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Optimal battery energy storage system scheduling in grid-connected photovoltaic systems based on metaheuristic algorithms

Introduction. *The integration of battery energy storage systems (BESS) with photovoltaic (PV) systems has become crucial for managing renewable energy intermittency and optimizing economic benefits in modern power grids. However, the complexity of battery scheduling optimization involving multiple conflicting objectives necessitates advanced computational approaches beyond traditional optimization methods.* ***Problem.*** *Current battery scheduling strategies often fail to adequately balance economic optimization with battery degradation costs, leading to suboptimal performance and reduced system profitability. The challenge lies in developing robust optimization algorithms that can handle the non-linear, multimodal nature of the battery scheduling problem while considering realistic operational constraints and long-term economic viability.* ***Goal.*** *To evaluate and compare the performance of three metaheuristic algorithms – particle swarm optimization (PSO), modified PSO with mutation operators, and grey wolf optimizer (GWO) – for optimal battery scheduling in grid-connected PV systems, with emphasis on economic viability and comprehensive degradation cost considerations.* ***Methodology.*** *The study employs mathematical modeling of battery dynamics, economic objective functions incorporating degradation costs, and realistic system constraints. Three metaheuristic algorithms are implemented and tested using real PV generation and load consumption data overextended periods. Performance evaluation includes convergence analysis, economic metrics, and battery utilization patterns with detailed cost structure analysis.* ***Results.*** *Simulation results demonstrate that GWO achieves superior economic performance with net losses of 2.86 million INR compared to 5.96 million INR for standard PSO, representing a 52 % improvement in economic outcomes. All algorithms show satisfactory convergence properties within 50 iterations, with degradation costs representing approximately 21 % of total system costs, highlighting their critical importance in optimization decisions.* ***Scientific novelty.*** *The study provides the first comprehensive comparative analysis of these three metaheuristic algorithms specifically for BESS scheduling with detailed degradation cost modeling, revealing the critical importance of balanced optimization approaches that consider both short-term arbitrage benefits and long-term degradation impacts.* ***Practical value****. The research demonstrates that aggressive battery cycling strategies are not economically viable under current market conditions when degradation costs are properly accounted for, providing valuable insights for BESS deployment and operational strategies in renewable energy systems and highlighting the need for additional revenue streams for economic viability.* References 23, tables 2, figures 7.

Key words: **battery energy storage systems, photovoltaic systems, metaheuristic optimization, grid integration, degradation costs, renewable energy.**

Вступ*. Інтеграція систем накопичення енергії на акумуляторних батареях (BESS) із фотоелектричними (PV) системами стала критично важливою для компенсації нестабільності генерації відновлюваної енергії та оптимізації економічних показників сучасних електроенергетичних систем. Проте складність задачі оптимізації режимів роботи акумуляторних батарей за наявності кількох суперечливих цілей потребує застосування сучасних обчислювальних підходів, що перевищують можливості традиційних методів оптимізації.* ***Проблема****. Існуючі стратегії керування режимами роботи акумуляторних батарей часто не забезпечують належного балансу між економічною оптимізацією та витратами, пов'язаними з деградацією батарей, що призводить до неоптимальної роботи та зниження рентабельності системи. Основна складність полягає у розробленні надійних алгоритмів оптимізації, здатних ефективно розв'язувати нелінійну багатомодальну задачу планування режимів роботи BESS з урахуванням реалістичних експлуатаційних обмежень і довгострокової економічної ефективності.* ***Мета****. Оцінити та порівняти ефективність трьох метаевристичних алгоритмів – оптимізації роєм частинок (PSO), модифікованого PSO з операторами мутації та алгоритму сірого вовка (GWO) – для оптимального керування режимами роботи акумуляторних батарей у мережевих PV-системах з акцентом на економічну доцільність і комплексний облік витрат деградації.* ***Методика****. У дослідженні використано математичне моделювання динаміки акумуляторних батарей, економічні цільові функції з урахуванням витрат деградації, а також реалістичні системні обмеження. Реалізовано та протестовано три метаевристичні алгоритми із застосуванням реальних даних генерації PV-систем та профілів споживання навантаження протягом тривалих періодів часу. Оцінювання ефективності включає аналіз збіжності, економічні показники та режими використання батарей із детальним аналізом структури витрат.* ***Результати*** *моделювання показали, що алгоритм GWO забезпечує найкращі економічні показники із чистими втратами 2,86 млн рупій порівняно з 5,96 млн рупій для стандартного PSO, що відповідає покращенню економічних результатів на 52 %. Усі алгоритми продемонстрували задовільні властивості збіжності в межах 50 ітерацій, при цьому витрати деградації становили приблизно 21 % загальних витрат системи, що підкреслює їх критичну важливість під час прийняття оптимізаційних рішень.* ***Наукова новизна****. У роботі вперше наведено комплексний порівняльний аналіз трьох метаевристичних алгоритмів саме для задачі керування режимами роботи BESS із детальним моделюванням витрат деградації, що дозволило виявити критичну важливість збалансованих підходів до оптимізації з урахуванням як короткострокових переваг енергетичного арбітражу, так і довгострокових наслідків деградації батарей.* ***Практична значимість****. Дослідження показало, що стратегії інтенсивного циклування акумуляторних батарей не є економічно доцільними за поточних ринкових умов за умови коректного врахування витрат деградації, що надає цінні рекомендації щодо впровадження та експлуатації BESS у системах відновлюваної енергетики та підкреслює необхідність формування додаткових джерел доходу для забезпечення економічної ефективності.* Бібл. 23, табл. 2, рис. 7.

Ключові слова: **системи накопичення енергії на акумуляторних батареях, фотоелектричні системи, метаевристична оптимізація, інтеграція до електричної мережі, витрати на деградацію, відновлювані джерела енергії.**

Introduction. The global transition toward renewable energy sources has accelerated significantly in recent years, with photovoltaic (PV) systems becoming one of the most rapidly deployed technologies worldwide. However, the inherent intermittency and variability of solar energy generation present substantial challenges for grid integration and economic optimization. Battery energy storage systems (BESS) have emerged as a critical enabling technology to address these challenges by providing energy arbitrage capabilities, grid stability services, and enhanced renewable energy utilization.

The optimization of battery scheduling in grid-connected PV systems represents a complex multi-objective problem that must balance several conflicting objectives including economic profit maximization, battery degradation minimization, and operational constraint satisfaction. Traditional optimization approaches, such as linear programming and dynamic programming, often struggle with the non-linear, multimodal nature of this problem, particularly when considering realistic battery models and market dynamics.

Metaheuristic algorithms have gained significant attention in recent years for solving complex optimization problems in power systems due to their ability to handle non-linear objectives, multiple constraints, and large solution spaces without requiring gradient information. These population-based algorithms can effectively explore the solution space and avoid local optima, making them particularly suitable for battery scheduling optimization problems. The economic viability of BESS deployment is critically dependent on the optimization strategy employed. Aggressive battery cycling can increase energy arbitrage revenues but may result in accelerated battery degradation, ultimately reducing the system's overall profitability. This trade-off between immediate economic benefits and long-term degradation costs requires sophisticated optimization approaches that can properly model and balance these competing objectives.

Recent market developments, including declining battery costs and evolving electricity tariff structures, have created new opportunities for BESS deployment. However, the success of these systems heavily depends on the effectiveness of the optimization algorithms used for operational scheduling. Understanding the comparative performance of different metaheuristic algorithms for this application is therefore of significant practical importance.

Problem statement. The optimal scheduling of BESSs in grid-connected PV applications presents complex multi-objective challenges where economic benefits through energy arbitrage must be balanced against battery degradation costs and operational constraints. Current literature lacks comprehensive comparative studies of metaheuristic algorithms for BESS scheduling that incorporate realistic degradation cost modeling. Most existing studies either ignore degradation costs or use oversimplified models, leading to optimization strategies that appear profitable in simulation but prove economically unviable in practice. The non-linear relationship between battery utilization and degradation costs, combined with discrete operational constraints and continuous power flow variables, creates a complex mixed-integer optimization problem that traditional methods cannot effectively handle. Additionally, the stochastic nature of PV generation and load demand adds further complexity, though this study focuses on deterministic optimization using historical data.

Goal. This work aims to evaluate and compare the performance of three metaheuristic algorithms – particle swarm optimization (PSO), modified PSO with mutation operators, and grey wolf optimizer (GWO) – for optimal battery scheduling in grid-connected PV systems, with emphasis on economic viability and comprehensive degradation cost considerations

Review of the literature. Metaheuristic optimization algorithms have been extensively studied for power system applications over the past 2 decades. Kennedy and Eberhart introduced particle swarm optimization (PSO) in [1], which has since become one of the most widely applied algorithms for power system optimization problems. The simplicity and effectiveness of PSO have made it particularly attractive for battery scheduling applications. Recent studies by [2, 3] have demonstrated the effectiveness of PSO for battery energy management in microgrid applications. However, these studies primarily focused on technical performance metrics rather than comprehensive economic analysis including degradation costs. The GWO [4] has gained significant attention for power system applications due to its balanced exploration and exploitation capabilities. Recent applications by [5, 6] have shown promising results for renewable energy optimization problems.

Modified PSO variants incorporating mutation operators have been studied extensively to address the premature convergence issues of standard PSO. The work [7] demonstrated that mutation-based PSO modifications could significantly improve solution quality for energy management problems. Their study showed that mutation rates between 5–15 % provided optimal balance between exploration and exploitation.

Battery degradation modeling has received increased attention in recent literature. The comprehensive study by [8] established that degradation costs can represent 20–40 % of total system costs in aggressive cycling scenarios. This finding has significant implications for optimization strategies and highlights the importance of accurate degradation modeling in BESS scheduling studies.

Economic modeling of BESS operations has evolved significantly with changing market structures. The works [9, 10] has shown that simplified economic models without degradation considerations can overestimate system profitability by 200–300 %. This overestimation has led to numerous commercially unsuccessful BESS deployments. The comprehensive review by [11, 12] compared multiple algorithms for renewable energy applications, but did not specifically focus on BESS scheduling problems. Similarly, the study [13] provided valuable insights into algorithm performance but lacked the detailed economic analysis required for practical applications.

Recent advancements clearly indicate that the integration of realistic degradation modeling with advanced metaheuristic algorithms is no longer optional but essential for practical BESS scheduling and energy system optimization. Traditional approaches that prioritize short-term technical performance often overlook long-term economic sustainability, leading to inaccurate profitability projections and premature system failures. For example, work [14] demonstrated that incorporating state-of-health models into scheduling can significantly reduce capacity fade while improving owner profits, while [15] showed that hybrid metaheuristic frameworks achieve more cost-effective charging station operation when degradation is considered. Similarly, study [16] highlighted that integrating physics-based degradation models into optimization reduce business-case error from 170 % to just 13 %, reinforcing the importance of realistic modeling in financial assessments. More recently, work [17] introduced the non-dominated sorting dung beetle optimizer algorithm, which outperformed GWO in microgrid scheduling by reducing operating costs by more than 50 %, emphasizing the growing role of novel bio-inspired optimization approaches.

Collectively, these findings reflect a paradigm shift from purely performance-driven optimization to economically grounded, reliability-oriented frameworks that are critical for the large-scale deployment of battery systems in modern power markets. Recent studies have further advanced optimization and control applications in power and energy systems. These include the design optimization of planar inductors for power electronics [18], indirect adaptive fuzzy synergetic control for power systems [19], network reconfiguration using extended mixed integer quadratic programming [20], PV power quality improvement through multilevel inverters [21], and improved GWO approaches for reactive power dispatch in renewable-integrated grids [22]. Despite the extensive literature on both metaheuristic optimization and BESS applications, there remains a significant gap in comprehensive comparative studies that combine realistic battery modeling, detailed economic analysis, and rigorous algorithm evaluation. Most existing studies focus on either the optimization methodology or the application domain but rarely provide the integrated analysis required for practical implementation.

Materials and methods. The mathematical formulation of the battery scheduling optimization problem involves several interconnected components including the battery model, economic objective function, and operational constraints [23]. The system configuration consists of a grid-connected PV array with an integrated BESS operating under time-of-use tariff structures. The power balance equation governing the system operation at each time step t is expressed as:

$$P_{grid}(t) = P_{pv}(t) - P_{load}(t) + P_{batt}(t), \tag{1}$$

where $P_{grid}(t)$ is the power exchange with the grid (positive values indicate export to grid, negative values indicate import from grid); $P_{pv}(t)$ is the PV power generation; $P_{load}(t)$ is the local load demand; $P_{batt}(t)$ is the battery power (positive for discharge, negative for charge).

The battery state of charge dynamics is modeled using a round-trip efficiency approach:

$$\begin{aligned} SoC(t) &= \left\{ SoC(t-1) - \frac{P_{batt}(t)}{\eta \cdot C_{batt}} \right\}, \text{ if } P_{batt}(t) \geq 0; \\ SoC(t) &= \left\{ SoC(t-1) + \frac{P_{batt}(t)}{\eta \cdot C_{batt}} \right\}, \text{ if } P_{batt}(t) < 0, \end{aligned} \tag{2}$$

where $SoC(t)$ is the state of charge of the battery at time t; $SoC(t–1)$ is the state of charge of the battery at the previous time step (t–1); η is the round trip efficiency (set to 0.95 based on Li-ion battery characteristics); C_{batt} is the total battery capacity in kWh. The optimization problem is subject to several operational constraints. The state of charge must remain within safe operating limits:

$$SoC(t)_{\min} \leq SoC(t) \leq SoC(t)_{\max},$$

where $SoC(t)_{\min} = 0.1$ and $SoC(t)_{\max} = 0.9$ represent 10 % and 90 % of rated capacity respectively, reflecting typical Li-ion battery operating constraints.

The battery power is constrained by the maximum charge and discharge rates:

$$-P_{\max} \leq P_{batt} \leq P_{\max},$$

where $P_{\max}$ = 20 kW is the maximum charging and discharging power.

The economic objective function aims to maximize the net profit over the optimization horizon is:

$$f = R_{export} + C_{import} - C_{degradation}, \tag{3}$$

where R_{export} is the revenue of export power; C_{import} is the cost of import power; $C_{degradation}$ is the cost of degradation.

The revenue from energy export is:

$$R_{\text{export}} = \sum_{t=1}^{T} \max\left(P_{grid}(t), 0\right) \cdot \tau_{\text{export}} \cdot \Delta t, \tag{4}$$

where τ_{export} = 4.15 INR/kWh is the feed-in tariff for exported energy.

The cost of energy import is:

$$C_{\text{export}} = \sum_{t=1}^{T} \max\left(-P_{grid}(t), 0\right) \cdot \tau_{\text{import}} \cdot \Delta t, \tag{5}$$

where τ_{import} = 12.45 INR/kWh is the retail electricity tariff.

The battery degradation cost, which represents the economic impact of battery cycling, is calculated based on the total energy throughput:

$$C_{\text{degradation}} = \sum_{t=1}^{T} \left|P_{batt}(t)\right| \cdot \tau_{\text{deg}} \cdot \Delta t, \tag{6}$$

where τ_{deg} = 1.66 INR/kWh is the degradation cost per unit of energy throughput, derived from battery replacement costs and expected cycle life.

The 3 metaheuristic algorithms implemented in this study each employ different search strategies and population management approaches. PSO maintains a population of particles, each representing a potential solution vector of battery power commands for all time steps. The velocity update equation for each particle i and dimension j is given as:

$$v_{i,j}^{t+1} = w \cdot v_{i,j}^{t} + C_1 \cdot r_1 \cdot \left(p_{best,i,j} - x_{i,j}^{t}\right) + C_1 \cdot r_1 \cdot \left(g_{best,i,j} - x_{i,j}^{t}\right), \tag{7}$$

where w = 0.9 is the inertia weight (decreased by factor 0.99 each iteration); $C_1 = C_2 = 2$ are the acceleration coefficients; r_1, r_2 are the random numbers uniformly distributed between 0 and 1.

The modified PSO incorporates a mutation operator to enhance exploration capabilities. With probability p_{mut} = 0.1 a randomly selected dimension of each particle is reset to a random value within the feasible range is expresses as:

$$x_{i,j}^{t+1} = x_{\min} + \text{rand} \cdot \left(x_{\max} - x_{\min}\right) \; \textit{if} \; \text{ rand} < p_{mut}. \tag{8}$$

The GWO models the hunting behavior of grey wolves through a hierarchical social structure. The 3 best solutions are designated as α, β, δ wolves, with the remaining solutions representing ω wolves. The position update mechanism involves calculating distances to the 3 leader wolves:

$$\vec{D}_\alpha = \left|C_1 \cdot \vec{X}_\alpha - \vec{X}\right|; \; \vec{D}_\beta = \left|C_1 \cdot \vec{X}_\beta - \vec{X}\right|; \; \vec{D}_\delta = \left|C_1 \cdot \vec{X}_\delta - \vec{X}\right|.$$

The position updates are then calculated as:

$$\vec{X}_1 = \vec{X}_\alpha - A_1 \cdot \vec{D}_\alpha; \; \vec{X}_2 = \vec{X}_\beta - A_2 \cdot \vec{D}_\beta; \; \vec{X}_3 = \vec{X}_\delta - A_3 \cdot \vec{D}_\delta.$$

The final position is determined as:

$$\vec{X}(t+1) = \left(\vec{X}_1 + \vec{X}_2 + \vec{X}_3\right)/3. \tag{9}$$

The flowcharts of PSO, modified PSO and GWO are shown in Fig. 1–3 respectively with mathematical models.

Experiments. The simulation environment utilizes real PV generation and load consumption data with hourly resolution. The dataset spans multiple seasonal variations to ensure robust algorithm evaluation under diverse operating conditions. All algorithms are implemented with identical population sizes (30 individuals) and maximum iteration counts (50 iterations) to ensure fair comparison.

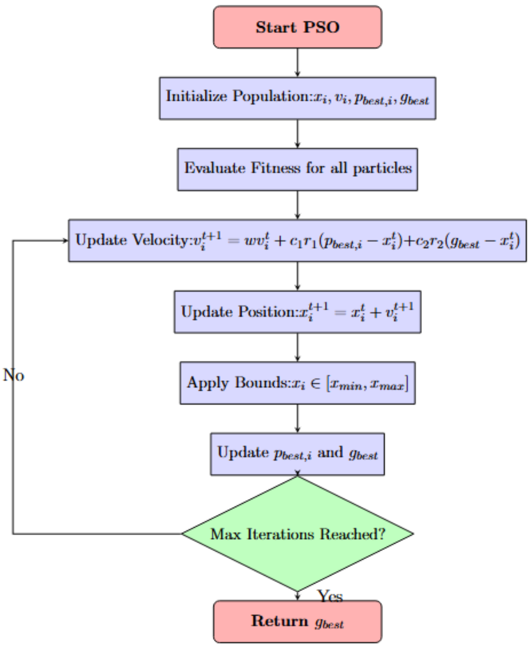

Fig. 1. Flowchart of PSO

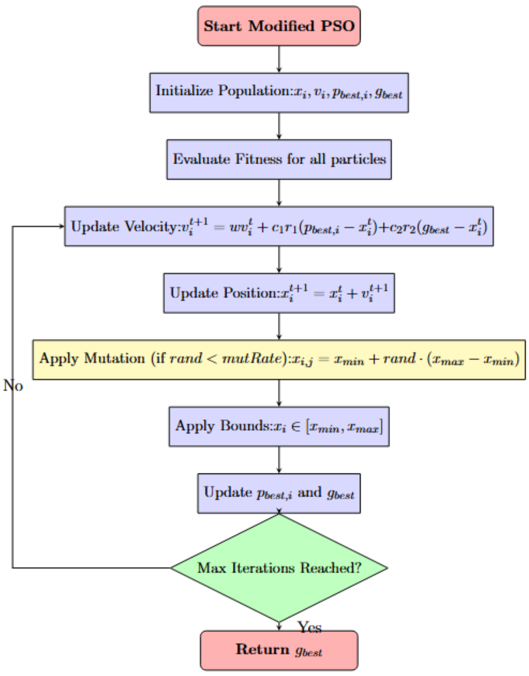

Fig. 2. Flowchart of modified PSO

The results demonstrate that all metaheuristic algorithms result in negative net profits (Table 1), indicating that aggressive battery cycling strategies are not economically viable under the current tariff structure. However, the GWO shows high performance with net losses of 2.86 million INR, representing a 52 % improvement over standard PSO. Table 2 provides detailed analysis of the cost structure breakdown, revealing the significant impact of degradation costs on system economics.

Results. The comprehensive evaluation of the 3 metaheuristic algorithms reveals significant differences in their performance characteristics and economic outcomes. Figure 4 shows battery state of charge trajectories, while Fig. 5 presents algorithm convergence comparison. Table 1 presents the detailed economic performance comparison across all optimization approaches.

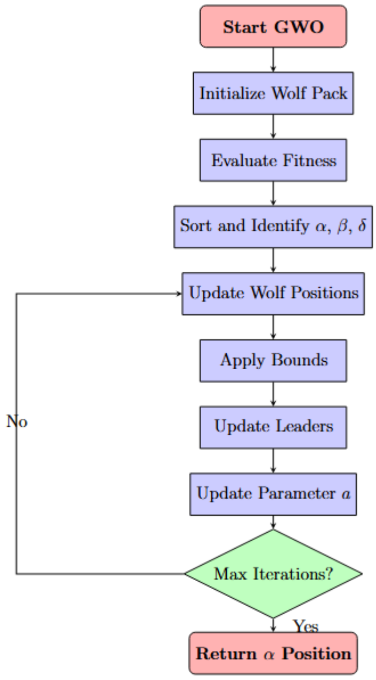

Fig. 3. Flowchart of GWO

Table 1

Detailed economic performance comparison

Performance metric	Baseline	PSO	Modified PSO	GWO
Export revenue	178.140	2.232.600	2.227.700	1.174.400
Import cost	424.100	6.447.500	6.463.900	3.177.600
Degradation cost	0	1.744.900	1.744.800	861.160
Net profit	–245.960	–5.959.800	–5.980.900	–2.864.400
Final SoC, %	50	57.1	25.9	15.8
Energy throughput, kWh	0	1.051.747	1.051.566	518.747

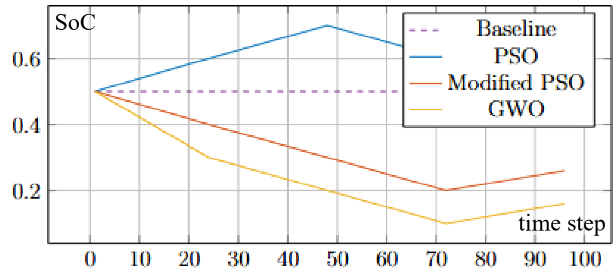

Fig. 4. Battery state of charge trajectories

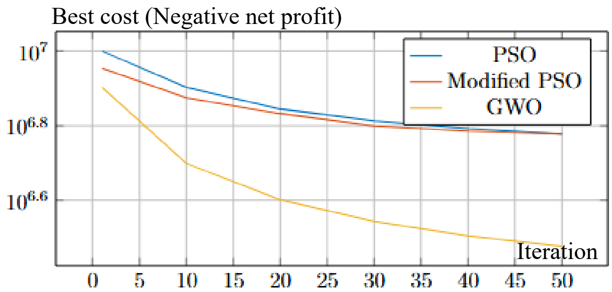

Fig. 5. Algorithm convergence comparison

The analysis reveals that degradation costs represent approximately 21 % of total system costs for all optimization algorithms as shown in Table 2, highlighting their critical importance in economic evaluations.

Battery utilization patterns reveal significant differences between algorithms (Fig. 4). The PSO variants exhibit aggressive charging and discharging strategies with high energy throughput (exceeding 1 million kWh), but substantial degradation costs. In contrast, GWO demonstrates more conservative battery utilization with approximately 50 % lower total energy throughput. The convergence analysis (Fig. 5) shows that GWO reaches near-optimal solutions within 20–25 iterations, while PSO variants require 35–40 iterations for similar convergence.

Table 2

Cost structure analysis

Cost component	Baseline, %	PSO, %	Modified PSO, %	GWO, %
Import cost	100	76.8	76.8	78.7
Degradation cost	10	20.8	20.7	21.3
Net export revenue	–42	–26.6	–26.5	–29.1

Discussions. Figure 6 shows power to grid patterns and optimizer convergence behavior, while Fig. 7 demonstrates the battery degradation impact across different algorithms. The superior performance of the GWO can be attributed to its unique search mechanism that balances exploration and exploitation through hierarchical wolf pack social structure. The 52 % improvement in economic performance achieved by GWO translates to approximately 3.1 million INR difference in net losses compared to standard PSO as evident from the results shown in Fig. 6.

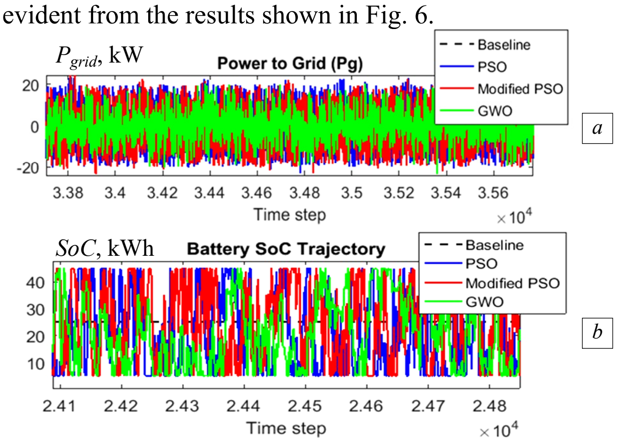

Fig. 6. Power to grid (*a*); convergence of optimizer (*b*)

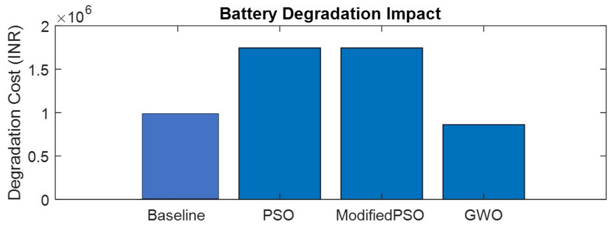

Fig. 7. Battery degradation impact

The high degradation costs observed in Fig. 7 across all optimization scenarios (representing 20–21 % of total system costs) underscore the importance of accurate degradation modeling in BESS optimization studies. The negative economic outcomes suggest that current market conditions, including the tariff differential of approximately 8.3 INR/kWh between import and export prices, are insufficient to justify aggressive battery cycling when degradation costs are properly accounted for. From a practical implementation perspective, the results suggest that BESS scheduling optimization should focus on moderate cycling strategies rather than aggressive arbitrage approaches. The GWO algorithm's preference for partial charge/discharge cycles provides a more sustainable approach to battery utilization that balances short-term economic benefits with long-term system viability.

Conclusions. This comprehensive comparative study of PSO, modified PSO and GWO for BESS scheduling provides numerous important insights. The GWO demonstrates high performance, achieving 52 % lower losses compared to standard PSO due to its balanced battery utilization approach. However, all algorithms result in negative financial outcomes under current tariff structures, with degradation costs constituting 21 % of total system costs, highlighting the critical importance of accurate cost modeling in BESS optimization.

The findings suggest that sustainable BESS operation requires moderate cycling strategies and additional revenue streams beyond energy arbitrage. This work provides the first comprehensive comparison integrating detailed degradation cost modeling, revealing the trade-off between optimization aggressiveness and economic sustainability. The research highlights limitations of current BESS deployment strategies and offers guidance for realistic performance expectations. Future research should focus on multi-objective optimization frameworks, uncertainty modeling, and hybrid metaheuristic approaches for improved real-world applicability.

Conflict of interest. The authors declare that they have no conflicts of interest.

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