

## Article

# Research on Improved Sparrow Search Algorithm-Based Scheduling Optimization for Wind–Solar–Hydrogen Storage System

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## Abstract

Integrating energy storage and hydrogen energy into wind–solar–hydrogen storage microgrids can effectively mitigate the intermittency, volatility, and unpredictability of renewable energy. Aiming at tackling excessively idealized traditional models, this paper establishes a system model for wind–solar–hydrogen storage microgrids by adopting real-world environmental parameters such as wind speed and solar irradiance. To improve the operational performance of the system, an optimal microgrid scheduling method is proposed, which adopts the minimum daily comprehensive operating cost as its core objective. The wind and solar curtailment penalty terms are embedded into the objective function to quantify energy efficiency requirements, and hard constraints including power balance, ramp rate of hydrogen power production, and state of charge (SOC) of energy storage are introduced to guarantee system stability. An improved sparrow search algorithm (ISSA) incorporating a sine function and a golden ratio coefficient is adopted to optimize the position updating process. The objective function is solved so that it satisfies all of the system's constraints, and the algorithm's performance is evaluated based on typical daily simulation data. The results demonstrate that the proposed algorithm can effectively optimize the scheduling process and improve the economic efficiency, stability, and overall performance of the system. The total economic benefit generated by the system is increased by 8.48%, which constitutes a remarkable enhancement of the system's economic efficiency.

**Keywords:** wind–solar–hydrogen storage system; scheduling optimization strategy; improved sparrow search algorithm



Academic Editor:

Herminio Martínez-García

Received: 4 May 2026

Revised: 23 June 2026

Accepted: 30 June 2026

Published: 1 July 2026

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## 1. Introduction

Against the backdrop of global efforts to address climate change and accelerate the energy transition, renewable energy represented by wind and solar power has seen rapid development. However, the high randomness, strong volatility, and non-dispatchability of renewable energy pose severe challenges to the stable operation of these power systems. As a clean and efficient secondary energy carrier, hydrogen energy features zero carbon emissions, high energy density, and great potential for cross-sector applications. It has become a key approach to advancing deep decarbonization in industry and the transportation and energy sectors, and can mitigate the intermittency and volatility of renewable energy so as to improve the stability and reliability of power grids [1–3].

A microgrid is a small-scale power generation and distribution system consisting of distributed generators, energy storage devices, and electrical loads. By integrating wind and photovoltaic power generation, energy storage, and other energy sources, microgrids can effectively alleviate the volatility of renewable energy and improve energy utilization efficiency, thus making their implementation potentially highly valuable. Accordingly, the optimal scheduling of microgrids is a complex systematic task that requires the coordination of and trade-offs among multiple objectives. Fluctuations in the output of wind and photovoltaic power generators will degrade power quality and system stability. Compared with traditional power grids, the optimal scheduling of distributed generation in microgrids is subject to more complicated constraints and imposes higher requirements on real-time performance. Hence, advanced optimization methods are urgently needed to tackle the above challenges [4,5].

At present, numerous optimization approaches have been proposed for integrated wind–solar–hydrogen systems. Some researchers have adopted non-dominated sorting genetic algorithms with an elite strategy to establish a multi-objective optimization scheme for hybrid energy systems, taking into consideration the output uncertainty of wind and photovoltaic power systems, and aiming to reduce carbon emissions and operational costs [6]. Based on correlation and periodicity analysis, a wind–solar–hydrogen storage system model, combined with multi-scale energy and load forecasting, was constructed. This method addresses the high complexity of system optimization and scheduling caused by the randomness of renewable energy and diversified load demands, and improves both economic performance and adaptability to renewable energy [7]. Haiji et al. proposed an optimal scheduling method for power systems based on the ant colony algorithm to enhance the operational stability of power grids integrated with renewable energy [8]. In terms of system operation and control, an optimal framework for capacity configuration and control of multi-energy systems based on the grey wolf optimizer was presented to increase system revenue [9].

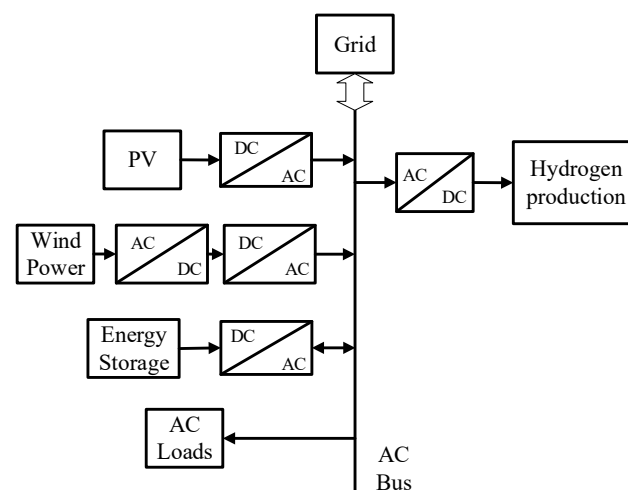
Reasonably formulated optimization objectives help improve the utilization rate of renewable energy and minimize operational costs. Fatma established an economic scheduling optimization model for microgrids that comprehensively considers maintenance costs, battery degradation costs, equipment costs, and grid transaction costs [10]. Regarding optimal scheduling strategies for off-grid hybrid power generation systems, Amrollahi constructed an optimal scheduling model for grid-connected hybrid power generation systems with the objective of minimizing operational costs [11]. Lagouir established a multi-objective scheduling model to minimize the total operational cost, pollutant emissions, and power loss of converters, and transformed the multi-objective problem into a single-objective optimization problem [12]. The above studies jointly promote the development of wind–solar–hydrogen storage systems in a manner that promotes their economic performance, stability, and efficiency, as well as reducing their carbon emissions.

In this paper, a day-ahead optimal scheduling model is established for wind–solar–hydrogen systems. The ramp rate and power limits of hydrogen production units, as well as the capacity limits and initial terminal state constraints of energy storage systems are fully taken into account. On the basis of a conventional improved sparrow search algorithm, a sine function and golden ratio coefficient are introduced to optimize the position updating mechanism. Simulations are carried out using daily data typical of a real-world region. Comparative analysis of the scheduling results verifies the feasibility and effectiveness of the proposed method.

## 2. Wind–Solar–Hydrogen Storage System

In the wind–solar–hydrogen storage system, the microgrid is connected to the main grid and is operated in grid-connected mode. This connection enables the microgrid to interact with the main grid in both directions, drawing electricity from the main grid and selling excess electricity back to it. Through this interactive approach, electricity is efficiently dispatched and managed, energy utilization efficiency is improved, and energy waste is effectively reduced. This operating mode not only optimizes energy allocation, but also promotes the sustainable development of energy utilization. In order to ensure the connected operation of microgrids and main grids, corresponding control systems need to be introduced. In order to accurately regulate and ensure the balance and stable supply of electricity, such control systems need to monitor the main grid's supply and demand of power in real time, while also tracking the power generation and consumption of the microgrid. By using the correct control method, not only can the operational efficiency of the power system be improved, but sustainable energy utilization can also be achieved.

The overall structural diagram of the wind–solar–hydrogen storage system is shown in Figure 1. The simulation model consists of a wind power generation system, a photovoltaic power generation system, a hydrogen production system, an electrochemical energy storage system, and a power grid. The wind power generation system is connected to the grid through AC–DC and DC–AC converters, and the photovoltaic power generation system, hydrogen production system, and energy storage system are connected to the grid through DC–AC inverters.



**Figure 1.** Overall structure diagram of wind solar hydrogen storage system.

## 3. Scheduling Method for Wind–Solar–Hydrogen Storage System

The goal of system scheduling in the wind–solar–hydrogen storage system is to maximize the efficiency and economy of the system by reasonably allocating the energy sourced from wind power generation, photovoltaic power generation, and hydrogen production.

- (1) Maximizing energy utilization efficiency: By optimizing scheduling and allocating energy for wind power generation, photovoltaic power generation, and hydrogen production, the energy utilization efficiency of the entire system can be maximized.
- (2) Reducing energy costs: This can be achieved by optimizing the plan for buying and selling electricity and adjusting the purchase and sale of electricity reasonably based on market prices and electricity demand.

- (3) High system stability and reliability: By optimizing scheduling and balancing the supply and demand of wind power, photovoltaic power, and hydrogen production, the stability and reliability of the system can be improved.

This wind–solar–hydrogen storage system utilizes an improved sparrow algorithm for optimization and scheduling. In order to achieve optimized scheduling, the following data needs to be collected and utilized:

- (1) Real-time data on electricity consumption for wind and photovoltaic power generation and hydrogen production, including parameters such as wind power, light intensity, and hydrogen power production, are used to determine the availability of various energy sources.
- (2) Market electricity price data are used to calculate the cost of buying and selling electricity.
- (3) System constraints and the system's objective function, including the maximum power generation capacity and maximum electricity demand of the system.

Through the above optimization of scheduling, the system can more effectively utilize the energy sourced from wind and photovoltaic power generation, as well as hydrogen production, reducing energy waste. By optimizing the plan for buying and selling electricity, it is possible to buy or sell electricity at the appropriate time, thereby reducing energy costs. By optimizing scheduling and balancing energy supply and demand, the system can operate more stably and improve power supply reliability.

The linear weighted sum method is employed to integrate multi-dimensional cost components such as power purchase costs, electricity sales revenue, hydrogen production operation and maintenance costs, wind and solar curtailment penalty costs, and energy storage loss costs into a single objective function for a comprehensive cost of operation.

#### *System Scheduling Optimization Objective Function*

This study takes the total daily operating cost of system  $F$  as the optimization objective, including operation and maintenance cost  $F_1$ , wind and solar power curtailment penalty cost  $F_2$ , hydrogen production and sales cost  $F_3$ , and electricity purchase and sales cost  $F_4$ . The below equation is the objective function.

$$\min F = F_1 + F_2 + F_3 + F_4 \quad (1)$$

$$F_1 = \sum_{t=1}^T \{ \lambda_w P_w(t) + \lambda_{pv} P_{pv}(t) + \lambda_{st} [P_{ch}(t) + P_{dis}(t)] \} \quad (2)$$

$$F_2 = \sum_{t=1}^T [\mu_w P_{w-q}(t) + \mu_{pv} P_{pv-q}(t)] \quad (3)$$

$$F_3 = \sum_{t=1}^T [\delta_{H_2} P_{H_2}(t) - \omega_{H_2} P_{sH_2}(t)] \quad (4)$$

$$F_4 = \sum_{t=1}^T [\delta_{buy} P_{buy}(t) - \delta_{sell} P_{sell}(t)] \quad (5)$$

$T$  is the operating cycle.  $\lambda_w$ ,  $\lambda_{pv}$ ,  $\lambda_{st}$  are the unit operation and maintenance cost coefficients for wind turbines, photovoltaics, and energy storage equipment, respectively.  $P_w(t)$ ,  $P_{pv}(t)$ ,  $P_{ch}(t)$ ,  $P_{dis}(t)$  are the charging and discharging power of wind turbines, photovoltaic output, and energy storage equipment, respectively.  $\mu_w$ ,  $\mu_{pv}$  are the penalty coefficients for wind and light abandonment.  $P_{w-q}(t)$ ,  $P_{pv-q}(t)$  are abandoned wind volume and abandoned solar quantity.  $\delta_{H_2}$  is the unit cost of hydrogen production in electrolytic cell.  $P_{H_2}(t)$  is the power of hydrogen production.  $\omega_{H_2}$  is the unit coefficient of hydrogen sales price.  $P_{sH_2}(t)$  is the equivalent power of selling hydrogen.  $\delta_{sell}$  is the electricity sales

revenue coefficient.  $P_{\text{sell}}(t)$  is the equivalent power of electricity sales.  $\delta_{\text{buy}}$  is the electricity purchase revenue coefficient.  $P_{\text{buy}}(t)$  is the equivalent power of electricity purchase.

By setting constraints on each parameter in the objective function, the stable operation of the microgrid system can be ensured, thereby also ensuring safety and improving economy, and ultimately optimizing the microgrid scheduling strategy. The system must meet the below constraints during operation.

$$P_w(t) + P_{pv}(t) + P_{dis}(t) + P_{buy}(t) = P_{H2}(t) + P_{ch}(t) + P_{sell}(t) \quad (6)$$

$$\begin{cases} P_{w\_min} \leq P_w \leq P_{w\_max} \\ P_{pv\_min} \leq P_{pv} \leq P_{pv\_max} \\ P_{H2\_min} \leq P_{H2} \leq P_{H2\_max} \\ P_{ch\_min} \leq P_{ch} \leq P_{ch\_max} \\ P_{dis\_min} \leq P_{dis} \leq P_{dis\_max} \end{cases} \quad (7)$$

$$\begin{cases} P_{H2U} \leq P_{H2Umax} \\ P_{H2D} \leq P_{H2Dmax} \end{cases} \quad (8)$$

$$\begin{cases} P_{w-q} = P_{w\_max} - P_w \\ P_{pv-q} = P_{pv\_max} - P_{pv} \end{cases} \quad (9)$$

$$\begin{cases} E_{bat\_min} \leq E(t) \leq E_{bat\_max} \\ E_T = E_1 \end{cases} \quad (10)$$

$$\begin{cases} P_{buy} \leq P_{buymax} \\ P_{sell} \leq P_{sellmax} \end{cases} \quad (11)$$

$P_{H2U}$ ,  $P_{H2Umax}$  are the hydrogen production power increase rate and its upper limit.  $P_{H2D}$ ,  $P_{H2Dmax}$  are the hydrogen production power decrease rate and its upper limit.  $E_{bat\_max}$ ,  $E_{bat\_min}$  are the energy storage system energy upper and lower limits.  $E_T$ ,  $E_1$  are the beginning and end states of energy storage system.  $P_{w\_min}$  and  $P_{w\_max}$  represent the lower and upper limits of wind turbine output, respectively;  $P_{pv\_min}$  and  $P_{pv\_max}$  represent the lower and upper limits of photovoltaic output, respectively;  $P_{H2\_min}$  and  $P_{H2\_max}$  represent the lower and upper limits of hydrogen production power, respectively;  $P_{ch\_min}$  and  $P_{ch\_max}$  represent the lower and upper charging power limits of the energy storage system, respectively;  $P_{dis\_min}$  and  $P_{dis\_max}$  represent the lower and upper discharging power limits of the energy storage system, respectively;  $P_{buy\_max}$  and  $P_{sell\_max}$  represent the maximum equivalent power for electricity purchase and electricity sales, respectively.

#### 4. Improved Sparrow Search Algorithm

The sparrow search algorithm is a novel swarm intelligence algorithm that simulates the foraging and anti-predation behavior of sparrows. Research has found that this algorithm has good optimization accuracy, convergence speed, local development ability, and global optimization ability. Inspiration for the sparrow search algorithm comes from the collaboration and cooperation of sparrows exhibiting group behavior. They can be divided into three categories according to the different tasks assigned to them regarding hunting for food and preventing predation: discoverers, followers, and scouts. The role of discoverers is similar to that of leaders, who are responsible for guiding the entire group in a specific direction to search for food and playing a leading role in population behavior. Discoverers have a large search range, generally comprise 10% to 20% of the population,

and are composed of the best-performing sparrows in each iteration. The formula for updating the position of the discoverer is expressed as indicated below.

$$X_{i,j}^{m+1} = \begin{cases} X_{i,j}^m \cdot \exp\left(\frac{-i}{\alpha \cdot \text{iter}_{\max}}\right), & R_2 < ST \\ X_{i,j}^m + Q \cdot L, & R_2 \geq ST \end{cases} \quad (12)$$

$j = 1, 2, 3, \dots, d$ ,  $d$  represents the dimensionality of variables in the problem to be optimized.  $\text{Iter}_{\max}$  is the maximum number of iterations.  $m$  is the current number of iterations.  $\alpha$  is an arbitrary value in  $(0, 1]$ .  $R_2$  is a warning value in  $[0, 1]$ .  $ST$  is the safe value in  $[0.5, 1]$ .  $Q$  is a random number generated by a normal distribution.  $L$  is a  $d$ -dimensional vector with elements all equal to 1.

In the standard sparrow algorithm, as the search process progresses, population diversity often gradually decreases, which may cause the algorithm to fall into local optima rather than global optima. In order to improve the algorithm's global search and local development capabilities, the sine function is used for iterative optimization, and the position update formula is adjusted using the golden ratio coefficient. This not only enhances detailed search of local areas, but also ensures that the algorithm maintains excellent optimization ability on a global scale, achieving a good balance between the two [13–17]. By virtue of the periodic fluctuation of trigonometric functions and the optimal partitioning characteristic of the golden section, the algorithm can alternately perform global exploration and local exploitation within the search space.

1. Adaptive step size adjustment: In the early iteration stage, a relatively large step size enables individuals to conduct extensive exploration across the entire search space. In later stages, a small step size facilitates fine searching around the optimal solution. As an irrational number, the golden ratio generates step size sequences with favorable uniformity. It prevents excessively large or small step sizes during the search process, realizes adaptive step size regulation, and improves overall search efficiency and solution accuracy.
2. This mechanism avoids the unidirectional convergence of the algorithm and effectively enhances population diversity.
3. The periodic fluctuation characteristic of the sine function allows individuals to continuously jump out of the current local optimal regions during iterations and re-explore new search spaces. Accordingly, the premature convergence problem of the standard Sparrow Search Algorithm (SSA) can be appropriately addressed.

This article proposes optimization of the sparrow search algorithm using the sine and golden ratio coefficients.

The core goal of improving the algorithm using the sine and golden ratio coefficients is to optimize the basic position update formula. The first step is to randomly generate  $n$  individuals, and the position of the  $i$ -th individual in the  $m$ -th iteration of the  $d$ -dimensional space is represented as indicated.

$$X_i^m = (X_{i1}, X_{i2}, \dots, X_{id}) \quad (13)$$

The optimal position of individual  $i$  in the  $m$ -th generation is represented as follows:

$$P_i^m = (P_{i1}, P_{i2}, \dots, P_{id}) \quad (14)$$

The second step is to update the position of each individual using formula (15) consisting of sine and golden ratio coefficients [18]:

$$X_i^{m+1} = X_i^m \times |\sin(R_1)| + R_2 \times \sin(R_1) \times |x_1 \times P_i^m - x_2 \times X_i^m| \quad (15)$$

where  $R_1$  is a random value in  $[0, 2\pi]$  and is used to determine the individual's movement distance in the next iteration.  $R_2$  is a random value in  $[0, \pi]$  and is used to determine the individual's movement direction in the next iteration.  $x_1$  and  $x_2$  are two coefficients calculated using the golden ratio coefficient  $\tau (\tau = (\sqrt{5} - 1)/2)$ .

From the formula for updating the discoverer's location, it can be seen that, when  $R_2 < ST$ , the dimensions of the discoverer decrease. When  $R_2 \geq ST$ , the discoverer will randomly move around the current location in a normal distribution. This method may cause the algorithm to approach the global optimal solution too quickly in the early iteration stage, increasing the likelihood of it becoming stuck in local optimal solutions and unable to find better solutions. Therefore, Formula (15) consisting of the sine and golden ratio coefficients is introduced to improve the method by which the discoverer's position is updated in the basic sparrow algorithm. The improved position update method is as indicated.

$$X_{i,j}^{m+1} = \begin{cases} X_{i,j}^m \times |\sin(R_1)| + R_2 \times \sin(R_1) \times |x_1 \times X_{\text{best}}^m - x_2 \times X_{i,j}^m| & , R_2 < ST \\ X_{i,j}^m + Q \cdot L & , R_2 \geq ST \end{cases} \quad (16)$$

Improved SSA algorithm flowchart is shown in Figure 2.

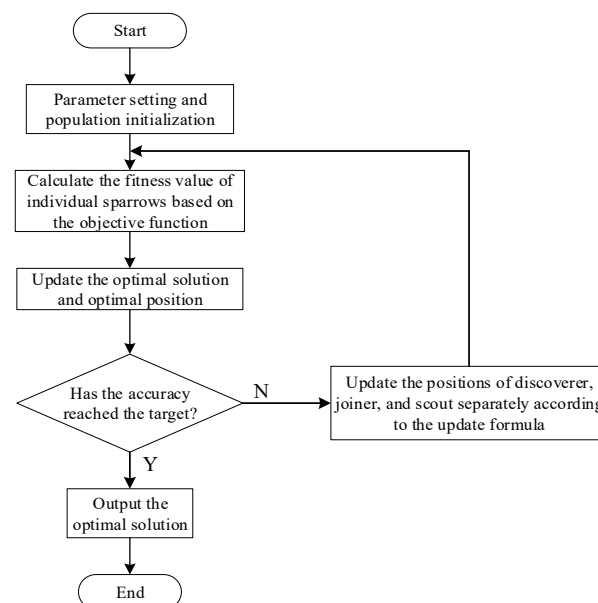


Figure 2. Improved SSA algorithm flowchart.

## 5. Simulation Results

According to the real-world electricity demand in the local area, the daily electricity cost is divided into three periods: peak period, normal period, and low valley period. This breakdown more accurately reflects the supply and demand relationships in the electricity market. Due to the fact that environmental parameters are not fixed, the output of each corresponding power generation system will fluctuate. In order to better optimize the scheduling of the wind–solar–hydrogen storage microgrid system, a day can be divided into 288 scheduling periods, each lasting 5 min, in order to schedule the output of various

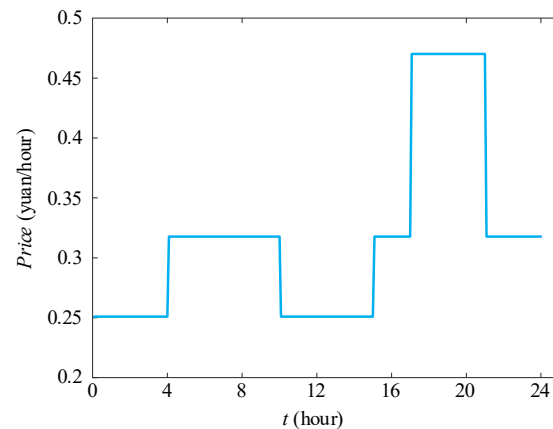
distributed systems and enable them to operate more reasonably within a typical daily cycle. In order to meet the various constraints for the operation of wind–solar–hydrogen storage systems, the objective function seeks to maximize the comprehensive benefits of operation, and an improved sparrow optimization algorithm is used to solve the objective function of the microgrid.

To ensure a fair algorithm comparison, the standard Sparrow Search Algorithm (SSA), adopted as the benchmark, shares identical parameter settings with the Improved Sparrow Search Algorithm (ISSA), including population size, maximum iterations, safety threshold, and role apportionment. Both algorithms are solved using the same system model, operational constraints, and input data. The control variable principle is strictly followed throughout the comparison, and the only difference lies in the position updating mechanism. During simulation, data from a typical day is used as simulation parameters. Throughout the entire scheduling optimization cycle, the optimal and reasonable allocation of power to each module in the system is ultimately obtained, maximizing the benefits of the microgrid system and arriving at its optimal operating state. The rated capacities of the above units are set to the maximum values of the corresponding constraints. Specifically, the rated installed capacities of wind power, photovoltaic power, the hydrogen production unit, and the energy storage system are 30 MW, 300 MW, 176 MW, and 60 MW, respectively, and the corresponding capacity proportions can be calculated accordingly. For the load profile, the average load of the typical day ranges from 190 MW to 210 MW, the peak load ranges from 270 MW to 290 MW, and the valley load ranges from 110 MW to 130 MW. The simulation parameters are shown in Table 1.

**Table 1.** The simulation parameters.

| Parameter           | Value                 | Parameter             | Value          |
|---------------------|-----------------------|-----------------------|----------------|
| $U_{\text{grid}}$   | 35 kV                 | $P_{\text{buymax}}$   | 50 MW          |
| $f_{\text{grid}}$   | 50 Hz                 | $P_{\text{sellmax}}$  | 50 MW          |
| $T$                 | 25 °C                 | $P_{\text{w\_max}}$   | 30 MW          |
| $I_r$               | 1000 w/m <sup>2</sup> | $P_{\text{w\_min}}$   | 0              |
| $I_{\text{sc}}$     | 10.78 A               | $P_{\text{pv\_max}}$  | 300 MW         |
| $I_{\text{mp}}$     | 10.21 A               | $P_{\text{pv\_min}}$  | 0              |
| $V_{\text{oc}}$     | 63.3 V                | $P_{\text{H2\_max}}$  | 176 MW         |
| $V_{\text{mp}}$     | 52.4 V                | $P_{\text{H2\_min}}$  | 12 MW          |
| $v$                 | 10 m/s                | $P_{\text{ch\_max}}$  | 60 MW          |
| $\beta$             | 9°                    | $P_{\text{ch\_min}}$  | 0              |
| $f_{\text{wind}}$   | 50 Hz                 | $P_{\text{dis\_max}}$ | 60 MW          |
| $P_{\text{wind}}$   | 30 MW                 | $P_{\text{dis\_min}}$ | 0              |
| $C_R$               | 8000 Ah               | $\lambda_{\text{pv}}$ | 0.041 Yuan/kWh |
| SOC                 | 80%                   | $\lambda_{\text{w}}$  | 0.037 Yuan/kWh |
| $V_{\text{batt}}$   | 1500 V                | $\lambda_{\text{st}}$ | 0.015 Yuan/kWh |
| $P_{\text{HL}}$     | 160 MW                | $\delta_{\text{H2}}$  | 0.026 Yuan/kWh |
| $P_{\text{HVUmax}}$ | 1 MW/min              | $\omega_{\text{H2}}$  | 1.071 Yuan/kWh |
| $P_{\text{HVDmax}}$ | 5 MW/min              |                       |                |

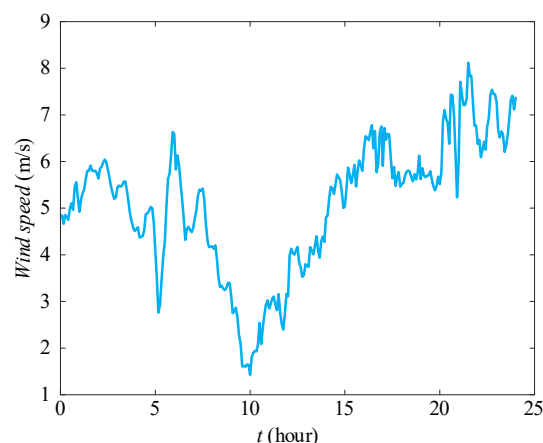
The time-of-use electricity price curve is shown in Figure 3. The periods from 0 to 4 and 10 to 15 are the low valley periods, and the electricity price is 0.2509 yuan/kWh; 4–10 o'clock, 15–17 o'clock, and 21–24 o'clock are normal periods, and the electricity price is 0.3177 yuan/kWh; the peak period is from 17:00 to 21:00, and the electricity price is 0.4702 yuan/kWh.



**Figure 3.** 24 h electricity price curves.

In accordance with the time-of-use electricity pricing rule combined with the profit coefficient, in order to achieve the optimal economy of the microgrid system, it is advisable to avoid purchasing electricity during peak periods. Instead, it is advisable to purchase electricity for energy storage or hydrogen production during low-cost periods in order to improve the economy of the system [18,19].

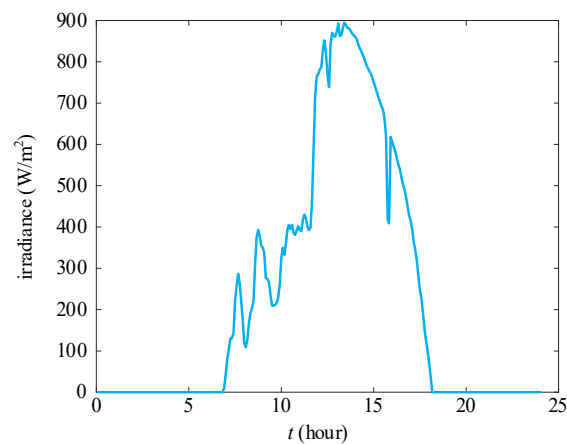
The typical daily wind speed curve for March in a certain region is shown in Figure 4. The wind speed's magnitude and rate of change are related to the season and the time of day. From the curve it can be seen that the wind speed varies rapidly within the range of 1–9 m/s, and its characteristics are consistent with the spring wind speed variation pattern. Wind speed is related to various factors such as solar radiation and atmospheric stratification. In spring, atmospheric activity increases and wind speeds are relatively high. At noon, due to strong solar radiation, the ground and atmosphere are heated, causing an increase in air temperature and an increase in the average distance between air molecules, resulting in a decrease in air density and a weakening of the pressure gradient force, leading to a decrease in wind speed. At night, the solar radiation disappears, the ground and atmosphere begin to cool down, the air temperature decreases, as does the average distance between air molecules, air density increases, the pressure gradient force increases, and thus the wind speed also increases.



**Figure 4.** Typical daily wind speed curve in a certain region.

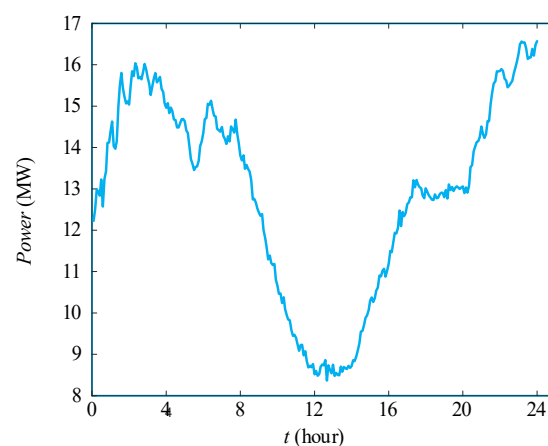
The typical sunlight intensity curve in a certain region is shown in Figure 5. The variation in light intensity is influenced by seasons, weather conditions, etc. From the curve it can be seen that the light intensity varies within the range of 0–900 w/m<sup>2</sup> from 6:50 am to 6:00 pm, and that the light intensity and duration are consistent with the springtime

light intensity variation pattern. As the sun rises and sets, the intensity of light gradually increases from 0 and reaches its maximum at noon, then gradually decreases again to 0. Due to fluctuating cloud cover, significant changes in light intensity can occur within a short period of time.



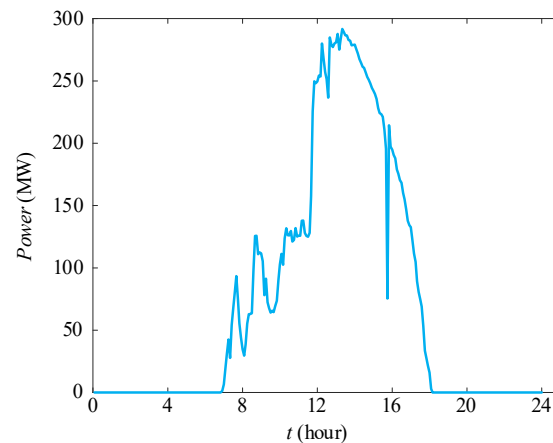
**Figure 5.** Typical sunlight intensity curve in a certain region.

A comparative simulation was conducted prior to using the optimized scheduling strategy and after using the improved sparrow algorithm to optimize scheduling. Figure 6 shows the typical daily planned output curve of the wind turbine generated by the simulation model. From the curve, it can be seen that, due to the lower wind speed during the day and the higher wind speed at night, the wind turbine generates less electricity during the day and usually provides auxiliary output. At night, it generates more electricity and is responsible for the main output. In line with the principles of wind power generation systems, it is known that the output power of wind turbines is approximately in a cubic relationship with wind speed. Therefore, although there are differences between the output curve of wind turbines and the wind speed variation curve, the general trend is consistent.



**Figure 6.** Planned output power of wind turbine.

Figure 7 shows the typical daily planned output curve of the photovoltaic cells generated by the simulation model. From the curve it can be seen that, due to the high light intensity during the day and low intensity at night, the photovoltaic power generation system produces electricity during the day but not at night. In line with the principles of photovoltaic systems, the output power of spring light intensity cells is approximately proportional to the light intensity, so the curve of photovoltaic output and light intensity is consistent.



**Figure 7.** Planned output power of photovoltaic.

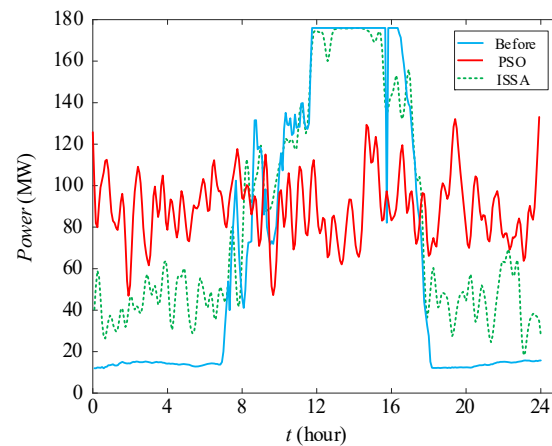
Combining the output curves of wind turbines and photovoltaics, it can be seen that there is a clear complementary relationship between wind power generation and photovoltaic power generation. However, due to the greater power generated by the photovoltaic cells, the entire system is most greatly affected by the photovoltaic power generation system.

Using a typical 24 h day as the cycle for microgrid scheduling optimization, each module of the system is optimized and scheduled every 5 min to obtain the power of each unit. The parameter settings for improving the sparrow algorithm are as follows: population size of 100, maximum iteration parameter of 160 times, safety value ST set to 0.8, discoverer ratio PD set to 0.2, and the proportion of aware sparrows SD set to 0.18.

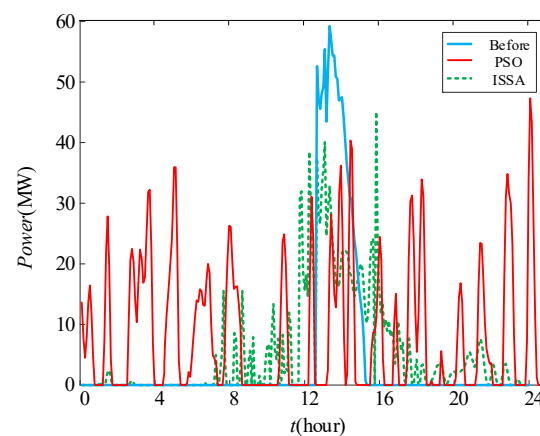
The sparrow algorithm model predicts the output based on known wind and solar conditions, with constraints such as electricity balance, hydrogen storage balance, and energy storage balance, and with grid revenue as the objective function. The sparrow algorithm generates a 24 h hydrogen production, delivery, storage, grid energy interaction, and energy storage output distribution curve for the system every 5 min, and draws the final revenue curve to calculate the total revenue.

As shown in Figure 8, in order to optimize the hydrogen production curve of the system before and after optimization, compared with the original planned output, there is no significant change in the optimized curve during the day (middle section), and there is a moderate increase in hydrogen power production at night (front and back sections). At night (early stage), the time-of-use electricity price is relatively low. After optimization, by appropriately purchasing electricity and storing hydrogen and energy, the efficiency of hydrogen production can be improved, the overall benefits of hydrogen production can be increased, and the efficiency of hydrogen storage and energy utilization can be enhanced. Although the time-of-use electricity price is higher at night (later stage), due to the large amount of energy stored during the day, optimizing the energy storage system through discharge can still increase hydrogen power production appropriately and increase the overall efficiency of the microgrid. During the day, due to sufficient photovoltaic power generation, power production from hydrogen remains basically the same before and after optimization.

As shown in Figure 9, in order to optimize the system's abandoned power curve before and after optimization, abandoned power is mainly concentrated on periods of high photovoltaic power generation, at which time the electricity price is relatively low and will not have a significant impact on the system's economy. After optimization, the increase in daytime hydrogen storage power reduces the amount of wasted electricity and improves the utilization rate of electricity as well as the overall system economy.

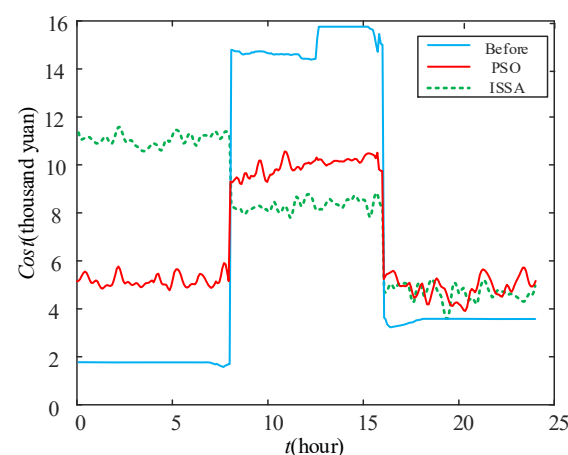


**Figure 8.** Hydrogen production power curve before and after optimization.



**Figure 9.** System abandoned power before and after optimization.

As shown in Figure 10, the optimized hourly revenue curve shows that the total revenue before optimization is 1.8709 million yuan on a typical day, the total revenue with PSO is 1.9794 million yuan, and the total revenue with ISSA optimization is 2.0295 million yuan. The revenue has increased by 8.48% compared to before optimization and 2.53% compared to PSO.



**Figure 10.** Hourly profit before and after optimization.

Based on the above analysis, prior to optimization the initial output plan had a relatively large fluctuation in wind and photovoltaic power, resulting in a low amount of

hydrogen production and supply at night. Therefore, there was no effective strategy to purchase electricity from the grid; the hydrogen supply during the day is relatively high, but there is still a large amount of wind and solar energy wasted, and the utilization rate of the hydrogen storage tanks is not high, which cannot effectively reflect the optimization and improvement of the hydrogen supply capacity of the system by hydrogen storage tanks. By optimizing the system and taking into account the charging and discharging of the energy storage modules and the purchase of electricity under time-of-use pricing, the problem of large fluctuations in wind and solar power output and their inability to provide stable energy for hydrogen production has been optimized. Electricity should be purchased in the early morning when electricity prices are low for hydrogen production, and a small amount should be used for energy storage to improve the efficiency of the hydrogen supply when wind and solar power output is low. At noon, the main consideration is to sell the remaining electricity after hydrogen production and store the excess energy to prepare for nighttime hydrogen supply requirements. At night, it is necessary to purchase electricity from the power grid to maintain hydrogen balance. When electricity costs are high, energy storage modules and hydrogen storage tanks can be used to produce hydrogen and improve hydrogen supply efficiency and the system's economic efficiency. Compared to the original strategy of increasing the power of hydrogen delivery when the wind and solar power output is low, due to the shorter time period of high photovoltaic power output, the delivery of hydrogen power for 8 h when wind and solar power output is high is reduced, resulting in hydrogen production and supply being more balanced. By combining the sparrow algorithm with time-of-use electricity pricing, the appropriate buying and selling of electricity can be achieved to reduce the system's abandoned power and improve overall system revenues.

The results are also affected by the following factors:

- (1) Electricity price fluctuation: This study takes electricity price fluctuation into account in its cost calculation. The time-of-use electricity price is a core factor determining the revenue from the sale of excess power. The proposed scheduling strategy leverages peak–valley price differences to arrange off-peak power purchase, hydrogen production, and electricity sales. Larger gaps between peak and valley prices result in greater profit margins, so the benefits of optimization are highly sensitive to electricity price fluctuation.
- (2) Hydrogen price: Hydrogen production and sales act as the microgrid's main sources of profit. The price at which hydrogen can be sold directly affects the economic performance of the hydrogen production units. A rise in the hydrogen price can remarkably increase the total profits of the system, while a price decline will narrow the profit space. The results of optimization are highly sensitive to variations in the hydrogen price.
- (3) Renewable energy penetration: A higher penetration rate leads to more surplus power generated by renewable energy and a higher risk of wind and solar curtailment. In this work, surplus power is converted into hydrogen to consume renewable energy and reduce curtailment losses. Performance gradually improves as the penetration rate of renewable energy increases.
- (4) Energy storage capacity: The electrochemical energy storage system is mainly used to mitigate short-term power fluctuations rather than realize long-duration energy transfer. Slight adjustments to the energy storage capacity around the rated configuration have negligible impacts on power distribution and overall economic benefits. Thus, the optimization results show a low sensitivity to energy storage capacity variations.
- (5) Weather uncertainty: Weather changes will make wind and photovoltaic output deviate from typical operating conditions, resulting in fluctuations in renewable

energy output and curtailment, further adjusting the scheduling schemes of hydrogen production, power purchase, and sales. Greater randomness in terms of wind–solar output causes more obvious fluctuations in system benefits, and the optimization results remain highly sensitive to weather uncertainty.

- (6) Load uncertainty: Severe load fluctuations will break the power balance of the system, which requires adjustments to power purchase and hydrogen production. Such changes directly affect the operating costs and total benefits, and the optimization results are also highly sensitive to load uncertainty.

## 6. Conclusions

This paper proposes a scheduling optimization model for a wind–solar–hydrogen storage microgrid that integrates wind power, photovoltaics, hydrogen production, energy storage, and grid interaction. The model formulates an objective function to maximize the overall economic and operational benefits of the microgrid system, while adhering to multiple constraints, including power balance, unit output limits, wind and solar curtailment, and grid interaction boundaries. To improve the performance of the optimization, an enhanced sparrow search algorithm (SSA) is developed by incorporating sine mapping and golden ratio coefficients into the position update mechanism, thereby strengthening both exploration and exploitation capabilities. The effectiveness of the improved SSA is rigorously evaluated through comparative simulations. The results demonstrate that the enhanced algorithm consistently outperforms the standard SSA, yielding superior objective function values and more stable convergence behavior. Furthermore, to benchmark its performance against a widely used population-based method, we also implement and test a particle swarm optimization (PSO) algorithm under identical conditions. The comparative results show that the improved SSA achieves faster convergence and higher solution quality than PSO, particularly under complex constraint scenarios, indicating its greater suitability for the nonconvex and multi-modal optimization landscape of the microgrid scheduling problem. By applying the improved SSA with full constraint enforcement, the model successfully determines the optimal output power for each microgrid unit, realizing the goal of maximizing the system's comprehensive benefits. The optimization framework is further validated using typical daily data, including realistic environmental profiles, time-of-use electricity prices, and load demands. Simulation outcomes confirm the correctness, feasibility, and robustness of the proposed scheduling strategy, highlighting its capability to enhance not only the economic efficiency but also the operational stability of the wind–solar–hydrogen microgrid system.

**Author Contributions:** Conceptualization, X.M.; methodology, E.B.; formal analysis, Y.D.; investigation, S.Z.; writing—original draft preparation, X.M.; writing—review and editing, Y.D.; project administration, G.L. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the Science and Technology Project of State Grid Jilin Electric Power Co., Ltd. grant number 2024JBGS-10.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

**Conflicts of Interest:** Author X.M., Y.D., S.Z. and E.B. were employed by the company Electric Power Research Institute of Jilin Electric Power Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## References

1. Lannelongue, J.; Cugnet, M.; Guillet, N.; De Vito, E.; Boulineau, A.; Kirchev, A. Operation of thin-plate positive lead-acid battery electrodes employing titanium current collectors. *J. Energy Storage* **2018**, *20*, 230–243.
2. Hsieh, S.H.; Wu, T.P. Experimental evidence and performance analysis of carbon cloth composite inserted lead-acid batteries under high-rate cycling. *J. Taiwan Inst. Chem. Eng.* **2026**, *181*, 106517.
3. Yang, T.; Qian, S.; Luo, Y.; Wang, X.; Wang, Z. Direct re-usability of lead-plated tin bronze as negative plate for lightweight lead-acid battery. *J. Electrochem. Energy Convers. Storage* **2021**, *18*, 030906.
4. Zhao, Y.; Zhang, S.; Wei, J.; Li, G. Low-carbon transition evaluation of park integrated energy systems incorporating hybrid energy storage systems and industrial by-product hydrogen. *J. Energy Storage* **2026**, *164*, 122250.
5. Alkhawani, Q.; Algburi, S.; Sabeeh, S.; Hakami, H.; Islam, S. Solar and wind powered green hydrogen systems: A review. *Energy Rep.* **2026**, *15*, 109324. [[CrossRef](#)]
6. Li, F.; Chen, Y.; Hu, Y.; Yu, Y.; Xing, L. Multi-objective optimization for integrated energy systems using non-dominated sorting genetic and swarm intelligence methods. *Swarm Evol. Comput.* **2026**, *104*, 102384.
7. Zhang, Y.; Xu, C.; Zhou, Y.; Wang, J. Optimal operation of wind-solar-storage-hydrogen system considering multi-scale forecasting of source-load. *Energy Convers. Manag.* **2025**, *344*, 120296.
8. Zhao, Y.; Zhao, Y.; Cao, S.; Zhu, Z.; Sun, H. Capacity configuration and control optimization of off-grid wind solar hydrogen storage system. *Energy* **2025**, *324*, 136002. [[CrossRef](#)]
9. Haiji, W.; Jiankun, H. Research on Optimal Scheduling of Power System Based on Ant Colony Algorithm. *J. Phys. Conf. Ser.* **2022**, *2404*, 012051. [[CrossRef](#)]
10. Hashim, F.A.; Houssein, E.H.; Mabrouk, M.S.; Al-Atabany, W.; Mirjalili, S. Henry gas solubility optimization: A novel physics-based algorithm. *Future Gener. Comput. Syst.* **2019**, *101*, 646–667. [[CrossRef](#)]
11. Amrollahi, M.; Bathaee, S. Techno-Economic Optimization of Hybrid Photovoltaic/Wind Generation Together with Energy Storage System in a Stand-Alone Micro-grid Subjected to Demand Response. *Appl. Energy* **2017**, *202*, 66–71.
12. Lagouir, M.; Badri, A.; Sayouti, Y. Multi-Objective Optimization Dispatch Based Energy Management of A Microgrid Running Under Grid Connected and Standalone Operation Mode. *Int. J. Renew. Energy Dev.* **2021**, *10*, 333–343. [[CrossRef](#)]
13. Mirjalili, S. SCA: A Sine Cosine Algorithm for solving optimization problems. *Knowl. Based Syst.* **2016**, *96*, 120–133. [[CrossRef](#)]
14. Tawhid, M.A.; Savsani, P. Discretesine-cosine algorithm(DSCA)with local search for solving traveling salesman problem. *Arab. J. Sci. Eng.* **2019**, *44*, 3669–3679.
15. Li, S.; Fang, H.; Liu, X. Parameter optimization of support vector regression based on sine cosine algorithm. *Expert Syst. Appl.* **2018**, *91*, 63–77. [[CrossRef](#)]
16. Nenavath, H.; Jatoth, D.R.K.; Das, D.S. A synergy of the sine-cosine algorithm and particles warm optimizer for improved global optimization and object tracking. *Swarm Evol. Comput.* **2018**, *43*, 1–30.
17. Gupta, S.; Deep, K. A hybrid self-adaptive sine cosine algorithm with opposition based learning. *Expert Syst. Appl.* **2019**, *119*, 210–230. [[CrossRef](#)]
18. Shao, R.; Li, K.; Teng, Q.; Li, R.; Li, Y.; Zhou, J. Research on Low-Carbon Optimization Scheduling of Microgrid Based on Improved Dream Optimization Algorithm. *J. Phys. Conf. Ser.* **2026**, *3229*, 012026. [[CrossRef](#)]
19. Sen, Z.; Weihao, H.; Xilin, C.; Jialin, D.; Chunguang, B.; Wen, L.; Ming, T.; Wei, Z.; Zhe, C. Low-carbon economic dispatch strategy for interconnected multi-energy microgrids considering carbon emission accounting and profit allocation. *Sustain. Cities Soc.* **2023**, *99*, 104987.

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