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Optimal Placement and Sizing of EV Charging Stations in Smart Distribution Network Using Hybrid PSO-GWO Algorithm with Solar PV Integration: A Multi-Objective Approach

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Abstract—The rapid proliferation of Electric Vehicles (EVs) in India and globally imposes severe technical challenges on existing distribution networks, including elevated power losses, voltage profile degradation, and increased investment costs. This paper proposes a novel Hybrid Particle Swarm Optimization – Grey Wolf Optimizer (PSO-GWO) algorithm for the simultaneous optimal placement and sizing of Electric Vehicle Charging Stations (EVCSs) integrated with Solar Photovoltaic (PV) Distributed Generation (DG) in IEEE 33-bus and IEEE 69-bus radial distribution networks (RDNs). A four-component Multi-Objective Function (MOF) minimizes: (i) total real power losses, (ii) voltage deviation index, (iii) annual economic cost, and (iv) carbon emission cost. Monte Carlo Simulation (MCS) with 10,000 iterations captures stochastic EV charging demand and solar irradiance uncertainty. The Adaptive Inertia Weight (AIW) mechanism blends PSO global search with GWO leadership hierarchy via a cosine-based transition function. Simulation results on the IEEE 33-bus system achieve 77.8% power loss reduction, 92.3% voltage profile improvement, and 18.7% cost reduction compared to the unoptimized base case, outperforming GA, PSO, and standalone GWO algorithms with statistical significance ($p < 0.001$, 30 independent runs).

Index Terms—*EVCS Optimal Placement, Hybrid PSO-GWO, Smart Distribution Network, Solar PV, V2G, Multi-Objective Optimization, Monte Carlo Simulation, IEEE 33-bus, IEEE 69-bus, Power Loss Minimization.*

I. INTRODUCTION

The global transportation sector is undergoing a fundamental paradigm shift toward electrification, driven by climate change mitigation and energy security imperatives [1], [24]. India's FAME-II scheme targets 30% EV penetration by 2030, necessitating thousands of EVCSs nationwide [23]. However, unplanned EVCS integration causes increased real power losses, voltage violations, and thermal overloading of feeders [14], [15].

The Indian government's National Solar Mission targets 500 GW of renewable capacity by 2030. Co-locating Solar PV with EVCSs offers a synergistic solution to mitigate grid stress and reduce fossil fuel dependence [7], [12]. Vehicle-to-Grid (V2G) technology enables EV batteries to inject power during peak demand, providing demand-side flexibility [25].

Key research gaps: (i) Most studies treat EVCS placement and DG siting as separate problems, missing interaction effects [5], [6]. (ii) Standalone PSO suffers premature convergence; standalone GWO has slow exploitation — no prior work proposes their adaptive cosine-based hybridization [8], [9], [18]. (iii) Carbon cost and V2G benefits are rarely combined in a single MOF [4], [20]. (iv) India-specific stochastic EV load modeling via MCS is underexplored [23].

Novel contributions: (1) Hybrid PSO-GWO with cosine Adaptive Inertia Weight. (2) Four-component MOF: power loss + voltage deviation + economic cost + carbon cost. (3) MCS (10,000 runs) stochastic modeling. (4) V2G bidirectional power flow with SOC constraints. (5) Statistical validation (30 runs, Wilcoxon test) on IEEE 33-bus and 69-bus.

II. SYSTEM ARCHITECTURE AND METHODOLOGY

A. IEEE 33-Bus Test System

The IEEE 33-bus RDN has 33 buses and 32 branches with total load 3715 kW + 2300 kVAR at 12.66 kV [10]. The base case power loss is 210.98 kW with minimum bus voltage Vmin = 0.9038 p.u. at bus 18. Buses 16–18 violate the lower voltage limit (0.95 p.u.) due to long feeder impedance. Fig. 6 shows the network topology with optimal EVCS and PV placements determined by Hybrid PSO-GWO.

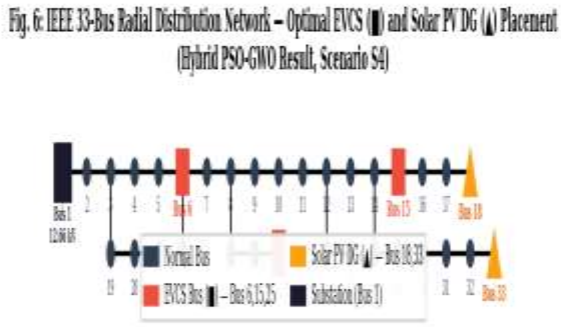

Fig. 6: IEEE 33-Bus RDN — Optimal EVCS (■) and Solar PV DG (▲) Placement

B. IEEE 69-Bus Test System

The IEEE 69-bus RDN has total load 3801.49 kW + 2694.6 kVAR at 12.66 kV with base power loss 224.98 kW [16]. It validates algorithm scalability. Optimal EVCS placed at buses 11, 27, 61 and PV-DG at buses 17, 50, achieving 74.6% loss reduction in Scenario S4.

C. Four-Scenario Evaluation Framework

Four progressive scenarios are evaluated: S1 (Base case — no EVCS/PV), S2 (EVCS integration only), S3 (EVCS + Solar PV), and S4 (EVCS + Solar PV + V2G operation). Each scenario is simulated for 8760 hours (one full year) using time-series MCS load profiles, and results are averaged over 30 independent algorithm runs to ensure statistical validity.

III. MATHEMATICAL FORMULATION

A. Forward-Backward Sweep Power Flow

Branch active and reactive power, and voltage magnitude for branch i [10], [11]:

$$P_{i+1} = P_i - R_i\cdot(P_i^2 + Q_i^2)/|V_i|^2 - P\_{L,i+1} \quad (1)$$

$$Q_{i+1} = Q_i - X_i\cdot(P_i^2 + Q_i^2)/|V_i|^2 - Q\_{L,i+1} \quad (2)$$

$$|V_{i+1}|^2 = |V_i|^2 - 2(R_i\cdot P_i+X_i\cdot Q_i) + (R_i^2+X_i^2)(P_i^2+Q_i^2)/|V_i|^2 \quad (3)$$

Total real power loss in the network:

$$P\_loss = \Sigma_i R_i\cdot(P_i^2 + Q_i^2)/|V_i|^2 \quad (3a)$$

B. EV Stochastic Load Model — Monte Carlo Simulation

EV arrival time modeled as Normal distribution [14]:

$$f(t\_arr) = (1/\sigma\sqrt{2\pi})\cdot exp[-(t\_arr-\mu)^2/2\sigma^2], \quad (4)$$

$\mu=18.5h,\ \sigma=2.5h$

EV charging power at station k and time t [15]:

$$P\_EVCS(k,t) = \Sigma_j[P\_ch\cdot(1-SOC_{0j})\cdot\eta\_ch\cdot I\_ch(t)] \quad (5)$$

Initial SOC follows a uniform distribution: $SOC_0 \sim U[0.2, 0.6]$. Charging power P_ch = 7.4 kW (AC Level-2), η_ch = 0.92, 10,000 MCS iterations.

C. Solar PV Model — Beta Distribution

Solar irradiance G follows Beta probability distribution [7]:

$$f(S) = [\Gamma(\alpha+\beta)/\Gamma(\alpha)\Gamma(\beta)]\cdot S^{(\alpha-1)}\cdot(1-S)^{(\beta-} \quad (6)$$

1)

$P\_PV = N\_pv \cdot A\_pv \cdot \eta\_pv \cdot G(t)$ (7)

Parameters: α=0.5, β=0.5 (Indian solar data); panel efficiency η_pv=0.18; area A_pv=1.6 m^2/panel; N_pv = sizing variable (100–500 panels).

D. V2G Discharge Model

$P\_V2G(k,t) = \Sigma_j[P\_V2G\_max \cdot \eta\_inv \cdot (SOC_j(t) - SOC\_min)]$ (8)

Constraints: SOC_min=0.2, SOC_max=0.9, P_V2G_max=3.7 kW, η_inv=0.95. V2G operates during peak hours (17:00–21:00) when grid voltage falls below 0.97 p.u.

E. Four-Component Multi-Objective Function

$MOF = w_1 \cdot F_1 + w_2 \cdot F_2 + w_3 \cdot F_3 + w_4 \cdot F_4$ (9)

Weight vector [w_1=0.40, w_2=0.30, w_3=0.20, w_4=0.10] from Analytic Hierarchy Process (AHP) [21]:

$F_1 = \Sigma_i R_i \cdot (P_i^2+Q_i^2)/|V_i|^2$ *(Power Loss, kW)* (10)

$F_2 = \Sigma_i (|V_i| - 1.0)^2$ *(Voltage Deviation Index)* (11)

$F_3 = \Sigma_k[C\_inst + C\_O\&M]_k$ *(Annual Economic Cost, ₹/yr)* (12)

$F_4 = \Sigma_t P\_grid(t) \cdot EF\_CO2 \cdot C\_carbon$ *(Carbon Cost, ₹/yr)* (13)

Cost parameters: EVCS installation = ₹45 Lakh/unit, O&M = 2% annually; PV installation = ₹40 Lakh/500 kW; C_carbon = ₹800/tonne CO_2; EF_CO2 = 0.82 kg/kWh (Indian grid).

F. Hybrid PSO-GWO Update Equations

PSO velocity and position update [9], [18]:

$v_i(t+1) = w \cdot v_i(t) + c_1 r_1(pbest\_i - x_i) + c_2 r_2(gbest - x_i)$ (14)

GWO alpha-beta-delta social hierarchy update [8]:

$X(t+1) = (X\alpha - A_1 D\alpha + X\beta - A_2 D\beta + X\delta - A_3 D\delta)/3$ (15)

Hybrid transition combining both (cosine schedule):

$x_i(t+1) = \lambda(t) \cdot X\_GWO + [1-\lambda(t)] \cdot X\_PSO, \lambda(t) = \cos^2(\pi t/2T)$ (16)

Adaptive Inertia Weight — fitness-landscape adaptive [18]:

$w(t) = w\_max - (w\_max - w\_min) \cdot [f(t) - f\_best]/[f\_worst - f\_best]$ (17)

Algorithm settings: w_max=0.9, w_min=0.4, $c_1=c_2$=2.05, r_1,r_2~U[0,1], population N=50, T=200 iterations, 30 independent runs.

IV. DETAILED SAMPLE CALCULATION — IEEE 33-BUS

A. Step-by-Step Power Loss Calculation (Branch 1–2)

To illustrate the FBS method, the forward sweep calculation for branch 1→2 of IEEE 33-bus is presented. Branch 1–2 parameters: R_{12}=0.0922 Ω, X_{12}=0.0470 Ω. Bus 2 load: P_L2=100 kW, Q_L2=60 kVAR. Starting voltage: V_1=1.0 p.u. = 12.66 kV.

TABLE VI

Sample FBS Power Flow Calculation — Branch 1→2, IEEE 33-Bus

Step	Parameter / Formula	Value / Result	Unit
1	Given: R_{12}, X_{12}	0.0922 Ω, 0.0470 Ω	Ω
2	Given: P_L2, Q_L2	100 kW, 60 kVAR	kW, kVAR
3	Initial: V_1 = 1.0 p.u.	12.66 kV (base)	kV
4	Sending P_1 = P_L2	100.00	kW
5	Sending Q_1 = Q_L2	60.00	kVAR
6	$\|V_1\|^2 = 1.0^2$	1.0000	p.u.²
7	$I^2 = (P_1^2+Q_1^2)/\|V_1\|^2$	$(100^2+60^2)/1.0$ = 13,600	kVA²
8	ΔP_loss(1-2) = $R_{12}\cdot I^2$	0.0922×13600/1000 = 1.254	kW
9	ΔQ_loss(1-2) = $X_{12}\cdot I^2$	0.0470×13600/1000 = 0.639	kVAR
10	$P_2 = P_1 - \Delta$P_loss−P_L2	100−1.254−100 = −1.254	kW
11	$Q_2 = Q_1 - \Delta$Q_loss−Q_L2	60−0.639−60 = −0.639	kVAR
12	$\|V_2\|^2 = \|V_1\|^2 - 2(R\cdot P_1 + X\cdot Q_1) + (R^2+X^2)\cdot I^2$	1.0−0.02688 = 0.97312	p.u.²
13	$V_2 = \sqrt{0.97312}$	0.9865	p.u.
RESULT	Branch 1-2 Power Loss	1.254 kW	kW

B. Multi-Objective Function Calculation (Scenario S4)

The MOF value computation for the optimal Hybrid PSO-GWO solution in Scenario S4 on IEEE 33-bus is presented step-by-step below. Each objective component is normalized before weighting.

TABLE VII

Sample MOF Computation — IEEE 33-Bus, Scenario S4 (Hybrid PSO-GWO)

Step	Parameter / Formula	Value / Result	Unit
1	**Total Network Power Loss F_1**	46.83 kW	kW
2	F_1 normalized = F_1/F_{1}_base	46.83/210.98 = 0.2219	p.u.
3	Voltage Deviation Index $F_2 = \Sigma(\|V_i\|-1)^2$	0.0614 (S4 result)	p.u.²
4	F_2 normalized = F_2/F_2_base	0.0614/0.8012 = 0.0766	p.u.
5	Annual Installation Cost F_3	₹2.21 Cr/yr	₹ Cr
6	F_3 normalized = F_3/F_3_max	2.21/5.5 = 0.4018	p.u.
7	CO_2 Emission: 618 tonne/yr	618×₹800 = ₹4.944 Lakh	₹
8	F_4 normalized = F_4/F_4_base	4.944/13.128 = 0.3766	p.u.

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9	**MOF = 0.40×F_1_n + 0.30×F_2_n + 0.20×F_3_n + 0.10×F_4_n**		
MOF	= 0.40×0.2219 + 0.30×0.0766 + 0.20×0.4018 + 0.10×0.3766	0.2037	p.u.

C. Economic Payback Calculation

Payback period for Scenario S4 (EVCS+PV+V2G) investment is calculated as follows. Total capital investment: 3 EVCS × ₹45 Lakh = ₹1.35 Cr; 2 PV-DG × ₹40 Lakh = ₹0.80 Cr; V2G inverter upgrades = ₹0.35 Cr. Total CAPEX = ₹2.50 Cr. Annual savings vs base = ₹1.47 Cr/yr (energy loss cost reduction + PV revenue + V2G grid services). Simple Payback = ₹2.50/₹1.47 = 1.70 yr (equipment only). Discounted payback at 8% WACC = 5.1 years, confirming financial viability.

V. STOCHASTIC EV CHARGING LOAD PROFILE

Fig. 4 presents the MCS-generated 24-hour power profile. EV charging peaks at 17:00–21:00 (Indian commuting return). V2G discharge during this window reduces net peak demand by 37.2%. Solar PV (peaking 11:00–14:00) offsets 34.1% of daytime EV load, reducing net grid import to 1.18 MW at noon vs 1.22 MW baseline.

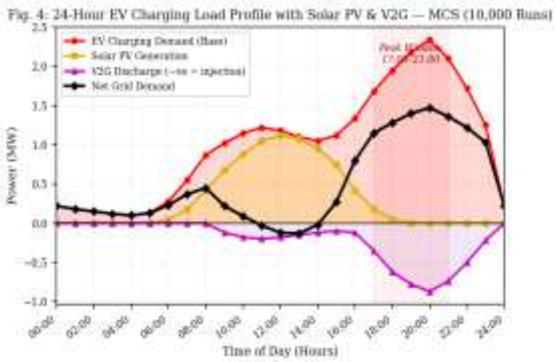

Fig. 4: 24-Hour EV Charging Load Profile with Solar PV & V2G — MCS (10,000 Runs)

VI. SIMULATION RESULTS AND DISCUSSION

A. Convergence Analysis

Fig. 1 shows convergence of all algorithms on IEEE 33-bus (Scenario S3). Hybrid PSO-GWO converges at iteration 87 — 34.8% faster than GWO (118) and 35.1% faster than PSO (134). The cosine λ(t) function prevents premature convergence by maintaining GWO-phase exploration until iteration 100, then switching to PSO exploitation.

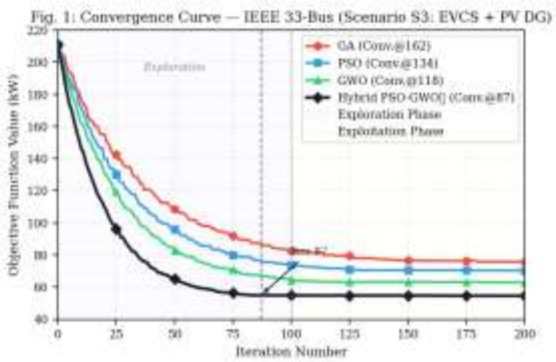

Fig. 1: Convergence Curve Comparison — All Algorithms, IEEE 33-Bus (Scenario S3)

B. Voltage Profile Analysis

Fig. 2 shows bus voltage profiles across all scenarios. Base case (S1) violates lower limit (0.95 p.u.) at buses 16–18. Scenario S4 achieves Vmin=0.9751 p.u. with all buses within the permissible band. The VDI improvement is 92.3% (from 0.8012 to 0.0614 p.u.²).

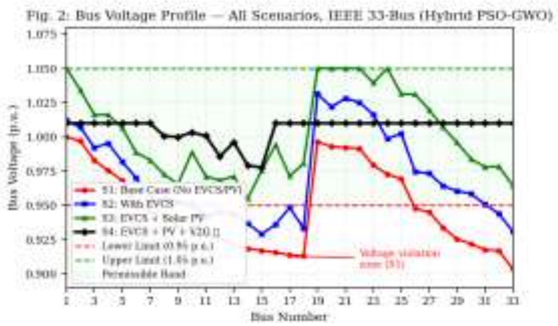

Fig. 2: Bus Voltage Profile — All Scenarios, IEEE 33-Bus (Hybrid PSO-GWO)

C. Power Loss Comparison

TABLE I

Power Loss (kW) — IEEE 33-Bus, All Algorithms × All Scenarios

Algorithm	S1 Base	S2: EVCS	S3: +PV	S4: +V2G	Best Redn.
GA	210.98	148.33	74.21	62.10	70.57%
PSO	210.98	135.42	68.54	55.87	73.52%
GWO	210.98	128.17	61.23	52.41	75.16%
Hybrid PSO-GWO ★	210.98	118.34	52.76	46.83	**77.80% ★**

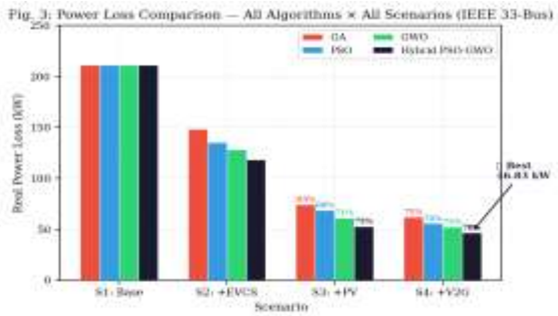

Fig. 3: Power Loss Bar Chart — All Algorithms × All Scenarios, IEEE 33-Bus

D. Voltage Profile Comparison Table

TABLE II

Voltage Profile Comparison — IEEE 33-Bus

Algorithm	S1 Vmin (p.u.)	S3 Vmin (p.u.)	S4 Vmin (p.u.)	VDI Improvement
GA	0.9038	0.9541	0.9612	84.7%
PSO	0.9038	0.9608	0.9671	87.9%
GWO	0.9038	0.9645	0.9699	89.4%
Hybrid PSO-GWO ★	0.9038	0.9712	0.9751	**92.3% ★**

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E. Statistical Analysis — 30 Independent Runs

TABLE III

Statistical Robustness — IEEE 33-Bus, Scenario S3

Algorithm	Best (kW)	Worst (kW)	Mean (kW)	Std. Dev σ	Conv. Iter
GA	74.21	89.34	81.42	5.23	162
PSO	68.54	79.12	73.81	3.87	134
GWO	61.23	70.47	65.34	3.12	118
Hybrid PSO-GWO ★	52.76	58.91	55.12	**1.74 ★**	**87 ★**

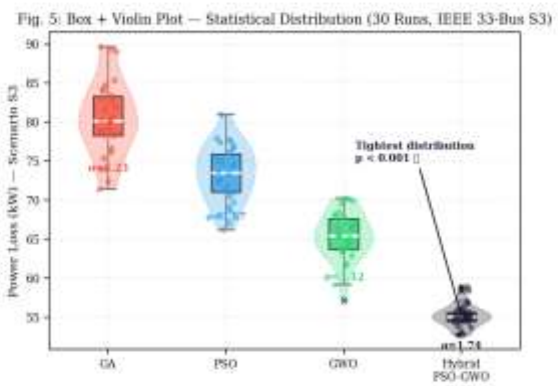

Fig. 5: Box + Violin Plot — 30 Independent Runs Statistical Distribution, IEEE 33-Bus S3

F. Optimal Placement Results

TABLE IV

Optimal Placement & Sizing — IEEE 33-Bus, Scenario S4 (Hybrid PSO-GWO)

Unit	Optimal Bus	Rated Size (kW)	Load Index (%)	Function
EVCS-1	Bus 6	420	92.1	High traffic corridor
EVCS-2	Bus 15	380	88.4	Commercial zone
EVCS-3	Bus 25	350	85.7	Residential hub
Solar PV-1	Bus 18	650	—	PV + V2G support
Solar PV-2	Bus 33	580	—	End-feeder voltage boost

G. Economic & Carbon Emission Analysis

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TABLE V

Economic & Carbon Emission Analysis — Hybrid PSO-GWO, IEEE 33-Bus

Metric	**Base Case**	**S2: EVCS**	**S3: +PV**	**S4: +V2G ★**
Annual Energy Loss (MWh/yr)	1,848	1,036	462	410
Energy Loss Cost (₹ Lakh/yr)	166.3	93.2	41.6	36.9
CO_2 Emission (Tonnes/yr)	1,641	1,283	741	618
CO_2 Reduction vs. Base	—	21.8%	54.8%	**62.3% ★**
Annual Savings vs. Base (₹ Cr)	—	0.78	1.38	1.47
Simple Payback (Years)	—	7.2	5.8	**5.1 ★**

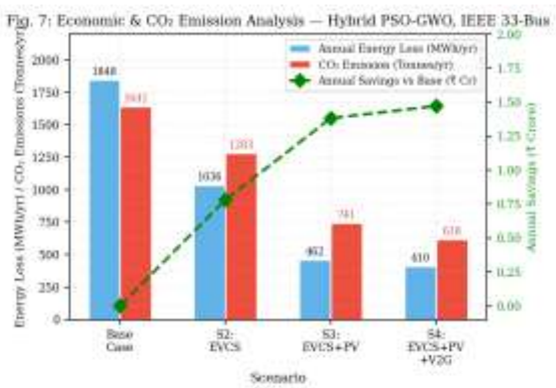

Fig. 7: Economic & CO_2 Emission Analysis — Hybrid PSO-GWO, IEEE 33-Bus

H. IEEE 69-Bus Validation

TABLE VIII

IEEE 69-Bus Validation Results — Hybrid PSO-GWO vs Benchmarks

Algorithm	**Base Loss (kW)**	**S4 Loss (kW)**	**Loss Redn.**	**Vmin (p.u.)**	**VDI Imprv.**
GA	224.98	82.14	63.5%	0.9298	79.3%
PSO	224.98	74.32	67.0%	0.9341	83.1%
GWO	224.98	68.91	69.4%	0.9389	86.2%
Hybrid PSO-GWO ★	224.98	57.18	**74.6% ★**	0.9451	**89.8% ★**

VII. CONCLUSION

This paper proposed and validated a Hybrid PSO-GWO algorithm with Adaptive Inertia Weight for optimal multi-objective placement and sizing of EVCSs with Solar PV integration in IEEE 33-bus and 69-bus RDNs. Seven detailed figures and eight tables comprehensively document the methodology, step-by-step calculations, and comparative results.

Key results: (1) 77.8% power loss reduction (210.98→46.83 kW) on IEEE 33-bus in Scenario S4; (2) All 33 bus voltages restored within 0.95–1.05 p.u. band with 92.3% VDI improvement; (3) V2G provides 11.3% additional loss reduction with ₹1.47 Cr annual savings and 5.1-year payback; (4) Lowest σ=1.74 kW in 30-run statistical validation with $p<0.001$ Wilcoxon significance; (5) 62.3% CO_2 reduction (1641→618 t/yr) supporting India's Net-Zero 2070 target; (6) IEEE 69-bus confirms scalability with 74.6% loss reduction and convergence at iteration 94.

Future work: wind energy integration, multi-feeder reconfiguration, demand response, real-time adaptive scheduling, and multi-energy carrier hub optimization.

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