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ENERGY STORAGE OPTIMIZATION OF POWER GRID COMBINING EMPIRICAL MODE DECOMPOSITION AND FUZZY CONTROL

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Abstract - To enhance the stability and system economy of wind power grid connection, this study proposes a power allocation strategy for grid energy storage that combines empirical mode decomposition and fuzzy control. This strategy improves the accuracy of empirical mode decomposition by introducing adaptive noise, extracts signal time-frequency characteristics using Hilbert transform, and designs a fuzzy controller to dynamically adjust the SOC of energy storage devices. On this basis, a comprehensive consideration of operation and maintenance costs and battery life loss is taken into account to construct an energy storage optimization model for the power grid. The experiment showed that the power allocation method combining empirical mode decomposition and fuzzy control increased the fluctuation shift rate by 17.86%. The total cost of the energy storage optimization model has been reduced by 14.26% compared to other optimization models, and the wind power prediction error, response time, and charge discharge loss rate of this model have been reduced by 26.42%, 7.34%, and 13.59%. Meanwhile, the energy utilization rate and equipment lifespan improvement rate of this model were 94.45% and 26.51%, showing significant advantages. This indicates that the optimization strategy can effectively suppress power fluctuations, achieve multi-objective optimization, enhance the adaptability and economy of energy storage systems, and provide more stable support for wind and solar power grid integration.

Keywords: EMD, Fuzzy control, Power allocation, Grid energy storage optimization, Battery cycle life.

1. Introduction

With the widespread application of Renewable Energy (RE), the power fluctuations and stability challenges faced by the power grid are becoming increasingly prominent. As an important clean energy source, the randomness and intermittency of wind and solar power may lead to frequency fluctuations in the power grid, which can have an effect on the safe operation of the power system [1]. Therefore, the importance of Grid Energy Storage Optimization (GESO) is becoming increasingly prominent. It can effectively regulate the storage and release of electrical energy during power fluctuations, improve the stability and reliability, ensure the continuity and quality of power supply, and provide strong support for the integration and consumption of large-scale RE. To enhance the stability of the power grid, various optimization strategies have been proposed, such as filter-based signal decomposition, Artificial Intelligence (AI) optimization control, and intelligent scheduling strategies [2]. However, traditional filtering methods suffer from the problem of mode aliasing when dealing with nonlinear and non-stationary signals. Fixed power allocation strategies are difficult to adapt to the dynamic changes in the State of Charge (SOC) of Energy Storage Devices (ESDs), which affects their lifespan and economic benefits [3]. Currently, Empirical Mode Decomposition (EMD) has attracted attention due to its adaptive decomposition ability for nonlinear and non-stationary signals. Combined with Hilbert transform, it can further obtain the time-frequency characteristics of electrical signals and improve power control accuracy [4-5]. However, power allocation based solely on signal frequency may overlook the SOC of ESDs, leading to overcharging or over-discharging of the devices. Fuzzy control, as an intelligent control method, can be combined with SOC to dynamically adjust the Charging and Discharging (C&D) process of ESDs and optimize the power grid operation [6]. Given this, this paper proposes a GESO method that combines EMD and fuzzy control. It incorporates an Adaptive Gaussian White Noise (AGWN) set EMD to improve signal decomposition stability and

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introduces fuzzy control to dynamically adjust SOC. At the same time, starting from multiple dimensions such as economy and reliability, this study comprehensively considers the Initial Investment Cost (IIC), Operating and Maintenance Cost (OMC), and Battery Cycle Life (BCL) loss cost of the Energy Storage System (ESS), and constructs an energy storage optimization model. It aims to complete the optimal allocation of energy storage resources and promote the sustainable development of the power grid towards green, stable, and intelligent direction. The innovation of the research lies in proposing a dual constraint power allocation strategy based on frequency characteristics and SOC, which balances fast response and equipment health management, providing an efficient and reliable solution for energy storage scheduling in the power grid.

2. Related Works

EMD and fuzzy control technology have become key means to solve non-stationary signal processing and multi-objective optimization problems due to their unique advantages. To accurately predict PM2.5 concentration, Yang G et al. developed a deep learning-based prediction model. By fusing gate controlled loop units and EMD, long-term accurate prediction of PM2.5 concentration has been achieved [7]. To solve the problem of EMD being greatly affected by the amplitude of white noise and the amount of integrated experiments, Li et al. developed a fast adaptive EMD method. By combining the advantages of sequential statistical filters and raw EMD, efficient extraction of key feature information from fault signals was achieved [8]. To recognize the existence, location, and damage severity in the Truss steel bridge model, Mousavi et al. proposed an application method that fully integrates EMD and adaptive noise technology. By extracting key features and improving damage indicators, the localization, quantification, and detection of damage were achieved [9]. To achieve tracking control of strictly feedback nonlinear systems, Wang Q et al. put forth an adaptive fuzzy predefined time and accuracy tracking control scheme. By deriving stability criteria and applying inversion techniques to develop controllers, chattering and energy consumption were reduced [10]. To study the fuzzy adaptive asymptotic tracking control problem of a 3-order heterogeneous vehicle exhaust system with input saturation, Li et al. proposed a control scheme with an auxiliary design system. By approximating unknown nonlinear functions through fuzzy logic systems, asymptotic convergence of zero spacing errors and fleet stability were completed [11].

Numerous studies are dedicated to optimizing the design and operation of ESSs in different scenarios. To optimize the design of ESSs in large-scale RE plants, Emrani et al. proposed an optimization algorithm that combines energy management strategies with the Fmington interior point method. This algorithm achieved system cost reduction and energy storage capacity optimization by integrating gravity ESSs and comparing them with battery energy storage [12]. To optimize the power grid planning under RE policies, Huan J et al. proposed a capacity allocation optimization method for wind power generation, solar power generation, and energy storage. It calculated the correlation between policy and planned capacity through grey relational analysis, achieving optimal planning of RE under different policies [13]. For the placement and capacity selection of battery ESSs in distribution networks, Gu et al. proposed an optimization method based on an improved NSGA-II. This algorithm achieved the goals of minimizing power loss, voltage fluctuations, and BESS capacity by increasing the choice coefficient of the population's optima and updating the congestion distance function [14]. To address the challenge of nonlinear constraints on automatic generation control frequency regulation in power systems, Morsali proposed a superconducting magnetic energy storage auxiliary control method based on fractional order controllers. This method achieved the goal of superconducting magnetic energy storage effectively participating in the supervision of automatic power generation control based on actual dynamics by parallel designing superconducting magnetic energy storage and automatic power generation control while minimizing performance indicators [15]. To support the frequency of microgrids and improve system stability, Hassanzadeh M E et al. proposed a best control plan built on fuzzy logic. It achieved improved frequency stability and smooth response by introducing auxiliary control units to save the battery and manage its charging status [16].

Based on the above, existing achievements in optimizing ESSs mainly focus on capacity planning and control strategies in different scenarios. However, there is a lack of a comprehensive method that can integrate the advantages of signal processing and intelligent control, while balancing the fast response of ESSs with the long lifespan and low-cost operation of equipment. Based on this, this study proposes a GESO method that combines EMD and fuzzy control, aiming to break through existing technological bottlenecks and achieve efficient and stable operation of power grid ESSs through multi-technology collaboration.

3. Methods and Materials

3.1 Energy Storage Power Allocation Method for Power Grid based on EMD and Fuzzy Control

In GESO's research, wind power generation, as an important RE, directly impacts the stability and power scheduling of the operation. Therefore, effective methods are needed for power regulation and energy storage optimization. To grow the stability of Wind Power Grid Connection (WPGC), it is needed to allocate the power response of the ESS reasonably, so that it can effectively stabilize wind power fluctuations and lift the reliability and economy.

On this basis, this study first analyzes the basic principles of wind power generation, as shown in Fig.1.

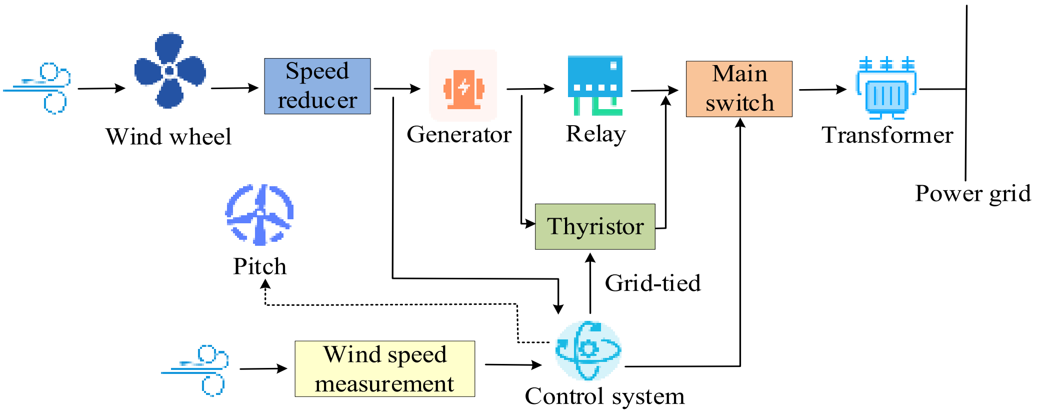


Figure 1: Schematic diagram of wind turbine power generation principle

Figure 1 shows the basic process of converting wind energy into electrical energy. Firstly, the wind turbine captures wind energy and drives the transmission system, causing the generator to rotate. The wind speed measurement device transmits data to the control system to optimize the operation status of the wind turbine. The electrical energy generated by the generator is converted by the rectifier, then regulated by the front-end tube, and further optimized for output quality by the inverter. The control system is responsible for adjusting the wind turbine angle, power output, and grid adaptation to ensure stable operation. Due to the randomness and volatility of wind power output, a reasonable mixed energy storage power allocation method can improve the stability and the lifespan of the ESS. Therefore, this study uses EMD to decompose and dynamically regulate wind power. To improve the stability of signal decomposition and the physical interpretability of modal components, and to make each Intrinsic Mode Function (IMF) clearer, this study introduces adaptive noise in each decomposition stage and adopts a set averaging strategy to enhance the completeness and stability of decomposition. Meanwhile, by combining Hilbert transform, the Instantaneous Frequency (IF) and energy characteristics of each IMF are further extracted to achieve accurate time-frequency analysis of wind power. Fig.2 shows the specific process.

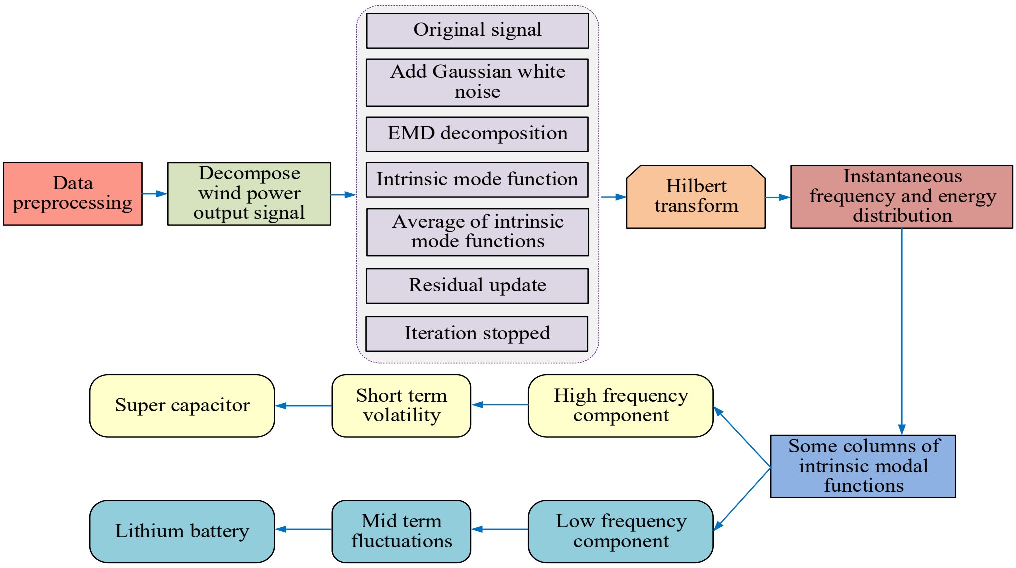


Figure 2: Grid power allocation method combining EMD and Hilbert transforms

According to Fig.2, firstly, the wind power output signal is preprocessed and the EMD method with AGWN is used to decompose the signal, obtaining multiple intrinsic mode functions to reduce mode aliasing. Next, Hilbert transform is applied to each modal function to gain its IF and amplitude information, to deeply analyze the dynamic characteristics of each wave component. Based on the dynamic characteristics of each modal function, corresponding control strategies are designed. Based on the characteristics of different frequency components, short-term fluctuations corresponding to high-frequency components are allocated to supercapacitors to quickly respond to short-term fluctuations in wind power. The low-frequency component corresponds to the long-term trend of wind power, which is stored in lithium batteries to enhance the stability of power grid operation. Through this allocation strategy, precise control of wind power can be achieved, improving the utilization efficiency of ESSs. According to the above principle, the formula for the original wind power output signal can be obtained as shown in equation (1).

$$P(t)=\sum_{k=1}^{m} IMF_k(t)+r_m(t) \tag{1}$$

In equation (1), $P(t)$ denotes the original wind power output signal. $IMF_k(t)$ is the k -th eigenmode function, representing the fluctuation components of different frequencies. $r_m(t)$ is the residual trend term, representing the long-term trend of wind power. According to the IF and amplitude characteristics, the power allocation function of the ESD is set as equation (2).

$$\begin{cases} P_{sc}(t)=\sum\limits_{k\in HF} IMF_k(t) \\ P_{bat}(t)=\sum\limits_{k\in LF} IMF_k(t) \end{cases} \tag{2}$$

In equation (2), $P_{sc}(t)$ and $P_{bat}(t)$ are the power allocated to the super-capacitor and battery. HF and LF are high-frequency and low-frequency components. Although the strategy combining EMD and Hilbert transform can effectively decompose wind power fluctuations and allocate energy storage, this method only relies on signal frequency characteristics and does not consider the operating status of ESDs, especially their SOC. Therefore, this study further introduces fuzzy control strategy to dynamically adjust SOC to ensure that super-capacitors and lithium batteries operate within a reasonable SOC range. The power allocation scheme for hybrid ESS based on fuzzy control is shown in Fig.3.

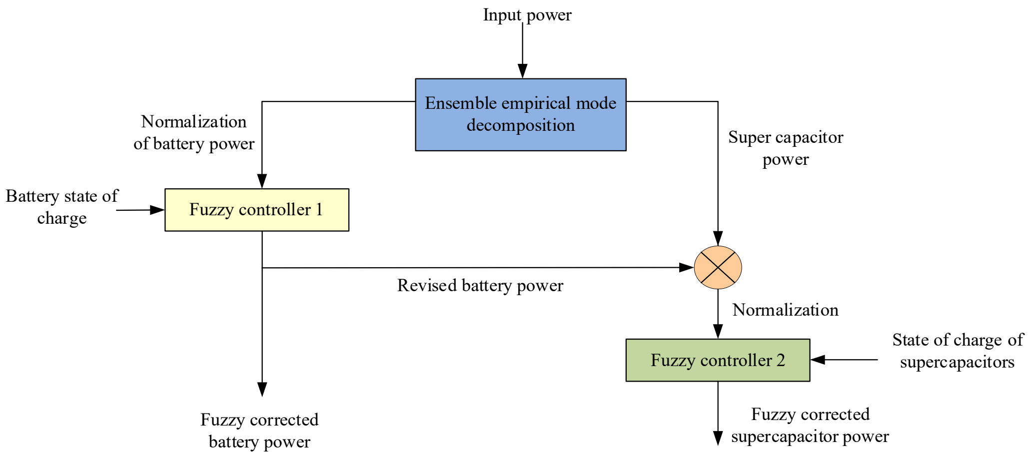


Figure 3: Fuzzy control-based power allocation method

According to Fig.3, the hybrid method mainly consists of an integrated EMD reconstruction module, a fuzzy controller, and a power correction module. Firstly, the wind power output signal is input and reconstructed through EMD decomposition to obtain the primary power allocation of super-capacitors and batteries. Fuzzy controller 1 is introduced to modify the initial power allocation of the battery to conform to the SOC characteristics of the battery, resulting in the corrected battery power. At the same time, the correction increment of battery power is calculated and applied to the initial power allocation of the super-capacitor. After normalization, fuzzy controller 2 is input to optimize and adjust the power allocation of the super-capacitor, obtaining the final corrected super-capacitor power. This strategy coordinates the C&D processes of batteries and super-capacitors through fuzzy control, enabling ESDs to operate within a reasonable SOC range.

3.2 Design of GESO Model Combining EMD and Fuzzy Control

The power grid energy storage allocation method based on EMD and fuzzy control can effectively improve the stability of WPGC and optimize the C&D strategies of ESS. On this basis, this study constructs a GESO model to improve the operational economy, reliability, and service life of ESSs. The basic structure of the GESO model combining EMD and fuzzy control is displayed in Fig.4.

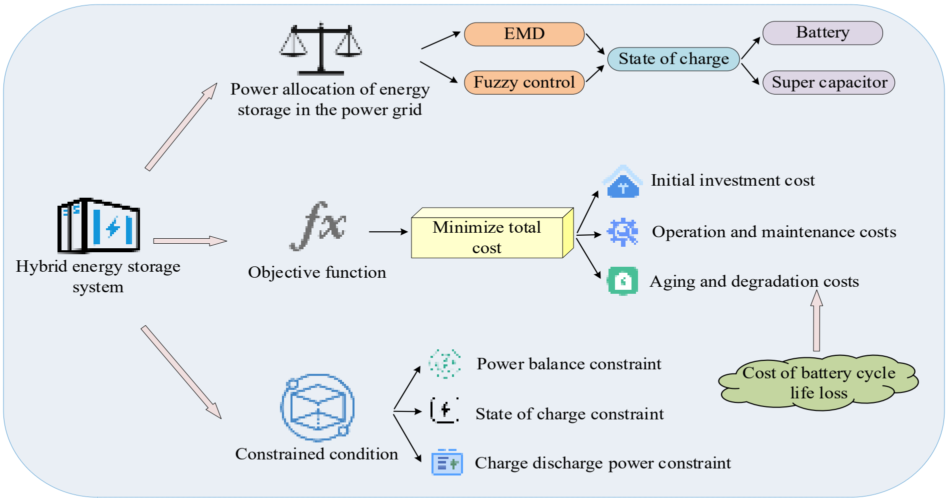


Figure 4: GESO model combining EMD and fuzzy control

In Fig.4, the designed GESO model combining EMD and fuzzy control aims to minimize the total cost of the ESS, considering various costs of the battery. To ensure the rationality of the optimization results, the model introduces power balance constraints, SOC constraints, and charge discharge power constraints to guarantee the safe operation of the ESS. The cycle life of lithium batteries is greatly affected by the discharge's depth. This study uses Rainflow Counting Method (RCM) to identify power data cycles and counts the number of cycles at different discharge depths to evaluate the attenuation characteristics of the battery and optimize the operation control of the ESS. The detailed steps for calculating the cycle life of lithium batteries using RCM are shown in Fig.5.

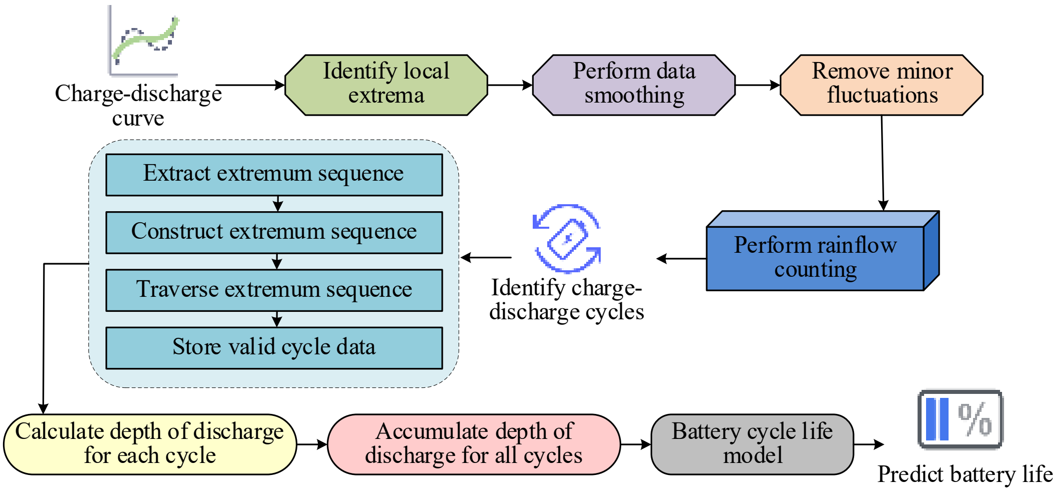


Figure 5: Steps for calculating the cycle life of lithium batteries by the RCM

In Fig. 5, RCM is used in GESO to evaluate the BCL, optimize C&D strategies, and improve the reliability and economy of ESSs. Firstly, the current or voltage data of the battery is collected and smoothed. Subsequently, RCM is used to identify charge and discharge cycles with different amplitudes, and based on empirical life models, cycles with different discharge depths are corrected. Next, the equivalent life contributions of all discharge cycles are counted and normalized to calculate the total BCL.

Finally, the health status of the battery is evaluated based on the calculated results. Assuming that the BCL is related to the depth of discharge, the total BCL can be calculated by equivalent cycle times, as shown in equation (3).

$$L = \frac{\sum_i n_i \cdot f(DoD_i)}{N_{rated}} \tag{3}$$

In equation (3), L is the equivalent operating BCL. DoD_i is the i -th level discharge depth. n_i is the number of cycles with a discharge depth of DoD_i obtained from RCM statistics. $f(DoD_i)$ is an empirical relationship function between discharge depth and battery life. N_{rated} is the rated BCL at 100% discharge depth. The GESO's objective function is given by equation (4).

$$\begin{cases} C_{cap} = P_{bat} \cdot C_{bat,unit} + P_{sc} \cdot C_{sc,unit} \\ C_{O\&M} = T_{op} \cdot \left(C_{bat,O\&M} + C_{sc} \cdot C_{sc,O\&M} \right) \\ C_{deg} = \dfrac{C_{bat}}{N_{bat}} \cdot \sum_{i=1}^{N_{cycle}} \dfrac{n_i}{f(DOD_i)} \end{cases} \quad (4)$$

In equation (4), C_{cap} is the IIC of the hybrid ESD, including the battery and super-capacitor. $C_{O\&M}$ is the OMC of hybrid energy storage. C_{deg} is the aging and degradation cost of hybrid ESS, which considers the cost of BCL loss. P_{bat} and P_{sc} are the rated capacities of batteries and super-capacitors. $C_{bat,unit}$ / $C_{sc,unit}$ and $C_{bat,O\&M}$ / $C_{sc,O\&M}$ are the unit power cost and average annual maintenance cost of batteries and super-capacitors. T_{op} is the operating cycle. N_{bat} is the theoretical lifespan of the battery. N_{cycle} is the gross of C&D cycles. The power balance constraint for energy storage optimization is shown in equation (5).

$$P_{grid} + P_{bat} + P_{sc} = P_{load} \quad (5)$$

In equation (5), P_{grid} means the power supplied by the power grid. P_{load} is the load demand power.

The SOC constraint of the hybrid ESS is given by equation (6).

$$\begin{cases} SOC_{bat,\min} \le SOC_{bat}(t) \le SOC_{bat,\max} \\ SOC_{sc,min} \le SOC_{sc}(t) \le SOC_{sc,max} \end{cases} \quad (6)$$

In equation (6), $SOC_{bat,\min}$ and $SOC_{bat,\max}$ denote the minimum and maximum SOC limits allowed by the battery. $SOC_{bat}(t)$ is the SOC at time t. $SOC_{sc,min}$ and $SOC_{sc,max}$ are the min and max SOC limits allowed for super-capacitors. $SOC_{sc}(t)$ is the SOC of a super-capacitor. The C&D power constraints of the hybrid ESS are given by equation (7).

$$\begin{cases} 0 \le P_{bat}(t) \le P_{bat,max} \\ 0 \le P_{sc}(t) \le P_{sc,max} \end{cases} \quad (7)$$

In equation (7), $P_{bat,max}$ and $P_{sc,max}$ are the maximum C&D powers of the battery and super-capacitor. Finally, this paper introduces the Improved Particle Swarm Optimization (IPSO) algorithm based on Gaussian mutation as the solving algorithm, as shown in Fig.6.

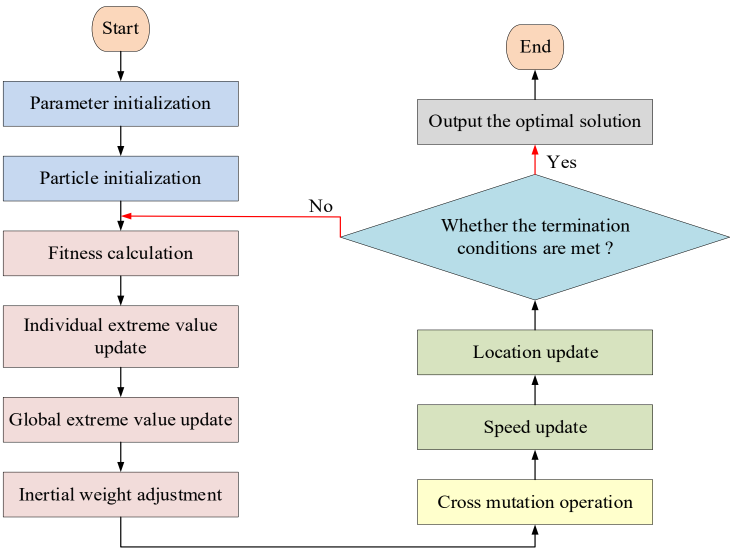


Figure 6: The basic flow of the IPSO algorithm

In Fig. 6, the IPSO algorithm demonstrates good performance in GESO by introducing non-linear decreasing inertia weights and Gaussian mutation operations. The first step is to initialize the particle swarm parameters, particle positions, and velocities. The second step is to calculate the fitness of each particle and update the individual and global extremum. The third step is to adjust the inertia weight according to the non-linear decreasing strategy, and conduct extensive search in the early stage of the algorithm, while focusing on local search in the later stage. Meanwhile, Gaussian mutation operation is performed to increase particle swarm diversity and avoid getting stuck in local optima. The next step is to update the particle velocity and position based on the formula, repeat the fitness calculation, extreme value update, and other steps. The optimal solution of GESO is obtained through iteration and optimization. Finally, by constructing an economic optimization objective function and solving it with constraints, efficient optimization configuration of ESD in the power grid is achieved, which improves the stability of the power grid and the economic benefits of the ESS.

4. Results

4.1 Verification of Power Allocation Approach for Energy Storage in Power Grid Built on EMD and Fuzzy Control

To validate the effectiveness of the GESO model combining EMD and fuzzy control, this study conducts simulation experiments based on the Windows 11 system.

The processor is Intel Core i7-10700K @ 3.80GHz, and the memory is 32GB DDR4. The experimental simulation platform is Matlab/Simulink 2022a. Using measured data from a certain wind farm as the experimental data source, the sampling frequency is 1Hz and the duration is 24 hours.

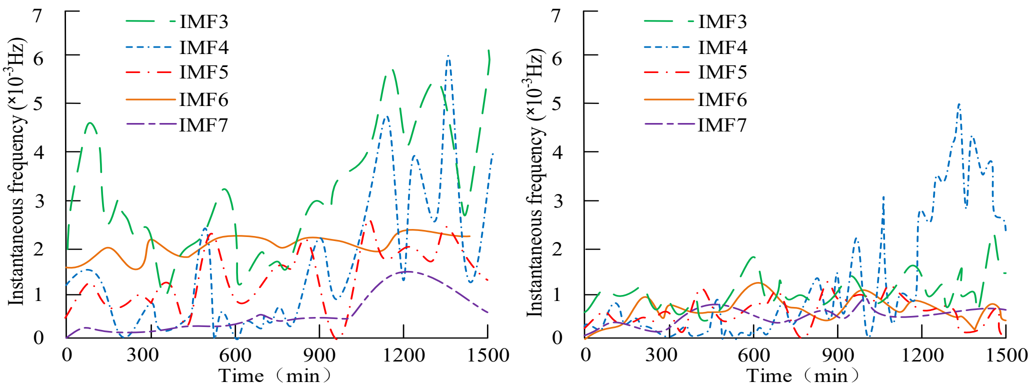
Table 1 shows the main configurations utilized in the experiment.

Table 1. Main equipment in the experiment

Parameter	Battery	Super capacitor
Rated voltage	400V	48V
Rated power	500kW	100kW
Converter efficiency	95%	95%
Maximum charging current	200A	300A
Maximum discharging current	250A	350A
Rated temperature range	-20℃ to 60℃	-20℃ to 60℃
Sampling time step	0.001s	0.001s
Unit power cost	500 CNY/kW	800 CNY/kW
Maintenance cost	50 CNY/kW per year	50 CNY/kW per year
Equipment lifespan	10 years	15 years

In Table 1, this study first analyzes the power allocation data of the ESS using EMD and compares the traditional EMD with the ensemble EMD with AGWN added.

From each order of IMF components, IMF3~IMF7 are selected to obtain the time-frequency distribution curve of the hybrid ESS through Hilbert transform, as displayed in Fig.7.



(a) IMF time-frequency profile under pooled EMD assignment

(b) IMF time-frequency profile with conventional EMD allocation

Figure 7: Comparison of power distribution effects of EMD

Fig. 7 (a) shows the time-frequency distribution curve of power allocation in a traditional EMD ESS. The time-frequency curves of each IMF component fluctuate more violently and complexly, for example, IMF4 has a larger IF change amplitude between 900 and 1,200 minutes. This situation occurs because traditional EMD is prone to mode aliasing when processing nonlinear and non-stationary signals such as wind power, which affects the decomposition accuracy and leads to inaccurate reflection of the fluctuation characteristics of wind power signals by various IMF components. Comparing the time-frequency distribution curves of power allocation in the ESS with the ensemble EMD incorporating AGWN in Fig.7 (b), it is found that the time-frequency changes of different IMF components are relatively stable. IMF3 fluctuates in IF between 1×10^{-3}Hz~3×10^{-3} Hz within the time period of 300-600 minutes. This is because ensemble EMD introduces adaptive noise in each decomposition stage and adopts ensemble averaging strategy, effectively reducing mode mixing problem and improving the completeness and stability of decomposition. This enables each IMF component to more clearly represent the fluctuating components of different frequencies and amplitudes in the wind power signal.

Meanwhile, this study compares the SOC of the hybrid ESS before and after fuzzy control, as shown in Fig.8.

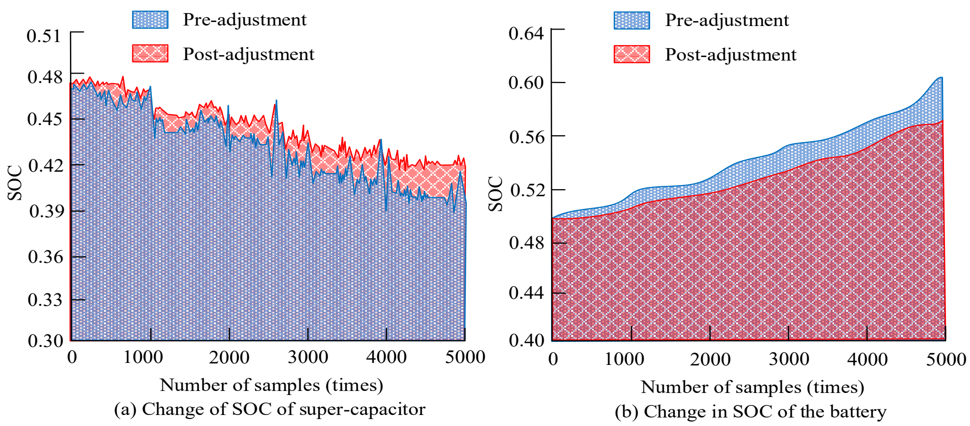


Figure 8: Change in charge state before and after fuzzy control based

Fig. 8 (a) shows the SOC changes of super-capacitors in a hybrid ESS before and after fuzzy control. Before adjustment, the SOC of the super-capacitor fluctuates between 0.30 and 0.51, and the fluctuations are relatively frequent. After adjustment, SOC fluctuates between 0.33 and 0.48, with a significantly reduced amplitude and a more stable overall change. This indicates that the strategy optimizes and adjusts the power allocation of super-capacitors by introducing a fuzzy controller, making the C&D process more reasonable, avoiding excessive C&D, and thus maintaining SOC within a more stable range. Based on Fig.8 (b), the SOC changes of the battery before and after fuzzy control are displayed. Before adjustment, the battery SOC is between 0.40~0.64, and after adjustment, it is between 0.44~0.60. Before adjustment, the growth trend is relatively flat and fluctuated greatly, while after adjustment, the SOC growth trend becomes more obvious and the fluctuation decreases. This further indicates that the fuzzy controller adjusts the initial power allocation of the battery to conform to its SOC characteristics. Moreover, by coordinating the C&D processes of the battery and super-capacitor, the battery operates within a reasonable SOC range, improving its stability.

4.2 Verification of GESO Model Combining EMD and Fuzzy Control

To test the effectiveness of the research model, this study introduces a comparison between traditional Low Pass Filtering (LPF)-based power allocation and energy storage optimization methods that only use EMD. Fig.9 uses the power fluctuation suppression effect and the fluctuation smoothing rate under different wind speeds as the test indicators.

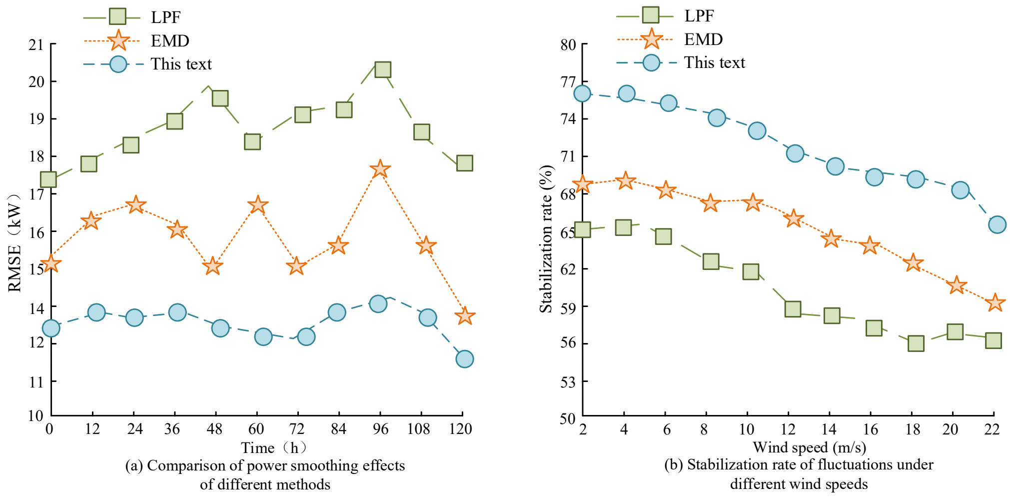


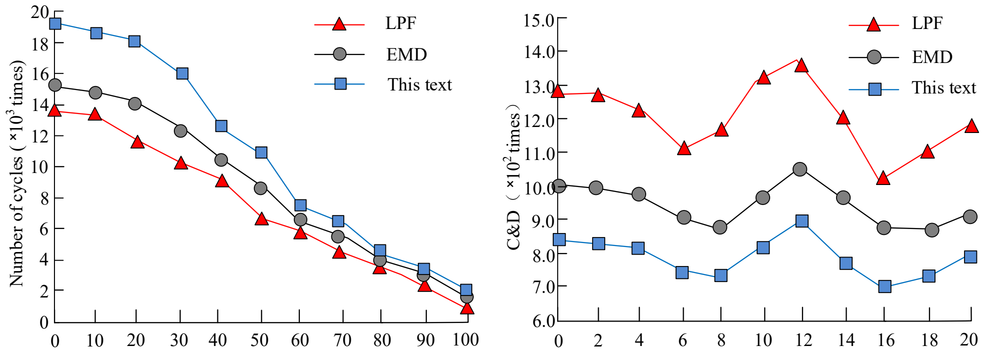
Figure 9: Fluctuation smoothing effect comparison

Fig.9 (a) compares the power smoothing effects of different methods. The RMSE value of the LPF method mostly fluctuates between 18-21kW, while the EMD fluctuates between 15-17kW. The research method is basically between 12 and 14 kW, with the minimum RMSE value and relatively gentle variation.

This indicates that combining EMD and fuzzy control can more accurately decompose wind power fluctuations and allocate energy storage power reasonably, effectively stabilizing wind power fluctuations. Fig.9 (b) shows a comparison of the fluctuation smoothing rates of various methods under different wind speeds.

The fluctuation suppression rate of the research method is always at the top of the image, and with the rise of wind speed, the decrease in fluctuation suppression rate is the smallest, and the fluctuation stability rate is relatively high. When the wind speed is 12m/s, the fluctuation suppression rate of this method is about 72.13%, which is an average improvement of about 17.86% compared to other methods. This indicates that the research strategy can better cope with fluctuations in wind power at different wind speeds and improve system stability.

Meanwhile, this study compares the cycle life and charge discharge performance of equipment under different methods, as shown in Fig.10.



(a) Variation of computational overhead with the number of attributes

(b) Comparison of C&D times of supercapacitors

Figure 10: Comparison of cycle life of ESDs and C&D times of super-capacitors

Fig. 10 (a) shows the variation of cycle life of ESDs with discharge depth under different methods. The equivalent cycle times of the three methods gradually decrease with the growth of discharge depth. The number of cycles of the research method is consistently higher than other methods at various discharge depths. When the discharge depth is 50%, the equivalent cycle number corresponding to this method is about 11,000 times, which is an average increase of 37.23% compared to the comparative method. This indicates that the combination of EMD and fuzzy control methods can allocate energy storage power more reasonably, reduce deep discharge, and thus extend the cycle life of ESDs. In Fig.10 (b), the amount of C&D cycles of super-capacitors under different methods shows that the LPF method has a large fluctuation in the number of C&D cycles, reaching a maximum of 1380 cycles. The research method consistently maintains the lowest level of C&D cycles, with a maximum of 910 cycles, which is an average reduction of 39.47% compared to other methods. This indicates that optimizing the high-frequency component allocation strategy can greatly reduce the frequent C&D times of super-capacitors and lower their aging rate. Finally, this study introduces other energy storage optimization models for performance comparison, as listed in Table 2.

Table 2. Performance of energy storage optimization model in different power grids

Model	Total cost (ten thousand yuan)	Wind power RMSE (kW)	Energy utilization rate (%)	Response time (ms)	C&D loss rate (%)	Equipment lifespan improvement(%)
Emrani A [12]	350.78	14.68	88.37	95.61	5.91	19.24
Gu T [14]	370.12	10.58	92.12	88.47	5.27	23.86
Abdelghany M B [18]	400.56	12.37	89.63	92.15	5.52	21.38
This text	320.5	9.23	94.45	85.32	4.81	26.51

In Table 2, the total cost of the research model is the lowest, at 3.205 million yuan, which is an average decrease of 14.26% compared to others. This shows that the strategy of integrating EMD and fuzzy control can accurately decompose wind power fluctuations, optimize energy storage allocation, and effectively reduce IIC, OMC, and life loss costs. The wind power prediction error, response time, and charge discharge loss rate of the research model are 9.23kW, 85.32ms, and 4.81%, which are on average 26.42%, 7.34%, and 13.59% lower than other models, showing significant advantages. In addition, the proposed energy utilization rate and equipment lifespan improvement rate are 94.45% and 26.51%, which are significantly higher than other models. Overall, the energy storage optimization model based on EMD and fuzzy control has significant advantages in multi index balance optimization through multi strategy collaboration. It can greatly reduce the loss of energy storage equipment, extend its service life, further reduce long-term operating costs, and has high application value.

5. Discussion and Conclusions

The widespread application of RE poses challenges to power fluctuations and stability in the power grid. To guarantee the secure operation of the power system and improve the economy and stability of the power grid, this study constructed a hybrid energy storage optimization model that combined EMD and fuzzy control. By formulating dynamic power allocation strategies, utilizing improved EMD to decompose wind power fluctuations, and combining fuzzy control to dynamically adjust SOC, refined allocation of energy storage power has been achieved. In the experiment, compared with traditional LPF and single EMD methods, the research method reduced the RMSE of wind power to 9.23kW and increased the fluctuation smoothing rate to 72.13%. The comprehensive cost of energy storage equipment was 3.205 million yuan, which was 14.26% lower than others. The response time was 85.32ms, a decrease of 7.34%. Meanwhile, the C&D loss rate, energy utilization rate, and equipment life improvement rate of this model were 4.81%, 94.45%, and 26.51%, which were significantly better than others. The data prove that the proposed optimization model can well decompose power grid signals, improve the adaptability of power allocation, avoid equipment overcharging or over-discharging, and perform excellently in smoothing power fluctuations, extending the ESD lifespan, and reducing operating expenditures. However, there are still some shortcomings in this study, such as not considering adaptability under extreme working conditions. Future research will further integrate AI algorithms to improve the precision, adaptability, and robustness of the system, and explore collaborative optimization strategies for multi-energy complementary ESSs to provide better solutions for GESO.

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