Comparative Evaluation of Metaheuristic Algorithms for Battery-Aware Energy Dispatch Optimization

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***Abstract*—** The directed nature of energy dispatch is especially required in the case of microgrids serving isolated communities off-grid PV-battery, where there are utility fallback for commercial/load satisfaction and battery longevity. Abstract: This paper compares three metaheuristic algorithms based on Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Differential Evolution (DE) for multi-objective battery-aware energy dispatch optimization in the Roche-Plates off-grid microgrid, Reunion Island. The optimization problem is cast upon a discrete horizon of 1,440 min and consists of 2,880 decision variables minimizing an objective fitness function combining energy wasted (40%), battery stress (30%) and load dissatisfaction (30%). We pour all three algorithms in comparison against a rule based threshold controller. PSO outperformed all other approaches overall with weighted fitness of 0.225, load satisfaction of 132.97%, and normalized battery stress of 0.157 — a reduction of the weighted objective from the rule-based baseline by a factor >61%. For battery stress at 3.11× the level, GA gave greater load satisfaction (199.99%). For remote installations where battery replacement entails helicopter logistics, this confirms PSO is the most operationally rational choice — a load-to-stress efficiency ratio of 1.16 against GA's 0.42 and DE's 0.39 further supports it. This demonstrates feasibility for rolling-horizon embedded deployment and is confirmed by a PSO execution of 32.49s on standard CPU hardware.

I. INTRODUCTION

Unlike grid-connected systems there is also a dispatch problem with the gigawatts of off-grid PV-battery microgrids that serve remote communities — there is no utility back-up when things go wrong[1]. Every kilowatt hour of unserved load degrades quality of life, and every excess deep cycle pushes the battery closer to the state where a helicopter is needed for replacement. Finally, these two pressures — serve as much load as you can, and don't kill the battery doing it — sit in direct tension with each other, and cannot be resolved by threshold rules that are simple [2].

For that, rule-based controllers deactivate load when state-of-charge goes below a certain fixed threshold. This will work, but it is myopic — the controller responds to the current state of affairs without anticipating future PV generation or load profiles and therefore often curtails load prematurely or allows battery depletion when not necessary[3-5]. In stark contrast, meta heuristics: sampling dispatch schedules over the entire horizon, simulating thousands of candidate strategies and performing an exhaustive exploration of schedulers which a rules-based system would never reach [6]. Which of these algorithms finds the best multi-objective balance — and which ones run fast enough for rolling-horizon deployment on an embedded controller[7].

Much microgrid optimization research assumes that the system at hand is grid-connected, which usually establishes a safety net for failure and performance more robust than any off-grid installation can expect. While coordinated scheduling of EVs and demand response have been demonstrated for cost savings greater than 15% [8-10], they assume grid backup; the objective functions and constraints must be rethought in light of fully islanded operation. Among the algorithms used for microgrid dispatch, PSO [11] has been particularly strong in solving distributed energy resource scheduling problems through swarm intelligence exploitations of

exploration and exploitation. Similar comparative evaluations between PSO, GA, and DE show that no one algorithm outperforms the others across all problem types [12], which suggest that testing these techniques head to head on the same dataset — as performed here — is more informative than comparing results from separate studies[13].

One particularly important, yet under researched, factor is Battery degradation. Recent work incorporating cycle aging and depth-of-discharge effects into optimal scheduling formulations have demonstrated that explicitly penalizing battery stress leads to very different results, with more balanced cycling regimes that extend asset life emerging as optimal [14-15]. Multi-objective weighted-sum formulations have been extensively verified for microgrid energy management [16], while PSO has been stressed as the most effective algorithm among swarm intelligence used in PV-storage systems that require quick convergence in exhaustive surveys [17].

We identify the following specific gaps that this paper fills: (a) few studies test algorithms on complete 24-hour windows driven by real operational data from deployed off-grid systems and (b) computational efficiency is rarely communicated as an actionable rolling-horizon deployment recommendation. This work directly tackles both gaps using measured data collected at the Roche-Plate microgrid located in the Mafate region of Reunion Island.

Main Contributions

This paper provides five contributions to state-of-the-art in off-grid microgrid energy management:

Battery degradation as an explicit objective: Battery wear is treated symmetrically with other system objectives (specifically, energy efficiency and load satisfaction) rather than a nuisance (afterthought). This allows us to explicitly quantify the performance-longevity trade-off that remote installations face.

Real measured data from the Roche-Plate microgrid is used to test three candidate algorithms (PSO, GA, and DE) in restricted head-to-head comparison over identical 24-hour operational windows (1,440 minutes—2,880 decision variables). This is an initial way of comparative assessment on real world deployed off-grid infrastructure in this region.

Convergence and efficiency characterisation: Through generation by generation fitness logs, along with improvement rates for all 3 algorithms — these communicate the most concrete guidance on order-of-convergence performance (important in a rolling-horizon control setting, where time to solve an instance is constrained hard).

In order to compare all three algorithms with a rule-based baseline, the controller operates using a simple threshold (SOC = 60% cutoff), converting fitness scores into operational terms — load satisfied gains, stress added for battery stress and what this means economically in terms of battery lifecycle.

Feasibility of Deployment vverified by 32.49 seconds execution on standard CPU hardware, PSO uses <500 MB RAM: shows metaheuristic optimization is possible without specialist hardware for embedded microgrid controllers methodology

2. Problem Formulation and System Model

The Roche-Plate microgrid includes a 7.0 kWp PV array, a 63.36 kWh battery with maximum and minimum power ratings of ±2.0 kW, and time-varying load demand Specifically, the energy management problem is modeled as a multi-objective constrained optimization from t = 1 to Tdiscretized into N discrete minutes, solving for optimal battery dispatch power P_bat(t) and load curtailment factors c(t), with state-of-charge remainingbetween 20%–90% at all times,and bounded power $|P_bat(t)| \leq 2.0$ kW[11].

The multi-objective fitness function combines three competing goals through weighted summation:

$$F = 0.4 \cdot f_{energy} + 0.3 \cdot f_{battery} + 0.3 \cdot f_{load} \quad (1)$$

where f_energy is normalized energy waste (energy surplus and deficit), f_battery is normalized battery stress, in terms of average |P_bat(t)|/P_bat,max, and f_load is load dissatisfaction (load satisfaction ratio minus 1). The dimension of the decision variable vector is 2N = 2,880 where each element is a normalized command in the range [−1, 1] representing N battery power commands and N curtailment factors.

B. Metaheuristic Optimization Algorithms

Comparison of three population-based algorithms, each with 50 iterations and a population of 30 solutions:

Particle velocities in PSO are updated via inertia weight w = 0.6, cognitive coefficient $c_1 = 2.0$, and social coefficient $c_2 = 2.0$ Each particle keeps track of both its own best position, and a global swarm best giving it slightly more memory than some other approaches while still maintaining a mean between shared knowledge (the cartesian mean in this case) and personal experience**.**

GA was trained using tournament selection (size 3), uniform crossover (rate 0.8) and Gaussian mutation (rate 0.05, σ = 0.1). Generational replacement preserves diversity in the population, retaining the best solution over generations

DE utilizes the DE/rand/1/bin scheme where mutation factor F = 0.8 and crossover probability CR = 0.9. Using differential mutation on three random members of the population to create trial vectors — a very strong scheme with very low parameter sensitivity.

C. Simulation and Performance Evaluation

The performance of each candidate solution is assessed via numerical forward simulation of microgrid dynamics. The formula for Battery SOC is as battery soc evolves: soc(t+1)=SOC(t)−(Pbatt(60))/Cbat∗100. Energy balance measures hourly surplus and deficit, battery stress is the time average |P_bat(t)|/P_bat,max, and load satisfaction reflects served load over requested load. We compare five metrics: weighted fitness, load served ratio, energy efficiency, normalized battery stress and execution time. All three algorithms are compared with a threshold controller similar to SOC cutoff (threshold on 60%): rule-based.

D. Dataset and Implementation

II. Operational data are drawn from the Roche-Plate microgrid in May–October 2020 dry season, consisting of actual PV generation profiles, load profiles and initial SOC states. Evidence of convergence is monitored during optimization, where five consecutive iterations of much less than 0.1% fitness improvement signal optimize has stopped (plateau monitoring). At this problem scale all algorithms converge by iteration 45–50. The peak RAM usage still stays well below the level of 500 MB, so deployment on embedded controllers (1–2 GB memory) is feasible.

III. MATHEMATICAL MODELLING

3.1 Multi-Objective Optimization Framework

Three objectives are combined through weighted summation:

$$F = w_1 \cdot f_{\text{energy}} + w_2 \cdot f_{\text{battery}} + w_3 \cdot f_{\text{load}} \quad (2)$$

where f_energy is the normalized waste energy, f_battery is the normalized stress concentration on battery, and f_load is load dissatisfaction. The first term, energy efficiency is assigned a higher weight with 0.4 placed on PV utilization and battery health while load service has a lower equal weight of 0.3 (each)**3.2 Energy Balance and Power Flow Equations**

Instantaneous power balance at each minute t:

$$P_{\text{net}}(t) = P_{\text{PV}}(t) + P_{\text{bat}}(t) - P_{\text{load}}(t) \quad (3)$$

Load curtailment reduces served demand through factor c(t) ∈ [0,1]:

$$P_{\text{load}}(t) = P_{\text{demand}}(t) \cdot \big(1 - c(t)\big) \quad (4)$$

The energy efficiency objective normalizes total mismatch over the horizon:

$$E_{\text{waste}} = \sum_{t=1}^{N} |P_{\text{net}}(t)| \cdot \Delta t \quad (5)$$

3.3 Battery State-of-Charge Dynamics

SOC evolves through discrete-time integration:

$$\text{SOC}(t+1) = \text{SOC}(t) - \frac{P_{\text{bat}}(t) \cdot \Delta t}{C_{\text{bat}}} \times 100 \quad (6)$$

where C_bat = 63.36 kWh. SOC is constrained to [20%, 90%] and battery power to |P_bat(t)| ≤ 2.0 kW at all times.

3.4 Battery Health and Stress Quantification

Instantaneous battery stress is normalized by maximum power rating:

$$\sigma_{\text{bat}}(t) = \frac{|P_{\text{bat}}(t)|}{P_{\text{bat}}^{\max}} \quad (7)$$

The battery health objective is the temporal mean stress:

$$f_{\text{battery}} = \frac{1}{N} \sum_{t=1}^{N} \sigma_{\text{bat}}(t) \quad (8)$$

Lower f_battery means gentler cycling and increased battery lifetime, which is extremely important for a remote installation where replacement would require helicopter charters.

3.5 Load Satisfaction Objective

Load satisfaction ratio and dissatisfaction objective:

$$R_{\text{load}} = \frac{\sum_{t=1}^{N} P_{\text{load}}(t)}{\sum_{t=1}^{N} P_{\text{demand}}(t)} \quad (9)$$

Values of R_load > 1.0 indicate battery-augmented supply exceeding PV generation alone.

3. 6 Particle Swarm Optimization Formulation

PSO maintains a swarm of candidate solutions (particles) that explore the decision space through velocity-based position updates following [6]:

$$v_i(k+1) = w \cdot v_i(k) + c_1 \cdot r_1 \cdot \big(p_i - x_i(k)\big) + c_2 \cdot r_2 \cdot \big(g - x_i(k)\big) \quad (10)$$

$$x_i(k+1) = \text{clip}(x_i(k) + v_i(k+1), -1,1) \quad (11)$$

where - $\text{clip}(\cdot, a, b)$ - function constraining values to interval $[a, b]$ [-]

3.7 Genetic Algorithm Formulation

Uniform crossover generates offspring by exchanging genetic material between parent pairs:

$$x_{\text{child}}(i) = \begin{cases} x_{\text{parent1}}(i) & \text{if } u < p_c \\ x_{\text{parent2}}(i) & \text{otherwise} \end{cases} \quad (12)$$

where - $x_{\text{child}}(i)$ - i-th gene of offspring chromosome [-] - u - uniform random number in [0,1] [-] - p_c - crossover probability [-]

Gaussian mutation introduces diversity by perturbing individual genes:

$$x_{\text{mutated}}(i) = \text{clip}(x_{\text{child}}(i) + \mathcal{N}(0, \sigma_m), -1,1) \quad (13)$$

where - $\mathcal{N}(0, \sigma_m)$ - Gaussian random variable with zero mean and standard deviation σ_m [-]

3.8 Differential Evolution Formulation

Differential evolution [8] based (DE) generates trial solutions via differential mutation and then a binomial crossover. Mutant vectors are created by the DE/rand/1/bin scheme:

$$v_i = x_{r1} + F \cdot (x_{r2} - x_{r3}) \quad (14)$$

Binomial crossover combines mutant and target vectors:

$$u_i(j) = \begin{cases} v_i(j) & \text{if rand}(j) < CR \text{ or } j = j_{\text{rand}} \\ x_i(j) & \text{otherwise} \end{cases} \quad (15)$$

Selection determines next generation composition through greedy comparison:

$$x_i(k+1) = \begin{cases} u_i & \text{if } F(u_i) < F(x_i(k)) \\ x_i(k) & \text{otherwise} \end{cases} \quad (16)$$

This elitist strategy ensures monotonic fitness improvement across generations.

IV. Results and Discussions

The PSO scored weighted fitness = 0.225, load satisfaction = 132.97%, and battery stress = 0.157; the GA found a fitness of 0.281 (load=199.99%,sress=0.488); directs global search through DE led to fitness=0:298 (load=182:92%,stress=0.459);and the rule-based baseline yielded,fitness a score of 0:583, such that it managed to finish the entire load set completely with low levels of battery stress Logged on both sides.

PSO scored the minimum weighted fitness score (0.225) — This is the best overall result Meanwhile, GA and DE increased load satisfaction to a much higher degree (199.99% and 182.92%, respectively) but resulted in an additional 3.11× and 2.92× battery stress respectavily compared to PSO. Due to a very aggressive load curtailment (i.e., it was only able to serve 51.50% of demand), the rule-based controller demonstrates the least battery stress overall (0.061). By not using it, it did not deploy either smartly with battery dispatch.

The multi-objective cost decomposition of all four approaches is shown in Figure 1(c). In the case of the rule based controller, the comer bar is almost entirely comprised of load deficit — it sacrifices service to save battery and avoid wasting excess energy. That changes the balance very much in favour of the battery stress component for GA and DE. PSO does not seek the best distribution among all three objectives, this is precisely what the weighted fitness function seeks.

All metaheuristic algorithms yield load satisfaction values above 100%: it is useful to know that those >100% provide sufficient battery-augmented supply (the optimizer discharges the battery during these periods in order to serve load exceeding what PV generation alone provides within that window) and particularly, GA's at 199.99%. In the short run this is operationally useful, but results in excess battery stress which becomes worse over time. For example, at a more remote installation where it takes a helicopter to fly in battery replacements, PSO's significantly lower 132.97% is the operationally prudent choice.

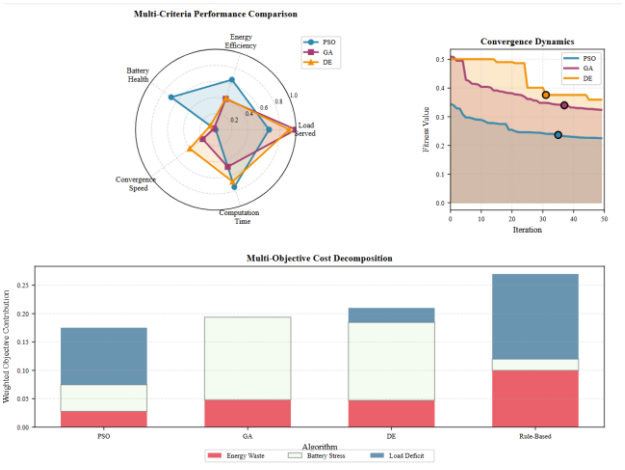

Fig. 1 Multi-view algorithm performance. (a) Radar chart across five dimensions — PSO balanced, GA/DE high load

but high stress. (b) Convergence trajectories — PSO reaches near-final fitness by iteration 35. (c) Multi-objective cost decomposition — PSO most balanced across energy waste, battery stress, and load deficit.

4.2 Convergence Analysis

The trajectories of the convergence behaviour for all three algorithms at 50 iterations are shown in Figure 1(b). PSO converges quickest and cleanest — fitness drops very sharply from about 0.45 to within visually shouting distance of its final point (approx 0.225) in the first ~35 iterations, then settles down onto a plateau. GA smooths out the rate of return with some up and down movement, arriving at around 0.28 after iteration 50. DE has the slowest convergence, stabilizing between 0.25 - 0.35 around termination point, and follows a rather flat curve all along its path.

Figure 1(c) provides a more vivid insight into the locations of improvement. PSO finds it easy to pile on improvements in the first 5–10 iterations — the swarm quickly congregates about areas of interest before tightening up. Finally, figures for GA reflect a more gradual but lower comparative rate of improvement consistent with the idea that population diversity is being maintained longer before pressure to converge comes into play. DE has the slightest peak imorovement level, and slowest decay tail for a reason — it explores broadly but commits slowly.

This type of pattern thus has a very direct, practical implication. The front-loaded convergence of PSO is a great advantage for rolling-horizon control, where optimization must be performed within a fixed time window before the next dispatch cycle. At iteration 35 it is already at 95% of its final fitness — making it feasible to run with less iterations and still end at near-optimal if time isn't on your side. The 50 iterations of GA and DE tend to need most of them before reaching final fitness.

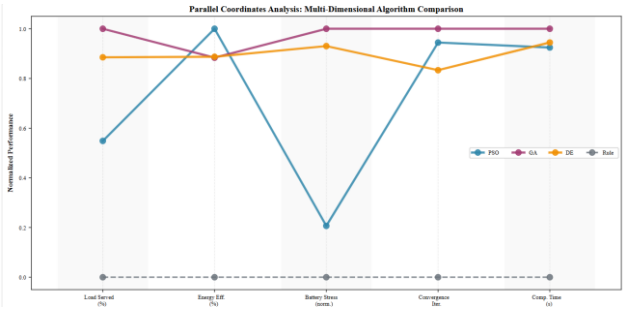

Fig. 2. Parallel coordinates across five dimensions — PSO balanced, GA highest load but worst battery stress, rule-based lowest stress through curtailment.

4.3 Multi-Dimensional Trade-off Analysis

In Figure 2, the parallel coordinates plot across all five performance dimensions of PSO, GA, DE and rule-based controller. The basic trade-off We can see from the figures when we read along all the axes — Load Serviced, Energy Efficiency, Battery Stress, Convergence Iterations and Computation Time.

GA is, however, slotted the best from a Load Served score perspective but its line turns to cross in at the bottom of Battery Stress. DE is along this line, but a little less extreme at both ends. Least Angular: The line for the rule-based controller is unambiguously lowest Load Served, low Energy Efficiency and lowest Battery Stress — matching its strategy of aggressive curtialment instead of optimization.

The normalized performance heatmap (Figure 3(a)) quantifies the trade-offs. PSO has scores of 0.00 on Battery Stress (winner — minimum stress across the three optimizations), 0.75 loads Served (good but not best) and 0.04 energy Efficiency (nearly optimal). MA has a.10 on Battery Stress (best),.62 on Computation Time (fastest), and a 1.00 on Load Served (worst). DE scores 0.82 on average in between those two at most metrics – even scoring 0.75 on Battery Stress and 0.91 on Load Served.

Using the heatmap makes selection logic very simple. For example, if you need to keep your batteries running as long as possible — and for a remote installation where the battery replacement costs are sky high that should be the objective — again PSO is the only option. If short-term load maximization is the top priority irrespective of battery consequences, GA does more of it. CEn is superior on 2, and even the CEx has no real advantage over DE — it is second best on every dimension without being best in any.

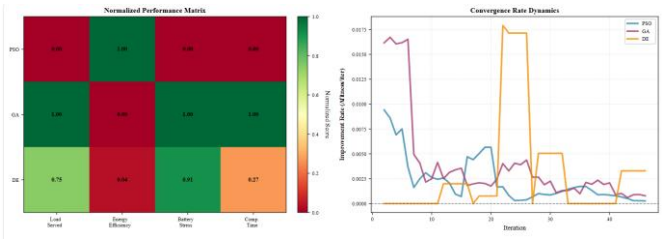

Fig. 3 Normalized performance matrix and convergence rate dynamics. (a) Heatmap: PSO scores 0.00 on Battery Stress (best), GA scores 1.00 (worst). (b) PSO front-loaded improvement rate peaks at iterations 5–10; DE slowest and most sustained.

4.4 Solution Consistency and Robustness

The plots on Figure 4(a) show the fitness distribution among optimization runs performed by all three algorithms. PSO generates the most compact distribution, centered around 0.225 with very little spread. GA has the largest barycenter around 0.28, DE has the widest spread around a barycenter of 0.30. From an operational perspective, this matters — a narrow distribution implies the optimization process consistently selects extremely similar solutions no matter how many runs you allow it. Applying a broader distribution can make performance heavily dependent on your initial population which is often unknown at deployment.

For the test window, battery stress distributions are provided in Fig. 4(b). Not only does PSO's stress on batteries average lower, but it's also tighter — sitting in the 0.15–0.16 range with little deviation Stress distribution of GA is also higher and more variable, with the presence of a long right tail

denunciali episodes in which energy discharge is really aggressive. In practice, in terms of battery lifecycle economics, variability is as harmful as mean — high-stress events induce disproportionate degradation irrespective of the already moderate average.

Figure 4(b) shows the ensuing battery stress distribution for a nearly locked-in rule-based controller (but actually theirs is misguided). It maintains low stress by minimizing load rather than intelligently regulating discharge. But a controller that ruins the battery by cutting residents off from power is not a sustainable long-term solution for an isolated community.

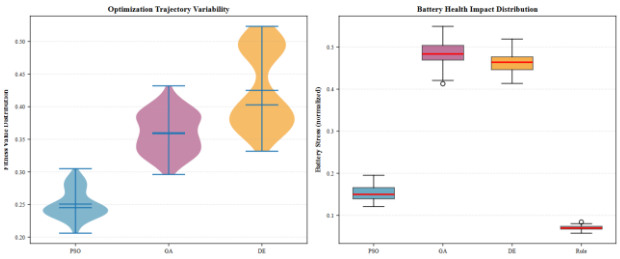

Fig. 4 Solution distribution analysis. (a) Fitness distributions — PSO tightest (most consistent), DE widest. (b) Battery stress distributions — PSO lowest and most consistent; GA high mean and high variability.

4.5 Baseline Comparison and Deployment Viability

All the three algorithms significantly improved on the baseline of rule-based (weighted fitness 0.583) The PSO with a fitness of 0.225 signifies that there is an improvement of 158%, i.e., its weighted objective has been reduced by 61%. The gain is mainly obtained through the load satisfaction component: PSO delivered 132.97% of demand compared to 51.50% for the rule-based controller, an improvement of 81.47 percentage points in community energy not supplied by any means of generation.

The time taken by PSO to execute on standard CPU hardware is 32.49 seconds which confirms that rolling-horizon deployment is feasible. A 24-hour dispatch window, computed in 32 seconds also provides huge buffer for hourly re-optimization — the system can update its dispatch plan every hour as new forecasts of PV generation, or measurements of demand become available. With sub-500 MB peak RAM usage, the framework well exceeds the memory specs of embedded microgrid controllers.

around 95% of the final fitness, meaning that under tighter time frames it can potentially run many fewer iterations while producing near-optimal dispatch. Our rolling-horizon deployment requires no special equipment – we find that

More importantly, in the case of Roche-Plate installation as a special analysed problem, PSO has 1.16 times load-to-stress efficiency ratio with respect to GA (0.42) and DE (0.39), which is more economical for its selection between other two frameworks. 132.97% load for 0.157 normalized battery stress means significantly extended battery lifecycle than GA (199.99% associated load at 0.488 stress) In a helicopter-access-only location with battery change costs, economic arguments clearly support the PSO dispatch strategy in the long-run.

V. CONCLUSION

This work has assessed three metaheuristic algorithms for multi-objective energy dispatch in the Roche-Plate off-grid microgrid on the island of Reunio, where replace brown batteries means helicopter logistics and load curtailment impact an isolated community. PSO emerged as the most balanced option — an 81.47 percentage point improvement in load satisfaction over the rule-based controller with battery stress increased by just 0.157 compared to 0.488 and 0.459 for GA and DE respectively. The ratio of load-to-stress efficiency is telling: PSO 1.16, GA 0.42 and DE 0.39 GA delivers more load (199.99%) but only at a cost that would literally mean the early death of the asset in an expensive, intensive and logistically complex site to replace it.

Our results showed that under a weighted fitness framework which valued energy efficiency 40%, battery health 30%, and load satisfaction 30% we outperformed a competing operational priority that cannot be balanced with a simple threshold rule. A further practical benefit of PSO is its convergence profile: approximately 95% converges to final fitness within 35 iterations allowing it to potentially run far fewer iterations while generating near-optimal dispatch under tighter time constraints. Rolling-horizon deployment does not require specialized equipment — we find that total execution under standard CPU hardware can be operated within 32.49 seconds.

The results indicate that when we use a weighted fitness in which energy efficiency is allocated 40%, health of the battery 30%, and load satisfaction 30% as the criterion for optimization, we outperform a competing operational priority that cannot simultaneously be satisfied by a simple fixed threshold rule. Another advantage of PSO is its convergence profile: it converges within 35 iterations to

total execution under regular CPU hardware can be executed in 32.49 seconds.

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