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Optimal Configuration Strategy of Hybrid Energy Storage System to Stabilize Wind Power Fluctuations

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Abstract: Regarding the issue of optimal configuration for hybrid energy storage to independently stabilize wind power fluctuations, this paper proposes a hybrid energy storage optimization method considering the life-cycle economics of supercapacitors and lithium batteries. First, at the upper level of power allocation, an Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise combined with superposition reconstruction is used to decompose the wind power into a grid-connected component that meets fluctuation standards and a component requiring smoothing by hybrid energy storage. At the lower level of power allocation, a frequency division parameter is introduced to further decompose and reconstruct the smoothing component into low-frequency and high-frequency power demands. Furthermore, a zonal power control strategy based on state of charge recovery is proposed to adjust the allocated power for supercapacitors and lithium batteries. Finally, considering constraints such as charge–discharge power and capacity of the hybrid energy storage, an optimization model for hybrid energy storage configuration is established with the objective of minimizing the annualized cost over the full life cycle. The model is solved using an improved particle swarm optimization algorithm. Case study results demonstrate that the proposed method can effectively enhance the economic performance of the hybrid energy storage system in smoothing wind power fluctuations.

Keywords: Fluctuation power mitigation, hybrid energy storage system, power allocation, full life cycle, improved particle swarm optimization.

1. Introduction

With the implementation of China's "3060 dual carbon" strategy, renewable energy generation has become a prevailing trend. However, renewable energy sources such as wind power are highly fluctuating due to natural environmental influences, posing significant challenges to grid stability and other aspects [1-3]. Equipping wind farms with a certain capacity of energy storage, particularly hybrid energy storage systems (HESS), which leverage the complementary advantages of energy-type and power-type storage, can effectively smooth wind power fluctuations and improve system economy, attracting research attention [4-7]. Nevertheless, the configuration cost of the energy storage system and the power smoothing effect are contradictory [8-9]. Therefore, how to optimize energy storage configuration to ensure system economy while meeting wind power grid integration standards is a critical issue to be considered when HESS participate in wind power smoothing [10-11].

Ref. [12] provides a review of energy storage systems participating in wind power fluctuation smoothing, covering topics such as selection of energy storage equipment, power and capacity configuration, smoothing control algorithms, and hybrid energy storage energy management. Ref. [13] uses spectrum analysis combined with wind power fluctuation constraints to calculate the optimal cutoff frequency for energy storage smoothing, thereby obtaining the minimum required storage power. Ref. [14] applies wavelet decomposition to grid-connected wind power fluctuating components and proposes a fuzzy control strategy to optimize power allocation in hybrid energy storage, but does not consider the influence of storage capacity on the control strategy. Ref. [15] employs a model predictive control algorithm to address the issue of frequent charge-discharge cycles in a single energy storage unit. Considering state-of-charge (SOC) constraints, it controls two battery banks to charge and discharge separately, thereby reducing battery lifetime loss. Ref. [16] establishes a power model for photovoltaic, wind turbine, thermal power, and energy storage systems, balancing the cost of curtailment (wind and solar) with the total system operating cost. An improved grey wolf optimizer is used to determine the optimal capacity for each device. Ref. [17] proposes a hybrid energy storage control strategy that accounts for SOC self-recovery. Model predictive control is used to rapidly adjust the SOC of the energy storage, while a weighted moving average-fuzzy control strategy dynamically allocates power within the HESS.

In summary, most existing studies focus on how to achieve optimal power allocation based on a fixed capacity of the energy storage system. However, in practice, the power allocation strategy and capacity configuration interact with and constrain each other, leading to inaccurate storage configuration results. Furthermore, most researches are based on energy storage assisting conventional units for power smoothing, and the optimization of hybrid energy storage configuration primarily targets the economic benefits of auxiliary units and the overall storage system, without considering the perspective of new independent entities such as storage aggregators. Energy storage, as an independent entity participating in wind farm construction and operation, can better realize the value of flexible storage resources.

Therefore, this paper proposes an optimal configuration method for a hybrid energy storage system based on supercapacitors and lithium batteries to smooth wind power fluctuations. First, in the upper layer of power allocation, the wind power fluctuation is decomposed using Improved Complete Ensemble Empirical Mode Decomposition with

Adaptive Noise (ICEEMDAN). The decomposed components are reconstructed according to the wind power grid-connection fluctuation limits to obtain the grid-connected component and the component to be smoothed by the hybrid energy storage system. Then, in the lower layer of power allocation, the component to be smoothed by the hybrid energy storage system is decomposed again and reasonably divided into high-frequency and low-frequency power demand based on the frequency division parameter. A zone-based power control strategy considering State of Charge (SOC) recovery is applied to adjust the power of the supercapacitor and lithium battery. Finally, considering constraints such as the charge/discharge power limits and capacity limits of the HESS, an optimization model for HESS configuration is established with the objective of minimizing the annualized life-cycle cost. The improved particle swarm optimization (IPSO) algorithm is used to solve for the optimal configuration of the HESS.

2. Smoothing Strategy for Wind Power Fluctuations

2.1. ICEEMDAN-Based Bi-level Power Allocation

At the upper level of power allocation, wind power signal $x(n)$ after ICEEMDAN processing yields residual and IMF components.

$$x(n) = \sum_{i=1}^{I} Imf_i(n) + Res(n) \tag{1}$$

If the HESS processes the power components obtained from Eq. (1) individually, the computational burden increases dramatically. Therefore, reconstruction is performed considering power fluctuation limits before power allocation to improve computational efficiency [18, 19]. In addition, China's wind power fluctuation grid connection standards mainly limit the maximum power fluctuation of wind power for 1 minute and 10 minutes [20].

The Res and the Imf_i components are superimposed from bottom to top to generate the reconstructed signals $f_{(l)}$ of each order.

$$\begin{cases} f_{(1)} = Res \\ f_{(2)} = Res + Imf_I \\ \cdots \\ f_{(I+1)} = Res + Imf_I + \ldots + Imf_2 + Imf_1 \end{cases} \tag{2}$$

Therefore, the wind power is reconstructed the directly grid-connectable power component P_{grid} and the power component requiring energy storage smoothing P_{ES}.

$$\begin{cases} P_{\text{grid}} = f_{\max(i)},\ \Delta P_{\Delta t}(f_{\max(k)}) \le \Delta P_{\text{lim},\Delta t} \\ P_{\text{ES}} = P_{\text{wind}} - P_{\text{grid}} \end{cases} \tag{3}$$

Where the $\Delta P_{\text{lim},\Delta t}$ is the fluctuation limits of wind power grid-connected power in the relevant standards, $f_{\max(k)}$ represents the highest order reconstruction signal that meets the volatility limit.

At the lower level of power allocation, to reduce lithium battery life degradation, it should primarily smooth low-frequency, low-power fluctuations, while the supercapacitor handles high-frequency fluctuations. Therefore, the P_{ES} is further decomposed. A frequency division parameter d is introduced to reconstruct the residual and the IMF components obtained from this secondary decomposition. This ultimately yields the low-frequency power component P_{low} and the high-frequency power component P_{high}.

$$\begin{cases} P_{\text{low}} = f_{(d)} \\ P_{\text{high}} = P_{\text{ES}} - P_{\text{low}} \end{cases} \tag{4}$$

The Bi-level power distribution task is completed through the above two decomposition and reconstruction of wind power fluctuation.

2.2. SOC Recovery-based Zonal Power Control

This letter proposes a zonal power control strategy based on SOC recovery of HESS to control the charge-discharge power of supercapacitors and lithium batteries. SOC_{SC} and SOC_{BT} represent the SOC of supercapacitor and lithium battery, respectively. The SOC zones for the HESS are shown in Table 1.

Table 1. State of charge zones

SOC_{SC} \ SOC_{BT}	(0.1, 0.3)	(0.3, 0.7)	(0.7, 0.9)
(0.1, 0.3)	S1	S2	S3
(0.3, 0.7)	S4	S5	S6
(0.7, 0.9)	S7	S8	S9

Fig. 1 shows the recovery interval of hybrid energy storage SOC. The recovery command can only be executed when the SOC recovery trends of the supercapacitor and the lithium battery are mutually exclusive.

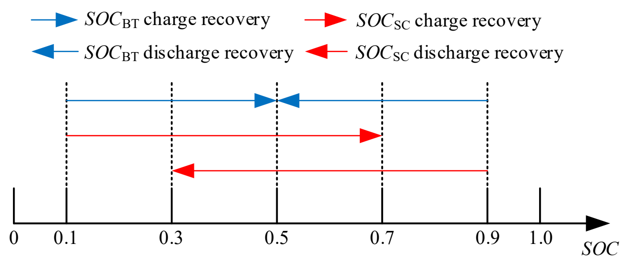


Figure 1. SOC recovery interval

The maximum charge-discharge power of the supercapacitor and lithium battery must also consider their power and capacity limits [21], since the expressions of both are similar, take supercapacitors as an example:

$$\begin{cases} P_{\text{SC},t}^{\text{dis,max}} = \min\left[P_{\text{SC,rat}}, \dfrac{(0.9 - SOC_{\text{SC},t}) E_{\text{SC,rat}} \eta_{\text{SC}}^{\text{dis}}}{\Delta t} \right] \\ P_{\text{SC},t}^{\text{cha,max}} = \max\left[-P_{\text{SC,rat}}, \dfrac{(0.1 - SOC_{\text{SC},t}) E_{\text{SC,rat}}}{\eta_{\text{SC}}^{\text{cha}} \Delta t} \right] \end{cases} \tag{5}$$

Based on the above analysis, the zonal power control strategy for HESS SOC recovery is as follows.

1) Discharge state

In states S5, S6, S8, and S9:

$$\begin{cases} P_{\text{SC},t}^{\text{dis}} = \min(P_{\text{high},t}, P_{\text{SC},t}^{\text{dis,max}}) \\ P_{\text{BT},t}^{\text{dis}} = P_{\text{ES},t} - P_{\text{BT},t}^{\text{dis}} \end{cases} \tag{6}$$

In states S2 and S3:

$$\begin{cases} P_{\mathrm{BT},t}^{\mathrm{dis}} = \min(P_{\mathrm{low},t} - P_{\mathrm{re\_sc}}, P_{\mathrm{BT},t}^{\mathrm{dis,max}}) \\ P_{\mathrm{re\_sc}} = \dfrac{(SOC_{\mathrm{SC},t} - 0.3)E_{\mathrm{SC,rat}}}{\eta_{\mathrm{SC}}^{\mathrm{cha}}\Delta t} \\ P_{\mathrm{SC},t}^{\mathrm{dis}} = P_{\mathrm{ES},t} - P_{\mathrm{BT},t}^{\mathrm{dis}} \end{cases} \tag{7}$$

Where the $P_{\mathrm{re\_sc}}$ is the SOC_{SC} recovery instruction.

In states S4 and S7:

$$\begin{cases} P_{\mathrm{SC},t}^{\mathrm{dis}} = \min(P_{\mathrm{high},t} - P_{\mathrm{re\_bt}}, P_{\mathrm{SC},t}^{\mathrm{dis,max}}) \\ P_{\mathrm{re\_bt}} = \dfrac{(SOC_{\mathrm{BT},t} - 0.5)E_{\mathrm{BT,rat}}}{\eta_{\mathrm{BT}}^{\mathrm{cha}}\Delta t} \\ P_{\mathrm{BT},t}^{\mathrm{dis}} = P_{\mathrm{ES},t} - P_{\mathrm{BT},t}^{\mathrm{dis}} \end{cases} \tag{8}$$

Where the $P_{\mathrm{re\_bt}}$ is the SOC_{BT} recovery instruction.

In state S1:

$$\begin{cases} P_{\mathrm{SC},t}^{\mathrm{dis}} = \min(P_{\mathrm{ES},t}, P_{\mathrm{SC},t}^{\mathrm{dis,max}}) \\ P_{\mathrm{BT},t}^{\mathrm{dis}} = P_{\mathrm{ES},t} - P_{\mathrm{BT},t}^{\mathrm{dis}} \end{cases} \tag{9}$$

2) Charging state

In states S1, S2, S4, and S5:

$$\begin{cases} P_{\mathrm{SC},t}^{\mathrm{cha}} = \max(P_{\mathrm{high},t}, P_{\mathrm{SC},t}^{\mathrm{cha,max}}) \\ P_{\mathrm{BT},t}^{\mathrm{cha}} = P_{\mathrm{ES},t} - P_{\mathrm{SC},t}^{\mathrm{cha}} \end{cases} \tag{10}$$

In states S7 and S8:

$$\begin{cases} P_{\mathrm{BT},t}^{\mathrm{cha}} = \max(P_{\mathrm{low},t} - P_{\mathrm{re\_sc}}, P_{\mathrm{BT},t}^{\mathrm{cha,max}}) \\ P_{\mathrm{re\_sc}} = \dfrac{(SOC_{\mathrm{SC},t} - 0.7)E_{\mathrm{SC,rat}}\eta_{\mathrm{SC}}^{\mathrm{dis}}}{\Delta t} \\ P_{\mathrm{SC},t}^{\mathrm{cha}} = P_{\mathrm{ES},t} - P_{\mathrm{BT},t}^{\mathrm{cha}} \end{cases} \tag{11}$$

In states S3 and S6:

$$\begin{cases} P_{\mathrm{SC},t}^{\mathrm{cha}} = \max(P_{\mathrm{high},t} - P_{\mathrm{re\_bt}}, P_{\mathrm{SC},t}^{\mathrm{cha,max}}) \\ P_{\mathrm{re\_bt}} = \dfrac{(SOC_{\mathrm{BT},t} - 0.5)E_{\mathrm{BT,rat}}\eta_{\mathrm{BT}}^{\mathrm{dis}}}{\Delta t} \\ P_{\mathrm{BT},t}^{\mathrm{cha}} = P_{\mathrm{ES},t} - P_{\mathrm{SC},t}^{\mathrm{cha}} \end{cases} \tag{12}$$

In state S9:

$$\begin{cases} P_{\mathrm{SC},t}^{\mathrm{cha}} = \max(P_{\mathrm{ES},t}, P_{\mathrm{SC},t}^{\mathrm{cha,max}}) \\ P_{\mathrm{BT},t}^{\mathrm{cha}} = P_{\mathrm{ES},t} - P_{\mathrm{SC},t}^{\mathrm{cha}} \end{cases} \tag{13}$$

The power distribution lower layer is reconstructed into high and low frequency power requirements through the parameter d, and the power control strategy is used to adjust.

3. Optimization Model of HESS Configuration

A configuration optimization model is established that takes into account the technical aspects of wind power fluctuation and the economy of HESS.

3.1. Objective Function and Constraints

The optimization model aims to minimize the annualized cost C_{ES} of the whole life cycle, that is the sum of the annualized investment cost C_{inv}, replacement cost C_{rep}, and maintenance cost C_{run} as the objective function, and does not consider other costs for the time being [22-23]. The formula is:

$$C_{\mathrm{ES}} = \min(C_{\mathrm{inv}} + C_{\mathrm{rep}} + C_{\mathrm{run}}) \tag{14}$$

$$\gamma_{\mathrm{CRF}} = \frac{\gamma(1+\gamma)^{T_{\mathrm{life}}}}{(1+\gamma)^{T_{\mathrm{life}}} - 1} \tag{15}$$

$$\begin{aligned} C_{\mathrm{inv}} = (&c_{\mathrm{BT},P}P_{\mathrm{BT,rat}} + c_{\mathrm{BT},E}E_{\mathrm{BT,rat}} + \\ &c_{\mathrm{SC},P}P_{\mathrm{SC,rat}} + c_{\mathrm{SC},E}E_{\mathrm{SC,rat}})\gamma_{\mathrm{CRF}} \end{aligned} \tag{16}$$

$$\begin{aligned} C_{\mathrm{rep}} = [&(c_{\mathrm{BT},P}P_{\mathrm{BT,rat}} + c_{\mathrm{BT},E}E_{\mathrm{BT,rat}})n_{\mathrm{BT}} + \\ &(c_{\mathrm{SC},P}P_{\mathrm{SC,rat}} + c_{\mathrm{SC},E}E_{\mathrm{SC,rat}})n_{\mathrm{SC}}]\gamma_{\mathrm{CRF}} \end{aligned} \tag{17}$$

$$C_{\mathrm{run}} = c_{\mathrm{BT,up}}E_{\mathrm{BT,rat}} + c_{\mathrm{SC,up}}E_{\mathrm{SC,rat}} \tag{18}$$

Where the $c_{\mathrm{SC,P}}$, $c_{\mathrm{BT,P}}$, $c_{\mathrm{SC,E}}$, and $c_{\mathrm{BT,E}}$ are the unit power cost and unit capacity cost of supercapacitor and lithium battery. γ is the discount rate of funds. n_{SC} and n_{BT} are the number of replacements of supercapacitor and lithium battery, n_{BT} can be derived from lifetime models in Ref. [24]. $c_{\mathrm{BT,up}}$ and $c_{\mathrm{SC,up}}$ are the average annual maintenance cost per unit capacity of lithium battery and supercapacitor.

In order to meet the requirements of wind power fluctuations and the good operation of the system, HESS must meet certain constraints.

1) Power balance constraints:

$$P_{\mathrm{ES},t} = P_{\mathrm{SC},t} + P_{\mathrm{BT},t} \tag{19}$$

2) Charging and discharging power constraints:

$$\begin{cases} P_{\mathrm{SC},t}^{\mathrm{cha,max}} \le P_{\mathrm{SC},t} \le P_{\mathrm{SC},t}^{\mathrm{dis,max}} \\ P_{\mathrm{BT},t}^{\mathrm{cha,max}} \le P_{\mathrm{BT},t} \le P_{\mathrm{BT},t}^{\mathrm{dis,max}} \end{cases} \tag{20}$$

3) SOC constraints:

$$\begin{cases} \mathbf{0}.1 \le SOC_{\mathrm{SC},t} \le 0.9 \\ 0.1 \le SOC_{\mathrm{BT},t} \le 0.9 \end{cases} \tag{21}$$

4) Rated capacity constraints

The rated capacity of supercapacitor and lithium battery should meet their maximum energy accumulation in one working cycle, which is as follows:

$$E_{\mathrm{ES,rat}} \cdot \cdot \max\left[\frac{\max\limits_{u\in T}\int_0^u P_{\mathrm{ES},t}\eta dt}{0.9 - SOC^{\mathrm{ini}}}, \frac{-\min\limits_{v\in T}\int_0^v P_{\mathrm{ES},t}\eta dt}{SOC^{\mathrm{ini}} - 0.1}\right] \tag{22}$$

Where SOC^{ini} is the initial SOC, η is efficiency, taking into account the impact of charging and discharging.

3.2. Solution Method

As mature meta-heuristic global optimization methods, PSO algorithm and GA algorithm are often used to solve multivariate, multi-constraint and hybrid nonlinearity programming problems [25-27].

The mechanism of the improved particle swarm optimization algorithm adopted in this paper is as follows: record the initial individual best and global best of the particle swarm, retain the top half of elite particles with better objective function values, and perform crossover and mutation operations on them to form the other half of new particles [28]. The two halves are merged to form a new population, and then the individual best and global best of the particle swarm are updated. Under constraints, the objective function with the rated power and rated capacity of the supercapacitor and lithium battery as decision variables is solved to obtain the optimal full-life-cycle annualized cost and configuration scheme for the HESS.

4. Case Analysis

4.1. Basic Data

Based on the actual wind power generation data of 1 minute in 2025 in a region with an installed capacity of 1500 MW, the parameters of the example [29] are shown in Table 2.

Table 2. Relevant parameter settings

Category	Parameter	Value
Lithium battery	$c_{BT,P}$ (yuan/MW)	$500*10^4$
	$c_{BT,E}$ (yuan/MWh)	$180*10^4$
	$c_{BT,up}$ (yuan/MWh)	$50*10^4$
	η_{BT} (%)	95
	SOC	[0.1, 0.9]
Supercapacitor	$c_{SC,P}$ (yuan/MW)	$150*10^4$
	$c_{SC,E}$ (yuan/MWh)	$2500*10^4$
	$c_{SC,up}$ (yuan/MWh)	$50*10^4$
	η_{SC} (%)	95
	SOC	[0.1, 0.9]
Others	SOC^{ini}	0.5
	γ/(%)	5
	Life cycle/(year)	20
	n_{SC}	1

In addition, the particle swarm size in the algorithm is 200, the maximum number of iterations is 50, the selection strategy adopts tournament selection, the crossover strategy adopts two-point crossover, and the crossover probability is 0.8, the mutation strategy adopts Gaussian mutation with a mutation probability of 0.08.

In order to avoid the unrepresentative wind power of a certain day in the selected area, the iterative self-organizing data analysis algorithm is used to cluster the wind power data of the year, and the typical days of wind power corresponding to various scenarios are selected based on the median cumulative fluctuation [30]. This paper takes the typical daily 1 wind power data with the greatest probability as an example.

4.2. Power Allocation Strategy Validation

For the typical daily wind power, 1 Res and 8 IMF components are obtained by decomposition at first time. The results obtained after reconstruction are shown in Fig. 2.

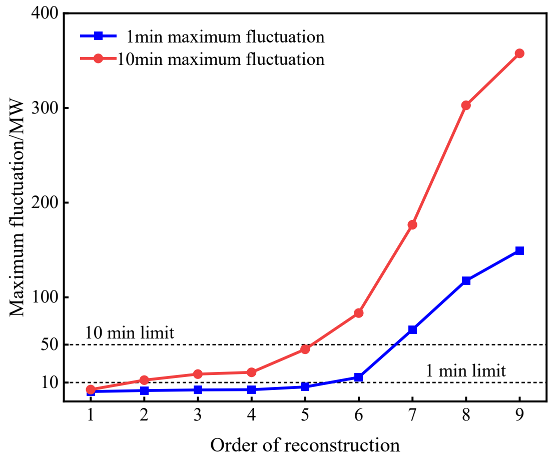


Figure 2. Reconstruction results

From the analysis of Fig. 2, it can be seen that the maximum power fluctuation value of 1 minute of typical daily wind power is 149.25 MW, and the maximum power fluctuation value of 10 minutes is 357.67 MW, which does not meet the grid connection standard of wind power.

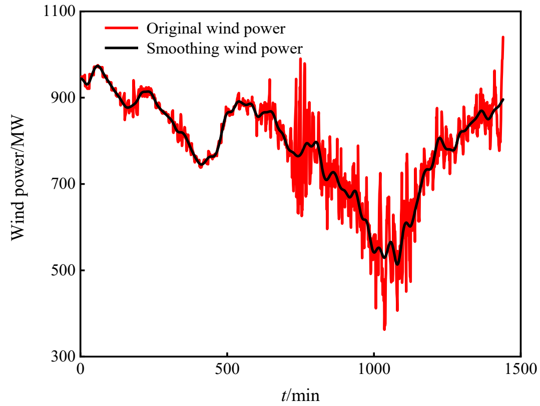


Figure 3. The upper layer of power distribution

At the upper layer of power distribution, the limit of wind power grid-connected fluctuation is used as the dividing line, and the reconstruction component $f_{(6)}$ does not meet the conditions, and $f_{(5)}$, that is, the sum of $Res{\sim}Imf_5$ is selected as the direct grid-connected power, as shown in Fig. 3. The remaining part, the sum of $Imf_1{\sim}Imf_4$ is used as the hybrid energy storage smoothing task, as shown in Fig. 4.

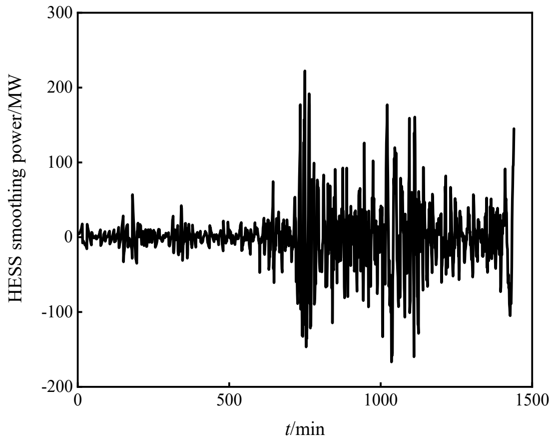


Figure 4. HESS smoothing power

At the lower layer of power distribution, the HESS smoothing power is further decomposed to obtain 1 Res and 8 IMF components, and allocated according to the frequency division parameter d.

4.3. Configuration Results and Analysis

To further demonstrate the economic viability of this proposed solution, a comparative analysis of multiple alternatives is conducted. Option 1: Single lithium battery energy storage configuration method. Option 2: Power allocation strategy using the EMD method. Option 3: Traditional zoning strategy without SOC recovery consideration in power control strategy. Configuration results of different options are shown in Tab. 3. Fig. 5 shows the relationship curve of the annualized cost corresponding to the parameter d under the method proposed in this paper.

Table 3. Configuration results for different options

Results	This paper	Option 1	Option 2	Option 3
$P_{BT.rat}$/MW	85.27	217.70	115.14	68.03
$E_{BT.rat}$/MWh	144.65	121.25	132.69	95.37
$P_{SC.rat}$/MW	173.39	—	168.43	192.63
$E_{SC.rat}$/MWh	17.85	—	17.10	38.11
T_{year}/year	5.36	2.15	5.08	4.33
C_{ES}/yuan	4.15×10^8	12.14×10^8	4.45×10^8	4.71×10^8

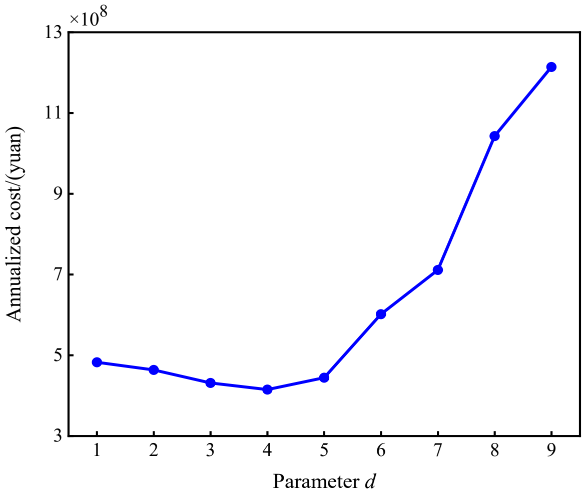
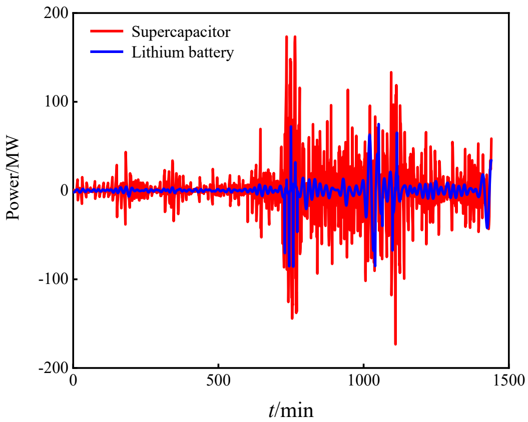
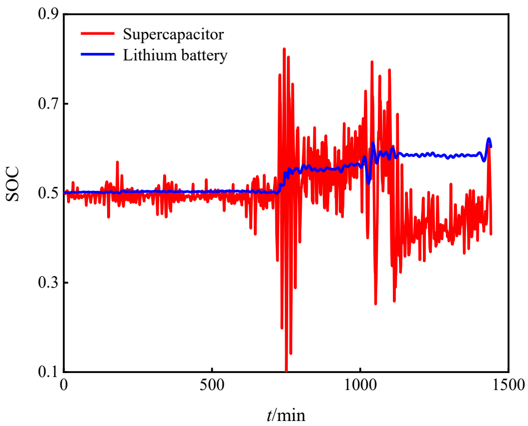


Figure 5. The relationship curve of the annualized cost corresponding to the parameter d



(a)



(b)

Figure 6. d=4, the output of HESS

From Table 3 and Fig. 5, it can be seen that the annualized cost of hybrid energy storage as a whole shows a trend of first decreasing and then increasing with the increase of the parameter d, mainly because the output of lithium batteries is getting larger and larger with the increase of parameter d, and the life loss of lithium batteries is also getting higher and higher. The annualized cost is the lowest at d=4, which is 415 million yuan. The equivalent life of lithium battery is 5.36 years, and it needs to be replaced three times during the whole life cycle. In addition, the rated power of supercapacitors and lithium batteries is 173.39 MW and 85.27 MW, respectively, and the installed capacity accounts for 17.24% of the installed capacity of wind farms, meeting the recommended proportion range of energy storage capacity in wind farms. The ratio of rated power to rated capacity of supercapacitors and lithium batteries is about 10:1 and 1:2, which satisfies the respective characteristics of power-type and energy-type energy storage.

The charging and discharging power and SOC curves of hybrid energy storage at the optimal frequency division parameter d=4 are shown in Fig. 6. It can be seen that the charging and discharging power of supercapacitors changes frequently, and the SOC changes largely. However, the charging and discharging power of lithium batteries changes slowly and the SOC changes slowly and the amplitude is small, and there are only a few time points when there are large power changes to adjust and restore the hybrid energy storage SOC, which verifies the effectiveness of the power control strategy proposed in this paper.

5. Conclusion

This paper proposes a power distribution control strategy based on ICEEMDAN secondary distribution calculation and hybrid energy storage SOC recovery, and the optimal configuration of hybrid energy storage is solved by the improving particle swarm algorithm.

ICEEMDAN has more accurate power distribution and reduced the power adjustment of lithium batteries, realizing the complementary advantages between frequent deep charging and discharging of supercapacitor and sustainable charging and discharging of lithium batteries.

The complementary mechanism of hybrid energy storage greatly reduces the flattening cost of single energy storage, and at the same time, taking into account the power control strategy of SOC recovery, reasonably adjusting the hybrid energy storage configuration, balancing the utilization rate and replacement cost of hybrid energy storage, which is more conducive to the long-term economic operation of hybrid energy storage.

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