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Techno-Economic Co-Planning of Hybrid Battery and Hydrogen Energy Storage for Renewable-Rich Distribution Networks Under Severe Contingencies

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ABSTRACT

Hybrid battery–hydrogen energy storage (HBHES) systems are emerging as a promising solution for renewable-rich distribution networks, as they combine the fast-response capability of batteries with the long-duration backup capability of hydrogen storage. However, single-shot optimization rarely produces designs that are simultaneously cost-effective, resilient, and electrically feasible under severe contingencies. This paper proposes a techno-economic co-planning framework that jointly determines the siting, sizing, and operating roles of battery and hydrogen subsystems, and iteratively refines candidate designs through feedback-assisted replanning. A mixed-integer linear programming (MILP) planning problem is coupled with nonlinear AC power flow validation, so that electrically weak designs identified after validation are converted into updated capacity requirements for subsequent iterations. A multistate HBHES model is developed to represent the differentiated roles of battery and hydrogen subsystems under both normal and screened $N-1/N-2$ contingency conditions, while composite severity-based contingency screening preserves computational tractability. The framework is demonstrated on the IEEE 123-bus feeder with renewable generation and load profiles representing a renewable-rich operating environment. Among six candidate architectures, the selected B1H2 configuration reduces the screened-state unserved energy from 201.4 to 98.3 MWh (−51.2%), improves the average served ratio under screened $N-1$ contingencies from 53.8% to 57.5%, and raises the minimum post-contingency voltage from 0.921 to 0.952 p.u. while eliminating overload and nonconvergence events after three feedback iterations. The comparative analysis reveals that the preferred architecture is not the largest-capacity option (B3H2, 62.1 MWh screened-state unserved energy at 1.93 B KRW/yr) but a moderately expanded hybrid layout (B1H2, 1.39 B KRW/yr) offering the highest compromise score (0.711) and the lowest resilience premium (0.15 B KRW/yr per pp). These results indicate that coordinated battery–hydrogen storage planning, when combined with closed-loop AC validation, provides physically credible and economically interpretable design insight for hybrid energy storage deployment in renewable-rich distribution networks.

1 | Introduction

1.1 | Motivation

Hybrid energy storage is attracting growing attention in renewable-rich power networks because no single storage technology

can simultaneously provide high-efficiency, short-duration support and economically viable, long-duration backup. Battery energy storage systems (BESSs) have been extensively studied as a flexibility resource for distribution networks, with demonstrated effectiveness for energy balancing [1], reliability improvement [2],

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risk mitigation under renewable penetration [3], robust planning [4], and bi-level allocation [5]. However, battery-only designs can become less attractive when contingency support must be sustained over longer durations or when a significant fraction of stored energy must be preserved as an emergency reserve. Hydrogen energy storage systems (HESSs), composed of electrolyzers, hydrogen tanks, and fuel cells, offer a complementary capability by providing longer duration support despite lower round-trip efficiency and have been investigated as seasonal storage in low-carbon systems [6], hydrogen-based energy management in retailer operations [7], and active-distribution hybrid planning [8]. These different operating characteristics motivate the coordinated planning of BESS and HESS rather than the isolated deployment of a single storage technology.

A further challenge is that hybrid storage planning cannot be addressed adequately by a one-shot optimization alone. Even when an initial design appears acceptable in terms of aggregate cost and contingency service, subsequent evaluation may reveal non-negligible service shortfalls, voltage weakness, or overloaded operating states. In renewable-rich distribution networks, hybrid storage should therefore be planned not only as an economic flexibility resource but also as a physically credible design whose battery-side and hydrogen-side capacities remain coordinated under realistic network constraints. For this reason, storage planning requires a framework that can jointly determine storage siting, sizing, and operating roles while refining electrically weak designs through postsolution validation.

1.2 | Literature Review

Hybrid battery–hydrogen storage planning has emerged from two converging research streams: hybrid energy storage systems (HESSs) for general renewable integration and resilience-oriented storage planning for distribution networks. This section reviews both streams and identifies the methodological gap addressed in the present study.

1.2.1 | HESSs for Renewable Integration

An early work established the conceptual foundations of hybrid storage architectures. Bocklisch [9] provided an overview of hybrid storage concepts for renewable applications, highlighting the complementarity of short- and long-duration technologies. Garcia-Torres and Bordons [10] developed a model-predictive control scheme for hydrogen-based microgrids with hybrid storage, demonstrating operational benefits at the dispatch level. Multiobjective optimization approaches have also been explored. Xuan et al. [11] applied particle swarm optimization to hybrid electric–hydrogen storage sizing, while Hemmati et al. [12] examined hybrid hydrogen–battery storage for solar energy smoothing and energy arbitrage under load uncertainty. These studies established that coordinated battery and hydrogen deployment can yield meaningful operational and economic benefits, but they focused primarily on operational optimization or single-objective sizing rather than on joint siting, sizing, and contingency-aware planning.

1.2.2 | Resilience-Oriented Planning of Distribution Systems

A parallel research stream has addressed resilience-aware planning of distribution systems under severe disturbances. Panteli

and Mancarella [13] introduced a widely adopted conceptual framework that distinguishes robustness, response, and recovery as complementary pillars of power system resilience enhancement. Wang et al. [14] provided a comprehensive review of power system resilience under natural disasters, systematizing metrics, methodologies, and mitigation strategies. Ma et al. [15] formulated a resilience-oriented design problem for distribution systems with explicit treatment of outage severity and service-restoration capability. Gilasi et al. [16] extended resilience-oriented planning specifically to battery storage, showing that storage siting and sizing decisions materially influence post-disturbance serviceability. Oraibi et al. [17] developed a stochastic mixed-integer linear programming (MILP)-based resilience-driven planning model that simultaneously locates and sizes stationary BESSs and renewable resources under both normal and emergency conditions, while Panwar et al. [18] demonstrated that reserve-preserving storage operation can be linearized and embedded within contingency-aware planning formulations for advanced distribution grids.

1.2.3 | Recent Hybrid Battery–Hydrogen Resilience Studies

Recent studies have begun to merge these two streams by investigating hybrid battery–hydrogen configurations explicitly for resilience enhancement. Li et al. [19] formulated a distributionally robust configuration problem for multi-microgrid electric–hydrogen hybrid storage, showing that hydrogen-side capacity materially improves robustness against renewable uncertainty. Lin et al. [20] proposed a two-stage decision-making framework for grid-connected PV/battery/hydrogen-integrated systems, systematically comparing six candidate schemes and reporting that hydrogen tank capacity dominates both cost and curtailment behavior. Shi et al. [21] introduced an event-oriented resilient planning model that jointly sizes BESS and HESS against extreme heatwave events, demonstrating that hydrogen-side long-duration capacity becomes cost-effective once the event-induced load increase exceeds a critical threshold. Oikonomou et al. [22] further expanded this perspective to capacity expansion planning for heatwaves and wildfires across regional grids, confirming that even modest cost increments can meaningfully enhance storage-supported resilience. Atawi et al. [23] focused on techno-economic–reliability joint assessment of wind–PV–hydrogen–battery hybrid systems, providing design-insight evidence for the complementarity of battery and hydrogen storage in reliability-constrained operation.

Prior battery-allocation studies for solar-enhanced grids [24] motivate storage siting as a planning lever, which the present work generalizes to hybrid battery–hydrogen co-planning. Reliability-oriented studies combining dynamic thermal rating with battery storage on wind-integrated networks [25] and battery-based reactive power support with dynamic line rating [26] underscore the resilience role of storage, which this framework extends with hydrogen-side long-duration backup and feeder-level AC feasibility. The two-stage dispatch framework with real-time feedback [27] is conceptually adjacent; the present study provides its planning-stage counterpart through validation-assisted replanning. Data-driven transmission capacity prediction with dynamic line rating [28] and the review of vehicle-

to-grid and dynamic-line-rating synergies [29] further reinforce that storage planning must remain physically credible and coordinate multiple flexibility resources, which the proposed AC-validated hybrid design directly supports. Unlike these operation-oriented or single-technology studies, the proposed framework jointly determines battery-hydrogen siting and sizing and closes the loop between MILP planning and nonlinear AC validation under screened severe contingencies.

Beyond storage-planning studies, recent operational works have advanced renewable-microgrid management, including demand-flexible energy trading in islanded microgrids [30], battery storage for electric-vehicle charging infrastructure [31], energy–water sector-coupled microgrid operation [32], and fuzzy-cloud stochastic energy management with high electric-vehicle penetration [33]. These studies primarily optimize operation or trading under given assets, whereas the present framework addresses investment-level hybrid battery–hydrogen co-planning whose candidate designs are explicitly validated against nonlinear AC feasibility under screened contingencies.

1.2.4 | Research Gap

Despite these advances, three methodological limitations persist across the hybrid storage planning literature. First, explicitly embedding many severe contingency states into a multiperiod planning problem imposes a substantial computational burden when siting, multitechnology sizing, and multistate operating trajectories are optimized simultaneously [15–18]. Second, AC power flow analysis is typically used as a post-processing check after the planning solution has been obtained rather than as a closed-loop mechanism that feeds electrical weakness back into the planning iteration [13–16]. Third, even the recent hybrid battery–hydrogen studies [19–23] have largely focused on aggregate techno-economic performance or event-triggered capacity expansion rather than on explicit feeder-level post-contingency serviceability under closed-loop AC validation in renewable-rich distribution networks. The present study addresses these gaps by developing a techno-economic co-planning framework that couples MILP-based hybrid storage design with AC validation-assisted replanning, as elaborated in the contribution statement below.

1.3 | Contribution

The main contributions of this study can be summarized as follows:

- Techno-economic co-planning framework for hybrid battery–hydrogen energy storage (HBHES) in renewable-rich distribution networks
This study develops a techno-economic co-planning framework for HBHESs that jointly determines storage siting, sizing, and operating roles under practical network constraints. Unlike formulations centered only on economic scheduling or single-technology capacity optimization, the proposed framework explicitly combines battery-side and hydrogen-side design decisions within a unified planning structure.
- Multistate HBHES design and operation model reflecting complementary battery and hydrogen roles

A multistate HBHES model is developed to represent the complementary operating characteristics of BESSs and HESSs. In the proposed formulation, BESS provides fast response and short-duration support, whereas the hydrogen subsystem, composed of an electrolyzer, hydrogen tank, and fuel cell, provides long-duration backup and renewable-energy-shifting capability under both normal and contingency conditions.

- Validation-assisted refinement of physically weak hybrid storage designs
This study introduces a validation-assisted refinement process in which storage designs obtained from MILP-based co-planning are replayed in an AC feeder model under screened contingencies, and post-validation deficiencies are converted into updated planning requirements for subsequent iterations. This feature enables the final hybrid storage design to be assessed not only in terms of economic feasibility but also in terms of physical credibility under severe operating conditions.
- Practical design insight into hybrid storage architecture selection under cost–resilience trade-offs
The proposed framework provides an interpretable basis for comparing candidate hybrid storage architectures with different levels of battery-side and hydrogen-side expansion. The case study shows that the preferred HBHES design is not necessarily the largest-capacity option but the architecture that best balances resilience improvement, economic acceptability, and practical deployment burden.

1.4 | Organization of This Paper

The remainder of this paper is organized as follows: Section 2 introduces the HBHES architecture and multistate design model. Section 3 presents the techno-economic co-planning, AC validation, and architecture-evaluation framework. Section 4 describes the case study and simulation setup. Section 5 discusses the comparative results of the candidate hybrid storage architectures. Finally, Section 6 concludes the paper.

2 | HBHES Architecture and Multistate Design Model

2.1 | HBHES Architecture and Design Scope

HBHES is considered in this study as a coordinated storage architecture that combines the fast response capability of batteries with the long-duration support capability of hydrogen storage. The target application is a renewable-rich distribution network in which hybrid storage is deployed to improve operational flexibility and post-disturbance serviceability under practical feeder constraints. Within this architecture, the battery subsystem primarily provides short-duration balancing and rapid local support, whereas the hydrogen subsystem, composed of an electrolyzer, a hydrogen tank, and a fuel cell, provides longer-duration backup and renewable energy-shifting capability. In this sense, the planning problem is not only to determine how much total storage capacity should be installed but also to determine how battery-side and hydrogen-side capacities should be coordinated so that the resulting layout remains physically meaningful, economically acceptable, and

operationally credible. This unified treatment is consistent with the overall planning structure illustrated in Figure 1, which links system inputs, architecture planning, validation-assisted refinement, and final outputs into a single hybrid storage design process. Battery and hydrogen capacities are therefore evaluated as coordinated design components whose sizing, operating roles, and post-validation adequacy must be interpreted together rather than independently.

The architecture definition therefore combines installation decisions, sizing bounds, and practical coupling relations for the hydrogen subsystem. Equation (1) defines the admissible BESS sizing range, while Equation (2) defines the corresponding sizing ranges of the electrolyzer, fuel cell, and hydrogen tank. Equation (3) then limits the total numbers of battery and hydrogen sites so that each candidate architecture represents a practically deployable hybrid storage layout rather than an unrestricted capacity allocation result. In addition, the hydrogen subsystem is constrained by practical coordination conditions so that the electrolyzer, fuel cell, and hydrogen tank capacities do not evolve independently in a physically inconsistent manner. In particular, the first inequality of Equation (4), $P_b^{\text{EL}} \geq \kappa P_b^{\text{FC}}$, prevents the electrolyzer side from becoming unrealistically small relative to the fuel-cell side so that hydrogen replenishment capability is preserved during normal operation. The second inequality, $M_b^{\text{H}_2} \geq (\tau^{\text{H}_2} / \alpha^{\text{FC}}) P_b^{\text{FC}}$, guarantees that the installed hydrogen inventory is sufficient to sustain the fuel-cell subsystem at rated output for at least τ^{H_2} hours, as confirmed by the unit analysis $[\text{h}] \cdot [\text{kW}] / [\text{kWh/kg}] = [\text{kg}]$. With $\kappa = 0.75$ and $\tau^{\text{H}_2} = 12 \text{ h}$ adopted in this study (Table 1), Equations (1)–(4) jointly define the feasible deployment region of each candidate hybrid storage architecture as follows:

$$\underline{P}_b^B y_b^B \leq P_b^B \leq \bar{P}_b^B y_b^B, \quad \underline{E}_b^B y_b^B \leq E_b^B \leq \bar{E}_b^B y_b^B, \quad (1)$$

$$\underline{P}_b^{\text{EL}} y_b^{\text{H}} \leq P_b^{\text{EL}} \leq \bar{P}_b^{\text{EL}} y_b^{\text{H}}, \quad \underline{P}_b^{\text{FC}} y_b^{\text{H}} \leq P_b^{\text{FC}} \leq \bar{P}_b^{\text{FC}} y_b^{\text{H}}, \quad (2)$$

$$\underline{M}_b^{\text{H}_2} y_b^{\text{H}} \leq M_b^{\text{H}_2} \leq \bar{M}_b^{\text{H}_2} y_b^{\text{H}}$$

$$\sum_{b \in \mathcal{B}} y_b^B \leq N_B^{\text{max}}, \quad \sum_{b \in \mathcal{B}} y_b^{\text{H}} \leq N_H^{\text{max}}, \quad (3)$$

$$P_b^{\text{EL}} \geq \kappa P_b^{\text{FC}}, \quad M_b^{\text{H}_2} \geq \frac{\tau^{\text{H}_2}}{\alpha^{\text{FC}}} P_b^{\text{FC}}. \quad (4)$$

The electrolyzer-to-fuel-cell coupling in Equation (4) should be interpreted as a capacity coordination condition rather than a guarantee of hourly hydrogen replenishment. In practice, hydrogen reserve restoration during normal operation depends on the availability of renewable surplus or off-peak grid import, feeder import limits, electrolyzer operating constraints, and the recovery time between successive severe events. Therefore, a design satisfying Equation (4) can be considered replenishment-capable only when sufficient surplus energy and network headroom are available over the recovery window. Explicit optimization of hydrogen refilling trajectories under renewable uncertainty and sequential contingencies is beyond the scope of the present architecture-level planning model and is left for future operational-stage extension.

2.2 | Multistate Storage Operation Model

The hybrid storage system is operated under both normal and retained severe conditions. The multistate operating structure is introduced to preserve the complementary roles of the battery and hydrogen subsystems within the same design. On the battery side, the main requirement is to capture intertemporal charging and discharging behavior while preventing the normal-state schedule from depleting the battery to a level that would undermine its contingency-support role. For this reason, the model combines energy balance dynamics with operating bounds and reserve preservation conditions. Equation (5) describes the intertemporal evolution of the battery energy state, while Equation (6) imposes

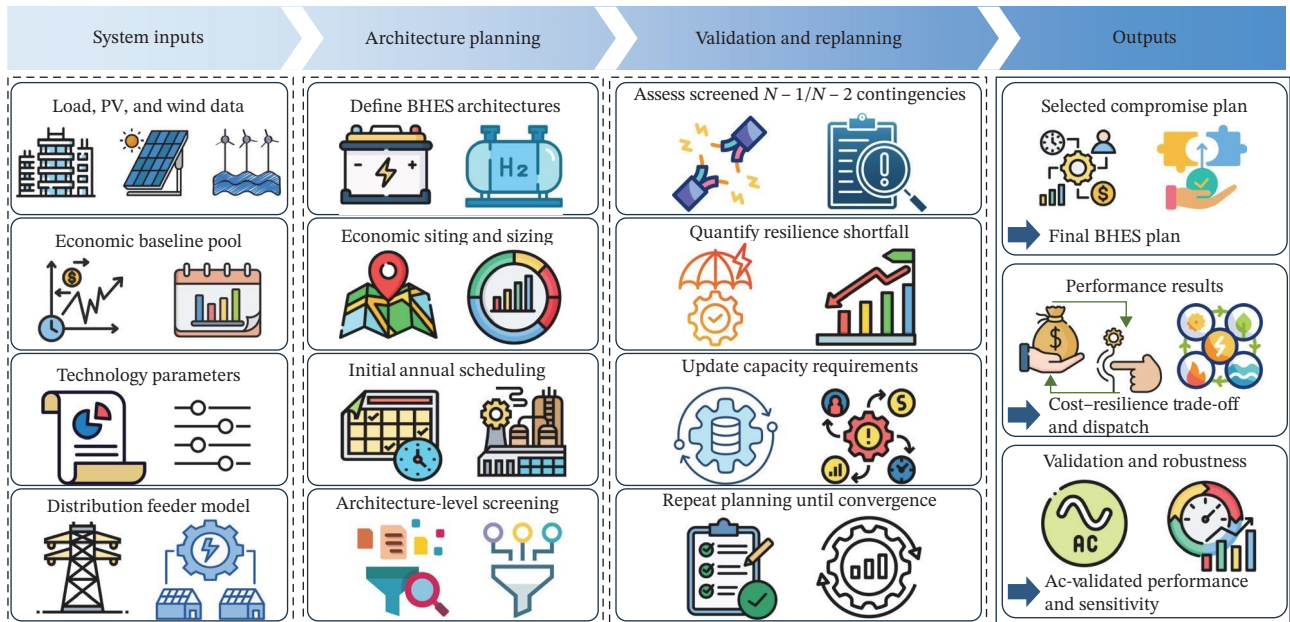


FIGURE 1 | Overall four-stage framework of the proposed HBHES planning methodology: system inputs, architecture planning, validation and replanning, and outputs.

charging, discharging, and stored-energy limits. Equation (7) then preserves a reserve margin during normal operation and initializes each retained severe state from a reserve-preserving battery condition. This distinction is important because the battery subsystem is intended to represent fast response and short duration support rather than unrestricted energy exhaustion.

On the hydrogen side, the main requirement is to represent hydrogen production, hydrogen consumption, and hydrogen inventory evolution in a way that is consistent with a longer duration support capability. Equation (8) tracks the conversion of electrical energy into stored hydrogen through the electrolyzer and the reconversion of stored hydrogen into electricity through the fuel cell, using constant conversion coefficients α^{EL} and α^{FC} . This linear representation implicitly assumes effective aggregate efficiencies that envelope typical operating ranges, which preserves the MILP structure; the implied planning-level round-trip efficiency is $\alpha^{\text{FC}}/\alpha^{\text{EL}} \approx 34.6\%$ under the values in Table 1, consistent with reported values for commercial electrolyzer–fuel-cell pairs. Equation (9) imposes the corresponding operating and storage limits of the hydrogen subsystem, and Equation (10) preserves a minimum hydrogen inventory in normal operation while initializing each retained severe state from a reserve-preserving hydrogen condition. As on the battery side, this reserve logic prevents the hydrogen subsystem from being treated as fully disposable in advance of severe states. Instead, Equations (8)–(10) ensure that the hydrogen subsystem functions as an intentional long-duration backup resource within the proposed architecture.

Taken together, Equations (5)–(10) establish a multistate operating model in which the battery subsystem provides rapid short-duration support and the hydrogen subsystem provides sustained long-duration support. This operational distinction is central to the proposed HBHES design because it allows battery-side and hydrogen-side capacities to be coordinated according to their differentiated support roles rather than being treated as interchangeable storage resources.

$$e_{b,t,s}^B = e_{b,t-1,s}^B + \eta^{\text{ch}} p_{b,t,s}^{\text{ch}} \Delta t - \frac{1}{\eta^{\text{dis}}} p_{b,t,s}^{\text{dis}} \Delta t, \quad (5)$$

$$0 \leq p_{b,t,s}^{\text{ch}} \leq P_b^B, \quad 0 \leq p_{b,t,s}^{\text{dis}} \leq P_b^B, \quad 0 \leq e_{b,t,s}^B \leq E_b^B, \quad (6)$$

$$e_{b,t,0}^B \geq \rho^{B,\text{res}} E_b^B, \quad e_{b,0,s}^B = \rho^{B,\text{init}} E_b^B \quad \forall s \in \mathcal{S}, \quad (7)$$

$$m_{b,t,s}^{\text{H}_2} = m_{b,t-1,s}^{\text{H}_2} + \frac{p_{b,t,s}^{\text{EL}} \Delta t}{\alpha^{\text{EL}}} - \frac{p_{b,t,s}^{\text{FC}} \Delta t}{\alpha^{\text{FC}}}, \quad (8)$$

$$0 \leq p_{b,t,s}^{\text{EL}} \leq P_b^{\text{EL}}, \quad 0 \leq p_{b,t,s}^{\text{FC}} \leq P_b^{\text{FC}}, \quad 0 \leq m_{b,t,s}^{\text{H}_2} \leq M_b^{\text{H}_2}, \quad (9)$$

$$m_{b,t,0}^{\text{H}_2} \geq \rho^{H,\text{res}} M_b^{\text{H}_2}, \quad m_{b,0,s}^{\text{H}_2} = \rho^{H,\text{init}} M_b^{\text{H}_2} \quad \forall s \in \mathcal{S}. \quad (10)$$

It is worth noting that the hydrogen subsystem in Equations (8)–(10) is represented using constant electricity-to-hydrogen and hydrogen-to-electricity conversion coefficients (α^{EL} and α^{FC}) in order to preserve the MILP structure of the planning problem. This linear formulation intentionally omits part-load efficiency curves of electrolyzers and fuel cells, stack degradation over the planning horizon, start-up/shutdown transients, compression losses, and hydrogen tank boil-off since incorporating them would

TABLE 1 | Main planning, operational, and validation parameters.

Category	Parameter	Value
BESS	Power CAPEX (c_p^B)	220,000 (KRW/kW)
	Energy CAPEX (c_E^B)	220,000 (KRW/kWh)
	Efficiency ($\eta^{\text{ch}}, \eta^{\text{dis}}$)	0.96
	Reserve fraction ($\rho^{B,\text{res}}$)	0.25
HESS	Electrolyzer CAPEX	1,400,000 (KRW/kW)
	Fuel cell CAPEX	2,400,000 (KRW/kW)
	H2 tank CAPEX	1,300,000 (KRW/kg)
	EL demand/FC yield	52/18 (kWh/kg)
	Reserve fraction ($\rho^{H,\text{res}}$)	0.20
	H2 backup duration (τ^{H_2})	12 (h)
Economic	EL/FC sizing ratio (κ)	0.75
	Discount rate	5%
	Planning horizon	20 (yr)
	Capital recovery factor	0.0802
Reliability	VOLL	25,000 (KRW/kWh)
	Failure rate (λ_i)	0.12 [fail/(km-yr)]
Voltage	Repair time (τ^{rep})	6 (h)
	Normal/ $N-1$ / $N-2$ limits	0.95/0.94/0.92 (p.u.)
Contingency	Target served ratio (γ_s)	0.65 ($N-1$), 0.40 ($N-2$)
Feedback	Convergence tolerance (ϵ)	50 (kW)
	Quantile level (q)	0.9
	Update coeffs. (β_P, β_E)	1.0/1.0
Selection	Score weights (w_c, w_r, w_b)	0.42/0.45/0.13

Note: BESS CAPEX values are based on the NREL 2023 Annual Technology Baseline for utility-scale battery storage (4-h system) converted at 1380 KRW/USD [34]. Electrolyzer and fuel-cell CAPEX values are based on IEA Global Hydrogen Review 2024 [35]. Hydrogen tank CAPEX is based on the DOE Hydrogen Program Storage Cost Analysis [36]. VOLL, line failure rate, and repair duration are set to representative values consistent with distribution-level resilience-planning practice for Korean-scale networks.

require a mixed-integer nonlinear reformulation beyond the scope of the present architecture-level planning framework. The numerical values adopted for these coefficients and the sensitivity of the results to hydrogen-side cost assumptions are discussed in Sections 4.3 and 5.4.

2.3 | Feeder-Side Balance and Contingency-Support Representation

The hybrid storage design is linked to feeder-level service performance through a set of demand-balance and contingency-support relations. At this stage, the objective is not to reproduce a full nonlinear feeder model inside the planning problem but to establish a compact planning-side representation that connects storage operation with demand serving, renewable curtailment, and PCC exchange. Total demand is partitioned into served and shed components so that contingency-support quality can be

measured explicitly. In this context, Equation (11) separates feeder demand into served and unserved portions, and Equation (12) aggregates the feeder-level electrical contribution of the hybrid storage system by combining battery discharge, fuel cell output, battery charging, and electrolyzer consumption into a single net term.

Building on this aggregated storage contribution, Equation (13) defines the feeder-level power balance by coordinating PCC import/export, renewable generation, renewable curtailment, and HBHES operation. Equation (14) imposes the PCC exchange limits, and Equation (15) introduces a minimum served load requirement under retained severe states. These conditions ensure that the candidate hybrid storage design is evaluated not only by its installed capacities but also by its ability to support feeder-level service under restricted grid exchange and adverse operating conditions.

In this way, Equations (11)–(15) provide a compact service-oriented planning representation that links storage design decisions directly to feeder-level support capability. The resulting formulation is intentionally simpler than the detailed validation model introduced later in Section 3, but it is sufficiently structured to

ensure that planning decisions already reflect feeder-level service implications before nonlinear AC replay is applied.

$$L_t = I_{t,s}^{\text{srv}} + I_{t,s}^{\text{shed}}, \quad (11)$$

$$p_{t,s}^{\text{BHES}} = \sum_{b \in \mathcal{B}} (p_{b,t,s}^{\text{dis}} + p_{b,t,s}^{\text{FC}} - p_{b,t,s}^{\text{ch}} - p_{b,t,s}^{\text{EL}}), \quad (12)$$

$$I_{t,s}^{\text{srv}} = p_{t,s}^{\text{imp}} - p_{t,s}^{\text{exp}} + p_{t,s}^{\text{BHES}} + P_t^{\text{PV}} + P_t^{\text{WT}} - p_{t,s}^{\text{curt}}, \quad (13)$$

$$0 \leq p_{t,s}^{\text{imp}} \leq \bar{P}^{\text{imp}}, \quad 0 \leq p_{t,s}^{\text{exp}} \leq \bar{P}^{\text{exp}}, \quad (14)$$

$$I_{t,s}^{\text{srv}} \geq \gamma_s L_t, \quad \forall s \in \mathcal{S}. \quad (15)$$

3 | Techno-Economic Co-Planning, Validation, and Architecture Evaluation

3.1 | Baseline Techno-Economic Planning Problem

The proposed hybrid storage planning problem is formulated as a techno-economic design problem that seeks an economically acceptable and physically credible architecture under both normal and retained severe operating conditions. The overall workflow of the proposed feedback loop is illustrated in Figure 2.

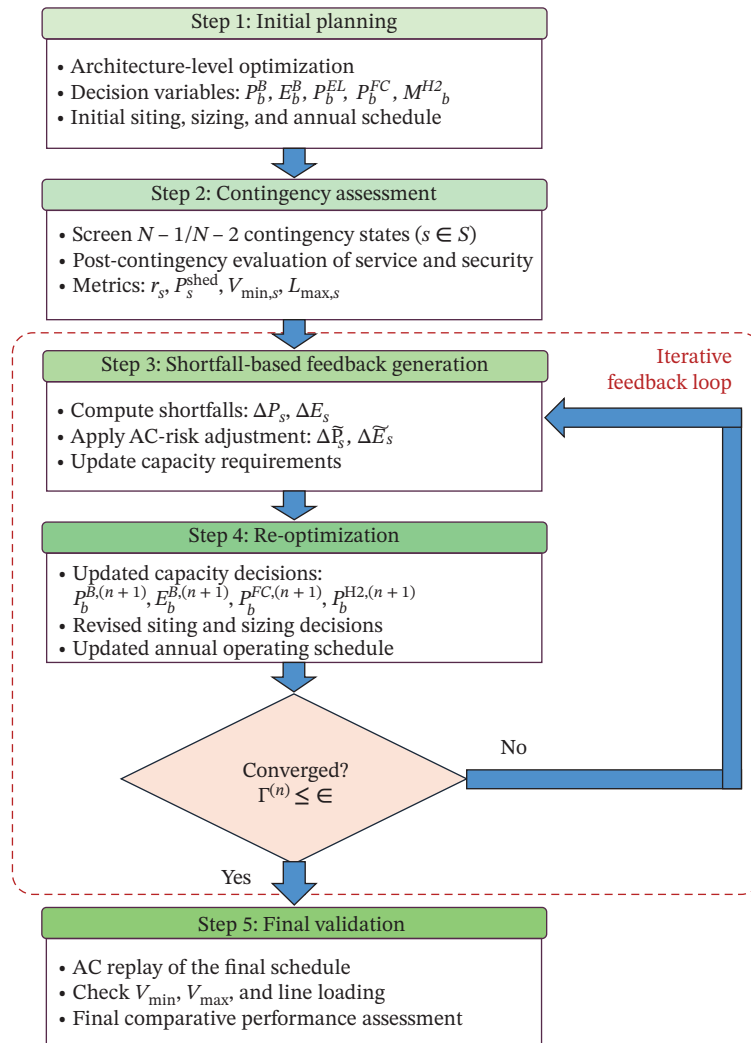


FIGURE 2 | Iterative five-step workflow of the proposed feedback-based co-planning loop. Steps 3 and 4 form the inner replanning loop that terminates when the convergence measure $\Gamma^{(n)} \leq \epsilon$.

The baseline objective combines annualized investment cost, operating cost, and contingency-related service penalty. In this formulation, Equation (16) defines the overall baseline planning objective, while Equation (17) evaluates the annualized investment burden associated with the installed battery-side and hydrogen-side capacities. The operating-side burden is then represented in Equation (18), where the operating cost and unserved energy term are accumulated over operating states and time periods through the stage-cost expression defined in Equation (19).

This structure is important because it prevents hybrid storage sizing from being interpreted as a pure capacity-minimization problem. Instead, the candidate architecture is evaluated not only by the capital burden of installed battery power, battery energy, electrolyzer capacity, fuel-cell capacity, and hydrogen inventory but also by its operating burden and the service consequences of insufficient support under retained severe states. In this sense, Equations (16)–(19) provide the first-stage techno-economic criterion of the proposed framework before physical validation and refinement are introduced.

The baseline planning formulation therefore establishes an economically interpretable design objective while retaining explicit sensitivity to contingency-related service deficiency. This balance between cost and service adequacy is essential because the goal of the framework is not to find the smallest storage design but to identify a hybrid storage architecture that remains meaningful once both operating cost and severe-state support performance are considered.

$$\min J^{\text{base}} = C^{\text{inv}} + C^{\text{op}} + C^{\text{ue}}, \quad (16)$$

$$C^{\text{inv}} = \sum_{b \in \mathcal{B}} \left(c_p^B P_b^B + c_E^B E_b^B + c_{EL}^B P_b^{\text{EL}} + c_{FC}^B P_b^{\text{FC}} + c_{H_2}^B M_b^{\text{H}_2} \right), \quad (17)$$

$$C^{\text{op}} + C^{\text{ue}} = \sum_{s \in \mathcal{O}} \sum_{t \in \mathcal{T}} w_s \Psi_{t,s} \Delta t, \quad (18)$$

$$\Psi_{t,s} = c_t^{\text{imp}} p_{t,s}^{\text{imp}} - c_t^{\text{exp}} p_{t,s}^{\text{exp}} + c_{\text{curt}}^{\text{curt}} p_{t,s}^{\text{curt}} + \chi_s c^{\text{VOLL}} I_{t,s}^{\text{shed}}. \quad (19)$$

3.2 | Screened Contingency Representation and Retained Severe States

The number of possible $N-1$ and $N-2$ outage combinations can be prohibitively large when hybrid storage sizing and multistate operation are optimized together. The initial candidate set Ω is constructed by deterministic enumeration of single- ($N-1$) and double- ($N-2$) feeder-line outages; electrically equivalent or duplicated outage states are merged, and outages whose isolated service area is empty are discarded, so that Ω retains only physically distinct, service-relevant contingencies, as defined in Equation (20).

$$\Omega = \{(l), (l, l') \mid l, l' \in L, l \neq l'\} \setminus \{\text{duplicate or service-empty states}\}. \quad (20)$$

For each retained candidate $s \in \Omega$, a lightweight feeder replay estimates the peak power deficit, the energy deficit, and the outage depth used by the severity indicators below. To preserve

tractability, the proposed method retains only the severe operating states that are most influential for hybrid storage design. The retained set is constructed in two stages. First, each candidate outage state is assigned a probability- or weight-like measure based on the failure and repair characteristics, as given in Equation (21). Second, a composite severity score is constructed in Equation (22) by combining probability-related information with peak stress, energy-severity, and outage-depth indicators. The screened set is then obtained in Equation (23) by selecting only the top-ranked severe states.

This screening step is important because the objective of the study is not exhaustive outage enumeration but practically interpretable hybrid storage design. Retaining only the severe states makes it possible to embed representative disturbance conditions into the storage design problem without overwhelming the planning model. In this sense, Equations (21)–(23) define a design-focused retained severe-state subset rather than a full probabilistic outage universe.

By concentrating the planning and validation process on the most influential states, the proposed framework preserves computational tractability while still capturing the disturbance conditions that are most relevant to hybrid storage sizing, reserve preservation, and post-contingency service adequacy.

$$\rho_s = \begin{cases} \lambda_l \tau^{\text{rep}}, & \text{for an } N-1 \text{ outage of line } l \\ \lambda_{l_1} \lambda_{l_2} (\tau^{\text{rep}})^2, & \text{for an } N-2 \text{ outage of lines } l_1, l_2 \end{cases}, \quad (21)$$

$$\Phi_s = w^{\text{peak}} \phi_s^{\text{peak}} + w^{\text{ene}} \phi_s^{\text{ene}} + w^{\text{dep}} \phi_s^{\text{dep}} + w^{\text{prob}} \rho_s, \quad (22)$$

$$\mathcal{S} = \{s \in \Omega : \Phi_s \text{ belongs to the top } K \text{ scores}\}. \quad (23)$$

3.3 | Design Shortfall Measures and Architecture-Level Resilience Indicator

Once an initial hybrid storage design is obtained, the next step is to quantify the remaining deficiency in meeting the required service level under the retained severe states. This is done through power and energy shortage measures. Equation (24) defines the state-level power shortfall as the maximum deficit, over the operating horizon, between the required served load $\gamma_s L_t$ and the actual served load $I_{t,s}^{\text{srv}}$; the positive-part operator $[\cdot]^+$ ensures that only hours with insufficient service contribute to the shortfall. Equation (25) then converts this deficiency into an energy-based quantity using the repair duration, and Equation (26) aggregates the retained-state energy shortfalls into the architecture-level screened-state unserved energy, defined as the unweighted sum of the physical unserved energy over the retained severe states.

This step is important because architecture comparison should not rely only on installed capacity or capital cost. A candidate design may install more storage and still fail to provide attractive service improvement relative to its added cost. The screened-state unserved-energy measure (USE_a) defined through Equations (24)–(26) therefore provides a direct performance bridge between retained severe-state behavior and architecture-level design comparison.

Within the comparative analysis, this quantity serves as one of the principal resilience-oriented indicators. It allows the final design to be interpreted not only in terms of how much storage is installed but also in terms of how effectively that storage reduces severe-state service deficiency under the retained contingency set.

$$\Delta P_s = \max_{t \in \mathcal{T}} [\gamma_s L_t - I_{t,s}^{snv}]^+, \text{ where } [x]^+ = \max(0, x), \quad (24)$$

$$\Delta E_s = \Delta P_s \tau^{\text{rep}}, \quad (25)$$

$$\text{USE}_a = \sum_{s \in \mathcal{S}} \Delta E_s. \quad (26)$$

3.4 | Feeder-Level AC Validation of Candidate Designs

The planning model in Sections 2 and 3.1 provides a compact techno-economic representation of hybrid storage design, but it does not guarantee that the resulting solution remains electrically credible in a detailed feeder model. For this reason, the candidate design is replayed under the retained severe states in a nonlinear AC feeder model. The purpose of this step is to determine whether the initial design exhibits electrical weakness such as low voltage, excessive loading, or nonconvergent operating points. Rather than treating AC validation as a purely diagnostic post-processing step, the present framework uses it as an active design refinement mechanism.

To make the validation step explicit, the nonlinear AC power flow is solved for each retained state $s \in \mathcal{S}$ and time t on the feeder model (N, L) . Equations (27) and (28) state the AC nodal active- and reactive-power balance, Equations (29) and (30) enforce the bus-voltage and line-thermal security limits, and Equation (31) bounds the reactive support of the storage inverters.

$$P_{i,t,s} = V_{i,t,s} \sum_{j \in N} V_{j,t,s} (G_{ij} \cos \theta_{ij,t,s} + B_{ij} \sin \theta_{ij,t,s}), \quad \forall i \in N, \quad (27)$$

$$Q_{i,t,s} = V_{i,t,s} \sum_{j \in N} V_{j,t,s} (G_{ij} \sin \theta_{ij,t,s} - B_{ij} \cos \theta_{ij,t,s}), \quad \forall i \in N, \quad (28)$$

$$V_{\min, \text{AC}} \leq V_{i,t,s} \leq V_{\max, \text{AC}}, \quad \forall i \in N, \quad (29)$$

$$|S_{ij,t}| = \sqrt{P_{ij,t}^2 + Q_{ij,t}^2} \leq S_{ij}^{\max}, \quad \forall (i,j) \in \mathcal{L}, \quad \forall s \in \mathcal{S}, \quad \forall t, \quad (30)$$

$$|Q_{i,t,s}^{\text{HBHES}}| \leq |P_{i,t,s}^{\text{HBHES}}| \tan \varphi_i^{\max}, \quad (31)$$

where $\theta_{ij,t,s} = \theta_{i,t,s} - \theta_{j,t,s}$, G_{ij} and B_{ij} are the real and imaginary parts of the bus admittance matrix, S_b^{inv} is the apparent-power rating of the storage inverter at bus b , and $\bar{\varphi}$ is the maximum power-factor angle. In the validation stage, the line-security limit in Equation (30) and the loading ratio in Equation (33) are evaluated on the apparent-power branch flow $|S_{ij}| = \sqrt{P_{ij}^2 + Q_{ij}^2}$ against the line's apparent-power (thermal) rating $S_{ij}^{\max}$, so that the AC check reflects the actual thermal/current loading rather than active power alone. The inverter reactive support in Equation (31) is bounded through the converter P - Q capability

relation $|Q_i| \leq \sqrt{((S_i^{\text{rating}})^2 - (P_i)^2)}$; the maximum power-factor angle $\varphi_i^{\max}$ thus defines the corresponding minimum operating power factor rather than an independent reactive limit, so the active- and reactive-power bounds remain mutually consistent.

The replay results are summarized through worst-case voltage and loading indicators, together with violation-frequency indicators. Equation (32) defines the worst-case minimum and maximum voltages observed in each retained state, while Equation (33) defines the corresponding maximum line-loading ratio. Based on these electrical stress measures, Equations (34)–(37) quantify the frequencies of undervoltage, overvoltage, overload, and nonconvergence events during AC replay, respectively. These indicators are chosen because they directly capture whether the selected hybrid storage capacities remain acceptable not only from an energy balance perspective but also from the viewpoint of feeder operability.

If the retained severe states reveal electrical weakness after the replay, the corresponding design is not accepted as final; instead, its update signal is strengthened in the subsequent replanning step. This logic is central to the proposed framework because it allows techno-economic design and feeder-level physical credibility to remain linked throughout the refinement process.

$$V_s^{\min} = \min_{t \in \mathcal{T}, i \in \mathcal{N}} V_{i,t,s}, \quad V_s^{\max} = \max_{t \in \mathcal{T}, i \in \mathcal{N}} V_{i,t,s}, \quad (32)$$

$$\rho_s^{\text{load}} = \max_{(i,j) \in \mathcal{L}} \max_t \frac{|S_{ij,t}|}{S_{ij}^{\max}} \leq 1, \quad (33)$$

$$v_s^{\text{UV}} = \frac{1}{|\mathcal{T}| |\mathcal{N}|} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} \mathbf{1}(V_{i,t,s} < V_{\min, \text{AC}}), \quad (34)$$

$$v_s^{\text{OV}} = \frac{1}{|\mathcal{T}| |\mathcal{N}|} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} \mathbf{1}(V_{i,t,s} > V_{\max, \text{AC}}), \quad (35)$$

$$v_s^{\text{OL}} = \frac{1}{|\mathcal{T}| |\mathcal{L}|} \sum_{t \in \mathcal{T}} \sum_{l \in \mathcal{L}} \mathbf{1}(|F_{l,t,s}| > \bar{F}_l), \quad (36)$$

$$v_s^{\text{NC}} = \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \mathbf{1}(\text{AC power flow does not converge}). \quad (37)$$

3.5 | Validation-Assisted Replanning Requirements

Once the AC replay identifies electrical weakness, the resulting validation indicators are used to strengthen the design update signal. This is done through an AC risk multiplier that aggregates voltage deviation, thermal stress, and violation frequencies into a state-level adjustment factor. The purpose of this multiplier is not to replace the underlying shortfall measures but to scale them so that electrically weak retained states exert greater influence during replanning. In this way, the update process reflects both service deficiency and post-solution electrical weakness.

The corresponding refinement relations are organized in three stages. First, Equation (38) defines the AC risk multiplier from deviation- and violation-based penalties. Next, Equation (39) converts the original power and energy shortfalls into AC-adjusted

shortfalls. Equations (40) and (41) map the state-level adjusted shortfalls into design-level replanning targets through a probability-weighted quantile operator. Equations (42) and (43) update the aggregate support power and support energy requirements for the next iteration. Finally, Equation (44) defines the convergence condition used to terminate the feedback-assisted replanning loop. The refinement process continues until the iteration-to-iteration change becomes sufficiently small according to the convergence condition.

This structure is important because it prevents the replanning logic from reacting only to the most severe numerical shortfall while ignoring electrical feasibility. At the same time, it avoids allowing a single extreme retained state to dominate the entire update process. The refinement step therefore strengthens physically weak hybrid storage designs in a controlled manner, making it possible to combine service-based and validation-based information within the same iterative update procedure.

$$\begin{aligned} \mu_s^{\text{AC}} = & 1 + \alpha_V^{\min} [V_s^{\min, \text{AC}} - V_s^{\min}]^+ + \alpha_V^{\max} [V_s^{\max} - V_s^{\max, \text{AC}}]^+ \\ & + \alpha_L^{\max} [L_s^{\max} - 1]^+ + \alpha_{UV} v_s^{\text{UV}} + \alpha_{OV} v_s^{\text{OV}} \\ & + \alpha_{OL} v_s^{\text{OL}} + \alpha_{NC} v_s^{\text{NC}}, \end{aligned} \quad (38)$$

$$\Delta P_s^{\text{AC}} = \mu_s^{\text{AC}} \Delta P_s, \quad \Delta E_s^{\text{AC}} = \mu_s^{\text{AC}} \Delta E_s, \quad (39)$$

$$\Delta P^{\text{req}, (n)} = Q_q(\{\rho_s \Delta P_s^{\text{AC}}\}_{s \in \mathcal{S}}), \quad (40)$$

$$\Delta E^{\text{req}, (n)} = Q_q(\{\rho_s \Delta E_s^{\text{AC}}\}_{s \in \mathcal{S}}), \quad (41)$$

$$P^{\text{sup}, (n+1)} = P^{\text{sup}, (n)} + \beta_P \Delta P^{\text{req}, (n)}, \quad (42)$$

$$E^{\text{sup}, (n+1)} = E^{\text{sup}, (n)} + \beta_E \Delta E^{\text{req}, (n)}, \quad (43)$$

$$I^{(n)} = \max(|P^{\text{sup}, (n+1)} - P^{\text{sup}, (n)}|, |E^{\text{sup}, (n+1)} - E^{\text{sup}, (n)}|) \leq \varepsilon. \quad (44)$$

In this study, the feedback update coefficients β_P and β_E are set to unity, as reported in Table 1. This unit-gain setting transfers the AC validation shortfalls into the next planning iteration without artificial amplification or attenuation so that one unit of validated support deficiency is mapped to one unit of additional planning requirement. Coefficients below unity would damp the update and mainly slow convergence, whereas coefficients above unity could accelerate correction but may temporarily oversize the support requirement. Because the update is further moderated by the probability-weighted quantile mapping, physical capacity bounds, the finite candidate architecture set, and the iteration cap, the unit-gain setting provides a transparent and numerically stable baseline for architecture-level replanning.

The feedback-assisted replanning loop terminates under any of three stopping conditions, summarized in Table 2 as follows: the iteration-to-iteration change in the required adjustment falls below the tolerance ε (set to 50 kW), the iteration count reaches the cap $n_{\max} = 3$, or no feasible architecture upgrade remains. The 50 kW threshold is an engineering tolerance below which further capacity refinements do not change the architecture-level planning outcome. In relative terms, the 50 kW tolerance corresponds to only about 1.6%–1.9% of the rated capacities of the

TABLE 2 | Termination criteria of the feedback-assisted replanning loop and their practical interpretation.

Stopping condition	Mathematical condition	Practical meaning
Tolerance satisfied	$ \Delta P_{\text{req}}^{(n)} - \Delta P_{\text{req}}^{(n-1)} \leq \varepsilon$ (50 kW)	Further update is too small to affect architecture-level planning
Iteration cap	$n \geq n_{\max}$	Prevents infinite looping in constrained cases
No feasible upgrade	Candidate set exhausted	Returns the best feasible refined architecture

selected B1H2 design (fuel cell 3.05 MW and battery 2.66 MW), so iteration-to-iteration refinements below this level cannot alter the architecture-level planning decision. The 50 kW tolerance also lies below the minimum load-serving shortfall increment resolved in the planning model, so a residual adjustment smaller than this level cannot correspond to a meaningful change in the served load and therefore cannot alter the architecture-level decision.

3.6 | Architecture-Level Evaluation and Compromise Selection

After refinement is completed for each candidate, the final comparison is carried out at the architecture level. The purpose of this stage is not to identify the design with the largest total installed capacity but to identify the hybrid storage architecture that provides the most attractive balance among annualized cost, service performance, and deployment burden. This distinction is important because a more extensive hybrid storage configuration may reduce severe-state service deficiency while still yielding an unattractive overall design once cost and practical deployment complexity are taken into account.

The evaluation; therefore, proceeds in four steps. First, the annualized total cost of each candidate architecture is defined as the sum of annualized investment cost, operating cost, and the contingency-weighted unserved-energy penalty.

$$C_a^{\text{ann}} = C_{\text{inv}, a}^{\text{ann}} + C_{\text{op}, a}^{\text{ann}} + C_{\text{pen}, a}, \quad C_{\text{pen}, a} = c_{\text{VOLL}} \sum_{s \in \mathcal{S}} w_s \Delta E_s, \quad (45)$$

where C_a^{pen} represents the full contingency-weighted unserved-energy cost evaluated on the retained severe-state set. In Equation (45) this penalty is evaluated as $c_{\text{VOLL}} \sum_{s \in \mathcal{S}} w_s \Delta E_s$, where w_s is the annual occurrence weight of retained severe state s and ΔE_s is the physical unserved energy of that state. The screened-state unserved energy reported in Table 3 is the unweighted aggregate sum over s of ΔE_s , whereas the monetary penalty in Equation (45) applies the annual occurrence weight w_s .

Beyond the absolute total cost, the marginal economic burden incurred per unit of resilience improvement provides additional design insight when comparing candidate architectures. To this end, the resilience premium of architecture a relative to a reference architecture is defined as follows:

TABLE 3 | Techno-economic comparison of candidate hybrid storage architectures.

Architecture	B1H1	B1H2 ^a	B2H1	B2H2	B3H1	B3H2
BESS (MW/MWh)	2.88/11.8	2.66/12.9	5.88/23.6	5.76/24.8	6.94/31.8	6.35/35.2
EL/FC (MW)	1.30/1.62	2.60/3.05	1.35/1.71	2.60/3.18	1.40/1.84	2.60/3.32
H2 tank (kg)	1100	2150	1280	2380	1450	2620
Annual total cost (B KRW/yr)	0.846	1.389	1.133	1.681	1.389	1.93
$N-1$ served (%)	53.8	57.5	55.4	57.1	56.9	57.4
$N-2$ served (%)	40.1	47.5	43.2	55.8	43.9	55.4
Screened-state unserved energy (MWh)	201.4	98.3	142.7	81.4	115.6	62.1
Compromise score (S_a)	0.498	0.711	0.553	0.52	0.608	0.432

^aSelected (preferred) architecture with the highest compromise score S_a .

$$RP_a = \frac{C_a^{\text{ann}} - C_{\text{ref}}^{\text{ann}}}{\Delta r_{s,a}}, \quad \Delta r_{s,a} = r_{s,a} - r_{s,\text{ref}}, \quad (46)$$

where $r_{s,a}$ denotes the average served ratio under retained $N-1$ contingencies for architecture a , and the reference architecture is taken as the smallest-capacity candidate against which resilience gain is measured. A lower RP_a indicates that resilience improvement is achieved at lower marginal cost. This metric is referenced alongside the compromise score S_a in the architecture-level comparison presented in Section 5.

Second, the deployment burden is defined as the total number of installed BESS and HESS sites.

$$D_a = N_a^B + N_a^H, \quad (47)$$

where N_a^B and N_a^H denote the number of BESS and HESS sites in architecture a , respectively. This captures the essential difference in installation complexity—land acquisition, civil works, interconnection procedures, and multisite operation and maintenance coordination—while avoiding additional tunable parameters. The resulting values are $D_{B1H1} = 2$, $D_{B1H2} = D_{B2H1} = 3$, $D_{B2H2} = D_{B3H1} = 4$, and $D_{B3H2} = 5$, which confirm that deployment burden increases monotonically with the number of installed storage sites.

Third, to allow comparable aggregation of these heterogeneous metrics, cost, resilience, and deployment burden are converted into normalized desirability measures on the unit interval $[0, 1]$, where a larger value consistently indicates a more desirable outcome. For cost, which should be minimized, the normalization is defined as follows:

$$\hat{C}_a = \frac{\max_{a' \in \mathcal{A}} C_{a'}^{\text{ann}} - C_a^{\text{ann}}}{\max_{a' \in \mathcal{A}} C_{a'}^{\text{ann}} - \min_{a' \in \mathcal{A}} C_{a'}^{\text{ann}}}. \quad (48)$$

For resilience, which is expressed through architecture-level screened-state unserved energy (USE_a) and should also be minimized, the normalization is given as follows:

$$\hat{R}_a = \frac{\max_{a' \in \mathcal{A}} USE_{a'} - USE_a}{\max_{a' \in \mathcal{A}} USE_{a'} - \min_{a' \in \mathcal{A}} USE_{a'}}. \quad (49)$$

For deployment burden, which reflects the practical complexity of installing multiple storage sites and is similarly minimized, the normalization is as follows:

$$\hat{B}_a = \frac{\max_{a' \in \mathcal{A}} D_{a'} - D_a}{\max_{a' \in \mathcal{A}} D_{a'} - \min_{a' \in \mathcal{A}} D_{a'}}. \quad (50)$$

Under this convention, each normalized desirability $\hat{C}_a, \hat{R}_a, \hat{B}_a \in [0, 1]$ equals 1.0 for the most desirable candidate on that metric and 0.0 for the least desirable one.

Finally, the compromise score S_a is defined as the weighted sum of the three normalized desirabilities, and the preferred architecture a^* is selected as the candidate that maximizes this score.

$$S_a = w_c \hat{C}_a + w_r \hat{R}_a + w_b \hat{B}_a, \quad (51)$$

$$a^* = \arg \max_{a \in \mathcal{A}} S_a, \quad (52)$$

where the non-negative weights satisfy $w_c + w_r + w_b = 1$. The specific weight values adopted in this study are listed in Table 1 and reflect a design emphasis that prioritizes resilience while retaining meaningful sensitivity to cost, with deployment burden serving as a tie-breaking consideration among architectures of comparable cost-resilience performance.

In this way, the final architecture selection is interpreted as a storage design trade-off problem rather than as a simple maximum capacity or minimum cost decision. The resulting decision criterion is particularly important for hybrid storage planning because the practically preferred architecture is not necessarily the one with the largest battery-side and hydrogen-side capacities but the one that provides the most balanced response to cost, resilience, and deployment burden.

4 | Case Study and Simulation Setup

4.1 | Renewable-Rich Testbed and Evaluation Scope

The proposed HBHES planning framework is examined on the IEEE 123-bus distribution feeder, which serves as a renewable-

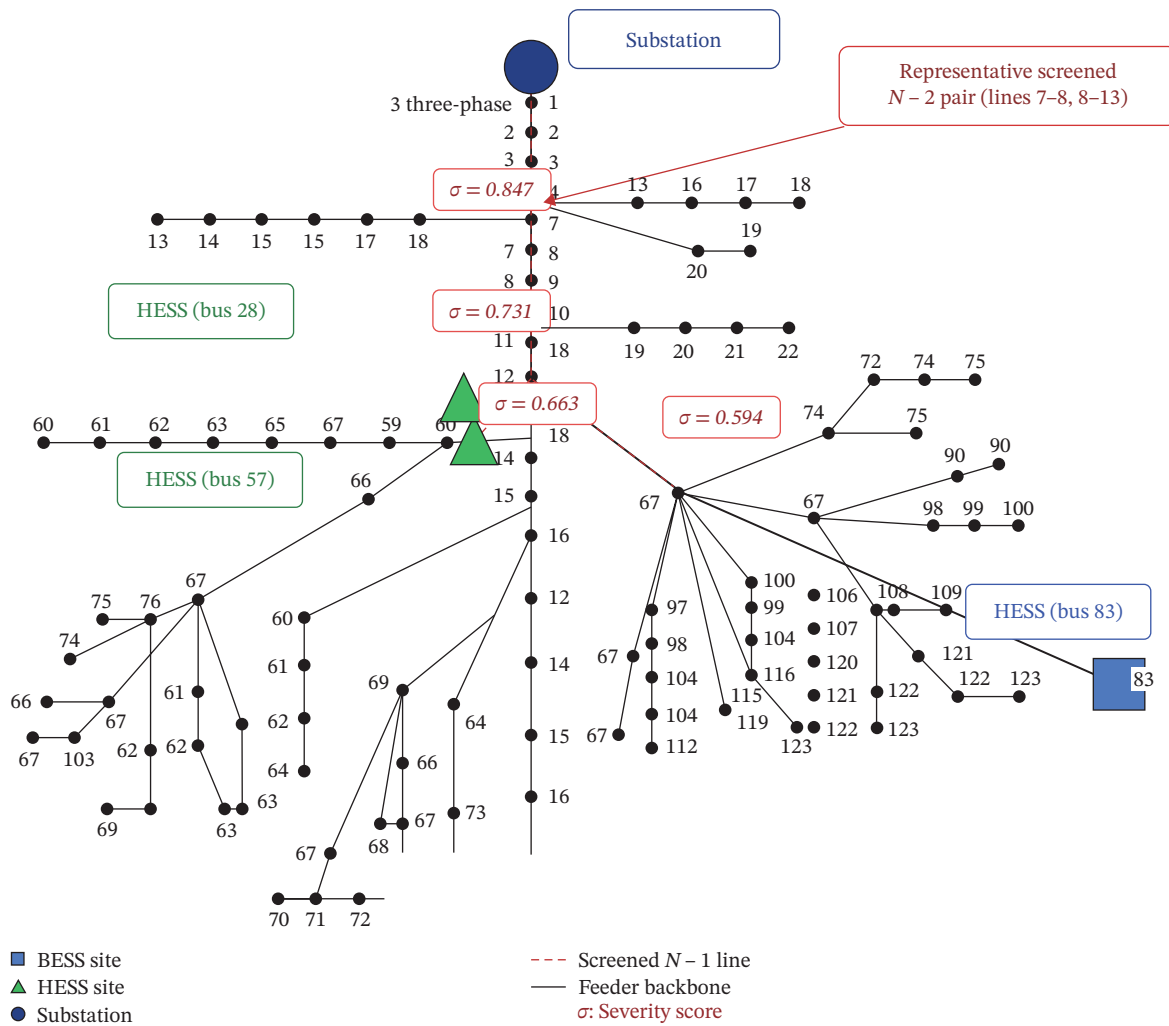


FIGURE 3 | IEEE 123-bus distribution feeder used in the case study. Selected HBHES candidate buses (BESS: Bus 83; HESS: Buses 28 and 57) and the representative $N-1/N-2$ screened contingencies are highlighted; composite severity scores (σ) are shown for the top-ranked retained outages.

rich testbed for evaluating how battery-side and hydrogen-side capacities, locations, and operating roles evolve under practical network constraints. The feeder is used here not only as a benchmark network but also as a realistic design environment in which candidate hybrid storage architectures can be compared in terms of techno-economic behavior, service-support capability, and post-solution electrical credibility.

The feeder is combined with renewable generation and load profiles representing a renewable-rich operating condition so that both normal operation flexibility and post-contingency support can be examined within a unified design framework. This setup allows the case study to reveal not only whether hybrid storage is beneficial but also how different balances between battery-side expansion and hydrogen-side expansion influence the final architecture choice. Representative feeder information and operating profiles are shown in Figures 3 and 4. The combined installed renewable capacity (photovoltaic and wind) in the case study represents approximately 65% of the peak feeder load, quantitatively consistent with the definition of a renewable-rich operating environment in which storage-supported flexibility and post-contingency serviceability must be examined together. These figures define the electrical and operating context in which the hybrid storage architectures are evaluated.

4.2 | Candidate Hybrid Storage Architectures and Comparative Setup

To evaluate how battery-side and hydrogen-side expansion affect hybrid storage architecture selection, six candidate HBHES architectures are considered: B1H1, B1H2, B2H1, B2H2, B3H1, and B3H2. These architectures represent systematic combinations of one to three BESS sites and one to two HESS sites, providing a structured comparison of compact and distributed hybrid storage layouts. Rather than treating them merely as deployment patterns, this study interprets them as alternative co-sizing configurations that clarify how the relative extent of battery-side and hydrogen-side expansion influences techno-economic design outcomes. This comparative setup makes it possible to examine whether battery expansion alone is sufficient, whether moderate hydrogen-side reinforcement yields additional value, and whether larger multi-site hybrid layouts provide benefits commensurate with their added cost and design complexity.

The retained screened-contingency counts and maximum feedback iteration settings associated with the candidate architectures are summarized in Table 4. Figure 5 summarizes the installed battery-side and hydrogen-side capacities across the candidate architectures, showing how electrolyzer/fuel-cell ratings and

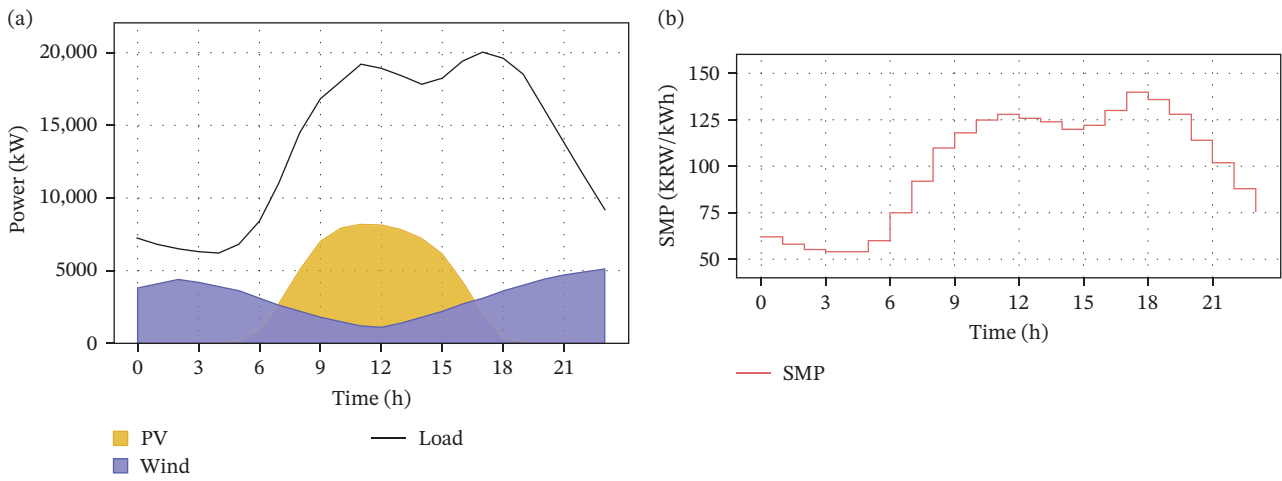


FIGURE 4 | Representative daily profiles used in the case study: (a) load, photovoltaic, and wind generation profiles (renewable nameplate capacity corresponds to approximately 65% of peak feeder load, representing a renewable-rich operating condition); (b) time-varying electricity price profile following the Korean system marginal price (SMP) pattern.

TABLE 4 | Summary of candidate HBHES architectures.

Architecture	B1H1	B1H2	B2H1	B2H2	B3H1	B3H2
BESS sites	1	1	2	2	3	3
HESS sites	1	2	1	2	1	2
Screened contingencies ($N-1/N-2$)	3/1	4/2	4/1	5/3	4/1	6/3
Max. feedback iterations ($n_{\max}$)	0	3	3	3	3	3

hydrogen inventory change with additional hydrogen-side deployment. The installed capacities shown in Figure 5 represent optimized continuous-valued outcomes after validation-assisted replanning and are therefore not restricted to coarse predefined capacity blocks. The contingency assumptions follow the screened-contingency strategy introduced in Section 3; rather than embedding exhaustive outage enumeration, the study retains a limited but severe set of $N-1$ and $N-2$ conditions so that the computational focus remains on the disturbance states most relevant to hybrid storage design refinement.

4.3 | Main Parameters and Evaluation Metrics

The main planning, operating, and validation parameters are summarized in Table 1. The table collects battery-side cost assumptions, hydrogen-side coupling parameters, reserve settings, service thresholds, and validation settings within a single techno-economic modeling framework. In particular, it distinguishes between battery-side reserve preservation and hydrogen-side reserve preservation while also specifying the hydrogen-coupling parameters used to maintain physically coordinated electrolyzer, fuel-cell, and tank sizing. These parameters define the practical storage design assumptions used throughout the case study.

The numerical results are evaluated using a combination of techno-economic, service performance, and electrical security indicators. At the architecture level, the principal metrics are annualized total cost, screened-state unserved energy (USE_a), served ratio under retained severe conditions, and compromise score. At the validation level, the key indicators are the worst-

case minimum voltage, maximum loading ratio, overload frequency, and nonconvergence rate. Together, these quantities make it possible to interpret the final hybrid storage design not only in terms of installed capacity but also in terms of whether that installed capacity yields a practically balanced architecture under realistic network constraints.

For computational tractability, the hydrogen subsystem uses the constant conversion coefficients introduced in Section 2.2, with values of 52 kWh/kg (electricity-to-hydrogen) and 18 kWh/kg (hydrogen-to-electricity), implying a planning-level round-trip efficiency of approximately 34.6%. Because the omitted equipment-level effects listed in Section 2.2 mainly cause a moderate underestimation of hydrogen-side operating cost and a slight overestimation of subsystem availability under deep part-load operation—and because all six candidate architectures are evaluated under identical assumptions—the relative ranking of architectures is preserved. The aggregated impact of these simplifications is examined through the $\pm 30\%$ variations in hydrogen-side CAPEX in Section 5.4, and a detailed hydrogen-subsystem model is identified as a natural extension in Section 6.

5 | Results and Discussion

5.1 | Architecture-Level Comparison of Candidate Hybrid Storage Designs

The first question addressed in the results is which candidate hybrid storage architecture provides the best techno-economic balance. Figure 6 compares the candidate architectures in the

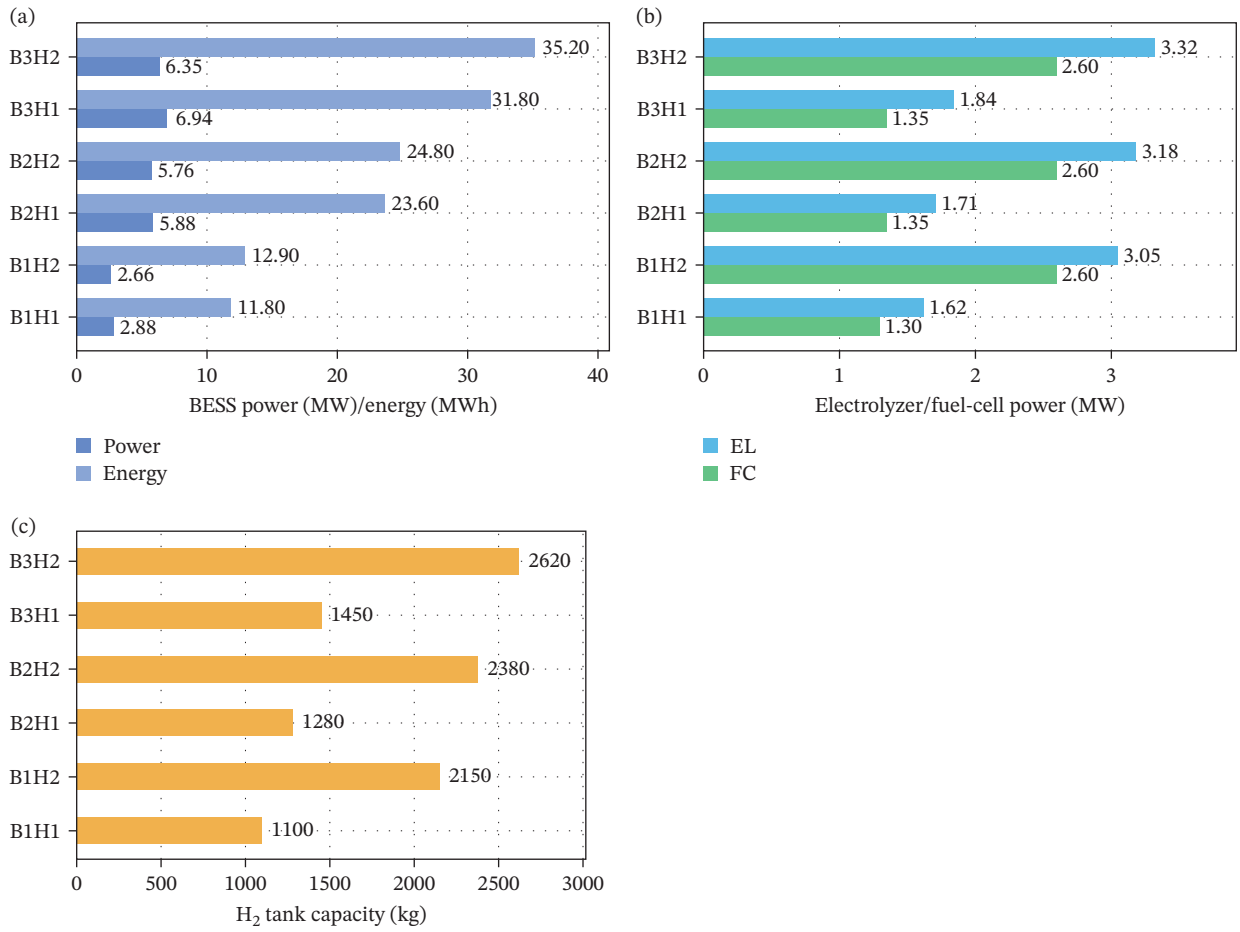


FIGURE 5 | Installed battery-side and hydrogen-side capacities across candidate hybrid storage architectures after validation-assisted replanning: (a) BESS power and energy capacities, (b) electrolyzer and fuel-cell capacities (identical electrolyzer ratings across H₂-type architectures reflect the active coupling constraint $P_b^{EL} = \kappa P_b^{FC}$ in Equation (4)), and (c) hydrogen-tank capacities.

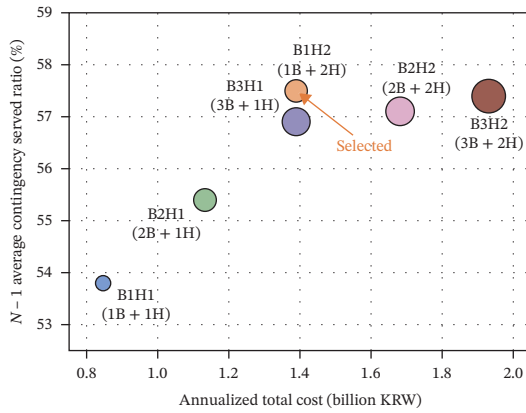


FIGURE 6 | Cost-service trade-off across candidate hybrid storage architectures, using annualized total cost and average served ratio under retained $N - 1$ contingencies. Architecture labels indicate the number of BESS and HESS sites (e.g., 1B + 2H denotes one BESS site and two HESS sites). The selected B1H2 configuration achieves the highest compromise score among the six candidates.

cost-service trade-off plane, while Table 3 summarizes the corresponding architecture-level metrics. This comparison is intended to identify the most attractive hybrid storage architecture under combined cost, serviceability, and deployment

considerations rather than to rank the candidates only by a single resilience-oriented metric.

As reported in Table 3, the annualized total cost increases from 0.846 B KRW/yr for B1H1 to 1.930 B KRW/yr for B3H2, while the corresponding screened-state unserved energy decreases from 201.4 to 62.1 MWh. This confirms that larger hybrid storage architectures can improve post-contingency serviceability but also shows that the lowest-cost architecture is not the most resilient one and the most resilient one is not necessarily the most attractive design. The practical design question is therefore not whether total capacity should simply be maximized but how much battery-side and hydrogen-side expansion is justified by the additional service benefit obtained. The unserved-energy values reported here and in Table 3 denote the physical unserved energy aggregated over the retained severe states, before the annual contingency weighting w_s of Equation (45) is applied; the corresponding monetary penalty applies w_s , as detailed in Section 5.2.

Among the candidate architectures, B1H2 achieves the highest compromise score of 0.711. This result indicates that a moderate increase in hydrogen-side deployment, combined with a limited battery-side layout, can provide a more balanced design than either the smallest-capacity architecture or the largest-capacity multisite alternative. The selected B1H2 architecture should

therefore be interpreted not as the largest-capacity option but as the hybrid storage design that best balances resilience enhancement against annualized cost and deployment burden.

The architecture comparison in Table 3 can also be interpreted qualitatively in terms of the deployment character. In this sense, B1H1 represents a compact baseline hybrid layout, B1H2 represents a moderate hydrogen-side expansion, and B3H2 represents an extensive multisite hybrid layout. This interpretation helps clarify why the selected architecture emerges from a balance between battery-side compactness and hydrogen-side support capability rather than from the monotonic expansion of all storage components. Architectures with greater hydrogen-side deployment generally exhibit lower screened-state unserved energy, but the associated annualized cost rises rapidly as the design becomes more extensive. Conversely, architectures with limited hydrogen-side support remain more economical but may leave substantial service deficiency under retained severe conditions.

5.2 | Validation-Assisted Refinement of the Selected Hybrid Storage Architecture

The second question addressed in the results is whether the selected hybrid storage design remains electrically credible after detailed feeder-level replay. Figures 7–10, together with the AC validation summary Table 5, illustrate how the selected B1H2 architecture is refined through the validation-assisted planning process. These results show that the proposed methodology does not stop at obtaining an economically attractive storage layout but further refines that layout when post-solution electrical weakness is identified.

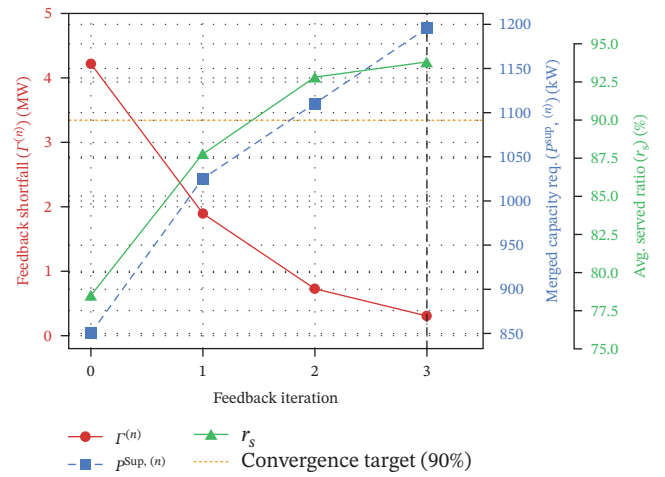


FIGURE 7 | Convergence behavior of the feedback-based replanning process for the selected B1H2 architecture. The feedback shortfall $\Gamma^{(n)}$ decreases monotonically, while the merged capacity requirement $P^{\text{sup}, (n)}$ and average served ratio r_s stabilize after three iterations. The dotted line indicates the convergence-phase aggregate target served ratio of 90% used as a design-level termination benchmark, distinct from the per-contingency thresholds γ_s listed in Table 1.

As shown in Figure 7, the feedback shortfall $\Gamma^{(n)}$ decreases monotonically across iterations and falls below the 50 kW tolerance, confirming convergence; the stopping criteria are summarized in Table 2 and the final shortfall ($31 < 50$ kW) is shown in Table 5. This behavior suggests that the initially planned hybrid storage configuration is not discarded after validation but rather

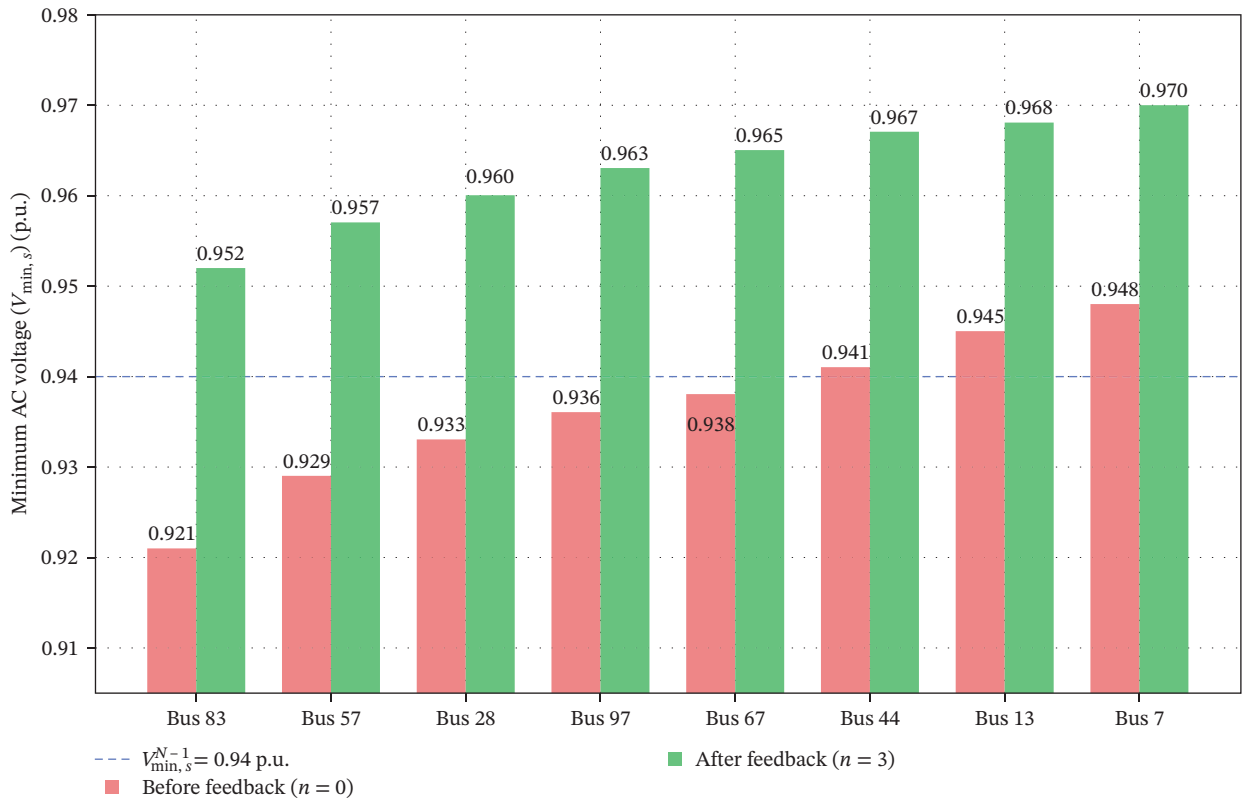


FIGURE 8 | Minimum AC voltage at critical buses before and after feedback replanning for the selected B1H2 architecture. All buses satisfy the $N-1$ voltage threshold $V_{\min, s}^{N-1} = 0.94$ p.u. after convergence ($n=3$).

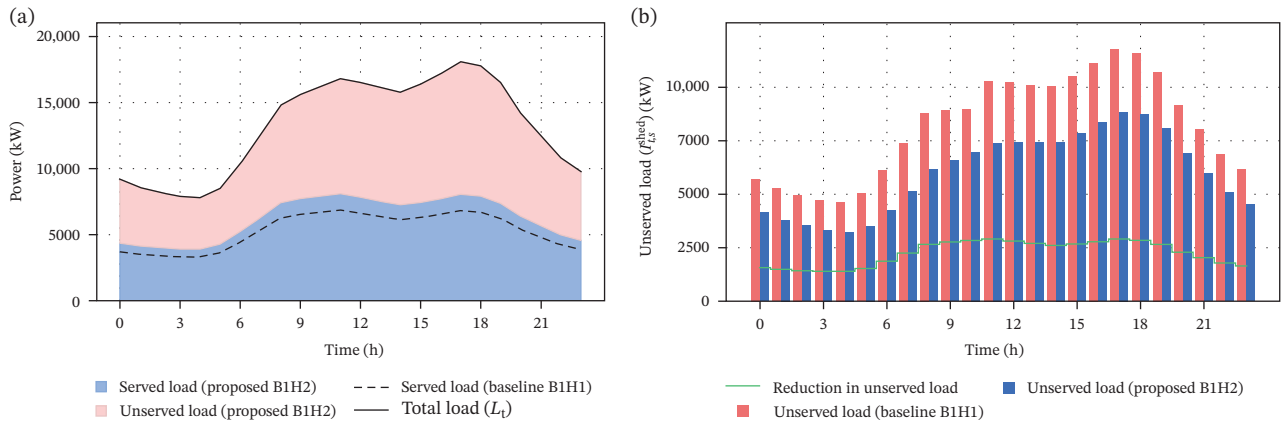


FIGURE 9 | Comparison of load-supply response between baseline B1H1 and selected B1H2 under a representative $N-2$ contingency (lines 7–8 and 8–13): (a) served and unserved load profiles with total demand L_t and (b) hourly unserved-load reduction achieved by the proposed B1H2 configuration.

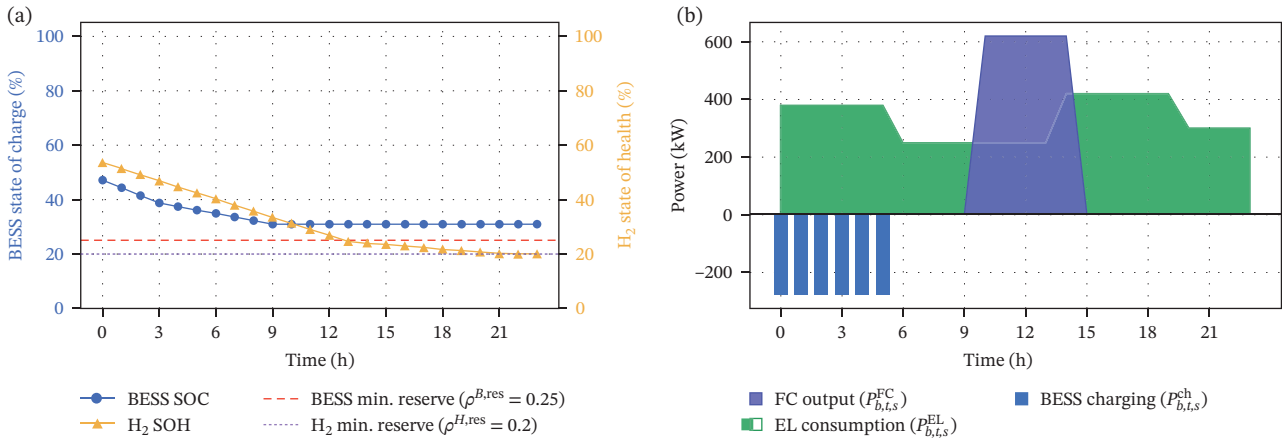


FIGURE 10 | Temporal role separation between BESS and HESS in the selected B1H2 architecture during a representative retained $N-2$ contingency event (lines 7–8 and 8–13): (a) BESS state of charge and H₂ state of health trajectories, with reserve thresholds $\rho^{B,res} = 0.25$ and $\rho^{H,res} = 0.20$ and (b) fuel-cell output, electrolyzer consumption, and battery-charging power profiles. The BESS discharges to provide rapid early-stage support, while the hydrogen subsystem sustains longer-duration service through fuel-cell output.

TABLE 5 | Electrical validation of the selected hybrid storage design before and after refinement.

Metric	Before feedback ($n = 0$)	After ($n = 1$)	After ($n = 2$)	After ($n = 3$) (converged)	Threshold
Minimum bus voltage (p.u.)	0.921	0.937	0.947	0.952	≥ 0.94
Maximum branch loading (%)	112.4	98.7	91.3	86.2	≤ 100
Undervoltage ratio (%)	14.2	7.6	3.1	0.0	0
Overload ratio (%)	18.7	8.3	2.1	0.0	0
Nonconvergence ratio (%)	6.3	2.8	0.7	0.0	0
Maximum shortfall (kW)	436	187	68	31	≤ 50
MILP objective (B KRW/yr)	0.831	0.839	0.845	0.850	—
Solve time (s)	347	412	398	381	≤ 3600

adjusted so that battery-side and hydrogen-side capacities become more consistent with the electrical weakness revealed during replay. Such behavior is especially important in practical hybrid storage planning because a design that appears acceptable in a simplified planning model may still prove insufficient when feeder-level voltage and loading constraints are considered explicitly.

It is worth clarifying the relationship between the MILP objective reported in Table 5 and the annualized total cost reported in Table 3. The MILP objective value J^{base} listed in Table 5 (0.831 $\rightarrow$ 0.850 B KRW/yr across iterations) corresponds to the planning-stage objective defined in Equation (16), which aggregates annualized investment cost C^{inv} (Equation (17)), expected operating cost C^{op} (Equation (18)), and the state-weighted contingency-

related service penalty C_a^{ue} evaluated on the retained severe-state subset $\mathcal{S}$ (Equations (18) and (19)). In contrast, the annualized total cost C_a^{ann} in Table 3 (1.389 B KRW/yr for B1H2) additionally includes the full contingency-weighted unserved energy penalty $C_a^{\text{pen}} = c^{\text{VOLL}} \sum_{s \in \mathcal{S}} w_s \Delta E_s$ evaluated on the retained screened severe-state set including contingency-probability weighting, as defined in Equation (45). The approximately 0.54 B KRW/yr gap between the two values therefore reflects the contingency-related unserved energy burden that is priced at value of lost load (VOLL) but is not fully embedded inside the optimization objective for tractability reasons. This distinction is important because the MILP objective drives the optimization decisions, whereas the annualized total cost provides the post-optimization techno-economic accounting used for architecture-level comparison. More precisely, the 0.54 B KRW/yr equals the probability-weighted unserved energy penalty $\text{VOLL} \cdot \sum_s w_s \cdot \Delta E_s$ evaluated on the screened severe states: the screened-state unserved energy of 98.3 MWh priced at $\text{VOLL} = 25,000$ KRW/kWh with an aggregate annual contingency weighting $\sum_s w_s \approx 0.219$ gives ≈ 0.54 B KRW/yr, which reconciles the MILP objective (0.850 B KRW/yr) with the annualized total cost (1.389 B KRW/yr). The unserved energy values in Table 3 (201.4 $\rightarrow$ 98.3 MWh) are the unweighted physical unserved energy of the retained severe states, so this penalty is not the unweighted product $\text{VOLL} \times (\text{screened-state unserved energy})$. To avoid any double counting, the contingency-related service term embedded in the MILP objective acts only as a tractable planning surrogate that steers the optimization, and the contingency-related cost is carried into the reported annualized total cost of Table 3 only once through the full VOLL-priced probability-weighted penalty of Equation (45).

Figure 8 and the AC validation summary confirm that the refined B1H2 design substantially improves the electrical feasibility. The minimum post-contingency voltage increases from 0.921 to 0.952 p.u., the maximum loading ratio is reduced from 112.4% to 86.2%,

and overload and nonconvergence events are removed in the final replay. These results indicate that validation-assisted replanning improves not only service adequacy but also the physical credibility of the selected hybrid storage architecture.

The operating profiles in Figures 9 and 10 further clarify the differentiated roles of the battery and hydrogen subsystems within the selected design. The BESS contributes fast response support and immediate load-serving assistance, whereas the hydrogen subsystem provides sustained support through fuel-cell output and hydrogen inventory utilization. This role separation is a central design feature of the proposed hybrid architecture and helps explain why the selected B1H2 layout can outperform smaller alternatives without requiring the full capacity expansion of larger multisite designs.

5.3 | Economic Composition and Design Trade-Off Across Candidate Architectures

A further design question is how the economic burden of hybrid storage expansion is distributed across battery-side capacity, hydrogen-side capacity, and service penalty reduction. Figure 11 decomposes the annualized cost of the candidate architectures into major components, thereby clarifying which part of the hybrid storage system is primarily responsible for the observed cost increase.

The cost decomposition shows that the economic burden of larger hybrid storage architectures is driven not only by battery expansion but also by the additional hydrogen-side investment required to sustain longer duration support capability. This explains why B3H2, although it delivers the lowest screened-state unserved energy, is not selected as the preferred baseline compromise design. The marginal service benefit obtained by moving from the balanced B1H2 design to larger multisite architectures

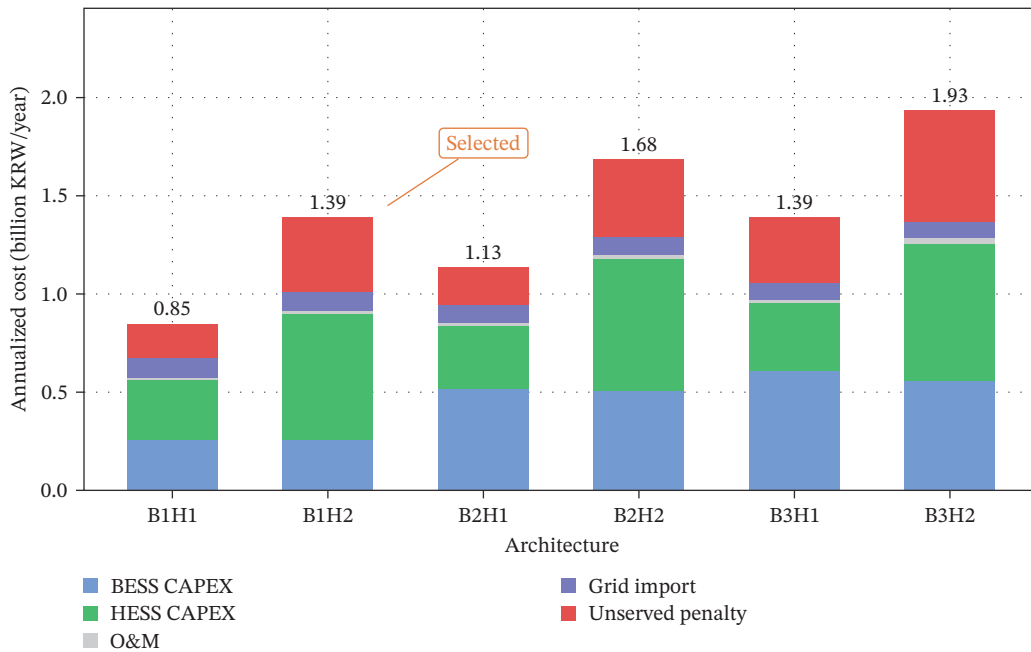


FIGURE 11 | Decomposition of annualized total cost across candidate hybrid storage architectures into BESS CAPEX, HESS CAPEX, operation and maintenance (O&M) cost, grid-import cost, and unserved-energy penalty $C_a^{\text{pen}} = c^{\text{VOLL}} \sum_{s \in \mathcal{S}} w_s \Delta E_s$. The selected B1H2 design achieves a balanced allocation between BESS and HESS investment with substantially reduced unserved-energy penalty relative to B1H1.

is accompanied by a disproportionately large increase in annualized cost. As a result, the most extensive architecture does not provide the most attractive techno-economic outcome once practical deployment burden is taken into account.

Figure 12 makes this trade-off more explicit by showing the resilience premium RP_a defined in Equation (46), with B1H1 serving as the reference architecture ($C_{ref}^{ann} = 0.846$ B KRW/yr, $r_{s,ref} = 53.8\%$). The selected B1H2 design achieves a resilience premium of approximately 0.15 B KRW/yr per pp, whereas larger alternatives require higher cost increments per additional unit of resilience improvement. This result strengthens the interpretation that the preferred architecture is the one that offers the most balanced hybrid storage deployment, not simply the one with the strongest disturbance-support capability in absolute terms.

These results suggest that hybrid battery–hydrogen storage planning should be interpreted as a co-sizing problem under diminishing techno-economic return. Moderate hydrogen-side expansion can provide a meaningful reduction in service deficiency and electrical weakness, but beyond a certain point, the added cost of more extensive hydrogen-side deployment may exceed the practical value of the additional gain. The comparative architecture results therefore provide a concrete design insight into how much hydrogen-side expansion is economically justifiable when coordinated with the battery-side support.

5.4 | Sensitivity Interpretation and Robustness of Hybrid Storage Design Insight

Sensitivity analysis is useful for assessing whether the selected design insight remains stable under parameter uncertainty. Figure 13 illustrates how the resilience premium responds to changes in key assumptions such as the VOLL, hydrogen-side cost parameters, battery-side cost parameters, contingency-related weighting, and repair duration. These results help determine whether the preferred hybrid storage architecture remains practically meaningful when underlying techno-economic assumptions vary.

The sensitivity trends indicate that the attractiveness of hybrid storage expansion is especially affected by the economic valuation of service interruption and by the cost assumptions associated with hydrogen-side equipment. This is consistent with the physical role of the hydrogen subsystem in the proposed architecture since longer-duration backup capability becomes more valuable when service disruption is heavily penalized and when hydrogen-side investment remains within a practically acceptable range. At the same time, the selected B1H2 architecture remains interpretable as a robust moderate-expansion design rather than as a fragile optimum dependent on only one narrow parameter set.

Overall, the sensitivity results reinforce the central design message of the study: the preferred hybrid storage architecture is not necessarily the one with the largest total capacity but the one that provides the most balanced response to techno-economic and service-performance considerations under realistic uncertainty. This type of result offers practical storage deployment insight beyond a benchmark-specific numerical comparison.

5.5 | Robustness of Architecture Selection to Weight Choice

The preferred architecture B1H2 is selected under the baseline weights $(w_c, w_r, w_b) = (0.42, 0.45, 0.13)$ listed in Table 1. To confirm that this selection is not an artifact of one particular weight vector, the compromise score S_a in Equation (51) is re-evaluated over the entire weight simplex $w_c + w_r + w_b = 1$, $w_c, w_r, w_b \geq 0$, and the maximizing architecture $a^* = \arg\max_a S_a$ is recorded at each weight combination. Figure 14 maps the selected architecture across this simplex.

B1H2 attains the highest baseline score ($S_{B1H2} = 0.711$) and remains the selected design across the entire resilience-leaning and balanced region of the simplex. Only when the cost weight becomes strongly dominant ($w_c \gtrsim 0.6$) does the smaller B1H1 layout become preferable, while the largest-capacity B3H2 architecture—despite achieving the lowest screened-state unserved energy (62.1 MWh)—is selected only under strongly resilience-dominant weights

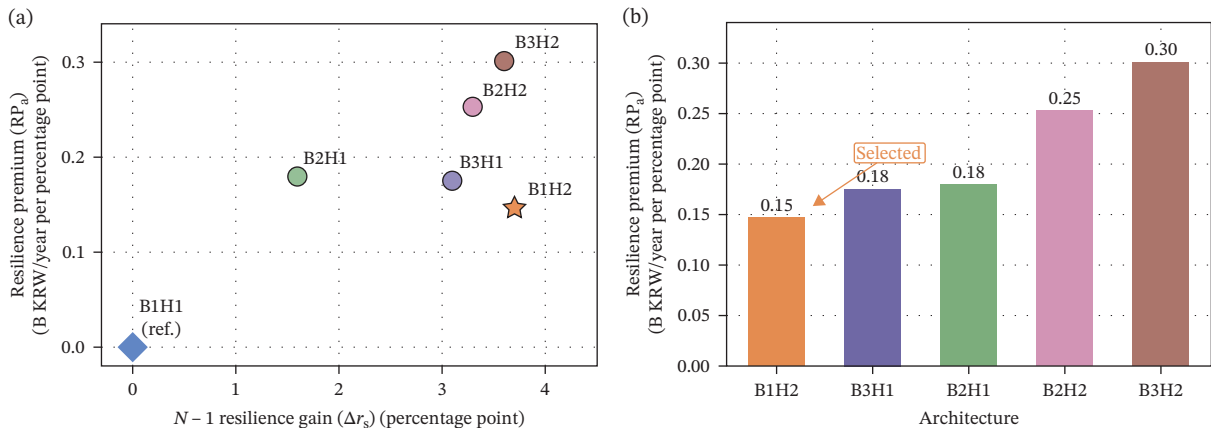


FIGURE 12 | Resilience premium trade-off among candidate hybrid storage architectures: (a) resilience premium RP_a versus $N-1$ resilience gain Δr_s relative to the reference architecture B1H1 and (b) ranked resilience premium values across resilience-improving architectures. The resilience premium is defined as $RP_a = (C_a^{ann} - C_{B1H1}^{ann}) / \Delta r_s$ and quantifies the annualized cost increment per percentage-point gain in served ratio. The selected B1H2 architecture exhibits the lowest premium (0.15 B KRW/yr per pp).

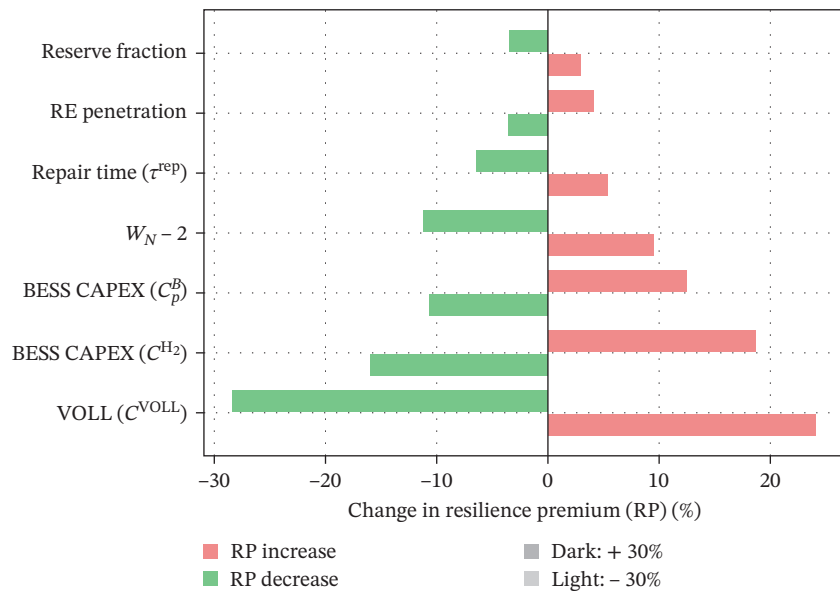


FIGURE 13 | Sensitivity of the selected B1H2 architecture's resilience premium ($RP_{B1H2}^{\text{base}} = 0.148$ B KRW/yr per pp) to $\pm 30\%$ variations in key planning parameters. Dark bars denote $+30\%$ parameter changes; light bars denote -30% . Red bars indicate an increase in RP (less favorable) and green bars indicate a decrease (more favorable). The selected design insight is most sensitive to VOLL and BESS CAPEX, consistent with the hydrogen subsystem's role in longer-duration backup.

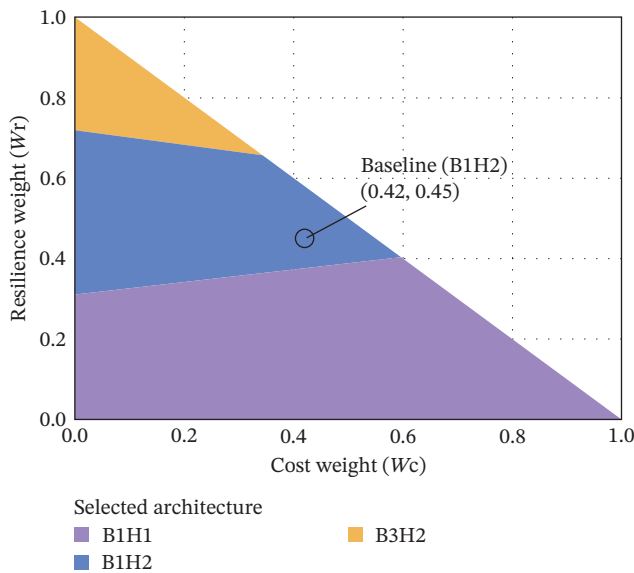


FIGURE 14 | Architecture-selection map over the cost-resilience-burden weight simplex.

(around $w_r \gtrsim 0.72$) and never in the balanced or moderately resilience-leaning region that contains the baseline, because outside that extreme corner, its annualized cost penalty outweighs its marginal resilience benefit. This confirms that the preference for B1H2 reflects a broad cost-resilience trade-off region rather than a single tuned weight set and that the proposed framework yields a robust architecture-level recommendation.

6 | Conclusion

This study presented a techno-economic co-planning framework for HBHES systems in renewable-rich distribution networks. The

proposed methodology jointly determines battery-side and hydrogen-side siting, sizing, and operating roles while refining candidate designs through screened-contingency AC validation and feed-back-assisted replanning. In the resulting hybrid architecture, the battery subsystem provides fast response and short-duration support, whereas the hydrogen subsystem provides longer-duration backup and renewable-energy shifting capability. This coordinated design structure makes it possible to assess hybrid storage not only as an aggregate flexibility resource but also as a physically meaningful combination of complementary technologies.

The case study on the IEEE 123-bus feeder showed that the selected hybrid architecture substantially improves serviceability under severe operating conditions. In particular, the preferred design reduced the screened-state unserved energy from 201.4 to 98.3 MWh, improved the average served ratio under retained $N-1$ contingencies from 53.8% to 57.5%, and increased the minimum post-contingency voltage from 0.921 to 0.952 p.u. These results indicate that coordinated battery-hydrogen storage planning can provide meaningful improvement in both service support capability and electrical feasibility under renewable-rich feeder conditions.

The comparative architecture results further showed that the preferred hybrid storage design is not necessarily the largest-capacity option. Although larger multisite architectures achieved lower screened-state unserved energy, their additional resilience benefit was accompanied by a disproportionately large increase in annualized cost. The selected B1H2 architecture emerged as the most balanced layout because it provided moderate hydrogen-side expansion together with limited battery-side deployment, thereby achieving the highest compromise score among the candidate designs. This result highlights that the main value of the proposed framework lies in identifying a practically balanced hybrid storage architecture rather than simply maximizing installed capacity.

The validation-assisted refinement process also confirmed that post-solution electrical weakness should be explicitly considered in hybrid storage design. The final refined design eliminated overload and nonconvergence events in the retained contingency replay, demonstrating that hybrid storage planning benefits from iterative coordination between techno-economic sizing and feeder-level validation. In this respect, the proposed method provides a practical design workflow for hybrid battery–hydrogen storage deployment under realistic network constraints.

A further consideration concerns battery degradation over a 20-year planning horizon. As noted by the analysis above, the present optimization annualizes the battery investment through Equation (17) and treats it as a static value, which can underestimate the long-term economic burden of battery-heavy architectures that are cycled frequently for fast response support. To make this explicit, the lifecycle cost can be augmented, as a post-accounting sensitivity, by a throughput- and replacement-based degradation adder.

$$C_{\text{BESS}}^{\text{deg}} = c_{\text{EFC}} \sum_t \frac{(p_t^{\text{ch}} + p_t^{\text{dis}}) \Delta t}{2 E_{\text{BESS}}} + c_{\text{rep}} E_{\text{rep}}, \quad (53)$$

where c_{EFC} is the equivalent-full-cycle degradation cost coefficient of the battery, p_t^{ch} and p_t^{dis} are the battery charging and discharging power at time t , Δt is the time-step length, E_{BESS} is the installed battery energy, c_{rep} is the replacement cost coefficient, and E_{rep} is the replacement or augmentation energy required over the planning horizon. The first term converts the cycled energy into an equivalent number of full cycles and the second accounts for capacity replacement; the degradation adder therefore tends to penalize battery-heavy and frequently cycled architectures—the throughput term scaling with the cycled energy (equivalent full cycles) and the replacement term with the installed energy—so that accounting for degradation widens the cost gap against battery-heavy designs and reinforces the preference for the selected B1H2 architecture. This degradation adder is evaluated as a post-accounting sensitivity and is not embedded in the MILP planning objective, so it does not change the optimized capacities; the corresponding three-case quantitative illustration (base, moderate, and severe) is reported in the response to the reviewers rather than in the main text, since these cases are post-optimization accounting variants rather than reoptimized 20-year lifecycle solutions. A degradation-aware reoptimization that embeds Equation (53) directly in the planning objective is identified as future work.

Future work may extend the present framework by incorporating broader uncertainty treatment for renewable generation and load, more detailed hydrogen system efficiency and degradation models, and market-oriented formulations that explicitly reflect additional revenue opportunities of hybrid storage. Another important extension is to examine whether the preferred balance between battery-side and hydrogen-side deployment remains consistent under alternative feeder structures, longer time horizons, and different cost trajectories of hydrogen-related equipment. These directions would further strengthen the practical relevance of hybrid battery–hydrogen storage planning for renewable-rich power networks.

Nomenclature

Abbreviations

BESS:	Battery energy storage system
HESS:	Hydrogen energy storage system
HBHES:	Hybrid battery–hydrogen energy storage
EL:	Electrolyzer
FC:	Fuel cell
PCC:	Point of common coupling
AC:	Alternating current
MILP:	Mixed-integer linear programming
pp:	Percentage point

Sets and indices

$\mathcal{A}$:	Set of candidate HBHES architectures
$\mathcal{B}$:	Set of candidate storage buses
$\mathcal{T}$:	Set of time periods
$\mathcal{O}$:	Set of operating states
$\mathcal{S}$:	Set of retained screened contingency states
Ω :	Full contingency candidate set
$\mathcal{N}$:	Set of feeder buses used in AC validation
$\mathcal{L}$:	Set of feeder lines used in AC validation
a :	Architecture index
b :	Candidate storage-bus index
t :	Time index
s :	Operating-state index
i :	Bus index in AC validation
l :	Line index in AC validation
n :	Feedback iteration index
$[x]^+$:	Positive part operator

Decision variables

(a) Installation and capacity variables

y_b^{B} :	Binary variable for BESS installation at bus, b
y_b^{H} :	Binary variable for HESS installation at bus, b
P_b^{B} :	Installed BESS power capacity at bus, b (kW)
E_b^{B} :	Installed BESS energy capacity at bus, b (kWh)
P_b^{EL} :	Installed electrolyzer capacity at bus, b (kW)
P_b^{FC} :	Installed fuel-cell capacity at bus, b (kW)
$M_b^{\text{H}_2}$:	Installed hydrogen storage capacity at bus, b (kg)

(b) Battery operating variables

$p_{b,t,s}^{\text{ch}}$:	BESS charging power (kW)
$p_{b,t,s}^{\text{dis}}$:	BESS discharging power (kW)
$e_{b,t,s}^{\text{B}}$:	Stored battery energy (kWh)

(c) Hydrogen operating variables

$p_{b,t,s}^{EL}$:	Electrolyzer electricity consumption (kW)
$p_{b,t,s}^{FC}$:	Fuel-cell electricity output (kW)
$m_{b,t,s}^{H_2}$:	Hydrogen inventory (kg)

(d) Feeder-side operating variables

$I_{t,s}^{srv}$:	Served demand (kW)
$I_{t,s}^{shed}$:	Shed demand (kW)
$p_{t,s}^{imp}$:	PCC import power (kW)
$p_{t,s}^{exp}$:	PCC export power (kW)
$p_{t,s}^{curt}$:	Curtailed renewable power (kW)
$p_{t,s}^{HBHES}$:	Net feeder-level power contribution of HBHES (kW)
$V_{i,t,s}$:	AC voltage magnitude at bus, i (p.u.)
$ S_{ij} $:	Apparent-power flow on line, l (kVA)
$\theta_{ij,t,s}$:	AC voltage angle difference between buses, i and j (rad)
$Q_{b,t,s}^{HBHES}$:	Reactive-power contribution of HBHES at bus, b (kVar)

Parameters

(a) Capacity bounds and architecture parameters

$\underline{P}_b^B$:	Minimum BESS power capacity at bus, b (kW)
$\bar{P}_b^B$:	Maximum BESS power capacity at bus, b (kW)
$\underline{E}_b^B$:	Minimum BESS energy capacity at bus, b (kWh)
$\bar{E}_b^B$:	Maximum BESS energy capacity at bus, b (kWh)
$\underline{P}_b^{EL}$:	Minimum electrolyzer capacity at bus, b (kW)
$\bar{P}_b^{EL}$:	Maximum electrolyzer capacity at bus, b (kW)
$\underline{P}_b^{FC}$:	Minimum fuel-cell capacity at bus, b (kW)
$\bar{P}_b^{FC}$:	Maximum fuel-cell capacity at bus, b (kW)
$\underline{M}_b^{H_2}$:	Minimum hydrogen storage capacity at bus, b (kg)
$\bar{M}_b^{H_2}$:	Maximum hydrogen storage capacity at bus, b (kg)
N_B^{max} :	Maximum number of BESS sites
N_H^{max} :	Maximum number of HESS sites
κ :	Adopted EL/FC sizing factor
τ^{H_2} :	Minimum hydrogen support duration (h)
D_a :	Deployment burden of candidate architecture, a (sites)

(b) Battery and hydrogen operating parameters

η^{ch} :	Battery charging efficiency
η^{dis} :	Battery discharging efficiency
α^{EL} :	Electricity-to-hydrogen conversion coefficient (kWh/kg)
α^{FC} :	Hydrogen-to-electricity conversion coefficient (kWh/kg)
$\rho^{B,res}$:	Battery reserve fraction in normal operation
$\rho^{H,res}$:	Hydrogen reserve fraction in normal operation
$\rho^{B,init}$:	Initial battery reserve fraction in contingency states
$\rho^{H,init}$:	Initial hydrogen reserve fraction in contingency states
Δt :	Time-step length (h)

(c) Feeder and service parameters

L_t :	Total feeder demand at time, t (kW)
P_t^{PV} :	Photovoltaic generation at time, t (kW)
P_t^{WT} :	Wind generation at time, t (kW)
$\bar{P}^{imp}$:	PCC import limit (kW)
$\bar{P}^{exp}$:	PCC export limit (kW)
γ_s :	Minimum served-load ratio requirement for state, s
S_{ij}^{max} :	Apparent-power (thermal) limit of line, l (kVA)
$V^{min,AC}$:	Minimum AC voltage threshold (p.u.)
$V^{max,AC}$:	Maximum AC voltage threshold (p.u.)
G_{ij} :	Real part (conductance) of bus admittance matrix entry (i, j) (S)
B_{ij} :	Imaginary part (susceptance) of bus admittance matrix entry (i, j) (S)
S_b^{inv} :	Apparent-power rating of HBHES inverter at bus, b (kVA)
$\bar{\varphi}$:	Maximum power-factor angle of HBHES inverter (rad)

(d) Contingency screening and weighting parameters

λ_l :	Failure rate of line, l
τ^{rep} :	Repair duration (h)
ρ_s :	Probability- or weight-like factor of contingency state, s
ϕ_s^{peak} :	Peak-severity indicator of state, s
ϕ_s^{ene} :	Energy-severity indicator of state, s
ϕ_s^{dep} :	Outage-depth indicator of state, s
w^{peak} :	Weight of peak-severity term
w^{ene} :	Weight of energy-severity term
w^{dep} :	Weight of outage-depth term
w^{prob} :	Weight of contingency-weight term
Φ_s :	Composite contingency severity score
K :	Number of retained severe contingencies

(e) Economic and penalty parameters

c_p^B :	Annualized BESS power-cost coefficient (KRW/kW)
c_E^B :	Annualized BESS energy-cost coefficient (KRW/kWh)
c^{EL} :	Annualized electrolyzer cost coefficient (KRW/kW)
c^{FC} :	Annualized fuel-cell cost coefficient (KRW/kW)
c^{H_2} :	Annualized hydrogen storage cost coefficient (KRW/kg)
c_t^{imp} :	Electricity import price at time, t (KRW/kWh)
c_t^{exp} :	Electricity export price at time, t (KRW/kWh)
c^{curt} :	Renewable-curtailment penalty coefficient (KRW/kWh)
c_{VOLL} :	Value of lost load (VOLL) (KRW/kWh)
w_s :	Annual occurrence/state weighting factor of retained severe state, s (1/yr)
χ_s :	Binary contingency indicator in the planning objective
c_{EFC} :	Equivalent-full-cycle battery degradation cost coefficient (KRW/cycle)
c_{rep} :	Battery replacement (augmentation) cost coefficient (KRW/kWh)

E_{rep} : Replacement or augmentation energy over the planning horizon (kWh)
 $C_{\text{BESS}}^{\text{deg}}$: Throughput- and replacement-based battery degradation cost adder (B KRW/yr)

(f) Validation and feedback parameters

α_V^{min} : Penalty coefficient for minimum-voltage deviation
 α_V^{max} : Penalty coefficient for maximum-voltage deviation
 α_L^{max} : Penalty coefficient for loading-ratio excess
 α_{UV} : Penalty coefficient for undervoltage frequency
 α_{OV} : Penalty coefficient for overvoltage frequency
 α_{OL} : Penalty coefficient for overload frequency
 α_{NC} : Penalty coefficient for nonconvergence frequency
 Q_q : Probability-weighted quantile operator
 q : Quantile level used in replanning
 β_P : Feedback update coefficient for power requirement
 β_E : Feedback update coefficient for energy requirement
 ε : Feedback convergence tolerance
 w_c : Weight of normalized cost metric in architecture score
 w_r : Weight of normalized resilience metric in architecture score
 w_b : Weight of normalized burden metric in architecture score

Performance indicators

J^{base} : Baseline planning objective value
 C^{inv} : Annualized investment cost
 C^{op} : Operating cost
 C^{ue} : Contingency-related unserved-energy penalty term
 C_a^{pen} : Contingency unserved-energy penalty of architecture a (B KRW/yr)
 USE_a : Screened-state unserved energy of architecture a (MWh)
 ΔP_s : Power shortfall of retained state s (kW)
 ΔE_s : Energy shortfall of retained state s (kWh)
 $\Delta r_{s,a}$: $N-1$ served-ratio gain relative to reference (pp)
 V_s^{min} : Minimum AC voltage in retained state s (p.u.)
 V_s^{max} : Maximum AC voltage in retained state s (p.u.)
 L_s^{max} : Maximum line-loading ratio in retained state s
 ν_s^{UV} : Undervoltage ratio in retained state s
 ν_s^{OV} : Overvoltage ratio in retained state s
 ν_s^{OL} : Overload ratio in retained state s
 ν_s^{NC} : Nonconvergence ratio in retained state s
 μ_s^{AC} : AC-risk multiplier of retained state s
 ΔP_s^{AC} : AC-risk-adjusted power shortfall (kW)
 ΔE_s^{AC} : AC-risk-adjusted energy shortfall (kWh)
 $\Delta P^{\text{req}, n}$: Design-level power replanning requirement at iteration n (kW)
 $\Delta E^{\text{req}, n}$: Design-level energy replanning requirement at iteration n (kWh)
 $P^{\text{sup}, n}$: Aggregate support-power requirement at iteration n (kW)

$E^{\text{sup}, n}$: Aggregate support-energy requirement at iteration n (kWh)
 Γ^n : Feedback convergence measure at iteration n
 C_a^{ann} : Annualized total cost of candidate architecture a
 $\widehat{C}_a$: Normalized cost desirability of candidate architecture a
 $\widehat{R}_a$: Normalized resilience desirability of candidate architecture a
 $\widehat{B}_a$: Normalized deployment-burden desirability of candidate architecture a
 S_a : Compromise score of candidate architecture a
 a^* : Selected preferred architecture
 RP_a : Resilience premium of architecture a (B KRW/yr per pp).

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data will be made available upon request.

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