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Multi-Objective Optimization of a Battery-Supercapacitor Hybrid Energy Storage System Based on the Concept of Cyber-Physical System

Chenyun Pan 1,2,3, Shengyu Tao 1,2,3, Hongtao Fan 1,2,3, Mengyao Shu 1,2,3, Yong Zhang 4 and Yaojie Sun 1,2,3,*

1 Department of Light Sources and Illuminating Engineering, Fudan University, Shanghai 200433, China; 17110720033@fudan.edu.cn (C.P.); 19210720062@fudan.edu.cn (S.T.); 18110720036@fudan.edu.cn (H.F.); 18210720066@fudan.edu.cn (M.S.)
2 Institute for Six-Sector Economy, Fudan University, Shanghai 200433, China
3 Shanghai Engineering Research Center for Artificial Intelligence and Integrated Energy System, Fudan University, Shanghai 200433, China
4 AISWEI Renewable Energy Technology (Jiangsu) Co., Ltd., Suzhou 215011, China; yong.zhang@aiswei-tech.com
* Correspondence: yjsun@fudan.edu.cn; Tel.: +86-021-55665508

Abstract: Optimal operation of energy storage systems plays an important role in enhancing their lifetime and efficiency. This paper combines the concepts of the cyber-physical system (CPS) and multi-objective optimization into the control structure of the hybrid energy storage system (HESS). Owing to the time-varying characteristics of HESS, combining real-time data with physical models via CPS can significantly promote the performance of HESS. The multi-objective optimization model designed in this paper can improve the utilization of supercapacitors, reduce energy consumption, and prevent the state of charge (SOC) of HESS from exceeding the limitation. The new control scheme takes the characteristics of the components of HESS into account and is beneficial in reducing battery short-term power cycling and high discharge currents. The rain-flow counting algorithm is applied for battery life prediction to quantify the benefits of the HESS under the control scheme proposed. A much better power-sharing relationship between the supercapacitor and the lithium–ion battery (LiB) can be observed from the SIMULINK results and the case study with our new control scheme. Moreover, compared to the traditional low-pass filter control method, the battery lifetime is quantifiably increased from 3.51 years to 10.20 years while the energy efficiency is improved by 1.56%.

Keywords: hybrid energy storage system; cyber–physical system; multi-objective optimization; battery lifetime extension

1. Introduction

With the significant increase in the penetration of renewable energy power generation such as photovoltaics power and wind power in the power grid, the contradictions between the randomness of renewable energy power generation and the safe operation of the power grid have become increasingly prominent [1–3]. The input parameters of the sources considered are randomly varying with time [4]. Considering the output characteristics of wind power, photovoltaic power, and thermal power flexibility transformation, the energy storage system, as an important part of the renewable energy power generation system, can effectively suppress power fluctuations and maintain the stability of the bus voltage [5,6].

This paper proposes a hybrid energy storage system and a corresponding control scheme for photovoltaic generation. The hybrid energy storage system (HESS) combines supercapacitors and lithium–ion batteries (LiBs). According to the renewable energy generation characteristics, the power exchanges in HESS can be classified into high-frequency components and low-frequency components. The high-frequency part requires the storage systems to have a small response time, while the low-frequency part needs the storage
systems to have a high-energy density [7,8]. Combining the advantages of supercapacitors and LiBs, the high-frequency component is handled by the supercapacitor to reduce the battery cycle times. HESS has the characteristics of prolonging the life of LiBs and better suppressing power fluctuations [9]. Most studies of HESS control methods focus on the optimization of hybrid energy storage topology and energy power allocation strategies. The mainstream energy distribution strategies include low-pass filter distribution, fuzzy control, and particle swarm optimization algorithms [10–13]. The above control strategies can make better use of the advantages of the HESS and achieve the purpose of suppressing power fluctuations. However, these methods fail to consider the time variability of the HESS caused by factors such as changes in the battery’s internal resistance characteristics and temperature variation resulted from different charge and discharge rates and the state of charge (SOC).

Therefore, the operation process of the HESS is time-varying. In Wu et al.’s study, a novel knowledge-based, multiphysics-constrained energy management strategy is proposed with an emphasized consciousness of both thermal safety and degradation of onboard LiB system [14,15]. To solve the time-varying characteristics for the real-time accuracy of system control, this paper adopts a HESS control strategy based on a cyber–physical system (CPS). The CPS system monitors the SOC of HESS in real time for further optimization, which is intended to minimize the system loss and stabilize the battery power by increasing the supercapacitor utilization.

Some other studies consider the HESS from the multi-objective optimization perspective. Abdelkader et al. applied the NSGA-2 algorithm to optimize the capacity configuration of the HESS. The objective function is the minimization of the total cost of electricity and the loss of power supply probability of the load [16]. Amara et al. dealt with an improvement of an optimal sizing of a hybrid off-grid microgrid system to minimize the cost of produced energy and the reliability level required by customers [17]. Fantauzzi et al. proposed an original matrix formulation to solve the optimal sizing of energy storage for minimizing power losses [18]. Song et al. proposed the total cost of HESS and battery capacity loss as an objective function to obtain the optimized capacity configuration of the HESS, and the NSGA-2 algorithm was also adopted to obtain the Pareto front [19]. Choi et al. presented a power management system that provides the optimal solution to control the current flow in each energy storage element by solving multi-objective function with boundary parameters found through the multiplicative-increase-additive-decrease principle [20]. Since the above-mentioned multi-objective optimization research is to obtain the optimized capacity configuration of HESS, the genetic algorithm is suitable for global configuration. However, the processing method above cannot meet the real-time and robustness requirements of the CPS system. The CPS system needs to collect and calculate the field data of the HESS for real-time scheduling instructions. Dimensionality curse occurs if the optimization is applied with the vectorized objective function. For the real-time computing and stability requirements, the weighted sum scalarization method used in this article converts a multi-optimization problem into a single objective function which sacrifices the number of optimal solutions in exchange for computing performance to better adapt to the CPS system. As a result, the system can obtain the optimal power output of the hybrid energy storage system at every moment to ensure the real-time performance of the algorithm in practical applications. The weighted sum scalarization formula is shown in Equation (1):

$$F_j = \lambda_1 F_{1,j} + \lambda_2 F_{2,j} + \ldots + \lambda_m F_{m,j}$$  

where \( j \) represents the system state at the \( j \)-th moment, \( \lambda \) is the weighting coefficient, \( F_m \) is the \( m \)-th objective function, and \( \lambda_m \) is the weight of the \( m \)-th object to be optimized. According to Equation (1), the multi-objective optimization problem can be transformed into a single objective optimization problem for simplicity. The weighted sum scalarization method ensures the real-time performance of the algorithm in practical applications as well as avoid the dimensionality curse.
Few papers have so far studied the application of CPS in the field of HESS. This paper focuses on the multi-objective optimization control of HESS based on CPS. CPS relies on sensors and communication network to feed back the SOC of LiBs and supercapacitors to the cyber layer. Relevant research on reliable online estimation of SOC suggests that the proposed method estimates the model parameters, SOC, and capacity in real time with fast convergence and high accuracy [21]. A cyber–physical system that integrates communication, calculation, and control functions can provide a more precise and more effective dynamic control [22–24]. The novel multi-objective optimization control strategy can suppress power fluctuations, maximize system utilization efficiency, and minimize system losses.

This paper is organized as follows: in Section 2, a general framework for the topology of HESS with photovoltaic power generation systems (PV systems) and thermal power is proposed. The procedure of controlling the HESS based on the concept of CPS is discussed. Section 3 introduces the system model, including the multi-objective optimization control model. Section 4 gives the simulation result with the novel control scheme and the traditional control scheme compared in detail. In Section 5, a rain-flow counting algorithm for battery lifetime prediction is introduced to quantitatively analyze the battery lifetime extension. Finally, in Section 6, the conclusion is further emphasized.

2. System Design for Integrating CPS into HESS

This section introduces the HESS control model based on the CPS architecture. The CPS integrates the information control system with the primary equipment of HESS. The system relies on sensors and communication network to obtain the information of the state of HESS. The cyber layer uses the data collected from the physical layer to calculate and make accurate strategies for the HESS to allocate energy.

CPS is composed of two parts: one is a physical system operating under the physical laws, which directly affects the real devices. In this part, the physical layer includes LiBs, supercapacitors, and bidirectional DC/DC converters. Another part is the cyber layer which perceives, exchanges, and analyzes physical information within all parts of the physical devices. The control instructions generated by the cyber layer gives control commands to the physical layer. The cyber layer includes monitoring sensors, which are used to collect the SOC of LiBs and supercapacitors, multi-objective optimization control module and PI controllers, etc. The topology of HESS with PV is shown in Figure 1 [25]. The content indicated by the purple box is the main research object in this paper.

![Figure 1. The topology of HESS with PV.](image-url)
2.1. Physical Layer

In this paper, the power equipment at the physical layer includes LiBs, supercapacitors, and bidirectional DC/DC convertors.

In Figure 2, the LiB model is composed of a resistor and a controlled voltage source [26]. The SOC has been used as an indicator of the method, so the battery model uses only the SOC as a state variable. The proposed battery model is based on specific assumptions and has limitations: (1) the internal resistance is supposed constant during the charge and discharge cycles and doesn’t vary with the amplitude of the current, and (2) the temperature doesn’t affect the model’s behavior. The open-circuit voltage and battery voltage are determined by Equations (2) and (3).

\[
E = E_0 - K \frac{Q}{\int i_{\text{bat}} dt} + A \exp \left( -B \cdot \int i_{\text{bat}} dt \right) \tag{2}
\]

\[
V_{\text{bat}} = E - R \cdot i_{\text{bat}} \tag{3}
\]

where the \(E\) is the open-circuit voltage, \(E_0\) is the voltage constant, \(K\) is the polarization voltage, \(Q\) is the battery capacity, \(i\) is the battery current, \(A\) is the voltage amplitude in exponential area, \(B\) is the inverse of the time constant in the exponential area, and \(R_{\text{bat}}\) is the battery internal resistance.

![Figure 2. The equivalent model for LiB.](image)

The parameter of the controlled voltage source is obtained from the discharging curve in Figure 3 for accurate modelling.

![Figure 3. Typical discharging curve for LiB.](image)
According to Figure 6, the model parameters can be obtained from Equations (4)–(6).

\[ A = V_{\text{full}} - V_{\text{exp}} \]  
\[ B = 3/Q_{\text{exp}} \]  
\[ K = \left( V_{\text{full}} - V_{\text{nom}} + A(\exp(-BQ_{\text{nom}}) - 1) \right)(Q - Q_{\text{nom}})/Q_{\text{nom}} \]  

where \( Q_{\text{exp}} \) is the capacity in the exponential area, and \( Q_{\text{nom}} \) is the nominal capacity.

The SOC of LiB is determined by Equation (7)

\[ SOC_{\text{bt}}(t) = SOC_{\text{bt0}} - \int_{0}^{t} \frac{i_{\text{bt}}}{Q_{\text{bt}}} dt \]  

where \( SOC_{\text{bt0}} \) is the initial SOC.

The basic models for supercapacitors are the typical RC serial model and simplified RC model.

The RC serial model is shown in Figure 4a, where \( R_s \) is the internal resistance, while \( R_p \) is the self-discharging resistance. The typical value for \( R_p \) is large enough to be considered as an open circuit. Therefore, the simplified RC model can be obtained in Figure 4b, which is widely used for simplicity and good accuracy. The SOC of the supercapacitor is determined by Equation (8).

\[ SOC_{\text{sc}}(t) = SOC_{\text{sc0}} - \int_{0}^{t} \frac{V_{\text{sc}}i_{\text{sc}}}{0.5C_{\text{sc}}V_{\text{sc max}}^{2}} dt \]  

where \( SOC_{\text{sc0}} \) is the initial SOC, \( V_{\text{sc max}} \) is the maximum voltage, and \( C_{\text{sc}} \) is the capacity.

![Figure 4](image_url)  

Figure 4. (a) Typical supercapacitor RC model and (b) simplified supercapacitor RC model.

The fully active topology controls the power flow of LiBs and supercapacitors by bidirectional DC/DC. Since the CPS system is a real-time iterative process for HESS control, the equipment at the physical layer is required to respond quickly and accurately to the control commands from the cyber layer. This control scheme meets the requirements for rapid response and robustness of physical layer equipment during the real-time iteration of the CPS system. Figure 5 shows the control scheme of the DC/DC converter. The cyber layer gives control instructions. The control command is converted into the reference power signal of the LiBs and supercapacitor and input to the PI control loop. The instantaneous current of the LiBs and the supercapacitor is corrected by adjusting the duty cycle of the PWM signal.

2.2. Cyber Layer

Each state transition during the operation of the system can be defined as a cyber–physical coupled event. Typical cyber–physical coupled events include examples such as supercapacitor transits from charging mode to discharging mode and battery charging...
current changes, etc. Cyber–physical coupled events can be used as mediums that establish the relationship between discrete information flow and continuous power flow [27–29]. In consideration of the optimization problem with multiple objectives, the state of the system evolves through several transient states to the next steady state.

![Figure 5. The current control loop for DC/DC converter.](image)

Figure 5. The current control loop for DC/DC converter.

Figure 6 shows the procedure of controlling the HESS based on the concept of CPS. There may be several ways to combine multiple coupled events to achieve the target state. Therefore, it is necessary to arrange and combine a series of coupled events according to the multi-objective optimization strategy to determine the uniquely optimal combination [30]. The control of the HESS can be abstracted into an optimization problem, and the result follows the optimization goal setting. A certain combination of a series of coupled events can be regarded as the optimal strategy for the HESS.

![Figure 6. The procedure to control the HESS based on the concept of CPS.](image)

Figure 6. The procedure to control the HESS based on the concept of CPS.

For the cyber layer of HESS control, the power allocation strategy applied to HESS elements is a critical aspect that influences the result of the utilization of renewable energy and the service life of the HESS. The control and computation units (cyber parts) are responsible for managing the proposed control scheme in the small scale and household scenario, which ensures the system robustness and shortens the time delay for control instructions. Conversely, for large scale PV systems, electrical interconnections exist with each other, which leads to a commonly complicated control for coordinated operation. Under this circumstance, cloud computation takes over the control [31].

Generally, the optimization objectives of the energy management system (EMS) can be summarized into three aspects: (i) optimizing system performance, (ii) enhancing system reliability, and (iii) lowering set-up and operating cost [32]. In this paper, a low-pass filter combined with a multi-objective optimization control strategy is proposed. Figure 7 shows...
the power allocation scheme. The sensors collect the SOC of batteries and supercapacitors, with signals fed back to the multi-objective optimization module of the cyber layer. The cyber layer can perform real-time energy distribution according to the time-varying state of the system. This control strategy is designed to make the system more stable, more economical and energy-saving. It is our innovation to combine the concepts of CPS and multi-objective optimization into the control structure of HESS. The related data of neighbor energy resources and the SOC of LiBs and supercapacitors is needed to decide the allocation for each energy resource which is aligned with the concept of CPS. Otherwise, if the control strategy is designed without the relevant data, the effectiveness of cooperative control cannot be achieved. This would make the results in the control process of each energy resource be out of synchronization. Hence, the control structure of the allocation of the $j$-th energy resource is as follows.

![Power allocation scheme](image)

**Figure 7.** Power allocation scheme.

### 2.2.1. Low-Pass Filtering Algorithm

Up to date, to increase the economic feasibility of the expensive battery energy storage system, the proper control scheme is worthy of consideration. However, the intermittency of renewable energy sources harms battery life due to large power fluctuations and extra cycle times. The supercapacitor is therefore introduced to help absorb the high-frequency component. On this basis, this paper combines the battery system and the supercapacitor as a HESS for further optimized control. HESS includes LiBs and supercapacitors. LiBs are characterized by large energy storage capacity but low instantaneous charging and discharging power. Supercapacitors are characterized by a fast response, high instantaneous charging/discharging power and long cycle life but low energy storage capacity [10]. Therefore, HESS combines the advantages of LiBs and supercapacitors to maximize the advantages of the two types of energy storage and improve service life. The energy undertaken by HESS is divided into two parts: high-frequency component and low-frequency component. The high-frequency component is processed by supercapacitors, while the low-frequency component is processed by LiBs. Therefore, the power distribution in the HESS has the following relationship:

$$P_{\text{bat}}(s) = \frac{1}{1+sT_f} P_{\text{HESS}}(s)$$

$$P_{\text{sc}}(s) = P_{\text{HESS}}(s) - P_{\text{bat}}(s) = \frac{sT_f}{1+sT_f} P_{\text{HESS}}(s)$$

where $T_f$ is the filter time constant of the low pass filter, $P_{\text{HESS}}$ is the power for HESS, $P_{\text{bat}}$ is the low-frequency component allocated to the LiB, and $P_{\text{sc}}$ is the high-frequency component allocated to the supercapacitors.

Since this algorithm is operated by CPS, it needs to be implemented in a digital processor, so the low-pass filtering algorithm needs to be discretized. Suppose $\Delta T$ is the sampling period, the following equations can be obtained:

$$P_{\text{bat}}(j) = \frac{T_f}{T_f + \Delta T} P_{\text{bat}}(j-1) + \frac{T_f}{T_f + \Delta T} P_{\text{HESS}}(j)$$
\[
   P_{sc}(j) = \frac{T_f}{1/J + \Delta T} \{P_{sc}(j - 1) + [P_{\text{HESS}}(j) - P_{\text{HESS}}(j - 1)]\}
\]

According to Equations (11) and (12), it can be seen that \( P_{\text{bat}} \) slowly changes with \( P_{\text{HESS}} \), while \( P_{SC} \) changes rapidly with \( P_{\text{HESS}} \). This distribution rule also conforms to the performance of LiBs and supercapacitors.

2.2.2. Multi-Objective Optimization Model

The widely used hybrid energy storage control method is to pass the energy through a low-pass filter and then directly make the separated high-frequency part and low-frequency part generated by the batteries and the supercapacitors, respectively. However, this method has a limitation in that it fails to take the real-time SOC state of the HESS into consideration, which is a time-invariant system. In addition, this control strategy is passive and cannot improve the utilization efficiency of supercapacitors. Therefore, this paper is based on the CPS, with the time-variability of the batteries and the status of supercapacitors considered. The status data of the HESS are fed back to the cyber layer for decision-making in real time. The control strategy can prevent the SOC of HESS from exceeding the limitation, improving the utilization of supercapacitors, and reducing energy consumption. The objects to be optimized include the loss of the system and the utilization rate of the supercapacitor. The control variable is the battery current at each moment (i.e., the \( j \)-th moment). This paper is designed to solve the optimized combination of the above-mentioned two objectives by indicating an optimal battery current at each moment (i.e., the \( j \)-th moment).

(a) Loss model

Suppose that the loss of energy transfer is \( P_{j,\text{loss}} \), including the internal resistance loss of battery and supercapacitor \( P_{j,\text{lossbat}} \) and \( P_{j,\text{losssc}} \), the loss of convertors which control the LiBs and supercapacitors \( P_{j,\text{losscon1}} \) and \( P_{j,\text{losscon2}} \) (considering the switch loss and conduction loss), the loss of lines \( P_{j,\text{line}} \). The loss model is as follows:

\[
P_{j,\text{loss}} = P_{j,\text{lossbat}} + P_{j,\text{losssc}} + P_{j,\text{losscon1}} + P_{j,\text{losscon2}}
\]

\[
P_{j,\text{lossbat}} = i_{j,\text{bat}}^2 R_{bat}
\]

\[
P_{j,\text{losssc}} = i_{j,\text{sc}}^2 R_{sc}
\]

\[
P_{j,\text{losscon1}} = V_{bus} f_s i_{j,\text{bat}} \left( t_r + t_f \right) + i_{j,\text{bat}}^2 \left( R_{L1} + R_{S1} D_1 + R_{S2} D_2 \right)
\]

\[
P_{j,\text{losscon2}} = V_{bus} f_s i_{j,\text{sc}} \left( t_r + t_f \right) + i_{j,\text{sc}}^2 \left( R_{L1} + R_{S1} D_1 + R_{S2} D_2 \right)
\]

\[
P_{j,\text{line}} = i_{j,\text{bat}}^2 \rho L_{bat} / S + i_{j,\text{sc}}^2 \rho L_{sc} / S
\]

where \( R_{sc}, R_{bat} \) are the internal resistance loss of the battery and supercapacitor; \( V_{bus} \) is the bus voltage; \( f_s \) is the switching frequency; \( R_{S1}\)–\( R_{S4} \) are the conduct resistor; \( R_{L1}, R_{L2} \) are the resistance of inductance; \( D_1\)–\( D_4 \) are the duty cycles of convert switching; \( t_r, t_f \) are the rising time and falling time of switch current; \( \rho \) is the specific resistance; \( L_{bat} \) is the wiring length for batteries; \( L_{SC} \) is the wiring length for supercapacitor; and \( S \) is the sectional area of the wiring.

According to Equations (13)–(18), in order to minimize the energy loss of HESS, the loss model can be obtained as follows:

\[
\begin{align*}
    \min & \ L_j(i_{\text{bat}}) = \sum_{j=1}^{n} \left| P_{j,\text{loss}}(i_{\text{bat}}) / P_{j,\text{HESS}} \right| \\
    \text{s.t.} & \ P_{\text{HESS}} - V_{j,\text{bat}} V_{j,\text{SCmax}} \leq i_{j,\text{bat}} \leq i_{\text{batmax}}
\end{align*}
\]

where \( L \) is the normalized energy loss of the HESS, and \( i_{\text{batmax}}, i_{\text{scmax}} \) are the maximum current flowing through LiBs and supercapacitors.
(b) Optimization model of supercapacitor utilization

By improving the utilization rate of the supercapacitors, the fluctuation of the charge/discharge power of the batteries can be better smoothed, and the battery life can be extended. The control strategy in this paper is to use the cyber layer to monitor the SOC of the batteries and supercapacitors in real-time and allocate the energy more accurately. The optimization model of supercapacitor utilization is designed as follows:

\[
\begin{aligned}
\min U_j(i_{bat}) &= \sum \left( \frac{SOC_{bat}(i_{bat}) - SOC_{sc}}{SOC_{sc_{max}} - SOC_{sc_{min}}} \right) \\
\text{s.t.} \quad &P_{HESS} - V_{j,sc}i_{j,sc} \leq i_{j,sc} \leq i_{bat_{max}}
\end{aligned}
\]  

(20)

where \(U\) represents the difference between the SOC of the supercapacitor and the expected SOC.

In the optimization model, \(SOC_{j,sc}^*\) is the expected SOC of the supercapacitors. When \(P_{j,HESS} > 0\), HESS is in discharging state and \(SOC_{j,sc}^*\) is equal to \(SOC_{sc_{low}}\). When \(P_{j,HESS} < 0\), HESS is in a charging state and \(SOC_{j,sc}^*\) is equal to \(SOC_{sc_{high}}\). \(SOC_{sc_{high}}\) and \(SOC_{sc_{low}}\) are set as the maximum and minimum limits of the SOC of supercapacitors to prevent the supercapacitors from being over-charged or over-discharged. When HESS needs to discharge with the SOC of the supercapacitors is more than \(SOC_{sc_{low}}\), the supercapacitors would allocate more discharging power. When HESS needs to charge with the SOC of the supercapacitor is less than \(SOC_{sc_{high}}\), the supercapacitors will allocate more charging power. Thus, the purpose of improving the utilization rate of the ultracapacitor is realized. The diagram of the principle mentioned above is described in Figure 8. Figure 9a,b shows the charging/discharging regions for LiBs and supercapacitors.

![Figure 8. Diagram of supercapacitor state management.](image)

![Figure 9. Charging/discharging regions.](image)
(c) Integration of multi-objective optimization model

The solving process of multi-objective optimization is complicated. Therefore, it is not easy to achieve simultaneous optimization of multiple objectives. The optimal power output of the HESS at every moment should be obtained to ensure the real-time performance of the algorithm in practical applications. Taking the complexity of this process and the requirements for system reliability into account, the weighted sum scalarization method is applied to rewrite the multi-objective optimization problem into a single-objective optimization problem which can avoid the dimensionality curse. The solving process of multiple optimization objectives is as shown in Equation (21):

\[
\begin{align*}
\min & \quad M_j(t_{bat}) = \lambda L_j(t_{bat}) + (1 - \lambda)U_j(t_{bat}) \\
\text{s.t.} & \quad \frac{P_{j,HESS} - V_j \cdot \lambda_{sc}}{i_{j,bat}} \leq i_{j,bat} \leq i_{bat,max}
\end{align*}
\]

where \( \lambda \) is the weight coefficient, \( 0 \leq \lambda \leq 1 \). \( \lambda \) can be adjusted according to different control purposes. In this design, the loss reduction will be treated equally with the SOC management of the supercapacitor, that is \( \lambda = 0.5 \).

The cyber layer processes the real-time feedback data through the multi-objective optimization module to obtain the set of \( L \) and \( U \) at \( j \)-th time. The four black point sets in Figure 10 are the solution sets in the feasible region obtained at four different time slices, and the red star points are the optimal operating points. When the solution at each moment is the optimal solution, it can be considered as the global optimal solution by accumulating and iterating the same optimization process.

![Figure 10. The optimization process of the cyber layer.](image)

Additionally, according to Equation (21), \( L_j \) and \( U_j \) are determined by the battery current \( i_{j, bat} \). Hence, the original optimal problem can be solved by solving \( L_j \) and \( U_j \) stepwise. In addition, the lower limit and upper limit of \( i_{j, bat} \) at the \( j \)-th moment are both constant values. As a result, the feasible region of the decision variable \( i_{j, bat} \) in the feasible space is a line segment as a convex set. Therefore, the optimal solution of \( M_j \) at time \( j \) can be achieved by the weighted sum scalarization of \( L_j \) and \( U_j \).

(d) Charge/discharge protect model

The states of over-charge and over-discharge will cause the rapid decay of the cycle life of the energy storage. In order to avoid the occurrence of over-charge and over-discharge, a power pre-control method is adopted to ensure that the SOC of each energy storage component runs within the normal operating range.
According to the characteristics of the LiB, the SOC is generally controlled between 0.2 and 0.8. When the SOC of the LiB is between 0.2 and 0.4, it demonstrates stronger charging capacity; when the SOC is among 0.4–0.6, it presents more balanced charging and discharging capacity; when the SOC is among 0.6–0.8, it shows stronger discharge capacity.

For supercapacitors, it can be seen from Equation (22) that the SOC of a supercapacitor is the square function of the ratio of the supercapacitor’s terminal voltage to the maximum voltage of the supercapacitor. Its energy storage value can be managed by controlling the terminal voltage of the supercapacitor. Owing to the low terminal voltage during discharge requires highly for the bidirectional DC/DC converter when working in the boost state, the low limit of supercapacitors is set to 0.15. Similarly, to avoid overcharging of supercapacitors, the high limit of supercapacitors is set to 0.95. When it is between 0.8 and 0.95, the supercapacitor presents weak charging ability; when it is between 0.15 and 0.25, it presents weak discharge ability.

\[
SOC = \frac{E_{j,sc}}{E_{sc,max}} = \frac{\frac{1}{2}C U_{j,sc}^2}{\frac{1}{2}C U_{sc,max}^2} = \left( \frac{U_{j,sc}}{U_{sc,max}} \right)^2
\]  

(22)

Based on the performance of the energy storage unit, SOC is divided into five regions: no charging area, charging pre-control area, balance area, discharging pre-control area, and no discharging area. Figure 9 shows the charging/discharging regions of LiBs and supercapacitors.

The process of over-charge and over-discharge protection is as follows: in the balance area, the energy storage units directly assume the power-by-power distribution instruction. In the no charging/discharging area, the energy storage units are forbidden to charge and discharge. In the discharging pre-control area, the discharge power can be calculated by Equation (23). In the charging pre-control area, the charge power can be calculated by Equation (24).

\[
P_{j,dis} = P_{j,dis,max} \max \left\{ 0, \frac{SOC_j - SOC_{min}}{SOC_{low} - SOC_{min}} \right\}
\]  

(23)

\[
P_{j,ch} = P_{j,ch,max} \max \left\{ 0, \frac{SOC_{max} - SOC_j}{SOC_{max} - SOC_{high}} \right\}
\]  

(24)

According to Equations (23) and (24), the power will decrease after being processed. The reduced part will be assumed by the other energy storage unit. As the energy density of the supercapacitor is low, it is easy to over-charge and over-discharge. Therefore, the protection of the supercapacitor should be considered first in the process. The flow chart of over-charge and discharge protection is shown in Figure 11.
3. Simulation Results

To verify the effectiveness of the multi-objective optimization control system for HESS, this paper uses two schemes for simulation comparison. Scheme 1 is the multi-objective optimization control system based on CPS, and scheme 2 is the traditional low-pass filter control. The system simulation platform is built in MATLAB. The main parameter values of the simulation system are given in Table 1.

Since the power of the HESS mainly comes from the output power of renewable energy and thermal power generation and the load end, the final power composition has high random fluctuations. Therefore, the test power profile is given in Figure 12. The maximum amplitude of the given power fluctuation is ±2500 W. The simulation time is 5000 s. It is obvious that the test power contains a large amount of high-frequency components.

The efficiency = the loss energy / \( \int_0^t \text{the net power} \, dt \)  \hspace{1cm} (25)
schemes. The LiBs in scheme 2 bear a larger power, which will affect the service life of the LiBs. The LiBs adopting scheme 1 bear less power, which will greatly reduce the number of charge/discharge cycles of the LiB, and the current stress is lower. Figure 15 compares the results of the power undertaken by the LiBs of the two schemes. It can be seen from the two figures that both control methods can allocate the high-frequency part to the supercapacitors and the low-frequency power part to the LiBs, which can effectively suppress the instantaneous fluctuation of LiB power.

Table 1. HESS parameters.

| Parameter Name                     | Parameter Symbol | Parameter Values |
|------------------------------------|------------------|------------------|
| Rated capacity of LiB              | Q_{bat}          | 10 Ah            |
| Battery nominal voltage            | V_{bat}          | 90–110 V         |
| Battery internal resistance        | R_{bat}          | 0.5 Ω            |
| Rated capacity of supercapacitor   | C_{sc}           | 20 F             |
| Supercapacitor nominal voltage     | V_{sc}           | 40–100 V         |
| Supercapacitor internal resistance | R_{sc}           | 50 mΩ            |
| Inductance resistance              | R_{L1}, R_{L2}   | 0.2 Ω            |
| Switch on resistance               | R_{s1}–R_{s4}    | 0.1 Ω            |
| Low-pass filtering time constant   | T_f              | 30 s             |
| Sampling period                    | T_{sam}          | 5 s              |
| Switching frequency                | f_s              | 20 kHz           |
| Switch current rising time         | t_r              | 0.5 μs           |
| Switch current falling time        | t_f              | 0.5 μs           |
| Battery maximum current            | i_{batmax}       | 30 A             |
| Supercapacitor maximum current     | i_{scmax}        | 50 A             |
| Multi-objective optimization weight coefficient | λ               | 0.5              |
| The resistance of the copper rate  | ρ                | 1.75*10^{-8} Ω m|
| Sectional area                     | S                | 2.5 mm^2         |
| Wire length                        | L                | 10 m             |

Figure 12. The testing power profile.

The simulation comparison results of scheme 1 and scheme 2 are shown in Figures 13–19. Figure 13a,b show the power distribution results of the supercapacitor and the LiB by scheme 1 and scheme 2. It can be seen from the two figures that both control methods can allocate the high-frequency part to the supercapacitors and the low-frequency power part to the LiBs, which can effectively suppress the instantaneous fluctuation of LiB power. Figure 14 compares the results of the power undertaken by the LiBs of the two schemes. The LiBs in scheme 2 bear a larger power, which will affect the service life of the LiBs. The LiBs adopting scheme 1 bear less power, which will greatly reduce the number of charge/discharge cycles of the LiB, and the current stress is lower. Figure 15 compares the SOC of the LiBs between the two schemes. The SOC range in scheme 1 is between 0.21 and 0.54, and the range in scheme 2 is between 0.05 and 0.9. Scheme 1 can significantly reduce the depth of charge and discharge of LiBs.
the SOC of the LiBs between the two schemes. The SOC range in scheme 1 is between 0.21 and 0.54, and the range in scheme 2 is between 0.05 and 0.9. Scheme 1 can significantly reduce the depth of charge and discharge of LiBs.

Figure 16 compares the power taken by the supercapacitors in the two schemes. The utilization efficiency of the supercapacitor in scheme 1 is higher than that of scheme 2. The power allocated to the LiB can be better smoothed by improving the utilization rate of the supercapacitors. Figure 17 shows the SOC of supercapacitors in the two strategies. The SOC fluctuation range of the supercapacitors in the first scheme is 0.29–0.92, while that in the second scheme is 0.38–0.84. The utilization efficiency of supercapacitors increases by 36.96% with the CPS-based multi-objective optimization control strategy.

The L and U are previously defined as two objective functions. The Pareto front of the optimization problem is shown in Figure 18. As the U means the difference between the SOC of the supercapacitor and the expected SOC, the larger U indicates the lower the utilization rate of the supercapacitor. It can be seen from Figure 18 that when the U decreases as the supercapacitor participate more in the power regulation, the L accordingly increase as more energy loss. Table 2 depicts the values of the objective functions according to some founded solution points. These solutions include the least energy loss Sol.#1 and the maximum utilization of the supercapacitor Sol.#3, as well as the inflection solution Sol.#2. Comparing with Sol.#1 and Sol.#3, the L in Sol.#1 is lower than that in Sol.#3, which means the energy loss is less; it can also be verified from the simulation result that the power of energy loss is 60.25 W in Sol.#1 while 74.02 W in Sol.#3. The U in Sol.#1 is higher than that in Sol.#3. As the U represents the difference between the SOC of the supercapacitor and the expected SOC, the less U means the utilization rate of the supercapacitor is high. Therefore, the utilization rate of the supercapacitor in Sol.#1 is lower than that in Sol.#3. Simulation results also support the view that the utilization rate of the supercapacitor is 69.12% in Sol.#1 and 72.31% in Sol.#3.

Figure 13. (a) Hybrid energy storage power distribution operation result of CPS-based hybrid energy storage multi-objective optimization control strategy and (b) traditional low-pass filter control.

Figure 14. LiBs assumed power comparison.
Figure 13. (a) Hybrid energy storage power distribution operation result of CPS-based hybrid energy storage multi-objective optimization control strategy and (b) traditional low-pass filter control.

Figure 14. LiBs assumed power comparison.

Figure 15. LiBs SOC comparison.

Figure 16. Supercapacitors assumed power comparison.

Figure 17. Supercapacitors SOC comparison.

Figure 18. Optimal Pareto front.
Figure 16 compares the power taken by the supercapacitors in the two schemes. The utilization efficiency of the supercapacitor in scheme 1 is higher than that of scheme 2. The power allocated to the LiB can be better smoothed by improving the utilization rate of the supercapacitors. Figure 17 shows the SOC of supercapacitors in the two strategies. The SOC fluctuation range of the supercapacitors in the first scheme is 0.29–0.92, while that in the second scheme is 0.38–0.84. The utilization efficiency of supercapacitors increases by 36.96% with the CPS-based multi-objective optimization control strategy.

Figure 19 compares the system energy loss under the control strategy of the two schemes. Within 5000 s of the system simulation time, the energy loss in scheme 1 is $8.25 \times 10^5$ J comparing with $9.17 \times 10^5$ J in scheme 2. The efficiency can be calculated according to Equation (25); the energy efficiency of scheme 1 is improved by 1.56% compared with scheme 2.

Figure 18 compares the power taken by the supercapacitors in the two schemes. The utilization efficiency of the supercapacitor in scheme 1 is higher than that of scheme 2. The power allocated to the LiB can be better smoothed by improving the utilization rate of the supercapacitors. Figure 17 shows the SOC of supercapacitors in the two strategies. The SOC fluctuation range of the supercapacitors in the first scheme is 0.29–0.92, while that in the second scheme is 0.38–0.84. The utilization efficiency of supercapacitors increases by 36.96% with the CPS-based multi-objective optimization control strategy.

The L and U are previously defined as two objective functions. The Pareto front of the optimization problem is shown in Figure 18. As the U means the difference between the SOC of the supercapacitor and the expected SOC, the larger U indicates the lower the utilization rate of the supercapacitor. It can be seen from Figure 18 that when the U decreases as the supercapacitor participate more in the power regulation, the L accordingly increase as more energy loss. Table 2 depicts the values of the objective functions according to some founded solution points. These solutions include the least energy loss Sol.#1 and the maximum utilization of the supercapacitor Sol.#3, as well as the inflection solution Sol.#2. Comparing with Sol.#1 and Sol.#3, the L in Sol.#1 is lower than that in Sol.#3, which
means the energy loss is less; it can also be verified from the simulation result that the power of energy loss is 60.25 W in Sol.#1 while 74.02W in Sol.#3. The U in Sol.#1 is higher than that in Sol.#3. As the U represents the difference between the SOC of the supercapacitor and the expected SOC, the less U means the utilization rate of the supercapacitor is high. Therefore, the utilization rate of the supercapacitor in Sol.#1 is lower than that in Sol.#3. Simulation results also support the view that the utilization rate of the supercapacitor is 69.12% in Sol.#1 and 72.31% in Sol.#3.

Table 2. The solution point of the Pareto front.

| Solution | L   | U   | Energy Loss(W) | Utilization Rate of the Supercapacitor |
|----------|-----|-----|----------------|----------------------------------------|
| #1       | 0.085 | 0.334 | 60.25         | 69.12%                                 |
| #2       | 0.093 | 0.316 | 62.75         | 71.24%                                 |
| #3       | 0.114 | 0.295 | 74.02         | 72.31%                                 |

Figure 19 compares the system energy loss under the control strategy of the two schemes. Within 5000 s of the system simulation time, the energy loss in scheme 1 is $8.25 \times 10^5$ J comparing with $9.17 \times 10^5$ J in scheme 2. The efficiency can be calculated according to Equation (25); the energy efficiency of scheme 1 is improved by 1.56% compared with scheme 2.

4. Rain-Flow Counting Algorithm for Battery Lifetime Prediction

Many researchers have already studied how to extend battery life [33–35]. Thus, the studies mentioned above in this paper cannot well demonstrate to what extent the battery life can be prolonged. To better verify the improvement of the battery life in the scheme, it is essential to conduct a quantitative analysis of the battery lifetime extension. Therefore, the rain flow cycle counting algorithm for battery lifetime prediction is applied for further analysis.

The rain flow cycle counting algorithm is typically applied to analyze the fatigue data and has been widely used in various fields, such as metal fatigue estimation [2], life prediction [36,37], and energy storage system [38,39]. In this paper, the algorithm is applied to extract the charging and discharging cycles that the battery experienced, and simulation is conducted in SIMULINK. The cycle counting can be determined by the following steps:

1. Firstly, the local maximum and minimum points are stored in a numerical matrix by determining the critical point between charging and discharging.

2. Secondly, amplitude and duration time in each cycle is recorded. As can be seen from Figure 20a,b, the SOC of LiBs in the two schemes are resolved and recombined by several cycles and several half-cycles.

3. Thirdly, the total cycle number N, the DOD of each sub-cycle, and the time duration of each sub-cycle can be stored in a matrix.

Since one of the objectives to be optimized is the supercapacitor utilization, the supercapacitor takes over more power fluctuation. As shown in Figure 20a,b, the battery system takes less SOC fluctuation (in scheme 1) compared to scheme 2. In this way, the battery system cycles less for a longer life expectancy.

The battery lifetime model introduced in [37] can calculate the effect of both the charge/discharge cycles and the discharging rate on battery degradation. Therefore, based on the cycle-counting results, this battery lifetime model is effectively applied to this study.

Based on the battery lifetime prediction method, Table 3 demonstrates the lifetime improvement of the battery in the HESS. The smaller peak-to-peak current in scheme 1 means that the battery undergoes less stinging current. Based on the battery lifetime model, the battery lifespan in scheme 1 is predicted to be 10.20 years, whereas, in scheme 2, it is 3.51 years.
Figure 20. (a) Cycle counting of the DOD of LiBs in scheme 1. (b) Cycle counting of the DOD of LiBs in scheme 2.

Table 3. Battery lifetime prediction result.

| Scenarios | Peak to Peak Current | Prediction of Battery Lifetime |
|-----------|----------------------|------------------------------|
| Scheme 1  | 9.1A                 | 10.20 years                  |
| Scheme 2  | 27.9A                | 3.51 years                   |

5. Case Study

To further validate the effectiveness of the proposed method, a case study is conducted. To be specific, a typical output power profile of solar energy in a remote rural community, China, is given as 5 kW for household use. Figure 21 is the typical output power and load profile in a Chinese new energy community. The intermittent nature of solar energy and unstable load demand cause extreme fluctuation in power generation and load, and it is suitable for the simulation under noisy conditions.

In the case study, the maximum PV output power is 5 kW. The load profile is the red line in Figure 21, where the maximum load is hit during 20–23 pm. The configuration parameters for this case are listed in Table 4.
power and load profile in a Chinese new energy community. The intermittent nature of solar energy and unstable load demand cause extreme fluctuation in power generation and load, and it is suitable for the simulation under noisy conditions.

In the case study, the maximum PV output power is 5 kW. The load profile is the red line in Figure 21, where the maximum load is hit during 20–23 pm. The configuration parameters for this case are listed in Table 4.

Table 4. HESS parameters.

| Parameter Name                        | Parameter Symbol | Parameter Values |
|---------------------------------------|------------------|------------------|
| Rated capacity of LiB                 | \( Q_{\text{bt}} \) | 1000 Ah          |
| Battery nominal voltage               | \( V_{\text{bt}} \) | 90–110 V         |
| Battery internal resistance           | \( R_{\text{bt}} \) | 0.5 \( \Omega \) |
| Rated capacity of supercapacitor      | \( C_{\text{sc}} \) | 1000 F           |
| Supercapacitor nominal voltage        | \( V_{\text{sc}} \) | 40–100 V         |
| Supercapacitor internal resistance    | \( R_{\text{sc}} \) | 50 m\( \Omega \) |
| Inductance resistance                 | \( R_{L1, L2} \) | 0.2 \( \Omega \) |
| Switch on resistance                  | \( R_{s1-s4} \)  | 0.1 \( \Omega \) |
| Low-pass filtering time constant      | \( T_f \)        | 30 s             |
| Sampling period                       | \( T_{\text{sam}} \) | 30 s             |
| Switching frequency                   | \( f_s \)        | 20 kHz           |
| Switch current rising time            | \( t_r \)        | 0.5 \( \mu s \)  |
| Switch current falling time           | \( t_f \)        | 0.5 \( \mu s \)  |
| Battery maximum current              | \( i_{\text{batmax}} \) | 30 A           |
| Supercapacitor maximum current       | \( i_{\text{scmax}} \) | 50 A           |
| Multi-objective optimization weight coefficient | \( \lambda \) | 0.5          |
| The resistance of the copper rate     | \( \rho \)       | \( 1.75 \times 10^{-8} \) \( \Omega \cdot \text{m} \) |
| Sectional area                        | \( S \)          | 2.5 mm\(^2\)     |
| Wire length                           | \( L \)          | 10 m             |

Figure 22a,b are the comparative analysis for the effectiveness of the control scheme in this paper and the traditional low pass filter-based control method. It can be observed from the green circle in Figure 23 that less power fluctuation and cycles are taken by the battery system, while in Figure 24, the supercapacitor takes over more power fluctuations by increasing its utilization rate with the optimization method in this paper. Figure 25 depicts that the energy loss in scheme 1 is \( 3.35 \times 10^7 \) J compared with \( 4.24 \times 10^7 \) in scheme 2, and the energy efficiency is improved by 2.73%.
Figure 22. (a) Hybrid energy storage power distribution operation result of CPS-based hybrid energy storage multi-objective optimization control strategy and (b) traditional low-pass filter control.

Figure 23. LiBs assumed power comparison.
proposed model is also suitable for a set of more batteries and supercapacitors. When the CPS can prominently improve the performance of HESS under real-world cases. The proposed multi-objective optimization control strategy based on CPS is designed. A multi-objective optimization (MOP) based low-pass filter scheme is proposed to actively control the energy flow by setting the supercapacitor utilization rate as one of the control objectives. In this way, the supercapacitor takes over more high-frequency components to mitigate both power fluctuation and depth of discharge of the battery system for life expectancy extension purposes. As a result, compared with the traditional low-pass filter control method, the utilization efficiency of supercapacitors is increased by 42.22%. The battery lifespan in this study is predicted to be 10.20 years, which is much longer than that in the traditional low-pass method of 3.51 years. Moreover, the energy loss is decreased to $8.46 \times 10^5$ J comparing with $9.47 \times 10^5$ J in the scheme of a low-pass filter, which indicates a 1.54% efficiency increase. Additionally, a case study is conducted in a remote rural community, where the typical PV generation is given as 5kW for household use. The supercapacitor in the system absorbs short term power fluctuations, and the energy efficiency ratio reaches 89.74%. Therefore, it can be concluded that the proposed multi-objective optimization control strategy based on CPS can prominently improve the performance of HESS under real-world cases. The proposed model is also suitable for a set of more batteries and supercapacitors. When the system includes a set of more batteries and supercapacitors, the real-time SOC states of each battery and supercapacitor are different. Therefore, specific energy scheduling instructions need to be adjusted according to the SOC states of each battery and supercapacitor. Another case is that the proposed model can also apply to other types of HESS. No matter what

Figure 24. Supercapacitors assumed power comparison.

Figure 25. Comparison of energy loss.

6. Conclusions
In this paper, a multi-objective optimization control of battery–supercapacitor hybrid energy storage system based on CPS is designed. A multi-objective optimization (MOP) based low-pass filter scheme is proposed to actively control the energy flow by setting the supercapacitor utilization rate as one of the control objectives. In this way, the supercapacitor takes over more high-frequency components to mitigate both power fluctuation and depth of discharge of the battery system for life expectancy extension purposes. As a result, compared with the traditional low-pass filter control method, the utilization efficiency of supercapacitors is increased by 42.22%. The battery lifespan in this study is predicted to be 10.20 years, which is much longer than that in the traditional low-pass method of 3.51 years. Moreover, the energy loss is decreased to $8.46 \times 10^5$ J comparing with $9.47 \times 10^5$ J in the scheme of a low-pass filter, which indicates a 1.54% efficiency increase. Additionally, a case study is conducted in a remote rural community, where the typical PV generation is given as 5kW for household use. The supercapacitor in the system absorbs short term power fluctuations, and the energy efficiency ratio reaches 89.74%. Therefore, it can be concluded that the proposed multi-objective optimization control strategy based on CPS can prominently improve the performance of HESS under real-world cases. The proposed model is also suitable for a set of more batteries and supercapacitors. When the system includes a set of more batteries and supercapacitors, the real-time SOC states of each battery and supercapacitor are different. Therefore, specific energy scheduling instructions need to be adjusted according to the SOC states of each battery and supercapacitor. Another case is that the proposed model can also apply to other types of HESS. No matter what
type of energy storage is used, it is under the framework of energy-type energy storage and power-type energy storage. The control principle of hybrid energy storage is to use power-type energy storage to smooth out power fluctuations, thereby extending the cycle life of energy-type energy storage. Therefore, the model proposed in this paper can also be further applied to other types of hybrid energy storage.

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