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Exploring the Optimal Battery Sizing in Grid-Connected PV Systems: A Comparative Study of PSO and GA in Oax, Mx

Exploración del dimensionamiento óptimo de baterías en sistemas FV conectados a la red: un estudio comparativo de PSO y GA en Oax, Mx

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Abstract

The optimal sizing of Battery Energy Storage Systems is crucial for maximizing the efficiency and output of grid-connected photovoltaic (PV) systems. This study explores Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), both aimed at minimizing total system costs. The analysis evaluates several performance indicators, including total life cycle cost, optimal battery capacity and power ratings, integrated Levelized Cost of Energy (LCOE), and charge/discharge energy profiles. The results indicate that GA achieves a total cost reduction of approximately 3-4% compared to PSO, alongside a modestly lower integrated LCOE. However, PSO displays enhanced control over discharge depth, yielding a more stable state of charge trajectory.

Keywords— Battery storage, grid-connected PV, PSO

Resumen

La dimensión óptima de los Sistemas de Almacenamiento de Energía en Baterías es fundamental para aprovechar el potencial de las plantas fotovoltaicas (FV) conectadas a la red. Este estudio evalúa la Optimización por Enjambre de Partículas (PSO) y el Algoritmo Genético (AG), con el objetivo de minimizar los costos totales. Los indicadores de rendimiento evaluados incluyen el costo total del ciclo de vida, la capacidad y potencia óptimas de la batería, el Costo Nivelado de Energía integrado (LCOE) y los perfiles de energía de carga/descarga. Los resultados revelan que el AG resulta en un costo total entre un $3\,\%$ y un $4\,\%$ menor que el obtenido con PSO, así como un LCOE ligeramente inferior. Sin embargo, PSO muestra un control superior sobre la profundidad de descarga, lo que resulta en una trayectoria de carga más uniforme.

Palabras clave— Almacenamiento de baterías, FV conectada a la red, PSO

I. Introduction

In recent years, the integration of renewable energy sources into electrical grids has gained significant global momentum [1, 2, 3]. This trend primarily arises from increasing energy demand, growing environmental concerns, and the urgent need to address climate change, [4, 5, 6, 7].

Photovoltaic (PV) generation stands out among renewable technologies. It produces minimal greenhouse gas emissions. Its installation costs are declining. PV systems are scalable and suitable for both small rooftop installations and large utility installations [8]. However, solar irradiance is highly variable due to weather changes, sea-

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sons, and daily cycles. This variability causes operational challenges. These include supply instability, voltage fluctuations, and mismatches between generation and demand [9, 10, 11].

The Battery Energy Storage Systems (BESS) are widely recognized as an effective solution for managing fluctuations in energy production [12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]. By storing excess PV energy during periods of high sunlight and releasing it during times of low production or peak demand, BESS enhances flexibility, reliability, and overall power quality [23, 24, 25, 26, 27, 28, 29]. However, the high initial cost of batteries makes optimal sizing crucial [30]. Oversizing a BESS can lead to excessive investment and underutilization, while undersizing can result in curtailed PV energy output, reduced reliability, and increased operational costs. Classical optimization techniques often struggle with the non-linear, multi-modal, and constraint-rich nature of PV–BESS sizing [31].

Metaheuristic algorithms particularly Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) have attracted increasing attention in the recent literature, [32, 33, 34, 35, 36]. In [37], a binary PSO is proposed to optimize hybrid energy generating systems (HEGS) in the Galapagos Islands, Ecuador, offering a simple and powerful tool for efficient energy system sizing. In another study, the authors propose the PSO technique to achieve optimal sizing of the hybrid energy storage system (HESS) and an improved low-pass filter for electric vehicle applications, achieving considerable performance [38].

Other work proposes a hybrid technique that combines an extended Kalman filter (EKF), PSO, and long short-term memory (LSTM), achieving an excellent accuracy and robustness, [39]. As to approaches GA, a study's whole objective is to solve a constrained chance model for optimizing the expansion of energy storage (ESSs) and renewable energy integration in an electric grid which considers the initial investment cots for energy storage and renewable energy, as well as conventional generation systems to meet load demand, [40].

In other work, the author applies GA to determine the optimal configuration of subsystems, specifically including the battery capacity, for an autonomous renewable energy multi-source system [41]. In [42], a GA-based method is proposed to determine the optimal energy and power capacities of energy storage systems (ESS) in microgrids.

Other interesting work presents a methodology for the optimal sizing of stand-alone PV/Wind-Generator systems, including the determination of the optimal number and type of batteries, by minimizing the 20-year total system cost. The collective behavior of biological populations, such as bird flocks or fish schools, inspires PSO. Particles explore the decision space cooperatively by sharing information on promising regions. GA, by contrast, emulates natural selection through crossover and mutation, balancing exploration and exploitation across generations. Both algorithms have shown the ability to deliver near-global optima within reasonable computational timeframes for complex, non-convex problems. However, their performance may vary depending on problem specifics and parameter tuning [43, 44, 45, 46, 47, 48, 49].

This study presents a thorough comparison of PSO and GA for optimizing the sizing of Battery BESS in grid-connected PV systems in Oaxaca, Mexico. The analysis utilizes hourly profiles of irradiance and temperature from the National Solar Radiation Database (NSRDB-NREL) for the period spanning January 1, 2024, to December 31, 2024, based on approximate coordinates of 17.06° N and 96.72° O. The analysis focuses on several key performance indicators, including total system cost, optimal battery capacity and power, LCOE, and charge/discharge energy profiles—all of which play a crucial role in the practical design of PV-BESS systems.

This study makes three significant contributions:

- Development of a unified optimization model integrating PV power estimation, detailed battery dynamics, mismatch penalties, and maintenance costs.
- Implementation of calibrated PSO and GA solvers with identical population sizes and iteration limits, allowing for a fair, side-by-side comparison.
- Execution of a 360-day simulation to evaluate trade-offs between economic performance (total cost, LCOE) and operational behavior (state-of-charge profile, depth of discharge).

The remainder of this paper is organized as follows: Section 2 presents the mathematical formulation, including the objective function and system constraints. Section 3 describes the optimization methodology and parameter settings. Section 4 discusses the results obtained with PSO and GA, including both a representative-day case study and a year-long simulation. Finally, Section 5 presents the conclusions and outlines directions for future work and real-world deployment.

II. Problem formulation

The optimization problem concerns a grid-connected (PV) plant equipped with a BESS. The aim is to choose the 24-hour battery set points that minimize the total daily operating cost while satisfying all physical constraints. The formulation comprises three parts: the PV generation model, the battery state model, and the cost function.

II.1. Photovoltaic power model

PV output depends on solar irradiance and cell temperature. Cell temperature is estimated from ambient temperature by the empirical relation

$$T_{\text{cell}}(t) \;=\; T \;+\; \frac{GHI(t)}{800}\big(T_{\text{NOCT}}-20\big), \qquad (1)$$

where T is ambient temperature (°C), GHI is global horizontal irradiance (W m^{-2}), and T_{NOCT} is the nominal operating cell temperature [4]. The impact of temperature on module efficiency is

$$\eta_{\text{loss}}(t) \;=\; 1-\lambda\big(T_{\text{cell}}(t)-25\big), \qquad (2)$$

with λ the temperature coefficient and $25\,^{\circ}\mathrm{C}$ the standard test condition reference. The DC power produced at hour t is therefore calculated by:

$$P_{PV}(t) \;=\; C_{PV}\,\frac{GHI(t)}{S_{\text{STD}}}\,\eta_{\text{loss}}(t)\,\eta_{DC/DC}, \qquad (3)$$

where C_{PV} is the nominal PV capacity (kW), $S_{\text{STD}} = 1000\,\mathrm{W\,m^{-2}}$ is the standard irradiance, and $\eta_{DC/DC}$ is the DC–DC converter efficiency, explicitly set as:

$$\eta_{DC/DC} = 0.95 \qquad (4)$$

II.2. Battery energy storage model

Let the state of charge be $C_{\text{BES}}(t)$ (kWh) and the battery power set point be $P_{\text{BES}}(t)$ (kW, positive when charging). At the beginning of the day the SoC is initialized to the mid point between its limits

$$C_{\text{BES}}(0) \;=\; \frac{C^{\max}_{\text{BES}}+C^{\min}_{\text{BES}}}{2}. \qquad (5)$$

For each subsequent hour, the dynamic model for the state of charge (SoC) is given by:

$$C_{\text{BES}}(t+1) = \min\Big[C_{\text{BES}}(t) + P_{\text{BES}}(t)\,\eta_{\text{charge}},\; C^{\max}_{\text{BES}}\Big], \qquad (6a)$$

$$C_{\text{BES}}(t+1) = \max\Big[C_{\text{BES}}(t) + \tfrac{P_{\text{BES}}(t)}{\eta_{\text{discharge}}},\; C^{\min}_{\text{BES}}\Big], \qquad (6b)$$

where (6a) applies when $P_{\text{BES}}(t) \geq 0$ (charging) and (6b) when $P_{\text{BES}}(t) < 0$ (discharging). To maintain the feasibility of the SOC over the upcoming hour, it is imperative that the set point adheres to the established dynamic constraints.

$$P^{\max}_{\text{BES}}(t) = \;\min\Big[C^{\max}_{\text{BES}} - C_{\text{BES}}(t),\; \tfrac{(C_{\text{BES}}(t)-C^{\min}_{\text{BES}})\,\eta_{\text{discharge}}}{\Delta t}\Big], \qquad (7a)$$

$$P^{\min}_{\text{BES}}(t) = \;\max\Big[C^{\min}_{\text{BES}} - C_{\text{BES}}(t),\; \tfrac{C_{\text{BES}}(t)-C^{\max}_{\text{BES}}}{\eta_{\text{charge}}\,\Delta t}\Big], \qquad (7b)$$

and we enforce

$$P_{\text{BES}}(t) \;\in\; \big[P^{\min}_{\text{BES}}(t),\, P^{\max}_{\text{BES}}(t)\big]. \qquad (8)$$

II.3. Cost function

With demand $D(t)$, the supply–demand mismatch is

$$\Delta(t) \;=\; P_{PV}(t) + P_{\text{BES}}(t) - D(t).$$

The hourly costs $C_{mis}(t) = c_m|\Delta(t)|$, $C_{mnt}(t) = c_{mnt}|P_{\text{BES}}(t)|$, $C_{pen}(t) = k_p \max\big\{0, -\Delta(t)\big\}$ are mismatch, maintenance, and unserved load, respectively. and the total daily operating cost to be minimized is

$$\min_{P_{\text{BES}}(t)} \sum_{t=1}^{24}\Big[c_m\,|\Delta(t)| + c_{mnt}\,|P_{\text{BES}}(t)| + k_p\,\max\{0, -\Delta(t)\}\Big] \qquad (9)$$

where the coefficients are determined as follow, $c_m = 0.30$ MXN kWh^{-1} [50], $c_{mnt} = 0.25$ MXN kWh^{-1} [30], $k_p = 100$ MXN kWh^{-1}. The large value $k_p \gg c_m$ reflects the contractual penalty for unserved demand. Equations (2)–(9) define a non convex optimization problem with 24 continuous decision variables $P_{\text{BES}}(1), \ldots, P_{\text{BES}}(24)$ limited by the inverter rating

$$P_{\text{BES}}(t) \in [-30,\, 30]\text{ kW}.$$

The LCOE is explicitly calculated as follows:

$$LCOE = \frac{1}{\sum_{t=1}^{T} D(t)} \sum_{t=1}^{T} \big(c_m|\Delta(t)| + c_{mnt}|P_{BES}(t)| + k_p \max\{0, -\Delta(t)\}\big) \qquad (10)$$

where $T = 360$ days. For this extended evaluation, daily profiles of solar irradiance, ambient temperature, and power demand are considered. The cumulative daily operational and energy-related costs provide an annualized LCOE. Since conventional solvers are prone to local optima, we resort to meta-heuristic algorithms, specifically PSO and GA, whose detailed configurations are presented in Section III.

III. Methaheuristic Optimization: PSO ans GA

This section describes the configuration and execution of the two metaheuristic solvers (PSO and GA) used to optimize the 24-element battery power vector

$$\mathbf{P}_{BES} = \big[P_{BES}(1),\, \ldots\,,\, P_{BES}(24)\big]^{T}.$$

III.1. Search Space and Common Settings

The optimization variables comprise a 24 dimensional real valued vector $\mathbf{P}_{BES}$, where each component $P_{BES}(t)$ denotes the battery charge/discharge power (kW) at hour t. Each variable is constrained to

$$P_{BES}(t) \in [-30, 30] \quad (\text{kW}),$$

To ensure a fair comparison between the PSO and GA, both solvers will use identical settings. The population size consists of 30 candidate solutions, which refer to particles in PSO and individuals in GA. The iteration limit is set to 100 for both PSO and GA. The convergence criterion states that the process should stop if the relative improvement in the best cost falls below 10^{-5}. For reproducibility, a fixed random seed is used. For constraint handling, after each update, any values of $P_{BES}(t)$ that fall outside the range $[-30, 30]$ will be clipped back into this range before evaluating the cost. In terms of objective evaluation, for each candidate solution, the battery dynamics will be simulated using Equations (5) to (7).

The simulation will accumulate mismatch, maintenance, and penalty costs, ultimately allowing for the computation of the total cost as described in Equation (9). All other parameters (e.g. PV data, load profiles, cost coefficients) are held identical. Both PSO and GA adhere to the same evaluation loop:

1. **Initialization.** Generate population $\{\mathbf{x}_i^0\}$ (and $\{\mathbf{v}_i^0\}$ for PSO).
2. **Evaluation.** For each $\mathbf{x}_i^k$:
   - Compute PV output $P_{PV}(t)$ via (3).
   - Simulate SoC via (5)–(6b), enforce (7a)–(8).
   - Compute total cost $f(\mathbf{x}_i^k)$ by (9).
3. **Update.**
   - PSO: update $\mathbf{v}_i, \mathbf{x}_i$ by Equations (13) and (14); refresh personal/global bests.
   - GA: produce next generation via selection, crossover, mutation, elitism.
4. **Convergence.** Stop if iteration/gen $= 100$ or best cost improves by $< 10^{-5}$ over 20 steps.
5. **Logging.** Record best and mean costs for convergence plots.

III.2. Particle Swarm Optimization

We apply PSO to the 24-hour scheduling problem defined by Eqs. (5)–(6b) and objective (9), subject to power limits (7a)–(8). Each particle i holds a 24 vector $\mathbf{x}_i \in [-30, 30]^{24}$. Initialize

$$\mathbf{x}_i^0 \sim \mathcal{U}\big([-30, 30]^{24}\big), \tag{11}$$

$$\mathbf{v}_i^0 \sim \mathcal{U}\big([-v_{\max}, v_{\max}]^{24}\big), \quad v_{\max} = 15\,. \tag{12}$$

Set personal best $\mathbf{p}_i^{\text{best}} = \mathbf{x}_i^0$, and global best $\mathbf{g}^{\text{best}} = \arg\min_i f(\mathbf{x}_i^0)$. At iteration $k+1$, update velocities and positions via

$$\mathbf{v}_i^{k+1} = w\,\mathbf{v}_i^k + c_1\,r_1\big(\mathbf{p}_i^{\text{best}} - \mathbf{x}_i^k\big) + c_2\,r_2\big(\mathbf{g}^{\text{best}} - \mathbf{x}_i^k\big), \tag{13}$$

$$\mathbf{x}_i^{k+1} = \mathbf{x}_i^k + \mathbf{v}_i^{k+1}, \tag{14}$$

where $r_{1,2} \sim \mathcal{U}(0,1)$. After each update, clip $|v_{i,t}| \leq v_{\max}$ y $x_{i,t} \in [-30, 30]$ The parameters are determined as follow $w = 0.7$, $c_1 = c_2 = 1.5$, $v_{\max} = 15$kW, $N = 30$, $K_{\max} = 100$.

III.3. Genetic Algorithm (GA)

GA evolves a population of 30 chromosomes, each encoding $\mathbf{x} \in [-30, 30]^{24}$. Details:

The initialization process starts by selecting 30 individuals randomly within the range of $[-30, 30]^{24}$. We evaluate how well each individual performs using the fitness function $f(\mathbf{x})$ described in Equation (9). For selecting individuals, we use a tournament method with a size of 3. During crossover, we apply single-point crossover. We randomly choose a cut point p from $\{1, \ldots, 23\}$ to combine the genes of two parents. In the mutation phase, each gene has a 5% chance of changing. If it does, we add a value from the normal distribution $\mathcal{N}(0, \sigma^2)$ where $\sigma = 3$ kW. We make sure any resulting values stay within the range of $[-30, 30]$. We use an elitism strategy, where we copy the best individual directly into the next generation without changes. The parameters for this process are: population size (Pop) is 30; tournament size is 3; mutation rate is 5%; elitism is 1; the number of genes is 100; crossover size is 1; and σ is 3 kW.

IV. Results

IV.1. convergence analysis for optimization algorithms

First, a *representative day* (24 h) is analyzed in depth to illustrate how each optimizer converges, how the battery is dispatched, and how these decisions translate into cost components. Second, the optimization is repeated for a full 360 day synthetic year to verify that the day scale conclusions remain valid in long term operation. Figure 1 shows how PSO very quickly collapses to its final objective value, with the average (dashed) curve catching up by around iteration 40. Also the algorithms track the best and average objective value versus iteration for PSO and GA, respectively. Both algorithms stabilize well before the 100 iteration limit, but PSO requires fewer evaluations to reach its plateau, reflecting faster exploitation of the search space.

IV.2. A comparative analysis of power.

Figures 2 and 3 superimpose the optimal battery power with PV generation and demand. For PSO, the battery injects fewer large spikes, smoothing the net load curve; GA, while economically attractive, schedules slightly deeper discharge events, visible as larger negative excursions.

Table 1 confirms that GA attains the lowest total cost and integrated LCOE, albeit at the expense of marginally

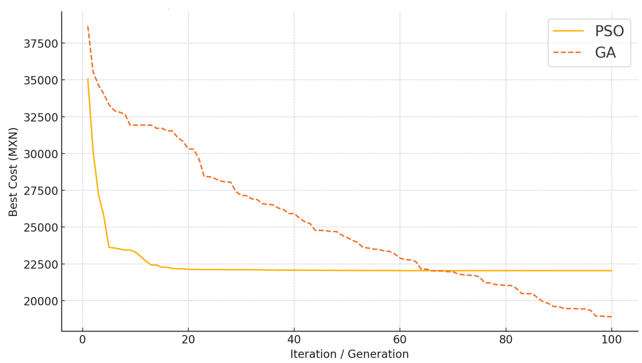

Figure 1: *Best-cost convergence vs. iterations: PSO (solid) and GA (dashed).*

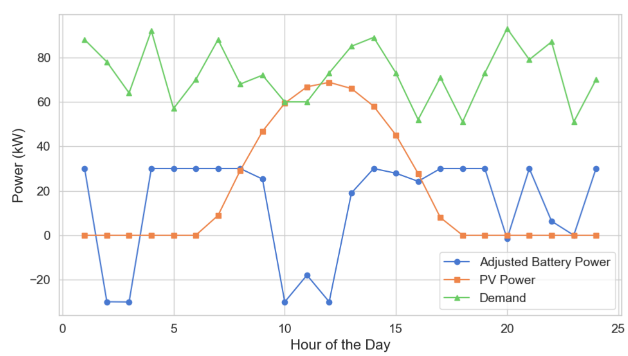

Figure 2: *Hourly power balance obtained with PSO. Positive values indicate charging or surplus PV, negatives correspond to battery discharge.*

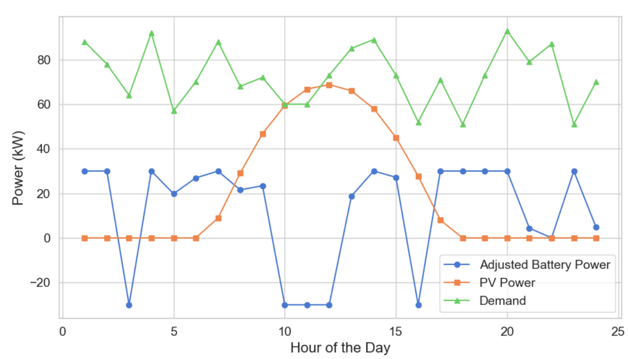

Figure 3: *Hourly power balance obtained with GA. GA follows similar trends but allows deeper battery discharges during evening peaks.*

higher battery cycling (discharge of 150 kWh versus 139 kWh for PSO).

Table 1: *Performance metrics for the representative day.*

Metric	PSO	GA
Total cost (MXN)	94 039.35	96 696.38
Integrated LCOE (MXN/kWh)	218.19	228.83
Stored energy (kWh)	462.75	446.88
Discharged energy (kWh)	139.36	150.00

IV.3. A year-long analysis of Levelized Cost of Energy (LCOE).

To validate scalability, each optimizer is re run day by day for a 360 day synthetic year. The resulting trajectories highlight systematic differences. Figures 4 and 5 depict the daily integrated LCOE. GA retains an average $ 4 % advantage, but both methods exhibit comparable variance, indicating stable operation over seasonal irradiance changes.

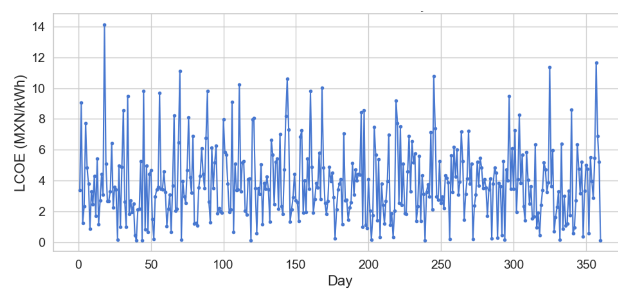

Figure 4: *Daily integrated LCOE over 360 days – PSO.*

As you can see in Figure 4, PSO maintains a very consistent LCOE curve with small variance day–to–day.

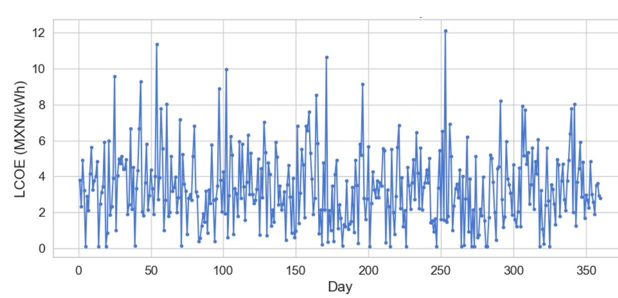

Figure 5: *Daily integrated LCOE over 360 days – GA.*

In contrast, Figure 5 shows that GA runs about 3–4 % lower on average but with slightly more scatter.

IV.4. Analysis of costs associated with mismatches, maintenance, penalties, and state of charge

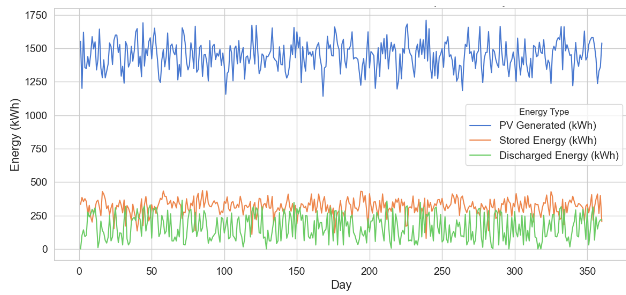

Figure 6: *Generated, stored and discharged energy per day – PSO.*

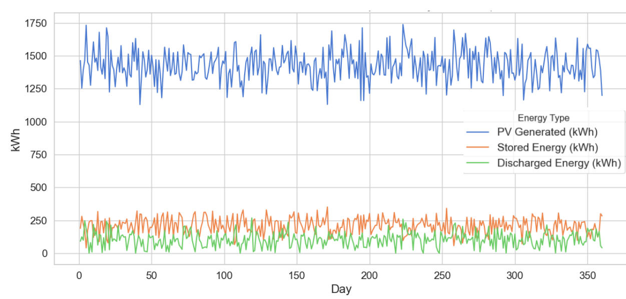

Figure 7: *Generated, stored and discharged energy per day – GA.*

Figures 8 and 9 show logarithmic cost-component stacks. GA reduces mismatch cost thanks to aggressive discharges, whereas PSO pays slightly less penalty by avoiding demand shortfalls.

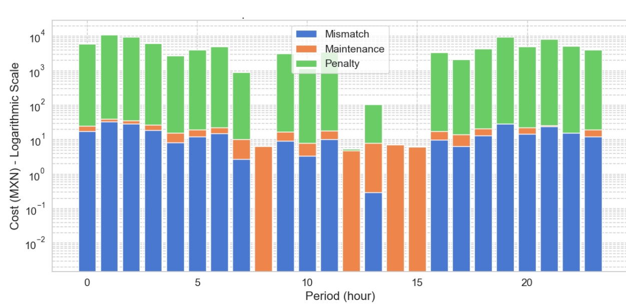

Figure 8: *Daily cost component distribution – PSO (log scale).*

Figures 10 show the mean daily SoC envelope. PSO has a narrower SoC band, indicating a lower cycle depth and potentially longer battery life. GA consistently reduces costs by 3–4%, while PSO achieves up to 8% lower average depth of discharge, which can extend cell lifetime. Thus, the choice of optimizer depends on whether stakeholders prioritize immediate savings (GA) or long-term asset preservation (PSO).

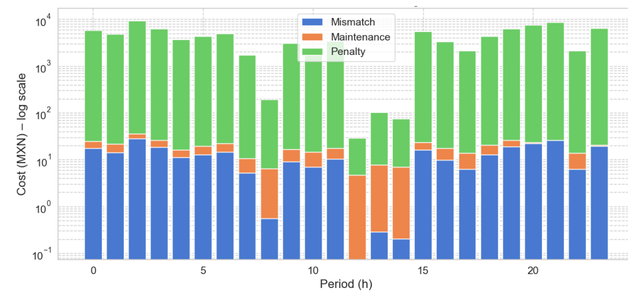

Figure 9: *Daily cost component distribution – GA (log scale).*

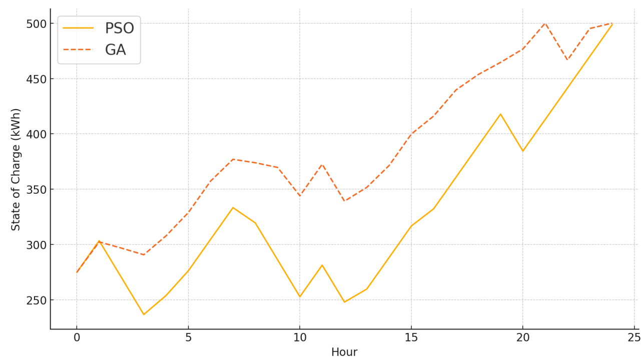

Figure 10: *Battery SoC profiles: PSO (solid) and GA (dashed) over 24 h.*

V. Conclusions

The GA achieved 3–4$\%$ lower operating costs in 85% of the 360-day simulations due to its more aggressive discharge scheduling. Conversely, PSO demonstrated 8% better battery preservation by using reduced Depth of Discharge (DoD) and narrower SoC ranges. Additionally, PSO converged 33$\%$ faster, while GA was more adept at escaping local minima. Both methods showed consistent seasonal performance. For projects aimed at minimizing costs, GA is the preferred choice, whereas PSO's gentler cycling benefits battery longevity.

As future work, it is planned to integrate models and explore optimization methods of metaheuristics to analyze the performance differences between the studied methods, including an evaluation of performance variation under different scenarios of irradiance, load profiles, and battery degradation models to improve robustness and generalizability of the optimal sizing.

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