Dual-Regulating Feedback Optimization Control of Distributed Energy Storage System in Power Smoothing Scenario Based on KF-MPC

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ABSTRACT Taking the photovoltaic (PV)-hybrid energy storage system (HESS) composed of the distributed PV power generation and the distributed energy storage as the research object, under the scenario of smoothing PV power fluctuation, a dual-regulating feedback optimization control strategy of the PV-HESS based on double Kalman filters (KFs) and model predictive control (MPC) is proposed. The first Kalman filter (KF1) is used to realize the effective decomposition of the PV power, the MPC is used to optimize the output and the state of charge (SOC) of the HESS, and the output of the HESS is optimized by the second Kalman filter (KF2) to realize the energy distribution between the energy storage battery and supercapacitors. The optimized output of the HESS is fed back to the KF1 to realize the closed-loop optimization of the entire PV-HESS. The effectiveness and correctness of the proposed optimization control method are verified by simulating the actual operation data of a certain PV-HESS station in China. The simulation results show that the service life of the HESS can be extended by the dual feedback regulating control, and the overall economics of the PV-HESS can be improved.

INDEX TERMS Optimal control, Kalman filters, predictive control, distributed energy storage system.

I. INTRODUCTION

Due to low voltage levels of traditional distribution network, weak grid structure and insufficient regulation capability, the photovoltaic (PV) power generation connected to the grid has a huge impact on the power flow, power quality, and power supply reliability of distribution networks [1]. The advantages of energy storage systems are high power density and fast response [2], so it has been widely used to smooth the fluctuations of the PV output power. However, the operating status of energy storage systems and different application scenarios can directly affect the life and operation and maintenance cost of energy storage systems [3]. Thus, it is very important for energy storage systems to rationally select the optimal control strategy.

Some scholars have carried out related research on working modes and power smoothing control of energy storage systems. The methods for the power smoothing control of energy storage systems mainly focus on first-order inertial filtering, moving average filtering and wavelet analysis. In [4], the wavelet analysis is used to decompose the output power of wind power into two parts, high frequency as the power command of supercapacitors and low frequency as the power parallel power where the power fluctuation constraint is satisfied. However, the wavelet analysis only decomposes the high frequency part of the signal no longer, and can only characterize the signal with low frequency information as its main component. In [5], a fuzzy adaptive Kalman filter (KF)-based energy storage system (ESS) control strategy was proposed, and the Kalman filter gain and energy storage system state of charge (SOC) were dynamically adjusted through two fuzzy regulators to smooth the fluctuation of wind power. However, this method did not consider the relationship between the filter gain and the SOC of the energy storage system. In [6], a hybrid energy storage system (HESS) consisted of the lithium battery, and the supercapacitors were used to track the planning output of the wind power to improve the operational scheduling capability of the grid. The difference between the measured power and predicted power at a wind farm was decomposed by the Hilbert-Huang transform to realize the energy distribution of the HESS. In [7], the output of the wind power was smoothed and the...
energy of the HESS was distributed by adjusting the filtering orders of the empirical mode decomposition. Combined with the SOC of the HESS and the fluctuation limit of wind power connected to the grid, taking the overall economic efficiency of wind power and HESS as a goal, a game theory-based optimization control model of the HESS was established to optimize the filtering orders of the empirical mode decomposition. In [8], the smoothing control method of wind power based on a fuzzy neural network was proposed. Due to the batteries and supercapacitors are complementary in characteristics, the fuzzy neural network was used to optimize the parameters of the HESS, which not only can prolong the service life of the battery energy storage system but also smooth the fluctuation of the wind output power.

In order to prevent the over-charge or over-discharge of the HESS due to the fluctuations of renewable energy connected to the grid, the SOC of the ESS needs to be maintained within a reasonable range [9]. However, the SOC optimal control of the ESS described in the above documents was achieved according to the current SOC, which will cause a certain time delay [10]. Model predictive control (MPC) can predict the future output value according to the current control input and historical information of the process, so as to optimize the output power and SOC of the ESS. In [11], the optimized cost function was applied to the MPC, and the fluctuation of PV output power was smoothed by optimizing the cost function to maintain the SOC within the limit. In [12], an optimization control method of PV-ESS based on the MPC was proposed, which can effectively smooth the fluctuation of PV output power while avoiding the overcharge and over-discharge of the energy storage system. In practical applications, the hybrid energy storage system including batteries and supercapacitors has high practicability in power smoothing application scenarios, but the above-mentioned literature only studied the application of a single type (batteries) energy storage system without considering the role of supercapacitors.

Therefore, in order to overcome the above-mentioned problems, under the premise of the overall economic optimal of the PV-HESS and the fluctuation limit of the grid connected to the grid, a dual regulating feedback optimal control method with the combination of the double Kalman filters (KFs) and MPC is employed to smooth fluctuations in the PV output power and to keep the SOC of the HESS in an optimal state, while effectively avoiding the time delay effect of filtering and control. The adjusting factor 1 is introduced in the first Kalman filter (KF1), and the filter gain is dynamically adjusted in real-time to smooth according to the adjusting factor 1. In the HESS, the adjusting factor 2 is introduced in the second Kalman filter (KF2), the filter gain is dynamically adjusted in real-time to reasonably distribute the power of the battery and the supercapacitors; In the model predictive controller, taking the minimum cost of the HESS as the objective function, the HESS is optimized by dynamic matrix rolling, and the optimized SOC is fed back to the KF1 to form the dual adjusting feedback control of the PV-HESS, ensuring that the SOC of the HESS is maintained within a reasonable range. The analysis of the simulation example shows that the control strategy proposed in this paper can effectively smooth fluctuations in output power of PV power stations, considering the economics of the HESS, and realizing the real-time optimal control of the PV-HESS, which has a certain value in engineering applications.

II. DUAL REGULATION FEEDBACK OPTIMAL CONTROLS OF THE PV-HESS BASED ON KF-MPC

A. STRUCTURE OF THE PV-HESS IN THE POWER SMOOTHING SCENARIO

In the power smoothing scenario, the PV-HESS mainly consists of distributed PV plants, PV inverters, hybrid energy storage systems, energy storage converters, transformers, and the power grid. The output of the PV plants is composed of the combined output of multiple sets of solar panels. Each group of solar panels is powered by sunlight, and is transmitted to the grid after being connected to the transformer by the power conversion system (PCS). The HESS is connected to the transformer through the PCS, and is boosted and connected to the bus. The HESS has consisted of the lithium-ion battery and the supercapacitors [13], and the PCS has a Direct Current/Alternating Current (DC/AC) conversion function [14]. The schematic diagram of the grid-connected distributed PV-HESS is shown in Fig. 1.

According to the law of energy conservation and the operating conditions of the grid, the relationship can be described as (1).

\[ P_{\text{grid}}(t) = P_v(t) + P_{\text{Hess}}(t) \]  

(1)

where \( P_v(t) \) is the output power of the PV plants; \( PV\text{-HESS}(t) \) is the output power of the HESS; \( P_{\text{grid}}(t) \) is the output power of the grid-connected distributed PV-HESS.
B. DUAL REGULATION FEEDBACK CONTROL PRINCIPLE OF THE PV-HESS BASED ON KF-MPC

According to the measured PV power $P_v$, the priori estimate and covariance priori estimate of the combined output power of the PV-HESS are calculated by the KF1, and then the filter gain is adjusted by the adjustment factor $\lambda$ according to the estimated state of the actual output power of the PV. The model predictive control is used to optimize the output of the HESS and smooth the fluctuation of the PV connected to the grid, and the initial value of the SOC of the HESS is obtained. To avoid the SOC of the HESS from changing sharply in a short time meanwhile satisfying the charging or discharging demands at the next moment, the $\Delta S$ is optimized by the regulator 2 according to the SOC and $\lambda$ at the current moment, and fed back to the KF1 to improve the smoothing effect. Before the model predictive control, the fluctuation rate calculation unit is added to calculate the fluctuation rate of the PV power at the current moment. If the fluctuation rate exceeds the limit, the gain of the KF1 is dynamically adjusted by the regulator 1 to obtain a better smoothing effect. The energy division between the batteries and the supercapacitors is achieved by the KF2. The diagram of dual regulation feedback optimization control for the PV-HESS based on the KF-MPC is shown in Fig. 2.

In Fig. 2, the relationship between the various powers is described as (2).

$$
P_v = P_h + P_l
$$

$$
P_{\text{exp}} = P_r + P_v
$$

$$
P_g = P_v + P_{\text{ess}}
$$

where $P_h$ is the high-frequency signal after the KF1; $P_l$ is the low-frequency signal after the KF1; $P_r$ is the output power optimized by the MPC controller; $P_{\text{exp}}$ is the charge and discharge power command signal of the HESS; $P_{\text{ess}}$ is the output of the HESS; $P_g$ is the grid connected power of the system.

III. POWER SMOOTHING OF THE PV OUTPUT BASED ON THE KF1

A. SMOOTHING PRINCIPLE OF THE PV OUTPUT POWER BASED ON THE KF1

Kalman filtering [15], [16] is a widely used linear digital filtering method, which is applied to the power smoothing of the PV-HESS, and the output of the PV power $P_v$ is regarded as the predictor of the KF1 for the state estimation. The mathematical model of the PV-HESS based on KF1 is given by (3).

Time update equation:

$$
(P_v)_{k+1} = (P_v)_k + (P_{\text{ess}})_k + Q
$$

State update equation:

$$
(P_v)_k + (P_{\text{ess}})_k + K_k [(P_v)_{k+1} - (P_v)_{k+1}]
$$

$$
K_k = \frac{(P_{k+1})_k}{P_{k+1} + R}
$$

$$
P_{k+1} = (1 - K_k)P_{k+1}
$$

where $(P_v)_k$ is the output of the PV plants before adding the HESS; $(P_v)_k$ is the smoothing value of the grid-connected power after the PV plants is added to the HESS at the moment $k$; $(P_v)_{k+1}$ is the smoothing value of the grid-connected power after the PV plants is added to the energy storage system at the moment $k + 1$; $(P_v)_{k+1}$ is the state prior estimate at the $k + 1$ moment obtained from the moment $k$ of the PV plants; $P_{k+1}$ is the covariance at the moment $k$; $P_{k+1}$ is the priori estimate covariance; $Q$ is the process noise covariance; $K_k$ is the gain of the KF1; $R$ is the measurement noise covariance.

The adjusting factor $\lambda$ is introduced into the gain of the KF1, and the output of the PV-HESS is adjusted by dynamically adjusting the gain of the KF1 in real time. The definition of $\lambda$ is given by (7) [17], [18].

$$
\lambda = \max \left \{ 1, \frac{\text{tr} [N_k]}{\text{tr} [T_k]} \right \}
$$

$$
\lambda = \frac{N_{k+1}}{B_{k+1}} + \text{tr} [Q_{k+1}B_{k+1}^T] - R
$$

where $V_{k+1}$ is the measurement noise; $B_{k+1}$ is the measurement matrix; $\phi_{k+1}$ is the state transition matrix.

In order to avoid over-discharge of the HESS, the adjustment factor $\lambda$ should be increased to make the HESS charge; similarly, when the SOC of the HESS is at a high level and continues to increase, the adjustment factor $\lambda$ should be reduced to make the battery discharge. The SOC of the HESS is calculated by (8).

$$
SOC = \frac{SOC_{\text{bat}} \cdot E_{\text{bat}} + SOC_{\text{sc}} \cdot E_{\text{sc}}}{E_{\text{bat}} + E_{\text{sc}}}
$$
where $SOC_{bat}$ is the SOC of the battery; $SOC_{sc}$ is the SOC of the supercapacitors; $E_{bat}$ is the capacity of the battery; and $E_{sc}$ is the capacity of the supercapacitors.

In order to prevent the power distortion of the HESS caused by the SOC over-limit, $\Delta S$ is regarded as an optimization variable. $\Delta S$ is calculated by (9).

$$\Delta S = \left\{ SOC (k) \cdot \frac{[1 - \lambda (t)] \cdot [P_{bat} (k + 1) - P_{bat} (k)] \cdot \Delta t}{E_b} \right\}$$

The state update equation (4) is changed to (10).

$$(P_{s})_{k+1,k+1} = K_k \cdot \frac{[P_{v}]_{k+1} - (P_v)_{k+1,k}}{\Delta S \cdot (P_{ess})_{k} + (P_v)_{k+1,k}}$$

(10)

The filter adjusting factor $\lambda$ is introduced in the KF1 to dynamically adjust the gain of the KF1, and the state update equation (5) is changed into (11).

$$K_k = \frac{P_{k+1,k}}{P_{k+1,k} + \lambda R}$$

(11)

The KF1 can be equivalent to a filter with prediction and no time delay by introducing a filter adjustment factor $\lambda$. The PV power signals are effectively decomposed by adjusting the bandwidth of the KF1. At the same time, the delay phenomenon of the traditional filter can be avoided according to the prediction characteristics and real-time correction characteristics of the KF1.

### B. CASE STUDY

In term of a PV plants in China with the installed capacity of 8 MW, a typical daily PV output power curve is decomposed by the KF1. The decomposed result is shown in Fig. 3.

It can be seen from Fig. 3 that the PV output power is decomposed into the high-frequency component and the low-frequency component by varying the gain of the KF1. The low-frequency component obtained by the KF1 is the dominant part of the PV output power, the amplitude of which is large and close to the PV output power. The volatility of the PV output power is greatly reduced with no delay phenomenon, so it is regarded as the reference value of the grid-connected PV power. The amplitude of the high-frequency component obtained by the KF1 is much lower than that of the PV output power, and the volatility of the high-frequency signal is strong. The high-frequency signal is absorbed by the HESS to achieve the power smoothing, which can effectively avoid the influences of the frequent charge and discharge on the life of the HESS.

### IV. ENERGY DISTRIBUTION OF THE DISTRIBUTED HESS BASED ON KF2

It can be seen from Table 1 that when both types of energy storage equipment are in normal working states (states 1, 2), the HESS can coordinate the power according to the power change rate, and the lithium battery absorb the low-frequency power signal (i.e., the small power change rate), the supercapacitors absorbs the high-frequency power signal (i.e., the large power change rate); when only one of energy storage equipment is in the normal working state (from state 3 to state 16), the HESS in abnormal working state stops working, and the energy storage equipment in the abnormal working state adjusts the HESS from the abnormal working state to the normal working state through changing the output of the HESS; when both types of energy storage equipment are in an abnormal state (states 17, 18), the HESS stops running.

The optimal output of the HESS optimized by the MPC is regarded as the synthetic output of the HESS. The KF2 is used to reasonably distribute the energy between the battery and supercapacitors. The output power $P_{ess}$ of the HESS is regarded as the predictor of the KF2 for the state estimation. The mathematical model of the KF2 is described as (12).

Time update equation:

$$(P_{ess})_{k+1,k+1} = (P_{bat})_{k+1,k} + (P_{sc})_{k+1,k}$$

$$P_{k+1,k} = P_{k,k} + Q'$$

(12)

State update equation:

$$(P_{bat})_{k+1,k+1} = (P_{bat})_{k+1,k} + K_k [(P_{ess})_{k+1} - (P_{ess})_{k+1,k}]$$

$$K_k' = \frac{P_{k+1,k}'}{P_{k+1,k} + R'}$$

$$P_{k+1,k+1} = (1 - K_k') P_{k+1,k}$$

(13)

| Type | SOC of lithium battery | SOC of supercapacitor | Charge/discharge | Control strategy |
|------|------------------------|-----------------------|------------------|-----------------|
| 1    | normal range           | normal range          | charge           | Coordinating operation |
| 2    | normal range           | normal range          | discharge        | Internal energy coordinating control |
| 3    | lower limit            | lower limit           | charge           |                 |
| 4    | lower limit            | normal range          | charge           |                 |
| 5    | lower limit            | normal range          | discharge        |                 |
| 6    | lower limit            | upper limit           | charge           |                 |
| 7    | lower limit            | upper limit           | discharge        |                 |
| 8    | normal range           | lower limit           | charge           |                 |
| 9    | normal range           | lower limit           | discharge        |                 |
| 10   | normal range           | upper limit           | charge           |                 |
| 11   | normal range           | upper limit           | discharge        |                 |
| 12   | upper limit            | lower limit           | charge           |                 |
| 13   | upper limit            | lower limit           | discharge        |                 |
| 14   | upper limit            | normal range          | charge           |                 |
| 15   | upper limit            | normal range          | discharge        |                 |
| 16   | upper limit            | upper limit           | charge           |                 |
| 17   | lower limit            | lower limit           | discharge        | Stop running    |
| 18   | upper limit            | upper limit           | charge           |                 |
where \((P_{ess})_k\) is the output power of the HESS optimized by the MPC; \((P_{bat})_{k+1}\) is the output power of the battery at the moment \(k\); \((P_{sc})_{k+1}\) is the output power of the supercapacitors at the moment \(k\); \((P_{bat})_{k+1}\) is the output power of the battery at the moment \(k+1\); \((P_{ess})_{k+1}\) is the prior state estimation at the moment \(k+1\) obtained by the moment \(k\) of the HESS; \((P_{sc})_{k+1}\) is the covariance estimation at the moment \(k\); \((P_{ess})_{k+1}\) is the a priori estimated covariance; \(Q'\) is the process noise covariance; \(K'_{ij}\) is the gain of the KF2; \(R'\) is the measurement noise covariance.

In a standard Kalman filter system, both process noise and measurement noise are subject to a Gaussian white noise distribution. The KF2 is adopted to distribute the energy of the HESS, and the filter coefficient \(\tau\) is defined by (14).

\[
\tau = 1 \left( \sum_{i=0}^{n} \sum_{j=0}^{n} \text{Abs} (k'_{ij}) \right)
\]

(14)

where \(\text{Abs}(k'_{ij})\) is the sum of absolute values of the gain matrix \(K'\) in the \(i\)-th row and \(j\)-th column elements; \(K'\) is an \(n\)-dimensional matrix composed of the gains of the KF2.

The energy distribution principle of the HESS via the KF2 is given by (15).

\[
P_{bat}(t) = (1 - \tau)P_{bat}(t - 1) + \tau P_{ess}(t)
\]

\[
P_{sc}(t) = (1 - \tau)\left(\left| P_{ess}(t) - P_{bat}(t - 1) \right| \right)
\]

(15)

The real-time energy distribution of the HESS is realized by KF-MPC. According to the output of the HESS obtained by the KF2, the SOC of the HESS is respectively obtained by (8), which is fed back to the KF1 to adjust the filter adjusting factor \(\lambda\) and the SOC in the optimal state.

V. OPTIMIZING CONTROL OF THE PV-HESS BASED ON THE MPC

The MPC [19], [20] can estimate the state of the next moment according to the state of the PV-HESS at the current moment, and can cope with the uncertainty disturbance. In this paper, the MPC is combined with the KF to achieve optimal control of the PV-HESS.

For the PV-HESS shown in Fig. 1, suppose that the PV system and the load of the grid are uncontrollable, the model of the PV-HESS can be equivalent to the predicting model of the HESS responding to the controller command. The MPC is used to optimize the HESS. The control time domain is \(T\) and the predicting time domain is \(B\). The relationship between the grid-connected power \(P_{g}(k)\) of the PV-HESS, the output of the HESS \(P_{ess}(k)\) and the measured PV power \(P_{v}(k)\) is shown in (1). The SOC of the HESS is expressed as (16).

\[
SOC (k + 1) = SOC (k) - \frac{TP_{ess}(k)}{E_{b}}
\]

(16)

where \(E_{b}\) is the capacity of the HESS.

The grid-connected power and the SOC of the HESS are regarded as the state variable, the output power \(P_{ess}\) of the HESS is regarded as the control variable and the output power \(P_{v}\) of the PV is regarded as the disturbance variable. The predicting model of the HESS at the moment \(k\) is established.

The state space is expressed as (17).

\[
\begin{bmatrix}
P_{g} (k + 1) \\
SOC (k + 1)
\end{bmatrix} =
\begin{bmatrix}
0 & 0 \\
0 & 1
\end{bmatrix}\begin{bmatrix}
P_{g} (k) \\
SOC (k)
\end{bmatrix} +
\begin{bmatrix}
1 & \frac{T}{E_{b}} \\
0 & 1
\end{bmatrix}\begin{bmatrix}
P_{ess}(k) \\
0
\end{bmatrix}
\]

\[
\begin{bmatrix}
y_{1} (k) \\
y_{2} (k)
\end{bmatrix} =
\begin{bmatrix}
1 & 0 \\
0 & 0
\end{bmatrix}\begin{bmatrix}
P_{g} (k) \\
SOC (k)
\end{bmatrix}
\]

(17)

The output model of the HESS in the predicting period depends on the control command of the predicting model, expressed as (18).

\[
P_{ess,T} (k) = P_{ess,T0} + B (k) - P_{ess,T0} (k) + \Delta P_{ess}(k)
\]

(18)

where \(P_{ess,T}(k)\) is the output of the HESS at the moment \(k\) (equivalent to \(P_{ess}(k)\)); \(P_{ess,T0}(k)\) is the output of the HESS at a certain time \(T_{0}\); \(\Delta P_{ess}(k)\) is the output power difference of the HESS.

The value of \(T\) is inversely proportional to the control stability and directly proportional to the control sensitivity when \(B\) is determined. From the point of simplification, first, an available value of \(B\) can be determined and then adjust the value of \(T\) to achieve the control goal. When \(B\) is greater than 1 min, the stability of the system will not increase significantly with the increase of \(B\), but it will reduce the response speed and increase the computational burden. Then physically, \(T\) should be less than or equal to \(B\), and when \(T = 1\) min, it does not cause instability and has the best dynamic response. To sum up, both \(T\) and \(B\) are taken as 1 min.

The coordination control of the PV-HESS has to consider the smoothing effect of the actual grid-connected power, the output and the SOC of the HESS, so the objective function is established according to (19).

\[
\min J (k) = \sum_{k=1}^{B} \left[ \frac{P_{g} (k + 1) - P_{g} (k)}{P_{cap}} \right] + \sum_{k=1}^{B} P_{ess}^{2} (k) + \sum_{k=1}^{B} \left[ E_{b} (SOC (k) - SOC_{exp}) \right]
\]

(19)

where \(SOC_{exp}\) is the expected SOC of the HESS; \(P_{cap}\) is the output power of the supercapacitors.

It can be known from the objective function of the MPC that the initial parameters of the PV-HESS are input into the model predicting controller, and the forward rolling optimization is realized by the step of the control time domain. The feedback correction in this section is used to correct the deviation between the actual output of the HESS and the command, and continuously modify the predicting error, which can control the output of the HESS and optimize the SOC of the HESS in advance, so that the coordination control of the PV-HESS is sustainable.

Restrictions conditions:

\[
|P_{ess}(k)| \leq P_{ess,max}
\]

\[
SOC_{min} \leq SOC (k) \leq SOC_{max}
\]

\[
\gamma = \frac{P_{g} (k + 1) - P_{g} (k)}{P_{cap}} \leq \gamma_{0}
\]

(20)
where $P_{ess, max}$ is the upper limit of the charge and discharge power of the HESS; $SOC_{min}$ and $SOC_{max}$ are the upper and lower limits of the SOC of the HESS; $\gamma$ is the fluctuation rate of the PV output power; $\gamma_0$ is the fluctuation rate limit of the PV output power, $\gamma_0 = 5\%$.

The optimization control and coordination flow chart of the PV-HESS based on KF-MPC is shown in Fig. 4.

VI. CASE ANALYSES

A system model of 10 kV/0.4 kV radial distribution network is used for the simulation analysis shown in Fig. 5. The nodes 6, 11, and 29 are respectively connected to the PV power generation unit with the capacity of 3.5 MW, 2 MW, and 2.5 MW, the total installed capacity of 8 MW. The capacity of the node 5 connected to the Lithium battery is 1 WMh, and the node 28 connected to the capacity of the supercapacitors is 0.5 WMh.

Taking the actual operation data of a distributed PV power generation system with an installed capacity of 8 MW in Xinjiang as an example, and the sampling interval is 1 min. Due to the long sunshine duration in the summer of Xinjiang, a typical daily curve from 06:00 to 21:00 in summer is selected. The comparison results respectively obtained by the KF-MPC (ModelII) and KF (ModelI) to smooth fluctuations in output power of PV power plants are shown in Fig. 6 and Fig. 7.

It can be seen from Fig. 6 that the smoothed effect obtained by the ModelII is better than that obtained by the ModelI. Since both the KF and the MPC have predictive characteristics, the variation characteristics of the PV measured power are considered while smoothing fluctuations in output power of PV power plants.

It can be seen from Fig. 7 that the fluctuation rate of the original PV output power is larger (the maximum fluctuation rate is 0.16 MW), and the percentage of the part exceeding the fluctuation rate limit of 0.05 is 15.6%; The fluctuation rate of the PV output power obtained by the ModelII is better than that of the original PV output power, but there are still some that exceed the fluctuation rate limit, and the excess part accounts for 8.3%; Since the fluctuation rate limit is
fully considered in the regulator 2, the fluctuation rate of the PV output power obtained by the ModelII falls within the limit, and meets the requirements of grid-connected PV power generation. Fig. 8 shows the output curve of the HESS under the two models.

Assume that the discharge of the HESS is positive, and the output change of the HESS ranges from $-0.5$ MW to $0.75$ MW before being optimized. The output change of the HESS ranges from $-0.25$ MW to $0.25$ MW after being optimized by the Model I, and the output of the HESS ranges from $-0.3$ MW to $0.5$ MW. The output of the HESS obtained by ModelI is larger than that obtained by the ModelII. In summary, the KF-MPC control strategy proposed in this paper can effectively ensure the optimal output of the HESS and realize the economic operation of the HESS.

It can be seen from Fig. 9 that the fluctuation range of the SOC of the HESS before being optimized is from $10\%$ to $95\%$, the larger fluctuation range is not conducive to the safe and stable operation of the battery; after being optimized by the ModelII, the maximum SOC of the HESS reaches $90\%$. There is still an over-discharging phenomenon and a large fluctuation range of the SOC of the HESS is not conducive to the safe and stable operation of the HESS. The control capability of different strategies is given in Table 2.

It can be seen from Table 2 that the control effect of the control strategy on the PV-HESS is better than that without the control strategy and the fluctuating rate of photovoltaic power, the output of HESS and SOC are improved; compared with ModelI, the control effect of ModelII on the PV-HESS is better, specifically as follows: the fluctuating rate of photovoltaic power is all kept within the limited range; the SOC of the energy storage system does not exceed the limit and maintains near the expected value; meanwhile, the output of HESS range is smaller, which is conducive to extending the service life of the HESS. In summary, the KF-MPC control strategy proposed in this paper can effectively keep the SOC of the HESS within a reasonable range.

The energy distribution method for the HESS is given in Section IV. The power distribution and SOC between the lithium battery and the supercapacitors are shown in Fig. 10 and Fig. 11.

It can be seen from Fig. 10 that the output of the HESS is distributed by both the lithium battery and the supercapacitors. The output power of the smoothed PV-HESS can well track the output power of the PV before being smoothed, and fluctuations in output power of PV power plants is significantly reduced. The battery takes on a large amount of slowly varying components in the HESS, and the supercapacitors take on the remaining fast-changing components.

It can be seen from Fig. 11 that after the KF-MPC optimization control, the SOC of the HESS changes between $0.2$ and $0.8$. The charge and discharge depth of the batteries is significantly improved. The high-power density characteristic of
the supercapacitors can effectively absorb the high-frequency part of the PV power, it is helpful to extend the life of the batteries and improve the economics of the HESS.

VII. CONCLUSION
In order to smooth the fluctuations of the PV output power, a dual-regulation feedback optimization control method for the PV-HESS based on KF-MPC is proposed. The main conclusions are as follows:

1) The fluctuation rate of the PV output power is reduced to 4% by adjusting the gain of KF1 according to the SOC of the HESS;
2) The SOC and grid-connected power of the HESS is optimized by using the MPC to achieve the smoothing control of the PV output power and keep the SOC within the range of 20% and 80%;
3) The power between the batteries and the supercapacitors of the HESS is distributed by adjusting the gain of KF2, and the optimal control of the PV-HESS is realized according to the real-time SOC fed back to KF1. The percentage exceeding the fluctuation range reaches 0.

The effectiveness and correctness of the proposed optimization control method are verified by the simulation of the actual operation data from a certain PV-HESS station in China. The service life of the HESS can be extended by the dual feedback regulating control, and the overall economics of the PV-HESS can be improved.

REFERENCES
[1] E. M. Gado, “Impact the expansion of the production of generation of solar power on the low voltage network in Egypt,” in Proc. Saudi Arabia Smart Grid (SASG), Dec. 2015, pp. 1–4. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7449281
[2] H. Akbari, M. C. Browne, A. Ortega, M. J. Huang, N. J. Hewitt, B. Norton, and S. J. McCormack, “Efficient energy storage technologies for photovoltaic systems,” Sol. Energy, vol. 192, pp. 144–168, Nov. 2019.
[3] E. Jafari, S. Soleymani, B. Mozafari, and T. Amraee, “Scenario-based stochastic optimal operation of wind/PV/FO/CHP/biogas/energy storage system considering DR programs and uncertainties,” Energy, Sustainability Soc., vol. 8, no. 1, pp. 11–23, Dec. 2018.
[4] T. Trung, S.-J. Ahn, J.-H. Choi, S.-I. Go, and S.-R. Nam, “Real-time wavelet-based coordinated control of hybrid energy storage systems for denoising and flattening wind power output,” Energies, vol. 7, no. 10, pp. 6620–6644, Oct. 2014.
[5] W. Xiaodong, Z. Lei, and Y. Jiaxing, “Research of wind farm power fluctuations controller considering the SOC of battery,” J. Power Supply, vol. 2, no. 3, pp. 73–77, Feb. 2014.
[6] X. Li, T. Zhou, and J. Huang, “The HESS capacity configuration in tracking wind power project output,” Acta Energiae Solaris Sinica, vol. 37, no. 9, pp. 2194–2200, Sep. 2016.
[7] X. Han, X. Yu, and Y. Liang, “A game theory-based coordination and optimization control methodology for a wind power-generation hybrid energy storage system,” Asian J. Control, vol. 20, no. 1, pp. 86–103, Jan. 2017.
[8] Y. Lu and Y. L. Zhao, “Optimal control in a wind power HESS based on fuzzy neural network,” Power Syst. Protection Control, vol. 42, no. 3, pp. 113–118, Dec. 2014.
[9] Y. Zhou, Z. Yan, and N. Li, “Design of multiple SOC feedback strategy in wind power smoothing algorithm using bess,” Acta Energiae Solaris Sinica, vol. 38, no. 7, pp. 1459–1467, Jun. 2017.
[10] C. Dong, H. Jia, Q. Xu, J. Xiao, Y. Xu, P. Tu, P. Lin, X. Li, and P. Wang, “Time-delay stability analysis for hybrid energy storage system with hierarchical control in DC microgrids,” IEEE Trans. Smart Grid, vol. 9, no. 6, pp. 6633–6645, Nov. 2018.
[11] M. Lei, Z. Yang, Y. Wang, H. Xu, L. Meng, J. C. Vasquez, and J. M. Guerrero, “An MPC-based ESS control method for PV power smoothing applications,” IEEE Trans. Power Electron., vol. 33, no. 3, pp. 2136–2144, Mar. 2018.
[12] X. Yan, Y. Xu, and R. Li, “Multi-time scale reactive power optimization of distribution grid based on model predictive control and including DG regulation,” Trans. China Electrotech. Soc., vol. 34, no. 4, pp. 2022–2037, Oct. 2019.
[13] X. Lu, G. Li, and Y. Tong, “A review of negative electrode materials for electrochemical supercapacitors,” Sci. China Technol. Sci., vol. 58, no. 11, pp. 1799–1808, Nov. 2015.
[14] D. Reddy and S. Ramasamy, “Design of RBFN controller based boost type Vienna rectifier for grid-tied wind energy conversion system,” IEEE Access, vol. 6, pp. 3167–3175, 2018.
[15] W. Bai, W. Xue, Y. Huang, and H. Fang, “On extended state based Kalman filter design for a class of nonlinear time-varying uncertain systems,” Sci. China Inf. Sci., vol. 61, no. 4, pp. 1–16, Apr. 2018.
[16] D. Lamsal, V. Sreeram, Y. Mishra, and D. Kumar, “Kalman filter approach for dispatching and attenuating the power fluctuation of wind and photovoltaic power generation systems,” IET Gener., Transmiss. Distrib., vol. 12, no. 7, pp. 1501–1508, Apr. 2018.
[17] Y. Cai, P. Cheng, and X. Li, “Kinematic point positioning with Kalman filtering,” Bull. Surveying Mapping, vol. 6, no. 1, pp. 6–8, May 2016.
[18] X. Huang and J. Chen, “Digital filter design,” J. Lanzhou Inst. Technol., vol. 2, no. 1, pp. 9–11, Jan. 1999.
[19] J. Hou, J. Sun, and H. Hofmann, “Adaptive model predictive control with propulsion load estimation and prediction for all-electric ship energy management,” Energy, vol. 150, pp. 877–889, May 2018.
[20] P. Fulkowski and A. Sikorski, “Finite control set model predictive control for grid-connected AC–DC converters with LCL filter,” IEEE Trans. Ind. Electron., vol. 65, no. 4, pp. 2844–2852, Apr. 2018.
[21] Y. Zhang and M. Lei, “An improved predictive control strategy of continuous control set model for PV power fluctuation damping,” Power Syst. Technol., vol. 43, no. 5, pp. 1543–1549, May 2019.
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