

Analysis of the configuration optimization and fixed-proportion power supply strategy of smart microgrids combining wind and photovoltaic power generation

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Abstract

In this study, a grid-connected microgrid system is developed, which consists of photovoltaic generation, wind power generation, battery storage, and electrical loads. The system configuration is optimized using the Grey Wolf Optimizer (GWO), and a fixed grid-supply strategy is proposed, in which the main grid provides a predefined proportion of the total demand. A case study based on a building in Okinawa, Japan, is conducted to evaluate the economic and operational performance of the proposed strategy. The results indicate that reducing the utility-grid supply ratio can significantly decrease CO₂ emissions and utility-grid load fluctuations. When the utility grid supply ratio is 30%, the system achieves the best environmental performance, the smoothest utility grid load profile, and satisfactory economic performance.

1 Introduction

Sustainable development has always been one of the major global topics. To reduce CO₂ emissions, countries around the world are striving to shift from reliance on fossil fuels to the development of renewable energy [1]. However, due to the instability and uncontrollability of renewable energy sources such as photovoltaic(PV) and wind power, ensuring their safe and reliable utilization remains a significant challenge [2]. Microgrids, as distributed energy systems capable of operating both independently and in grid-connected modes, provide an effective solution to this challenge [3]. Ullah et al. [4] proposed the approach using the hybridization of particle swarm optimization and gravitational search algorithms with Nash Bargaining to optimize power flow and energy trading between interconnected microgrids and the main grid. In [5], a microgrid system integrating hydrogen and battery energy storage with PV and wind power generation is developed. The Lévy Flight Algorithm is used to optimize the capacities of PV, wind turbines(WT), tanks, electrolyzers, fuel cells and batteries. The results demonstrate that the proposed method can significantly reduce the annual system cost, and that the Lévy flight algorithm outperforms particle swarm optimization, grey wolf optimization(GWO), and genetic algorithms. The study in [6] investigated the feasibility and efficiency of a grid-connected hybrid power system, combining PV, a biomass generator, and wind power. This study designed six different schemes, and the results indicate that the grid-connected PV-biomass generator system is the most cost-effective option. However, These studies primarily focus on the economic performance of the system, without taking into account the impact of the uncontrollability and variability of renewable energy on the stability of the main grid.

Hence, in this study, a microgrid system integrating PV, wind power, and battery storage is developed and a fixed-proportion power supply strategy is proposed to improve the

stability of the main grid and reduce CO₂ emissions.

2 Model formulation

The Fig. 1 shows the system model developed in this study, which includes the utility grid, PV, WT, battery, and the demand. The utility grid, PV panels, and WTs supply electricity to the demand side, while the batteries store excess power and release it when needed. The mathematical models of each component are showed as follows.

2.1 Utility grid model

The electricity supplied by utility grid, P_{grid} is calculated as

$$P_{grid} = P_{GRID} \times \eta_{grid} \quad (1)$$

where, P_{GRID} and η_{grid} stand for the power generated by the utility grid and the efficiency of power transmission from the utility grid, respectively.

2.2 PV model

The electricity generated by PV, P_{pv} is calculated as

$$P_{pv}(t) = N_{pv} \times P_{stc} \times \frac{I(t)}{I_{stc}}, \quad (2)$$

where N_{pv} , P_{stc} , $I(t)$ and I_{stc} stand for the number of PV panels, the power generation of the PV panels under standard test conditions(STC), the current solar irradiance and the solar irradiance under STC, respectively.

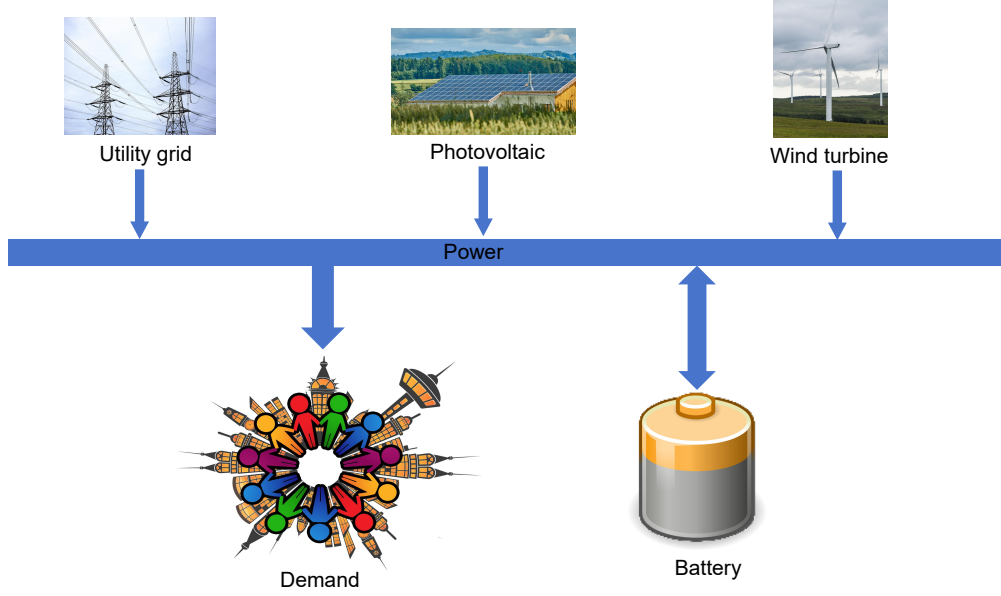


Figure 1: Model of system

2.3 WT model

The electricity generated by wind power, P_{wt} is calculated as [7]

$$P_{wt} = N_{wt} \times P_r \times \begin{cases} 0 & 0 \leq V < V_{in} \\ A_0 + A_1 V + A_2 V^2 & V_{in} \leq V < V_r \\ 1 & V_r \leq V < V_{out} \\ 0 & V \geq V_{out} \end{cases} \quad (3)$$

where,

$$A_0 = K_1(V_{in}K_2 - 4V_{in}V_rK_3) \quad (4)$$

$$A_1 = K_1(4K_2K_3 - 3V_{in} - V_r) \quad (5)$$

$$A_2 = K_1(2 - 4K_3) \quad (6)$$

$$K_1 = \frac{1}{(V_{in} - V_r)^2} \quad (7)$$

$$K_2 = V_{in} + V_r \quad (8)$$

$$K_3 = \left(\frac{V_{in} + V_r}{2V_r}\right)^3 \quad (9)$$

where, N_{wt} and P_r stand for the number of wind turbines, the rated electric power output, respectively. V , V_{in} , V_r and V_{out} stand for the current wind speed, the cut-in wind speed, the rate wind speed and the cut-out wind speed, respectively. A_0 , A_1 , A_2 , K_1 , K_2 and K_3 are the constants of the wind turbine power output curve.

2.4 Battery model

The amount of power stored in the battery at the current time, $E_{battery}(t)$ is calculated as

$$E_{battery}(t) = E_{battery}(t-1) + P_{cha}(t-1) - P_{dis}(t-1) \quad (10)$$

where, $E_{battery}(t-1)$, $P_{cha}(t-1)$ and $P_{dis}(t-1)$ stand for the power stored in the battery at the previous time, the amount of power charged in the previous time, and the amount of power discharged in the previous time, respectively.

The P_{cha} and P_{dis} are calculated as

$$P_{cha} = P_{grid} + P_{pv} + P_{WT} - P_{demand} \quad (11)$$

$$P_{dis} = P_{demand} - P_{grid} - P_{pv} - P_{WT} \quad (12)$$

where, P_{demand} stands for the demand for power.

The purpose of this study is configuration optimization and energy management rather than transient stability analysis. Therefore, simplified steady-state models are adopted to reduce computational complexity while retaining the essential characteristics required for long-term planning and operational evaluation.

3 Algorithm

In this study, the GWO is adopted as the optimization algorithm. The GWO is one of swarm intelligence based metaheuristics [8]. Inspired by the pack hunting and natural leadership of grey wolves, the GWO possesses several advantages, including ease of implementation, fast convergence speed, and excellent convergence results. Hence, it has been widely applied to solve optimization problems in various fields [9]. The mathematical model of the GWO is shown below.

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (13)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (14)$$

where t indicates the current iteration, A and C are coefficient vectors, X_p is the position vector of the prey, and X indicates the position vector of a grey wolf. The vectors A and C are calculated as follows.

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (15)$$

$$\vec{C} = 2\vec{r}_2 \quad (16)$$

where components of a are linearly decreased from 2 to 0 over the course of iterations and r_1 , r_2 are random vectors in $[0, 1]$.

The GWO retains the three best solutions, denoted as α , β , and δ , and updates the positions of the remaining wolves based on these three leaders. The mathematical model is shown as follows.

$$\begin{cases} \vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \\ \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \\ \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \end{cases} \quad (17)$$

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{cases} \quad (18)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (19)$$

The calculation process of the GWO is as follows:

First, a group of candidate solutions (the grey wolf population) is initialized, along with the parameters a , A , and C . Then, the fitness of each solution is evaluated using the objective function, and the three best solutions are identified and designated as α , β , and δ , respectively. Next, the positions of the grey wolves are updated according to the corresponding equations, and the parameters a , A , and C are updated. The fitness of each solution is then recalculated, and α , β , and δ are updated accordingly. This process is repeated until the maximum number of iterations is reached and the final result is output.

4 Simulation conditions

4.1 Constraints

To make the simulation more realistic, it is necessary to impose constraints on the system. First, the power supplied of each unit must lie within a certain range and cannot be infinitely large or infinitely small.

$$\begin{cases} P_{grid}(min) \leq P_{grid} \leq P_{grid}(max) \\ P_{pv}(min) \leq P_{pv} \leq P_{pv}(max) \\ P_{wt}(min) \leq P_{wt} \leq P_{wt}(max) \end{cases} \quad (20)$$

The battery cannot charge and discharge simultaneously, and the power stored in battery must remain within a certain range.

$$P_{cha} \times P_{dis} = 0 \quad (21)$$

$$E_{battery}(min) \leq E_{battery} \leq E_{battery}(max) \quad (22)$$

4.2 Objective function

In this study, the objective function is to minimize the economic cost C_{total} , which can be calculated as

$$C_{total} = C_{grid} + C_{pv} + C_{wt} + C_{battery} + C_{CO_2} \quad (23)$$

where, C_{grid} , C_{pv} , C_{wt} and $C_{battery}$ stand for the cost for utility grid, PV, WT and battery, respectively. C_{CO_2} stands for the cost of emitting CO_2 .

where,

$$\begin{cases} C_{grid} = P_{grid} \times C_{ele} \\ C_{pv} = N_{pv} \times C_{panel} \\ C_{wt} = N_{wt} \times C_{turbine} \\ C_{battery} = E_{battery}(max) \times C_{bat} \\ C_{CO_2} = P_{GRID} \times \eta_{CO_2} \times C_{carbon} \end{cases} \quad (24)$$

where, C_{ele} , C_{panel} , $C_{turbine}$, C_{bat} and C_{carbon} stand for the unit price of purchasing power from utility grid, panels, wind turbines, batteries and CO_2 emissions. η_{CO_2} stands for the CO_2 emission rate when the grid generates electricity.

5 Case study

This study considers a building in Okinawa, Japan, as the case study, and uses its electricity load over a specific day as the power demand for the analysis. The utility grid provides 0%, 30%, and 60% of the total system load, respectively.

Fig. 2 shows the electricity demand and weather parameters used in the study.

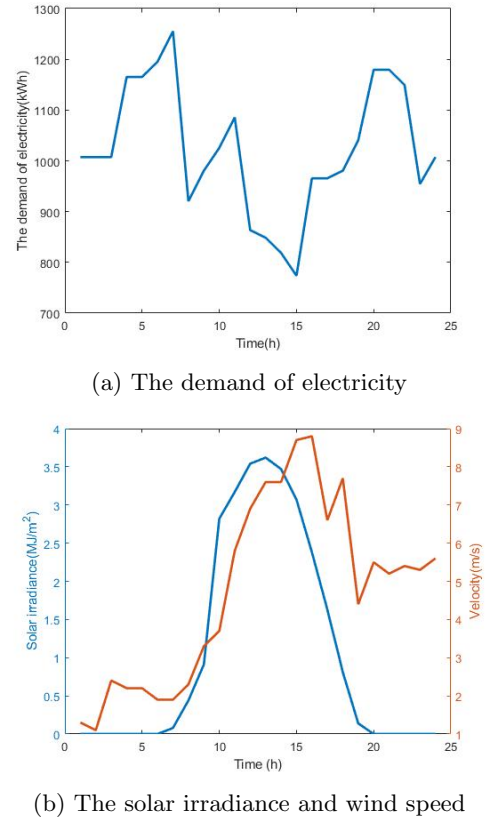


Figure 2: Electricity demand and weather parameters

The economic parameters and technical parameters used in this study are shown in Table 1 and Table 2.

Table 1: The economic parameters

Item	Symbol	Value	Unit	Reference
PV panel	C_{panel}	351	\$/kw	[10]
WT	$C_{turbine}$	410	\$/kw	[10]
Battery	C_{bat}	292	\$/kw	[10]
CO_2 emission	C_{carbon}	0.0075	\$/kg	[11]
Power form grid	C_{ele}	0.2	\$/kwh	/

Table 2: The technical parameters

Item	Parameter	Symbol	Value	Unit
Grid	Efficiency of grid	η_{grid}	0.98	/
	CO_2 emission rate	η_{CO_2}	1.2	kg/kwh
PV	Efficiency of PV panel	η_{pv}	0.2	/
	Power generation under STC	P_{stc}	0.25	kw
	Solar irradiance under STC	I_{stc}	1000	w/m^2
WT	Cut-in wind speed	V_{in}	3	m/s
	Rate wind speed	V_r	14	m/s
	Cut-out wind speed	V_{out}	25	m/s
	Rate power output	P_r	600	kw

In this study, due to the limitations of PV and wind power, the battery charging and discharging strategy is designed so that the battery is charged when sufficient power is supplied by renewable energy sources and discharged when the renewable energy supply is insufficient. In addition, the battery is expected to remain as fully charged as possible at the end of the day so that it can provide power for the next day. To extend the service life of the battery, the minimum state of charge(SOC) is set to 20% of its total capacity, and the initial SOC is set to 100%.

5.1 Results under different supply ratios

Fig. 3 shows the fitness curve of GWO algorithm.

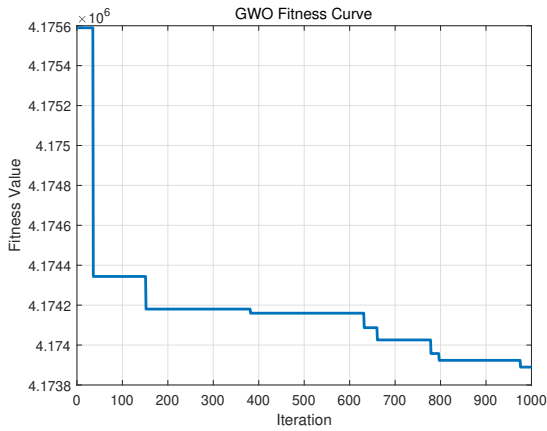
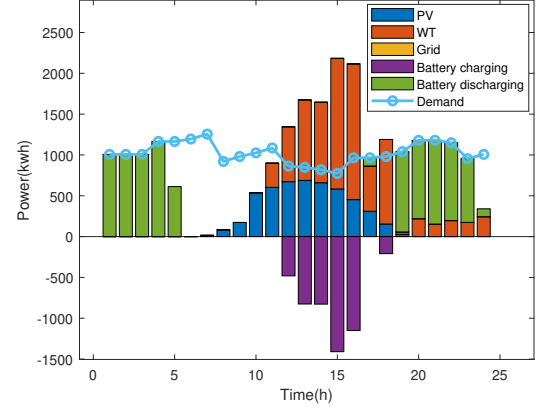
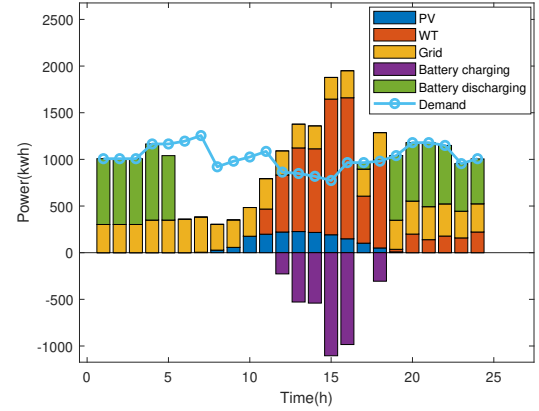


Figure 3: The fitness curve of GWO

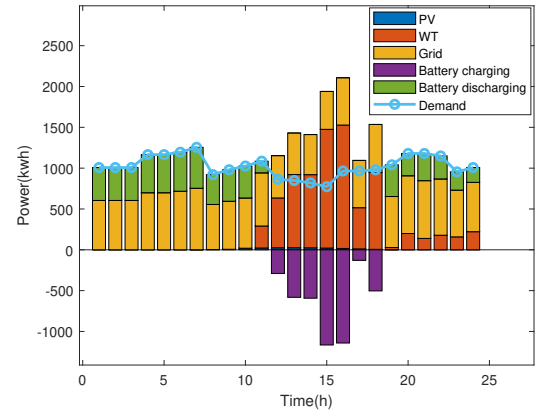
Fig. 4 shows the operation of each component under different utility-grid supply ratios.



(a) 0% utility-grid supply



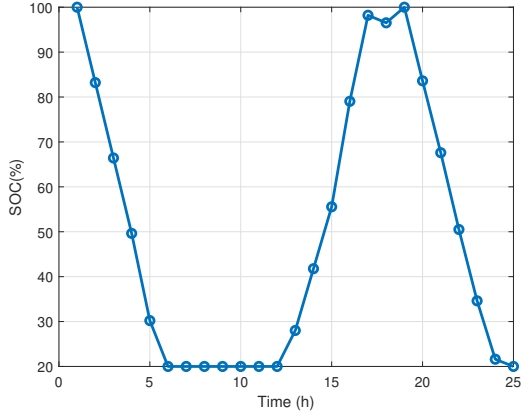
(b) 30% utility-grid supply



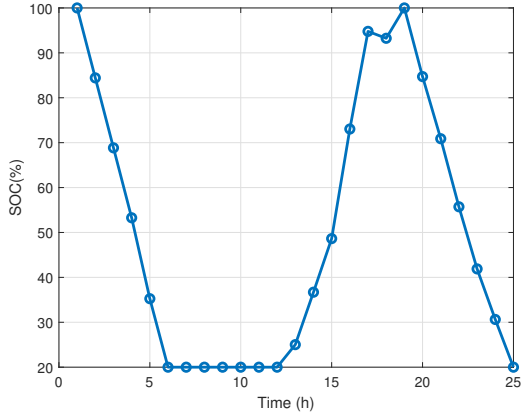
(c) 60% utility-grid supply

Figure 4: System operation under different utility grid supply ratios

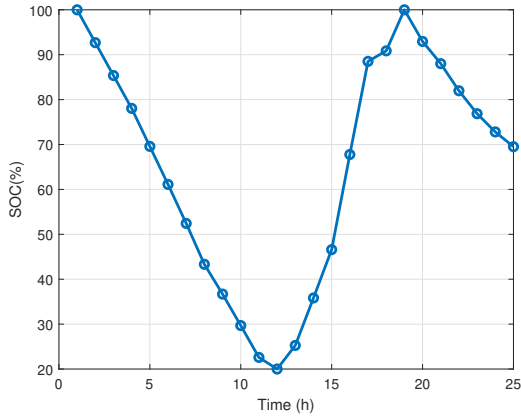
Fig. 5 shows the SOC of the battery under different utility grid supply ratios.



(a) 0% utility-grid supply



(b) 30% utility-grid supply



(c) 60% utility-grid supply

Figure 5: SOC of the battery under different utility grid supply ratios

Table 3 shows the results and cost of system configuration when the utility grid provides 0% of the demand.

Table 3: Cost when the utility grid provides 0% of the demand

Item	PV panel	WT	Battery	Grid	CO ₂ emission
Quantity	2738	11	6000	0	0
Cost(\$)	240260	4510	1752000	0	0
Total Cost(\$)	1.99×10^6				

Table 4 shows the results and cost of system configuration when the utility grid provides 30% of the demand.

Table 4: Cost when the utility grid provides 30% of the demand

Item	PV panel	WT	Battery	Grid	CO ₂ emission
Quantity	901	10	4527	7512(kwh)	9014(kg)
Cost(\$)	79063	4100	1321884	1502	68
Total Cost(\$)	1.41×10^6				

Table 5 shows the results and cost of system configuration when the utility grid provides 60% of the demand.

Table 5: Cost when the utility grid provides 60% of the demand

Item	PV panel	WT	Battery	Grid	CO ₂ emission
Quantity	100	10	5506	15026(kwh)	18031(kg)
Cost(\$)	8775	4100	1607752	3005	135
Total Cost(\$)	1.65×10^6				

5.2 Environmental and utility grid Load fluctuation Assessment

In this study, the variance of the utility grid power supply is adopted as an indicator of utility grid load fluctuation. A lower variance means that the power supplied by the utility grid changes more smoothly over time, which can help reduce peak-valley differences and operational stress on the utility grid. Therefore, it is used as a simplified index to evaluate the utility grid friendly performance of different supply scenarios.

Table 6 presents the environmental performance and utility-grid load fluctuation under different utility-grid supply ratios.

Table 6: Comparison of different utility-grid supply ratios

Utility Grid Supply Ratio (%)	Total Cost (\$)	CO ₂ Emission (kg)	Variance of Utility Grid Supply
30	1.41×10^6	9014	1484
60	1.65×10^6	18031	5938
100	5.13×10^3	29450	16493

It can be observed that the 100% utility-grid supply scenario achieves the lowest total cost. However, this scenario also results in the highest CO₂ emissions and the largest fluctuation in utility-grid power supply.

Compared with the 100% utility-grid supply scenario, the 30% utility-grid supply scenario reduces CO₂ emissions by 69.4% and decreases the variance of utility-grid power supply by 91.0%. These results demonstrate that the proposed strategy can significantly improve environmental performance and smooth utility-grid power fluctuations. Although the 100% utility-grid supply scenario exhibits the lowest cost in the one-day simulation, long-term economic factors such as equipment lifetime, renewable energy benefits, and investment payback period are not considered.

6 Conclusion

In this study, a smart microgrid integrating PV generation, wind power generation, battery storage, and utility grid support was developed. A fixed-proportion power supply strategy was proposed, and the system configuration was optimized using the GWO.

The results indicate that reducing the utility grid supply ratio can effectively smooth the utility grid load profile and reduce environmental impact. Compared with the 100%

utility-grid supply scenario, the 30% utility-grid supply scenario reduces CO₂ emissions by 69.4% and decreases the variance of utility-grid power supply by 91.0%, indicating a significant improvement in utility-grid-friendly operation.

Although the 100% utility-grid supply scenario achieves the lowest economic cost, it does not consider long-term economic factors such as renewable energy benefits, carbon costs, equipment lifetime, and investment payback period. Therefore, the proposed fixed-proportion power supply strategy provides a more balanced solution from environmental and utility-grid operation perspectives.

The main contributions of this study can be summarized as follows:

- A smart microgrid configuration optimization framework integrating PV, WT, battery storage, and utility-grid support was established.
- A fixed-proportion power supply strategy was proposed to coordinate renewable energy utilization and utility-grid participation.
- The proposed strategy was shown to significantly reduce CO₂ emissions and utility-grid load fluctuations compared with the conventional 100% utility-grid supply scenario.

7 Future work

- Future work will focus on incorporating demand response mechanisms and dynamic electricity pricing into the proposed optimization framework.
- More comprehensive system evaluation mechanisms will be introduced to assess the system from multiple perspectives, including economic performance, environmental impact, exergy efficiency, and energy utilization.
- The simulation period will be extended to evaluate the total system cost over a 20-year operational lifetime and to determine the investment payback period.

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