Application of the PSO algorithm in BESS operation scheduling for industrial park power grids

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Abstract

This study proposes an advanced methodological framework to optimize the operational strategy of Battery Energy Storage Systems (BESSs). The primary focus is to comprehensively address the multi-objective techno-economic operational problem in distribution networks, with particular attention to the characteristics of high-intensity industrial park loads subject to a time-of-use (TOU) electricity pricing mechanism. To optimize within the complex solution space of the 24-hour charging and discharging cycle, the Particle Swarm Optimization (PSO) algorithm is deployed as a black-box optimizer via a co-simulation mechanism that is deeply integrated with the PSS® SINCAL power system computing platform. The mathematical structure of the model strictly complies with boundary conditions regarding equipment physical constraints, notably the state of charge (SOC) limits and the BESS rated power limits. The central contribution of this research is the quantification of the inherent trade-off between minimizing electricity transaction costs and managing active power losses across the system. The simulation results demonstrate that the proposed framework effectively supports BESS scheduling under TOU pricing while satisfying operational constraints. The optimized operating strategy reduces daily operating costs and peak demand while contributing to lower active power losses and improved voltage performance in the studied industrial distribution network.

Keywords: *Battery energy storage system (BESS); black-box optimization; energy arbitrage; particle swarm optimization (PSO); peak shaving; time-of-use (TOU) pricing.*

Symbols

Symbols	Units	Description
SOC	%	State of Charge
SOC_{BESS}^{min}	%	Minimum allowable state of charge
SOC_{BESS}^{max}	%	Maximum allowable state of charge
$P_{BESS,ch}^{max}$	MW	Maximum allowable battery charging power
$P_{BESS,disch}^{max}$	MW	Maximum allowable battery discharging power
P_{BESS}^{t}	MW	BESS operating power at time t
P_{l}^{t}	MW	Load demand power at time t
P_{g}^{t}	MW	Grid power exchange at time t
ΔP	MW	Active power loss
η_{ch}		Battery charging efficiency
η_{disch}		Battery discharging efficiency
Δt	h	Scheduling time interval

Abbreviations

BESS	Battery Energy Storage System
PSO	Particle Swarm Optimization
TOU	Time-of-Use electricity pricing
LF	Load Flow
API	Application Programming Interface

1. Introduction

In Vietnam, amid power system modernization and the ongoing energy transition, growth in load demand consistently outpaces infrastructure development, posing significant risks to energy security and driving up operational costs. Consequently, the integration of Battery Energy Storage Systems (BESSs) has emerged as a pivotal solution to ensure grid flexibility and reliability. Given their rapid response capabilities and independent control over active and reactive power, BESSs are essential for peak shaving. This capability significantly reduces or defers the massive capital investments traditionally required for peaking power plants. Furthermore, BESSs actively support power supply reliability, thereby mitigating the risk of grid overload during peak consumption periods.

Modern distribution networks, particularly those serving industrial parks, face profound challenges due to the rapid escalation of load demand. Industrial loads are typically characterized by intensive power consumption during specific production shifts, which frequently causes localized overloading and exacerbates technical power losses along transmission lines. Additionally, the widespread implementation of time-of-use (TOU) electricity pricing mechanisms imposes an urgent mandate on management and investment entities to optimize operating costs.

Nevertheless, determining the optimal charging and discharging schedule for a BESS is a complex, nonlinear optimization problem characterized by a vast solution space. It requires the simultaneous evaluation of stringent technical constraints, including State of Charge (SOC) boundaries and

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nodal voltage limits. Traditional operational strategies often fail to fully exploit the equipment's capacity for peak shaving and economic optimization, particularly when dealing with highly volatile load profiles.

To address these limitations, this study develops a comprehensive optimal operation scheduling framework by seamlessly integrating the Particle Swarm Optimization (PSO) algorithm with the PSS® SINCAL power system calculation platform via an API. By treating the complex power grid model within PSS® SINCAL as a black box, the proposed framework avoids the need for complex mathematical linearization, ensuring high fidelity in representing real-world distribution network behavior. The proposed co-simulation tool enables:

- The automated generation of operation schedules derived from a direct analysis of 24-hour industrial load profiles.
- The minimization of electricity procurement costs from the main grid by leveraging the TOU pricing mechanism.
- The strict enforcement of operational safety margins for the BESS, including rigid control over SOC limits and rated charge/discharge capacities.
- An application framework for stability and economic feasibility studies in modern industrial park grids and microgrids.

The PSS® SINCAL software, which simulates power grids and calculates power flows via a flexible Python API, was chosen to implement the co-simulation mechanism. The development of this optimal operation scheduling method not only improves technical efficiency but also lays the groundwork for applying smart algorithms to energy management in smart grids and microgrids.

Recent studies have extensively investigated BESS scheduling using heuristic and metaheuristic optimization methods such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Mixed-Integer Programming techniques. These methods have been successfully applied to energy arbitrage, peak shaving, and microgrid energy management problems. However, most existing studies primarily rely on simplified mathematical formulations or benchmark test systems. The integration of optimization algorithms with commercial power system simulation platforms for realistic industrial distribution network studies remains underreported in the literature [1-9].

To address this gap, this paper proposes a co-simulation framework integrating PSO with the PSS® SINCAL platform through a Python API. The proposed framework enables direct optimization of BESS operation schedules while simultaneously considering realistic power flow constraints and industrial load characteristics. The main contributions of this work are summarized as follows:

- Development of an automated PSO-SINCAL co-simulation framework for BESS scheduling;
- Application of the proposed framework to an industrial park distribution network operating under a TOU pricing mechanism;
- Simultaneous evaluation of economic and technical performance indicators associated with BESS operation;
- Quantitative assessment of operating cost reduction, peak shaving capability, voltage profile improvement, and power loss reduction.

The remainder of this paper is organized as follows. Section 2 introduces the structure and technical characteristics of the BESS. Section 3 formulates the optimization problem. Section 4 presents the proposed PSO-SINCAL framework. Section 5 discusses the simulation results, and Section 6 concludes the paper.

2. Structure and technical characteristics of BESS

2.1 BESS architecture

A BESS is a highly sophisticated assembly capable of fast power responses within the millisecond range, providing power system support for frequency regulation and overall power grid stability. The overarching architecture of a typical BESS comprises four primary components, as illustrated in Figure 1. These include:

- ***Battery Pack:*** The foundational component responsible for storing chemical energy and facilitating its conversion into electrical energy. Lithium-ion technology dominates current BESS applications due to its high energy density and long cycle life.
- ***Battery Management System (BMS):*** Each battery pack is integrated with a dedicated BMS that serves as the primary protection layer. The BMS continuously monitors crucial parameters, such as voltage, current, and temperature, to maintain optimal operating conditions and ensure the safety of individual battery cells.
- ***Power Conversion System (PCS):*** Acting as the vital interface between the battery pack and the grid, the PCS enables bi-directional power flow. It functions both as an inverter (converting DC from the battery to AC for grid injection) and a rectifier (converting AC from the grid to DC for battery charging). The PCS dictates the system's maximum charge/discharge power limits and strictly regulates the quality of the injected power.
- ***Supervisory System Control (SSC):*** Functioning as the central intelligence unit, the SSC aggregates data from the BMS and measurement signals from the PCS to compute and dispatch optimal charge/discharge commands. The rigorous coordination between the SSC and BMS in managing thermal and electrical stresses is critical for minimizing capacity degradation and maximizing the system's operational lifespan.

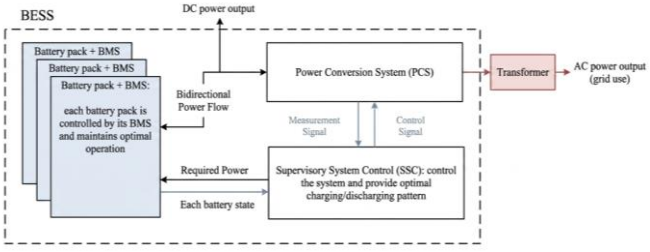


Figure 1: General structure of BESS [10]

2.2 Technical characteristics of BESS

As a flexible asset in modern power grids, a BESS is characterized by its ability to absorb and inject electrical power dynamically in response to operational demands. Technically, a BESS is defined by its rated charge/discharge power and nominal storage capacity. The system's round-trip efficiency typically ranges from 90% to 95%, directly reflecting the energy dissipated during the conversion processes. Another defining characteristic is its nearly instantaneous power response, making the BESS exceptionally well-suited for dynamic dispatching and time-series operational optimization problems [11].

The operational dynamics of a BESS are tracked via the State of Charge (SOC), representing the battery's residual energy level. To preserve battery health and ensure safety, the SOC is strictly confined within predefined upper and lower bounds. Equation (1) defines the instantaneous energy level of the BESS at time *t*, calculated recursively based on the preceding state and the net energy exchanged with the grid:

$$SOC_{BESS}^{t} = SOC_{BESS}^{t-1} + \frac{\eta_{ch} \cdot P_{BESS,ch}^{t} \cdot \Delta t}{E_{BESS,rate}} - \frac{P_{BESS,disch}^{t} \cdot \Delta t}{\eta_{disch} \cdot E_{BESS,rate}} \quad (1)$$

Where:

- $SOC_{BESS}^{t}, SOC_{BESS}^{t-1}$: State of charge of the battery at time t and $t-1$ (%).
- $P_{BESS,ch}^{t}, P_{BESS,disch}^{t}$: Active charge and discharge power of the BESS at time t (MW).
- η_{ch}, η_{disch}: Charge and discharge efficiencies of the BESS (%).
- $E_{BESS,rate}$: Rated capacity of the BESS system (MWh).
- Δt: Time step (hours).

Due to its finite energy capacity, the BESS demands a robust operational management strategy to prevent deep depletion or overcharging. This strategy must delicately balance immediate economic gains against long-term asset degradation caused by continuous charge/discharge cycling.

3. Optimization problem model

3.1 Objective function

Leveraging the physical characteristics of the BESS, the operation scheduling problem is formulated as an optimization model to maximize economic efficiency for the industrial park. The primary objective is to minimize the total cost of grid electricity over a 24-hour operational cycle by strategically exploiting the TOU pricing mechanism. The objective function is defined as follows:

$$min\, F = \sum_{t=1}^{24} (10^3 . C^t . P_g^t . \Delta t) \quad (2)$$

With the active power received from the grid P_g^t determined through the power balance equation:

$$P_g^t = P_l^t + \Delta P^t + P_{BESS,ch}^t - P_{BESS,disch}^t \quad (3)$$

Where:

- C^t: Unit price of electrical energy for the time frame t ($/kWh).
- P_g^t: Active power received from the grid at time t (MW).
- ΔP^t: Active power loss in the power grid at the time t (MW).
- P_l^t: Active power consumption of the load at time t (MW).
- $P_{BESS,ch}^t, P_{BESS,disch}^t$: Active charge and discharge power of the BESS at time t (MW).

3.2 Operational constraints

The optimization of equation (2) is strictly bounded by the physical limitations of the BESS and the operational safety parameters of the power grid [12]:

- ***State of Charge (SOC) Constraints:*** The energy level must remain within a permissible safety margin at all times. Enforcing strict SOC boundaries prevents detrimental deep discharging or overcharging, thereby preserving the internal chemical structure, mitigating fire risks, and prolonging the asset's lifespan:

$$SOC_{BESS}^{min} \leq SOC_{BESS}^{t} \leq SOC_{BESS}^{max} \quad (4)$$

- ***Charge/Discharge Power Constraints:*** The system's active power exchange is rigidly capped at its maximum design rating. This limitation ensures adequate thermal dissipation, preventing internal power electronic components from failing due to overcurrent:

$$0 \leq P_{BESS,ch}^{t} \leq P_{BESS,ch}^{max} \quad (5)$$

$$0 \leq P_{BESS,disch}^{t} \leq P_{BESS,disch}^{max} \quad (6)$$

- ***Simultaneous Operation Prevention:*** A mutual exclusion constraint is applied to prevent the physically impossible scenario of the BESS charging and discharging at the same moment:

$$P_{BESS,ch}^{t} . P_{BESS,disch}^{t} = 0 \quad (7)$$

- ***Power Balance Constraint:*** As defined in (3).
- ***Nodal Voltage Limits:*** The high-power injection or absorption by the BESS can induce localized voltage fluctuations. To comply with the power quality regulations mandated for Vietnam's distribution grids, the voltage magnitude across all network nodes must be rigorously maintained within predefined tolerances relative to the nominal voltage [13].

4. Optimal operation scheduling for BESS

To solve the established complex nonlinear optimization problem, this study proposes using the Particle Swarm Optimization (PSO) algorithm, combined with PSS® SINCAL software and the Python environment.

4.1 PSO algorithm

The particle swarm optimization algorithm was first introduced by James Kennedy and Russell Eberhart in 1995, inspired by simulated models of simplified social behavior [14]. This algorithm is based on observing social interactions and synchronous movements within biological populations in nature, such as flocks of birds or schools of fish. The fundamental principle of PSO involves information sharing among swarm individuals, enabling the collective to leverage individual experiences for efficient global optimization.

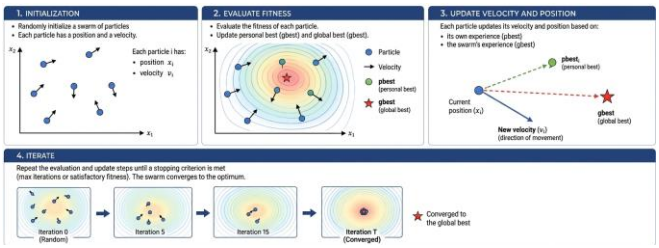


Figure 2: Operating principle of PSO

Within the solution space of the BESS scheduling problem, candidate operational strategies are conceptualized as "particles". Each particle represents a distinct operational vector, encompassing the specific time milestones and corresponding charge/discharge power setpoints for the BESS. Two key components drive each particle's trajectory:

- ***pbest (Personal Best):*** The optimal position a specific particle has individually achieved, acting as a personal memory trace.
- ***gbest (Global Best):*** The superior position discovered by any particle within the entire swarm, functioning as the collective standard of excellence.

The PSO update mechanism adjusts each particle's velocity toward a stochastic weighted average of its *pbest* and *gbest*. This combination of momentum and stochastic variations enables the swarm to effectively balance the global exploration of new search spaces with the local exploitation of known optimal solutions.

At each iteration t, the particles will automatically update their velocity v and position x based on their personal best record, pbest, and the entire swarm's best position gbest, according to the system of equations:

$$v_i^{k+1} = \omega . v_i^k + c_1 . r_1 . (pbest_i - x_i^t) + c_2 . r_2 . (gbest - x_i^k) \quad (8)$$

Where:

- v_i^{k+1}: The new velocity of the particle i at iteration $(k+1)$.
- v_i^k: The current velocity of the particle i at iteration k.
- ω: Inertia weight.
- c_1, c_2: Coefficients.
- r_1, r_2: Uniformly distributed random numbers between 0 and 1.
- x_i^k: The current position of the particle at iteration k.
- $pbest_i$: The particle's personal record.
- $gbest$: The swarm's record.

Then, the new position of particle *i* is updated as follows:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (9)$$

Given the complex, nonlinear nature of the BESS scheduling problem and its numerous constraints on battery State of Charge (SOC) and charge/discharge power, the PSO algorithm proves especially effective thanks to its conceptual simplicity, ease of implementation, and minimal memory and computational requirements. PSO occupies an intermediate position between long-term evolutionary search methods and rapid neural processing, providing flexibility and powerful capabilities to find the most economical operating point for the power system. Numerous benchmark tests have proven PSO's ability to optimize complex objective functions, establishing it as a reliable tool for solving modern energy management challenges [15].

4.2 Libraries and co-simulation tools

4.2.1 PSS® SINCAL software

PSS® SINCAL is specialized software by Siemens used to analyze, simulate, and optimize power systems [16]. This tool allows users to perform tasks such as Load Flow (LF) calculations, short-circuit analysis, voltage stability evaluations, and time-series operational simulations. With robust database integration capabilities and API-based automation, PSS® SINCAL is widely used in the research, design, and operation of power grids, making it especially suitable for modern challenges such as integrating renewable energy and BESS. In this framework, PSS® SINCAL is tasked with receiving the generated BESS charge/discharge scenarios, executing 24-hour load flow simulations, and returning precise network operational parameters. Any scenario that violates grid safety margins is immediately penalized and eliminated from the viable solution space.

4.2.2 Python tool

Python is a high-level, flexible programming language widely used in engineering applications. In this study, Python serves as the central orchestration environment, dynamically bridging the computational algorithms with the PSS® SINCAL engine to execute daily time-series load flows [17].

Some main libraries installed in Python for this study include:

- scikit-opt (sko.PSO) library: provides the core PSO algorithm to initialize the population and execute evolutionary loops.
- pandas, numpy, and openpyxl libraries: processes large databases, including reading load profiles and electricity prices from *.xlsx and *.csv files.
- sqlite3 library: access and extract loss results in the database from SINCAL's *.db file.
- SINCAL API interface (COM Component): is the essential bridge, allowing Python code to directly intervene in PSS® SINCAL's memory to overwrite BESS power and trigger simulation commands automatically [18].

4.3 Implementation process

The coordination between the above tools operates in a closed loop through the process shown in Figure 3, including the following steps:

- ***Step 1:*** Read input data and initialize the PSO algorithm. This involves importing essential data files, including daily load profiles and time-of-use (TOU) electricity tariffs (*.xlsx), alongside defining the Python configuration parameters for the swarm size and maximum number of iterations.
- ***Step 2:*** Run SINCAL API simulation: PSO generates charge/discharge time scenarios, and Python sends these scenarios to SINCAL for the software to run LF calculations for the time steps of the day.
- ***Step 3:*** Based on PSO settings, calculate the objective function value for each individual.
- ***Step 4:*** Update *pbest* and *gbest*.

- ***Step 5:*** Update the velocity according to (8) and the new position of each individual according to (9).
- ***Step 6:*** Check the convergence condition: The error between generations is smaller than the allowable level, or the pre-set maximum number of iterations is reached. If the convergence condition is met, proceed to Step 7. If the condition is not met, the process loops back to Step 2 and continues until convergence.
- ***Step 7:*** Python returns the optimal solution, which is the charge/discharge schedule bringing the highest economic benefit, and plots the required charts.

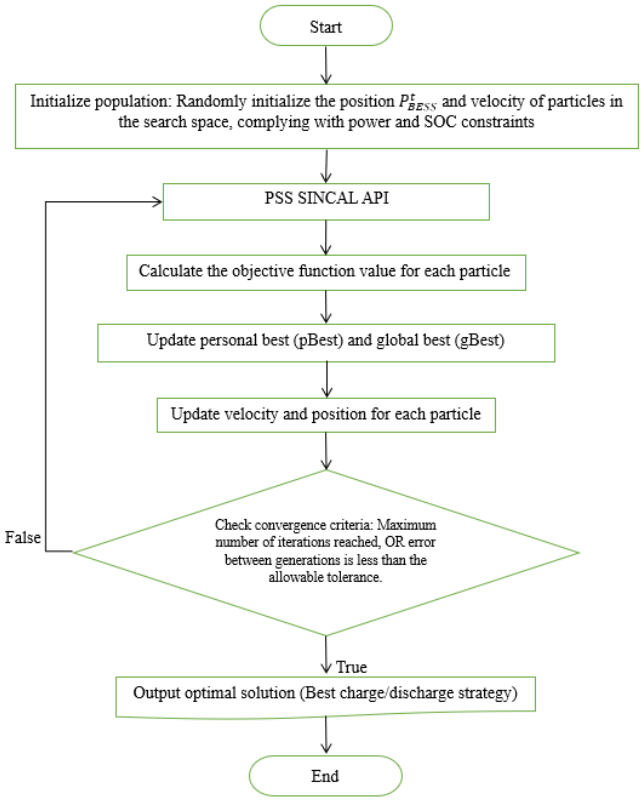


Figure 3: Calculation implementation workflow

5. Research results and evaluation

5.1 Scenarios and input parameters

5.1.1 Power grid parameters

The BESS scheduling problem is applied on a distribution grid model supplying power to an industrial park in a 24-hour cycle ($\Delta t = 0.5\ h$).

Figure 5 illustrates the daily load profile of the industrial park over a 24-hour operating cycle. The load demand exhibits noticeable variations throughout the day, reflecting the operational characteristics of industrial production activities. Higher demand levels are observed during the daytime and evening periods, while lower demand occurs during off-peak hours. These fluctuations create opportunities for Battery Energy Storage System (BESS) scheduling to shift energy consumption from high-price periods to low-price periods under the Time-of-Use (TOU) tariff mechanism. Consequently, the load profile serves as a key input for determining the optimal charging and discharging schedule of the BESS.

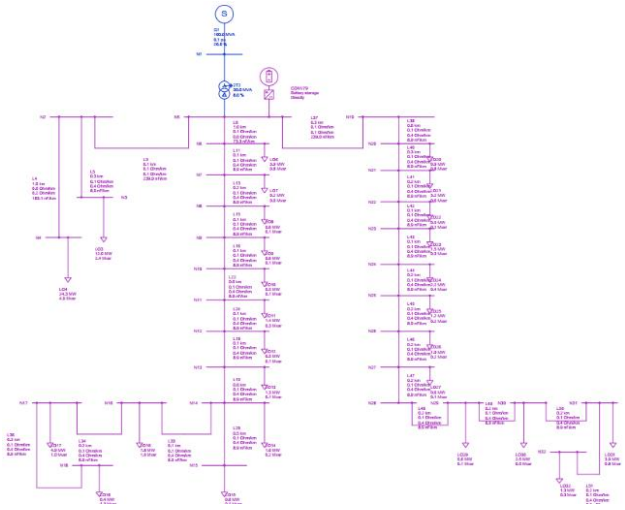


Figure 4: Power grid structure

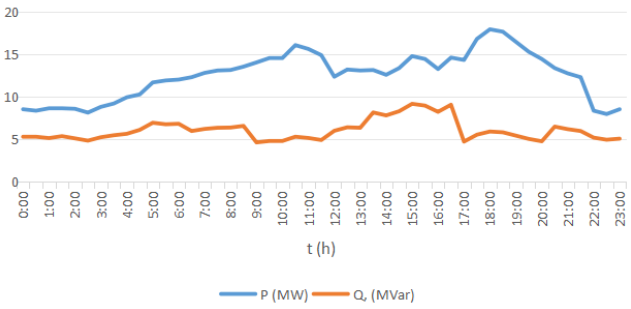


Figure 5: Daily load profile chart

The combination of the daily load profile and the TOU electricity tariff forms the basis of the optimization problem. The objective is to minimize the daily electricity procurement cost while satisfying all BESS operational constraints and network requirements.

Table 1 presents the Time-of-Use (TOU) electricity tariff applied to customers connected at voltage levels from 22 kV to below 110 kV [19]. The tariff structure consists of three pricing periods: peak, normal, and off-peak hours. The highest electricity price is applied during peak demand periods, while the lowest tariff is available during off-peak hours. This pricing mechanism provides economic incentives for shifting energy consumption and storage operations toward lower-cost periods. In this study, the TOU tariff serves as the primary economic signal used by the optimization algorithm to determine the most cost-effective BESS charging and discharging schedule.

Table 1: Electricity tariff by time frame

Time of day	Hours (h)	Price ($/kWh)
Peak hours	09:30 - 11:30 17:00 - 20:00	0.127
Off-peak hours	22:00 - 04:00	0.043
Normal hours	Others	0.069

5.1.2 BESS parameters

Figure 6 shows the BESS configuration parameters.

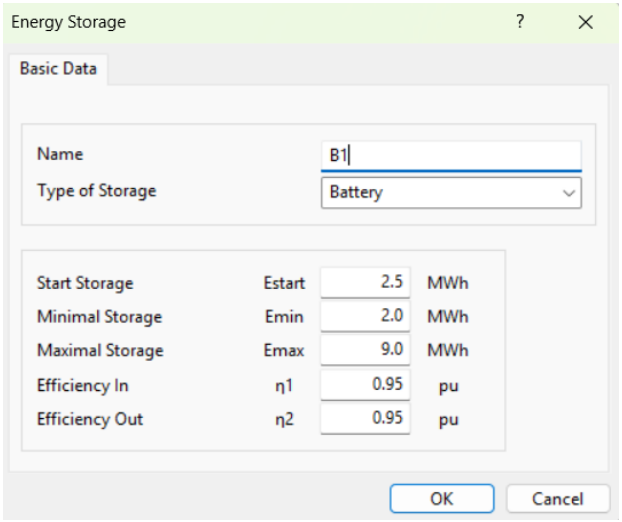


Figure 6: BESS parameters

The maximum rated capacity is 9.0 MWh, with a minimum allowable stored energy of 2.0 MWh; the maximum charge/discharge limit is 5.0 MW; the initial stored energy is 2.5 MWh; the conversion efficiency during charging/discharging is 95%.

5.1.3 PSO algorithm parameters

The configuration parameters for the PSO algorithm will be set via Python, such as an initial population of 30 particles, a maximum of 30 iterations, and an inertia weight configuration $\omega = 0.8$, and cognitive coefficients $c_1 = c_2 = 2$.

5.2 Optimization results

Upon execution through the SINCAL API, the PSO algorithm exhibited stable convergence, successfully isolating the global optimal solution that dictates the most profitable operational strategy.

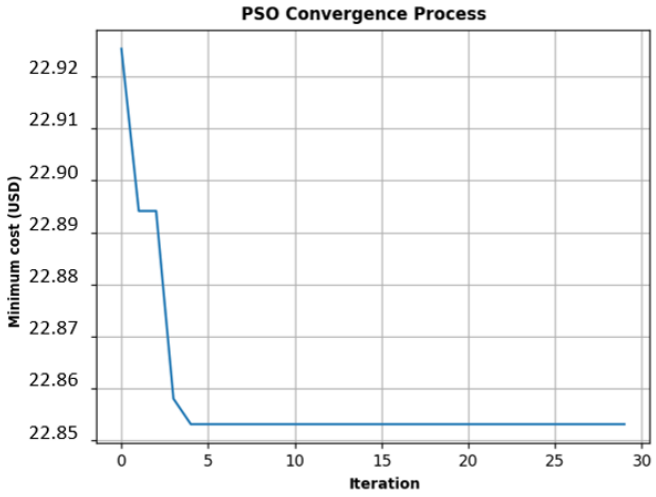


Figure 7: Convergence curve of the PSO objective function

The convergence curve shown in Figure 7 indicates that the objective function stabilizes after several iterations, suggesting satisfactory convergence of the optimization process.

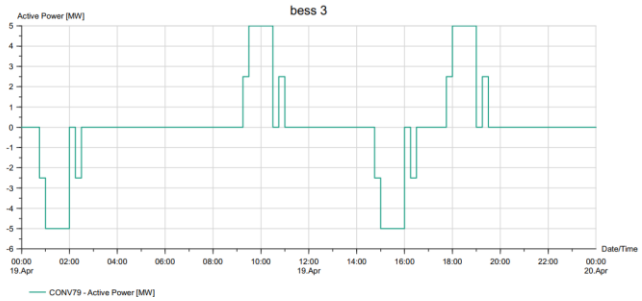


Figure 8: Active power response of BESS

As the battery's energy level approaches its maximum capacity, the BESS gradually curtails its charging power to comply with physical constraints. This action protects battery cell temperatures and prevents overcurrents that degrade the system's lifespan.

Unlike theoretical studies confined to pure mathematical abstractions, these results faithfully replicate the non-linear physical realities of commercial BESS hardware:

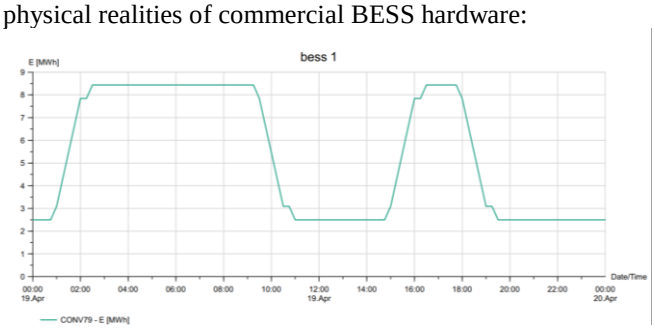


Figure 9: Energy state of BESS

Figure 9 presents the variation of stored energy in the BESS throughout the scheduling horizon. The energy level increases during charging intervals and decreases during discharging intervals, reflecting the operational strategy determined by the optimization process. It can be observed that the stored energy remains within the allowable operating range throughout the day, indicating compliance with the BESS operational constraints. The resulting energy profile demonstrates effective utilization of the available storage capacity under the TOU electricity pricing scheme.

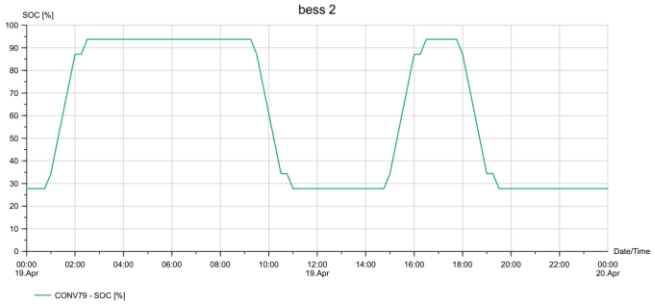


Figure 10: BESS SOC level percent

Figure 10 illustrates the variation of the battery State of Charge (SOC) throughout the scheduling horizon. The SOC increases during charging intervals and decreases during discharging periods, reflecting the operational strategy shown in Figure 9. It can be observed that the SOC remains within the prescribed operational limits throughout the entire day, confirming that the optimization process satisfies the battery constraints. Furthermore, the SOC trajectory demonstrates

effective utilization of the available storage capacity while maintaining safe operating conditions.

The combined analysis of Figures 9 and 10 confirms that the proposed PSO-based scheduling strategy effectively utilizes the available storage capacity while maintaining compliance with all operational constraints. The obtained charging and discharging pattern is consistent with the TOU pricing mechanism and supports the objective of reducing electricity procurement costs.

5.3 Economic and technical efficiency evaluation

To evaluate the effectiveness of the proposed scheduling strategy, a comparative analysis was conducted between the reference case without BESS and the proposed PSO-based BESS operation scenario. The comparison considers both economic and technical performance indicators relevant to industrial distribution network operation.

Table 2: Technical and Economic Comparison of Operation Scenarios

Indicator	Without BESS	With BESS	Improvement
Daily Operating Cost ($)	23,798	22,858	3.95%
Peak Demand (MW)	17.979	12.979	27.8%
Active Power Loss (MWh)	4.773	4.681	1.93%
Minimum Bus Voltage (p.u.)	0.9767	0.9785	0.18%

As shown in Table 2, the proposed PSO-based BESS scheduling strategy provides both economic and technical benefits. The daily operating cost is reduced by 3.95%, while the peak demand decreases by 27.8%, demonstrating the effectiveness of the BESS in peak shaving applications. In addition, active power losses are reduced by 1.93%, and the minimum bus voltage is slightly improved from 0.9767 p.u. to 0.9785 p.u. These results indicate that the proposed scheduling strategy not only achieves cost savings but also contributes to improved distribution network performance.

- *Technical Efficacy:* By injecting stored energy during critical high-demand periods, the BESS effectively reduces peak demand by 27.8%. Furthermore, active power losses are reduced by 1.93%, while the minimum bus voltage improves from 0.9767 p.u. to 0.9785 p.u., indicating enhanced operational performance of the industrial distribution network.
- *Economic Efficacy:* Financial gains are primarily driven by energy arbitrage, specifically, charging during off-peak periods ($0.043/kWh) and discharging during peak price intervals ($0.127/kWh). Consequently, the total daily expenditure for grid electricity is reduced from $23,798 to $22,858, as shown in Figure 11. This operational paradigm generates a net daily profit margin of approximately $940, representing a 3.95% reduction in total daily electricity costs. This result demonstrates the economic effectiveness of the proposed scheduling strategy and its potential applicability for industrial energy management.

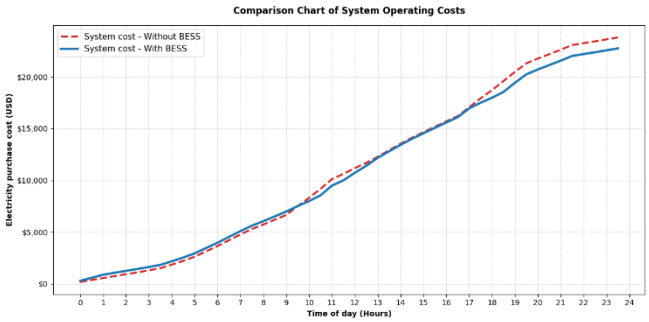


Figure 11: System operating costs in two cases

5.4 Computational performance

All simulations were performed on a computer equipped with an Intel® Core i5-12500H processor (12 cores, 16 logical processors), 16 GB RAM, and the Windows 11 operating system. The proposed optimization framework was implemented in Python and integrated with the PSS® SINCAL platform through its application programming interface.

For the studied industrial park network, the PSO algorithm was executed with a population size of 30 particles. The optimization process required approximately 35 minutes to complete 30 iterations, including repeated power flow calculations performed through the PSS® SINCAL simulation environment. Although the computational time is influenced by the co-simulation architecture and network complexity, the obtained runtime remains acceptable for day-ahead BESS scheduling applications, where optimization is typically performed offline. The computational burden is primarily associated with the repeated load flow simulations executed in PSS® SINCAL rather than the PSO algorithm itself.

6. Conclusion

This paper presented a PSO-based co-simulation framework for BESS operation scheduling in an industrial park distribution network. The proposed approach integrates the PSO optimization algorithm with the PSS® SINCAL simulation platform through a Python API, allowing the optimization process to account for practical power system constraints and realistic industrial load characteristics.

Simulation results demonstrate that the proposed scheduling strategy reduces daily operating costs and peak demand while improving selected technical performance indicators, including active power losses and minimum bus voltage. These findings indicate that the proposed framework can effectively support both economic and technical objectives in industrial distribution network operation under TOU electricity pricing.

Future work may consider the integration of battery degradation models, renewable energy sources, and uncertainty analysis to further evaluate the applicability of the proposed framework under different operating conditions.

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