

Digital-Twin-in-the-Loop Dual-Layer Time–Frequency Decomposition and Capacity Configuration of Hybrid Energy Storage for Wind Power

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Abstract

INTRODUCTION: Conventional hybrid energy storage sizing often relies on fixed frequency thresholds and insufficiently considers device constraints and economic objectives. This study proposes a digital-twin-in-the-loop capacity configuration method based on dual-layer time–frequency decoupling.

METHODS: ICEEMDAN was used to decompose wind power, while power, energy, and duration characteristics were extracted for mode classification. SGMD was applied only to transition modes identified from battery, supercapacitor, and PCS capabilities. SAC determined the SGMD parameters and critical-mode allocation ratios. Initial capacities were obtained from the 95th-percentile power and cumulative energy trajectories and corrected through multi-scenario digital-twin evaluation.

RESULTS: For a 50 MW wind farm, the final battery and supercapacitor capacities were 1.53 MW/2.65 MWh and 0.50 MW/0.10 MWh, respectively. The total cost was RMB 31.2561 million, corresponding to reductions of 15.75% and 8.76% relative to the single-layer ICEEMDAN configuration and the fixed-parameter ICEEMDAN+SGMD configuration considered in the component-wise comparison. Rapid grid-power fluctuations were also reduced.

CONCLUSION: The proposed method coordinates time-scale separation, device constraints, and configuration economy, providing an effective approach for wind-power hybrid energy storage planning.

Keywords: Hybrid energy storage, Capacity configuration, Digital twin, Soft Actor–Critic, ICEEMDAN, SGMD

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1. Introduction

Driven by the carbon peaking and carbon neutrality goals, the installed capacity of renewable energy sources such as photovoltaic and wind power has continued to increase, and these sources have gradually become an important component of modern power systems. However, renewable energy output is characterized by strong randomness, large

fluctuations, and multi-time-scale variations, and its power generation exhibits significant uncertainty with changes in meteorological conditions [1]. Under large-scale grid integration, the above characteristics significantly increase the difficulty of maintaining power balance in the grid and may lead to problems such as frequency fluctuations, increased peak-regulation pressure, and restricted local accommodation. These issues impose higher requirements on the secure and stable operation of the power grid as well as on dispatching flexibility [2,3].

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Existing studies have investigated energy storage planning and operation from different perspectives. In [4], an MPC-based coordinated control strategy was developed for wind turbines and battery energy storage participating in frequency regulation, in which the BESS participation state was adjusted according to wind speed and SOC to improve system frequency-regulation performance. In [5], a synchronization-based grid-connection method for grid-forming energy storage was proposed to support isolated grid operation. In [6], an adaptive collaborative optimization strategy was combined with an improved deep deterministic policy gradient method to optimize grid-side energy storage allocation and improve renewable energy accommodation. In [7], a hybrid-energy-storage capacity-allocation method based on successive variational mode decomposition was proposed for wind-power frequency regulation, where high- and low-frequency power components were assigned to flywheel and lithium-battery storage, respectively, and the storage capacities were optimized considering economic objectives and operational constraints.

The inherent performance limitations of a single energy storage technology make it difficult to simultaneously satisfy multiple requirements, such as energy density, power density, response speed, and cycle life. To overcome these technical bottlenecks, hybrid energy storage systems integrate energy-type storage devices with power-type storage devices, thereby achieving complementary advantages. Current research on hybrid energy storage systems (HESSs) mainly focuses on capacity configuration, control strategies, and future development directions [8]. In [9], a two-stage scheduling framework for an active distribution network with hybrid energy storage was developed to improve economic performance. In [10], a power management strategy based on a hybrid artificial neural network and model predictive control was proposed to extend battery life and stabilize the DC bus voltage. In [11], a hierarchical multi-timescale reinforcement learning framework was proposed for battery-supercapacitor HESS energy management, separating fast constraint enforcement, learning-based power allocation, and slow SOH-aware adaptation to improve operational safety and battery lifetime. In [12], a communication-free adaptive coordinated control strategy was developed for grid-forming hybrid energy storage converters, which improved supercapacitor utilization and battery service life. In [13], an adaptive power allocation and power predictive control strategy for HESS was proposed, and its advantages in maintaining voltage stability and improving system response speed were verified.

Given the complementary characteristics of HESSs in terms of power density and energy density, as well as their significant advantages in enhancing system stability, their capacity configuration needs to reasonably coordinate the power and energy allocation among different types of energy storage units. Regarding renewable generation-storage planning, [14] jointly optimized the siting and sizing of photovoltaic generation, wind turbines, and battery storage in a distribution network by considering flicker mitigation, power-loss reduction, voltage deviation, and storage cost. This method can effectively improve the economic benefits

of wind-storage combined systems under power smoothing and automatic generation control assessment conditions. In [15], the minimum mean envelope entropy was taken as the optimization objective, and the particle swarm optimization algorithm was used to optimize the parameters of variational mode decomposition. A simulation model was then constructed based on typical area control error data from a wind farm to verify the feasibility of the method. Among the capacity configuration methods for HESSs, one important approach is to decompose the fluctuation characteristics of power and then distinguish energy-type and power-type capacity requirements. In [16], a bi-level capacity optimization configuration model for a park-level integrated energy microgrid with HESSs was proposed by considering flexibility adequacy and stepped carbon trading. In [17], a HESS capacity configuration strategy based on variational mode decomposition optimized by an improved Harris hawks optimization algorithm was proposed. Through adaptive decomposition and reconstruction, grid-compliant power was obtained, which improved system stability while effectively reducing the energy storage configuration cost compared with the original algorithm. In [18], a wavelet-transform-based capacity allocation method for secondary frequency regulation with HESSs was proposed. Although the above studies have improved the modeling, control, and capacity configuration of hybrid energy storage systems, most of them still focus on offline sizing or fixed power allocation. In practical wind-storage systems, wind power, grid-connected power, storage state of charge, power conversion limits, and data quality vary continuously with operating conditions. If these time-varying operational data are not incorporated into the scheduling and sizing process, the obtained capacity configuration may be difficult to maintain stable performance under different wind fluctuation scenarios. Therefore, hybrid energy storage configuration should be further extended from static capacity sizing to data-driven adaptive scheduling and rolling capacity recommendation.

With the development of data-driven methods, deep reinforcement learning (DRL) has increasingly been applied to energy-storage scheduling and complex parameter decision-making, enabling adaptive policies to be learned from operating states and environmental feedback. A digital twin (DT), meanwhile, provides a virtual operating environment for storage-state prediction, control validation, and device-constraint verification. However, existing studies have mainly focused on operational scheduling, condition monitoring, or fault diagnosis under prescribed storage capacities. Few studies have incorporated time-frequency decomposition parameters, modal power allocation, dynamic storage states, and long-term capacity requirements into a unified evaluation framework. In particular, a clear engineering pathway for correcting capacity-configuration results using feedback from multiple wind conditions has yet to be established.

In summary, three major limitations remain. First, decomposition-parameter optimization is commonly based on signal-level metrics such as envelope entropy and reconstruction error, whereas capacity planning ultimately concerns storage power requirements, energy requirements,

device operating states, and configuration costs. A clear quantitative linkage between these two levels is still lacking. Second, although assigning high-frequency modes to the supercapacitor and low-frequency modes to the battery is intuitively reasonable, the assignment of critical modes may be strongly affected by wind conditions, window length, and sampling resolution when physical criteria such as power amplitude, ramp rate, duration, energy requirement, state of charge (SOC), terminal voltage, and PCS capability are not considered. Third, existing case studies primarily focus on capacity and cost, while providing insufficient validation of engineering indicators such as compliance rates for 1-min and 10-min power fluctuations, grid-connection limit violations, SOC trajectories, supercapacitor terminal voltage, PCS saturation, and lifetime degradation. It is therefore difficult to determine whether the resulting capacities can satisfy both grid and device constraints during continuous multi-scenario operation.

To address these limitations, this paper proposes a physics-informed power-allocation and capacity-verification method for wind-power HESSs under grid-connection and device operating constraints. First, ICEEMDAN is used to identify multiscale regulation requirements in wind power. Transition modes are determined according to frequency-band overlap, power persistence, and operational feasibility when handled by a single storage technology. Secondary SGMD is triggered only for modes that cannot be reasonably accommodated by either the battery or the supercapacitor alone. Second, a constrained soft actor–critic (SAC) algorithm is employed to determine the secondary-decomposition parameters and the allocation of critical modes. The resulting decisions are evaluated through downstream power requirements, device operating states, grid-connection performance, and minimum feasible capacity. Finally, initial capacities are derived from power quantiles and energy trajectories. Continuous operating verification is then conducted in a planning-and-validation-oriented DT environment under multiple seasons, wind conditions, and variations in device parameters, thereby determining the HESS capacities and engineering reserve margins that satisfy both grid and device constraints.

The main contributions of this paper are as follows:

- (i) A planning-and-validation-oriented DT model is developed for wind-power HESS capacity configuration. The model jointly represents the dynamic characteristics of the lithium-ion battery, supercapacitor, PCS, and point of common coupling (PCC), thereby providing a unified simulation environment for the continuous multi-scenario verification of different capacity schemes.
- (ii) A DT-driven DRL decision-making method is proposed. SAC adaptively optimizes the SGMD parameters and critical-mode allocation, while grid-connection performance, device operating states, lifetime degradation, and configuration cost form a closed-loop feedback mechanism. This framework enables coordinated optimization of decomposition decisions and capacity-configuration objectives.
- (iii) A HESS capacity-configuration method integrating dual-layer time–frequency decoupling with DT-based verification is proposed. Secondary decomposition of transition modes is triggered using physical criteria, initial capacities are obtained through annual sliding-window analysis, and the minimum feasible capacities and reserve margins satisfying grid and device constraints are determined from operating results under multiple wind conditions.

2. Digital Twin System and Engineering Constraints for Wind-Power Hybrid Energy Storage

2.1. Structure of the Grid-Connected Wind-Power Hybrid Energy Storage System

As shown in Figure 1, the wind power–energy storage system mainly consists of a wind farm, a hybrid energy storage system (HESS), power conversion systems (PCSs), an energy management system (EMS), and a grid-connection interface. These components jointly coordinate and smooth the wind power delivered to the grid [19].

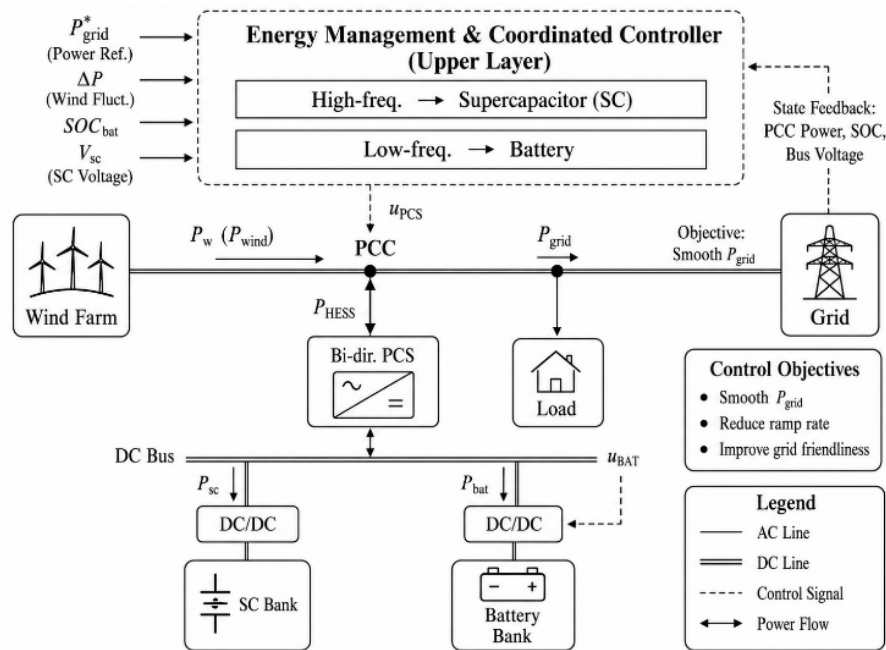


Figure 1. Topology of the wind-storage integrated system

The HESS is connected to the PCC through a bidirectional PCS. On the DC side, the supercapacitor bank and lithium-ion battery bank are connected to a common DC bus through their respective bidirectional DC/DC converters, thereby enabling bidirectional power exchange between the individual storage units and the grid-connected system. In addition, operating variables, including the PCC power, battery SOC, and DC-bus voltage, are fed back to the coordinated controller in real time. Based on this feedback, the controller adjusts the control commands of the PCS and DC/DC converters to maintain stable system operation under wind-power fluctuations, load variations, and changes in the storage operating states.

The measured wind-power records originate from a 50 MW wind farm and are sampled at a one-minute interval. Figure 2 presents the normalized representation used for numerical processing and fluctuation characterization. The normalized signal is dimensionless, whereas the storage power, energy-capacity, PCS-rating, and economic quantities reported in the engineering evaluation are expressed in physical units of MW, MWh, and RMB.

The original wind-power measurements are recorded in units of 10 kW. Accordingly, the physical wind power is obtained as $P_{\text{phys}}(t) = 0.01P_{\text{raw}}(t)\text{MW}$. The physical power is subsequently normalized by the rated wind-farm capacity as $P_{\text{pu}}(t) = P_{\text{phys}}(t)/50$. All storage-power, energy-capacity, PCS-rating, and economic calculations are performed after conversion back to physical units.

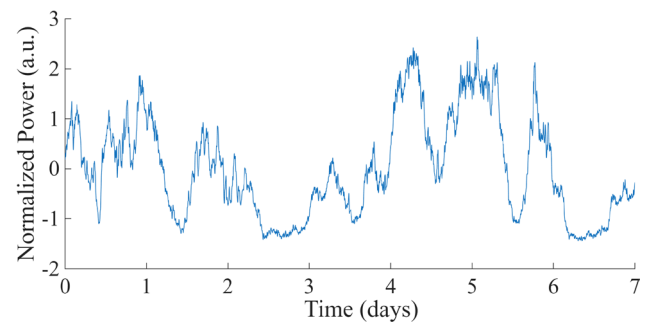


Figure 2. Normalized representation of the measured wind-power sequence

2.2. Dynamic Digital-Twin Models of the Hybrid Energy Storage System and Power Conversion Devices

2.2.1 Dynamic Model

The lithium-ion battery is a typical energy-oriented storage device characterized by high energy density, sustained energy-delivery capability, and flexible capacity sizing. It is therefore well suited to compensating for low-frequency components of wind-power fluctuations that exhibit long durations and substantial cumulative energy requirements [21].

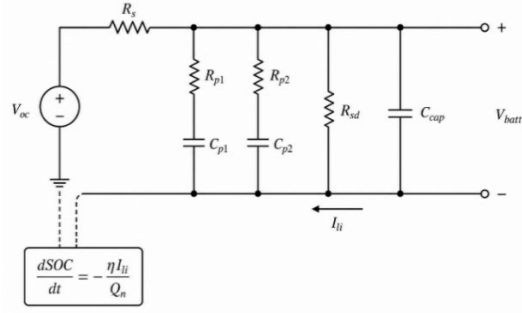


Figure 3. Equivalent circuit model of the lithium-ion battery

As shown in Figure 3, its terminal voltage can be expressed as

$$V_{batt}(t) = V_{oc}(S_{li}(t)) - I_{li}(t)R_s - V_p(t) \quad (1)$$

where $V_{batt}(t)$ is the battery terminal voltage; $V_{oc}(S_{li}(t))$ is the open-circuit voltage related to the SOC; $I_{li}(t)$ is the battery charging or discharging current; R_s is the equivalent series resistance; and $V_p(t)$ is the dynamic voltage deviation generated by the polarization branch. When the battery is required to compensate for rapidly varying power components, frequent variations in $I_{li}(t)$ cause repeated fluctuations in the ohmic voltage drop and polarization voltage, thereby increasing resistive heating losses and electrochemical stress.

Supercapacitors are characterized by high power density and rapid charge/discharge capability, but their relatively low energy density limits their ability to provide sustained energy support. In battery–supercapacitor HESSs, coordinated energy management can therefore assign high-frequency power components to the supercapacitor and slower energy components to the battery [22]. In this study, the dynamic characteristics of the supercapacitor are represented by the second-order simplified equivalent circuit model shown in Figure 4. The R_1-C_1 branch has a relatively small time constant and is used to model the instantaneous charging and discharging behavior of the supercapacitor. The R_2-C_2 branch has a relatively large time constant and describes charge redistribution during and after the charging or discharging process. R_L denotes the leakage resistance and characterizes the self-discharge behavior of the supercapacitor during prolonged idle periods.

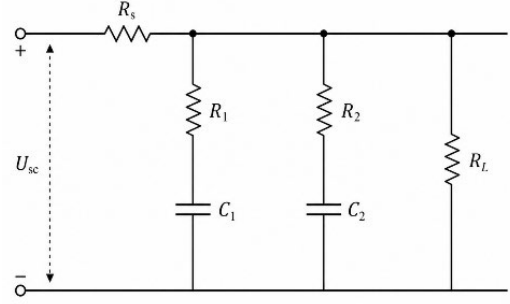


Figure 4. Second-order simplified model of the supercapacitor

From the perspective of the energy-storage mechanism, the relationship between the energy stored in the supercapacitor and its terminal voltage is expressed as

$$E_{sc}(t) = \frac{1}{2} C_{sc} U_{sc}^2(t) \quad (2)$$

where $E_{sc}(t)$ is the energy stored in the supercapacitor, C_{sc} is the equivalent capacitance, and $U_{sc}(t)$ is the supercapacitor terminal voltage. The charging and discharging processes directly change the terminal voltage, while the available energy is constrained by the capacitance and allowable operating-voltage range. Therefore, the supercapacitor is suitable for rapidly absorbing or releasing short-duration power, but is unsuitable for continuously compensating for low-frequency energy imbalances over extended periods.

Considering the allowable terminal-voltage range, the available energy of the supercapacitor can be expressed as

$$E_{sc}^{use} = \frac{1}{2} C_{sc} \left[\left(U_{sc}^{max} \right)^2 - \left(U_{sc}^{min} \right)^2 \right] \quad (3)$$

where U_{sc}^{max} and U_{sc}^{min} are the upper and lower allowable operating-voltage limits of the supercapacitor, respectively. Equation (3) indicates that the energy-regulation capability of the supercapacitor is strictly constrained by its operating-voltage range. When the supercapacitor compensates for sustained low-frequency power, its terminal voltage changes continuously in one direction and may approach either voltage limit, thereby reducing the available regulation margin for subsequent high-frequency fluctuations.

To exploit the complementary characteristics of the lithium-ion battery and supercapacitor in terms of power capability, energy capacity, and dynamic response, the compensation power is no longer allocated solely according to a fixed frequency threshold. Instead, the modal characteristic power, cumulative energy requirement, equivalent duration, and available capabilities of the storage devices and PCS are jointly considered to perform physics-based assignment and coordinated allocation of different regulation requirements.

2.2.2 PCS Dynamic Response and Power-Saturation Model

The battery-side and supercapacitor-side branches perform AC/DC power conversion through their respective PCSs. For storage type i , where $i \in \{\text{BAT}, \text{SC}\}$, the executable power limits jointly imposed by the PCS and storage device are

$$\bar{P}_i(t) = \min\{P_{\text{PCS},i}^N, P_{i,\text{dis}}^{\text{ava}}(t)\} \quad (4)$$

$$\underline{P}_i(t) = \min\{P_{\text{PCS},i}^N, P_{i,\text{ch}}^{\text{ava}}(t)\} \quad (5)$$

where $P_{\text{PCS},i}^N$ is the rated power of the PCS in the corresponding branch, and $P_{i,\text{dis}}^{\text{ava}}(t)$ and $P_{i,\text{ch}}^{\text{ava}}(t)$ are the available discharge and charge powers of the storage unit, respectively.

The reference power generated by the DRL and power-allocation modules is physically limited as

$$P_i^{\text{lim}}(t) = \min[\bar{P}_i(t), \max(-\underline{P}_i(t), P_i^{\text{ref}}(t))] \quad (6)$$

To represent the dynamic tracking process of the PCS and storage branch, a first-order lag model is used to calculate the actual AC-side power:

$$P_i^{\text{act}}(t+1) = e^{-\Delta t/\tau_i} P_i^{\text{act}}(t) + (1 - e^{-\Delta t/\tau_i}) P_i^{\text{lim}}(t) \quad (7)$$

where τ_i is the equivalent response time constant of storage branch i . Different time constants are assigned to the battery and supercapacitor branches to reflect their different dynamic response capabilities.

Considering the PCS conversion efficiency, the DC-side power of the storage unit is calculated as

$$P_i^{\text{dc}}(t) = \begin{cases} \frac{P_i^{\text{act}}(t)}{\eta_i(t)}, & P_i^{\text{act}}(t) \geq 0 \\ \eta_i(t) P_i^{\text{act}}(t), & P_i^{\text{act}}(t) < 0 \end{cases} \quad (8)$$

where $\eta_i(t)$ is the PCS conversion efficiency. When a complete efficiency curve is unavailable, the rated efficiency may be adopted. When detailed equipment data are available, the efficiency should be modeled as a function of the PCS loading ratio.

The PCS saturation indicator is defined as

$$\delta_i^{\text{sat}}(t) = \begin{cases} 1, & P_i^{\text{ref}}(t) > \bar{P}_i(t) \text{ or } P_i^{\text{ref}}(t) < -\underline{P}_i(t) \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

and the corresponding unmet power is

$$P_i^{\text{unmet}}(t) = P_i^{\text{ref}}(t) - P_i^{\text{act}}(t) \quad (10)$$

The number and duration of PCS saturation events, together with the unmet power, can be used to determine whether the rated PCS power is insufficient.

2.2.3 Digital-Twin State Updating and Decision Interface

Based on the reference power and candidate capacity configuration, the DT model updates the battery SOC and SOH, supercapacitor terminal voltage, PCS power margin, actual grid-connected power, and unmet power, and feeds these updated states back to the DRL agent. The agent subsequently adjusts the SGMD parameters and critical-mode allocation ratio so that its decisions satisfy not only the signal-decomposition requirements but also the dynamic operating limits of the storage devices. The main input and output variables of the edge-side coordination module are summarized in Table 1.

Table 1. Main Input and output variables of the edge-side coordination module

Module	Key variables	Function
Wind farm	Wind power, ramping rate, time stamp	Input for fluctuation decomposition
PCC	Grid-connected power, voltage, frequency	Smoothing assessment
Battery system	SOC, voltage, current, allowable power	Low-frequency energy regulation
Supercapacitor system	SOC, terminal voltage, power margin	High-frequency power compensation
PCS	Operating state, power limit, efficiency	Power command correction
Edge-side module	Fast/slow demand, power command, capacity result	Scheduling and sizing output

2.3. Grid-Connected Operating Constraints and Capacity Evaluation Metrics

When a wind farm is directly connected to the power grid, rapid increases or decreases in output power over short time intervals may cause voltage fluctuations and changes in power flow, thereby increasing the regulation burden on the grid. Therefore, the energy storage system is required to

smooth the wind-power output so that the power delivered to the grid satisfies the relevant operating requirements [20], as summarized in Table 2.

Table 2. National Standard for Wind Power Grid

Installed Capacity/MW	ΔP_{1min}	ΔP_{10min}
<30	3	10
30~150	Prated/10	Prated/3
>150	15	50

When the variation in grid-connected power exceeds the allowable range, a power-fluctuation limit violation occurs. With reference to the grid-connection assessment mechanism, the magnitude of the violation can be expressed as

$$Q_{lim}(t) = \begin{cases} \alpha_{PH}\Delta T[P_{grid}(t) - P_{uplim}(t)], & P_{grid}(t) > P_{uplim}(t) \\ 0, & P_{dnlim}(t) \leq P_{grid}(t) \leq P_{uplim}(t) \\ \alpha_{PH}\Delta T[P_{dnlim}(t) - P_{grid}(t)], & P_{grid}(t) < P_{dnlim}(t) \end{cases} \quad (11)$$

where $Q_{lim}(t)$ is the assessed energy corresponding to the power-fluctuation limit violation at time t ; $P_{uplim}(t)$ and $P_{dnlim}(t)$ are the upper and lower allowable limits of grid-connected power fluctuations, respectively; ΔT is the sampling interval of the wind-power data; and α_{PH} is the conversion coefficient for power-fluctuation assessment. No power-fluctuation assessment is incurred when $P_{grid}(t)$ remains within the allowable upper and lower limits.

The basic parameters of the lithium-ion battery, supercapacitor, and PCS are listed in Table 3.

Table 3. Basic Parameters

Parameter	Value (p.u.)	Parameter	Value (p.u.)
Battery SOC range	0.1–0.9	Initial battery SOC	0.5
Initial battery SOH	1	Battery SOH limit	0.8

Battery charge efficiency	0.97	Battery discharge efficiency	0.97
Max. battery C-rate	1.0 C	Normal battery C-rate	≤0.5 C
Initial SC energy state	0.5	SC charge/discharge efficiency	0.98
PCS charge efficiency	0.98	PCS discharge efficiency	0.98
Power reserve factor	1.1	Energy reserve factor	1.1
Allowable SC voltage range	0.50–1.00	Initial SC terminal voltage	0.707
Capacity convergence tolerance	0.01	Maximum capacity correction per iteration	0.05

2.4. Digital-Twin Architecture

To avoid treating the lithium-ion battery, supercapacitor, and PCS as ideal actuators during capacity configuration, this paper develops a DT system for wind-power smoothing and HESS capacity planning. The wind farm, lithium-ion battery, supercapacitor, PCSs on both storage branches, and PCC are modeled as the principal twin objects. Based on the candidate capacities and reference power commands, the system calculates the actual storage power, battery SOC and SOH, supercapacitor terminal voltage, and grid-connected power, thereby providing a simulation environment for subsequent DRL decision-making and capacity verification.

The present study is mainly based on historical wind-power data, equipment specifications, and MATLAB/Simulink models. Therefore, the proposed model is defined as a planning-validation DT intended primarily for offline and quasi-online operational verification of candidate capacity schemes. It is not equivalent to a real-time DT established using field measurements from an operating system.

As shown in Figure 5, the system comprises four layers: physical entities, data mapping, virtual twin and decision-making, and engineering applications. After preprocessing and parameter mapping, equipment operating data are input into the battery, supercapacitor, PCS, and PCC models. The DT then calculates the device states and grid-connection metrics and feeds them back to the SAC agent and the outer capacity-planning module, ultimately producing the capacity-configuration and operational-evaluation results.

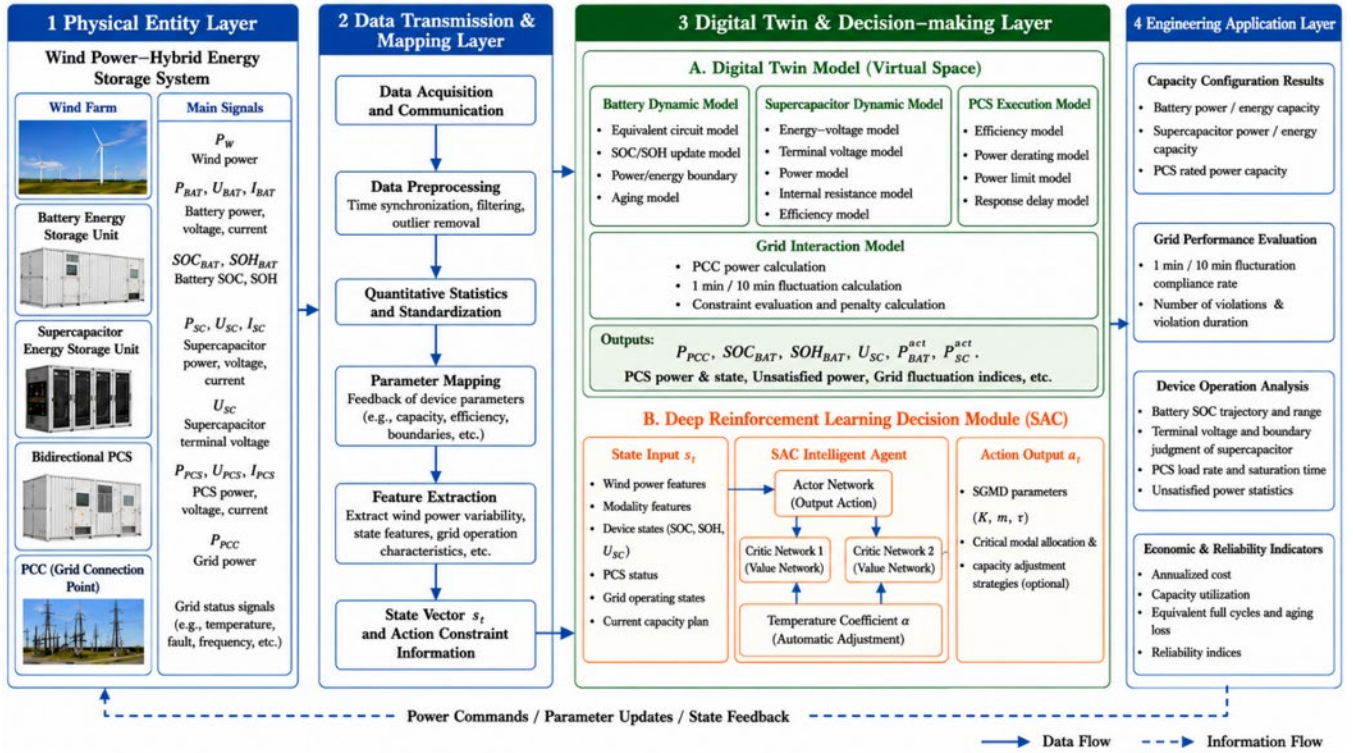


Figure 5. Interaction architecture of digital twin and deep reinforcement learning for wind–hybrid energy storage system

The DT model calculates the device states and actual grid-connected power using the battery, supercapacitor, PCS, and PCC models. It then feeds the SOC, SOH, supercapacitor terminal voltage, PCS loading ratio, unmet power, and grid-connection metrics back to the decision-making module, thereby providing feedback for SGMD parameter optimization, critical-mode allocation, and capacity verification.

3. Digital-Twin-in-the-Loop Deep Reinforcement Learning Method for Capacity Decision-Making

3.1. Multi-Scenario Digital-Twin Environment and Decision Process

Wind power exhibits pronounced randomness, intermittency, and seasonal variability. Capacity configuration based solely on a single wind condition or an isolated time window cannot adequately capture the cumulative evolution of storage states during continuous operation or evaluate the adaptability of candidate capacities to different wind conditions and equipment degradation states. Therefore, the wind-power HESS digital-twin model established in Section 2 is adopted as the interactive environment to construct a multi-scenario, dual-timescale sequential decision process.

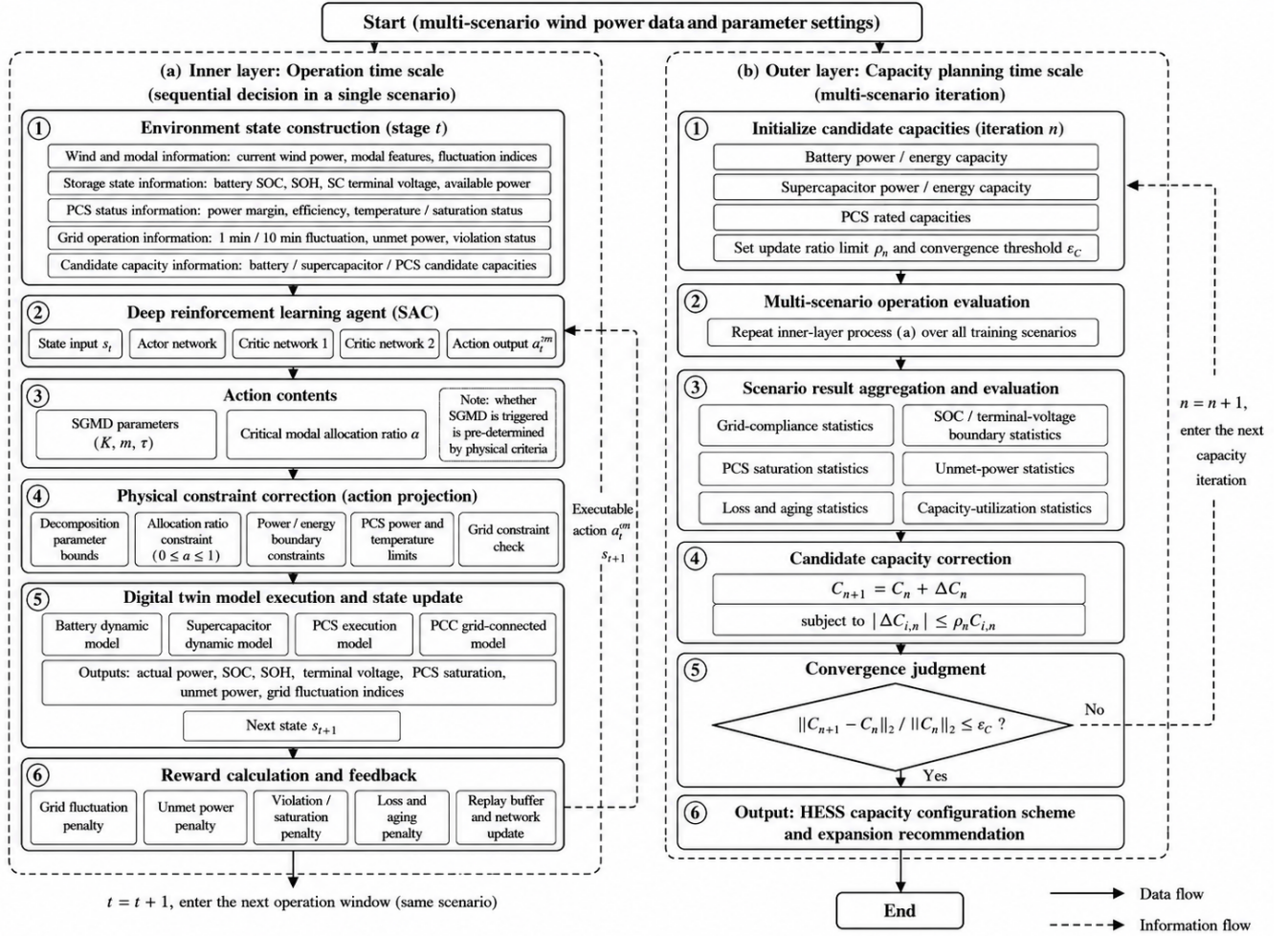


Figure 6. Dual-time-scale decision framework based on a multi-scenario digital twin environment

The SAC interaction loop shown in Figure 6 corresponds to the training-stage scenario set. After the policy and capacity scheme are finalized, the adverse seasonal test scenarios are evaluated separately without further policy or capacity updating.

As shown in Figure 6, a multi-scenario database is established using year-round historical wind-power data. For the purpose of separating policy learning, model selection, and final engineering evaluation, the historical operating scenarios are divided into mutually non-overlapping training, validation, and test sets. The training set is used for SAC interaction, policy updating, and DT-based capacity adjustment. The validation set is used exclusively to compare the independently trained policies and select the final policy. The test set remains untouched during training and model selection and is evaluated only after the policy and capacity configuration have been fixed. The same chronological data partition is adopted for all independent SAC runs.

Specifically, 28 chronological blocks are assigned to the training set, 8 blocks to the validation set, and 10 blocks to

the independent test set. The training set contains representative seasonal operating conditions with different levels of wind-power variability and is used for SAC interaction, policy updating, and DT-based capacity adjustment. In contrast, the adverse seasonal scenarios are included only in the independent test set and are evaluated as described in Sections 5.2.2 and 5.5. The engineering test scenarios are used only after the SAC decision process and candidate capacity configuration have been finalized. The samples are classified into spring, summer, autumn, and winter scenarios according to season and fluctuation intensity. Representative wind conditions, including low, moderate, and high variability as well as extreme ramping events, are selected for each season. Different initial battery SOC and SOH values, initial supercapacitor terminal voltages, PCS conversion efficiencies, and power-limiting states are also considered. The resulting DT operating scenarios therefore jointly represent wind conditions, storage states, and power-conversion-device states.

A dual-timescale structure is adopted to separate operational decision-making from capacity planning. At the inner operational timescale t , each complete scenario is divided into a series of consecutive operating windows, with each window corresponding to one decision stage. During the execution of a single scenario, the candidate rated capacities of the battery, supercapacitor, and PCSs remain unchanged. At the beginning of stage t , the DT model constructs the environmental state s_t from the current wind power, modal characteristics, storage states, PCS power margins, and grid-connection metrics. Based on this state, the DRL agent outputs the SGMD parameters and critical-mode allocation scheme, which are corrected according to the physical constraints before being applied to the DT model.

The DT model executes the corrected decision and calculates the actual battery and supercapacitor powers, battery SOC and SOH, supercapacitor terminal voltage, PCS saturation states, and grid-connected power at the PCC. The reward r_t is then determined from the grid-connected power fluctuations, unmet power, device-constraint violations, energy losses, and lifetime degradation during the current stage, after which the state is updated to s_{t+1} . This interaction process can be formulated as a Markov decision process (MDP).

The battery SOC and SOH, supercapacitor terminal voltage, and PCS operating states are transferred continuously between adjacent operating windows:

$$s_{t+1} = \mathcal{F}_{DT}(s_t, a_t^{\text{exe}}, C_n, w_t) \quad (12)$$

where $F_{DT}(\cdot)$ is the DT state-transition function; a_t^{exe} is the executable action after physical-constraint correction; C_n is the candidate capacity vector in planning iteration n ; and w_t represents the current wind power and external operating conditions. This formulation captures the effects of the current power-allocation decision on the subsequently available energy, equipment lifetime, and grid-regulation capability.

At the outer capacity-planning timescale n , the candidate capacities are updated only after the simulation of a complete scenario or a group of training scenarios has been completed. The update is based on the grid-connection compliance rate, SOC and terminal-voltage violations, PCS saturation, capacity utilization, and lifetime degradation:

$$C_{n+1} = C_n + \Delta C_n \quad (13)$$

Here,

$$C_n = [P_{\text{BAT},n}^N, E_{\text{BAT},n}^N, P_{\text{SC},n}^N, E_{\text{SC},n}^N, P_{\text{PCS},B,n}^N, P_{\text{PCS},S,n}^N] \quad (14)$$

This vector denotes the candidate power and energy capacities of the lithium-ion battery and supercapacitor, together with the rated powers of the PCSs on the two storage branches. Capacity updates are performed only during the planning iteration after the complete scenario simulation and do not imply that the capacities of the

commissioned devices vary in real time between operating windows.

To prevent an excessively large capacity adjustment in a single iteration, the correction is constrained by

$$|\Delta C_{i,n}| \leq \rho_i C_{i,n} \quad (15)$$

where ρ_i is the maximum allowable adjustment ratio for capacity component i in a single iteration. After multi-scenario iterations, the capacity-planning process is considered converged when

$$\frac{\|C_{n+1} - C_n\|_2}{\|C_n\|_2} \leq \varepsilon_C \quad (16)$$

3.2. State Space, Action Space, and Physical Constraints

To enable the agent to simultaneously perceive wind-power fluctuation characteristics, energy-storage operating states, and grid-connection constraints, the state of the DT environment at decision stage t is represented as:

$$s_t = [s_t^W, s_t^M, s_t^H, s_t^G, s_t^C]^T \quad (17)$$

where s_t^W , s_t^M , s_t^H , s_t^G , and s_t^C denote the wind-condition features, modal features, HESS states, grid-connected operating states, and candidate-capacity states, respectively.

To reduce the effects of differences in variable dimensions and numerical ranges on the training process, all state variables are normalized using the lower and upper bounds of the training dataset. States exceeding the training range are clipped to the corresponding boundaries. The definitions, units, and data sources of the state variables are listed in Table 4.

Table 4. State Variables of the DRL Agent and Their Physical Meanings

State Category	State Variable	Physical Meaning
Wind-condition features	$\bar{P}_{W,t}, V_{W,t}$	Output and fluctuations
Modal features	$f_{c,t}, \eta_{E,t}$	Frequency and energy
Battery state	$SOC_{\text{BAT},t}, SOH_{\text{BAT},t}$	Energy and health
Supercapacitor state	$U_{\text{SC},t}$	Voltage margin

PCS state	$M_{PCS,t}$	Power margin
Grid-connection state	$V_{1,t}, V_{10,t}, N_{vio,t}$	Fluctuations and limit violations
Capacity state	C_t	Candidate capacities

The action space of the agent at the inner operational timescale consists of two components: SGMD parameter tuning and critical-mode power allocation:

$$\mathbf{a}_t = [a_t^D, a_t^A]^T \quad (18)$$

where a_t^D is the secondary-decomposition decision, where a_t^D denotes the SGMD parameter-tuning decision for transition modes identified by the physical capability-boundary criterion, and a_t^A denotes the critical-mode power-allocation decision. and specifies the corresponding decomposition parameters; and a_t^A is the critical-mode power-allocation decision.

The secondary-decomposition decision is expressed as

$$\mathbf{a}_{j,t}^D = [K_{j,t}, m_{j,t}, \tau_{j,t}]^T \quad (19)$$

where K_t , m_t , and τ_t are the number of submodes, embedding dimension, and delay step, respectively. Whether secondary decomposition is triggered is predetermined by the energy-storage capability boundary criterion established in Section 4.2. SAC only tunes the parameters of the identified transition modes.

Because SAC outputs continuous actions, the actor network first generates normalized variables, which are then converted into K_t , m_t , and τ_t through threshold decisions and integer mapping. This approach retains continuous-policy training while satisfying the discrete-value requirements of the SGMD parameters.

For the j th critical mode that remains within the overlapping capability region of the two storage devices after secondary decomposition, the allocation coefficient $\alpha_{j,t}$ is used for coordinated power allocation:

$$P_{BAT,j}(k) = \alpha_{j,t} P_j(k) \quad (20)$$

$$P_{SC,j}(k) = (1 - \alpha_{j,t}) P_j(k) \quad (21)$$

where $P_j(k)$ is the power of the j th critical mode; $P_{BAT,j}(k)$ and $P_{SC,j}(k)$ are the corresponding powers allocated to the battery and supercapacitor, respectively; and $\alpha_{j,t} \in [0, 1]$. A larger $\alpha_{j,t}$ assigns a greater proportion of the critical-mode power to the battery, whereas a smaller value assigns a greater proportion to the supercapacitor. Agent actions and outer-layer capacity-adjustment variables are summarized in Table 5.

Table 5. Agent Actions and Outer-Layer Capacity-Adjustment Variables

Action Category	Action Variable	Engineering Meaning
SGMD parameters	K_t, m_t, τ_t	Tune decomposition parameters
Critical-mode allocation	α_t	Adjust power allocation

With the above state and decision-variable design, the inner-layer SAC agent tunes the SGMD parameters and allocates critical-mode power according to the wind conditions, modal features, and device operating states. The outer-layer planning process updates the candidate capacities based on the multi-scenario DT simulation results, thereby establishing a closed-loop relationship among modal features, power allocation, device states, grid-connection performance, and capacity planning.

3.3. SAC-Based Decision Method and Feedback Mechanism

SAC is adopted to adaptively determine the SGMD parameters of transition modes and the allocation ratios of critical modes. The maximum-entropy policy retains a certain degree of action stochasticity while maximizing the long-term operational return. Its optimization objective can be expressed as.

$$J_\pi = \mathbb{E}_{s_t, a_t} [Q(s_t, a_t) - \beta \ln \pi(a_t | s_t)] \quad (22)$$

where $Q(s_t, a_t)$ is the state–action value function, $\pi(a_t | s_t)$ is the actor-network policy, and β is the entropy coefficient. This mechanism prevents the agent from prematurely converging to a single capacity scheme and improves its adaptability to different seasons, wind conditions, and device states.

Because the number of SGMD submodes, embedding dimension, and delay step are discrete integers, whereas the critical-mode allocation ratio is continuous, an action-mapping layer is added after the actor network. The actor network first outputs normalized continuous variables. The SGMD parameters are then mapped to predefined integer ranges, while the allocation ratio is restricted to its valid range. The mapped actions are corrected according to the physical constraints before being input into the DT environment.

For implementation transparency, the principal SAC settings adopted in this study are specified as follows. The actor and critic networks are trained using the Adam optimizer, with learning rates of 3×10^{-4} . The discount factor, soft-update coefficient, minibatch size, and replay-buffer capacity are set to 0.99, 0.005, 256, and 10^6 , respectively. Training is conducted for 600 episodes after

5,000 random warm-up steps, with each episode corresponding to one complete DT operating scenario randomly sampled from the training scenario set. The entropy coefficient is adjusted automatically, and the target entropy is set to $-d_a$, where d_a is the action-space dimension. The normalized actor outputs are mapped to $K_t \in \{2, 3, 4, 5\}$, $m_t \in [20, 80] \cap \mathbb{Z}$, $\tau_t \in \{1, 2, \dots, 6\}$,

while the critical-mode allocation ratio is constrained to $\alpha_{q,t} \in [0, 1]$. The maximum correction applied to each capacity component in one outer-layer iteration is limited to 5%.

To quantify the influence of stochastic initialization and exploration, five independent SAC training realizations are conducted using random seeds 11, 37, 79, 127, and 181. All realizations use the same chronological training, validation, and test sets, actor and critic architectures, learning rates, minibatch size, replay-buffer capacity, warm-up length, and training budget of 600 episodes. After training, each policy is evaluated on the fixed validation set. The final policy is selected solely according to its validation score and is subsequently evaluated once on the untouched test set. Test-set results are not used for policy selection or hyperparameter tuning.

3.3.1 Engineering Feedback Design

Because the capacity cost, lifetime degradation, and conversion losses can all be converted into unified annualized economic indices, the total annualized cost is used to evaluate feasible solutions, while unified penalties are imposed for violations of device or grid-connection constraints.

$$r_t = -[J_{\text{ann},t} + \lambda_{\text{vio}} \Phi_t] \quad (23)$$

where $J_{\text{ann},t}$ includes the energy-storage-device cost, PCS cost, battery lifetime-degradation cost, and conversion-loss cost; and Φ_t represents the aggregate magnitude of constraint violations, including SOC and terminal-voltage violations, PCS saturation, unmet power, and grid-connected power limit violations.

The constraint penalty jointly considers SOC and terminal-voltage violations, PCS saturation, unmet power, and noncompliance with the 1-min and 10-min grid-connected power fluctuation limits. The reconstruction error is used only to verify decomposition completeness. Device states and grid-connection metrics are used to assess operational feasibility, while capacity cost and lifetime degradation are used to compare the economic performance of feasible solutions.

3.3.2 Digital-Twin Interaction and Policy Updating

After executing an action, the DT model stores the interaction sample $(s_t, a_t^{\text{exe}}, r_t, s_{t+1})$ in the experience replay buffer to update the actor and critic networks. When the device capabilities are insufficient to fully execute the reference power, the DT records the unmet power, PCS saturation, and action-correction magnitude and returns them to the agent as negative feedback.

After all training scenarios have been completed, the adverse scenarios reserved for engineering testing do not participate in the policy-update procedure or the training-stage capacity correction. The outer-layer planning module aggregates the grid-connection compliance rate, SOC and terminal-voltage violations, PCS saturation, capacity utilization, and annualized cost. It then updates the candidate capacities according to the capacity-update relationship. This process is repeated until all training scenarios satisfy the engineering constraints and the capacity-change rate meets the convergence criterion.

4. Conditional Secondary Decomposition and Physical Power Allocation for the HESS

4.1. Identification of Multi-Timescale Regulation Requirements for Wind Power

Wind-power fluctuations contain short-term rapid disturbances, medium-timescale variations, and low-frequency trends. These timescales impose substantially different requirements on storage power, energy capacity, and sustained regulation capability. Dividing the battery and supercapacitor power using only a single fixed frequency threshold may result in insufficient allocation of high-frequency power or inaccurate estimation of low-frequency energy requirements. Therefore, ICEEMDAN is first applied to decompose the wind-power signal, and the regulation characteristics of each mode are extracted in terms of power magnitude, energy requirement, and duration. These characteristics provide the basis for subsequent transition-mode identification and conditional triggering of SGMD.

Let the pre-processed wind-power sequence of length N be $P_W(k)$. After ICEEMDAN decomposition, it is expressed as:

$$P_W(k) = \sum_{j=1}^J c_j(k) + r_j(k) \quad (24)$$

Here $c_j(k)$ is the j th intrinsic mode component, J is the total number of modes, and $r_j(k)$ is the residual trend. The modes are arranged from high to low frequency. High-frequency modes mainly represent rapid random fluctuations, whereas low-frequency modes mainly represent power variations with longer durations. The residual term characterizes the overall trend of wind-power output.

To establish a relationship between the modal decomposition results and HESS capacity requirements, the power quantile, energy requirement, energy proportion, and equivalent duration of each mode are extracted. The characteristic power of the j th mode is defined as

$$P_{95,j} = Q_{0.95}(|c_j(k)|) \quad (25)$$

where $Q_{0.95}(\cdot)$ denotes the 95th percentile. Using quantile power instead of a single maximum value reduces the influence of a small number of abnormal peaks on the estimated storage-power requirement.

Based on the cumulative energy trajectory of the j th mode, its energy requirement is expressed as

$$E_j^{\text{req}} = \max_{1 \leq k \leq N} \left[\sum_{n=1}^k c_j(n) \Delta t \right] - \min_{1 \leq k \leq N} \left[\sum_{n=1}^k c_j(n) \Delta t \right] \quad (26)$$

where Δt is the sampling interval, and E_j^{req} represents the effective energy range that the storage system must provide when compensating for this mode. The corresponding equivalent duration is

$$T_{\text{eq},j} = \frac{E_j^{\text{req}}}{P_{95,j}} \quad (27)$$

This index jointly characterizes the power and energy features of the mode. In general, modes with high characteristic power and short equivalent duration are more suitable for the supercapacitor, whereas modes with long duration and high energy requirements are more suitable for the battery. Modes that simultaneously exhibit relatively high power requirements and appreciable duration may lie near the capability boundary between the two storage devices.

To quantify the contribution of each mode to the overall wind-power fluctuations, the energy proportion of the j th mode is defined as

$$\eta_{E,j} = \frac{\sum_{k=1}^N c_j^2(k)}{\sum_{j=1}^J \sum_{k=1}^N c_j^2(k)} \times 100\% \quad (28)$$

Modes with a low energy proportion and limited influence on grid-connected power fluctuations do not, in principle, trigger secondary SGMD decomposition, but they are retained in the final power reconstruction. Modes with a high energy proportion or the potential to cause significant ramp-rate violations are passed to the subsequent device-capability matching process. Therefore, the modes obtained from the primary decomposition are no longer assigned solely according to their indices or a fixed frequency threshold. Instead, their actual regulation requirements are jointly characterized by $P_{95,j}$, E_j^{req} , $T_{\text{eq},j}$, and $\eta_{E,j}$. The primary decomposition is shown in Figure 7.

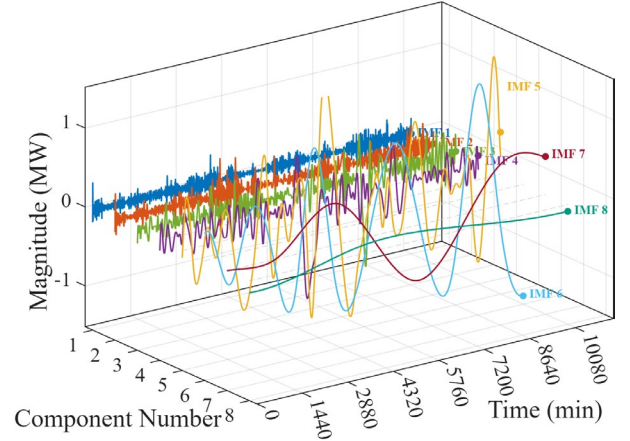


Figure 7. ICEEMDAN decomposition results of wind power fluctuations

The above modal features serve as the fundamental inputs for transition-mode identification, device-capability matching, and capacity configuration.

4.2. Transition-Mode Identification and Conditional SGMD Decomposition

The primary ICEEMDAN decomposition extracts multi-timescale fluctuation components from wind power. However, some modes may simultaneously exhibit high instantaneous power and appreciable sustained energy requirements. Directly assigning such modes to either the battery or supercapacitor based solely on the mode index or a fixed frequency boundary may force the battery to frequently compensate for rapid fluctuations or cause supercapacitor terminal-voltage violations due to insufficient energy. Therefore, modes that cannot be clearly assigned to either device in terms of power, energy, and sustained regulation capability are defined as transition modes, and secondary SGMD decomposition is triggered only for these modes.

For the j th mode, the ratios of its power and energy requirements to the available capabilities of each storage device are calculated.

$$\begin{cases} \rho_{P,i,j} = \frac{P_{95,j}}{P_i^{\text{ava}}} \\ \rho_{E,i,j} = \frac{E_j^{\text{req}}}{E_i^{\text{ava}}} \end{cases}, i \in \{\text{BAT}, \text{SC}\} \quad (29)$$

Here, P_i^{ava} and E_i^{ava} are the available power and energy, respectively, of storage device i under the current SOC, SOH, or terminal-voltage state, as calculated by the DT model; BAT and SC denote the battery and supercapacitor, respectively.

A mode is classified as a fast mode when it has high characteristic power and a short equivalent duration, and the power and energy margins of the supercapacitor are sufficient to satisfy its regulation requirements. A mode is classified as a slow mode when it has a long duration and a high energy requirement, and the battery can accommodate it within the allowable SOC and C-rate ranges. A mode is classified as a transition mode when its device assignments based on power, energy, and duration are inconsistent, or when neither storage device alone can simultaneously satisfy its power, energy, and operating constraints.

Let the SGMD parameters output by the agent and corrected according to the physical constraints be K_t , m_t , and τ_t . The transition mode $c_j(k)$ can then be expressed as

$$c_j(k) = \sum_{l=1}^{K_t} g_{j,l}(k) + \varepsilon_j(k) \quad (30)$$

where $g_{j,l}(k)$ is the l th submode obtained by applying SGMD to the j th transition mode; K_t is the number of submodes; m_t and τ_t are the embedding dimension and delay step, respectively; and $\varepsilon_j(k)$ is the residual of the secondary decomposition.

After secondary decomposition, as shown in Figure 8, the power, energy, and duration characteristics of each submode are recalculated and then passed to the device-capability matching process.

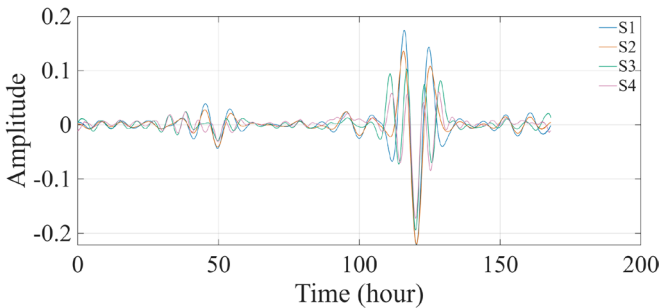


Figure 8. SGMD Secondary Decomposition Results for the Typical Transition Mode IMF4

4.3. Mode Assignment Based on Device Capability Boundaries

After the conditionally triggered decomposition described in Section 4.2, the wind-power regulation demand consists of the ICEEMDAN modes that do not undergo secondary decomposition and the submodes obtained by SGMD. For a unified description, all effective modes requiring storage compensation are denoted by $x_q(k)$, where $q = 1, 2, \dots, Q$. The low-frequency trend and stationary components that do not require storage compensation are excluded from the device-assignment process.

For each effective mode, the characteristic power $P_{95,q}$, energy requirement E_q^{req} , center frequency $f_{c,q}$, and equivalent duration $T_{eq,q}$ are extracted. These features are then physically matched with the available power, available energy, and dynamic response capabilities of the battery and supercapacitor calculated by the DT model.

To quantify the ability of the two storage devices to track power components at different frequencies, the combined dynamics of each storage device and its PCS are represented by an equivalent first-order response model. Its frequency-response magnitude is expressed as

$$G_{i,q} = \frac{1}{\sqrt{1 + (2\pi f_{c,q} \tau_i)^2}}, \quad i \in \{\text{BAT}, \text{SC}\} \quad (31)$$

where $G_{i,q}$ denotes the dynamic tracking capability of storage device i for the q th mode, and τ_i is the equivalent response time constant of the storage device and its PCS. The supercapacitor has a smaller response time constant and can therefore track higher-frequency rapid fluctuations, whereas the battery responds more slowly and is better suited to low-frequency power components with longer durations.

Following the power- and energy-demand ratios defined, a mode is considered to lie within the feasible capability range of a storage device when the device simultaneously satisfies its power, energy, and dynamic-response requirements. The corresponding feasibility criterion is expressed as

$$F_{i,q} = \begin{cases} 1, & \rho_{P,i,q} \leq 1, \rho_{E,i,q} \leq 1, G_{i,q} \geq G_{\min} \\ 0, & \text{otherwise} \end{cases} \quad (32)$$

where $F_{i,q}$ is the device-feasibility indicator, and $G_{\min}$ is the minimum required dynamic tracking capability. The available power and energy are jointly determined by the current SOC, SOH, terminal voltage, PCS rated capacity, and derating state. Therefore, modal assignment varies with the device operating states rather than being determined directly by a fixed frequency threshold.

When a mode satisfies the capability requirements of only one storage device, it is assigned directly to that device. When both the battery and supercapacitor can accommodate the mode, a capability-matching index is further constructed:

$$J_{i,q} = \max \left\{ \rho_{P,i,q}, \rho_{E,i,q}, \frac{G_{\min}}{G_{i,q}} \right\} \quad (33)$$

where $J_{i,q}$ is the overall matching index when storage device i accommodates the q th mode. A smaller $J_{i,q}$ indicates a better match between the modal characteristics and the capabilities of the corresponding storage device.

Based on the feasibility indicators and matching indices, the effective modes are classified into battery modes, supercapacitor modes, and critical modes:

$$x_q(k) \in \begin{cases} \Omega_{\text{BAT}}, & F_{\text{BAT},q} = 1, F_{\text{SC},q} = 0 \\ \Omega_{\text{SC}}, & F_{\text{BAT},q} = 0, F_{\text{SC},q} = 1 \\ \Omega_{\text{BAT}}, & F_{\text{BAT},q} = F_{\text{SC},q} = 1, J_{\text{BAT},q} < J_{\text{SC},q} - \delta_J \\ \Omega_{\text{SC}}, & F_{\text{BAT},q} = F_{\text{SC},q} = 1, J_{\text{SC},q} < J_{\text{BAT},q} - \delta_J \\ \Omega_C, & |J_{\text{BAT},q} - J_{\text{SC},q}| \leq \delta_J \end{cases} \quad (34)$$

where Ω_{BAT} , Ω_{SC} , and Ω_C denote the sets of battery modes, supercapacitor modes, and critical modes, respectively, and δ_J is the matching-difference threshold. When the matching indices of the two storage devices are similar, assigning the entire mode to a single device may deepen battery cycling or cause supercapacitor terminal-voltage deviation. Such modes are therefore retained as critical modes and are coordinately allocated in Section 4.4.

A mode that cannot be accommodated independently by either the battery or supercapacitor but can be supported by their combined power and energy capabilities is also included in the critical-mode set. When their combined capabilities remain insufficient to meet the regulation demand, the mode is marked as a capacity-deficient mode and fed back to the DT capacity-adjustment module as a basis for increasing the storage or PCS capacity.

The power corresponding to the critical modes is not directly incorporated into the above assignment results. Instead, it is co-ordinately allocated in the next section according to the DT feedback and the allocation ratios output by the agent.

Through the above procedure, modal assignment is transformed from a fixed frequency-based division into a device-capability matching process jointly constrained by power, energy, and dynamic response. This improves the physical rationality of power allocation between the battery and supercapacitor and provides the basis for subsequent coordinated allocation of critical modes and compensation-power reconstruction.

4.4. Coordinated Allocation of Critical Modes and Compensation-Power Reconstruction

After the device-capability matching described in Section 4.3, modes that can be accommodated by a single storage device are assigned to the battery-mode set Ω_{BAT} or the supercapacitor-mode set Ω_{SC} , whereas modes located near the capability boundary between the two storage devices are assigned to the critical-mode set Ω_C . Assigning an entire critical mode to a single device may increase the battery depth of cycling, cause supercapacitor terminal-voltage violations, or result in short-term PCS saturation. Therefore, the power-allocation coefficients output by the

agent in Section 3.2 are used to coordinately allocate critical modes between the battery and supercapacitor.

For the q th critical mode $x_q(k)$, the power-allocation relationship is

$$P_{\text{BAT},q}(k) = \alpha_{q,t} x_q(k) \quad (35)$$

$$P_{\text{SC},q}(k) = (1 - \alpha_{q,t}) x_q(k) \quad (36)$$

where $\alpha_{q,t} \in [0, 1]$ is the proportion of the q th critical mode assigned to the battery during decision stage t . A larger $\alpha_{q,t}$ assigns more power to the battery, whereas a smaller value assigns more power to the supercapacitor. The agent determines this allocation coefficient by jointly considering the modal power and duration, battery SOC and SOH, supercapacitor terminal voltage, PCS power margins, and grid-connected power fluctuations.

Based on the directly assigned modes and the coordinated allocation of critical modes, the reference compensation powers of the battery and supercapacitor are reconstructed as

$$P_{\text{BAT}}^{\text{ref}}(k) = \sum_{x_q \in \Omega_{\text{BAT}}} x_q(k) + \sum_{x_q \in \Omega_C} \alpha_{q,t} x_q(k) \quad (37)$$

$$P_{\text{SC}}^{\text{ref}}(k) = \sum_{x_q \in \Omega_{\text{SC}}} x_q(k) + \sum_{x_q \in \Omega_C} (1 - \alpha_{q,t}) x_q(k) \quad (38)$$

where $P_{\text{BAT}}^0(k)$ and $P_{\text{SC}}^0(k)$ are the initial battery and supercapacitor compensation powers, respectively, and $P_{\text{BAT}}^{\text{ref}}(k)$ and $P_{\text{SC}}^{\text{ref}}(k)$ are the reference powers after coordinated allocation.

The reconstructed powers are processed through the device models and corrected according to the physical boundaries to obtain the actual executable powers. Any portion that cannot be executed is recorded as unmet power and fed back to the outer-layer capacity-planning module.

Through this coordinated allocation, critical modes are no longer forcibly assigned to a single device according to a fixed frequency threshold. Instead, their allocation ratios are dynamically determined from the modal characteristics and current device capabilities. The reconstructed battery and supercapacitor power sequences are used to calculate the power quantiles and cumulative energy ranges and serve as inputs for initial capacity determination, DT-based iterative adjustment, and multi-scenario engineering validation in Section 5.

5. HESS Capacity Configuration and Multi-Scenario Engineering Validation

The capacity-configuration procedure consists of two stages. First, the training scenario set is used for SAC

interaction and DT-based capacity adjustment. During this stage, the outer-layer planning module adjusts the candidate capacities according to the SOC, terminal voltage, PCS saturation, grid-connected power fluctuations, and capacity utilization until the capacity scheme converges. After convergence, both the SAC policy and the finalized capacity configuration are fixed and subsequently evaluated under the adverse seasonal engineering test scenarios without further policy or capacity updating.

5.1. Initial Capacity Determination and Digital-Twin Iterative Adjustment

5.1.1 Initial HESS Capacity Determination

Based on the reference compensation powers $P_{\text{BAT}}^{\text{ref}}(k)$ and $P_{\text{SC}}^{\text{ref}}(k)$, the initial rated powers of the battery and supercapacitor are calculated separately. To reduce the influence of isolated abnormal peaks on capacity determination, the 95th percentiles of the absolute charging and discharging powers are used to determine the principal power requirements. For storage device i , where $i \in \{\text{BAT}, \text{SC}\}$, its initial rated power is given by

$$P_{i,0}^N = (1 + \mu_{P,i}) \max\{Q_{0.95}(P_i^+), Q_{0.95}(P_i^-)\} \quad (39)$$

where $P_i^+(k) = \max[P_i^{\text{ref}}(k), 0]$ and $P_i^-(k) = \max[-P_i^{\text{ref}}(k), 0]$ are the magnitudes of the absorbed and delivered powers, respectively; $Q_{0.95}(\cdot)$ denotes the 95th percentile; and $\mu_{P,i}$ is the power reserve factor.

Considering the charging and discharging efficiencies, the cumulative energy trajectory of storage device i is expressed as

$$E_i(k) = \sum_{n=1}^k \left[\frac{P_i^+(n)}{\eta_{i,c}} - \eta_{i,d} P_i^-(n) \right] \Delta t \quad (40)$$

where $\eta_{i,c}$ and $\eta_{i,d}$ are the charging and discharging efficiencies, respectively, and Δt is the sampling interval. The effective energy requirement is determined by the maximum peak-to-valley difference of the cumulative energy trajectory:

$$E_i^{\text{req}} = \max_k E_i(k) - \min_k E_i(k) \quad (41)$$

The initial rated energy capacity is then obtained as

$$E_{i,0}^N = \frac{(1 + \mu_{E,i}) E_i^{\text{req}}}{D_i} \quad (42)$$

where $\mu_{E,i}$ is the energy reserve factor, and D_i is the allowable usable-energy fraction of the storage device. For the battery, D_{BAT} is determined by the allowable SOC range. For the supercapacitor, D_{SC} is determined by the usable-energy fraction corresponding to the allowable terminal-voltage range.

The initial rated power of the PCS on each branch is determined from the corresponding storage power capacity and short-term power margin:

$$P_{\text{PCS},i,0}^N = (1 + \mu_{\text{PCS},i}) P_{i,0}^N \quad (43)$$

where $\mu_{\text{PCS},i}$ is the PCS power-margin factor.

5.1.2 Digital-Twin Iterative Adjustment

The initial capacity scheme C_0 is input into the DT model for continuous-operation simulations over the training scenario set, which spans different seasons, wind conditions, initial SOC and SOH values, and PCS derating states. Each validation iteration mainly records the battery SOC range, supercapacitor terminal-voltage range, maximum PCS loading ratio and number of saturation events, compliance rates for 1-min and 10-min power fluctuations, number of grid-connected power limit violations, unmet power, and capacity utilization.

The outer-layer capacity-planning module generates capacity corrections from the aggregated DT results and updates the candidate capacities. When the battery SOC or supercapacitor terminal voltage remains close to its boundary for an extended period, the energy capacity of the corresponding storage device is adjusted. When PCS saturation occurs, or the 1-min power fluctuation requirement is not satisfied, priority is given to adjusting the power capacity of the corresponding branch. When the 10-min power fluctuation requirement is not satisfied, or capacity utilization is excessively low, the battery energy support is increased or redundant capacity is reduced, respectively.

These adjustment rules associate each capacity deficiency with a specific device, thereby avoiding the uniform attribution of all grid-connected power fluctuations or state-limit violations to insufficient total storage capacity.

5.1.3 Determination of the Capacity Scheme

The final capacity scheme is obtained when all training scenarios satisfy the device and grid-connection constraints and the change between successive capacity schemes falls below the specified threshold. The capacity configuration is considered converged when the engineering constraints are satisfied over the training scenario set for several consecutive iterations and the capacity-change rate between two successive iterations remains below the specified threshold.

The final outputs include the rated power and energy capacities of the battery and supercapacitor, the rated powers of the PCSs on both branches, and the recommended reserve margins. In this framework, the

statistically determined capacities provide the initial scheme, while the DT and DRL perform engineering validation and limited adjustment, thereby improving the operational feasibility and multi-scenario adaptability of the capacity configuration.

5.2. Capacity Configuration and Dynamic Operating Results of the Energy Storage System

5.2.1 Capacity Adjustment and Energy-Trajectory Results

Based on the identified multi-timescale regulation requirements of wind power and the reconstructed HESS compensation powers, the initial power and energy capacities of the lithium-ion battery and supercapacitor are determined from the power quantiles and the peak-to-valley differences of the cumulative energy trajectories. The statistically determined initial scheme provides the initial rated power and energy capacity of the lithium-ion battery. The statistical capacity-determination results are summarized in Table 6.

Table 6. Statistical Capacity-Determination Results

Configuration Item	Statistical Initial Capacity	Capacity after DT Adjustment	Change Rate
Battery rated power/MW	1.5	1.53	2.00%
Battery rated energy/MWh	3	2.65	−11.67%
Supercapacitor rated power/MW	0.5	0.5	0
Supercapacitor rated energy/MWh	0.03	0.1	233.33%
Configuration cost/(10 ⁴ RMB)	3425.65	3125.61	−8.76%

To analyze the energy-variation characteristics of the individual storage units during continuous operation, the reference compensation powers of the lithium-ion battery and supercapacitor are cumulatively integrated over time to obtain the corresponding cumulative energy trajectories, as shown in Figure 9.

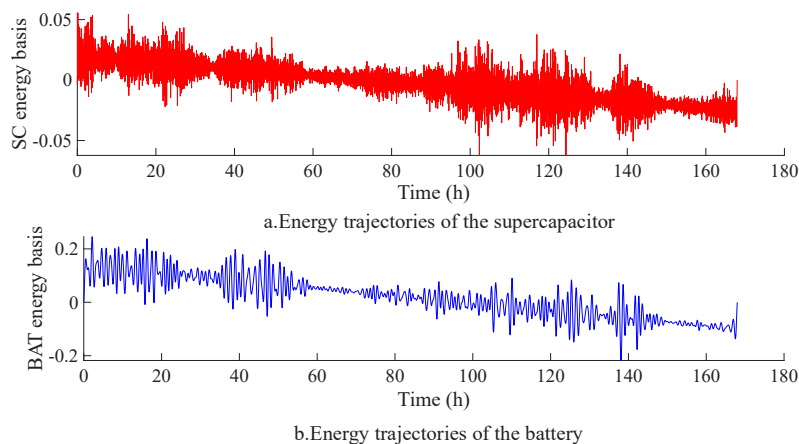


Figure 9. Cumulative energy trajectories corresponding to the reference compensation power of the battery and supercapacitor

Figure 9 shows that the supercapacitor energy trajectory fluctuates rapidly within a relatively narrow range, indicating that it mainly compensates for short-term high-frequency power fluctuations. In contrast, the lithium-ion battery energy trajectory varies more slowly but exhibits a

larger peak-to-valley range, indicating that it primarily accommodates sustained energy imbalances. The differences between the two trajectories confirm the functional complementarity of the HESS in providing rapid power support and long-duration energy regulation.

5.2.2 Engineering Test under Adverse Seasonal Scenarios

After completion of the SAC decision process and DT-based capacity adjustment, the finalized HESS configuration is evaluated using the engineering test scenarios. These test cases correspond to the most adverse wind condition selected for each season, including spring high variability, summer extreme ramping, autumn high variability, and winter sustained power deviation. The test-stage evaluation does not update the SAC policy or modify the finalized capacity configuration; it is used only to

assess the operational feasibility of the obtained solution under adverse operating conditions. The device-side constraints include the battery SOC range, normalized supercapacitor terminal-voltage range, PCS loading ratio, saturation events, and unmet power. The grid-side criteria include the compliance rates for 1-min and 10-min power fluctuations and the number of consecutive limit-violation events. In this study, the minimum acceptable compliance rate is set to 99.5%, and a violation event is recorded when the corresponding limit is exceeded for two or more consecutive sampling intervals.

Table 7. Engineering Test Results of the Final HESS Configuration under Adverse Seasonal Scenarios

Season and Adverse Wind Condition	Battery SOC Range	SC Voltage Range / p.u.	Maximum Battery-PCS Loading Ratio	Maximum SC-PCS Loading Ratio	PCS Saturation Events
Spring—high variability	0.22–0.80	0.64–0.90	0.91	0.94	0
Summer—extreme ramping	0.19–0.83	0.58–0.94	0.96	0.98	0
Autumn—high variability	0.24–0.78	0.66–0.89	0.88	0.91	0
Winter—sustained power deviation	0.17–0.85	0.61–0.92	0.97	0.95	0

As shown in Table 7, the battery SOC remains within 0.17–0.85 under all seasonal scenarios, while the normalized supercapacitor terminal voltage remains within 0.58–0.94 p.u. The maximum loading ratios of the battery-side and supercapacitor-side PCSs are 0.97 and 0.98, respectively, and no PCS saturation event occurs. The maximum unmet power is 0.009 MW under the summer extreme-ramping scenario, accounting for only 0.018% of the wind-farm rated power. These results demonstrate the operational feasibility of the final capacities under the four selected adverse seasonal scenarios. Table 7 therefore provides targeted stress-test evidence for representative seasonal operating conditions, whereas complete annual adequacy is evaluated separately through the uninterrupted chronological replay reported in Section 5.5.

5.3. Grid-Connected Power Smoothing and Engineering Economic Analysis

After determining the statistically derived initial HESS capacities, the effectiveness of the capacity scheme is further evaluated in terms of the time-domain variation in grid-connected power and the configuration cost. The grid-connected power-smoothing results primarily demonstrate the suppression of rapid wind-power fluctuations through coordinated compensation by the lithium-ion battery and supercapacitor, whereas the engineering economic analysis reveals how different storage capacities and regulation-demand identification methods affect the system configuration cost.

5.3.1 Grid-Connected Power-Smoothing Performance

Based on the reconstructed compensation powers of the battery and supercapacitor, the actual output powers of the two storage devices are jointly applied at the wind-power PCC. The resulting grid-connected power before and after HESS compensation is compared in Figure 10.

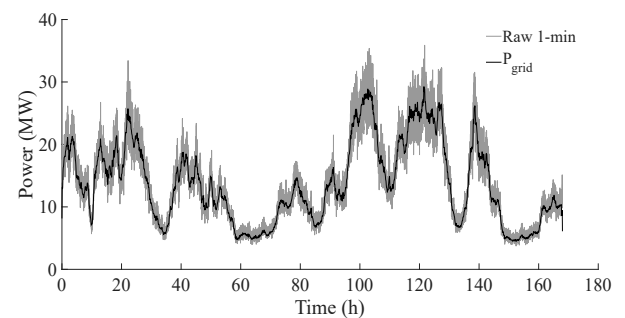


Figure 10. Comparison of Original Wind Power and Grid-Connected Power after Compensation

Figure 10 shows that the compensated grid-connected power preserves the original long-term variation trend, while local surges, drops, and rapid fluctuations are attenuated. The supercapacitor primarily suppresses short-term rapid disturbances, whereas the lithium-ion battery accommodates sustained power deviations. This indicates that coordinated compensation by the two storage devices

improves the time-domain smoothing performance of wind-power integration.

5.3.2 Comparison of Different Processing Configurations within the Proposed Framework

To analyze the effects of primary regulation-demand identification, secondary modal decomposition, and parameter optimization on the initial capacities and configuration cost, different offline processing combinations are compared using the same wind-power data, storage parameters, and capacity-calculation criteria. The results are presented in Table 8.

Table 8. Capacity and Cost Results under Different Processing Configurations of the Proposed Framework

Strategy	P_{bN}	P_{sN}	E_{bN}	E_{sN}	Cost
	MW		MWh		(10 ⁴) RMB
ICEE	0.52	1.5	3.13	0.37	3709.88
ICEE+SGMD	1.5	0.5	3	0.03	3425.65
DT-Based Method	1.53	0.5	2.65	0.1	3125.61

The combined analysis of grid-connected power smoothing and configuration cost shows that the HESS attenuates local rapid fluctuations in wind-power output through the functional complementarity of the battery and supercapacitor. Meanwhile, the results of regulation-demand identification and modal decomposition significantly affect the power and energy capacities of both storage devices, as well as the overall system configuration cost. Determining the initial capacities from year-round window statistics and subsequently incorporating them into the DT-based engineering-validation framework helps balance wind-power smoothing performance, the physical characteristics of the storage devices, and the economic efficiency of capacity configuration.

5.4. Multi-Season, Multi-Wind-Condition, and Parameter-Sensitivity Validation

Wind power exhibits pronounced seasonal differences and variations in fluctuation intensity across different periods of the year. Capacities determined from a single representative window cannot fully reflect the energy-storage requirements under long-term operating conditions. To evaluate the adaptability of the capacity-configuration results to different seasons, wind conditions, and variations in regulation-demand identification parameters, year-round sliding-window statistics are used to analyze three aspects: the scale of modal identification, variations in power and energy requirements, and the

capacity-configuration results obtained using different decomposition methods. Because the decomposition parameters are coupled with the modal structure, parameter sensitivity is comprehensively evaluated by comparing the results before and after parameter tuning and those obtained using different regulation-demand identification methods.

5.4.1 Stability of Regulation-Demand Identification under Year-Round Sliding Windows

The frequency structure and fluctuation complexity of wind power vary across different wind conditions. Accordingly, the number of critical modes subjected to secondary decomposition and the resulting number of submodes also vary. The statistical results for the numbers of different modal components under year-round sliding windows are shown in Figure 11.

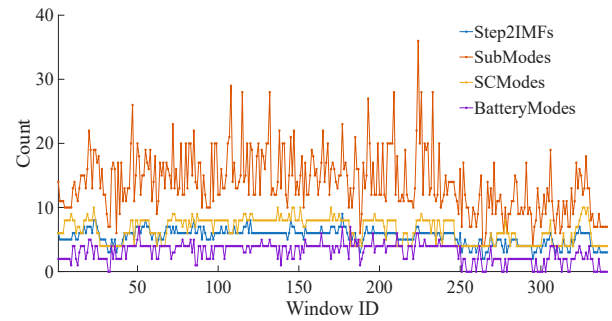


Figure 11. Variations in the number of key modes and secondary decomposition scale under annual sliding windows

Across the year-round windows, the number of transition modes is mainly concentrated between 4 and 7, while the number of submodes generated by secondary decomposition is generally between 10 and 20, increasing only under complex wind conditions. This indicates that the conditional triggering mechanism can adapt the decomposition scale to the power structure while avoiding repeated decomposition of all modes.

5.4.2 Variations in Statistical Sizing Indicators under Different Seasons and Wind Conditions

To further analyze how HESS statistical sizing indicators vary with year-round wind conditions, the statistical power and energy requirements of the lithium-ion battery and supercapacitor in each sliding window are ranked, as shown in Figure 12.

The quantities analyzed in this subsection are window-wise statistical sizing indicators derived from the reconstructed compensation signals before the final DT-based engineering correction. Their primary purpose is to characterize the variability of local regulation demand under different annual wind conditions. Therefore, individual window-wise values should not be interpreted

directly as the required final installed capacities of the HESS.

The final configuration is determined after coordinated battery–supercapacitor operation and device/grid

constraints are incorporated through the DT-based capacity-adjustment procedure.

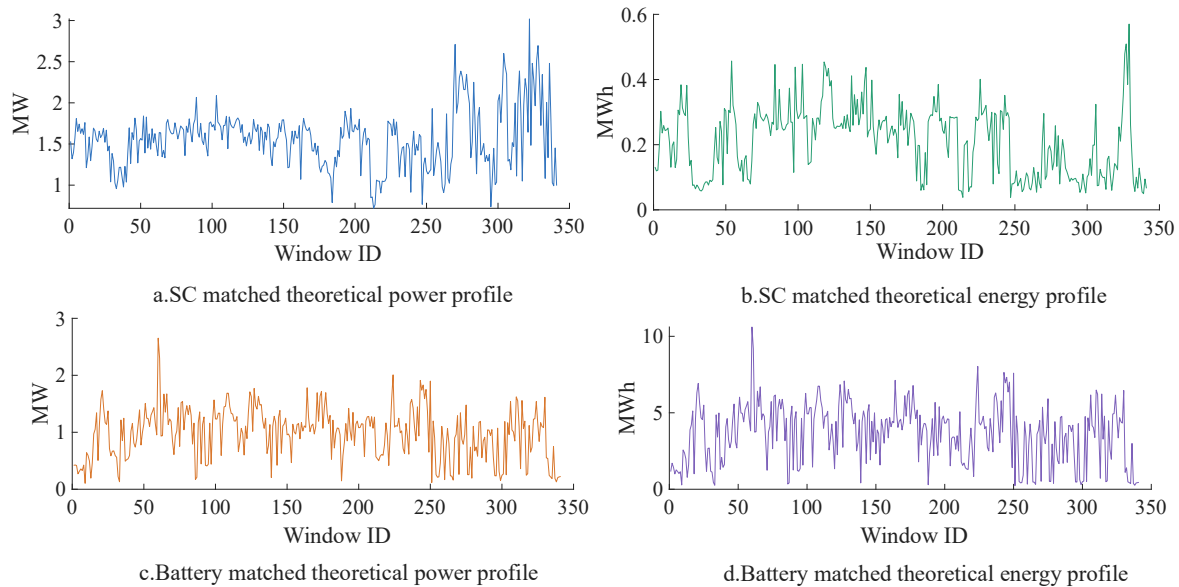


Figure 12. Window-wise statistical pre-DT power and energy sizing indicators under annual sliding-window analysis

Year-round window statistics show that the supercapacitor power requirement is relatively sensitive to local rapid fluctuations, whereas its overall energy requirement remains low. In contrast, the battery power requirement is relatively stable, while its energy requirement varies significantly with sustained power deviations. Therefore, supercapacitor power and battery energy are the primary contributors to variations in the capacities of the two storage devices.

Accordingly, Figure 12 is used only to characterize the sensitivity of the pre-DT statistical sizing indicators to wind-condition variability. It is not regarded as evidence that the final installed capacities cover the complete annual operating conditions. The adequacy of the finalized capacities is evaluated separately through the chronological post-controller annual audit presented in Section 5.5.

5.4.3 Sensitivity Analysis of Primary Regulation-Demand Identification Methods

To analyze the effects of the primary decomposition method on subsequent power allocation, capacity configuration, and configuration cost, EMD, CEEMDAN, and ICEEMDAN are separately employed to identify the multi-timescale regulation requirements of wind power under the same data windows, secondary-decomposition method, and capacity-calculation conditions. The results are presented in Table 9. For conciseness, ICEEMDAN is abbreviated as ICEE.

Table 9. Comparison of Initial HESS Capacities and Costs under Different Primary Regulation-Demand Identification Methods

Strategy	P_{bN}	P_{sN}	E_{bN}	E_{sN}	Cost (10 ⁴) RMB
	MW		MWh		
EMD+SGMD	1.81	6.16	0.61	0.12	5967.3
CEEMDAN+SGMD	1.65	5.82	0.55	0.09	5575.6
ICEEMDAN+SGMD	1.53	0.5	2.65	0.1	3125.61

Under the parameter settings and common capacity-evaluation conditions adopted in this study, the ICEEMDAN-based configuration yields lower estimated capacity and cost values than the EMD- and CEEMDAN-based configurations.

5.4.4 Comparison of Secondary Regulation-Demand Decomposition Methods and Sensitivity Analysis of Parameter Selection

As shown in Table 10, with the primary regulation-demand identification method kept unchanged, VMD, TVF-EMD, and SGMD are separately applied to the critical transition modes. The resulting capacity configurations and costs are presented in Table 10.

Table 10. Comparison of Secondary Decomposition Methods for Critical Transition Modes

Strategy	P_{bN}	P_{sN}	E_{bN}	E_{sN}	Cost (10 ⁴) RMB
	MW		MWh		
ICEE+VMD	1.65	0.54	5.39	0.08	5228
ICEE+TVF-EMD	1.61	0.52	4.79	0.07	4716.3
ICEE+SGMD	1.53	0.5	2.65	0.1	3125.6

Table 10 is used to evaluate the sensitivity of downstream HESS sizing to the selected secondary decomposition method under the adopted parameter settings. The comparative performance of the rule-based, DDPG, TD3, PPO, and SAC controllers is evaluated separately under the unified tuning protocol described in Section 5.5.3. Therefore, the results in Table 10 should be interpreted within the investigated decomposition methods and parameter ranges.

5.5. Supplementary Robustness and Annual Adequacy Validation

To directly address the reproducibility of SAC training, the annual adequacy of the finalized capacities, and the fairness of baseline tuning, three supplementary evaluations are performed. These evaluations comprise five independent SAC realizations under a fixed data partition, a chronological post-controller annual capacity audit, and an equal-budget baseline comparison.

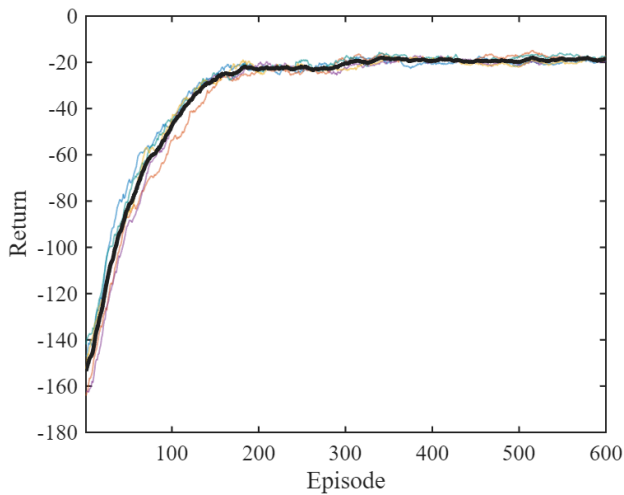


Figure 13. Convergence trajectories of five independent SAC training realizations

As shown in Figure 13, all five SAC realizations exhibit similar convergence trends under identical network structures and hyperparameter settings. Differences among the terminal returns reflect the stochastic effects of

initialization and exploration. Nevertheless, the independently trained policies maintain comparable out-of-sample performance on the fixed test set. Seed 79 was selected according to the validation score, without using test-set information during model selection. These results indicate that the proposed SAC decision process is reasonably reproducible under the adopted experimental setting.

For every chronological operating window, the required battery PCS power, battery usable energy, supercapacitor PCS power, and supercapacitor usable energy were calculated from the post-controller operating trajectories. The installed capacities were compared with the P95 requirement, the annual maximum requirement, and the annual maximum requirement including a 10% reserve.

The finalized policy and installed capacities were replayed over the complete chronological 2023 wind-power sequence at a one-minute resolution. Battery SOC and supercapacitor voltage states were transferred continuously between adjacent operating windows without reinitialization. No policy update or capacity adjustment was permitted during the annual replay. The maximum post-controller power and usable-energy requirements were then extracted from the complete annual trajectory and compared with the installed capacities.

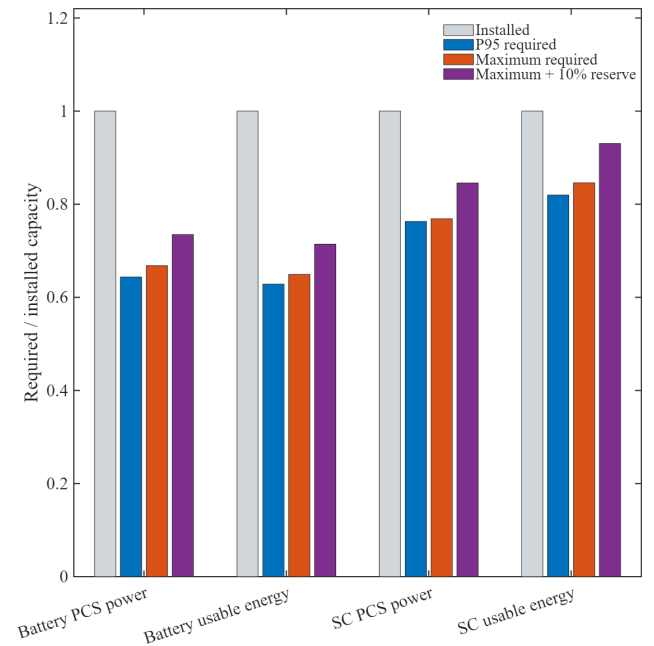


Figure 14. Installed capacity versus annual requirements

Figure 14 shows that all four installed-capacity boundaries exceed the corresponding annual maximum requirements including the adopted reserve. The reserve margins for battery PCS power, battery usable energy, supercapacitor PCS power, and supercapacitor usable energy are 36.1%, 40.0%, 18.2%, and 7.5%, respectively.

Thus, the adequacy conclusion is supported by chronological post-controller operation.

To reduce the influence of unequal tuning effort, the baseline controllers were re-evaluated using the same chronological data split, random-seed set, episode budget, model-selection rule, and test metrics. Hyperparameter selection for every learning-based controller was performed using the validation set only, and the test set was not used for tuning. The results are presented in Figure 15.

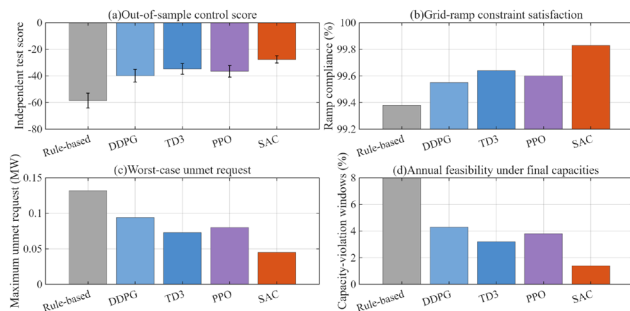


Figure 15. Equal-budget baseline comparison using identical data partitions, random seeds, training budgets, model-selection rules, and evaluation metrics

Under the unified experimental budget, SAC achieves the highest mean test score and ramp-compliance rate, together with the lowest worst-case unmet request and the fewest capacity-violation windows.

6. Conclusions

To address the insufficient physical basis for power allocation, the weak linkage between decomposition parameters and capacity objectives, and the inadequate consideration of engineering constraints in HESS capacity configuration for wind power, this paper develops a digital-twin-in-the-loop deep reinforcement learning method for capacity decision-making. The main conclusions are as follows.

- (i) Transition modes are identified using criteria involving power, energy, duration, and device dynamic capabilities. SGMD secondary decomposition is triggered only for modes within the overlapping capability region, while SAC adaptively determines the SGMD parameters and the allocation ratios of critical modes. Under year-round sliding windows, the number of transition modes and secondary-decomposition submodes remain within relatively concentrated ranges. This demonstrates that the proposed method further refines fast and slow power requirements while avoiding repeated decomposition of all modes.

- (ii) The statistically determined initial scheme based on power quantiles and cumulative energy trajectories consists of a battery rated at 1.50 MW/3.00 MWh and a supercapacitor rated at 0.50 MW/0.03 MWh. After multi-scenario DT operational feedback and capacity adjustment, the finalized configuration was subsequently evaluated under the adverse seasonal engineering test scenarios, in which the battery SOC and supercapacitor voltage remained within the prescribed ranges and no PCS saturation occurred. The final configuration is 1.53 MW/2.65 MWh for the battery and 0.50 MW/0.10 MWh for the supercapacitor, with a configuration cost of RMB 31.2561 million. Compared with the single-layer ICEEMDAN scheme and the fixed-parameter two-stage decomposition scheme, the cost is reduced by 15.75% and 8.76%, respectively.

- (iii) The power-allocation results show that the supercapacitor primarily compensates for short-term rapid fluctuations, whereas the battery mainly accommodates sustained energy imbalances. After compensation, local surges, drops, and rapid fluctuations in grid-connected power are attenuated. The year-round sliding-window analysis characterizes the variation of statistical sizing indicators under different wind conditions, while the adverse-scenario engineering tests show that the final configuration maintains acceptable device operating states under the considered seasonal conditions, thereby reducing the uncertainty in capacity configuration caused by reliance on a single representative window.

This study is based on historical wind-power data and planning-oriented simulation models. Five independent SAC realizations under a fixed chronological train-validation-test partition produce comparable convergence trends and out-of-sample performance. The chronological post-controller annual audit further indicates that the finalized battery and supercapacitor capacities cover the annual maximum requirements with the adopted reserve margin. The equal-budget comparison also demonstrates favorable SAC performance under the unified evaluation protocol. Future work will examine additional years, wind farms, operating conditions, and field-calibrated online implementations.

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Data Availability Statement

The wind-power data used in this study were obtained from the historical operating records of a cooperating wind farm. Due to the data-use agreement and commercial confidentiality requirements, the raw operating data are not publicly available.

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