–RIME hybrid algorithm
DG	Distributed Generation
DPSP	Deficiency of Power Supply Probability
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
HRES	Hybrid Renewable Energy System
IGWO	Improved Grey Wolf Optimizer
LCOE	Levelized Cost of Energy
LPSP	Loss of Power Supply Probability
MGWO	Modified Grey Wolf Optimizer
MVO	Multi-Verse Optimizer
NPC	Net Present Cost
NR	Not Reported
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PSO	Particle Swarm Optimization
REF	Renewable Energy Fraction
SA	Simulated Annealing
TAC	Total Annual Cost
TDO	Tasmanian Devil Optimization
WOA	Whale Optimization Algorithm