Power fluctuation and allocation of hybrid energy storage system based on optimal exponential smoothing method and energy entropy

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Abstract
In order to solve the problems of power quality reduction and power fluctuation caused by large-scale wind power grid-connected, an advanced control strategy to smooth the power fluctuation and allocation of hybrid energy storage system is proposed. Based on theoretical researches, the mathematical model of hybrid energy storage system is adopted to well analyse the fluctuation and smoothing strategy of wind power. Compared with the traditional filtering algorithms, the study proposes a method combined optimal exponential smoothing with complete ensemble empirical mode decomposition with adaptive noise and normalized energy entropy to improve the accuracy of grid-connected output power and power allocation. Furthermore, the fuzzy control theory is used to improve the reliability of the algorithm after obtaining the smoothed power output and initial power allocation instructions. To prove the validity of the algorithm, case studies are constructed to demonstrate the performance in this paper. Experiments and example simulations show that the proposed method can effectively realize adaptive power allocation and improve the accuracy of identification. After effectively improving the efficiency and service life of the energy storage system, it provides a basis for large-scale grid operation.

1 INTRODUCTION

Wind power renewable energy has entered the stage of large-scale development. However, wind power output presents inherent properties, like randomness and uncertainty due to the factors such as climate, environment and geography. According to relative researches, wind power fluctuations will bring voltage and power fluctuations to the power system. Therefore, large-scale wind power grid will inevitably cause system power fluctuations, power quality reduction, system voltage flicker and even serious power system disorder problems [1, 2]. The randomness of wind power leads to the fluctuation of wind power, and the influence of the fluctuation of wind power limits the large-scale grid-connected. Therefore, wind power fluctuations are the most important factor affecting the power grid-connected. To prevent the influence of the fluctuation on the power grid, the energy storage system to decompose the wind power fluctuation according to the frequency should be reliable and effectively. How to use the hybrid energy storage system effectively to suppress the wind power fluctuation, and improve the stability of grid-connected operation are of strategic significance to the large-scale development of wind power system [3, 4].

With the rapid development of battery energy storage, super-capacitor energy storage and flywheel energy storage, the use of new energy storage systems to suppress wind power fluctuations has become a hot topic of theoretical research in China. At present, the main research on wind power fluctuation smoothing in China is to adopt the new energy storage system to absorb the fluctuations in different frequency bands [5]. The output of wind power can be divided into high frequency bands and low frequency bands. And energy storage elements play an important role to participate in the absorption of power fluctuations in different frequency bands [6]. Super-capacitor and superconducting magnetic energy storage are the main power-type energy storage devices, which have higher power density and...
lower energy density. On the contrary, as the main energy storage element, storage battery has higher energy density, lower power density and higher working efficiency. But it is not suitable for frequent charging and discharging [7, 8]. Therefore, the key point of energy coordination of hybrid energy storage system is to take advantage of different energy storage components, and solve the problem of single energy storage components over charge and discharge. The hybrid energy storage system composed of power and energy storage elements can give full play to their respective characteristics and achieve complementarity, which effectively absorb the power fluctuations in different frequency bands due to the randomness of wind power fluctuations [9]. And we need both of them. Currently, the main algorithms for smoothing wind power fluctuations are wavelet packet decomposition, exponential smoothing, moving-average model, and ensemble empirical mode decomposition (EEMD). The wavelet packet decomposition algorithm is well developed and is widely used to smooth power fluctuations [10]. In literature [11], the wavelet packet decomposition algorithm is used to decompose wind power signals at multiple scales. And then the hybrid energy storage system model is established to further decompose different frequency signal according to the characteristics of the energy storage element.

In order to prolong the service life of the hybrid energy storage system, it is proposed to reduce the charge and discharge times of the battery and ensure the super-capacitor to work in the present charging interval after we get the initial power allocation instructions. By introducing the concept of singular value decomposition and fuzzy control theory, wavelet decomposition can be used to smooth wind power fluctuations with high permeability [12, 13].

However, there exist a problem of poor applicability caused by artificially present charging and discharging response time cut-off point in wavelet packet decomposition algorithm, which is easy to produce a certain error [14]. Relative to the wavelet decomposition algorithm, EEMD algorithm adds white noise to the raw data uniformly and iterate over and over, which overcomes the problem that the accuracy of empirical mode decomposition (EMD) is not enough because of the mode mixing phenomenon [15, 16]. In relative researches, the EEMD algorithm is usually combined with the State of Charge (SOC) to realize the optimization of internal power flow. And the goal of maximum net benefit is achieved by setting up the optimization model of frequency modulation energy storage capacity [17, 18]. However, the decomposition and reconstruction process of EEMD algorithm adding white noise repeatedly is easy to cause certain error. Usually, EEMD is divided into different intrinsic mode functions (IMF) according to the frequency, which can adaptively distinguish the fluctuation components of high and low frequency bands. Therefore, the concept of normalized energy entropy (NEE) is introduced in this paper. The energy entropy overcomes the problem of assigning an instruction to a frequency of piecewise response based on response time [10]. NEE can adaptively search for the two IMF components which occupy the largest weight. It is regarded as the cut-off point of power allocation, which can effectively distinguish the power fluctuation in high frequency band from that in middle and high frequency band. To a certain extent, it can effectively improve the accuracy of power allocation identification. In this paper, the problem and result of dividing point distribution to different energy storage elements will be discussed further.

Although EEMD overcomes the mode mixing phenomenon in EMD, the error of the system will be increased during the process of adding white noise repeatedly. In order to overcome the reconstruction error, we introduce the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) algorithm in this study. According to the uniqueness of the margin, the accurate IMF components can be obtained, and the error can be effectively reduced to almost zero [19, 20]. Therefore, CEEMDAN algorithm combined with neural network and fuzzy control theory can greatly improve the accuracy of the results [21]. The exponential smoothing algorithm is based on the moving-average model, by calculating the exponential smoothing value and setting different weights in combination with the time series. Consequently, it can achieve a short-term prediction smoothing effect, which can continue the original trend. Based on CEEMDAN and NEE, this paper proposes an efficient algorithm for power allocation. It is combined with exponential smoothing to smooth wind power fluctuation effectively. However, there are few researches on the application of exponential smoothing algorithm to wind power fluctuation mitigation, and the related researches use exponential smoothing as the reference value of the overall power output [22], but it is isolated and used alone. At present, the research on CEEMDAN and the application of NEE to the decomposition of wind power and the allocation of power instructions is relatively insufficient in China.

In order to solve the above problems, a quadratic optimization algorithm based on optimal exponential smoothing and CEEMDAN is proposed in this paper. Combined with the NEE algorithm, the output power of the grid-connected wind power system is modified accordingly to solve the universal problem of initial power allocation. At the same time, according to the characteristics of energy-type and power-type energy storage components, the SOC fuzzy control optimization of the hybrid energy storage system are carried out, which realizes the second optimization of power allocation. Finally, the accuracy of the example results will be verified by simulations.

2 | ANALYSIS OF WIND POWER FLUCTUATION AND ENERGY STORAGE SYSTEM CHARACTERISTICS

2.1 | Analysis of wind power fluctuation characteristics

Wind power output is highly stochastic and uncertain. A case study of 49.5 MW installed capacity wind power generation in Xinjiang. Taking into account factors such as geography, climate, air pressure etc., the wind power output of the wind
turbine cluster can be expressed as follows:

\[
\begin{bmatrix}
P_{c1} \\
P_{c2} \\
\vdots \\
P_{cn}
\end{bmatrix} = \frac{1}{2\pi \rho} \begin{bmatrix}
D_1^2 & \vdots & D_n^2
\end{bmatrix} \ast \begin{bmatrix}
\alpha_{1f}^2 \\
\alpha_{2f}^2 \\
\vdots \\
\alpha_{nf}^2
\end{bmatrix} C_i \eta_i \eta_g
\]

(1)

where \(C_i\) is the coefficient of wind energy utilization, \(\eta_i\) is the mechanical efficiency of wind turbine and \(\eta_g\) is the mechanical efficiency of generator.

At this point, the attenuation coefficient is also related to the relative humidity, temperature, unit correlation and frequency of different units. If two wind turbines are independent, the correlation is zero.

Wind power fluctuation is also one of the important indexes. The fluctuation of wind power is related to the disturbance frequency. Therefore, it is considered that the power fluctuation occurs when the fluctuation exceeds a proportion range of installed capacity, and the occurrence of the fluctuation is positively correlated with the range, and the greater the probability of the range, the greater the wind power fluctuation. The coefficient of fluctuation is as follows:

\[
\tau = B_m \begin{bmatrix}
B_1 \\
B_2 \\
\vdots \\
B_m
\end{bmatrix} \begin{bmatrix}
f_1 \\
f_2 \\
\vdots \\
f_m
\end{bmatrix}
\]

(2)

where \(\tau\) is the coefficient of fluctuation, \(B_m\) is the wave probability matrix and \(f_m\) is the range matrix.

The standard of fluctuation in China is 1 min power fluctuation. According to the concepts of power fluctuation ratio range in 1 min and power range in 1 min, this paper sets the fluctuation probability and range in 60 s as follows:

\[
B_m = \sum_{r=1}^{N} r_i \begin{bmatrix}
\frac{|X_{i-k+1}-X_i|}{C_w} \\
\frac{|X_{i+1}-X_i|}{C_w}
\end{bmatrix} \leq \sigma\%, r_i = 0,
\]

\[
> \sigma\%, r_i = 1,
\]

(3)

\[
J_m = \max(X_i) - \min(X_i)\in\left[|f_{\text{min}}(X_i) - f_{\text{max}}(X_i)|\times 60\right].
\]

In the study of wind power fluctuation, the power amplitude-frequency characteristic curve is of great importance, which can directly reflect the relationship between frequency and power.

Therefore, according to the original active power data of two wind turbines, sampling period \(T = 1\) s, total data of 80,000 sample points, the corresponding amplitude-frequency curve is drawn. On the basis of Fourier algorithm, after adding noise to original data to form new signal data, the unilateral spectrum based on bilateral spectrum is calculated, and the frequency domain \(f\) Hz\(^{-1}\) is defined. Draw the frequency domain corresponding to the one-sided spectrum, as shown in Figure 1.

As shown in Figure 1, wind farm power output is concentrated below 0.05 Hz. The low frequency band is the main part of the power output. Therefore, as the main part of the power output, the low frequency band is the expected value of the power output. The amplitude of middle-high frequency band and high-frequency band is small and smoothed by hybrid energy storage system. Therefore, it further validates the idea that the smoothing output power allocation and fluctuation can be both achieved.

2.2 Hybrid energy storage system configuration

In order to better explain the effect of hybrid energy storage system in power fluctuation smoothing, we take the power-energy hybrid energy storage system model for study in this paper. Take the example of a battery-super-capacitor, as shown in Figure 2. According to the principle characteristics of different energy storage elements, we can get the attenuation of different frequency bands.

In the non-linear super-capacitor model, the three RC models have different time constants, and the three working branches are transient, delay and steady. In practice, different adjustments are made to the DC/AC inverter according to the actual power and voltage of storage battery and super-capacitor.

According to Gustav Kirchhoff’s voltage definition, the equivalent circuit model of the battery as follows:

\[
\begin{bmatrix}
\frac{dU_b}{dt} \\
\frac{dU_p}{dt}
\end{bmatrix} = \begin{bmatrix}
0 & 0 \\
0 & 0
\end{bmatrix} \begin{bmatrix}
U_b \\
U_p
\end{bmatrix} + \begin{bmatrix}
\frac{1}{C_p} & 0 \\
0 & \frac{1}{C_p}
\end{bmatrix} \begin{bmatrix}
I_b \\
I_p
\end{bmatrix}.
\]

(4)

\[
\begin{bmatrix}
U_i \\
U_i
\end{bmatrix} = \begin{bmatrix}
-1 & -1 \\
1 & 0
\end{bmatrix} \begin{bmatrix}
U_b \\
U_p
\end{bmatrix} + [-I_c] [R_0] + [U_{oc}]
\]

Therefore, the battery can bear the high amplitude power fluctuation, mainly absorbing the middle and high frequency fluctuation. For super-capacitors, when the super-capacitor operates in a steady state, the equivalent circuit model as follows:

\[
[U_d] = [R_1][I_c] + \frac{1}{C_1 + C_2} \int -I_c dt.
\]

(5)
3.1 Adaptive power smoothing method

The basic idea of exponential smoothing is to process the current time power weighted on the basis of the power data smoothed in the last time, and treat the processed data as the current time smoothing value. In this paper, we present an optimal exponential smoothing method combined with adaptive power allocation, which can adaptively solve the optimal grid-connected output power.

Let $W(t)$ be a matrix of order $n \times n$. $S(t)$ be a matrix of order $n \times n$.

$$
[S(t)]_{n \times n} = \alpha[W(t)]_{n \times n} + \beta[S(t-1)]_{n \times n},
$$

(6)

Usually $\alpha + \beta = 1$. If the original data of wind power output meets the grid-connected condition, then we skip the weighted processing of optimal exponential smoothing. However, under normal circumstances, the wind power output does not meet the grid-connected conditions, then the smooth coefficient of a regional division. According to the power requirement of wind farm in China, the fluctuation of 1 min power does not exceed 1/10 of installed capacity, and the fluctuation of 10 min power does not exceed 1/3 of installed capacity. Therefore, we propose a concept of fitting degree of active power in this paper, and we call it FIT% in this paper.

$$
\gamma_1 = \left\{ \begin{array}{ll}
\text{MAX}_{(3k+1)} \{ [W(t)]_{n \times n} \} - \text{MIN}_{(3k+1)} \{ [W(t)]_{n \times n} \} & - \frac{1}{10} P_w \\
\frac{1}{10} P_w & \end{array} \right.
$$

(7)

$$
\gamma_2 = \left\{ \begin{array}{ll}
\text{MAX}_{(3k+10)} \{ [W(t)]_{n \times n} \} - \text{MIN}_{(3k+10)} \{ [W(t)]_{n \times n} \} & - \frac{1}{3} P_w \\
\frac{1}{3} P_w & \end{array} \right.
$$

(8)

The FIT% represents the difference between the fluctuation limit at this point and the measured value. The larger the difference, the greater the deviation. In order to ensure that the output power meets the limits of power fluctuation in China, it can also have the minimum fitting degree of active power, which can reduce the impact of load on the power system. In order to compare with the installed capacity, we use the percentage standard deviation (PSD) to describe the difference between the smoothed power and sample data.

$$
\text{PSD} = \frac{\sqrt{\frac{1}{n} \sum_{t=1}^{n} [S(t) - W(t)]^2}}{P_w} \times 100\%.
$$

(9)

In theory, the smaller the smoothing coefficient is, the better the smoothing effect of the grid-connected power is. But in fact, with the improvement of power smoothing effect, the higher the requirement of system stability, and the higher the requirement of energy storage technology and wind farm configuration. Therefore, when the fitting degree approaches to zero, the value at this time is chosen as the optimal smoothing correction coefficient. After the optimal smoothing correction coefficient is obtained, the original data is decomposed according to CEEMDAN decomposition method.

CEEMDAN algorithm works by adaptively adding white noise $\mathcal{N}(0,1)$ to each signal as it decomposes. The IMF components of each order are calculated by the only residual component. After adding adaptive white noise to the first order residuals, we carry on the decomposition algorithm of EMD. By
repeating all the stages \( k \) \((k = 2, 3, \ldots, K)\) over and over again, we can solve for the \((k+1)\) IMF component until the residual can no longer be decomposed and we get the final residual:

\[
\begin{align*}
IMF_{k+1}(t) &= \frac{1}{N} \sum_{i=1}^{N} E_i[r_k(t) + \varepsilon_k E_k f^i(t)]. \\
R(t) &= \|x_n(t)\|_{\infty} - \sum_{k=1}^{K} IMF_k(t).
\end{align*}
\]

(10)

Based on adaptive power decomposition, CEEMDAN can obtain k-order IMF components and allowances. But for the smoothing of wind power fluctuation, we can choose the optimal exponential smoothing method.

### 3.2 Normalization analysis of energy entropy

The decomposed IMF component itself is of energy, so we combine the CEEMDAN and energy entropy together, and then we propose the NEE algorithm. The normalization principle is designed to filter out the larger weights, the larger the IMF energy, the larger the weighting ratio. Finally, we find the maximum difference between the adjacent IMF as the cut-off point.

\[
\begin{align*}
\mathbf{M}_k &= \sum_{i=1}^{K} \|E_i[r_k(t) + \varepsilon_k E_k f^i(t)]\|^2, \\
\mathbf{M}_t &= \sqrt{\sum_{k=1}^{K} M_k^2}.
\end{align*}
\]

(11)

Therefore, the normalized value \( p_k \) has the following expression:

\[
p_k = \frac{M_k}{M_t}.
\]

(12)

The greater the difference in the energy entropy of the adjacent IMF, the greater the energy ratio, which can be used to distinguish between high and low frequencies. The maximum IMF determines a standard order \( J \), which serves as a power allocation instruction for both high and low frequencies. The high frequency band before \( f \) comes to super-capacitor power instruction, and after \( f \) belongs to battery power instruction.

\[
\begin{align*}
P_{sc1} &= \sum_{k=1}^{J} IMF_k(t), \\
P_{bat1} &= \sum_{k=J+1}^{K} IMF_k(t) + R(t).
\end{align*}
\]

(13)

### 3.3 State of charge fuzzy control and optimization

The SOC is an important constraint condition of the energy storage system. The SOC constraint optimization of the hybrid energy storage system can improve the accuracy of power allocation [23].

\[
SOC(t) = \begin{cases} 
SOC(t - 1) + \frac{P_{sc1}\Delta t}{Q_{sc1}} P_{sc1}(t) > 0 \\
SOC(t - 1) - \frac{P_{sc1}\Delta t}{Q_{sc1}} P_{sc1}(t) < 0 .
\end{cases}
\]

(14)

The \( P_{sc}(t) \) will adjust itself when the SOC\( (t) \) turn lower or higher without considering the self-discharge rate of the energy storage element. When SOC turn lower, \( P_{sc}(t) > 0 \): Charging state, there is no action. \( P_{sc}(t) < 0 \): Discharging state, and increase \( P_{sc}(t) \). When SOC goes higher, \( P_{sc}(t) > 0 \): Charging state, and reduce \( P_{sc}(t) \). \( P_{sc}(t) < 0 \): Discharging state, there is no action.

The main input mode is the SOC\( (t) \) of the super-capacitor at the end of the \((t-1)\) time period and \( \Delta SOC(t) \) after \( t \) time period. After that, we output \( K_p \). We set fuzzy control to supply the energy entropy and continue to perform the secondary power distribution on the basis of the existing primary power distribution. According to SOC optimization, we get the secondary power allocation command:

\[
\begin{align*}
P_{sc2} &= K_p P_{sc1}, \\
P_{bat2} &= P_{bat1} + (1 - K_p) P_{sc1}.
\end{align*}
\]

(15)

The purpose of SOC optimization is to make the super-capacitor work in a reasonable SOC range, and to allocate some power to the battery when the set SOC range is exceeded, thus maintaining the stability of the system. So we can obtain the SOC curves, which also indicate the fluctuation of the power. In the example simulation analysis, we will consider the contrast of 1min Max SOC fluctuations before and after the adjustments for different algorithms.

After introducing in detail the principle of normalization of energy entropy followed by SOC module and optimization, the implementation flow of the algorithm in this chapter is shown in Figure 3.

The second improvement strategy proposed in this paper gets the optimized SOC curve, and the evaluation index is defined as follows:

\[
\begin{align*}
\delta &= \frac{1}{M} \sum_{i=1}^{M} \left| SOC_i(t) - SOC_{i-1}(t) \right|, \\
\delta_{max} &= \left| SOC_{max}(t) - SOC_{min}(t) \right|.
\end{align*}
\]

(16)

The SOC deviation and the maximum SOC deviation can be used as the comparison group between the secondary improvement strategy and the traditional method. It can be regarded as an important reference for the power allocation method proposed in this paper.

After we get the SOC curves before and after adjustments, how to relate the power fluctuation rate with the SOC of the storage systems means a lot. So we propose the 1min Max SOC fluctuation \( \delta_{1\text{minSOC}} \), and the evaluation index is defined as
\[ \delta_{\text{min, SOC}} = \max \{\text{SOC}(t)\} - \min \{\text{SOC}(t)\}. \]  

Different from FIT%, the \( \delta_{\text{min, SOC}} \) shows the relation between SOC and power fluctuation. According to the \( \delta_{\text{min, SOC}} \), we can evaluate the effectiveness of different algorithms in this paper.

### 4 Simulation and Experimental Analysis

#### 4.1 Simulation analysis

We construct two 40 MW random windfarm data with large fluctuation. We make sample period as 1 s and the total time as 60 min. In total, we have 3600 sample points. As is shown in Figure 4.

The constructed fluctuation data has certain randomness and satisfies the inherent attribute of wind power. In order to simulate the power fluctuation under different smoothing correction coefficients, we choose the correction coefficients \( \alpha \) as 0.1, 0.3 and 0.5, respectively. Figure 5 shows the power curves of two groups of wind farm data with different correction coefficients.

![Figure 4](image1.png) 

**Figure 3** The control flow of the proposed algorithm

As we can see from Figure 5, with the decrease of the smoothing coefficient, the grid-connected output power tends to be smooth. In the process of continuous smoothing, the optimal exponential smoothing method proposed in this paper is of good use to calculate the optimal smoothing coefficient, and finally we get the most appropriate grid-connected output power. As can be seen from the Figure 5, the optimal smoothing coefficient is constantly changing according to the data of different wind farms. According to the method of combining the optimal exponential smoothing and CEEMDAN decomposition presented in this paper, the optimal coefficient can be adaptively solved, and get the most suitable grid-connected power.
Table 1 shows the power fluctuation data of two groups of wind farm data with different correction coefficients. According to the wind farm data with installed capacity of 40 MW, the corresponding 1 and 10 min national active power limit values are 4 and 13.333 MW. For different stochastic volatility series, there are different optimal exponential smoothing values. In different wave sequences and smoothing coefficients, we get different fluctuations. In this paper, we only consider the smoothed fluctuation corresponding to one single exponential smoothing algorithm.

Figure 6 shows that the CEEMDAN decomposition method is used to obtain the IMF₁ and IMF₇ components in the case of 0.1, 0.3 and 0.5, respectively. The IMF components and allowances are different for different correction coefficients. The fluctuation of IMF₁ and IMF₇ components decreases with the increase of the correction coefficient.

In the process of simulation, because of the particularity of the wind farm data. So we use the original data of Xinjiang windfarm data. According to the NEE and the secondary power allocation command, we carry it out in the experiment.

### 4.2 Case analysis of Xinjiang electric field

According to the measured data of 49.5 MW wind farm in Xinjiang, the 1 and 10 min active power limits are 4.95 and 16.5 MW, respectively [10]. According to the different values of smoothing correction coefficient at different times, we can

| Smoothing correction | 1 min power fluctuation/MW | 10 min power fluctuation/MW |
|----------------------|----------------------------|------------------------------|
| Factor α             | Data 1 value | Data 2 value | Data 1 value | Data 2 value |
| 0.1                  | 3.273       | 2.750         | 4.355       | 6.924         |
| 0.3                  | 4.031       | 3.662         | 5.064       | 7.563         |
| 0.5                  | 4.170       | 3.824         | 5.255       | 7.675         |
obtain different power conditions. Then, we construct the power curves corresponding to different correction coefficients, as shown in Figure 7.

As can be seen from Figure 7, the greater the correction coefficient is, the less smooth the power is. Assuming that below the active power limit is negative, above the active power limit is positive. According to the fitting accuracy of the different modified smoothing coefficients, we get the Table 2.

\[ \alpha = 0.13 \] meets the requirements of China’s grid-connection standards for wind farms. The fitting degree of 1 min power fluctuation is close to zero, and the corresponding 10 min active power fluctuation is within the limit of 16.5 MW, which all meet the grid-connected standard. PSD% shows the difference between the smoothed power and the sample data, and it is below 1%, which means it will not overly smooth. Therefore, the value of \( \alpha \) at this time is selected as the optimal smoothing correction coefficient to output the smoothing correction power and the original wind power output, as shown in Figure 8.

In this paper, we use the CEEMDAN method to decompose the 12-order IMF components and allowances. According to the NEE algorithm proposed in this paper, Figure 9 shows the difference of IMF energy entropy and energy entropy in different smooth coefficient scales. As the IMF increases, the overall energy entropy decreases and the maximum increases.

As you can see in Figure 9, there is a fairly significant peak at IMF5. With the increase of smoothing correction coefficient, the difference decreases. Usually, the difference will appear the highest value at the initial point, but choosing this point as the cut-off point is easy to produce the algorithm error. According to the principle of the algorithm proposed in this paper, we take \( J = 5 \) as the cut-off point of the power instruction between the super-capacitor and the battery. Then, we obtain the initial power instruction.

Figure 10 shows the power distribution of \( J = 5 \) IMF5 as storage battery and super-capacitor, respectively. It can be seen that there is a significant difference in power distribution of the battery, reflected in the charge and discharge times have increased significantly.

Table 3 compares the distribution of the boundary point \( J = 5 \) to the super-capacitor and to the battery, respectively. When IMF5 is distributed to super-capacitor, the charge–discharge times of the battery and fluctuation ranges are greatly reduced, which can effectively improve the service life of the battery. In addition, it can bring a certain working threshold for super-capacitor, and make super-capacitor work SOC have a buffer range. What is more, the charge and discharge times both reduce when IMF5 to super-capacitor. Therefore, the IMF5 was chosen to be assigned to the super-capacitor. Now we have already considered the service life of the battery. At the meantime, the service life of the super-capacitor is also important. So we can improve the using life by keeping the SOC of super-capacitor in the reasonable working interval.

### Table 2

| Smoothing Correction Factor \( \alpha \) | 0.1 | 0.13 | 0.14 | 0.3 | 0.5 |
|----------------------------------------|-----|------|------|-----|-----|
| 1 min power fluctuation/MW             | Measured value | 4.153 | 4.826 | 4.957 | 6.251 | 7.232 |
| Limit difference                       | −0.797 | −0.124 | 0.007 | 1.301 | 2.282 |
| FIT%                                   | 16.10% | 2.51% | 0.14% | 26.28% | 46.10% |
| 10 min power fluctuation/MW            | Measured value | 10.394 | 10.762 | 10.866 | 11.890 | 12.405 |
| Limit difference                       | −6.106 | −5.738 | −5.634 | −4.61 | −4.095 |
| FIT%                                   | 37.01% | 34.78% | 34.15% | 27.94% | 24.82% |
| PSD%                                   | 1.086% | 0.919% | 0.873% | 0.446% | 0.221% |
FIGURE 9 The normalized energy entropy of intrinsic mode functions with different smoothing coefficients

According to the determined initial power allocation instruction, now we carry out the fuzzy control and SOC optimization method proposed in this paper. But first of all, we need to set the initial energy storage system parameters. In this paper, according to the 49.5 MW wind farm data and relative literature in China. We choose the initial parameters, as is shown in Table 4.

In order to avoid the over-high and over-low state of SOC, we set the initial state of SOC value to 0.5 in this paper. Therefore, it is possible to visualize the up-down variation of the charged state away from the centre. Under the initial parameter configuration, we obtain the SOC operating range of the battery and the super-capacitor before and after the second optimization from Figure 11.

As can be seen from Figure 11, the SOC curve of storage battery basically keeps floating up and down at 0.5, and there is no obvious change before and after adjustment. But the SOC curve of super-capacitor has a relatively obvious shift toward the centre of the SOC setting value. Because of the large sampling point, it is not easy to see the changes before and after the adjustment, so we use quantitative data to analyse and compare. Table 5 shows the comparative data of SOC analysis before and after optimization. As can be seen from Table 5, the adjusted SOC operating range is smaller than the pre-adjusted SOC operating range. However, the adjusted $\delta$ and $\delta_{\text{max}}$ of super-capacitor are smaller than the pre-adjusted SOC operating range, while the battery has no change.

It can be concluded that the proposed algorithm has some improvement on the fluctuation curve, and the shift of the super-capacitor SOC curve to the set value of 0.5 centre can reduce the fluctuation of SOC to a certain extent. However, there is no obvious change in the working process of the battery, and it works in a relatively stable range. The large sampling points in this paper can reflect the effect of SOC correction and the reliability of power fluctuation smoothing for hybrid energy storage system.

TABLE 3 Comparison of power allocation between two kinds of cut-off points

| Cut-off power allocation | Fluctuation range of storage battery | Battery charge and discharge times | Super-capacitor charge and discharge times |
|--------------------------|-------------------------------------|-----------------------------------|-------------------------------------------|
| IMF$_2$ to battery       | $[-3.547,3.426]$                   | 126                               | 1056                                      |
| IMF$_3$ to super-capacitor| $[-2.850,1.946]$                   | 69                                | 881                                       |
TABLE 4  Initial parameter configuration of energy storage system

| Parameter type       | Battery | Super-capacitor |
|----------------------|---------|-----------------|
| Rated capacity /MWh  | 2.984   | 0.871           |
| Initial capacity /MWh| 1.492   | 0.436           |
| Initial SOC          | 0.500   | 0.500           |
| SOC ranges           | [0.200,0.800] | [0.250,0.950] |
| Rated power /MW      | 3.565   | 6.278           |
| Rated discharge      | 3.324   | 4.763           |
| Power/MW             |         |                 |
| Charging and discharging efficiency/% | 100     | 100             |

FIGURE 11  The second power adjustment of super-capacitor and the state of charge of storage battery

TABLE 5  SOC analysis index before and after adjustment

| Analytic Index                                      | Battery | Super-capacitor |
|-----------------------------------------------------|---------|-----------------|
| SOC operating range before secondary adjustment     | [0.426,0.526] | [0.413,0.530] |
| SOC operating range after secondary adjustment      | [0.425,0.526] | [0.420,0.528] |
| Pre-adjustment SOC bias $\delta$                    | 0.031   | 0.037           |
| Adjusted SOC bias $\delta$                         | 0.031   | 0.035           |
| Pre-adjustment max $\delta_{max}$                  | 0.100   | 0.117           |
| SOC bias $\delta_{max}$                             |         |                 |
| Adjusted max SOC bias $\delta_{max}$               | 0.100   | 0.108           |

FIGURE 12  The comparison between the algorithm in this paper and complete ensemble empirical mode decomposition with adaptive noise algorithm state of charge output

After analysing the quantitative index of the proposed algorithm, the CEEMDAN with optimal exponential smoothing algorithm is compared with single CEEMDAN algorithm and EEMD algorithm to verify the superiority and reliability of the proposed algorithm compared with the traditional algorithm. Figure 12 shows the comparison between CEEMDAN with optimal exponential smoothing method and single CEEMDAN algorithm for super-capacitor and battery charge states.

After comparing the presented algorithm with CEEMDAN algorithm, we continue to compare the single CEEMDAN algorithm with EEMD algorithm for super-capacitor and battery charge state, as shown in Figure 13.

It is obvious from Figures 12 and 13 that the curves move up and down as a whole, but there cannot be a quantitative analysis from the figures alone. Therefore, the three algorithms are
As can be seen from Table 6, there is no obvious difference between the SOC work interval and $\delta_{\text{max}}$ of the proposed algorithm and CEEMDAN algorithm. However, the super-capacitor SOC bias of the proposed algorithm is smaller than that of CEEMDAN algorithm. The SOC bias of the proposed algorithm is smaller than that of CEEMDAN algorithm, although it does not change before and after battery adjustment. CEEMDAN algorithm SOC bias is obviously reduced compared with EEMD algorithm, and CEEMDAN algorithm SOC working range is also smaller than EEMD algorithm. SOC control pay more attention to the super-capacitor and reduce the operating range. It changes few the index after adjustments. According to Table 6, SOC control will not affect the battery's lifespan. Besides, the proposed algorithm has the smallest 1 min max SOC fluctuation before and after adjustments, which indicates that the proposed algorithm has the best performance. Therefore, compared with CEEMDAN algorithm and EEMD algorithm, the presented algorithm in this paper has a higher recognition and accuracy, and it is more reliable. Also, the SOC working interval of super-capacitor reduce, which in a way improve the service life of the super-capacitor. In short, the proposed algorithm can effectively improve the service life of the hybrid energy storage system.

5 | CONCLUSION

In this paper, an optimal exponential smoothing algorithm combined with CEEMDAN decomposition algorithm is proposed to solve the problem of large-scale grid-connected wind power generation, which can accurately smooth the wind power output power and improve the power quality. So, the conclusion to be drawn is as follows:

1. The optimal exponential smoothing with CEEMDAN decomposition algorithm proposed in this paper overcomes the problem of low precision caused by the aliasing of the traditional EEMD algorithm. Not only it is more accurate than CEEMDAN algorithm, but also has certain reference value in power fluctuation smoothing. According to the analysis of the indexes presented in this paper, the state of charge deviation can reflect the degree of deviation from the original SOC. Through the maximum state of charge deviation, we can well evaluate the change of SOC curve and reflect the effect of wave smoothing. And it also improve the service life of the hybrid energy storage system.

2. The traditional wavelet decomposition algorithm has the problems of time and frequency by artificial presupposition, which makes it easy to cause large error. In this paper, the CEEMDAN decomposition method is used to get the cut-off point through the normalization of the energy entropy, which can get more accurate power allocation instructions. By fully regulating the coordination between super-capacitor and battery, the effect of wave smoothing can be improved. Therefore, the NEE is reliable in solving the problem of power partition.

The algorithm proposed in this paper has the characteristics of anti-noise, stable operation and universal applicability. So it is an effective method in the power smoothing and active power distribution of wind power grid-connected. In further research, the concept of "standby system" will be introduced to build a hybrid energy storage system model of super-capacitor-battery-standby system, and "N + 1" (N hybrid energy storage system and one standby system) hybrid energy storage system will be
### Table 6  Comparison between the algorithms in this paper and CEEMDAN algorithm index

| Comparative analysis table | EEMD algorithm | CEEMDAN algorithm | The presented algorithm |
|----------------------------|----------------|-------------------|-------------------------|
|                            | Battery        | Super-capacitor   | Battery                 | Super-capacitor         | Battery | Super-capacitor | Battery | Super-capacitor |
| SOC operating range before |               |                   |                         |                         |         |                 |         |                 |
| secondary adjustment       | [0.437,0.537]  | [0.424,0.540]     | [0.430,0.530]           | [0.417,0.534]           | [0.426,0.526] | [0.413,0.530] |
| SOC operating range after  |               |                   |                         |                         |         |                 |         |                 |
| secondary adjustment       | [0.436,0.536]  | [0.430,0.538]     | [0.429,0.530]           | [0.420,0.532]           | [0.425,0.526] | [0.420,0.528] |
| Pre-adjustment SOC bias $\delta$ | 0.036         | 0.053             | 0.034                   | 0.039                   | 0.031   | 0.037           |
| Adjusted SOC bias $\delta$ | 0.036         | 0.049             | 0.0340                  | 0.036                   | 0.031   | 0.035           |
| Pre-adjustment max         | 0.100         | 0.117             | 0.100                   | 0.117                   | 0.100   | 0.117           |
| SOC bias $\delta_{\text{max}}$ |         |                   |                         |                         |         |                 |         |                 |
| Adjusted max SOC           | 0.100         | 0.108             | 0.100                   | 0.108                   | 0.100   | 0.108           |
| Bias $\delta_{\text{max}}$ |         |                   |                         |                         |         |                 |         |                 |
| 1 min MAX SOC fluctuation  | 0.0016        | 0.0121            | 0.0017                  | 0.0010                  | 0.0013  | 0.0093          |
| before adjustments         |               |                   |                         |                         |         |                 |         |                 |
| 1 min MAX SOC fluctuation  | 0.0015        | 0.0112            | 0.0017                  | 0.0092                  | 0.0013  | 0.0086          |
| after adjustments          |               |                   |                         |                         |         |                 |         |                 |

Introduced to achieve the internal optimization of the hybrid energy storage system.

### NOMENCLATURE

#### VARIABLES

- $P_{\text{w}_i} (i = 1, 2, \ldots, n)$: the corresponding active power of different units in a wind turbine group
- $D_i (i = 1, 2, \ldots, n)$: the impeller diameter of the Wind Turbine Group at this time
- $[B_m]$: wave probability matrix
- $[J_m]$: range matrix
- $X_i = \{x_i, x_i+1, \ldots, x_i+60\}$: wind power data within 1 min from time $i$
- $L_{\text{max}}(X_i) - L_{\text{min}}(X_i)$: the position of two points on the first range
- $L_{\text{max}}(X_i) - L_{\text{min}}(X_i)$: the distance between two points at which a range occurs
- $S(t)$: smoothed power
- $L(t)$: actual wind power data
- $P_w$: installed capacity
- $f^i(t), i = 1, 2, \ldots, n$: white noise
- $x_0(t)$: initial signal
- $E_k$: the $k$ order IMF component obtained by EMD decomposition
- $r_k(t)$: CEEMDAN’s $k$ order residuals
- $\text{IMF}_k(t)$: the $k$ order of IMF component
- $M_k$: each order of IMF energy entropy
- $M_t$: total energy
- $P_{\text{sc}1}$: super-capacitor initial power
- $P_{\text{bat}1}$: battery initial power instruction
- $P_{\text{sc}1}$: super-capacitor power value at $t$ time
- $P_{\text{bat}1}$: battery initial power instruction
- $SOC(t)$: SOC value at $t$ time
- $SOC_{\text{max}}(t)$: maximum SOC value at $t$ time
- $SOC_{\text{min}}(t)$: minimum SOC value at $t$ time
- $\rho$: the density of the air here and now
- $\nu$: the wind speed at this time
- $\alpha_i$: wind speed attenuation coefficient for different units
- $C_t$: coefficient of wind energy utilization
- $\eta_t$: mechanical efficiency of Wind Turbine
- $\eta_g$: mechanical efficiency of generator
- $T$: coefficient of fluctuation
- $C_w$: rated capacity of wind turbine
- $i$: time
- $\sigma$: power ratio threshold
- $M$: sampling points
- $U_{\text{oc}}$: open circuit voltage source
- $C_b$: open-circuit voltage source capacitance
- $U_b$: open-circuit capacitance voltage
- $R_0$: polarization resistance
- $C_p$: polarization capacitance
- $U_p$: polarization voltage
- $R_p$: polarization resistance
- $I_{t}$: discharge current from battery
- $U_L$: battery output voltage
- $\omega$: angular frequency of the output voltage
- $f$: frequency of output voltage
- $I_{\text{C}}$: discharge current from super-capacitor
- $\alpha$: correction factor
- $\beta$: weighted correction factor
- $\gamma_1$: 1 min fitting degree of active power
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How to cite this article: Xidong Z, Xiubo J. Power fluctuation and allocation of hybrid energy storage system based on optimal exponential smoothing method and energy entropy. IET Gener Transm Distrib. 2021;15:533–545. https://doi.org/10.1049/gtd2.12041