

Reinforcement Learning-Adaptive Hybrid Metaheuristic for Optimal Distributed Generation and Shunt Capacitor Placement with Embedded V2G Dispatch in Distribution Networks

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ABSTRACT

This paper benchmarks six metaheuristics—including a reinforcement-learning-adaptive Grasshopper–Grey Wolf optimiser (RL-GOA-GWO) with Q-learning-based adaptive operator selection—and a four-layer multi-layer perceptron (MLP) surrogate for joint placement of distributed generation (DG) and shunt capacitor (SC) banks with embedded rule-based vehicle-to-grid (V2G) dispatch. A six-objective weighted-sum formulation is evaluated on five systems (IEEE 33, 69, 123-bus balanced equivalent, MV Oberrhein 179, Custom 567-bus) under identical budgets (30 agents, 100 iterations, $n=5$ runs). The RL-adaptive advantage is topology-dependent: marginal on small radial feeders but producing a large effect on the rugged IEEE-123 landscape (mean improvement 6.8%, Cohen's $d = -1.12$, 95% confidence interval (CI) $[-2.43, 0.19]$). Particle Swarm Optimization (PSO) is competitive throughout, consistent with No-Free-Lunch theory. Friedman rank tests and Cohen's d with 95% CIs provide exploratory validation; confirmatory studies with $n \geq 25$ are recommended.

1. Introduction

The rapid adoption of electric vehicles (EVs) alongside distributed renewable energy sources (RES) is transforming distribution networks from unidirectional delivery systems into complex, bidirectional power systems characterised by voltage variations, uncertain peak loads, and reverse power flows Panda et al. [21]; Jin et al. [9]; Zabihi and Parhamfar [28]. Coordinated placement of distributed generators (DGs), shunt capacitors (SCs), and EV infrastructure is essential for mitigating these issues—reducing energy losses, improving voltage stability, and lowering infrastructure costs Kumar and Farhan [15]; Wang et al. [27]; Selim et al. [24]. Vehicle-to-grid (V2G) scheduling can further flatten load profiles and reduce feeder loading Meiers and Frey [16]; Bouhouras et al. [2].

Optimising these networks under high EV and renewable penetration is challenging due to uncertain generation profiles, stochastic consumer behaviour, and intermittent solar/wind resources Jodeiri-Seyedian et al. [10]. Risk-aware coordination between transmission and distribution operators has emerged as critical for large-scale renewable and EV integration [29]. Conventional metaheuristics—the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Grey Wolf Optimizer (GWO), and Grasshopper Optimization Algorithm (GOA)—suffer from premature convergence in such high-dimensional,

multi-objective problems Ahmadi Kamarposhti et al. [1]; Jayabarathi et al. [8]. Recent hybrid methods—combining exploration strength of one algorithm with exploitation capability of another—have shown improved convergence Kumar et al. [13]; Singh et al. [25]. The Hybrid GOA-GWO, which merges grasshopper swarm dynamics with the GWO leadership hierarchy, has demonstrated reduced local-optima trapping Gurumoorthi et al. [7]; Byeon et al. [3]. In parallel, deep learning surrogates trained on sensor/AMI data have emerged for accelerating load-flow approximations Kilwein et al. [12]; Mohammadi et al. [20], though limitations in interpretability and generalisation persist Mersha et al. [17]. Physics-informed surrogates with graph neural network (GNN) message-passing have recently been proposed to improve topology-aware approximation [30]. Taken together, these trends expose a compounding gap: static or hand-tuned hybrid metaheuristics cannot adapt their exploration–exploitation balance to the run-time difficulty of a specific network topology, rule-based EV/V2G scheduling is rarely embedded jointly with DG/SC placement, and DL surrogates are seldom stress-tested across systems of markedly different scale. This motivates a framework that couples run-time-adaptive operator selection with joint DG/SC/V2G optimisation and an honestly-evaluated DL surrogate, benchmarked consistently across systems ranging from 33 to 567 buses.

1.1 Research Gap and Contributions

Table 1 benchmarks recent studies against seven dimensions. No existing work simultaneously addresses all dimensions.

This paper presents a benchmarking framework for joint DG/SC placement with embedded rule-based V2G dispatch evaluation. The contributions are:

1. A unified multi-objective framework jointly optimising DG/SC siting and sizing with V2G dispatch, LSF/VSI-based seeding, and lifecycle economics, validated on five systems (33–567 buses) with algorithm–topology mapping.
2. An RL-adaptive GOA–GWO instantiating adaptive operator selection (AOS) Fialho et al. [6]; Da Costa et al. [4] via tabular Q-learning over 60 states and four operators. No classical AOS baselines are included (Sec. 5).
3. A four-layer MLP surrogate evaluated as a preliminary feasibility study (R^2 : 0.275–0.931 across systems; Sec. 4.7).
4. Exploratory statistical benchmarking (n=5) using Friedman tests, Holm–Bonferroni-corrected Wilcoxon tests, and Cohen’s d with 95% CIs.

The remainder of the paper is organised as follows: Sec. 2 presents the problem formulation; Sec. 3 introduces the solution methodology; Sec. 4 reports numerical results; Sec. 5 provides a critical discussion; and Sec. 6 concludes the paper.

2. Problem Formulation

2.1 Joint DG and SC Sizing & Placement

The planning task selects bus locations and ratings for $N_{DG} = N_{SC} = 3$ DG units and SC banks. The decision vector is

$$x = [b_1^{DG}, S_1^{DG}, \dots, b_3^{DG}, S_3^{DG}, b_1^{SC}, Q_1^{SC}, \dots, b_3^{SC}, Q_3^{SC}]^T \quad (1)$$

Where $b \in \{1, \dots, N_{bus}\}$ is an integer bus index, S_i^{DG} is DG rating (MW), and Q_j^{SC} is SC rating (MVar). The V2G schedule is not encoded in x ; for each candidate solution the rule-based V2G dispatch (Sec. 2.3) is evaluated within the fitness function as a dependent sub-problem.

2.2 Multi-objective Fitness Function

The formulation minimizes a weighted sum of six objectives:

$$\begin{aligned} \min_{x \in X} F(x) = & w_1 f_1 + w_2 f_2 + w_3 f_3 \\ & + w_4 f_4 + w_5 f_5 + w_6 f_6 \\ & \sum_{i=1}^6 w_i = 1, \quad w_i \geq 0 \end{aligned} \quad (2)$$

where the sub-objectives (all normalized to [0,1], smaller preferred) are: $f_1 = P_{loss}/P_{loss,0}$ (loss), $f_2 =$

$\sum_i |V_i - 1|/\Delta V_0$ (voltage deviation), $f_3 = C_{inv}/C_{base}$ (cost), $f_4 = 1 - P_{V2G}/P_{V2G}^{max}$ (V2G deficit), $f_5 = 1 - PF$ (power-factor gap), and $f_6 = 1 - P_{avg}/P_{peak}$ (flatness deficit). The baseline weight vector is $\mathbf{w} = [1/6, \dots, 1/6]$; a sensitivity analysis over four alternative scenarios is in Sec. 4.7.

Limitation of weighted sum aggregation. The weighted-sum approach collapses from the six-dimensional Pareto front to a single point per weight vector, preventing identification of knee-point solutions. We adopt this formulation for computational tractability; evaluating a Pareto-based algorithm (e.g., NSGA-III, the Non-dominated Sorting Genetic Algorithm III) with six objectives and physics-based fitness on five systems would be prohibitively expensive. A weight-sensitivity analysis (Sec. 4.7) partially mitigates this limitation.

Constraints.

All power quantities below are expressed in MW (real power) or MVar (reactive power) and all voltages in per unit (p.u.):

$$0 \leq S_i^{DG} \leq S_{max}^{DG}, \quad 0 \leq Q_j^{SC} \leq Q_{max}^{SC} \quad (3a)$$

$$\sum_{i=1}^3 S_i^{DG} \leq 0.80 P_{peak} \quad (3b)$$

$$0.95 \leq V_i \leq 1.05 \text{ p.u.} \quad (3c)$$

$$\text{AC power flow balance at every bus} \quad (3d)$$

Per unit caps are 2MW/1.5MVar (33/69-bus), 5MW/3MVar (123/179-bus), and 30MW/15MVar (Custom-567).

Cost model.

$$\begin{aligned} C_{inv}(x) = & \sum_{i=1}^3 \left[1.2 \frac{\text{M\$}}{\text{MW}} \times k_{bi}^{DG \text{ zone}} \right] S_i^{DG} \\ & + \sum_{j=1}^3 (53 \text{ k\$}) Q_j^{SC} \end{aligned} \quad (4)$$

where 1.2M\$/MW is a technology-agnostic DG benchmark (utility-scale solar PV ≈ 1.0 , gas turbine ≈ 1.5 M\$/MW). DGs are modelled as dispatchable units operating at unity power factor; $k^{zone}=1.5$ (urban), 1.2 (suburban), 1.1 (peri-urban), 1.0 (rural).

2.3 EV Charging & V2G Dispatch Model

The nodal EV load follows a three-phase deterministic profile: constant-current ramp (0–4h), exponential decay (4–5h), and idle ($t > 5$ h) at $p^{max}=11$ kW per vehicle. For every EV in the real power set point is

$$p_n(t) = \begin{cases} p^{max}, & t \in O_{charge} \\ -\eta p^{max}, & t \in O_{discharge}, \eta \leq 0.7 \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

with the energy-neutrality constraint $\int_0^{24h} p_n(t) dt = 0$. Charging/discharging set-points are determined by solving

$$\text{minimise } \max_{\{p_n(t)\}} |P_{net}(t) - P_{avg}| \quad \text{s.t. (5), } \forall n \quad (6)$$

Table 1

Comparative Overview of recent DG/SC/EV optimization studies vs. the proposed framework

Reference	Year	Method	Test System	DG+ SC	VE/ V2G	DL Sur.	Cost	Stat.
Wang et al. [27]	2024	Competitive Alg.	33 bus	✓	✓	×	Simplified	×
Kumar & Farhan [15]	2025	PSO	33, 69 bus	✓	✓	×	NPV	×
Selim et al. [24]	2023	Hybrid GA-PSO	33, 69 bus	✓	×	×	Linear	×
Jayabarathi et al. [8]	2024	Plant Growth	33, 69 bus	✓	×	×	Simplified	×
Gurumoorthi et al. [7]	2024	Hybrid GWO-GOA	33 bus	✓	×	×	Linear	×
Kilwein et al. [12]	2023	NN Surrogate	Various	×	×	✓	×	×
Sahay et al. [22]	2025	Enh. AHB	33 bus	✓	✓	×	Multi-obj.	×
Singh et al. [25]	2025	Hybrid DE-GWO	33, 69 bus	✓	×	×	Simplified	×
This Work	2026	RL-GOA-GWO+DL	33-567	✓	✓	✓	Lifecycle	(n=5)

Off-peak charging (0–6h) and peak-period discharge (17–21h) maximize the load-flattening index $L_{\text{flat}} = P_{\text{avg}}/P_{\text{peak}}$ by shifting—not adding—demand. Fig. 1 illustrates the schedule.

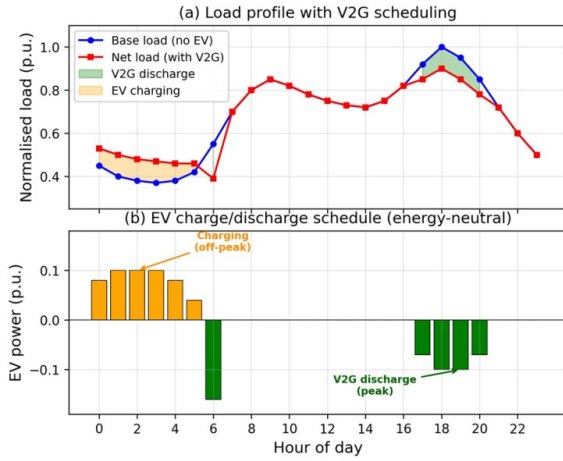


Fig. 1. Rule-based V2G schedule: (a) base vs. net load profile showing peak shaving, and (b) hourly EV charge/discharge set-points.

2.4 LSF/VSI Pre-screening

Candidate buses are pre-screened using Loss Sensitivity Factor (LSF) and Voltage Stability Index (VSI):

$$LSF_j \approx \frac{2r_{ij}P_j}{|V_j|^2},$$

$$VSI_j = |V_i|^4 - 4(P_jX_{ij} - Q_jR_{ij})^2 - 4(P_jR_{ij} - Q_jX_{ij})|V_i|^2 \quad (7)$$

The top K buses from each index are merged into a candidate pool. Approximately 30% of the initial population is seeded from this pool (DG from LSF, SC from VSI rankings); the remaining 70% is random.

2.5 Expanded Economic Model

Beyond capital costs, the lifecycle analysis incorporates three benefit streams over $T=20$ yr: capacity deferral ($B_{\text{defer}} = 0.30 \sum S_i^{\text{DG}} \times 100\$/\text{kW}\cdot\text{yr} \times T$), carbon credits ($B_{\text{carbon}} = 0.5 \text{ tCO}_2/\text{MWh} \times 0.25 \times 8760 \times \sum S_i^{\text{DG}} \times C_{\text{CO}_2}$, $C_{\text{CO}_2}=50\$/\text{tCO}_2$), and reliability benefit ($B_{\text{reliab}} =$

$(10/60)\text{h} \times P_{\text{peak}} \times 10\$/\text{kWh} \times T$). Note: B_{reliab} is an upper-bound estimate assuming location-independent 10-minute SAIDI reduction, uniform interruption cost, and full DG availability during outages; since it constitutes 15–40% of total benefits on larger systems, the economic conclusions are sensitive to this assumption. The expanded net present value (NPV) and benefit cost ratio (BCR) are

$$NPV_{\text{exp}} = (B_{\text{loss}} + B_{\text{defer}} + B_{\text{carbon}} + B_{\text{reliab}}) - C_{\text{total}} \quad (8)$$

$$BCR_{\text{exp}} = \frac{B_{\text{loss}} + B_{\text{defer}} + B_{\text{carbon}} + B_{\text{reliab}}}{C_{\text{total}}} \quad (9)$$

3. Proposed Solution Methodology

Implementation and computational platform: all algorithms are implemented in Python 3.13 with pandapower v3.3.2 for AC power flow evaluation, NumPy 1.26 for numerical routines and TensorFlow 2.15 for the DL surrogate (Sec. 3.1). All experiments were executed on a single desktop work station (Intel Core i7-12700 CPU, 16 GB RAM, no GPU acceleration); the wall-clock times reported in Sec. 4.4 are specific to this hardware and are not directly transferable to the other platforms.

3.1 DL-Based Surrogate Model

We evaluate the DL surrogate as a preliminary feasibility study for accelerating fitness evaluation rather than as a production-ready substitute for physics based verification in all cases (Sec. 4.7). A four-layer MLP ([128,256,256,128], rectified linear unit (ReLU) activations, early stopping) maps the 12-dimensional decision vector (1) to a scalar fitness prediction. Training uses 1000 Latin-hypercube samples per system (85%/15% split, Adam optimizer, 500-epoch budget). Inference latency ($<0.3\text{s}$) enables a two-stage pipeline: (1) train the surrogate on physics-based evaluations, then (2) screen 800 fresh candidates, retaining the top 50 for *physics-based* verification—hence the DL pre-screening pipeline’s final fitness reflects physics evaluation, not DL prediction. Per-system test-set accuracy: $R^2=0.735$

(IEEE-33), 0.648 (IEEE-69), 0.812 (MV-Oberrhein), 0.275 (IEEE-123), 0.931 (Custom-567), with 5.9–6.6× speedup; full mean absolute error (MAE) and training curves are in the Supplementary Material (S6). Fig. 2 depicts the architecture.

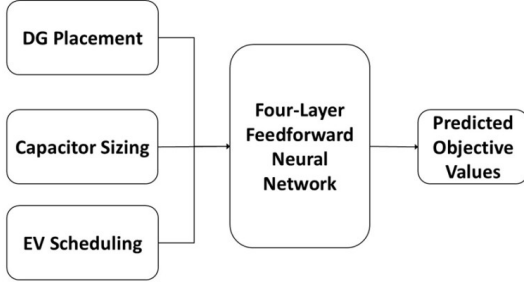


Fig. 2. Deep learning surrogate model architecture.

3.2 Optimization Frameworks

Six algorithmic engines are evaluated under identical budgets ($N=30$ agents, $T=100$ iterations): three GOA-based variants (GOA, Fuzzy-GOA, Hybrid GOA–GWO), two state-of-the-art (SOTA) comparators, (Particle Swarm Optimization (PSO) Kennedy et al, the Whale Optimization Algorithm (WOA) Mirjalili and Lewis (2016)), and the proposed RL-GOA-GWO. Fig. 3 shows the shared pipeline.

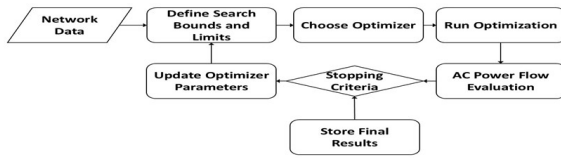


Fig. 3. Optimization framework flow-chart.

Standard GOA.

The GOA component follows the grasshopper swarming formulation of Saremi et al. Saremi et al. (2017), where inter-agent social forces governed by $s(r) = fe^{-r/l} - e^{-r}$ ($f=0.5$, $l=1.5$) attract or repel agents. Population of 30 agents, comfort zone coefficient $c(t) = 1 - t/T_{\max}$, integer bus indices rounded after each update.

Fuzzy-GOA.

A Mamdani fuzzy controller with three inputs (progress, improvement, diversity) outputs $\Delta c \in [-0.2, +0.2]$ to adapt the comfort zone coefficient. The 27-rule base is in the Supplementary Material.

GWO Component.

The GWO component follows the standard grey-wolf hierarchy Mirjalili et al. (2014): the convergence parameter $a = 2(1 - t/T)$ decreases linearly. Each agent updates towards the weighted average of the three best agents (α, β, δ): $X(t+1) = \frac{1}{3}(X_\alpha + X_\beta + X_\delta)$, with stochastic perturbations controlled by $A = 2ar - a$ and $C = 2r$.

Hybrid GOA–GWO.

A three-phase schedule shifts from GOA-dominated exploration to GWO-dominated exploitation. The blended

update is

$$X_i(t+1) = X_i(t) + \alpha_{GOA}(\emptyset) \cdot \Delta_{GOA} + \alpha_{GWO}(\emptyset) \cdot \Delta_{GWO}$$

Table 2

Hybrid GOA-GWO parameters and phase schedule

Parameter	Value	Description
N_{agents}	30	Population Size
$T_{\max}$	100	Maximum Iterations
a	$2 \rightarrow 0$	GWO Convergence parameter
C	$1 \rightarrow 0$	GOA control coefficient
Phase	GOA Share	GWO Share
0–40%	70%	30%
40–70%	50%	50%
70–100%	30%	70%

Algorithm 1 RL-Adaptive GOA-GWO with Lévy Flight
Require: Population $\mathbf{X}$, bounds, T iterations, Q-table $\mathbf{Q}$ (zero-init)

- 1: Initialize $\varepsilon \leftarrow 1.0$, best solution $\mathbf{x}^*$
- 2: **for** $t = 1, 2, \dots, T$ **do**
- 3: Observe state $s_t \leftarrow (\text{progress}(t/T), \text{stagnation}, \text{diversity})$
- 4: Select action $a_t \leftarrow \begin{cases} \text{random} & \text{w.p. } \varepsilon \\ \arg \max_a Q(s_t, a) & \text{otherwise} \end{cases}$
- 5: **if** $a_t = \text{GOA-DOM}$ **then**
- 6: Apply GOA update to all agents
- 7: **else if** $a_t = \text{GWO-DOM}$ **then**
- 8: Apply GWO update to all agents
- 9: **else if** $a_t = \text{LévyFlight}$ **then**
- 10: Apply Lévy steps: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \alpha_0 \mathbf{L}$
- 11: **else**
- 12: Apply arithmetic crossover between random pairs
- 13: **end if**
- 14: Evaluate fitness, update best $\mathbf{x}^*$
- 15: $r_t \leftarrow \max(0, f_{\text{best}}(t-1) - f_{\text{best}}(t)) / f_{\text{best}}(t-1)$
- 16: $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)]$
- 17: Decay $\varepsilon \leftarrow \max(\varepsilon_{\min}, \varepsilon_0 - t(\varepsilon_0 - \varepsilon_{\min})/T)$
- 18: **end for**
- 19: **return** $\mathbf{x}^*$, Q-table, action history

where Δ_{GOA} is the GOA perturbation step and $\Delta_{GWO} = \frac{1}{3}(X_\alpha + X_\beta + X_\delta) - X_i$ is the GWO leadership hierarchy displacement. Weights $(\alpha_{GOA}, \alpha_{GWO})$ follow $(0.7, 0.3) \rightarrow (0.5, 0.5) \rightarrow (0.3, 0.7)$ at progress thresholds $\{0.4, 0.7\}$ (Table 2).

PSO Kennedy and Eberhart (1995) and WOA Mirjalili and Lewis (2016).

PSO uses inertia weight $w:0.9 \rightarrow 0.4$, $c_1 = c_2 = 2.0$. WOA emulates the bubble-net hunting strategy of hump-back whales with $a:2 \rightarrow 0$, $b=1$. Full update equations are in the Supplementary Material.

Proposed: RL-Adaptive GOA-GWO with Lévy Flight.

A fixed or hand-tuned exploration–exploitation schedule assumes that the same GOA/GWO weighting is appropriate at a given iteration regardless of how the search is actually progressing on that specific network. This assumption breaks down whenever the fitness landscape is rugged: on a topologically complex feeder with many local optima (e.g. IEEE-123, Sec. 4.2), switching to GWO-dominated exploitation at iteration 40 (Table 2) may prematurely commit the population to a local optimum, whereas the identical switch is well timed on a smoother landscape. Because the schedule is a function of iteration index alone, it cannot detect stagnation (repeated iterations without improvement) or loss of population diversity, both of which signal that continued exploitation is unproductive and that a more exploratory operator—or an escape mechanism such as Lévy flight—is needed instead.

We therefore propose an RL-Adaptive GOA-GWO that replaces the fixed schedule with a tabular Q-learning agent—an instance of adaptive operator selection (AOS) Fialho et al. [6]; Da Costa et al. [4]—whose state explicitly encodes progress, stagnation, and diversity (below) so that the operator choice responds to how the search is actually unfolding rather than to elapsed iterations alone. When stagnation is high and diversity is low, the learned policy is expected to favour Lévy flight or crossover (diversification); when fitness is still improving under exploitation, it is expected to favour GWO-dominant updates. Classical AOS decomposes operator selection into credit assignment and a selection rule; our Q-learning formulation unifies both: the reward signal provides credit assignment while the ε -greedy policy over Q-values serves as the selection rule. Compared to multi-armed bandit AOS, the Q-learning agent additionally conditions its selection on a discrete optimization *state*, enabling context-dependent preferences.

The agent observes s_t =(progress, stagnation, diversity) with $5 \times 4 \times 3 = 60$ states and selects among four actions: (1) GOA-dominant, (2) GWO-dominant, (3) Lévy flight ($\beta=1.5$, Mantegna’s algorithm) for heavy tailed jumps escaping local optima, and (4) arithmetic crossover ($\mathbf{x}_{\text{child}} = \alpha \mathbf{x}_a + (1-\alpha) \mathbf{x}_b$, $\alpha \sim U(0, 1)$) for genetic diversity. The reward is $r_t = \max \left(0, \frac{f_{\text{best}}^{(t-1)} - f_{\text{best}}^{(t)}}{f_{\text{best}}^{(t-1)}} \right)$ (normalized improvement). Q-learning uses $\alpha=0.10$, $\gamma=0.90$, and ε -greedy action selection decaying from 1.0 to 0.05. Algorithm 1 formalizes the procedure.

4. Results

All experiments use pandapower v3.3.2 Thurner et al. (2018) with Python 3.13. Statistical validation uses $n=5$ independent runs per algorithm with shared seeds for paired comparisons.

Five distribution systems are used, where P_D denotes total active-power demand: (i) IEEE 33-bus ($P_D=3.72\text{MW}$, 0.203MW loss), (ii) IEEE 69-bus ($P_D=3.80\text{MW}$, 0.355MW), (iii) MV-Obererrhein 179-bus (pandapower Thurner et al. (2018) synthetic network; $P_D=61.86\text{MW}$, 1.018MW, $V_{\min}=0.976\text{p.u.}$), (iv) IEEE 123-bus balanced equivalent ($P_D=3.89\text{MW}$, 0.218MW)—converted from the three-phase unbalanced IEEE 123 feeder by averaging per-phase impedances and aggregating per-phase loads; inter-phase coupling is removed, and (v) Custom 567-bus ($P_D=42.66\text{MW}$, 0.587MW). Table 3 summarizes topological characteristics.

Viol. = buses with $V < 0.95\text{p.u.}$ in the base case. P_D = total active demand; $P_{\text{loss},0}$ in MW.

Bolding convention. Bold values denote the best-performing entry per system.

4.1 Cross-System Performance Comparison

Table 4 consolidates best-run (seed 0) fitness and loss reduction. Table 5 presents optimized placements.

Single DL run (physics-verified pipeline); repeated-run statistics unavailable. DL standalone omitted on IEEE-123 ($R=0.275$) & Custom-567.

Custom-567: SC at bus 0 (substation slack bus) reflects absence of explicit substation-exclusion constraint.

Custom-567: all DGs at minimum size (0.1MW), reflecting severe capacity constraint (3 DGs in 567 buses).

4.2 Case Study Results

IEEE 33-Bus (Case 1).

RL-GOA-GWO achieves fitness 0.376 (mean 0.378 ± 0.001), comparable to the Hybrid’s mean of 0.376; ($d=+1.25$ in favor of the Hybrid). The Hybrid and RL-GOA-GWO outperform all other algorithms in composite fitness, with loss reductions of 79.9–87.2% across all metaheuristics. Literature comparisons: Selim et al. [24] 71.0%, Jayabarathi et al. [8] 69.8%, Gurumoorthi et al. [7] 65.4%. This work achieves 83–87% with three DG units and three SC banks (3+3) DG+SC under a six-objective composite—loss reduction is a by-product, not the primary target—making the comparison structurally asymmetric.

IEEE 69-Bus (Case 2).

Higher loss reductions (87–96%) reflect higher base losses. PSO achieves the best single-run fitness (0.393) and loss reduction (95.8%), but exhibits high variance ($\sigma=0.048$), whereas RL-GOA-GWO has the smallest standard deviation (0.002).

MV-Obererrhein 179-Bus (Case 3).

Loss reductions are modest (3.8–19.2%) because the base-case voltage is well-regulated ($V_{\min}=0.976$).

Custom-567: SC at bus 0 (substation slack bus) reflects absence of explicit substation-exclusion constraint.

Custom-567: all DGs at minimum size (0.1MW), reflecting severe capacity constraint (3 DGs in 567 buses).

Table 3

Topology descriptors for the five benchmark systems

System	Buses	Lines	Loads	Vmin,0	Viol.	P_D (MW)	$P_{loss,0}$
IEEE-33	33	32	32	0.904	16	3.72	0.203
IEEE-69	69	68	48	0.866	27	3.80	0.355
MV-Oberrhein	179	175	115	0.976	0	61.86	1.018
IEEE-123(eq)	123	122	91	0.907	38	3.89	0.218
Custom-567	567	565	371	0.910	42	42.66	0.587

Table 4

Cross-system best-run performance (seed 0). Bold = lowest fitness per system among meta-heuristics. LR = loss reduction.

Algorithm	IEEE-33		IEEE-69		MV-Ober.		IEEE-123(eq)		Custom-567	
	Fit.	LR%	Fit.	LR%	Fit.	LR%	Fit.	LR%	Fit.	LR%
Standard GOA	0.393	83.5	0.422	87.2	0.731	15.0	0.589	38.9	0.644	2.4
Fuzzy GOA	0.387	83.2	0.421	90.6	0.829	5.0	0.596	38.5	0.643	2.9
Hybrid GOA-GWO	0.376	87.2	0.408	92.6	0.533	4.9	0.421	80.2	0.638	2.3
RL-GOA-GWO	0.376	83.2	0.394	94.7	0.528	3.8	0.354	84.2	0.630	1.7
PSO	0.378	85.3	0.393	95.8	0.782	12.5	0.379	72.5	0.628	1.5
WOA	0.388	79.9	0.448	78.9	0.528	4.1	0.363	80.5	0.631	1.5
DL Pre-scr.	0.416	72.6	0.405	89.1	0.529	3.8	0.354	84.2	0.628	1.6

Table 5

Best-run optimised DG/SC siting and sizing (best metaheuristic per system)

System	Best Algo	DG: Bus (MW)			SC: Bus (MVar)			ΣDG	ΣSC
IEEE-33	Hybrid (tied)	26(0.52)	32(0.74)	14(0.75)	8(0.71)	29(1.03)	23(0.65)	2.00	2.39
IEEE-69	RL-GOA-GWO	59(0.27)	60(1.49)	21(0.52)	60(1.43)	49(0.83)	19(0.50)	2.28	2.76
MV-Ober.	RL-GOA-GWO	155(0.15)	141(0.10)	116(0.10)	58(0.10)	224(0.48)	51(1.46)	0.36	2.04
IEEE-123(eq)	RL-GOA-GWO	35(0.40)	85(0.41)	100(1.30)	16(0.18)	30(0.35)	15(1.07)	2.11	1.59
Custom-567	RL-GOA-GWO	451(0.10)	463(0.10)	443(0.10)	415(0.10)	0(3.32)	277(0.10)	0.30	3.52

RL-GOA-GWO and WOA tie at 0.528 composite fitness. The multi-objective trade-off structure explains this: algorithms investing minimal DG capacity (0.36MW) achieve low-cost sub-objectives, more than compensating for high normalized loss.

IEEE 123-Bus (Case 4).

This system reveals the most dramatic inter-algorithm differentiation. RL-GOA-GWO achieves mean fitness 0.354 ± 0.003 , outperforming the Hybrid (0.380 ± 0.033 , $d = -1.12$, large effect). GOA and Fuzzy-GOA appear trapped in local optima (fitness 0.589–0.596), suggesting static exploration schedules are insufficient for this topology. Note: the balanced-equivalent simplification removes inter-phase coupling; results should not be directly compared to three-phase studies.

Custom 567-Bus (Case 5).

All algorithms converge to a narrow fitness band (0.628–0.644) with negligible loss reductions (1.5–2.9%). With only 3 DGs for 567 buses the optimizer is capacity-starved: all DGs settle at minimum rating (0.10MW) and one SC is placed at the slack bus due to the absence of a substation-exclusion constraint. In practice this location is not a meaningful reactive-support target: the

slack/substation bus voltage is already held fixed by the upstream transformer's on-load tap changer, so a capacitor sited there provides negligible downstream voltage benefit; the optimiser is exploiting an incomplete constraint set rather than identifying a genuine planning recommendation, and real deployments should explicitly exclude the substation bus from the candidate pool (Sec. 5). This system therefore serves as a scalability stress test rather than a planning case; its primary value is confirming sub-linear runtime scaling (Table 7).

4.3 Statistical Validation

Each algorithm was run $n=5$ times with shared seeds. Table 6 consolidates the repeated-run statistics.

Friedman Rank Tests.

Friedman tests yield significant rank differences on all five systems: IEEE-33 ($\chi^2=17.0$, $p=0.0045$), IEEE-69 ($\chi^2=15.97$, $p=0.0069$), MV-Oberrhein ($\chi^2=22.83$, $p=3.64 \times 10^{-4}$), IEEE-123 ($\chi^2=21.8$, $p=5.71 \times 10^{-4}$), and Custom-567 ($\chi^2=20.54$, $p=9.88 \times 10^{-4}$).

Effect Sizes

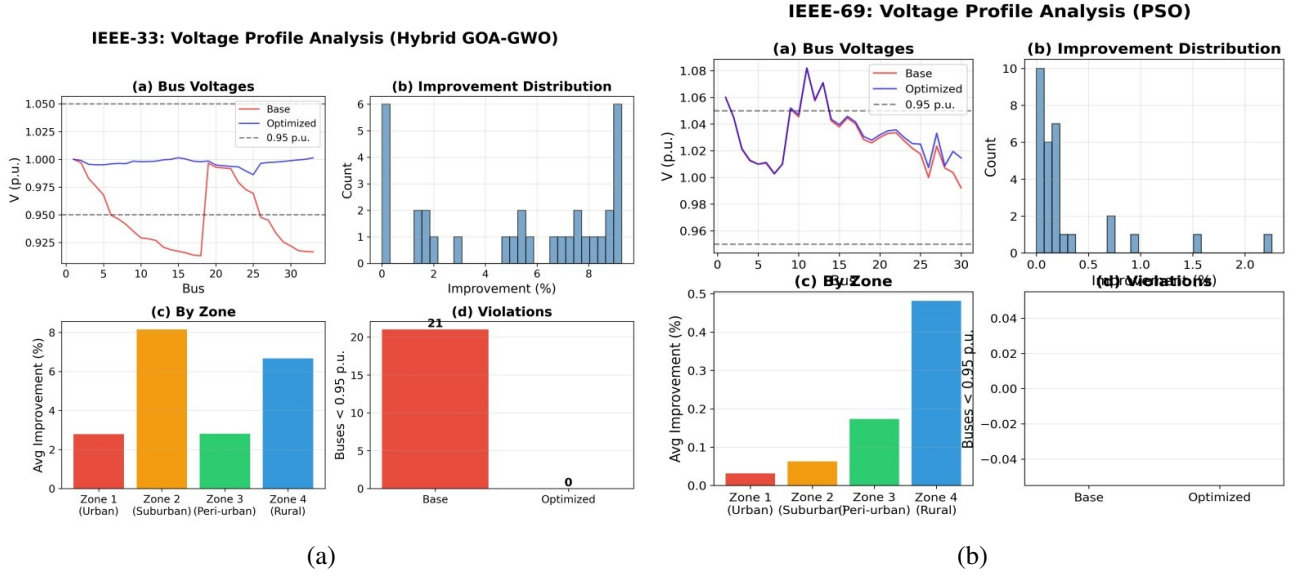


Fig. 4. Bus voltage profiles: base case vs. RL-GOA-GWO optimized placement

Cohen's d quantifies practical significance: $d = (\bar{F}_A - \bar{F}_B) / s_{\text{pooled}}$, where $s_{\text{pooled}} = \sqrt{(s_A^2 + s_B^2) / 2}$; $|d| < 0.2$ is negligible, $0.2 \leq |d| < 0.5$ small, $0.5 \leq |d| < 0.8$ medium, and $|d| \geq 0.8$ large. With $n=5$, the minimum Wilcoxon p -value is 0.0625, precluding pairwise significance at $\alpha=0.05$. Cohen's d therefore serves as the primary metric: on IEEE-123, all RL-GOA-GWO pairwise comparisons show large effects ($|d| > 1.0$), with the RL vs. Hybrid comparison yielding $d = -1.12$ (CI $[-2.43, 0.19]$, narrowly including zero). Several CIs include zero (marked with * in the Supplementary Material), indicating effect *direction* is not confirmed at 95% confidence due to small sample size. Detailed Holm-Bonferroni tables are provided in the Supplementary Material.

4.4 Convergence and Scalability

RL-GOA-GWO converges in 127s (about 4 minutes) on IEEE-123 (Table 7) while GOA and Fuzzy-GOA stagnate at suboptimal fitness (Fig. 5(b)), as the RL agent steers the population towards feasible regions, reducing Newton-Raphson re-initialization overhead. Per-bus time generally decreases with system size (3.82s/bus on IEEE-33 to 0.45s/bus on Custom-567) due to fixed-overhead amortization; MV-Oberrhein's higher per bus time (2.45s/bus) reflects its denser meshed topology (175 lines, 115 loads) and slower power-flow convergence.

4.5 Ablation Study

Table 8 compares the three-phase schedule against three alternatives on IEEE-33. All variants converge to identical fitness (0.376 ± 0.001), confirming that the small search space saturates easily. The RL mechanism's value emerges on larger systems: on IEEE-123, RL-GOA-GWO achieves mean fitness 0.354 ± 0.003 vs. the

Hybrid's 0.380 ± 0.033 —a 6.8% mean improvement ($d = -1.12$; Table 6)—suggesting the Q-learning agent's state-conditional operator selection pays off when the landscape contains multiple local optima.

Why the schedule ablation is restricted to IEEE-33.

The four-schedule sweep (Three-Phase, Fixed-50, Random, Linear, plus the full RL agent) was executed only on IEEE-33 for computational tractability: repeating four schedules across five seeds and 100 iterations on all five test systems would roughly quintuple the compute budget described in Sec. 3. As an indirect probe of whether schedule-variant sensitivity itself scales with topology, note that the Hybrid GOA-GWO is the fixed three-phase schedule, evaluated at full scale on every system (Table 6): on IEEE-33 it is statistically indistinguishable from RL-GOA-GWO ($d = +1.25$; Sec. 4.2), mirroring the near-identical schedule variants in Table 8, whereas on IEEE-123 the same fixed-schedule Hybrid trails RL-GOA-GWO by 6.8% ($d = -1.12$). This parallel is suggestive, not confirmatory, that schedule-variant sensitivity grows with landscape ruggedness; a full four-schedule ablation on IEEE-123 and MV-Oberrhein is left for future work.

4.6 Economic Analysis

Table 9 presents the lifecycle cost breakdown (20-year, $r=5\%$), including the internal rate of return (IRR).

Economic viability is scale-dependent: IEEE-33 and IEEE-123 yield negative NPV, while MV-Oberrhein provides the strongest returns (BCR=2.29, IRR=17.7%) driven by reliability benefits. DG economics at scale are dominated by reliability and capacity-deferral credits rather than loss of savings. Discount-rate sensitivity ($r=3-8\%$) is reported in the Supplementary Material (S7).

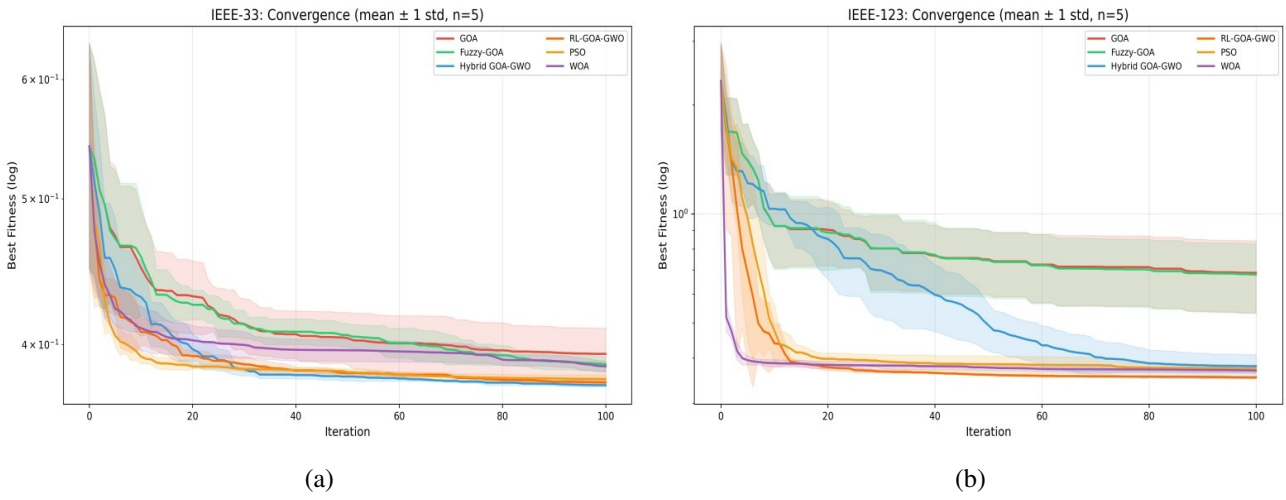


Fig. 5. Convergence comparison. On IEEE-123 (b), RL-GOA-GWO converges rapidly while GOA/Fuzzy-GOA stagnate.

Table 6

Statistical Summary over $n=5$ runs. Best mean per system in bold.

Algorithm	Mean $\pm$ Std	Best	Worst
IEEE-33			
GOA	.394 $\pm$.18	.379	.421
Fuzzy GOA	.388 $\pm$.005	.382	.394
Hybrid GOA-GWO	.376 $\pm$.001	.374	.377
RL-GOA-GWO	.378 $\pm$.001	.376	.379
PSO	.380 $\pm$.003	.375	.382
WOA	.387 $\pm$.004	.382	.390
IEEE-69			
GOA	.424 $\pm$.13	.405	.437
Fuzzy GOA	.427 $\pm$.16	.407	.446
Hybrid GOA-GWO	.396 $\pm$.003	.393	.400
RL-GOA-GWO	.397 $\pm$.002	.395	.400
PSO	.419 $\pm$.48	.395	.505
WOA	.412 $\pm$.019	.398	.446
MV-Ober.			
GOA	.657 $\pm$.47	.594	.704
Fuzzy GOA	.628 $\pm$.048	.585	.707
Hybrid GOA-GWO	.532 $\pm$.001	.530	.533
RL-GOA-GWO	.528 $\pm$.001	.526	.530
PSO	.538 $\pm$.011	.532	.558
WOA	.535 $\pm$.004	.529	.538
IEEE-123(eq)			
GOA	.687 $\pm$.175	.519	.870
Fuzzy GOA	.680 $\pm$.165	.509	.865
Hybrid GOA-GWO	.380 $\pm$.033	.360	.437
RL-GOA-GWO	.354 $\pm$.003	.350	.356
PSO	.374 $\pm$.011	.363	.386
WOA	.369 $\pm$.007	.362	.379
Custom-567			
GOA	.642 $\pm$.03	.638	.645
Fuzzy GOA	.641 $\pm$.002	.639	.644
Hybrid GOA-GWO	.642 $\pm$.002	.638	.644
RL-GOA-GWO	.629 $\pm$.001	.628	.631
PSO	.629 $\pm$.001	.628	.631
WOA	.629 $\pm$.001	.628	.631

4.7 Supplementary Analysis

Weight sensitivity analysis (four scenarios), EV penetration robustness (10–30%), DL surrogate feasibility metrics, MV-Oberrhein sub-objective decomposition, Holm–Bonferroni corrected pairwise comparisons, RL action distribution analysis, and Q-table heatmaps are provided in the Supplementary Material. Key findings: Weight sensitivity (Sensitivity index, SI=26–40%) is moderate across all systems, with IEEE-123 most robust (SI=25.8%). EV robustness: fitness degradation at 30% EV penetration ranges from +1.1% (IEEE-33) to +17.6% (IEEE-123).

DL surrogate: R^2 ranges from 0.275 (IEEE-123) to 0.931 (Custom-567); graph neural networks are needed for complex topologies.

RL action analysis: as ε decays, the agent increasingly selects GWO-dominated exploitation; Lévy flight triggers during stagnation (~10% of iterations). Q-table heatmaps are in (S4).

5. Discussion

5.1 Technical Effectiveness and Algorithm Comparison

Three performance tiers emerge from the case studies (Tables 4–6):

Tier 1 (RL-GOA-GWO, PSO): Optimal or close-optimal fitness across all systems. PSO ties on small systems; RL-GOA-GWO is at the top of IEEE-69, MV-Oberrhein, IEEE-123, and Custom-567. On IEEE-123, RL-GOA-GWO outperforms the Hybrid in the mean fitness (6.8 versus 0.354; $d=-1.12$, large effect) whereas pso exploitation of the inertia is efficient on smooth landscapes—not surprising given No-Free-Lunch considerations, once more, on smooth landscapes only (Wolpert 1997).

Hybrid GOA-GWO, WOA tier: Compete well on small systems (IEEE-33/69) with increased variance on IEEE-123 (0.033 vs. 0.003 standard deviation of RL-GOA-GWO).

Tier 3 (GOA, Fuzzy-GOA): Will work on IEEE-33/69 but get stuck in local optima on larger systems.

Table 7

RL-GOA-GWO runtime and fitness vs. network size

System	Buses	Fit.	t (s)	t/bus	LR%
IEEE-33	33	0.376	126.0	3.82	83.2
IEEE-69	69	0.394	97.3	1.41	94.7
IEEE-123(eq)	123	0.354	126.8	1.03	84.8
MV-Oberrhein	179	0.528	438.2	2.45	3.8
Custom-567	567	0.630	257.6	0.45	1.7

Table 8Schedule-variant ablation on IEEE 33-bus ($n=5$)

Schedule	Mean $\pm$ Std	Best	Δ . (%)
Three Phase (default)	0.3760 $\pm$ 0.0012	0.3742	-
Fixed-50	0.3766 $\pm$ 0.0012	0.3753	+0.2
Random	0.3759 $\pm$ 0.0009	0.3751	-0.0
Linear	0.3767 $\pm$ 0.0011	0.3753	+0.2
Full RL-GOA-GWO	0.3776 $\pm$ 0.0014	0.3756	+0.4

Table 9Lifecycle economic analysis (20-year, $r=5\%$)

Metric	IEEE-33	IEEE-69	MV-Oberrhein	IEEE-123	Custom-567
Total cost (k\$)	3655	4017	818	4362	709
NPV (k\$)	-497	303	1056	-252	550
BCR	0.864	1.075	2.291	0.942	1.776
IRR (%)	3.34	5.87	17.67	4.27	13.02
Payback (yr)	14.4	11.6	5.4	15.1	7.0

Such levels are tentative, depending on 5n runs, although non-parametric tests indicate that the rank difference is statistically significant, but the sample size is so limited as to limit generalizability.

5.2 Conditions in topology that favor RL-adaptive search

The RL benefit is associated with the ruggedness of landscapes as opposed to the size of the system. Three predictors include base-case voltage stress ($V_{\min}$), share of voltage-violating buses, and load-bus-to-candidate-location ratio, which indicate when AOS is better than the results with the use of static schedules:

Low ruggedness (IEEE-33/69): enough smoothness of the search space such that PSO and underlying static GOA-GWO achieve near-optimal fitness; RL contributes less than 1-percent more.

High ruggedness (IEEE-123; 38 voltage-violating buses, several lateral branches): There are numerous local optima, and huge gains are offered by the state-conditional switching of the RL agent. Over-constrained (Custom-567; 3 DGs on 567 buses): The fitness landscape becomes completely degenerate and all the algorithms reach the same solutions.

This indicates that RL-adaptive AOS can be most useful in the medium complexity regime.

5.3 RL Mechanism and DL Surrogate Assessment

Q-learning agent quickly determines GWO-dominated exploitation policy as the most rewarding and transfers

the probability of mass exploration and exploitation during the search. Lévy flight, which is chosen very rarely in stagnation (10 percent), causes escape from local optima. Q-table coverage is low (26/240 non-zero entries on IEEE-33); the theory of convergence of Q-learning says that every state-action pair must be reached infinity many times, which is not met with a horizon of 100. They should be longer training horizons, reduced state space, or function approximation via a deep Q-network (DQN).

The DL surrogate has $R^2 = 0.735$ on IEEE-33 with a speedup of about 6 times, but it fails on IEEE-123 ($R^2 = 0.275$) due to steeper voltage gradients, which are beyond the capability of the shallow MLP. Graph neural networks consisting of message-passing layers are a logical solution and a direction of work to be considered in the future.

5.4 Economic Viability

The scale-dependent feature of economic viability: IEEE-33 and IEEE-123 report negative NPV, whereas MV-Oberrhein is reported to have the best returns (BCR, 2.29; IRR, 17.7) that are supported by the reliability advantages. Custom-567 also works well (BCR, =, 1.78) although 1.7

5.5 Limitations

1. *Statistical sample size*: The power of non-parametric omnibus tests at the $n = 5$ runs is sufficient, whereas the power of the test at the $n = 25$ runs is robust

enough to draw strong conclusions between two samples.

2. *DG count*: Set to 3 DG + 3 SC, it would be more useful to optimize the number of DGs and their placement, collectively, to exploit the possibilities of the framework.
3. *Load modelling*: No model is done of deterministic snapshot loads; stochastic models of solar/wind and EV arrival are not done.
4. *RL state discretization*: 60-state tabular Q-learning; DQN with continuous states could be better action selection on complicated landscapes.
5. *Surrogate accuracy*: MLP surrogate will decay when applied to more complex topologies ($R^2 = 0.275$ on IEEE-123); graph neural networks are recommended.
6. *Weighted-sum aggregation*: Pareto front reduction; NSGA-III extension postponed.
7. *Missing NSGA-II comparator*: Our weighted-sum model cannot be used with Pareto-based methods without further scalarization.
8. *Missing AOS baselines*: No classical AOS comparators (probability matching, UCB Fialho et al. [6]; Da Costa et al. [4], no baselines of a classical comparison of AOS.
9. *Uniform load increase to analyze penetration*: charging spatially heterogeneously not considered.

6. Conclusions

The presented paper introduced a multi-algorithm benchmarking scheme of joint DG/SC placement with V2G integration that was tested on five systems (33–567 buses) with six metaheuristics and a DL surrogate at the same budget. The principal findings are:

1. *Topology-dependent advantage* (preliminary, $n=5$): RL-GOA-GWO outperforms the Hybrid by 6.8% (mean fitness) on IEEE-123 ($d = -1.12$, large effect) and is statistically comparable on small systems.
2. *RL mechanism*: adapts operator selection to convergence state, shifting from exploration to exploitation.
3. *DL surrogate*: provides 5.9–6.6 $\times$ speedup but accuracy varies (R^2 : 0.275–0.931).
4. *Economics*: NPV ranges from $-\$497k$ to $\$550k$; reliability benefits dominate at scale; two of five systems yield negative NPV.
5. *Scalability*: per-bus time decreases 8.5 $\times$ from 33 to 567 buses (endpoint-to-endpoint; Table 7).

Future work should extend the RL agent to a DQN, validate on real utility feeders, replace the MLP with graph neural networks, and adopt an explicit Pareto-based formulation (e.g. NSGA-III Deb and Jain (2014)) to expose trade-off fronts. Co-design of DG/SC/EV placement with multi-stage scheduling and uncertainty quantification also merits investigation.

Declarations

Conflict of interest: None.

Data availability: All data generated from publicly available IEEE benchmark systems via pandapower.

Code availability: Repository URL withheld for double-blind review; will be made public upon acceptance with full reproducibility scripts.

Supplementary material:

1. Fuzzy rule base, PSO/WOA equations, Hybrid GOA-GWO algorithm pseudocode;
2. Custom 567-bus topology file;
3. Per-bus voltage profiles for IEEE-123 and MV-Oberrhein;
4. Convergence traces, Q-tables, RL action distributions;
5. Holm–Bonferroni pairwise tables, weight sensitivity, EV robustness;
6. MV-Oberrhein sub-objective decomposition, DL surrogate metrics;
7. Extended economic analysis with discount-rate sensitivity.

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