

Enhancing Renewable Energy Hosting Capacity in Unbalanced Microgrids via Empowering Smart Inverters

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Abstract— The rapid growth of photovoltaic (PV) generation, wind energy and plug-in electric vehicle (PEV) charging creates voltage unbalance, feeder congestion and power losses that limit the hosting capacity (HC) of renewable energy sources in practical unbalanced microgrids. A recent study coordinated PV systems and energy storage systems (ESSs) with smart-inverter functions on the unbalanced IEEE 123-bus microgrid using the Multi-Objective Grey Wolf Optimizer (MOGWO). This paper extends that work with a Multi-Objective Hippopotamus Optimizer (MOHO) and compares it with MOGWO. The microgrid is divided into six zones and includes a 1.5 MW wind generator and a 2 MW PEV load. PV inverters operate in combined volt-var/volt-watt mode, and a two-stage MATLAB–OpenDSS co-simulation minimises voltage unbalance and feeder overloading while maximising PV penetration. With an equal budget of 2440 power-flow evaluations over ten runs, the best MOHO plan reaches 215.9 % PV penetration against 184.5 % for MOGWO, reduces average voltage unbalance by 12.3 % (MOGWO 15.7 %), lowers the critical feeder peak loading from 175 % to 150 %, and cuts daily grid import by 43.9 % (MOGWO 43.0 %). MOHO raises reverse-flow losses and shows larger run-to-run variability, and the difference in mean performance is not statistically

significant, so it is a competitive alternative for hosting-capacity planning.

Keywords— hosting capacity, unbalanced microgrid, smart inverter, volt-var, volt-watt, energy storage, hippopotamus optimizer, MOGWO, OpenDSS.

1. INTRODUCTION

The electricity sector is shifting from centralised fossil-fuel plants to clean, distributed and inverter-interfaced resources. Climate targets, fuel-price volatility and energy-security concerns have made photovoltaic (PV) and wind generation the fastest-growing share of new capacity, and much of it connects to medium- and low-voltage feeders and microgrids rather than to the transmission grid [1]. Distribution networks were designed for one-way power flow, so high distributed-generation (DG) penetration can cause reverse power flow, voltage rise, voltage unbalance, thermal overloading and protection problems. These effects are stronger in North-American-style feeders, which are inherently unbalanced because of single- and two-phase laterals and unequal phase loading.

Transport electrification adds concentrated loads. Plug-in electric vehicles (PEVs) charged at home create an evening peak when solar output is absent, so midday surplus and evening deficit coexist. Energy storage systems (ESSs)

and intelligent inverter control are therefore central to modern microgrids (Fig. 1).

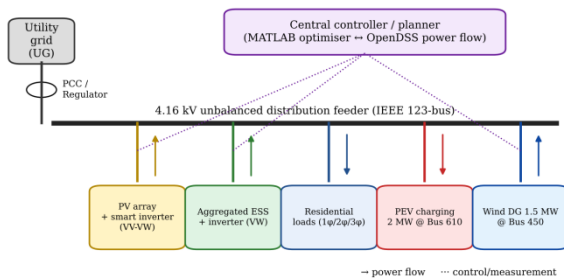


Fig. 1. Architecture of the grid-connected unbalanced microgrid.

Hosting capacity (HC) is the maximum DER capacity a network can accommodate without violating voltage, thermal, unbalance or power-quality limits [1]. Smart inverters raise HC: IEEE Std 1547-2018 requires reactive-power capability and voltage-responsive functions such as volt-var (VV) and volt-watt (VW) [2]. How much these functions help depends on where and how large the PV and ESS units are. The siting–sizing problem is discrete–continuous, non-convex and multi-objective, and every candidate needs a 24-hour unbalanced three-phase power-flow run, so metaheuristics coupled with a distribution simulator are the natural approach.

Mousa et al. [3] proposed coordinated PV–ESS planning with smart inverters on the unbalanced IEEE 123-bus microgrid, solved with MOGWO, and named the evaluation of other metaheuristics as future work. The Hippopotamus Optimization (HO) algorithm [4] has a balanced exploration–exploitation mechanism that suits this problem. The main contributions of this paper are:

- a reproduction of the six-zone IEEE 123-bus planning environment with VV-VW inverters, follow-mode ESSs, a 1.5 MW wind DG and a 2 MW PEV load;
- a Multi-Objective Hippopotamus Optimizer (MOHO) with a Pareto archive, a leader-directed male-hippo update and compromise-guided elitist selection;
- a statistically supported comparison of MOGWO and MOHO at equal evaluation budget over ten runs, including losses, congestion and hosting-capacity utilisation.

2. LITERATURE SURVEY

HC studies are classified as deterministic, stochastic, optimisation-based and data-driven [1]. Enhancement measures include on-load tap changer (OLTC) and VAR coordination, demand-side management, reconfiguration and storage; Ali et al. [5] showed that coordinated OLTC, VAR sources and stochastic EVs substantially raise PV HC. Zhang et al. [6] reviewed the planning aspects of DG and ESS deployment, covering objectives, horizons, uncertainties and constraints.

Early DG-planning work targeted loss and voltage-profile improvement on balanced 33- and 69-bus feeders; Jordehi [7] compared metaheuristics and found the grey wolf optimiser among the best. Later work added storage: Mukhopadhyay and Das [8] combined reconfiguration with PV and battery allocation, Khasanov et al. [9] sized DG and batteries under generation uncertainty, Ghaffari et al. [10] considered flicker, and Gu et al. [11] used an improved NSGA-II. Oskouei et al. [12] partitioned the network into supply-sufficient areas, similar to the zones used here. For unbalanced systems, Cikan and Cikan [13] allocated multiple DG types on the IEEE 123-bus feeder, and Jothibas et al. [14] studied PV HC with a two-stage circuit design. Zheng et al. [15] and Mahdavi et al. [16] addressed wind-DG planning and cost-minimising allocation. Table I summarises these studies.

TABLE I. SUMMARY OF LITERATURE ON
DG/ESS PLANNING

Ref.	System	Method	Remarks
[7]	IEEE 33-bus	GWO and others	Comparison of metaheuristics
[8]	IEEE 69-bus	PSO	PV, ESS, reconfiguration
[9]	IEEE 33/69-bus	Rider optimisation	WT, PV, ESS under uncertainty
[12]	IEEE 30-bus	GAMS/DIgSILENT	Supply-sufficient areas
[10]	Distribution net.	Crow search	Flicker mitigation
[11]	IEEE 33-bus	Improved NSGA-II	Battery ESS placement
[13]	IEEE 123-bus	EO, OpenDSS	Unbalanced, multiple DGs
[14]	IEEE 123-bus	LP, GAMS	PV hosting capacity

[3]	IEEE 123-bus, 6 zones	MOGWO, OpenDSS	Smart inverters, ESS, WT, PEV
This work	IEEE 123-bus, 6 zones	MOHO vs MOGWO	Statistical comparison

Smart-inverter functions include constant power factor, volt-var, volt-watt and ride-through. Volt-var control reduces voltage rise at the cost of extra reactive current, and volt-watt curtailment protects against over-voltage; Ullah et al. [17] showed that volt-var control markedly raises PV HC. EN 50160 limits voltage unbalance to 2 % and voltage magnitude to ± 10 % [18]. ESSs relieve congestion, reduce losses and smooth renewable variability [19].

Metaheuristics are widely used because the planning problem is non-convex and mixed-integer; the no-free-lunch theorem [20] justifies testing new algorithms on specific problems. For multi-objective problems, common approaches are non-dominated sorting [21] and archive-based methods such as MOPSO [22] and MOGWO [23]. The grey wolf optimizer [24] is strongly exploitative and can converge prematurely on multimodal landscapes. HO [4] models three herd behaviours and has not yet been applied to multi-objective PV-ESS planning in unbalanced microgrids. The research gaps are therefore: (i) most studies assume balanced systems; (ii) feeder congestion and inverter reactive capability are often neglected; (iii) the effect of the optimiser on solution quality and repeatability has not been examined; and (iv) comparisons rarely use independent runs at equal budget.

3. EXISTING SYSTEM

In the existing planning framework [3], PV and ESS units are placed in the unbalanced IEEE 123-bus microgrid with MOGWO and a two-stage strategy. The reported benefits are a 16 % reduction in feeder congestion, about 150 % PV penetration and a 13 % loss reduction, but the approach and conventional practice share several limitations:

- *Single optimiser*: only MOGWO was used, so the effect of the search algorithm on plan quality, convergence and repeatability is unknown.

- *Premature convergence*: the grey wolf update pulls solutions towards the centroid of three leaders and may stall on multimodal landscapes.
- *Balanced-system assumptions*: many studies use balanced radial feeders and ignore voltage unbalance, which is the limiting index in practical feeders.
- *Neglected inverter capability*: fixed unity-power-factor inverters waste reactive-power capability that could hold voltages inside limits.
- *Single-run evidence*: results are usually shown for one run, without statistical testing at equal computational budget.
- *Narrow objectives*: losses are not an explicit objective, so high-penetration plans may hide reverse-flow losses.

Table II contrasts the existing approach with the one proposed here.

TABLE II. EXISTING VERSUS PROPOSED APPROACH

Aspect	Existing system	Proposed system
Optimiser	MOGWO only	MOHO compared with MOGWO
Search update	Three-leader averaging	Leader-directed hippo phases with Lévy flights
Leader choice	Grid-based α , β , δ	Compromise or grid leader (50 %/50 %)
Evaluation	Single reported result	Ten runs, Wilcoxon test
Reporting	VUI, congestion, penetration	Plus losses, grid import, HC use

4. RESEARCH METHODOLOGY

A. Test System

The test system is the IEEE 123-bus feeder [25], a 4.16 kV unbalanced network with 3490 kW and 1920 kvar of spot load, four voltage regulators and shunt capacitors. It is divided into six operational zones (Fig. 2, Table III), each with a 400 A main feeder and candidate three-phase buses for PV and ESS placement. A 1.5 MW wind DG is connected at Bus 450 and a 2 MW aggregated PEV load at Bus 610.

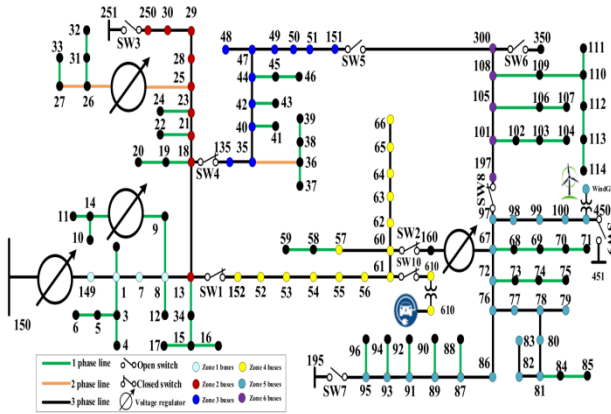


Fig. 2. Modified IEEE 123-bus microgrid with six operational zones.

TABLE III. OPERATIONAL ZONES AND MAIN FEEDERS

Zone	Candidate buses	Main feeder
Z1	149, 1, 7, 8	Line#115
Z2	13, 18, 21, 23, 25, 28, 29, 30, 250	Line#13
Z3	35, 40, 42, 44, 47–51, 135, 151	Line#114
Z4	52–57, 60–66, 152	Line#116
Z5	67, 72, 76–83, 86, 87, 89, 91, 93, 95, 97–100, 450	Line#117
Z6	101, 105, 108, 197, 300	Line#118

B. Smart-Inverter, ESS, Wind and PEV Models

Each PV array uses a single-diode model [26] with MPPT, a DC link and a three-phase grid-side converter with d-q current control. PV inverters are oversized so reactive power is available at full output, limited at time t by

$$Q_{i,t}^{lim} = \pm \sqrt{(S_i^{rate})^2 - (P_{i,t})^2} \quad (1)$$

with a 750 kvar cap, and are sized from 10 to 2500 kVA in 10 kVA steps. In the combined VV-VW mode (Fig. 3), the inverter injects full reactive power below 0.92 p.u., has a dead band from 0.98 to 1.0 p.u., absorbs full reactive power above 1.05 p.u. and curtails active power linearly from 1.02 to 1.10 p.u. These settings are implemented with the OpenDSS InvControl element.

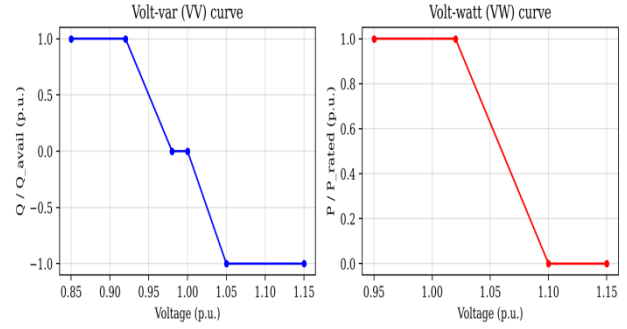


Fig. 3. Volt-var and volt-watt curves used in the simulation.

Each zone can host one aggregated ESS (100–1000 kW, 1000–4000 kWh) that follows a daily dispatch curve: it charges in the early morning, idles at midday and discharges in the evening peak, with VW limits on its inverter. Its state of charge evolves as

$$SoC_t = SoC_{t-1} + \frac{(\eta_{ch} P_t^{ch} - P_t^{dis} \eta_{dis}) \Delta t}{E_{rated}} \times 100 \quad (2)$$

The 1.5 MW wind turbine at Bus 450 runs at unity power factor with a Weibull-based 24-hour wind profile. The PEV load peaks between 19:00 and 21:00, coinciding with the residential peak, which makes it the main cause of evening feeder congestion.

C. Problem Formulation

For each zone the decision vector contains the PV bus, PV rating, ESS bus, ESS power and ESS energy, encoded in $[0, 1]$ and decoded to the nearest admissible bus or step size. Three objectives are combined with equal weights:

$$\min f_i = w_1 f_1 + w_2 f_2 - w_3 f_3, \quad w_1 = w_2 = w_3 = \frac{1}{3} \quad (3)$$

The first objective is the NEMA voltage unbalance index averaged over all three-phase buses and hours,

$$f_1 = \text{VUI}\% = \frac{\max_{ph} |V_i^{ph} - V_i^{avg}|}{V_i^{avg}} \times 100 \quad (4)$$

the second is the main-feeder overloading summed over six zones,

$$I_{OL}\% = \frac{\max_{ph} |I_{act}^{ph}|}{|I_{rate}|} \times 100, \quad f_2 = \sum_{z=1}^6 \overline{I_{OL,z}\%} \quad (5)$$

and the third, to be maximised, is the PV penetration relative to the 3983 kVA connected load,

$$f_3 = \lambda_{pv} \% = \frac{S_{pv}}{S_{load}} \times 100 \quad (6)$$

Constraints are: power balance (satisfied by the OpenDSS solution), load-bus voltages within $\pm 10\%$ and DG-bus voltages within $\pm 5\%$, PV and ESS rating limits, state-of-charge limits with no simultaneous charge and discharge, and feeder loading below 150 % of rating (VDE-AR-N 4105). Violations are handled by a static penalty, and every objective is normalised by its base-case value:

$$F_m = \frac{f_m}{f_{m,0}} + \rho \Phi, \quad \rho = 0.02 \quad (7)$$

where Φ accumulates hourly voltage violations and feeder overloads above 150 %. Pareto-optimal solutions are stored in an external archive of 50 members with an adaptive hypercube grid (seven divisions, inflation factor 0.1), and leaders are drawn by roulette wheel inversely proportional to cell occupancy [23].

D. Base Technique: MOGWO

In MOGWO [23], each wolf moves towards a prey position estimated from the alpha, beta and delta leaders selected from the archive. The control parameter a decreases linearly from 2 to 0, shifting the search from exploration to exploitation, and the new position is the mean of the three leader-guided moves. MOGWO is implemented here in the form used in the base paper, with the same archive, population and budget as MOHO.

E. Proposed Multi-Objective Hippopotamus Optimizer

MOHO follows the three HO behaviours [4] (Fig. 4) and adds an external Pareto archive. In *Phase 1* (river or pond position update), the dominant hippo is chosen with equal probability as the archive compromise solution or a grid leader from a sparse region of the front, and male hippos move towards it:

$$X_i^M = X_i + I_1 \vec{y}_1 \odot (D_{hippo} - X_i), \quad I_1 \in \{1, 2\} \quad (8)$$

The canonical HO form $X + y_1(D - I_1 X)$ contracts solutions towards the search-space origin, which here corresponds to the smallest PV and ESS sizes. MOHO applies I_1 to the difference vector so the step always points towards the leader. Immature hippos move

relative to the mean of a random group. In *Phase 2* (defence against predators), a hippo turns towards a randomly generated predator Pr using a Lévy-flight step RL generated with Mantegna's algorithm [27]:

$$X_i^{HP} = X_i + RL \odot (Pr - X_i) + \kappa \frac{b}{c - d \cos(2\pi g)} \cdot \frac{1}{2\bar{D} + \bar{r}_9} \quad (9)$$

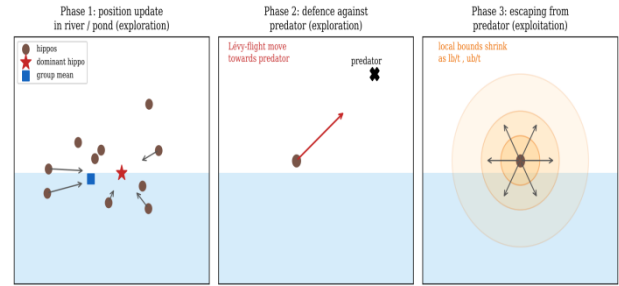


Fig. 4. Three behavioural phases of the hippopotamus herd modelled by HO.

In *Phase 3* (escape, exploitation), each hippo searches near its position within local bounds that shrink as the iteration counter t grows ($lb^{local} = lb/t$, $ub^{local} = ub/t$):

$$X_i^{HE} = X_i + r_{10}(lb^{local} + \vec{s} \odot (ub^{local} - lb^{local})) \quad (10)$$

Offspring from all phases are offered to the archive, and, following the elitist rule of HO, a hippo moves only if its mean normalised objective improves:

$$X_i \leftarrow X_i^{new} \text{ if } \bar{F}(X_i^{new}) < \bar{F}(X_i), \quad \bar{F} = \frac{1}{3} \sum_{m=1}^3 F_m \quad (11)$$

The population is therefore driven towards the preferred region of the front while the archive keeps the diversity of non-dominated trade-offs. A canonical variant with the origin-biased update and non-dominated-sorting survival is evaluated as an ablation.

F. Two-Stage Planning and Co-Simulation

Following the base paper [3], planning has two stages (Fig. 5). In Stage 1 each zone is optimised alone (five variables, population 10, 240 evaluations) to fix the best PV and ESS buses. In Stage 2, the sizes of all PVs and ESSs (18 variables, population 20, 1000 evaluations) are optimised together to produce the final archive and compromise plan. MATLAB generates candidate plans and drives OpenDSS [28] through its COM interface, which runs the 24-hour solution and returns voltages, currents, losses and grid power. One evaluation takes

about 0.06–0.1 s, so a complete run of 2440 evaluations takes about 100 s.

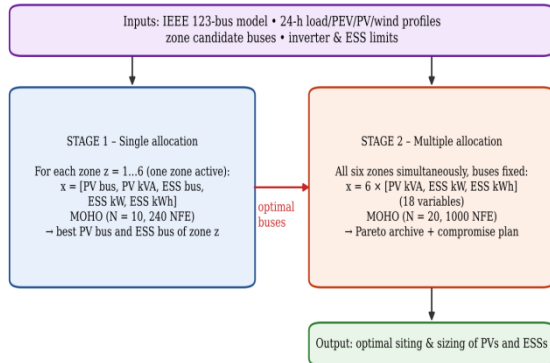


Fig. 5. Two-stage optimal planning strategy using MOHO.

TABLE IV. PARAMETER SETTINGS OF THE ALGORITHMS

Parameter	MOGWO	MOHO
Stage-1 pop. / evals. (per zone)	10 / 240	10 / 240
Stage-2 pop. / evals.	20 / 1000	20 / 1000
Archive / grid divisions	50 / 7	50 / 7
Control parameters	$\alpha: 2 \rightarrow 0$	$T = \exp(-t/T_{max}),$ Lévy 1.5
Leader selection	α, β, δ from grid	Compromise/grid (50 %)
Independent runs	10 (seeds 1–10)	10 (seeds 1–10)

G. Performance Metrics

Algorithms are compared on the best, mean, median, worst and standard deviation of the compromise objective over ten runs, and on the hypervolume (HV) [29] and spacing (SP) [30] of the final archives. HV is computed by Monte Carlo sampling in normalised objective space with reference point 1.1; larger HV and smaller SP are better. Significance is tested with the Wilcoxon rank-sum test at the 5 % level.

5. RESULTS AND DISCUSSIONS

A. Simulation Setup and Base Case

Daily quasi-static simulations with a one-hour step were run on a 2-core, 8 GB computer. Three cases are compared: Case 1 (no PV or ESS, with wind and PEV load), Case 2 (MOGWO plan) and Case 3 (MOHO plan), both the best of ten runs. In Case 1 the microgrid imports 65.26 MWh/day with a peak of 4.33 MW at 19:00. The average VUI is 0.719 % (maximum 1.239 % at Bus 30), and Line#115

averages 112.1 % loading with a 175.5 % evening peak, violating the 150 % limit. Daily losses are 1.732 MWh and 3.509 Mvarh.

B. Optimal Placement and Sizing

Table V lists the best plans. Both algorithms place 2310–2500 kVA PVs in Zones 1, 2 and 4, which have strong three-phase backbones and high local demand, and only token PV in Zones 5 and 6, where the wind DG and remote location already cause voltage rise. MOHO additionally installs 1080 kVA at Bus 151 in Zone 3 and 2500 kVA at Bus 64 in Zone 4, giving 8600 kVA in total against 7350 kVA for MOGWO. ESSs are placed near the zone feeder heads so that their evening discharge relieves the main feeders.

TABLE V. BEST PV AND ESS ALLOCATION PER ZONE

Zone	MOGWO PV (bus/kVA)	MOGWO ESS (bus/kW/kWh)	MOHO PV (bus/kVA)	MOHO ESS (bus/kW/kWh)
Z1	149/2500	1/400/4000	149/2500	8/300/4000
Z2	250/2500	21/300/3000	250/2500	250/400/4000
Z3	49/10	42/500/2000	151/1080	135/100/2000
Z4	61/2310	57/300/4000	64/2500	56/400/4000
Z5	86/10	91/200/2000	100/10	67/400/4000
Z6	300/20	105/300/3000	101/10	105/100/2000
Total	7350 kVA	2000 kW/18 MWh	8600 kVA	1700 kW/20 MWh
λ_{pv}	184.5 %	–	215.9 %	–

C. Convergence and Pareto Front

Fig. 6 shows the compromise objective f_t during Stage 2. MOGWO converges faster in the first 200 evaluations because of its strong attraction towards three leaders, whereas MOHO starts more slowly, since half of the herd performs exploratory predator-defence moves, but its best run keeps improving after 400 evaluations and ends at $f_t = -0.0648$ against -0.0042 for MOGWO.

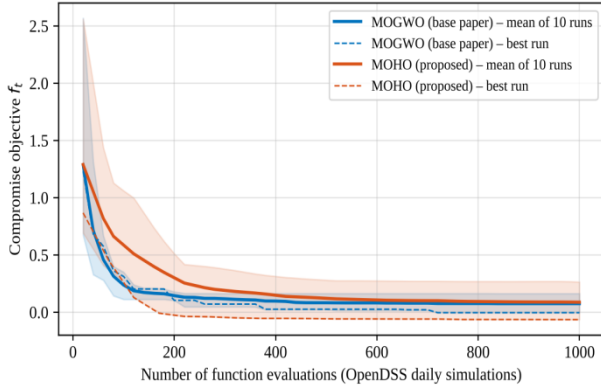


Fig. 6. Stage-2 convergence of MOGWO and MOHO over ten runs.

The final archives (Fig. 7) show that MOGWO solutions cluster at penetration terms of about 125–185, while the MOHO archive extends to about 195–215 at the cost of slightly higher normalised VUI and feeder loading. Neither compromise plan dominates the other; they are different trade-offs, with MOHO in the high-hosting-capacity region.

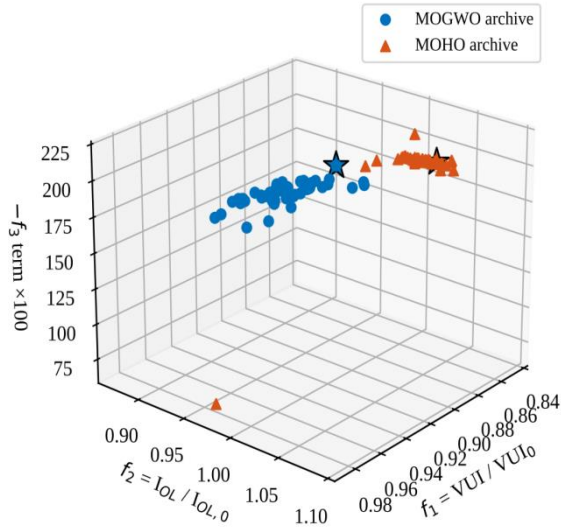


Fig. 7. Final Pareto archives (stars: compromise solutions).

D. Statistical Comparison

Table VI summarises ten independent runs. MOHO obtains the best overall compromise value and a slightly better median, but a slightly worse mean and larger standard deviation, because two runs (seeds 1 and 5) were trapped in poorer Stage-1 bus selections. MOGWO builds larger, more uniform archives (higher HV, lower SP). The Wilcoxon test gives $p = 0.88$ for f_t and $p = 0.26$ for HV, so the

differences are not significant at 5 %. The proposed modifications clearly improve on canonical HO, lowering mean f_t from 0.140 to 0.087 and the best from 0.058 to -0.065 . CPU time is about 100 s per run for all variants.

TABLE VI. STATISTICS OVER TEN RUNS (NFE = 2440)

Metric	MOGWO	MOHO (canon.)	MOHO (prop.)
Best f_t	-0.0042	0.0576	-0.0648
Median f_t	0.0728	0.1221	0.0711
Mean f_t	0.0746	0.1400	0.0870
Worst f_t	0.1634	0.2582	0.2650
Std. deviation	0.0579	0.0686	0.1192
Hypervolume (mean)	0.765	0.607	0.634
Spacing (mean)	0.035	0.058	0.060
CPU time/run (s)	101.3	103.8	98.1

E. Voltage Unbalance and Voltage Profile

Zones 2–4 show the highest unbalance because of large single-phase laterals (Fig. 8). The average VUI falls from 0.719 % to 0.606 % with MOGWO (-15.7 %) and to 0.630 % with MOHO (-12.3 %); the maximum falls from 1.239 % to 1.096 % and 1.104 %, all far below the 2 % EN 50160 limit. Bus voltages over the day lie between 0.958 and 1.052 p.u. in Case 1, but between 0.970 and 1.049 p.u. (MOGWO) and 0.972 and 1.049 p.u. (MOHO), so the voltage band narrows and the 1.05 p.u. DG-bus limit is respected through VV absorption and VW curtailment.

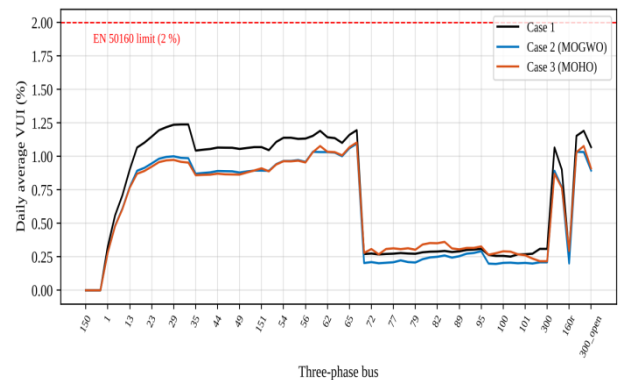


Fig. 8. Daily average VUI per three-phase bus.

F. Feeder Congestion and Losses

Both plans cut the evening peak of Line#115 from 175 % to about 150 % through ESS discharge (Fig. 9). MOGWO reduces the average feeder loading from 45.8 % to 42.9 %, the

whereas MOHO exports more midday PV power through Line#115 and Line#13 (reverse flow up to 147 %), so its average loading (48.4 %) is slightly higher although its peak is reduced. Net daily active losses are 1.732 MWh (Case 1), 1.708 MWh (MOGWO, -1.4 %) and 2.311 MWh (MOHO, +33.4 %); reactive losses are 3.509, 3.436 and 4.280 Mvarh. Losses are not an objective, so the higher penetration of MOHO comes with higher reverse-flow losses, a trade-off a planner should weigh, for example by adding losses as a fourth objective.

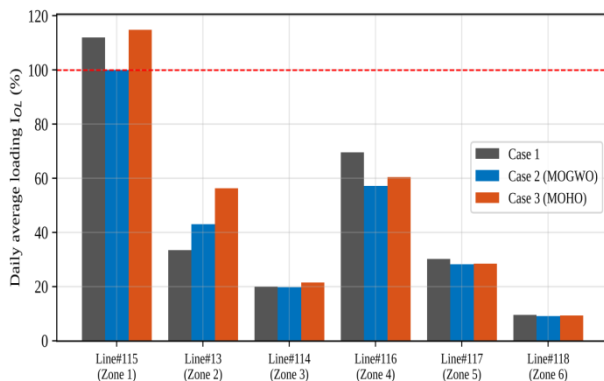


Fig. 9. Daily average loading of the main feeders.

G. Inverter, ESS and Wind Operation

The three 2500 kVA PVs of the MOHO plan inject up to 2.07 MW at noon, and their VV function absorbs reactive power up to the 750 kvar limit to counteract voltage rise. The ESSs charge between 02:00 and 07:00, idle at midday and discharge between 15:00 and 22:00, with state of charge rising from 50 % to 58–67 % and falling to the 20 % reserve or 28–35 % by evening. Their VW thresholds are not reached, so no storage curtailment occurs. The wind DG reaches its rated 1.5 MW at hours 14–15, coinciding with the PV peak, which explains why both optimisers avoid large PV capacity in Zone 5.

H. Grid Dependency and Hosting-Capacity Utilisation

With PV and ESS the microgrid becomes a net exporter between 08:00 and 16:00 (up to 4.4 MW for MOGWO and 5.3 MW for MOHO), while the evening import peak falls from 4.33 MW to 3.69 MW and 3.68 MW (Fig. 10). Daily grid import drops from 65.26 MWh to 37.17 MWh (-43.0 %) with MOGWO and 36.62 MWh (-43.9 %) with MOHO. Fig. 11 relates

installed PV to the 2882 kVA rating of each 400 A feeder: Zones 1, 2 and 4 operate within the 50–100 % band recommended for DSOs (80–87 %), MOHO uses 37.5 % of Zone 3, and Zones 5 and 6 remain under-utilised, so higher HC there needs extra voltage-control measures.

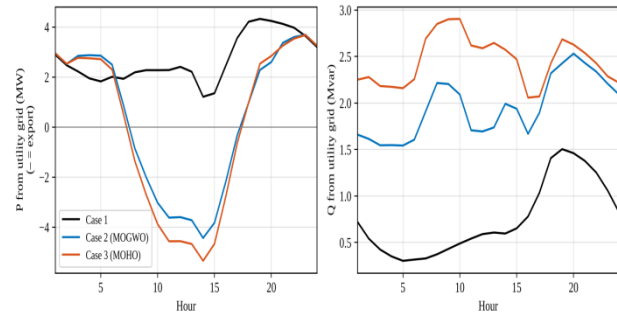


Fig. 10. Active and reactive power imported from the grid.

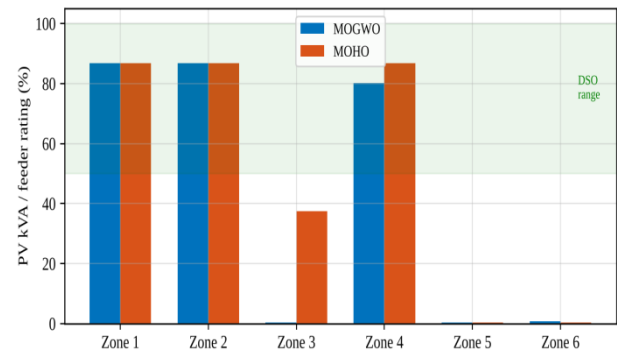


Fig. 11. PV hosting-capacity utilisation of each zone.

I. Overall Comparison and Discussion

Table VII and Fig. 12 compare the cases. The base paper reports an average VUI of 0.811 %, losses of 2.05 MWh and about 150 % penetration with its own data, so it is shown only for orientation; the fair comparison is between Cases 2 and 3, which share the same model. When the allocation reported in the base paper was simulated in the present model, it gave a 0.649 % VUI and 163.7 % penetration, but a Line#115 evening peak of 188.7 % and a 1.062 p.u. DG-bus voltage, which both optimised plans avoid.

TABLE VII. COMPARISON OF DAILY RESULTS

Index	Case 1	MOGWO	MOHO
PV capacity (kVA)	0	7350	8600
λ_{pv} (%)	0	184.5	215.9
Average VUI (%)	0.719	0.606	0.630
Active loss (MWh/day)	1.732	1.708	2.311

Avg. feeder loading (%)	45.8	42.9	48.4
Line#115 peak (%)	175.5	150.1	150.5
V min / V max (p.u.)	0.958/1.052	0.970/1.049	0.972/1.049
PV energy (MWh/day)	0	52.6	61.5
Grid import (MWh/day)	65.3	37.2	36.6

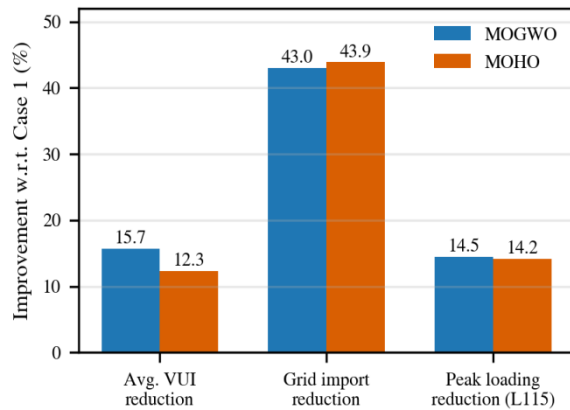


Fig. 12. Improvement of MOGWO and MOHO plans relative to Case 1.

The results show that: (i) both optimisers reproduce the key findings of the base paper, namely lower unbalance, relieved evening congestion and more than 40 % lower grid import; (ii) MOHO finds the best compromise of all twenty runs, with about 17 % more PV penetration and 8.9 MWh/day more PV energy than the best MOGWO plan; (iii) this comes with higher reverse-flow losses, while MOGWO gives a more conservative plan with lower losses and congestion; (iv) MOGWO is more repeatable, and mean differences are not significant; and (v) the leader-directed update is essential, because the origin-biased canonical update favours small PV sizes.

6. CONCLUSION

This paper extended coordinated PV–ESS planning with smart inverters for unbalanced microgrids by developing MOHO and comparing it with the MOGWO technique of the base paper on the six-zone IEEE 123-bus microgrid with wind DG and PEV load. Coordinated PVs with VV–VW inverters and follow-mode ESSs reduce the average VUI by 12–16 %, keep all VUI values below 1.11 % (limit 2 %), narrow the voltage band to 0.97–

1.05 p.u., cut the Line#115 evening peak from 175 % to 150 % and reduce daily grid import by about 43–44 %. MOHO obtained the best compromise objective (−0.0648 versus −0.0042) and 215.9 % PV penetration versus 184.5 %, and improved the mean objective of the canonical multi-objective HO by about 38 %. MOGWO showed lower run-to-run variability and lower losses, and the mean differences were not statistically significant ($p = 0.88$). Future work will add losses, cost and curtailment as objectives, make Stage 1 more robust through restarts or a joint siting–sizing formulation, apply probabilistic planning with seasonal profiles, co-optimize inverter curves and ESS dispatch, and extend the study to larger feeders such as the IEEE 8500-node system.

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