Received September 18, 2019, accepted October 6, 2019, date of publication October 10, 2019, date of current version October 22, 2019.
Digital Object Identifier 10.1109/ACCESS.2019.2946453

Direct Control Strategy of Real-Time Tracking Power Generation Plan for Wind Power and Battery Energy Storage Combined System

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This research was funded by the National Natural Science Foundation of China (51767004), the Guangxi Scientific Research and Technology Development Project (1599005-2-14), and the Natural Science Foundation of Guangxi (2018JJB160056; 2018JJB160064; 2018JJA160176).

ABSTRACT To improve the overall economy of the wind-energy storage power station, a direct control strategy is proposed to track the deviation of the wind power plan. Compared with the traditional strategy of wind power fluctuation mitigation, the control strategy in this paper can change the charge and discharge power of energy storage in real-time according to the deviation of wind power and the state of charge (SOC). When the power of wind power changes suddenly, the strategy can make the valid judgment and prevent control failure, so that Grid-connected power of wind farm in extreme cases can also meet the requirements of the safe and stable operation of the power system. The strategy uses the discrete Fourier transform (DFT) to analyze the power deviation of the wind farm in the frequency domain and obtains power compensation requirements for different time scales. Energy storage equipment with corresponding characteristics is used to classify control of deviation of wind power. The compensated power deviation can meet the requirements in market competition. At the same time, the power exchange between storage systems is carried out to optimize the state of charge in real-time and make the energy-type energy storage in shallow charge/discharge state, which effectively reduces the repeated regulation of energy storage systems. Finally, this paper establishes a comprehensive economic benefit model of the energy storage system. Combining the Markov Chain Monte Carlo method (MCMC) and backward scenario reduction technology generate multiple scenarios. The calculation results show that the proposed strategy can effectively track the deviation of the wind power plan. Furthermore, prolong the service life of the energy storage system and improve the market competitiveness of wind power.

INDEX TERMS Hybrid wind-energy storage (wind-ES) system, tracking wind power schedule output, discrete Fourier transform (DFT), electricity market.

I. INTRODUCTION

A. MOTIVATION

The global energy system is transitioning to renewable energy, and wind energy, as one of the most potential renewable energy sources, has been used on a large scale. In 2018, the cumulative installed capacity of wind power in the world exceeded 600GW for the first time, and China accounted for 36.8% [1]. When participating in power market competition, the randomness and intermittence of wind power make it unable to work strictly according to the plan curve issued by dispatch. So then, they are thus facing the penalty of deviation. With the increasing penetration of wind power, this problem becomes more prominent. To achieve stable and substantial benefits, wind power enterprises must reduce the cost of power generation, promote technological progress, and improve the reliability of power supply. The energy storage system has the characteristics of bidirectional charge and discharge, which can provide fast response-ability for the power system. Moreover, being crucial technical support means for wind power to participate in market competition, which can adequately compensate for the shortcomings of wind power output and improve the controllability. Using energy storage equipment for charging and discharging is one of the effective meth-

The associate editor coordinating the review of this manuscript and approving it for publication was Eklas Hossain.

ods to realize planned power generation, studied by many scholars.

B. LITERATURE REVIEW

According to the timeliness of control, the control strategies can divide into modeling control strategy and direct control strategy. In the aspect of the direct control strategy, reference [2] analyzes the energy storage scale needed to minimize hourly wind forecast error in the case of pre and post-compensation. Considering the SOC of energy storage, [3] establish fuzzy control rules to allocate the charging and discharging power of energy storage, and mitigate the fluctuation of wind power. The control performance standard for large scale wind farms is proposed in [4]. Based on this, the regulated power of the energy storage system is obtained by PI control, and control the power deviation of most sampling points within. Also, compensation of wind power deviation by frequency domain analysis method is developed in [5]–[7], including discrete wavelet transform, DFT et al. The direct control method has the advantages of fast response speed, no convergence problem, practical and straightforward. Correspondingly, when taken into account multiple factors at the same time, the formulation requirements of the strategy will be higher.

In the aspect of the modeling control strategy, the planning model based on the minimum deviation value of wind power output is studied in [8], which considers the lifetime of the battery energy storage system (BESS) and prediction errors. Reference [9], [10] update time constants by a particle swarm optimization method and propose a power-tracking method with a flexible learning rate. Analyzing the prediction error, reference [11] introduces the single objective optimization that is to minimize the SOC at the adjacent time and the power deviation between actual and planned values. Besides, a multi-objective optimization model for wind smoothing is presented in [12], including both the minimum of power variation between adjacent charging/discharging intervals and the maximum of the time duration of each cycle control period. The method of optimal modeling control can set optimization objectives flexibly and has good universality. However, when solving objectives is too many or too complicated, it may cause response delay and control deviation.

C. LIMITATIONS AND CONTRIBUTIONS

The above control strategies provide abundant theoretical support for reducing the deviation of the wind power plan, but there are still several problems to be improved. First, according to different time scale response characteristics of wind power deviation, corresponding energy storage equipment should be selected to realize accurate compensation of deviation. Second, while ensuring the accuracy of control, the number of charging/discharging times of energy storage equipment should be reduced, and avoid deep charging and discharging. Third, in order to guide investors in decision-making, quantitative analysis of the return on the investment economy of energy storage systems throughout the life cycle should be carried out.

A direct control strategy is proposed in this paper to solve the problems above. The contributions of this paper are summarized as follows.

1) DFT is used to divide the wind power deviation into three categories: high frequency, medium frequency, and low frequency. Which gives full play to the characteristics of energy storage equipment with different time scales.
2) According to the varied demands of wind power, using different energy storage equipment compensate in different layers. Meanwhile, the strategy divides control zones and formulates corresponding control methods for different wind power deviations to improve control accuracy, ultimately reduce the power deviation of wind power and the repeated regulation between energy storage.
3) The Markov Chain Monte Carlo method, combined with backward scene reduction technology, is used to generate wind power data of multiple scenarios. Based on this, the investment return of the hybrid energy storage system (HESS) in the whole life cycle is analyzed to verify its economy.

D. PAPER ORGANIZATION

This paper organized as follows. Section II and Section III introduce assessment requirements for wind power forecasting and characteristics of energy storage, respectively. The Markov Chain Monte Carlo method presented in Section IV. Section V proposes the control method. The case study and discussion are conducted in Section VI, and Section VII concludes this paper.

II. WINDPOWER FORECASTING AND ASSESSMENT REQUIREMENTS

The root-mean-square error (RMSE) used to define the accuracy of the wind power forecast, can better judge the deviation degree of wind power prediction results and inspect the accuracy of all-day prediction results.

$$R_{\text{MSE-day}} = \frac{\sqrt{\sum_{i=1}^{n} (P_{\mathrm{A}i} - P_{Pi})^2}}{C_{ap}\sqrt{n}} \leq \varepsilon \tag{1}$$

In (1), $P_{\mathrm{A}i}$ and P_{Pi} are the actual power and plan values at time i, respectively; n is the number of sampling points within the sampling interval; C_{ap} is the unit-operating capacity of the wind farm; ε is the control target.

According to [13], the deviation between the actual power output of thermal power units and the day-ahead scheduling curve should be within the 2.5% of planned power. The excess part is the assessment of electrical energy, which will be punished. Under the background of the continuous development of the power system, wind power will inevitably compete with traditional energy. Hence, this paper also calculates the deviation of wind power according to the assessment requirements of thermal power units.

The output electricity of a 100MW wind farm on a typical day is 1125.361 $MW \cdot h$. The deviation curve between the actual power and the planned power is shown in Fig. 1 (a) (sampling interval is 1s), and the corresponding assessment power is shown in Fig. 1 (b).

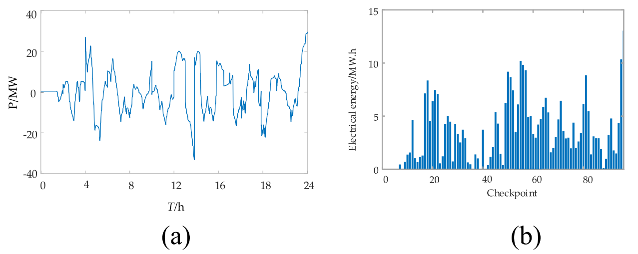

FIGURE 1. Wind power deviation curve and the assessment of electrical energy. (a) The deviation curve between the actual value and the planned value of wind power. (b) The assessment electrical energy of wind farm before energy storage compensation.

The RMSE in a day is 10.44%, which meet the assessment requirement that the RMSE of all-day forecast results is no more than 20%[14]. We take the third resource area as an example. When the wind farm transits from the current benchmark feed-in tariff to the guidance price in 2020, its daily electricity revenue will be reduced from US \$78313.2376 to US \$60732.6772. Furthermore, its assessment electrical energy accounts for 31% of the total electricity generation, and the wind farm will also bear high penalties.

In summary, to reduce economic losses and increase the competitiveness of wind power, wind farms must improve tracking capability that actual power coincides with planned power. For this reason, this paper proposes the control strategy of the hybrid wind-ES power system, and the whole system working diagram is below.

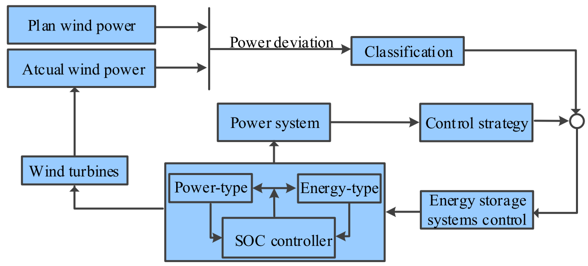

FIGURE 2. Power control process diagram of the wind storage system.

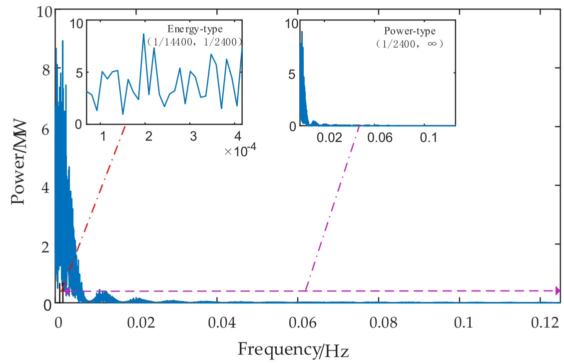

FIGURE 3. The frequency-domain analysis of the load fluctuation curve.

III. RESPONSE CHARACTERISTICS AND ECONOMIC EVALUATION METHOD OF ENERGY STORAGE EQUIPMENT

A. ANALYSIS OF ENERGY STORAGE RESPONSE CHARACTERISTICS

To analyze the response characteristics of energy storage equipment, we take the load fluctuation of a certain area on a certain day as an example. Which converts power deviation in the time domain to the frequency domain, the amplitude-frequency characteristic curve is in Fig. 3. As can be seen from the figure, the amplitude of the high-frequency part is generally small and changes rapidly, which requires the energy storage to charging and discharging quickly. While the fluctuation of the low-frequency part is massive, and requires a long-time charging and discharging of the energy storage equipment. Thus, faced with the different response characteristics in the frequency domain, single energy storage is difficult to meet the multi-time scale compensation demand. Energy storage devices can divide into power-type and energy-type depending on the different response characteristics. The former has high power density and long cycle life, but low energy density. Which is suitable for compensating power deviation at seconds and minute levels, while the latter is just the opposite. In this paper, HESS composed of supercapacitors and lithium-ion batteries is used to complement each other.

B. SOC

SOC refers to the percentage of the remaining electricity of the energy storage system to its nominal capacity (with a value of 0 to 1). The following formula calculates the residual capacity of the energy storage equipment at time i:
Charging:

$$E_{ESS}(t_i) = E_{ESS}(t_{i-1}) - \frac{P_S(t_i)\Delta t \eta_c}{3600} \tag{2}$$

Discharging:

$$E_{ESS}(t_i) = E_{ESS}(t_{i-1}) - \frac{P_S(t_i)\Delta t}{3600\eta_d} \tag{3}$$

The state of the energy storage systems can express as:

$$SOC(t_i) = \frac{E_{ESS}(t_i)}{E_{cap}} \tag{4}$$

where $E_{ESS}(t_i)$ is the remaining capacity of the energy storage system at time i, $P_S(t_i)$ is the setting power of the energy storage system at time i, charging is negative, and discharging is positive. η_c and η_d are charging and discharge efficiency of the entire energy storage system, respectively. E_{cap} is the total capacity of energy storage systems.

The life of the energy storage system is related to many factors. The depth of discharge (DOD) indicates the percentage

TABLE 1. The statistics of the average identification time of our mechanism.

DOD/%	Cycle times
10	6064
20	5000
30	4307
40	3941
50	3685
60	3428
70	3282
80	3136
90	2989
100	2916

TABLE 2. The division of three kinds of fluctuations.

The kinds of fluctuations	Response time	Frequency interval
The first	(0, 30s)	(1/120, ∞)
The second	(30s, 10min)	[1/12400, 1/120]
The third	(10min, 60min)	(0, 1/2400)

of battery discharge to battery rated capacity, and its unit is the percentage. This paper considers that energy-type storage is greatly affected by DOD. The smaller the depth of discharge is, the greater the number of cycles the energy storage system is, as shown in Table 1 [15]. The cycle life of power-type storage is relatively long, and the main influencing factor is the number of charge-discharge conversions.

C. ECONOMIC EVALUATION METHOD OF ENERGY STORAGE SYSTEM

The cost of energy storage is still high, so it is necessary to evaluate the income level of the energy storage project.

1) MATHEMATICAL MODEL OF COST

The cost part of the energy storage power station the infrastructure mainly includes the one-time investment construction cost, operation maintenance, and replacement cost. The total lifetime cost for the energy storage system is:

$$\begin{aligned} C_{LCC} &= (C_{inv} + C_{renew}) + C_{O\&M}\frac{(1+r)^T-1}{(1+r)^T r} \\ &= (\mathrm{P}_{ess}C_P + E_{cap}(C_{bop} + C_{cap}) \\ &\quad + n(P_{ess}C_p + E_{cap}C_{cap}) \\ &\quad + \mathrm{P}_{ess}C_{yw}\frac{(1+r)^T-1}{(1+r)^T r}) \end{aligned} \tag{5}$$

In the formula, P_{ess} is the rated power of energy storage. E_{cap} is the rated capacity of energy storage. C_p is the cost of unit power. C_{cap} is the unit capacity cost of energy storage equipment. C_{bop} is the unit capacity cost of auxiliary equipment. C_{yw} is the average annual operating cost per unit of power of energy storage equipment. T is the operating cycle of the energy storage power station. r is the discount rate. n is the number of replacements within the cycle life, which needs to be determined by the life estimation of energy storage equipment.

According to Section III, the key factors affecting energy type and power-type energy storage life are not the same. Therefore, this paper uses the ''rain-flow'' cycle counting algorithm and the equivalent cycle life method to calculate the battery life [16]. The life of supercapacitor is the ratio of the maximum number of charging /discharging to the number of actual charging/discharges per day.

2) MATHEMATICAL MODEL OF INCOME

Energy storage revenue takes into account the direct or indirect benefits of configuring energy storage systems, including daily electricity revenue, capacity income, penalty-free amount, environmental benefits, and battery recovery benefits. Daily income can express as:

$$\begin{aligned} S_{day} &= S_{ele,d} + S_{cap,d} + S_{punish,d} + \mathrm{S}_{eb,d} + \mathrm{S}_{rec,d} \\ &= m_d E_{S,out} + \frac{1}{365}m_{cap}P_{ess} + S_{punish,d} \\ &\quad + E_{ess,out}\sum_{i=1}^{n} Q_i B_i + \frac{\lambda}{365} \times \frac{r(1+r)^T}{(1+r)^T-1} \\ &\quad \times \sum_{i=1}^{n}(E_e m_{mental,i}\rho_i/\sigma) \end{aligned} \tag{6}$$

where, m_d and $E_{S,out}$ is the discharging price, discharging electric quantity of energy system. m_{cap} is the annual capacity electrovalence. $E_{es,out}$ is the daily discharging volume for the energy storage system . Q_i is the emission of pollutant i from conventional coal-fired power generation. B_i is the unit cost of the environmental load of the pollutant i. n is the total emissions of pollutants. λ is the number of recoveries in the life cycle .E_e is the capacity of the battery. $m_{mental,i}$ is the price for mental i. ρ is the content of metal i in battery per unit weight . σ is the specific energy of the battery.

3) COMPREHENSIVE ECONOMIC BENEFIT

During the entire life cycle, the difference between the total revenue and the total investment cost of HESS is the net profit of the whole life cycle, as follows:

$$S_T = \sum_{i=1}^{t} S_{day,i}\frac{(1+r)^T-1}{(1+r)^T r} - C_{LCC} \tag{7}$$

In (7), t is the number of days that wind farms generate electricity in a year.

IV. MCMC

Calculating the comprehensive economic benefits of the whole life cycle requires multiple simulation scenarios. In order to approach the actual value, this paper uses the MCMC method and backward scene reduction technology

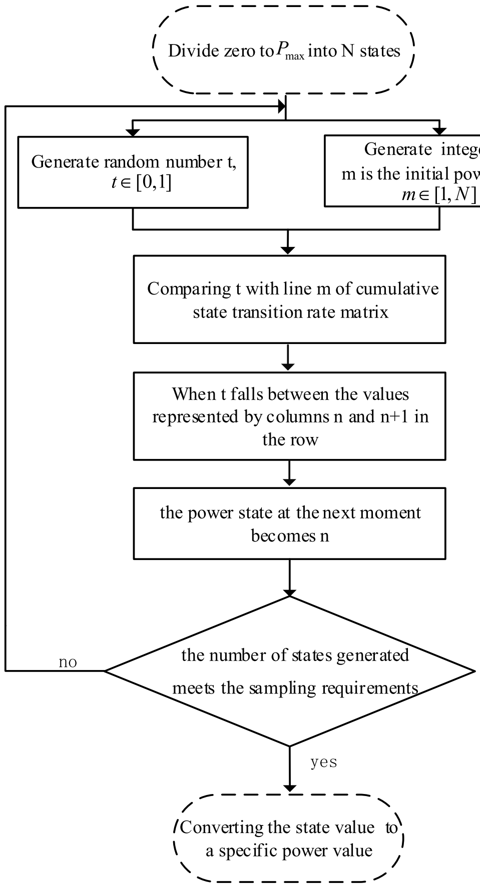

FIGURE 4. The flow chart of the MCMC method.

to generate multiple scenes [17], [18]. Define the maximum output value of the wind farm to be $P_{\max}$ and the minimum to be zero. State i indicates that the power falls in $(P_{\max} \cdot (i-1)/N, P_{\max} \cdot i/N]$. The steps are as follows:

The MCMC method has generated N scenarios. Firstly, we calculate the Kantorovich Distance (KD) between each scene and the remaining scene and multiply the minimum KD for each stage by the probability of the scene. Next, we need to seek scene$i$ and scene k, which correspond to the minimum above. Finally, we select the scene with a lower probability to cut, then, update the scene probability. We will repeat the iteration until the number of scenes reduces to the target scene.

V. CONTROL STRATEGY

A. CONTROL OBJECTIVES AND METHODS

This strategy takes time i as the starting point and 15 minutes forward as the sampling interval, and uses DFT to study the power deviation of wind power. The wind power deviation that directly reflects the current sampling point i can define as:

$$PD_{ev,i} = P_{Ai} - P_{Pi} \tag{8}$$

The deviation fluctuation will separate into three types in this paper, to prolong the operating life and give play to the characteristics of energy storage. First, the deviations are classified into three categories according to different response time, and we use DFT to complete the conversion from the time domain to the frequency domain:

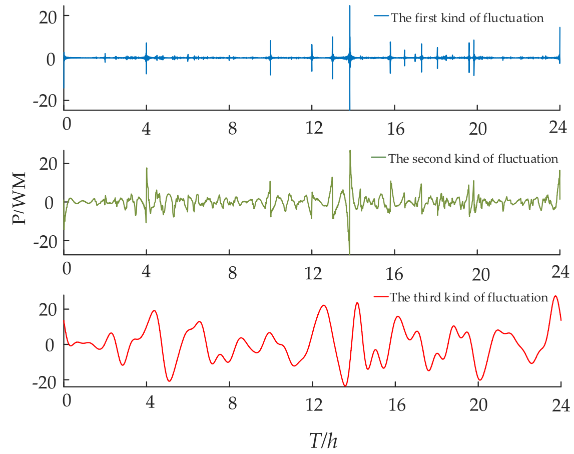

FIGURE 5. Classification curve of wind power deviation fluctuation.

$$P_E(k) = \sum_{n=0}^{N-1} PD_{ev}(n)e^{-j2\pi kn/N} \tag{9}$$

In (9), $PD_{ev,i}$ is the time domain signal of power deviation in the sampling period, which is to subtract the planned value from the actual value of wind power at a certain time. P_E is the signal of the frequency domain. n and k are sampling serial numbers in the time domain and frequency domain, respectively. N is the total number of samples during the sampling period.

The division of the three kinds of fluctuations is below.

The first kind of fluctuation: the characteristic of this type is high fluctuation frequency, small amplitude, and repeated zero-crossing.

The second kind of fluctuation: the change is fast, and the variation amplitude is small on the whole, which is compensated by power-type energy storage.

The third kind of fluctuation: the fluctuation is slow, but the amplitude is the largest, and the period is the longest, compensated by energy-type energy storage.

After obtaining the deviation fluctuation in the frequency domain, the deviation fluctuation in the frequency domain is separated by filtering principle. Finally, the deviation in the frequency domain is converted to the time domain by Inverse Discrete Fourier Transform (IDFT), which can express as:

$$PD_{ev}(n) = \sum_{k=1}^{N-1} \frac{P_E(k)}{N} e^{j2k\pi n/N} \tag{10}$$

The classification results of power deviation fluctuations are as follows:

In order to avoid frequent action of the energy storage system, the first kind of fluctuation is regarded as the dynamic dead zone of control. Moreover, the energy storage system does not issue control instructions. The second and third kinds of fluctuations are used as controlled inputs, and Passeval's theorem calculates the demand values of various kinds of energy storage power compensation:

$$P(f_1, f_2) = \sqrt{\sum_{f_2}^{f_1} |P_E(k)|^2} \tag{11}$$

In (11), f_1, f_2 represents the upper and lower bounds of the frequency band, respectively.

B. EVALUATION CRITERIA

The control strategy proposed aims to raise the output dispatch ability of wind farms to the same level as the thermal power unit through the HESS. Which can be seen by Section II, it is not enough to meet the traditional assessment index of wind power forecast.

The evaluation standards for wind power control performance should be able to suppress the deviation of the present output. We allow for a small amount of deviation, considering the violent local fluctuation caused by the randomness of wind power output. This paper consults the assessment criteria of the two regulations on the grid-connected thermal motor group, definites the indicator of 10min *RMSE* is $R_{MSE-10\,\min}$, and the indicator of 1min wind power deviation limit is $W_{PLD-1\,\min}$. The former is used to assess the extent, which the actual output power of wind farms deviates from the planned value. While the latter is used to evaluate the effect of short-term compensation and control the accumulation of deviations.

1) $R_{MSE-10\,\min}$

Transform the expression of the formula (1) to get the evaluation indicator K_1:

$$K_1 = 2 - \left\{ \frac{1}{n} \sum_{i=1}^{n} \left(\frac{PD_{ev,i}}{C_{ap}}\right)^2 \right\} / \varepsilon_1^2 \tag{12}$$

In (12), ε_1 is the root mean square value of the power control deviation of the wind farm for 1min throughout the year (10% of the maximum power deviation), which is assessed every 10min.

2) $W_{PLD-1\,\min}$

The standard is related to the real-time deviation of wind farms. When the actual output power is higher than the planned value, the average value of the power deviation in one minute is less than an upper limit value $W_{PLD,high}$. On the contrary, it is larger than a lower limit value $W_{PLD,low}$. The upper and lower limits are calculated as follows:

$$W_{PLD,high} = \frac{(P_{high} - P_{Pi})^2}{n_1} \sum_{i=1}^{n_1} \frac{1}{PD_{ev,i}} \tag{13}$$

$$W_{PLD,low} = \frac{(P_{low} - P_{Pi})^2}{n_2} \sum_{i=1}^{n_2} \frac{1}{PD_{ev,i}} \tag{14}$$

In the formula, $P_{high} = P_{Pi} + 3\varepsilon_1$, $P_{low} = P_{Pi} - 3\varepsilon_1$; n_1 is the number of sampling points when the actual output of a wind farm in 1min is greater than the planned value and $n_2$is the opposite. The evaluation index K_2 can be obtained by transforming the formula of (13) and (14):

$$K_2 = 2 - \frac{\left|\sum_{i=1}^{n} PD_{ev,i}\right|}{\left|\sum_{i=1}^{n} \frac{1}{PD_{ev,i}}\right| \cdot C_{ap} \cdot 9\varepsilon_1^2} \tag{15}$$

For each point of assessment, the eligibility criteria are:

1) $K_1 \geq 100\%$
2) $K_2 \geq 100\%$ and counted valid minutes, only when 30mins in a row are eligible.

C. CONTROL ZONE

In order to achieve better control effect, this strategy sets two thresholds, the partition conditions of each control area shown in the figure below.

1) DYNAMIC DEAD ZONE

PE_{Di} is the dynamic dead zone of the time i, i.e., the first type of fluctuation mentioned above. Which takes time i as the starting point and 15 minutes ahead as the sampling interval, and is obtained by time-frequency conversion, filtering and frequency-time conversion of the original power deviation curve. The compensation demand value calculated by DFT control at a certain time is P_R^i. When $\left|P_R^i\right| \leq |PE_{Di}|$, energy storage equipment does not charge or discharge. However, when the wind farm output is more than 20% of its rated total production, it participates in primary frequency modulation. The following formula determines the output power:

$$\Delta P_i = -K_w \Delta f = -\frac{P_{Ai}}{\delta_w f_{ref}} \Delta f \tag{16}$$

In the formula, ΔP_i is the change of active power at time i; δ_w is the droop gains, generally 0.04-0.06, the minimum is 0.02, this paper takes 0.04; Δf is the deviation of frequency, takes 0.03HZ; f_{ref} is the rated frequency of power systems, takes 50HZ.

The first type of fluctuation, whose amplitude exceeds 1MW, will be used as control input together with the other two types of fluctuations.

2) NORMAL REGULATION ZONE

After entering the normal regulation area, the regulation of energy storage is decided by K_1 and K_2 together. Which can divide into three cases according to Figure 6: a) Excellent control effect, energy storage equipment can meet control requirements without action. b) Good control effect, but there is the risk of substandard. We set up the action cycle T to reduce the number of actions of energy storage equipment. That is, after the energy storage device action once, no more action within cycle T. c) DFT distributes the power of energy storage equipment.

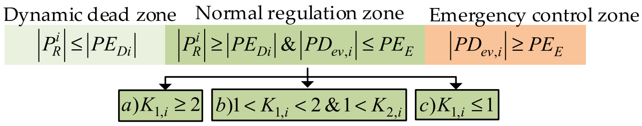

FIGURE 6. Division and judgment of control areas.

3) EMERGENCY CONTROL ZONE

It needs to ensure the real-time and practical of the strategy when the change of wind power is rapid. After entering the extreme control area, according to the maximum output and power deviation ratio of each energy storage element distribute the regulating power. However, when the power deviation between the before and after moments is too large, that is $|PD_{ev,i} - PD_{ev,i-1}| > PE_E$. In this case, the sampling time of DFT needs to be shortened. PE_E takes the absolute value of 10% maximum power deviation.

D. STRATEGY AND PROCESS

This paper presents a control strategy to realize the planned generation. The strategy aims at compensating for the deviation of wind power. The specific steps are as follows:

1) The time i is the starting point and rolling sampling 15 min forward. The original power deviation is separated, with the first type of fluctuation as the dynamic dead zone, and the remaining two types of fluctuations as the control input.
2) Control zones are judged based on compensation demand value and deviation value. DFT calculates the adjustment amount of different energy storage devices. Then, we determine the SOC of each energy storage equipment.
3) Power exchange does not perform when the SOC of energy-type and power-type energy storage is in the normal charge and discharge region. When both of them are in the state of over-discharged or over-charged, to avoid damaging the energy storage system, it is necessary to interact with the power of the system. When only one of them is in the state of over-discharged or over-charged, charging and discharging control is depending on both the SOC of each energy storage and the present state of charge/discharge.

The flow chart is as follows.

VI. CASE STUDIES

A. CASE SCENARIO

In order to verify the effectiveness of the proposed hybrid Wind-ES control strategy, a typical day's load data of a 100MW wind farm is tested on MATLAB. The total time of data studies is 24 hours, and the sampling interval is 1s. The entire control process is done in seconds, if the last instruction has been completed or more than one second, the control system can execute the next instruction. The energy storage capacity is optimized according to the literature [19].

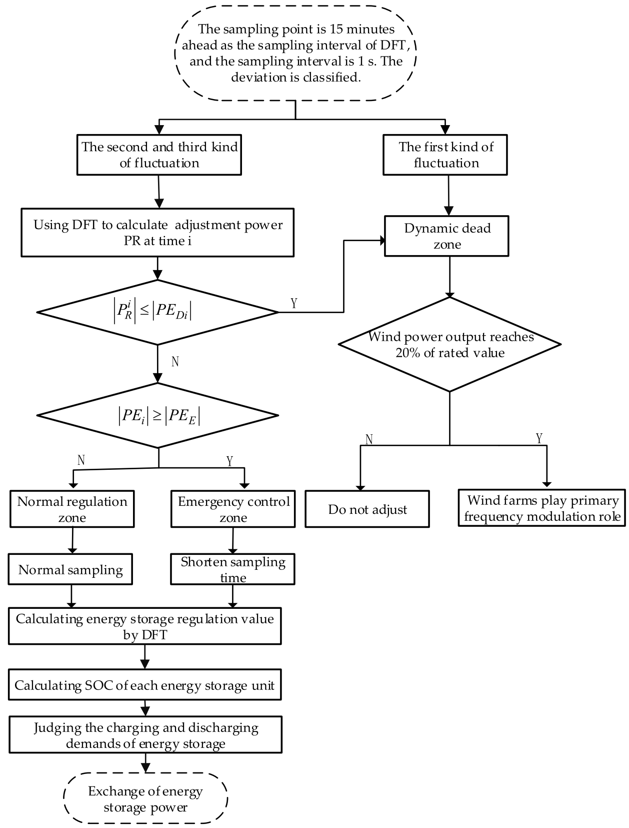

FIGURE 7. The control flow chart of tracking wind power generation plan.

The setting of simulation parameters: the capacity of the lithium-ion battery is 19 $MW \cdot h$, the maximum charging/discharging power is 12 MW, and the charging/discharging efficiency is 95%. The capacity of the supercapacitor is 7 $MW \cdot h$, the maximum charging/discharging power is 21 MW, and the charging/discharging efficiency is 98%; the initial SOC for both is 0.5.

The normal range of SOC for energy-type energy storage is set to 0.2-0.8, while power-type energy storage broadens to 0.1-0.9.

B. OVERALL CONTROL EFFECT

Figure 8 shows the effect of tracking wind power generation plans and the curves before and after the control. The original wind power deviation fluctuates greatly, up to 32.8MW. After control, the deviation changes slowly in the range of $\pm 5MW$, which shows the excellent results of tracking power generation real-time schedule. Table 3 and Figure 9 show the evaluating indicators before and after control. The passing rate of the assessment points after the adjustment has been significantly improved, and all meet the requirements of wind power control accuracy. Which sufficiently proves the correctness and effectiveness of the proposed strategy.

Figure 10 shows the charge/discharge power curve and the corresponding SOC curve for each energy storage device.

It can see from Figure 10 that power-type energy storage with small capacity but high charging/discharging power

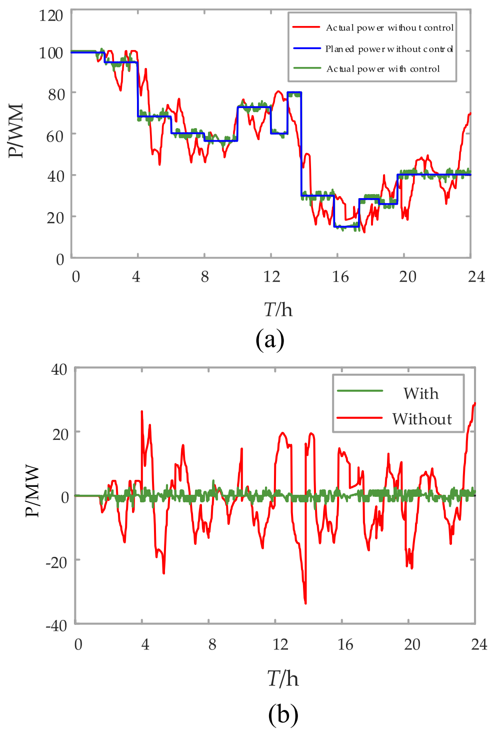

FIGURE 8. Control effect curve in all-day. (a) Actual power, planed power, and actual grid-connected power curve. (b) Power deviation before and after control.

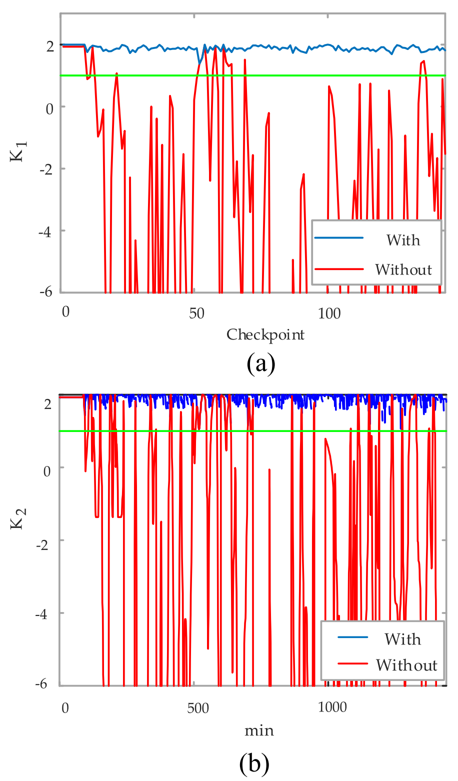

FIGURE 9. Changes of indicators before and after control. (a) Control effect of the indicator K_1. (b) Control effect of the indicator K_2.

regulates frequently. When the actual output maintains a large deviation for a long time, we use energy-type energy storage to charge/discharge, for restoring the adjustment margin of power-type energy storage quickly and preparing for

TABLE 3. Evaluation index and qualification rate of before and after control.

Standard	Control situation	Checkpoint/Value	Passing points	Passing rate
$R_{MSE-day}$	without	10.44%	/	/
	with	1.19%	/	/
K_1	without	144	47	32.64%
	with	144	144	100%
K_2	without	1440	135	9.38%
	with	1440	1440	100%

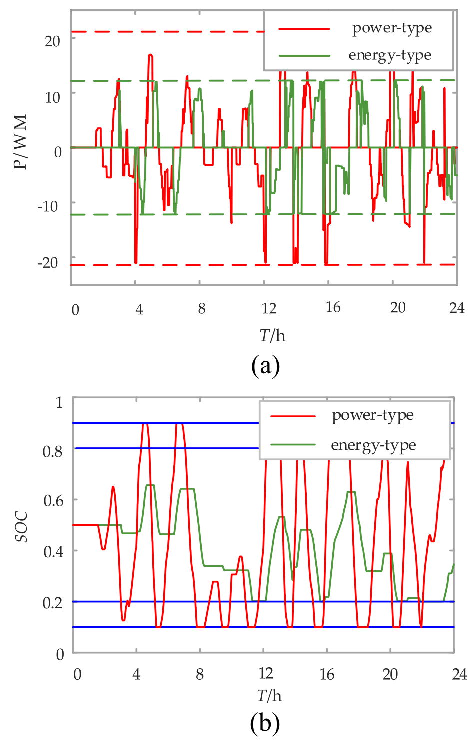

FIGURE 10. The operation of the hybrid energy storage system. (a) Charging and discharging power of the hybrid energy storage system (b) SOC curve of the hybrid energy storage system.

the subsequent unforeseen large power deviation. When the energy-type energy storage reaches the SOC limit, charging and discharging is mainly by power-type energy storage, which gives full play to the characteristics of the high power density of power-type energy storage. As shown in Table 4, this strategy can realize the shallow charging/discharging usage mode of energy storage, and effectively improve the operating life of energy storage.

C. ECONOMIC ANALYSIS

The entire life of the energy storage project is set at 10a. The discount rate r is 8% without considering the decrease in the installation cost of the energy storage system. The economical parameters of each energy storage project are listed in Table 5. The emission factor of standard coal thermal power generation refers to the literature [20], energy storage battery recovery-related data refers to reference [21].

TABLE 4. Charging and discharging times of energy storage.

Energy storage	Number of actions	Charging/ discharging times	lighter charging/discharging proportion
Power-type	601	92	97.67%
Energy-type	406	98	99.51

TABLE 5. Economic parameters of energy storage [22].

Parameter	Li-ion	Super-cap
C_p /[\$/kW]	1143	257
C_{cap} /[\$/ $kW \bullet h$]	600	1428
C_{yw} /[\$/kW-yr]	7	6
C_{bop} /[\$/ $kW \bullet h$]	88	

TABLE 6. Valuation of relevant economic parameters.

Economic parameters	Value
Average daily power generation in wind farms/(MW·h/day)	1077.586
Average daily discharging of energy storage /(MW·h/day)	95.64
Average daily reduction of assessment electrical energy /(MW·h/day)	301.610
Operating life of Li-ion /day	2322
Operating life of Super-cap /day	8095
Discharging price/($/MW·h)	53.97
The annual capacity electrovalence /($/kW)	64.42
Penalty costs / ($/MW·h)	53.97

In this paper, we use the Markov Chain Monte Carlo method to generate 1000 scenes, and then use backward scene reduction technology to reduce the total number of scenes to 60. The data of 60 typical days (5 days per month) are simulated. Assuming that the annual utilization hours of the wind farm are 2500h, the calculated data and related economic parameters are as shown in Table 6. Moreover, the energy storage system does not need to replace in the period T, according to Table 6.

In summary, the economic parameters (see Tables 5 and 6) are substituted into the cost-benefit model of energy storage, and the calculation results are shown in Table 7. The net income in the whole life cycle is US 749684.29$. The results show that the control strategy proposed in this paper can bring profits to wind farms, with certain theoretical significance and practical application value.

D. COMPARATIVE ANALYSIS OF DIFFERENT ALGORITHMS

In order to evaluate the effectiveness of the proposed strategy, this paper compares with the algorithm of tracking plan power generation, which is proposed in reference [4]. Table 8 shows the assessment and error analysis of wind power under two control algorithms. σ_{max} is the maximum prediction error.

From Table 8, the output performance of the wind farm has been significantly improved under the two control strategies.

TABLE 7. Calculation results of cost-benefit.

Parameters	Data
Initial investment cost/ $	42,797,000.00
O&M Cost/ $	1,409,117.00
Renewal replacement cost/$	0.00
Electricity revenue /($/day)	5,161.40
Capacity income /($/day)	5,824.78
Total penalty-free/($/day)	16,277.11
Environmental benefit/($/day)	1,586.35
Battery recovery benefits/($/day)	28.55
Life cycle cost / $	44,206,117.00
Life cycle income /$	44,955,801.29

TABLE 8. Assessment and error analysis of wind farm in different modes.

Algorithms	$R_{MSE-day}$	σ_{max}	Passing rate of K_1	Passing rate of K_2
This paper	1.19%	4.96MW	100%	100%
Reference	2.52%	20.44MW	95.83%	99.72%

The wind power grid-connected values are mainly consistent with planned values. However, it can clearly see that the strategy proposed in this paper has a better control effect on the output power. The maximum power deviation fluctuation after compensation can be controlled within ±5 MW, and the passing rate of the appraisal index can reach 100%.

VII. CONCLUSION

The evaluation standard of wind power control performance is divided into 1 min and 10 min in this paper, which are more in line with the characteristics of wind power output than the traditional assessment standard. Based on the evaluation standard, we propose the charging and discharging control strategy to regulate energy storage power.

The simulation analyses on the hybrid wind-ES power system illustrate the effectiveness of the proposed strategy and validate that it performs feasible in the economy. On the one hand, the control strategy solves the problem that the control of power exchange between wind and energy storage systems is too tight, which causes the repeated regulation of energy storage. After controlled, the daily root mean square error decreases from 10.44% to 1.19%. The maximum prediction error decreases from 32.84MW to 4.96MW. The strategy has controlled the power deviation within a small range, which meets the grid-connected requirements of thermal power units, so that wind power output meets the market competition requirements. On the other hand, the strategy considers the operation characteristics and life of different energy storage equipment and reduces the assessment electrical energy under the same demand. Through the calculation and analysis of the study case, it can be seen that the annual return on investment, static payback period and the net present value of the project are 15.16%, 6.6years, US 694152.119$, respectively, which prove that wind farm has a better economic benefit after equipping energy storage system.

The wind storage combined system is regarded as a frequency modulation mechanism. We can take the power deviation of the connection line exchange between the wind storage combined system and the power system, and frequency deviation as the influencing factor, when the power generation in the power system is not equal to the power consumption, the wind storage combined system can be used both as a energy-consuming system and as a power generation system, which can play the role of energy storage in frequency modulation and promote the frequency recovery of the power system. This is the direction for further research.

REFERENCES

[1] (2018). *World Wind Energy*. Accessed: Feb. 26, 2019. [Online]. Available: https://wwindea.org

[2] H. Bitaraf, S. Rahman, and M. Pipattanasomporn, "Sizing energy storage to mitigate wind power forecast error impacts by signal processing techniques," *IEEE Trans. Sustain. Energy*, vol. 6, no. 4, pp. 1457–1465, Oct. 2015.

[3] J. Cao, W. Du, H. Wang, and M. McCulloch, "Optimal sizing and control strategies for hybrid storage system as limited by grid frequency deviations," *IEEE Trans. Power Syst.*, vol. 33, no. 5, pp. 5486–5495, Sep. 2018.

[4] L. Bin, S. Wu, Y. Yang, P. Li, and Y. Su, "A research on the control performance standard and energy storage control strategy for large scale wind farms," *Proc. Chin. Soc. Elect. Eng.*, vol. 37, no. 16, pp. 4691–4698, 2017.

[5] T. Yang, "Optimal sizing of the hybrid energy storage system aiming at improving the penetration of wind power," in *Proc. IEEE PES Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Oct. 2016, pp. 2358–2362.

[6] I. N. Moghaddam and B. Chowdhury, "Optimal sizing of Hybrid Energy Storage Systems to mitigate wind power fluctuations," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Jul. 2016, pp. 1–5.

[7] S. R. Mohanty, N. Kishor, P. K. Ray, and J. P. S. Catalo, "Comparative study of advanced signal processing techniques for islanding detection in a hybrid distributed generation system," *IEEE Trans. Sustain. Energy*, vol. 6, no. 1, pp. 122–131, Jan. 2015.

[8] Q. Dai, X. Qin, J. Yang, P. Zeng, Q. Zhou, and F. Zhao, "Capacity planning of battery energy storage system within wind farm," in *Proc. IEEE PES Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Oct. 2016, pp. 1827–1831.

[9] M. Jannati, S. H. Hosseinian, B. Vahidi, and G.-J. Li, "Mitigation of wind-farm power fluctuation by adaptive linear neuron-based power tracking method with flexible learning rate," *IET Renew. Power Gener.*, vol. 8, no. 6, pp. 659–669, 2014.

[10] Q. Jiang, Y. Gong, and H. Wang, "A battery energy storage system dual-layer control strategy for mitigating wind farm fluctuations," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3263–3273, Aug. 2013.

[11] F. Liu, B. Hu, R. Li, and Y. Li, "A novel control strategy of energy storage system considering prediction errors of photovoltaic power," in *Proc. 15th Int. Conf. Control Automat. Robot. Vis. (ICARCV)*, Nov. 2018, pp. 1247–1251.

[12] F. Zhang, G. Wang, K. Meng, J. Zhao, Z. Xu, Z. Y. Dong, and J. Liang, "Improved cycle control and sizing scheme for wind energy storage system based on multiobjective optimization," *IEEE Trans. Sustain. Energy*, vol. 8, no. 3, pp. 966–977, Jul. 2017.

[13] *Management Rules for Generator Operation of Southern Region*, South China Bureau of SERC, Guangzhou, China, 2017.

[14] *Management Rules for Implementation of Grid-connected Operation and Auxiliary Service of Wind Power Plants in Southern Region*, South China Bureau of SERC, Guangzhou, China, 2017.

[15] B. Lunz, H. Walz, and D. U. Sauer, "Optimizing vehicle-to-grid charging strategies using genetic algorithms under the consideration of battery aging," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2011, pp. 1–7.

[16] G. Siqi, Y. Yuan, and X. Zhang, "Energy management strategy of isolated microgrid based on multi-time scale coordinated control," *Trans. China Electrotech. Soc.*, vol. 29, no. 2, pp. 122–129, 2014.

[17] Y. Peng, J. Li, J. Wen, X. Ai, T. Wu, H. Xie, and C. Yue, "A wind power time series modeling method based on its time domain characteristics," *Proc. CSEE*, vol. 34, no. 22, pp. 3715–3723, 2014.

[18] N. M. M. Razali and A. H. Hashim, "Backward reduction application for minimizing wind power scenarios in stochastic programming," in *Proc. 4th Int. Power Eng. Optim. Conf. (PEOCO)*, Jun. 2010, pp. 430–434.

[19] B. Li, S. Chen, and H. Wei, "Optimization of energy storage capacity based on spectral analysis for wind farm," *Proc. CSEE*, vol. 35, no. 9, pp. 2128–2134, 2015.

[20] W. Guangxia, "Study on environmental cost accounting and reporting of coal-fired thermal power enterprises," Ph.D. dissertation, Ocean Univ. China, Qingdao, China, 2012.

[21] W. Guangxu, L. Jia, and X. Zhenmin, "Recycling valuable metals from spent lithium ion batteries," *Mater. Rev.*, vol. 29, no. 7, pp. 113–123, 2015.

[22] X. Luo, J. Wang, M. Dooner, and J. Clarke, "Overview of current development in electrical energy storage technologies and the application potential in power system operation," *Appl. Energy*, vol. 137, pp. 511–536, 2015.

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