

Optimal Scheduling of a Microgrid Considering Multi-Source Information Fusion

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Abstract:

To address the insufficient scheduling economy of microgrids caused by renewable energy output fluctuations and the time-of-use (TOU) electricity pricing environment, a multi-source information fusion-driven optimal scheduling method is proposed. A source-load forecasting dynamic correction mechanism based on normalized electricity price factors is constructed, in which price signals are coupled with photovoltaic, wind power, and load forecasts to reserve safety margins for dispatch decisions. An economic dispatch model incorporating dynamic state-of-charge (SOC) constraints and cycling degradation costs of energy storage is established. The problem is solved using an improved particle swarm optimization algorithm integrating price-guided initialization and adaptive inertia weights. Simulation results under three scenarios show that the proposed strategy reduces the daily total operating cost to 1816.58 CNY, representing reductions of 12.4% compared with the scenario without energy storage and 8.2% compared with conventional scheduling. Moreover, the charging and discharging behaviors of the energy storage system are strictly synchronized with the electricity price tiers, and the SOC spans the complete safe interval of 0.10–0.95, thereby verifying the effectiveness of the proposed fusion mechanism.

Keywords:

Microgrid, Multi-source Information Fusion, Optimal Scheduling, Improved Particle Swarm Optimization, Energy Storage System, Time-of-use Electricity Price

1. Introduction

1.1. Research Background and Significance

Driven by the “dual-carbon” goals, distributed renewable energy sources such as photovoltaic and wind power have been rapidly integrated into distribution networks [1]. As a key approach for accommodating a high penetration of renewable energy, microgrids enable efficient regional energy utilization through the coordinated operation of generation, load, and storage [2]. However, renewable generation exhibits significant volatility and intermittency, while load demand is strongly influenced by user behavior and presents pronounced spatiotemporal heterogeneity. The combination of these factors poses severe challenges to the economical and secure operation of microgrids [3]. Meanwhile, the promotion of time-of-use (TOU)

electricity pricing mechanisms [4] has tightly coupled operating costs with market conditions. Therefore, how to collaboratively exploit multi-source information, including meteorological data, load demand, and electricity prices, to formulate optimal scheduling strategies has become a critical issue that urgently needs to be addressed in the field of microgrid research.

1.2. Literature Review

Existing studies generally follow two main approaches. The first approach is based on deterministic optimization models, where historical load and renewable generation forecasts are treated as inputs and solved using mathematical programming or heuristic algorithms [5,6]. Such methods commonly regard source-load forecasts as fixed inputs and neglect the guiding effect of electricity price signals on dispatch decisions, resulting in insufficient economic performance of energy storage operations. The second approach introduces uncertainty-handling techniques, such as stochastic programming and robust optimization [7,8]. Although these methods enhance system robustness, they often suffer from high model complexity and slow computational speed, which limits their practical engineering application. Although multi-source data fusion has been applied in fields such as load forecasting [9,10], studies that explicitly couple electricity prices with source-load forecasting to guide day-ahead scheduling remain limited. At the algorithmic level, particle swarm optimization (PSO) has been widely adopted due to its simple structure and ease of implementation [11]. However, the standard PSO tends to suffer from premature convergence when solving high-dimensional problems, and thus adaptive improvement mechanisms are required [12].

1.3. Main Contributions

The main contributions of this paper are summarized as follows: (1) A multi-source information fusion mechanism based on normalized electricity price factors is constructed. (2) An economic dispatch model incorporating dynamic SOC constraints and cycling degradation costs is established. (3) An improved PSO algorithm integrating price-guided initialization and adaptive inertia weights is designed. (4) The effectiveness of the proposed method is validated through comparative simulations under three scenarios. The microgrid scheduling decision-making flowchart of this study is shown in Figure 1.

Table 1. Nomenclature.

Symbol	Description	Unit
P_{pv}^{rated}	Rated capacity of photovoltaic generation	kW
P_{base}	Base output power of wind turbine	kW
A	Fluctuation amplitude of wind power	kW
φ	Phase shift of wind power	rad
P_t^{ch}	Charging power of the BESS	kW
P_t^{dis}	Discharging power of the BESS	kW
E_{bat}	Rated energy capacity	kWh
$SOC(t)$	State of charge (SOC)	—
η_{ch}	Charging efficiency	—
η_{dis}	Discharging efficiency	—

Symbol	Description	Unit
c_{bat}	Cycling degradation cost coefficient	CNY/kWh
λ_t^{buy}	Electricity purchase price	CNY/kWh
λ_t^{sell}	Electricity selling price / feed-in tariff	CNY/kWh
$\alpha_{pv}, \alpha_{wt}, \alpha_{load}$	Multi-source information fusion correction factor	—
T	Scheduling horizon	h
Δt	Time step	h
$w(k)$	Inertia weight	—
c_1, c_2	Learning factor	—
μ	Penalty coefficient	—

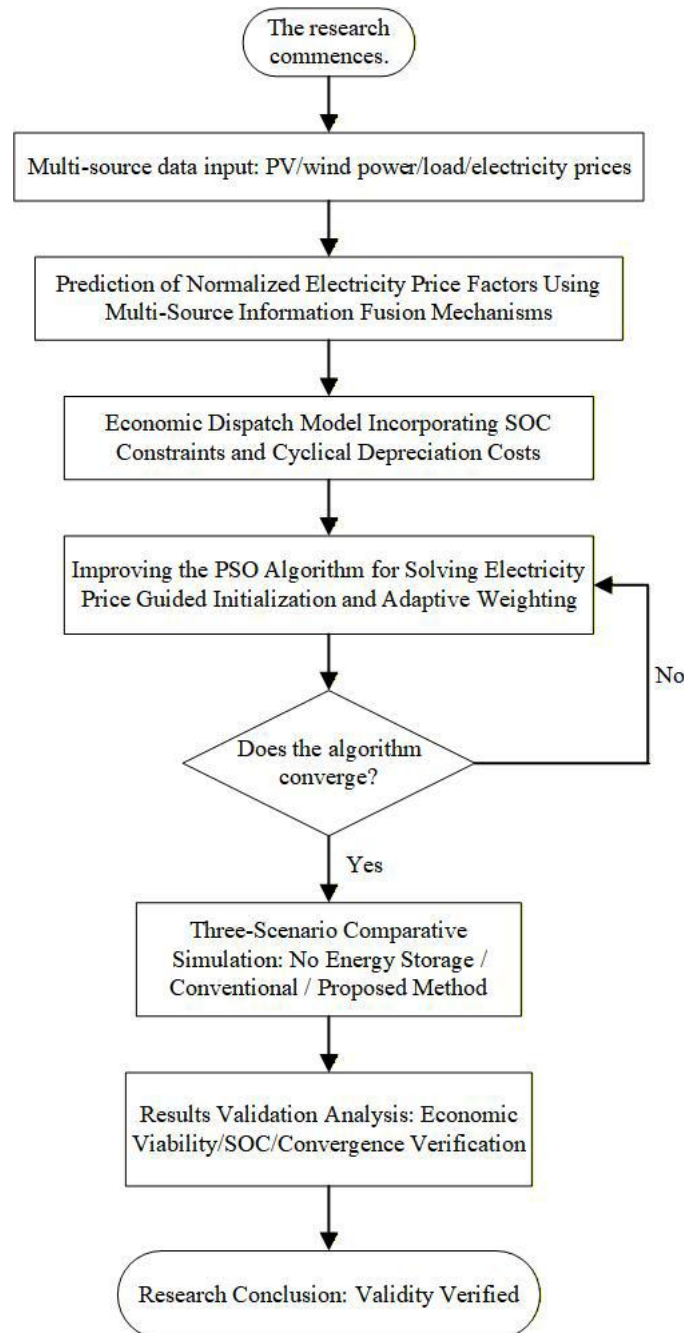


Figure 1. Microgrid Scheduling Decision Flowchart.

2. Microgrid System Modeling

2.1. System Topology Structure

The microgrid system investigated in this study consists of photovoltaic generation (PV), wind turbine generation (WT), battery energy storage systems (BESS), electrical loads, and the point of common coupling (PCC). All distributed units are coordinately controlled by an energy management system (EMS). The system operates in grid-connected mode, exchanging bidirectional power with the main distribution network through the PCC. The system topology is illustrated in Figure 2. The scheduling horizon is set to $T=24h$, and the time step is $\Delta t=1h$.

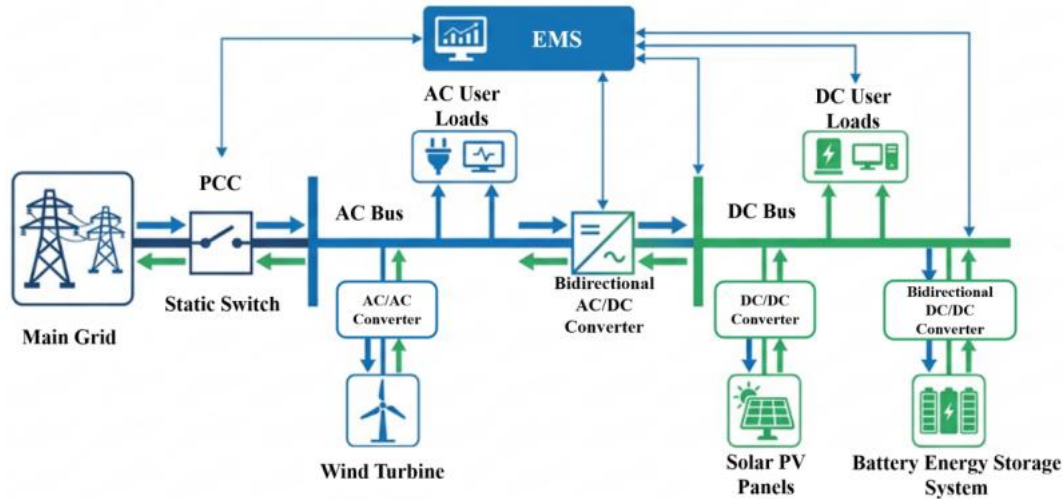


Figure 2. Microgrid Topology with Source-Grid-Load-Storage Coordination.

2.2. Distributed Generation Models

(1) Photovoltaic generation model. The photovoltaic output is constrained by solar irradiance and exhibits a periodic characteristic with a single daytime peak and zero output at night. In this study, a sinusoidal function is adopted to describe the maximum available PV output on a typical day:

$$P_{pv}^{max}(t) = \begin{cases} P_{pv}^{rated} \cdot \sin\left(\frac{\pi(t-t_{rise})}{t_{set}-t_{rise}}\right), & t_{rise} \leq t \leq t_{set} \\ 0, & \text{other time} \end{cases} \quad (1)$$

where $P_{pv}^{rated}=300kW$ denotes the rated installed capacity; $t_{rise}=6$, $t_{set}=18$ represent the sunrise and sunset times (h), respectively.

(2) Wind power generation model. Wind power output fluctuates throughout the day and exhibits a certain temporal complementarity with photovoltaic generation. A sinusoidal function with a DC offset is employed to characterize the maximum available wind power output on a typical day:

$$P_{wt}^{max}(t) = \max\left\{0, P_{base} + A \sin\left(\frac{2\pi t}{T} + \varphi\right)\right\} \quad (2)$$

where $P_{base}=120kW$ is the base output; $A=60kW$ is the fluctuation amplitude; and $\varphi=\pi/4$ is the phase shift.

2.3. Load Model

Electric load exhibits a typical dual-peak characteristic: the morning peak (9:00–11:00) is approximately 330–370 kW, and the evening peak (19:00–21:00) reaches 380–400 kW, while it decreases to 190–220 kW during nighttime. In this study, the measured load profile of a typical day is adopted as a deterministic input, with a cumulative daily energy demand of 7295 kWh.

2.4. Energy Storage System Model

The energy storage system is a key component for achieving energy time-shifting and power regulation. Let the charging power and discharging power at time period t be P_t^{ch} and P_t^{dis} (kW), respectively, and let the rated energy capacity of the storage system be E_{bat} (kWh). The dynamic evolution of the state of charge (State of Charge, SOC) is expressed as:

$$SOC(t) = SOC(t-1) + \frac{\eta_{ch}P_t^{ch} - P_t^{dis} / \eta_{dis}}{E_{bat}} \cdot \Delta t \quad (3)$$

where η_{ch} and η_{dis} denote the charging and discharging efficiencies, respectively; $SOC(0)=SOC_{init}$ is the initial state of charge.

The operation of the energy storage system must satisfy the following constraints:

(1) Charging/discharging power constraint:

$$0 \leq P_t^{ch} \leq P^{ch,max}, \quad 0 \leq P_t^{dis} \leq P^{dis,max} \quad (4)$$

(2) SOC safety boundary constraint:

$$SOC_{min} \leq SOC(t) \leq SOC_{max}, \quad \forall t \in [1, T] \quad (5)$$

(3) Charging/discharging mutual exclusiveness constraint:

Charging and discharging cannot occur simultaneously within the same time period, *i.e.*, $P_t^{ch} \cdot P_t^{dis} = 0$. In addition, considering the equivalent economic degradation caused by cycling operation, the operating cost of the energy storage system is defined as:

$$C_{storage} = c_{bat} \sum_{t=1}^T (P_t^{ch} + P_t^{dis}) \cdot \Delta t \quad (6)$$

where c_{bat} represents the unit energy degradation cost coefficient (CNY/kWh). This cost term avoids the simplified assumption of “zero loss” for energy storage and drives the optimization algorithm to seek an economically optimal balance between arbitrage revenue and cycling degradation.

2.5. Multi-Source Information Fusion Mechanism

Conventional microgrid scheduling methods treat load forecasting and renewable generation forecasting as independent external inputs, without incorporating electricity price signals into source–load forecasting. Consequently, the resulting scheduling strategies lack proactive responses to market incentives. To address this issue, this paper proposes a multi-source information fusion mechanism based on normalized electricity price factors, in which the time-of-use electricity price signals are coupled with the source–load forecasting sequences.

The normalized electricity price factor is defined as:

$$\phi(t) = \frac{\lambda_t^{buy} - \lambda_{min}^{buy}}{\lambda_{max}^{buy} - \lambda_{min}^{buy}} \in [0, 1] \quad (7)$$

where λ_t^{buy} denotes the electricity purchase price at time period t . The forecasts of photovoltaic, wind power, and load are respectively corrected as:

$$P_{pv}^{fused}(t) = P_{pv}^{max}(t) \cdot [1 - \alpha_{pv} \cdot \phi(t)] \quad (8)$$

$$P_{wt}^{fused}(t) = P_{wt}^{max}(t) \cdot [1 - \alpha_{wt} \cdot \phi(t)] \quad (9)$$

$$P_{load}^{fused}(t) = P_{load}(t) \cdot [1 + \alpha_{load} \cdot \phi(t)] \quad (10)$$

where $\alpha_{pv}=0.05$, $\alpha_{wt}=0.03$, and $\alpha_{load}=0.02$ are the correction coefficients. The underlying physical rationale is that when electricity prices are high, renewable outputs are conservatively estimated and the load expectation is moderately increased to reserve a deficit safety margin; when prices are low, optimistic estimates are adopted to fully utilize low-cost electricity. In this manner, market signals are embedded into the optimization input boundaries, thereby achieving coordination between data-level fusion and decision-level optimization.

3. Optimal Scheduling Strategy and Solution Algorithm

3.1. Objective Function

The objective is to minimize the total daily operating cost:

$$\min C_{total} = \sum_{t=1}^T (\lambda_t^{buy} P_t^{buy} - \lambda_t^{sell} P_t^{sell}) \cdot \Delta t + c_{bat} \sum_{t=1}^T (P_t^{ch} + P_t^{dis}) \cdot \Delta t + \Phi \quad (11)$$

where λ_t^{buy} and λ_t^{sell} denote the electricity purchase and selling prices at time period t , respectively, with $\lambda_t^{sell}=0.85\lambda_t^{buy}$; P_t^{buy} , P_t^{sell} represent the purchasing and selling power (kW), respectively; and Φ is the penalty term for constraint violations. The first term of the objective function reflects the net electricity purchasing cost associated with power exchange with the main grid, the second term quantifies the cycling degradation cost of the energy storage system, and the third term guides the algorithm toward the feasible region through a penalty mechanism. P_t^{buy} and P_t^{sell} are uniquely determined by the power balance relationship rather than independent decision variables, and they are mutually exclusive.

3.2. Constraints

(1) Power balance constraint:

$$P_{pv,t}^{fused} + P_{wt,t}^{fused} + P_t^{dis} + P_t^{buy} = P_{load,t}^{fused} + P_t^{ch} + P_t^{sell} \quad (12)$$

The energy storage constraints are defined by Eqs. (3)–(5).

The charging/discharging mutual exclusiveness is handled during the decoding stage through net-value correction: if charging and discharging occur simultaneously in a given time period, the larger net value is retained while the other is set to zero.

3.3. Improved Particle Swarm Optimization Algorithm

The microgrid economic dispatch problem involves nonlinear cost terms, temporally coupled SOC constraints, and charging/discharging mutual exclusiveness logic, which constitutes a high-dimensional non-convex optimization problem. Based on the standard particle swarm optimization (PSO), the following improvements are introduced. The flowchart of the improved PSO algorithm is shown in Figure 3.

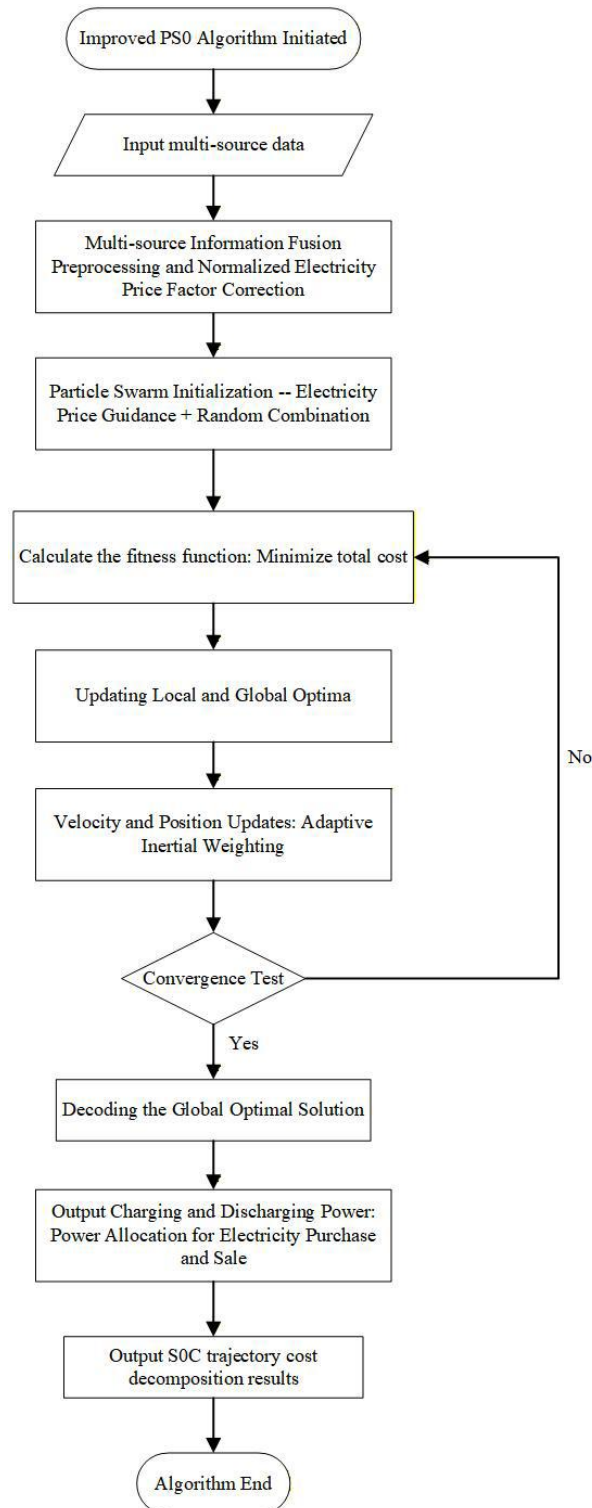


Figure 3. Flowchart of the PSO Algorithm with Adaptive Weight.

(1) Decision variable encoding. The charging and discharging powers at all time periods are encoded into a continuous vector of dimension $2T$: $\mathbf{x}=[P_1^{ch}, \dots, P_T^{ch}, P_1^{dis}, \dots, P_T^{dis}]$.

(2) Velocity and position update. The particle velocity and position are updated according to:

$$\mathbf{v}_i^{k+1} = w(k)\mathbf{v}_i^k + c_1r_1(\mathbf{p}_{best,i} - \mathbf{x}_i^k) + c_2r_2(\mathbf{g}_{best} - \mathbf{x}_i^k) \quad (13)$$

$$\mathbf{x}_i^{k+1} = \mathbf{x}_i^k + \mathbf{v}_i^{k+1} \quad (14)$$

where $c_1=2.0$ and $c_2=1.8$ represent the individual and social learning factors, respectively.

(3) Adaptive inertia weight. The inertia weight adopts a linearly decreasing strategy:

$$w(k) = w_{max} - (w_{max} - w_{min}) \cdot \frac{k}{K_{max}} \quad (15)$$

where $w_{max}=0.8$, $w_{min}=0.4$ and $K_{max}=150$. This linearly decreasing strategy maintains a relatively large inertia weight in the early iterations to enhance global exploration capability, and gradually reduces it in later stages to promote local fine convergence.

(4) Price-guided initialization. To improve the quality of the initial population, 80% of the particles are generated according to a price-based heuristic: charging is encouraged and discharging is suppressed during valley-price periods, whereas charging is suppressed and discharging is encouraged during peak-price periods. The remaining 20% are randomly initialized to maintain population diversity.

(5) Constraint handling. A quadratic penalty function is adopted for SOC violations:

$$\Phi = \mu \sum_{t=1}^T [\max(0, SOC_{min} - SOC(t))^2 + \max(0, SOC(t) - SOC_{max})^2] \quad (16)$$

where $\mu=100$ is the penalty coefficient, ensuring the engineering feasibility of the solutions produced by the algorithm.

4. Case Study Analysis

4.1. Parameter Settings

The main system parameters are listed in Table 2.

Table 2. Main Parameters of the Microgrid System.

Parameter	Symbol	Value	Unit
Rated capacity of PV system	P_{pv}^{rated}	300	kW
Wind power base output / fluctuation amplitude	P_{base} / A	120/60	kW
Rated energy capacity of BESS	E_{bat}	500	kWh
Maximum charging/discharging power	$P^{ch,max} / P^{dis,max}$	120	kW
Charging/discharging efficiency	η_{ch} / η_{dis}	0.95	—
SOC operating range	$[SOC_{min}, SOC_{max}]$	[0.10,0.95]	—

Parameter	Symbol	Value	Unit
Initial SOC	SOC_{init}	0.50	—
BESS degradation cost coefficient	c_{bat}	0.015	CNY/kWh
PSO population size / maximum iterations	N / K_{max}	80/150	—

The electricity price adopts a three-tier time-of-use structure: valley period (1:00–7:00) at 0.35 CNY/kWh; flat period (8:00–10:00, 16:00–18:00, 22:00–24:00) at 0.81 CNY/kWh; peak period (11:00–15:00, 19:00–21:00) at 1.25 CNY/kWh. The selling price is set at 85% of the purchasing price. The total forecasted renewable energy generation accounts for 70.7% of the daily load demand.

4.2. Scenario Design

To systematically evaluate the impacts of energy storage configuration and scheduling strategies on the economic performance of the microgrid, three logically progressive comparative scenarios are designed:

Scenario 1 (Baseline group) — No energy storage system is installed. The system operates according to the principle of “renewable priority, purchase when insufficient, and sell when surplus,” establishing the cost baseline under the condition without storage.

Scenario 2 (Control group) — An energy storage system is installed and scheduled using conventional rule-based dispatch, without explicitly utilizing electricity price signals to optimize the charging/discharging sequence, thereby quantifying the basic effect of “storage without intelligent optimization.”

Scenario 3 (Proposed group) — An energy storage system is installed and scheduled using the proposed joint strategy of “multi-source information fusion + improved PSO,” to verify the comprehensive effectiveness of the proposed method.

4.3. Result Analysis

4.3.1. Economic Performance Analysis

The cost comparison among the three scenarios is presented in Table 3 and Fig. 4.

The total daily operating cost of Scenario 3 is 1816.58 CNY, which is reduced by 12.4% (257.07 CNY) and 8.2% (162.26 CNY) compared with Scenario 1 and Scenario 2, respectively.

From the perspective of cost composition, the electricity purchasing costs of Scenario 3 and Scenario 2 are nearly identical (2012 CNY vs. 2002 CNY). However, the electricity selling revenue in Scenario 3 increases to 215.60 CNY, which is 7.7 times that of Scenario 2 (27.89 CNY).

Table 3. Comparison of Economic Indicators Under Three Scenarios.

Indicator	Scenario 1	Scenario 2	Scenario 3
Electricity purchasing cost (CNY)	2,166.61	2,002.27	2,012.30
Electricity selling revenue (CNY)	92.96	27.89	215.60
Energy storage degradation cost (CNY)	-	4.46	19.88
Total daily operating cost (CNY)	2,073.65	1,978.84	1,816.58
Reduction compared with Scenario 1	-	4.6%	12.4%

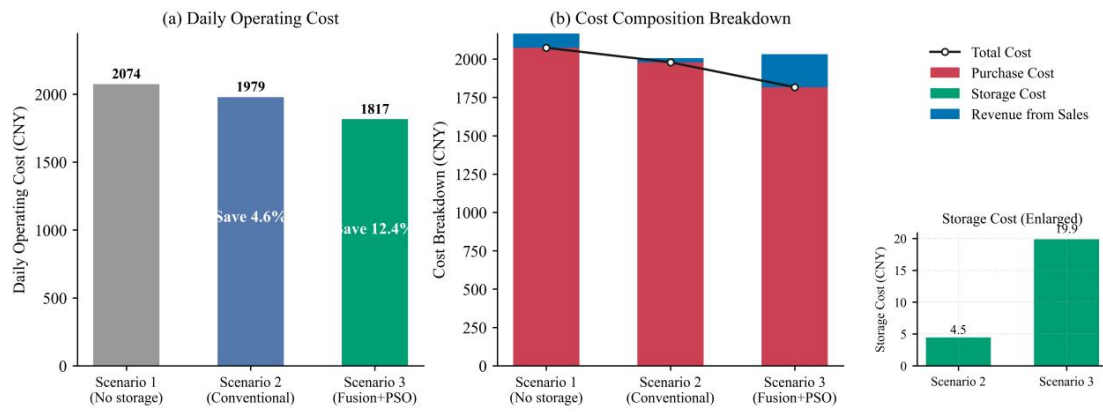


Figure 4. Cost comparison and composition breakdown across three scenarios.

The economic advantage of the proposed strategy originates from the optimal temporal scheduling of the energy storage system, which achieves structural benefits through “charging at low prices and discharging/selling at high prices,” rather than simply reducing electricity purchases. Although the energy storage degradation cost in Scenario 3 (19.88 CNY) is higher than that in Scenario 2 (4.46 CNY), the increment in selling revenue (187.71 CNY) is substantially greater. Consequently, the net total cost decreases significantly, confirming the economic rationality of an active energy storage scheduling strategy.

4.3.2. Dispatch Strategy Analysis

Figure 5 illustrates the power balance and the output composition of each power source in Scenario 3.

During daytime, photovoltaic generation is significant, with a cumulative energy of 2189.4 kWh and an effective utilization rate of 96.1%. Wind power fluctuates throughout the day, with a cumulative generation of 2844.3 kWh and a utilization rate of 98.8%. When renewable generation is insufficient, electricity is purchased from the grid to compensate, totaling 2433.1 kWh. The energy storage system discharges intensively during peak-price periods, with a total discharge energy of 728.7 kWh, effectively reducing electricity purchases during high-price intervals.

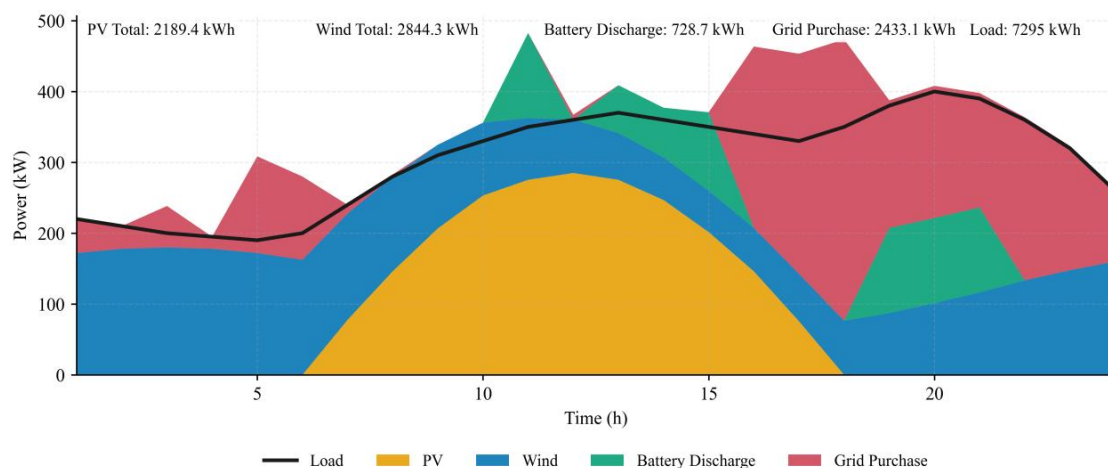


Figure 5. Power Balance and Generation Composition (Scenario 3).

Compared with the SOC trajectory shown in Fig. 6, Scenario 2 exhibits only small fluctuations within the range of 0.18–0.45, indicating insufficient utilization of storage capacity. In contrast, the SOC in Scenario 3 cycles widely within the interval of 0.10–

0.95. Specifically, the battery is charged to the upper limit during valley periods, discharged during the first peak period, recharged during flat periods, and discharged again to the lower limit during the second peak period. This “two-charge two-discharge” strategy fully exploits the storage capacity for energy shifting.

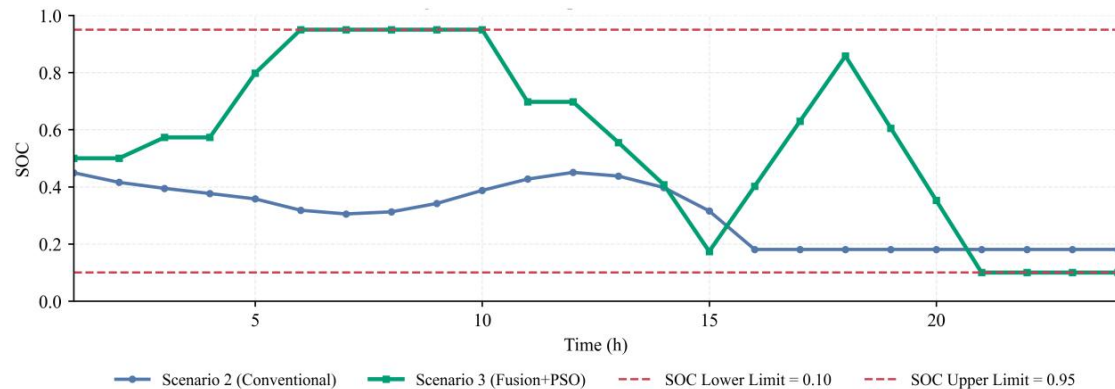


Figure 6. SOC Comparison Between Scenarios.

4.3.3. Algorithm Convergence Analysis

Figure 7 presents the convergence curve of the PSO algorithm.

Within the first eight iterations, the objective function value decreases rapidly from the initial value and approaches the optimum, after which it gradually stabilizes. At the 150th iteration, the solution converges to 1816.58 CNY. The price-guided initialization strategy accelerates early-stage convergence by concentrating 80% of the initial particles in high-quality solution regions. The adaptive inertia weight mechanism balances global exploration and local exploitation, ensuring smooth convergence in later stages. No significant oscillations are observed throughout the process, demonstrating that the improved PSO algorithm achieves stable convergence and high computational efficiency.

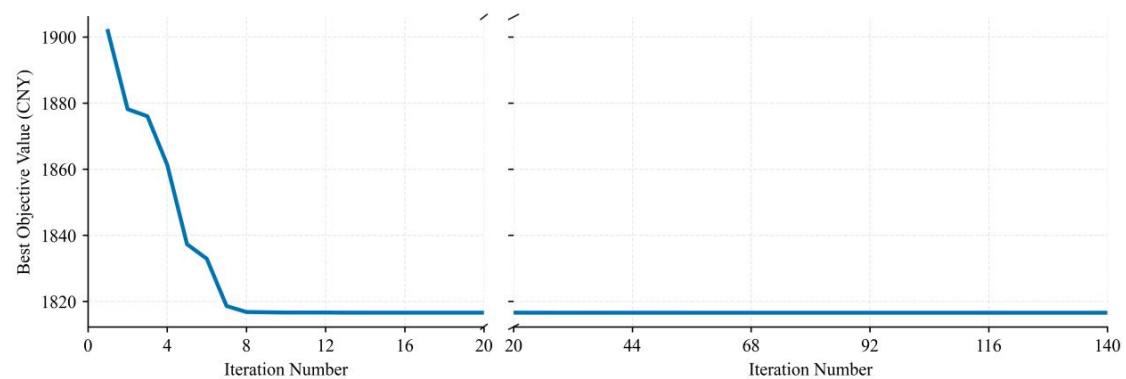


Figure 7. PSO Convergence Curve (First 20 Iterations Enlarged).

4.3.4. Price–Storage Coordination Verification

Figure 8 illustrates the correspondence between discharging behavior and electricity price signals.

In Scenario 3, the energy storage system charges 236.8 kWh and 360.0 kWh during valley and flat price periods, respectively, while the entire 728.7 kWh of discharged energy is concentrated in peak-price periods, showing strict synchronization with the price signals. Considering charging/discharging efficiency losses ($\eta = 0.95$) and

the degradation cost (0.015 CNY/kWh), the “valley/flat charging and peak discharging” temporal strategy still yields substantial benefits due to the peak–valley price difference (1.25 vs. 0.35 CNY/kWh). This verifies that the multi-source information fusion mechanism effectively transmits electricity price signals to energy storage scheduling decisions.

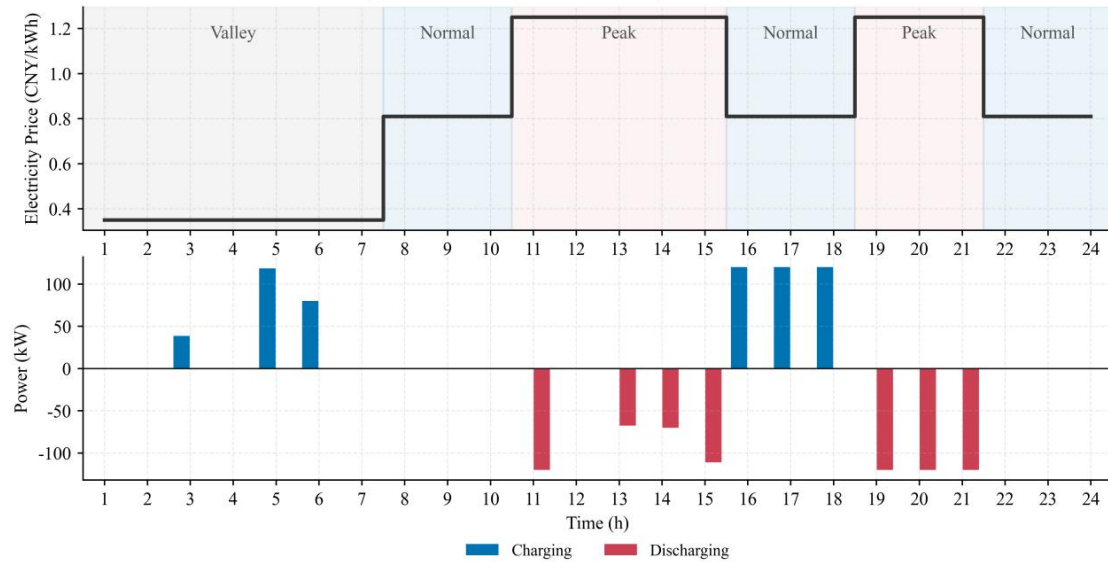


Figure 8. Time-of-Use Price and Storage Strategy (Scenario 3).

5. Conclusions

To address the insufficient economic performance caused by the disconnection between source–load forecasting and market signals in microgrid scheduling, this paper proposes a multi-source information fusion–driven optimal scheduling method. A dynamic correction mechanism for source–load forecasting based on normalized electricity price factors is constructed, an economic dispatch model incorporating dynamic SOC constraints and cycling degradation costs is established, and the problem is solved using an improved PSO algorithm. Comparative simulations under three scenarios demonstrate that:

(1) The proposed strategy reduces the total daily operating cost to 1816.58 CNY, achieving reductions of 12.4% compared with the baseline scenario without storage and 8.2% compared with the conventional scheduling scenario, showing significant economic advantages.

(2) The SOC of the energy storage system is fully utilized within the interval of 0.10–0.95, and the charging/discharging sequence closely follows the electricity price tiers, effectively realizing energy time-shifting; photovoltaic and wind power also achieve high utilization rates.

(3) The improved PSO algorithm converges rapidly and stably, without premature convergence in the 48-dimensional search space, satisfying the computational timeliness requirements of day-ahead scheduling.

In summary, the multi-source information fusion mechanism effectively enhances the economic performance and robustness of microgrid scheduling and provides a practical reference for the economic operation of microgrids with high penetration of renewable energy.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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