

Energy Storage for Renewable-Dominant Power Systems: Grid Flexibility, Long-Duration Storage, Safety, Degradation, and Circularity Pathways

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Received August 25, 2026; Accepted September 8, 2026; Published September 10, 2026

Renewable-dominant power systems require storage portfolios that deliver flexibility, adequacy, resilience, affordability, safety, and responsible resource use across timescales. This review synthesises electrical, mechanical, electrochemical, thermal, and chemical storage using a transparent evidence architecture comprising a 572-record citation reservoir, a 549-study bibliometric corpus, and 100 method-verified references for critical analysis. Technology suitability is shown to depend on response time, discharge duration, cycling duty, location, climate exposure, grid constraints, and revenue design; consequently, no universal option dominates. Batteries and power devices support rapid regulation and daily balancing, whereas pumped hydro, compressed-air, thermal, flow-battery, hydrogen, and hybrid systems address longer scarcity periods with distinct efficiency, siting, safety, and cost trade-offs. The synthesis treats degradation, operational safety, digital control, circularity, and bankability as coupled lifecycle considerations rather than isolated topics. It proposes a Storage-to-System Evidence Matrix linking duration, eligible services, risk, degradation, digital readiness, circularity, resilience, maturity, and finance. Priority actions include duration-aware valuation, representative demonstrations, harmonised safety standards, degradation-linked warranties, interoperable digital architectures, and closed-loop supply chains. Storage planning should therefore optimise service-matched portfolios against verified system needs and lifecycle constraints, strengthening reliable and equitable net-zero electricity transitions.

Keywords: Energy Storage; Renewable-Dominant Grids; Grid Flexibility; Long-Duration Energy Storage; Safety; Degradation

1. Introduction

Renewable-dominant power systems must balance electricity, flexibility, adequacy, and restoration capability across timescales extending from milliseconds to seasons. Energy storage is therefore valuable not because of installed capacity alone, but because it can deliver a required service at the location, duration, response speed, and reliability level demanded by the system. Technology comparisons based only on energy density or nominal round-trip efficiency obscure the effects of cycling duty, network constraints, degradation, climate exposure, safety, siting, and market design. Short-duration batteries and power devices are well suited to rapid regulation and daily shifting,

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whereas mechanical, thermal, flow-battery, hydrogen, and hybrid pathways may better address prolonged scarcity. These options should consequently be evaluated as complementary portfolio components rather than competitors in a universal ranking. Safety, degradation, digital control, circularity, and bankability further shape realised value throughout the asset lifecycle. Digital intelligence can improve forecasting, state estimation, maintenance, and dispatch, but requires representative data, uncertainty quantification, interoperability, cybersecurity, and safe fallback control. Circularity similarly extends assessment from operational performance to sourcing, repair, reuse, second-life qualification, recycling, and distributional justice. This review integrates these dimensions through a multiscale Storage-to-System Evidence Matrix that connects technology characteristics with duration, grid services, risk, lifetime, digital readiness, resource stewardship, resilience, maturity, and finance. The central argument is that storage should be planned as a service-matched, lifecycle-governed portfolio whose composition changes with system conditions and societal priorities.

Renewable dominance depends on variability becomes correlated across generation, demand, weather, and network conditions. Evaluation should quantify residual-load ramps, scarcity duration, curtailment, congestion, and restoration capability. The practical priority is planning storage around verified system needs rather than annual renewable shares [1-3].

Storage infrastructure depends on its value depends on location, controllability, availability, and coordination with generation and demand. Evaluation should quantify delivered flexibility, availability, response, duration, network relief, and resilience. The practical priority is treating storage as an integrated reliability resource with lifecycle obligations [4-7].

Cross-technology comparison depends on efficiency, cost, lifetime, and emissions change with boundaries, cycling, scale, and charging conditions. Evaluation should quantify service-adjusted efficiency, usable duration, degradation, availability, and lifecycle burden. The practical priority is reporting conditional rankings accompanied by uncertainty and evidence maturity [8, 9].

Hybrid storage portfolios depends on fast and energy-intensive services impose conflicting requirements on individual technologies. Evaluation should quantify service coverage, energy reservation, cycling allocation, control interactions, and redundancy.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is combining technologies whose strengths cover distinct temporal and operational requirements, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [10].

Climate-resilient storage depends on heat, flooding, storms, drought, wildfire, and renewable scarcity can occur simultaneously. Evaluation should quantify derating, outage duration, thermal margins, water dependence, repair time, and critical-load continuity. The practical priority is stress-testing portfolios against compound events rather than isolated historical disturbances [2].

The integrated review architecture depends on existing evidence frequently separates flexibility, safety, degradation, digitalisation, economics, and circularity. Evaluation should quantify cross-domain interactions, trade-offs, confidence, transferability, and governance implications. The practical priority is connecting

technology evidence to system decisions through the Storage-to-System Evidence Matrix [6, 11, 12].

Figure 1 presents an integrated framework connecting energy-storage deployment needs, pathway domains, persistent barriers, future solutions, and research priorities for renewable-dominant power systems. Current requirements—including variability balancing, peak shaving, ancillary services, congestion relief, reserve provision, and resilience—drive five interconnected domains: grid flexibility, long-duration storage, safety governance, degradation management, and circular resource stewardship. However, deployment remains constrained by temporal intermittency, uncertain valuation, high capital costs, thermal hazards, capacity fade, efficiency losses, mineral dependence, and end-of-life burdens. The framework consequently advances hybrid storage portfolios, innovative chemistries, artificial-intelligence-enabled control and health management, second-life applications, closed-loop recycling, and supportive policy and market reforms. These solutions inform enhanced research directions centred on renewable-storage co-optimisation, bankable long-duration pathways, safety-by-design, real-time diagnostics, degradation-aware operation, traceable circular materials, and resilient net-zero planning.

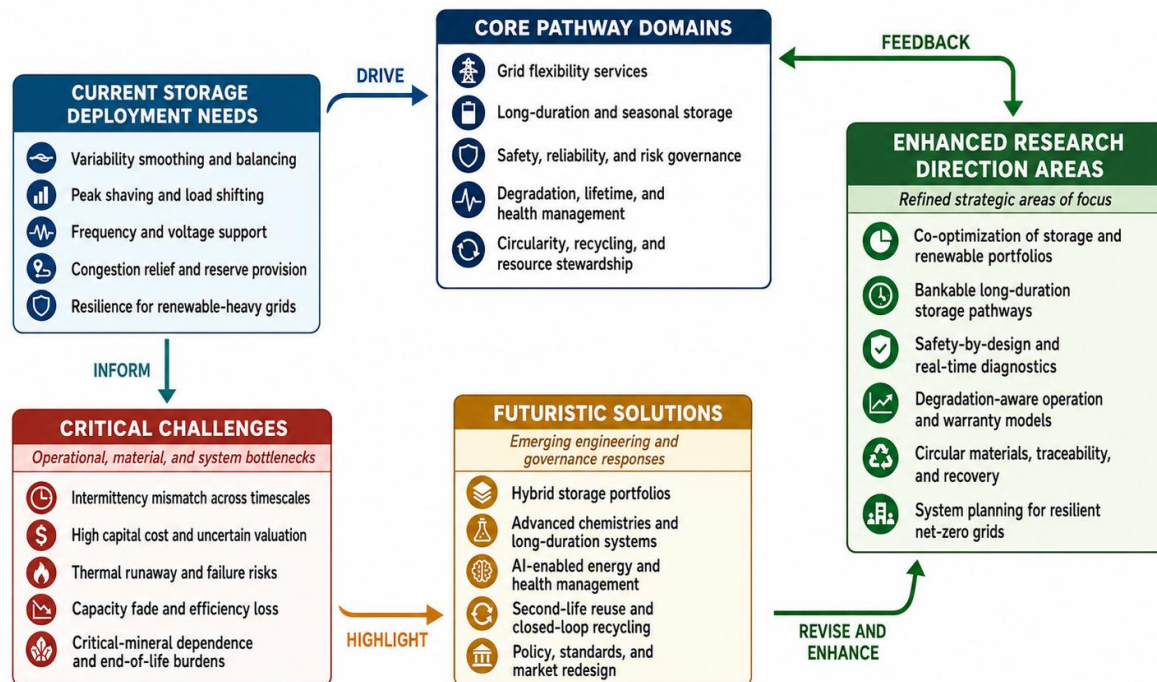


Figure 1. Integrated review architecture linking deployment needs, core storage pathways, critical challenges, emerging solutions, and strategic research directions

2. Methodology

2.1 Date- and Page-Level Search Log

The literature search was conducted using a structured, date-stamped, database-specific log that documented every query executed between 1 May and 8 July 2026, as shown in Figure 2. Each log entry recorded the database, search date, exact query, filters, results returned, results displayed per page, pages examined, export format, exported-record count, and reviewer initials. The initial multidisciplinary search was undertaken

from 1–4 May 2026, followed by a targeted update from 5–8 July 2026. Scopus and Web of Science were logged by results page and export batch, ScienceDirect by search-results page, and Google Scholar in sequential ten-record pages. Across all sources, 572 records entered the citation reservoir.

2.2. Search Period and Submission Timeline

The search and manuscript-development timeline was organised as a sequential, auditable workflow covering evidence published from January 2013 through December 2025. Protocol finalisation occurred on 1 May 2026 and established the research questions, database portfolio, keyword blocks, eligibility rules, evidence domains, and method-verification criteria. The first comprehensive search was performed across Scopus, Web of Science, ScienceDirect, and Google Scholar from 1–4 May 2026, followed by deduplication, metadata normalisation, and preliminary relevance screening from 5 May to 15 June 2026. Thematic coding and bibliometric validation were conducted from 16 June to 4 July 2026. A second targeted search, completed from 5–8 July 2026, captured late-indexed 2025 publications and corrected database-specific coverage gaps.

2.3. Databases and Search Sources

The systematic evidence search combined four electronic databases with manual citation screening to balance disciplinary breadth, bibliographic precision, and accessibility. Scopus and Web of Science supplied multidisciplinary citation metadata across engineering, materials science, energy economics, environmental science, computer science, and policy research. ScienceDirect strengthened full-text coverage of energy-storage technologies, renewable integration, long-duration storage, safety, degradation, artificial intelligence, lifecycle assessment, and circularity. Google Scholar was used as a supplementary discovery source for relevant studies that were recently indexed, inconsistently classified, or absent from conventional keyword fields. Backward reference screening examined the bibliographies of influential reviews and foundational studies, while forward citation tracking identified subsequent validation, replication, and system-level applications.

2.4. Exact Search Strings

Database searches used three concept blocks: storage technology, renewable-dominant power systems, and system-level performance. The Scopus query was: TITLE-ABS-KEY(("energy storage" OR "battery energy storage" OR "long-duration energy storage" OR LDES OR "pumped hydro" OR "compressed air energy storage" OR "thermal energy storage" OR "hydrogen storage" OR "flow battery") AND ("renewable-dominant" OR "renewable-rich" OR "high renewable penetration" OR "variable renewable energy" OR "renewable power system") AND (flexibility OR resilience OR reliability OR degradation OR safety OR circularity OR optimisation OR "grid services")) AND PUBYEAR > 2012 AND PUBYEAR < 2026. Web of Science used the equivalent TS= structure with PY=2013–2025. ScienceDirect combined "energy storage" with "renewable power systems" and the terms flexibility, long-duration, safety, degradation, digital control, or circularity. Google Scholar employed separate strings, including "energy storage" "renewable-dominant power systems", "long-duration energy storage" renewable grid, "battery degradation" grid storage, "energy storage safety" renewable, and "energy storage" circularity recycling, with custom dates restricted to 2013–2025.

2.5. Page-Level Search Log

The page-level search log was designed to preserve a reproducible record of how the 2013–2025 evidence base was assembled before deduplication and synthesis. For every results page, the log captured a unique page identifier, database name, query code, execution timestamp, applied filters, results-page number, displayed record range, number screened, number provisionally relevant, number exported, cumulative retrieved records, and stopping-status code. Individual records were linked to their originating page using DOI, database accession number, or a normalised title identifier. For example, a page coded GS-20260706-Q04-P007 represented page 7 of Google Scholar query 4, executed on 6 July 2026. Database interfaces offering exhaustive export were additionally documented by export batch, such as records 1–200 or 201–400.

2.6. Search-Result Page Stopping Criteria

Stopping criteria were established before searching to prevent subjective termination when later pages became less relevant. Scopus and Web of Science searches were not terminated on relevance grounds; all results satisfying the fixed query and 2013–2025 filters were exported, subject only to database export limits requiring sequential batches. ScienceDirect screening continued until the final available results page or until five consecutive pages yielded no previously unidentified potentially eligible record. Google Scholar results were screened in relevance order using ten results per page and were stopped after five consecutive pages produced zero new potentially eligible studies, or after the first 200 results for a query, whichever occurred first. A stopped query was extended when the final screened page contained a new technology class, major demonstration project, policy instrument, or highly cited study absent from the existing corpus.

2.7. Year Span: 2013–2025

The review adopted January 2013 to December 2025 as a fixed thirteen-year analytical window. The 2013 boundary captures the period in which rapidly declining battery costs, increasing variable-renewable deployment, grid-scale demonstrations, and advances in power-electronic control began shifting storage research from component-oriented investigation toward integrated power-system applications. The terminal year of 2025 provides the latest complete publication year available during the 2026 search, avoiding distortion from partial-year 2026 indexing. Publication-year eligibility was determined from the final journal issue or online publication metadata, with early-access articles retained only when their definitive publication year fell within 2013–2025. The bibliometric dataset records growth from three publications in 2013 to 143 in 2025, providing a numerical basis for assessing research acceleration.

2.8. Method-Verification Rule

A study entered the 100-reference critical-synthesis subset only when its research method and analytical contribution could be independently identified from the full text. Verification required at least four elements: a clearly defined storage technology or system boundary; an identifiable empirical, experimental, modelling, optimisation, lifecycle, techno-economic, or policy method; stated data sources or operating assumptions; and quantitative results or traceable analytical findings relevant to renewable-dominant power systems. Evidence was graded using a four-level verification

scale: V0, method not identifiable; V1, method named but insufficiently specified; V2, method reproducible in principle with partial data or parameter limitations; and V3, method and data sufficiently documented for substantive comparison. V0 studies were not used to support critical claims, while V1 studies supplied contextual background only. V2 and V3 studies were eligible for detailed synthesis and classification by technology, duration, service, risk, degradation, digital readiness, circularity, maturity, bankability, and policy relevance.

2.9. Final Reproducibility Statement

Reproducibility was ensured by preserving a complete methodological package comprising the review protocol, exact database strings, search dates, database filters, page-level logs, export batches, raw bibliographic files, deduplication rules, eligibility decisions, method-verification scores, and the final evidence matrix. The reported numerical architecture is internally reconciled: 572 source records minus 23 duplicates produced 549 unique studies; all 549 were retained for bibliometric characterisation, while 100 method-verified references were selected for detailed critical synthesis and 449 remained available for contextual landscape analysis. No study was reclassified as excluded merely because it was not included in the intensive synthesis subset. Reproducibility files should be archived with read-only raw exports and version-controlled cleaned datasets, accompanied by a data dictionary describing every field and code. Because database indexing and ranking algorithms change, exact result ordering may vary during replication; nevertheless, the archived dates, queries, page identifiers, accession numbers, and decision logs provide a transparent basis for reconstructing the evidence base and auditing every analytical transition.

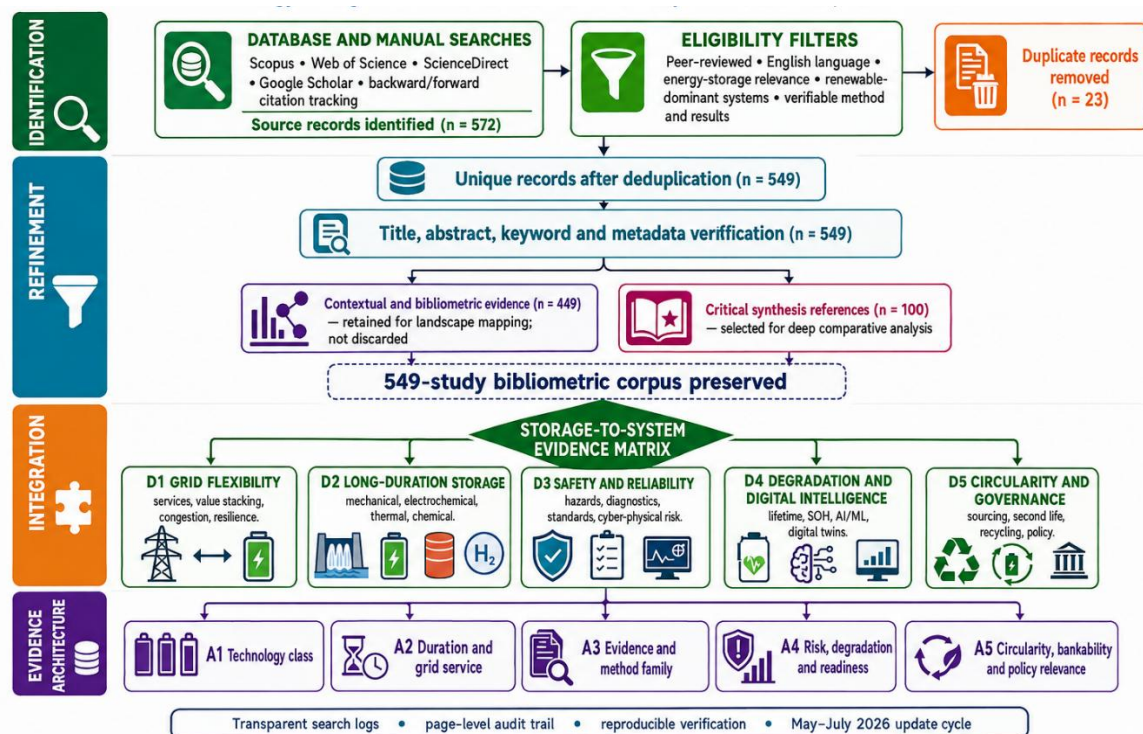


Figure 2. Study refinement and integration workflow for the 2013–2025 energy-storage evidence base

3. Bibliometric Analysis and State of The Art

Figure 3 presents an eight-panel bibliometric profile of 549 studies published between 2013 and 2025, revealing the intellectual, geographic, institutional, and thematic evolution of energy storage for renewable-dominant power systems. Annual output increased from three publications in 2013 to 143 in 2025, with pronounced acceleration after 2021, despite temporary fluctuations in 2018 and 2023. This trajectory indicates rapid consolidation of storage as enabling infrastructure for flexibility, adequacy, resilience, and decarbonisation. China dominates national contributions with 182 documents, exceeding the United States (85), India (44), United Kingdom (31), and Italy (30), while Spain, Australia, Canada, Germany, and Iran provide smaller but visible portfolios. Such concentration highlights strong innovation capacity but also potential geographic bias toward well-funded manufacturing and grid environments.

4. Technology Landscape Across Timescales

Storage technologies differ fundamentally in the physical form retained, achievable response speed, practical discharge duration, siting freedom, operating lifetime, and conversion pathway, as shown in Figure 4 and Table 1. Electrical devices provide rapid power with limited energy duration, whereas mechanical, thermal, electrochemical, and chemical systems progressively extend balancing capability [13]. Supercapacitors, flywheels, and superconducting magnetic systems respond within milliseconds or seconds, supporting power quality, frequency containment, and synthetic inertia. Their high-power density and cycling capability remain valuable despite limited stored energy, relatively high power-related cost, and application-specific infrastructure requirements. Lithium-ion batteries dominate daily balancing because mature supply chains, modular deployment, high efficiency, and rapid control suit peak shaving, arbitrage, and ancillary services. Sodium-ion, lead-acid, and flow batteries expand application choices through different material availability, cost, safety, lifetime, and duration characteristics [13]. Flow batteries decouple power and energy capacity, offering a potentially attractive pathway when repeated multi-hour cycling justifies additional balance-of-plant complexity [14]. Pumped hydro, compressed-air, liquid-air, gravity, and thermal systems serve longer durations where geography, infrastructure reuse, thermal integration, and construction lead times become decisive.

Hydrogen and derivative fuels extend storage toward seasonal balancing and sector coupling, accepting larger conversion losses in exchange for scale, duration, and transportability. Technology comparison must therefore begin with the required service envelope before applying cost, efficiency, maturity, risk, and sustainability filters. Hybrid portfolios can reserve high-efficiency batteries for frequent cycling while allocating prolonged deficits to lower-cycling, energy-intensive mechanical, thermal, or chemical storage. Such role separation reduces oversizing, limits avoidable degradation, and improves resilience when renewable variability spans several distinct temporal scales [15].

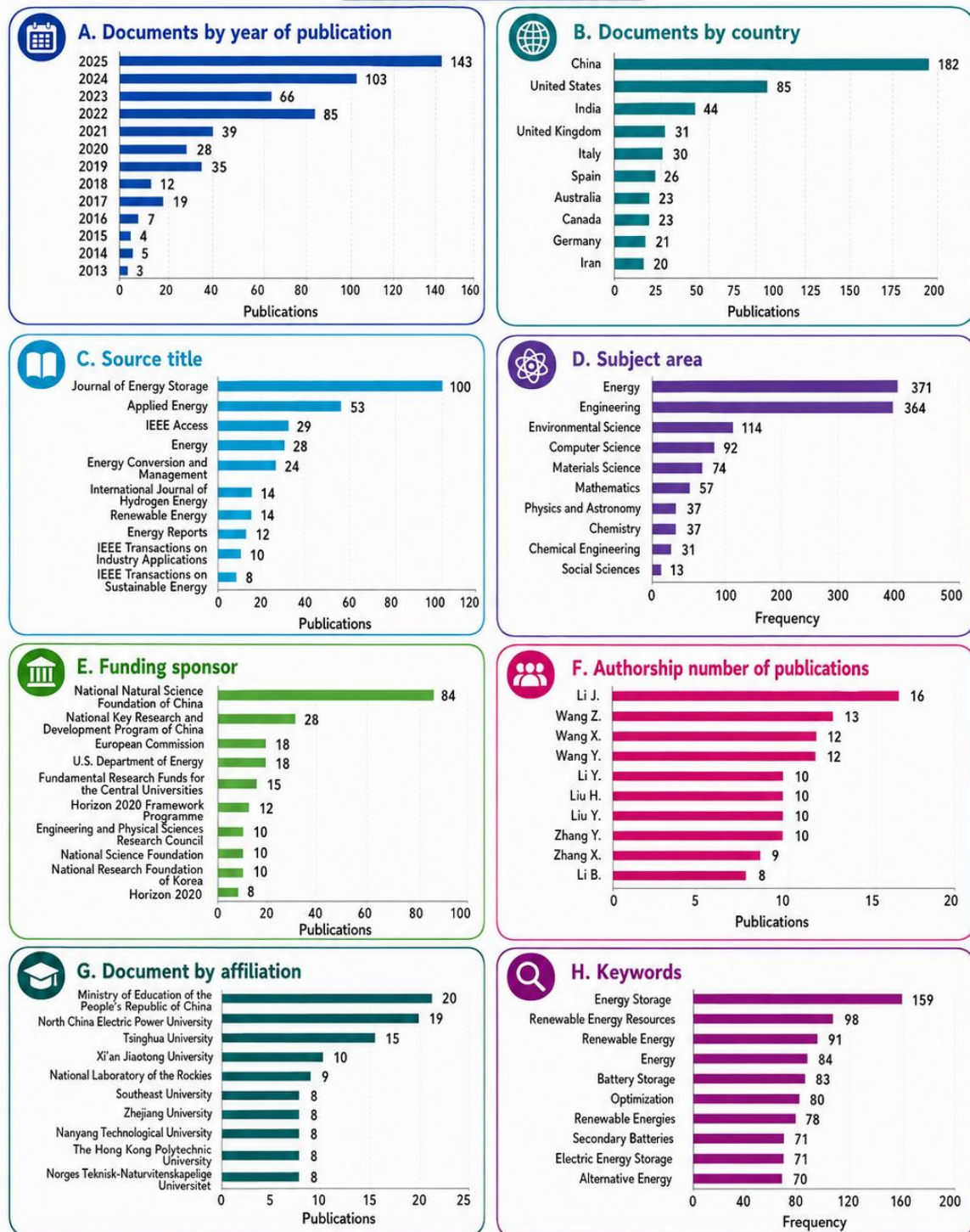


Figure 3. State-of-the-art bibliometric results for the supplied 549-study evidence base: publication year, country, source, subject area, funding, authorship, affiliation, and keywords

Figure 4 and Table 1 map energy-storage technologies across response timescales and grid functions in renewable-dominant power systems. Fast-response supercapacitors, flywheels, and superconducting magnetic energy storage provide millisecond-to-second power-quality, frequency-regulation, and inertia services. Lithium-ion, sodium-ion, and lead-acid batteries support minute-to-hour peak shaving, load shifting, and daily arbitrage.

Flow batteries and thermal storage extend flexibility from hours to days, strengthening renewable firming, capacity adequacy, and multi-day resilience. Pumped hydropower, compressed-air/liquid-air, gravity, and hydrogen storage address weekly-to-seasonal imbalances. Collectively, the landscape demonstrates that technology portfolios, rather than a single solution, are essential for reliability, resilience, affordability, and energy security.

Table 1. Technology–duration–grid-service matching matrix

Technology	Storage form	Typical duration	Response	Best-fit service	Principal constraint	Reference
Supercapacitor	Electrical	Milliseconds–minutes	Very fast	Power quality	Low energy duration	[27]
Flywheel	Mechanical	Seconds–minutes	Very fast	Frequency support	Self-discharge	[93]
Lithium-ion	Electrochemical	Minutes–hours	Fast	Balancing and arbitrage	Thermal ageing	[71]
Flow battery	Electrochemical	4–48 hours	Fast	Daily and multi-day	Balance-of-plant cost	[94]
Pumped hydro	Mechanical	Hours–seasonal	Moderate	Bulk shifting	Geographic dependence	[39]
Thermal storage	Thermal	Hours–weeks	Moderate	Heat and power shifting	Reconversion losses	[41]
Hydrogen	Chemical	Days–seasonal	Slow–moderate	Seasonal adequacy	Low round-trip efficiency	[25]

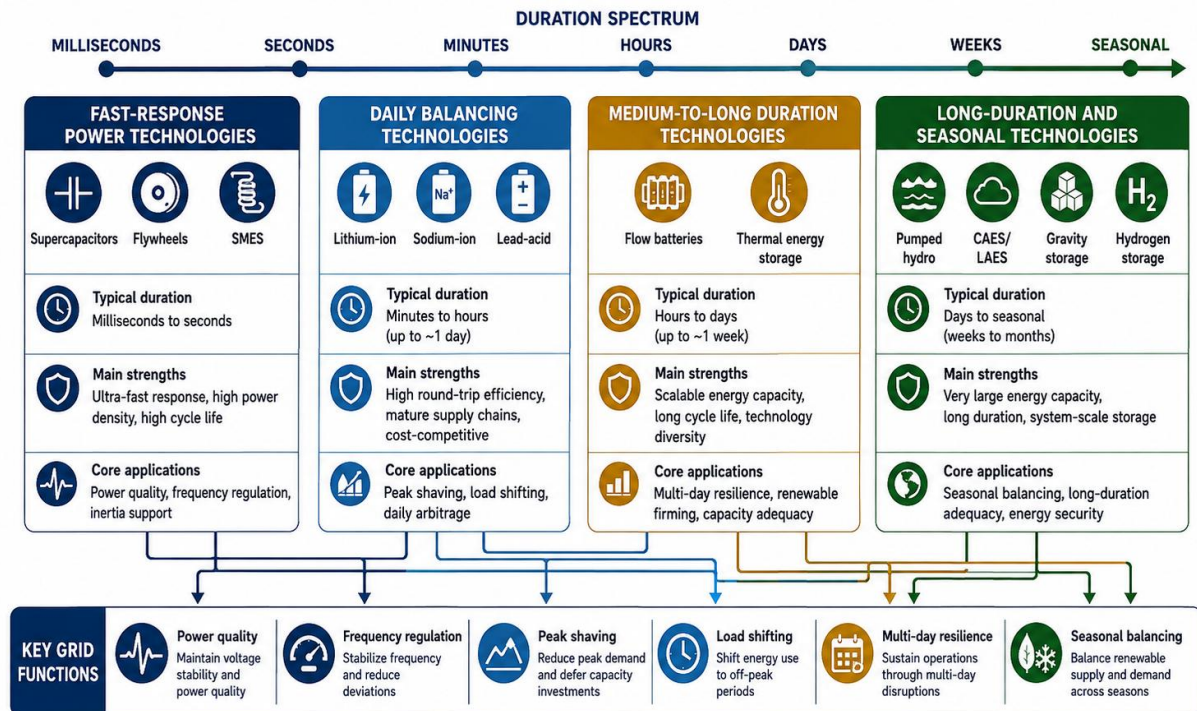


Figure 4. Storage technology landscape across response timescales, technology classes, typical durations, strengths, applications, and key grid functions

4.1 Electrical Power Technologies

Electrical storage devices depends on extreme response speed is achieved with limited energy duration and technology-specific standby losses. Evaluation should quantify power density, response, self-discharge, cycling endurance, footprint, and cost.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring

energy-system assets. The resulting decision priority is deploying electrical storage where rapid power quality services dominate, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [16].

4.2 Lithium-Ion Systems

Lithium-ion batteries depends on high efficiency and maturity coexist with thermal risk, degradation, critical materials, and duration-dependent economics. Evaluation should quantify usable energy, C-rate, temperature, SOC window, lifetime, and propagation resistance. The practical priority is matching chemistry and controls to the actual grid-duty profile [17].

4.3 Sodium and Lead-Based Batteries

Alternative battery chemistries depends on material availability and mature recycling can offset lower density or chemistry-specific lifetime limitations. Evaluation should quantify efficiency, energy density, temperature tolerance, cost, recyclability, and maintenance. The practical priority is selecting chemistry through local supply, climate, service, and recovery conditions [18].

4.4 Redox-Flow Batteries

Flow-battery systems depends on decoupled power and energy scaling competes with pumps, membranes, electrolyte costs, and lower energy density. Evaluation should quantify stack power, tank energy, crossover, efficiency, response, and electrolyte value. The practical priority is targeting repeated multi-hour cycling where modular duration creates system value [19].

4.5 Pumped-Hydroelectric Storage

Pumped-hydro storage depends on maturity and scale depend on topography, water, civil works, permitting, and environmental safeguards. Evaluation should quantify head, reservoir volume, efficiency, lead time, availability, and ecological effects.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is prioritising low-impact sites and infrastructure reuse through participatory planning, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [20].

4.6 Compressed and Liquid-Air Storage

Air-based storage depends on bulk capacity depends on thermodynamic integration, cavern or vessel design, and heat-management performance. Evaluation should quantify pressure, thermal recovery, efficiency, duration, siting, and ramp capability.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is evaluating complete thermodynamic systems under realistic charging and discharge profiles, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [21].

4.7 Gravity Storage

Gravity storage concepts depends on simple physical principles still require evidence for mechanical reliability, civil cost, land, and scale-up. Evaluation should quantify lifting mass, height, power train, efficiency, fatigue, and construction intensity.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is demanding pilot evidence that connects component performance with bankable system operation, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [10].

4.8 Sensible and Latent Thermal Storage

Thermal energy storage depends on low-cost media and industrial integration can be constrained by heat losses and reconversion penalties. Evaluation should quantify temperature range, heat capacity, insulation, cycling, heat quality, and conversion efficiency. The practical priority is deploying thermal storage where useful heat and electricity services can be co-optimised [22].

4.9 Thermochemical and Carnot Storage

Advanced thermal pathways depends on higher storage density and long retention require durable reactions, heat exchangers, and reversible system integration. Evaluation should quantify reaction stability, temperature, exergy, retention, power block, and cycling. The practical priority is validating complete systems beyond favourable material-level storage densities [23].

4.10 Hydrogen Storage Chains

Hydrogen energy storage depends on seasonal capacity and sector coupling require electrolyser, compression, storage, transport, and reconversion coordination. Evaluation should quantify chain efficiency, purity, leakage, degradation, infrastructure, safety, and utilisation. The practical priority is valuing hydrogen through multi-service benefits rather than electricity arbitrage alone [24, 105].

4.11 Technology Readiness

Deployment readiness depends on laboratory performance, pilot operation, commercial replication, and bankable delivery represent distinct maturity levels. Evaluation should quantify scale, operating hours, availability, warranties, cost evidence, and supply capability. The practical priority is linking readiness claims to verifiable demonstrations and repeatable project delivery [25].

4.12 Climate-Dependent Performance

Environmental operating envelopes depends on temperature, humidity, dust, altitude, flooding, and water availability alter performance and failure probabilities. Evaluation should quantify derating, cooling demand, corrosion, contamination, outage exposure, and recovery time. The practical priority is incorporating future climate conditions within technology screening and asset design [26, 106-110].

5. Grid Flexibility and Value Stacking

Grid flexibility encompasses rapid frequency containment, voltage support, ramping, balancing, congestion management, peak reduction, adequacy, black start, and islanded operation. Storage creates value when its location, response, energy availability, and control architecture satisfy the technical requirements of these services simultaneously, as shown in Figure 5 and Table 2. A coordination hub can integrate renewable plants, transmission, distribution, microgrids, industrial demand, households, and electric mobility through bidirectional power and information flows. This architecture transforms storage from a passive energy buffer into a controllable network resource participating across operational and market layers. Fast ancillary services require sufficient inverter headroom and state-of-charge reserves, preventing full energy arbitrage from occurring without service-delivery conflicts. Energy shifting instead requires sustained discharge, accurate forecasts, and charging opportunities that do not create new network congestion or intensify renewable scarcity. Capacity adequacy credits should decline when storage duration becomes insufficient for correlated scarcity events, especially during prolonged low-wind and low-solar conditions. Black-start and resilience services additionally require islanding controls, energisation sequences, auxiliary power, communication continuity, and dependable stored energy after extended outages. Value stacking can improve utilisation and revenue, but incompatible commitments may double-count capacity, increase degradation, or compromise reliability during coincident system stress. A defensible stacking strategy must represent service priority, activation probability, energy reservation, recovery time, network location, degradation cost, and market penalties. Demand-response coordination can reduce required storage capacity by shifting flexible consumption, although consumer constraints and communication latency must remain explicit. Sector coupling further expands flexibility by coordinating electricity with heat, mobility, hydrogen, water, and industrial processes under shared infrastructure constraints.

Table 2 and Figure 5 depict a storage coordination hub as the digital and operational nucleus connecting solar photovoltaic and wind generation, transmission and distribution networks, microgrids, electric-vehicle charging, industrial demand, and households. Through bidirectional power exchange, service coordination, and market feedback, storage dynamically aligns variable supply with system demand across multiple spatial and temporal scales. Its flexibility services encompass rapid frequency response, voltage support, ramping and balancing, congestion relief, reserve adequacy, black start, demand-response coordination, resilience, and islanded operation. By coupling real-time sensing, forecasting, optimisation, and controlled charging or discharging, the architecture converts storage from a passive asset into an intelligent grid orchestrator. Resulting system benefits include greater renewable hosting capacity, reduced curtailment, stronger reliability, deferred network reinforcement, and more efficient market participation. Overall, the framework demonstrates how interoperable control, distributed flexibility, and coordinated stakeholder signals can strengthen decarbonisation, affordability, adaptability, and energy security under deep uncertainty within increasingly renewable-rich electricity systems.

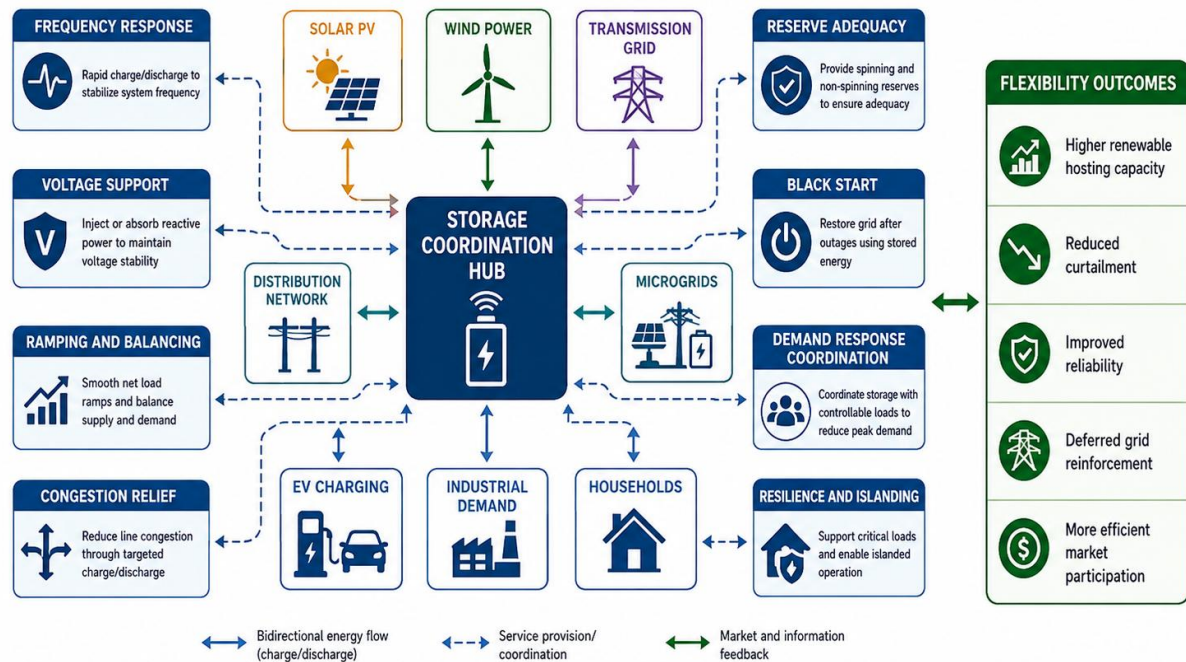


Figure 5. Grid-flexibility service architecture enabled by coordinated storage, renewable generation, networks, microgrids, controllable demand, and market feedback

Table 2. Grid-service eligibility and value-stacking compatibility.

Grid service	Timescale	Technical need	Operating reserve	Value channel	Stacking conflict	Reference	Grid service
Frequency response	Sub-second–minutes	High power	SOC headroom	Regulation payment	Energy saturation	[27]	Frequency response
Voltage support	Milliseconds–minutes	Reactive capability	Inverter margin	Network service	Local dependence	[95]	Voltage support
Ramping	Minutes–hours	Power and energy	Forecast reserve	Balancing market	Forecast error	[30]	Ramping
Congestion relief	Hours	Location-specific	Network signal	Deferred upgrade	Rebound charging	[93]	Congestion relief
Energy arbitrage	Hours	Energy capacity	Price spread	Wholesale margin	Degradation cost	[43]	Energy arbitrage
Capacity adequacy	Multi-hour–days	Firm duration	Scarcity reserve	Capacity payment	Duration derating	[96]	Capacity adequacy

5.1 Frequency and Inertia Services

Fast frequency support depends on activation speed competes with energy headroom, inverter limits, measurement quality, and recovery requirements. Evaluation should quantify response time, droop, power reserve, SOC, recovery, and availability. The practical priority is contracting verifiable performance without exhausting energy needed for later services [27].

5.2 Voltage and Reactive-Power Support

Voltage support depends on local network conditions determine whether inverter capability produces useful and deliverable voltage regulation. Evaluation should quantify reactive range, voltage sensitivity, location, thermal headroom, and control stability. The practical priority is co-optimising active and reactive services within inverter and network limits [28].

5.3 Ramping and Balancing

Ramping support depends on forecast errors and correlated renewable changes create uncertain power and energy requirements. Evaluation should quantify ramp magnitude, forecast distribution, reserve duration, SOC, and activation probability. The practical priority is reserving sufficient flexibility across multiple scheduling horizons [29].

5.4 Congestion Management

Locational congestion relief depends on charging and discharging can relieve one constraint while creating another during recovery. Evaluation should quantify power-transfer distribution factors, feeder limits, charging windows, losses, and curtailment. The practical priority is using location-specific network signals and coordinated recovery schedules [30].

5.5 Capacity Adequacy

Storage capacity contribution depends on firm value declines when scarcity duration exceeds usable discharge and recharging opportunities disappear. Evaluation should quantify effective load-carrying capability, duration, outage correlation, recovery, and seasonal conditions. The practical priority is accrediting capacity through chronological scarcity modelling rather than nameplate ratios [31].

5.6 Black Start and Restoration

Restoration storage depends on rare activation still requires retained energy, communication independence, sequencing, and auxiliary power. Evaluation should quantify energisation capability, reserve retention, islanding, communication, and restoration time. The practical priority is testing complete restoration procedures under degraded network conditions [32].

5.7 Demand Response Coordination

Storage-demand coordination depends on flexible loads can substitute or complement storage but remain constrained by service quality and participation. Evaluation should quantify shiftable energy, rebound, comfort, process limits, response, and persistence. The practical priority is optimising combined flexibility without transferring risk toward consumers [33].

5.8 Electric Mobility Integration

Vehicle-grid coordination depends on distributed batteries offer capacity while mobility needs, connection uncertainty, and ageing limit dependable availability. Evaluation should quantify plug-in probability, departure SOC, charger power, degradation, and compensation. The practical priority is valuing mobile flexibility through availability-aware contracts and equitable remuneration [34].

5.9 Revenue Stacking

Multi-service revenue depends on service combinations can improve utilisation while creating simultaneous obligations and hidden degradation exposure. Evaluation should quantify compatibility, activation overlap, energy reservation, penalties, and lifetime cost. The practical priority is preventing double counting through explicit priority and feasibility constraints [35].

5.10 Market Design

Flexibility-market design depends on valuable technical services may remain unbankable when products, settlement, duration, and access rules are misaligned. Evaluation should quantify qualification, payment structure, performance measurement, risk allocation, and contract duration. The practical priority is creating technology-neutral products that reward delivered system value [36] [27] [37].

6. Long-Duration Energy Storage

Long-duration energy storage should be defined functionally because a fixed hourly threshold cannot represent different climates, renewable mixes, demand profiles, and reliability standards. A useful definition connects discharge duration with the scarcity event, capacity requirement, cycling frequency, and avoided system cost addressed by the resource. Mechanical pathways provide bulk capacity and long service lives, although pumped hydro and compressed-air systems remain strongly influenced by topography, geology, water, and permitting. Liquid-air and gravity systems reduce some geographic constraints but retain efficiency, infrastructure, scale-up, and commercial-readiness challenges requiring field validation. Electrochemical LDES includes flow, sodium-based, and metal-air concepts whose modularity supports flexible siting while material, electrolyte, and balance-of-plant costs shape competitiveness. Thermal pathways store sensible, latent, thermochemical, or pumped heat, creating particular value where electricity and industrial heat can share charging or discharge infrastructure. Chemical storage converts electricity into hydrogen or derivatives, enabling seasonal balancing, transport, and sector coupling while imposing conversion losses and additional safety obligations. Low round-trip efficiency does not automatically eliminate chemical storage when alternatives cannot economically cover rare, prolonged, and spatially extensive renewable shortages. Cost comparison must separate power-related capital from energy-related capital because technologies scale differently when discharge duration expands from hours toward weeks. LCOS should also include charging cost, efficiency, utilisation, degradation, replacement, financing, residual value, network impacts, and reliability contribution. Bankability depends on revenue certainty, credible warranties, performance guarantees, permitting timelines, construction risk, offtake structures, and insurable operating histories. Demonstrations should therefore report comparable service delivery under representative conditions instead of emphasising nameplate duration without availability, cycling, and recovery evidence.

Table 3 and Figure 6 map the long-duration energy-storage landscape across mechanical, electrochemical, thermal, and chemical pathways, linking technological characteristics with duration classes, deployment logic, and system-level value. Mechanical options, including pumped hydropower, compressed-air, liquid-air, and gravity storage, provide mature, high-capacity services from intraday to seasonal periods but face siting, permitting, and lead-time constraints. Electrochemical systems, particularly flow, sodium-based, and metal-air batteries, enable modular, responsive multi-day balancing, although cost and material intensity remain limiting. Thermal storage delivers dense, diversified heat-based flexibility for daily and weekly applications but incurs conversion losses. Chemical carriers, especially hydrogen and ammonia, offer exportable, season-to-season storage and sector coupling, yet require efficient conversion

infrastructure. Collectively, these pathways establish a duration-matched portfolio supporting renewable firming, curtailment reduction, seasonal adequacy, extreme-weather resilience, industrial heat, and fuel substitution. The framework underscores that strategic technology selection must jointly optimise location, duration, efficiency, scalability, environmental performance, infrastructure compatibility, and whole-system economics for net-zero transitions.

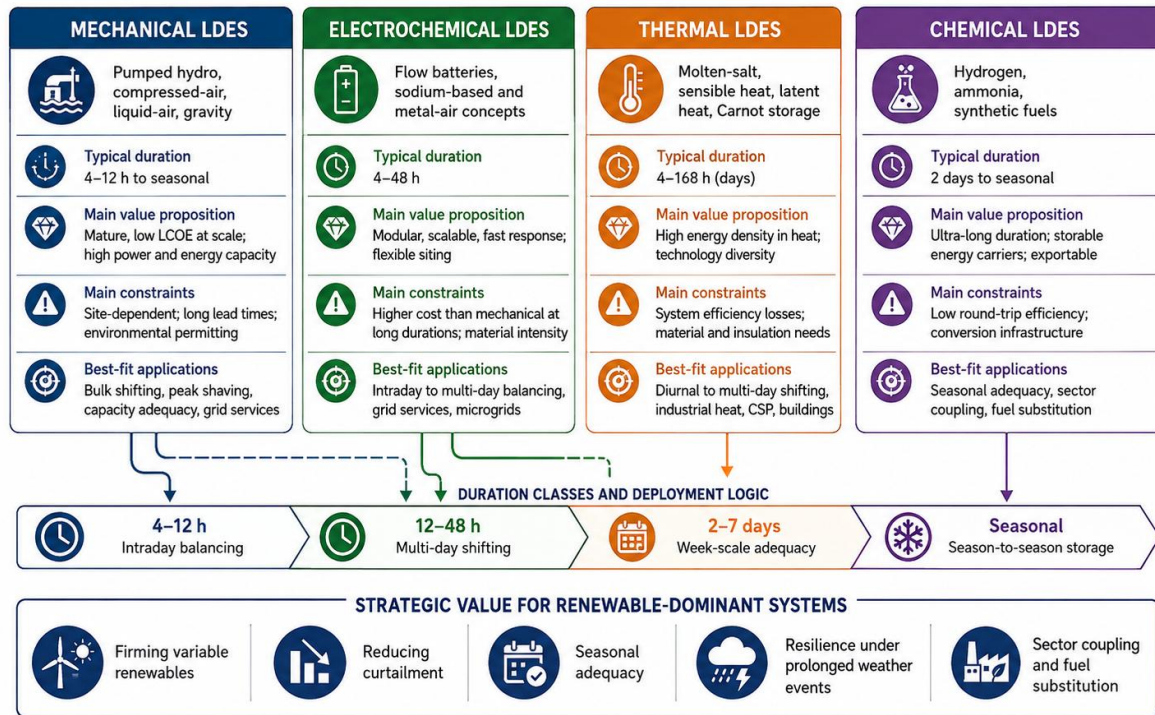


Figure 6. Long-duration energy-storage pathways, duration classes, principal value propositions, constraints, applications, and strategic renewable-system benefits

6.1 Functional Duration Definitions

LDES classification depends on fixed thresholds obscure whether storage addresses intraday shifting, multi-day adequacy, or seasonal balancing. Evaluation should quantify discharge duration, event frequency, recovery, utilisation, and avoided scarcity.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is defining duration relative to the system problem and renewable regime, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [38].

6.2 Power-Energy Cost Separation

LDES cost structure depends on power components and energy reservoirs scale differently as duration increases. Evaluation should quantify cost per power, cost per energy, balance-of-plant, construction, and replacement. The practical priority is reporting duration-dependent cost curves instead of single capital-cost values [39].

Table 3. Comparative long-duration pathways, value propositions, and deployment constraints.

Pathway	Class	Duration	Readiness logic	Main advantage	Principal constraint	Reference
Pumped hydro	Mechanical	4 hours–seasonal	Mature; low energy cost	Long life and scale	Siting and permitting	[39]
Compressed air	Mechanical	8 hours–weeks	Geology-dependent	Bulk capacity	Thermal integration	[97]
Flow battery	Electrochemical	4–48 hours	Modular	Decoupled power–energy	Electrolyte and pumps	[94]
Pumped thermal	Thermal	4 hours–days	Emerging	Heat integration	Efficiency and scale-up	[43]
Particle thermal	Thermal	Hours–days	Demonstration	Low-cost media	Reconversion equipment	[41]
Hydrogen	Chemical	Days–seasonal	Developing	Seasonal and exportable	Conversion losses	[25]
Hybrid portfolio	Multi-vector	Minutes–seasonal	Application-specific	Complementary services	Control complexity	[26]

6.3 Efficiency versus Adequacy

Round-trip efficiency depends on frequent cycling rewards efficiency while rare scarcity coverage values retained capacity and reliability. Evaluation should quantify energy losses, charging cost, scarcity probability, capacity value, and utilisation.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is evaluating efficiency within the frequency and consequence of service delivery, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [18].

6.4 Mechanical LDES

Mechanical long-duration systems depends on mature machinery interacts with geology, civil works, water, land, and lengthy permitting. Evaluation should quantify scale, efficiency, duration, lead time, availability, and environmental effects.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is screening sites through integrated technical, ecological, and community criteria, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [40].

6.5 Electrochemical LDES

Electrochemical long-duration systems depends on modular siting and rapid construction compete with electrolyte, material, replacement, and auxiliary-system costs. Evaluation should quantify duration scalability, cycling, efficiency, materials, footprint, and maintenance. The practical priority is targeting applications where frequent multi-hour service supports capital recovery [20].

6.6 Thermal LDES

Thermal long-duration systems depends on low-cost storage media require compatible heat sources, sinks, insulation, and power conversion. Evaluation should quantify heat quality, retention, exergy, conversion efficiency, cycling, and integration.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring

energy-system assets. The resulting decision priority is prioritising co-located applications that monetise both heat and electricity, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [21].

6.7 Chemical and Hydrogen LDES

Chemical long-duration storage depends on very long duration and transportability require multi-stage conversion, infrastructure, safety, and demand coordination. Evaluation should quantify chain efficiency, storage loss, purity, leakage, utilisation, and sector value. The practical priority is co-optimising electricity adequacy with industrial, mobility, and fuel markets [32].

6.8 Hybrid LDES Portfolios

Hybrid long-duration portfolios depends on multiple technologies can reduce total cost but introduce control, sizing, and contractual complexity. Evaluation should quantify service allocation, reserve sharing, degradation, redundancy, and interface losses.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is assigning each technology to the timescale where its marginal value is strongest, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [22].

6.9 Resource Adequacy Modelling

Chronological adequacy assessment depends on representative days can miss persistent weather events, seasonal correlation, and limited recharge opportunities. Evaluation should quantify hourly chronology, weather years, outages, transmission, demand, and recovery. The practical priority is using multi-year stress periods and climate-adjusted scarcity sequences [23].

6.10 Climate Extremes

Climate-resilient LDES depends on compound heat, drought, flooding, storms, and renewable scarcity affect technologies differently. Evaluation should quantify derating, water use, site exposure, access, repair time, and critical loads.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is diversifying portfolios and hardening infrastructure against correlated failures, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [41].

6.11 Bankability

LDES project finance depends on uncertain utilisation and market revenues interact with technology, construction, and performance risks. Evaluation should quantify contract tenor, warranties, contingencies, revenue floor, insurance, and residual value. The practical priority is aligning risk allocation with parties capable of measuring and managing each risk [25].

6.12 Demonstration Design

LDES demonstrations depends on pilot success may not establish commercial reproducibility, supply-chain capacity, or bankable performance. Evaluation should quantify scale, operating hours, duty cycles, availability, cost, and independent verification. The practical priority is publishing standardised operational datasets that support replication and finance [42-44].

7. Safety and Reliability Governance

Storage hazards differ across chemistries and physical architectures, yet their consequences commonly propagate through thermal, electrical, mechanical, chemical, control, and organisational pathways. A lifecycle framework must therefore address materials, design, manufacturing, transport, installation, operation, emergency response, decommissioning, and recovery as connected assurance layers. Lithium-ion thermal runaway can escalate through internal faults, heat accumulation, combustible gases, propagation, and inadequate separation between cells or enclosures. Hydrogen systems introduce leakage, ignition, pressure, embrittlement, purity, ventilation, and detection requirements that differ materially from electrochemical battery hazards. Mechanical and thermal systems face fatigue, pressure, rotating-equipment, corrosion, hot-material, containment, and structural risks requiring technology-specific inspection regimes. Cyber-physical threats can manipulate measurements, disable protection, falsify state estimates, disrupt dispatch, and amplify physical failures across aggregated storage fleets. Reliability assessment should combine component failure rates, common-cause events, degraded states, repair logistics, communication dependencies, and service-specific availability requirements. Safety-by-design prioritises inherently safer materials, robust thermal management, isolation, containment, redundant sensing, fault-tolerant control, and accessible emergency interfaces. Standards and certification remain necessary but insufficient when test conditions do not represent ageing, climate extremes, system interactions, or evolving software configurations. Operational governance requires incident reporting, diagnostic thresholds, periodic testing, cybersecurity controls, emergency coordination, and transparent learning across manufacturers and operators. Public acceptance improves when siting decisions communicate credible consequence analysis, response capability, environmental safeguards, and accountability for end-of-life handling. The most resilient architecture treats safety evidence as a design input rather than a compliance document assembled after technology and site selection. Table 4 and Figure 7 present a lifecycle-oriented safety framework for energy-storage systems, embedding continuous feedback and improvement across seven interconnected stages: materials selection, system design, manufacturing assurance, transport and installation, operational monitoring, emergency response, and end-of-life management. It links lifecycle decisions to major hazard pathways, including thermal runaway, fire and explosion, toxic or flammable gas leakage, electrical faults, pressure and mechanical failure, and cyber-physical reliability breaches. The architecture demonstrates that safety cannot be secured through reactive protection alone; it must be engineered into materials, components, controls, manufacturing processes, logistics, operation, and decommissioning. Core measures integrate advanced battery-management systems, distributed sensing, thermal control, electrical isolation, physical containment, certification and testing, predictive diagnostics, and safe transport and recycling protocols.

By coupling real-time detection with adaptive risk governance, the framework enables earlier intervention, limits failure propagation, preserves data integrity, protects personnel and infrastructure, and strengthens reliability throughout the asset lifecycle within renewable-dominant power systems globally.

Table 4. Safety hazards, diagnostic indicators, mitigation, and lifecycle controls.

Hazard	Exposed system	Failure pathway	Diagnostic signal	Primary mitigation	Lifecycle stage	Reference
Thermal runaway	Battery cells	Heat and gas propagation	Temperature and pressure	Isolation and cooling	Operation–end of life	[48]
Fire and explosion	BESS and hydrogen	Ignition and confinement	Gas and smoke sensing	Ventilation and suppression	Design–response	[49]
Pressure failure	CAES and hydrogen	Fatigue or overpressure	Pressure and strain	Relief and inspection	Manufacture–operation	[53]
Electrical fault	All power systems	Arc and insulation failure	Current and impedance	Protection coordination	Installation–operation	[46]
Cyberattack	Networked storage	False data or control	Anomaly detection	Segmentation and fallback	Operation	[43]
Capacity failure	Degraded assets	Unavailable service	SOH and performance	Derating and maintenance	Operation	[98]
Unsafe disposal	End-of-life assets	Residual energy and leakage	Traceability and testing	Safe transport and recovery	Decommissioning	[99]

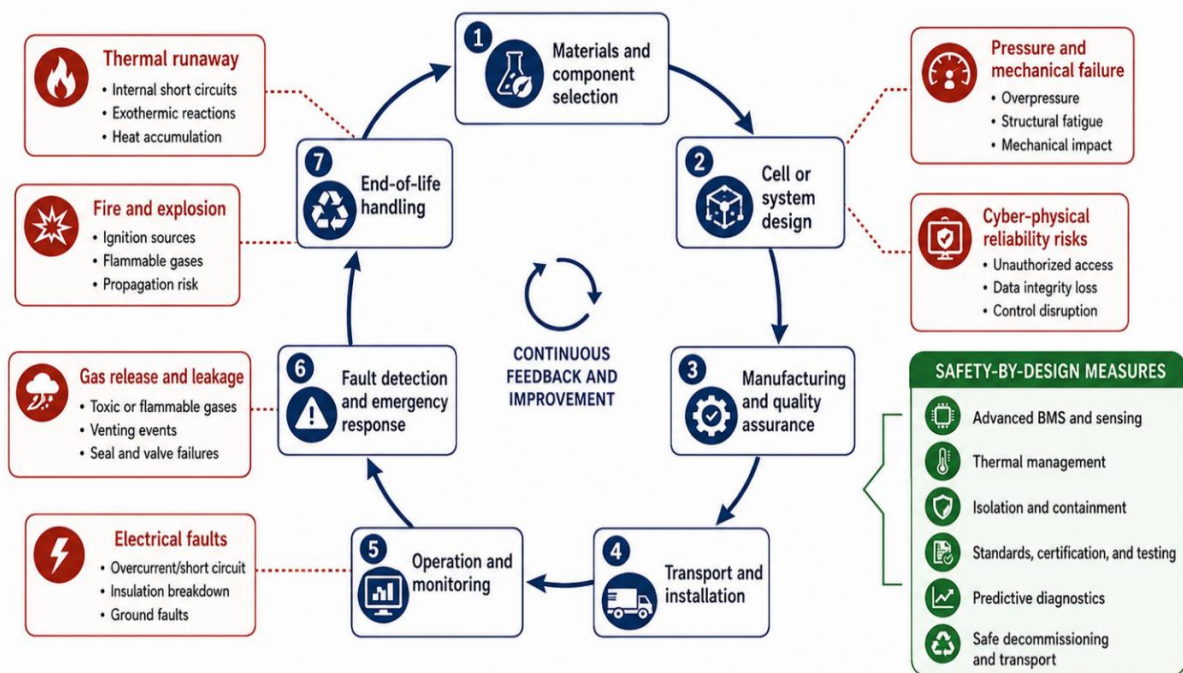


Figure 7. Safety and reliability governance across the storage lifecycle, connecting hazard sources, assurance stages, diagnostics, and safety-by-design measures

7.1 Hazard Identification

Storage hazard identification depends on different energy carriers create distinct initiating events, escalation mechanisms, and consequence zones. Evaluation should quantify stored energy, release rate, toxicity, flammability, pressure, and exposure. The practical priority is using technology-specific hazard analysis within a common lifecycle framework [45].

7.2 Thermal Runaway

Battery thermal runaway depends on cell defects, ageing, heat transfer, gas generation, and enclosure design determine propagation. Evaluation should quantify temperature, pressure, gas composition, propagation time, and heat release. The practical priority is preventing initiation while limiting cell-to-cell and enclosure-level escalation [46].

7.3 Hydrogen Safety

Hydrogen-system safety depends on leakage, buoyancy, ignition, pressure, embrittlement, and confined spaces shape risk. Evaluation should quantify leak rate, concentration, ventilation, ignition probability, and consequence distance. The practical priority is combining detection, ventilation, isolation, materials assurance, and emergency planning [47, 111].

7.4 Mechanical Integrity

Mechanical-storage integrity depends on pressure cycles, rotating equipment, civil structures, and geological uncertainty create interacting failure modes. Evaluation should quantify fatigue, vibration, pressure, deformation, leakage, and inspection findings. The practical priority is implementing risk-based inspection with defined intervention thresholds [48].

7.5 Electrical Protection

Electrical safety depends on high fault currents, inverter controls, insulation degradation, and grounding influence escalation. Evaluation should quantify current, impedance, isolation, arc detection, and protection coordination. The practical priority is designing selective protection across cells, converters, feeders, and network interfaces [49].

7.6 Cyber-Physical Security

Cyber-physical storage security depends on compromised data or control can alter SOC, dispatch, protection, and aggregated network behaviour. Evaluation should quantify authentication, anomaly residuals, latency, integrity, availability, and recovery. The practical priority is combining secure architecture with independent physical safeguards and fallback control [50].

7.7 Reliability Modelling

Storage reliability assessment depends on binary availability models overlook degraded states, common-cause failures, repair logistics, and service dependence. Evaluation should quantify failure rates, degraded capacity, repair time, spares, and service availability. The practical priority is linking component reliability to delivered grid-service performance [13].

7.8 Standards and Testing

Safety standards depends on rapid technology evolution can outpace tests for ageing, climate exposure, software changes, and system interactions. Evaluation should quantify test coverage, abuse conditions, ageing state, climate, and pass criteria. The

practical priority is harmonising minimum requirements while preserving technology-specific validation [51].

7.9 Emergency Response

Emergency preparedness depends on incident outcomes depend on detection, isolation, access, responder information, suppression, and post-event monitoring. Evaluation should quantify alarm time, isolation, propagation, toxic release, access, and recovery. The practical priority is integrating operators, responders, communities, and environmental authorities before commissioning [52].

7.10 Safety Governance

Lifecycle safety governance depends on responsibility can fragment across suppliers, integrators, owners, optimisers, recyclers, and emergency services. Evaluation should quantify accountability, records, incident reporting, training, audits, and corrective actions. The practical priority is maintaining traceable responsibility from design through decommissioning [53, 54].

8. Degradation and Digital Intelligence

Degradation converts operating decisions into delayed technical, economic, safety, and environmental consequences that cannot be represented adequately through constant efficiency or fixed lifetime assumptions. Lithium-ion ageing combines solid-electrolyte interphase growth, lithium plating, particle cracking, electrolyte decomposition, thermal stress, calendar ageing, and mechanically induced contact loss. Flow batteries experience crossover, membrane fouling, electrolyte imbalance, precipitation, shunt currents, pump deterioration, and corrosion across electrochemical and hydraulic subsystems. Hydrogen pathways face catalyst decay, electrolyser deterioration, compressor wear, storage-vessel embrittlement, leakage, and contamination that alter efficiency, availability, and safety. Thermal storage can lose performance through corrosion, insulation deterioration, heat-transfer impairment, phase segregation, and cycling instability under repeated temperature gradients. Mechanical systems accumulate fatigue, sealing losses, bearing wear, turbomachinery deterioration, and reservoir-related constraints that require condition-based inspection and maintenance. Observable outcomes include capacity fade, efficiency loss, resistance growth, power limitation, increasing hazard probability, downtime, and shortened economic life. Health-aware dispatch must balance immediate service revenue against future replacement, availability, warranty, and environmental costs created by accumulated operating stress. Digital control closes this loop through data acquisition, forecasting, state estimation, optimisation, execution, anomaly detection, prognostics, and adaptive model updating. Sensors should combine electrical, thermal, mechanical, chemical, environmental, grid, and market information with clear provenance and synchronised timestamps. AI models can improve nonlinear estimation and decision speed, although transferable performance requires representative degradation histories, uncertainty estimates, and cross-site validation. Physics-informed models remain valuable where sparse failure data make purely empirical learning unreliable, particularly for rare hazards and emerging storage chemistries. MPC supports constraint-aware coordination, whereas reinforcement learning requires safe exploration boundaries, explainable policies, fallback control, and validation beyond simulated

environments. Digital twins become operationally credible only when models update from measured data, quantify residual uncertainty, and inform actions that improve verified lifecycle outcomes. Open interfaces and edge–cloud architectures can support fleet coordination, but cybersecurity, latency, privacy, communication loss, and vendor lock-in require explicit governance. The combined objective is not maximum algorithmic sophistication, but dependable decisions that reduce cost, extend lifetime, preserve safety, and strengthen renewable integration.

Figure 8 develops a technology-agnostic degradation-to-intervention framework linking failure mechanisms across electrochemical, chemical, thermal, and mechanical storage systems with observable performance losses and targeted health-management responses. Lithium-ion batteries degrade through solid-electrolyte interphase growth, lithium plating, particle cracking, and electrolyte decomposition; flow batteries experience crossover, membrane fouling, and electrolyte imbalance. Hydrogen systems face catalyst decay, tank embrittlement, and compressor wear, while thermal and mechanical storage encounter corrosion, phase instability, fatigue, sealing losses, and turbomachinery wear. These mechanisms converge into capacity fade, declining round-trip efficiency, power limitation, resistance growth, escalating safety risk, and shortened service life. The framework consequently prioritises state-of-charge and depth-of-discharge optimisation, thermal control, condition monitoring, artificial-intelligence-enabled prognostics, digital twins, and predictive maintenance.

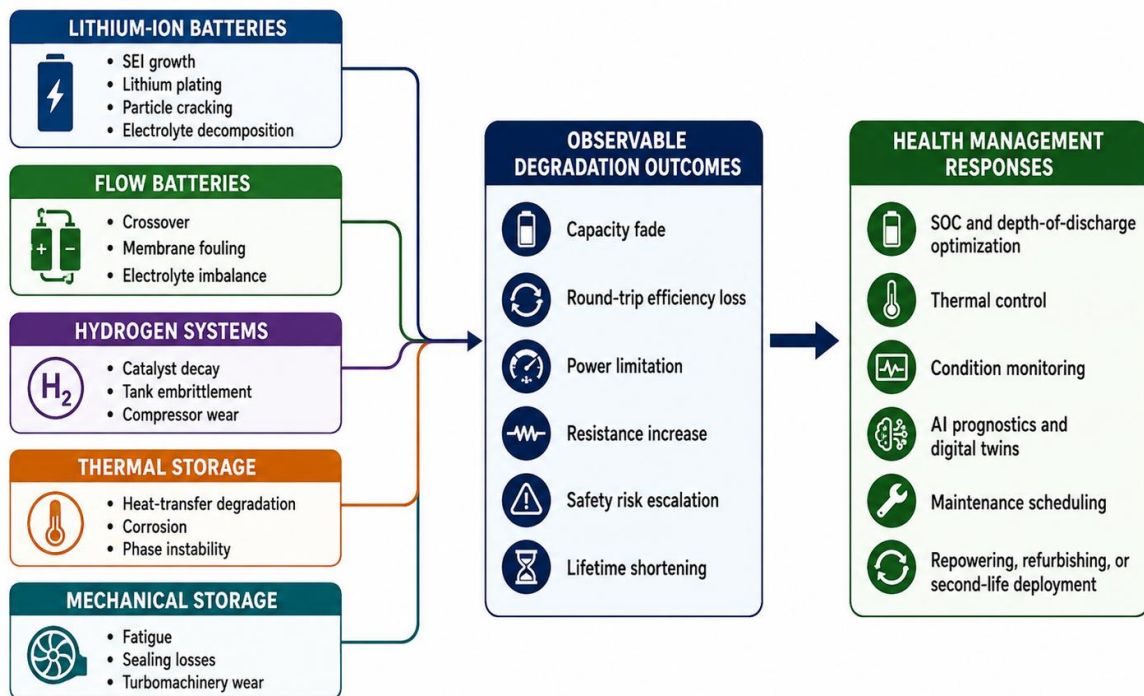


Figure 8. Technology-specific degradation mechanisms, observable system consequences, and lifetime-management responses across storage classes

Intelligent energy management improves coordination when models remain data-grounded, uncertainty-aware, interoperable, computationally feasible, and protected by safe fallback control [55]. Digital-control research combines forecasting, state estimation, optimisation, execution, diagnostics, and adaptive learning while retaining explicit reliability and operational constraints [56]. Table 5 and Figure 9 illustrate a closed-loop

intelligent energy-management architecture that converts heterogeneous operational data into adaptive storage decisions and continuous system improvement. Data acquisition integrates pack, inverter, environmental, and grid sensors; supervisory control and historian records; weather forecasts; and market signals. Forecasting and state-estimation modules then predict renewable generation and demand while estimating state of charge and state of health. A decision engine combines energy-management rules, model-predictive control, artificial intelligence, machine learning, and multi-objective optimisation across cost, risk, and technical constraints. The execution layer translates decisions into inverter commands, battery management, charge–discharge schedules, and hybrid-system coordination. Monitoring closes the loop through anomaly detection, predictive maintenance, digital twins, adaptive control, and model updating. Guided by cost minimisation, renewable integration, resilience, and lifetime extension, the framework depends on interoperable interfaces, cybersecurity, edge–cloud computing, and standardised communications. Collectively, these capabilities enable self-learning, degradation-aware, uncertainty-responsive storage operation for flexible, reliable, and renewable-dominant power systems globally.

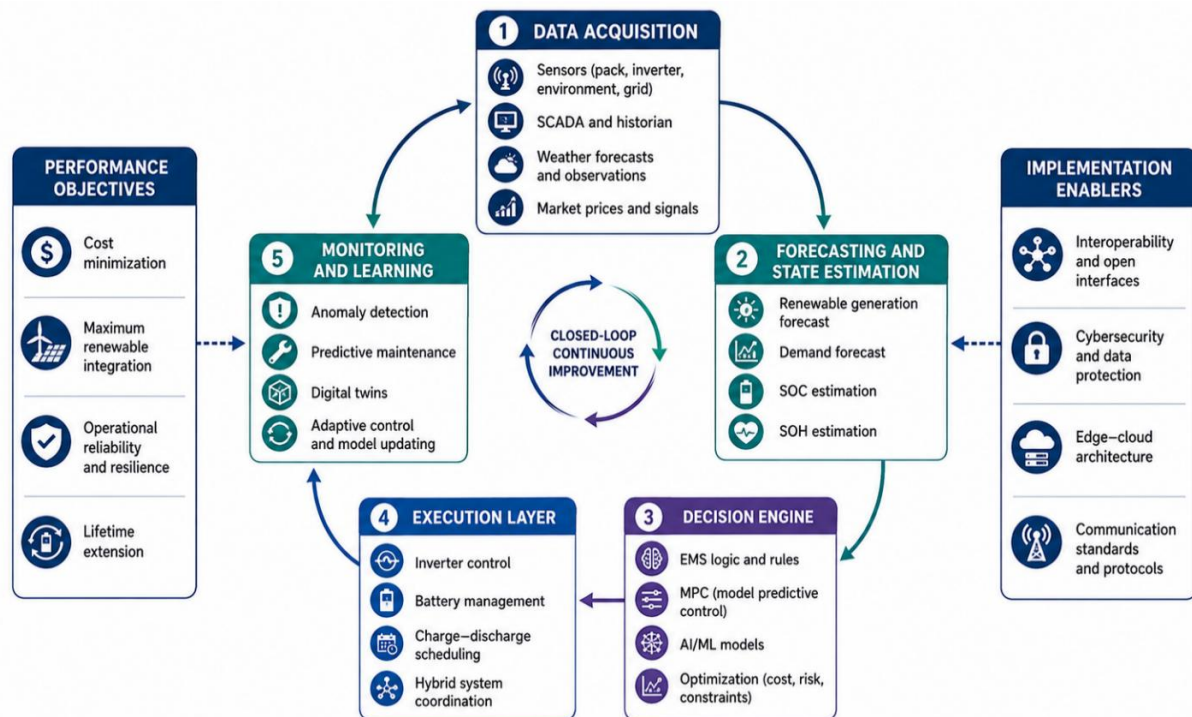


Figure 9. Digital intelligence and closed-loop control ecosystem for forecasting, state estimation, optimisation, execution, monitoring, and adaptive improvement

Table 5. Degradation mechanisms, observables, diagnostics, and management responses.

System	Dominant mechanism	System consequence	Observable	Digital method	Management response	Reference
Lithium-ion	SEI, plating, cracking	Capacity and resistance	Voltage, heat, impedance	Hybrid prognostics	SOC and thermal control	[59]
Flow battery	Crossover and fouling	Efficiency and imbalance	Electrolyte and pressure	State estimation	Rebalancing and service	[69]
Electrolyser	Catalyst and membrane decay	Efficiency and purity	Voltage and gas quality	Physics-informed models	Load-ramp limitation	[67]
Thermal store	Corrosion and heat loss	Reduced usable energy	Temperature gradients	Digital twin	Inspection and insulation	[55]

Mechanical store	Fatigue and seal wear	Availability decline	Vibration and pressure	Condition monitoring	Predictive maintenance	[11]
Hybrid system	Unequal component ageing	Dispatch constraints	Multisource telemetry	MPC or reinforcement learning	Health-aware coordination	[100]
Storage fleet	Data and model drift	Unsafe decisions	Residual and anomaly metrics	Continual validation	Fallback and human oversight	[101]

8.1 Degradation Taxonomies

Cross-technology degradation depends on chemical, thermal, electrical, mechanical, and control ageing produce different observable signatures. Evaluation should quantify capacity, resistance, efficiency, power, leakage, vibration, and availability. The practical priority is connecting mechanisms with measurable indicators and actionable thresholds [57].

8.2 Lithium-Ion Ageing

Lithium-ion lifetime depends on temperature, SOC, C-rate, depth of discharge, and rest periods interact nonlinearly. Evaluation should quantify capacity retention, resistance, lithium inventory, heat, and cycle throughput. The practical priority is using chemistry-specific models calibrated across representative duty cycles [58].

8.3 Flow-Battery Ageing

Flow-battery degradation depends on electrolyte imbalance, crossover, membrane fouling, corrosion, and pumps affect complete-system efficiency. Evaluation should quantify state of electrolyte, pressure, conductivity, crossover, and auxiliary consumption. The practical priority is coordinating rebalancing, maintenance, and stack replacement through condition evidence [59].

8.4 Electrolyser and Fuel-Cell Ageing

Hydrogen-conversion degradation depends on dynamic loading affects catalysts, membranes, purity, efficiency, and balance-of-plant equipment. Evaluation should quantify voltage, gas quality, pressure, efficiency, starts, and ramp history. The practical priority is co-optimising renewable following with conversion-system lifetime [60].

8.5 Thermal-Store Deterioration

Thermal-storage degradation depends on corrosion, phase instability, insulation ageing, and heat-exchanger fouling reduce usable performance. Evaluation should quantify temperature profile, heat loss, pressure drop, chemistry, and cycling. The practical priority is combining materials surveillance with thermal performance diagnostics [61].

8.6 Mechanical Ageing

Mechanical-storage degradation depends on fatigue, seals, bearings, turbomachinery, and civil assets accumulate distinct stresses. Evaluation should quantify vibration, pressure, efficiency, leakage, deformation, and operating hours. The practical priority is applying subsystem-specific maintenance within a unified availability model [62].

8.7 State Estimation

SOC and SOH estimation depends on unobservable internal states, sensor noise, ageing, and model mismatch create decision uncertainty. Evaluation should quantify estimation error, confidence interval, drift, residuals, and validation coverage. The practical priority is propagating estimation uncertainty into dispatch and protection decisions [63].

8.8 Forecasting

Renewable and demand forecasting depends on errors vary across horizons, weather regimes, locations, and extreme events. Evaluation should quantify bias, probabilistic calibration, ramp errors, tail performance, and update frequency. The practical priority is using probabilistic forecasts aligned with the controlled service timescale [64, 112-114].

8.9 Model Predictive Control

Predictive storage control depends on forecast horizons, constraints, model fidelity, and computational limits determine achievable performance. Evaluation should quantify cost, violations, solution time, forecast error, and closed-loop stability. The practical priority is balancing optimisation detail with reliable real-time execution [65].

8.10 Reinforcement Learning

Learning-based dispatch depends on simulation training may omit rare failures, changing markets, and unseen operating regimes. Evaluation should quantify reward robustness, constraint violations, transfer, interpretability, and fallback activation. The practical priority is requiring safe policies and out-of-distribution detection before field deployment [66, 115].

8.11 Digital Twins

Storage digital twins depends on useful twins require continuous data assimilation, model updating, uncertainty, and decision linkage. Evaluation should quantify prediction residuals, update rate, fidelity, uncertainty, and maintenance value. The practical priority is validating whether twin-informed actions improve measured lifecycle outcomes [67].

8.12 Edge-Cloud Architecture

Distributed intelligence depends on latency, connectivity, privacy, computation, and cybersecurity determine placement of analytical functions. Evaluation should quantify communication delay, availability, bandwidth, energy use, and recovery. The practical priority is placing protection and essential control near assets while coordinating fleets securely [68].

8.13 Interoperability

Digital interoperability depends on proprietary interfaces can fragment data, restrict competition, and prevent portfolio-wide optimisation. Evaluation should quantify semantic consistency, protocol coverage, data quality, portability, and conformance. The practical priority is adopting open information models with verified implementation profiles [69].

8.14 Degradation-Aware Finance

Lifetime-informed valuation depends on dispatch, warranties, replacement, insurance, and residual value depend on uncertain degradation. Evaluation should quantify damage cost, remaining life, replacement probability, downtime, and warranty exposure. The practical priority is integrating health uncertainty within investment and market decisions [70, 71].

9. Circularity and Responsible Resource Stewardship

Circular storage systems minimise virgin material demand by coordinating durable design, repair, modular upgrades, reuse, second-life deployment, recycling, and high-quality material reintegration. Operational efficiency alone cannot establish sustainability because manufacturing impacts, critical-mineral extraction, replacement frequency, transport, and end-of-life losses may dominate lifecycle burdens. Design for disassembly should use accessible fasteners, separable materials, modular interfaces, standardised diagnostics, replaceable subsystems, and digital records describing composition and operating history. Life extension through conservative dispatch, thermal control, predictive maintenance, refurbishment, and repowering can defer replacement while preserving safe service delivery. Second-life batteries require qualification procedures that estimate remaining capacity, power, resistance, heterogeneity, safety history, uncertainty, and suitability for the intended duty cycle. Economic viability depends on testing cost, aggregation, warranty, liability, remanufacturing, logistics, competing recycling value, and the degradation intensity of second-life services. Recycling pathways should be evaluated through recovery yield, material quality, energy use, emissions, water consumption, reagent demand, worker exposure, and regional infrastructure. Closed-loop recovery creates greater value when recovered materials meet performance requirements for new storage products rather than entering lower-value applications. Digital product passports can connect material provenance, component identity, operating history, repairs, ownership, safety events, and recovery outcomes across the value chain. Governance must include extended producer responsibility, ethical sourcing, transparent chain-of-custody, safe transport, regional recycling capacity, and protections for informal-sector workers. Circularity also applies beyond batteries because thermal media, pressure vessels, rotating equipment, electrolyser materials, electronics, concrete, and infrastructure require technology-specific recovery strategies. A just circular transition prevents decarbonisation benefits from externalising extraction, pollution, unsafe labour, or unrecoverable waste toward communities with limited regulatory protection.

Table 6 and Figure 10 conceptualises a circular lifecycle for energy-storage systems, transforming linear extraction–manufacture–use–disposal pathways into a regenerative value loop. The sequence begins with responsible critical-mineral sourcing and resource-efficient manufacturing, progresses through safe grid deployment and operational life extension, and continues through repurposing, second-life applications, recycling, material recovery, and reintegration into new storage products. Predictive maintenance, upgrades, refurbishment, and performance optimisation preserve embedded energy and delay premature retirement. Circular design levers, including durability, modularity, compatibility, disassembly-friendly architectures, recyclability, and digital traceability, enable materials and components to retain their highest feasible value. Environmental and economic gains include reduced virgin material demand, lower

resource dependence, decreased waste, recovered strategic minerals, and value-chain emission reductions. Achieving these outcomes requires standards, certification, extended producer responsibility, regional recycling infrastructure, accountable supply chains, and social safeguards. Overall, the framework positions circularity as a system-level strategy for resilient renewable grids, industrial competitiveness, supply security, and an equitable net-zero transition.

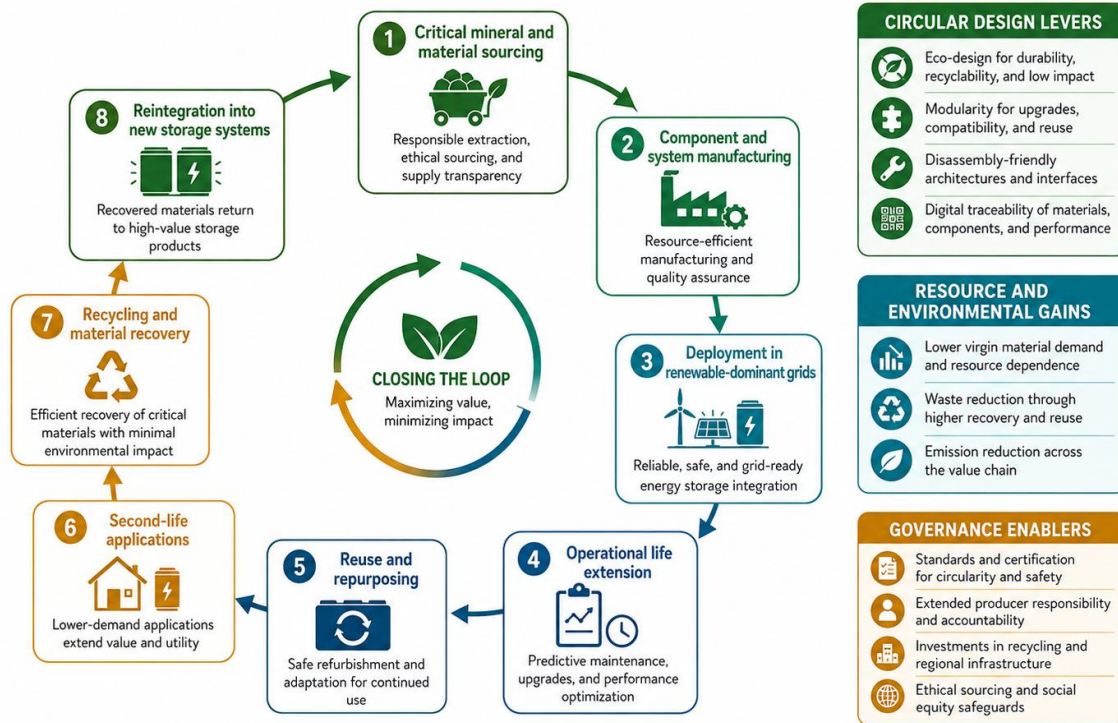


Figure 10. Circularity pathways connecting material sourcing, manufacturing, operation, life extension, reuse, second-life deployment, recycling, and reintegration.

Table 6. Circular design, recovery, governance, and lifecycle value.

Lifecycle stage	Primary asset	Circular indicator	Main barrier	Required enabler	System benefit	Reference
Material sourcing	Critical minerals	Traceable origin	Supply concentration	Responsible procurement	Lower exposure	(Donnelly, 2023)
Design	Modules and interfaces	Disassembly readiness	Proprietary architecture	Standardisation	Repair and upgrade	[72]
Operation	Health-aware control	Lifetime extension	Data fragmentation	Digital passport	Deferred replacement	[74]
Second life	Qualified used assets	Remaining utility	Safety uncertainty	Performance certification	Avoided new capacity	[73]
Recycling	Recovered materials	Closed-loop yield	Process emissions	Recovery standards	Lower virgin demand	[79]
Reintegration	Battery-grade outputs	Material quality	Downcycling	Quality assurance	Circular manufacturing	[78]
Governance	Value-chain accountability	Equitable safeguards	Burden shifting	Producer responsibility	Public legitimacy	[76]

9.1 Critical-Material Exposure

Critical-material dependence depends on technology expansion can transfer energy security risks toward concentrated mineral and processing supply chains. Evaluation should quantify material intensity, concentration, price volatility, provenance, and substitution. The practical priority is diversifying supply while reducing material demand through durable design [72, 116].

9.2 Design for Durability

Durable storage design depends on longer life can reduce material turnover but may conflict with upgradeability, repair, and changing requirements. Evaluation should quantify service life, repairability, modularity, efficiency, safety, and adaptability.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is optimising durable modules within replaceable and upgradeable architectures, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading (Donnelly, 2023).

9.3 Design for Disassembly

Disassembly-ready design depends on adhesives, mixed materials, hazardous residual energy, and proprietary construction hinder recovery. Evaluation should quantify disassembly time, tool access, separation quality, safety, and recovered value.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is embedding recovery requirements within product and system specifications, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [73].

9.4 Digital Product Passports

Lifecycle traceability depends on second-life and recycling decisions require reliable identity, composition, history, repair, and ownership data. Evaluation should quantify data completeness, authenticity, accessibility, interoperability, and custody.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is maintaining secure records that remain available beyond original ownership, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [74].

9.5 Second-Life Qualification

Second-life storage depends on heterogeneous ageing and uncertain history challenge safety, warranty, and application matching. Evaluation should quantify capacity, power, resistance, self-discharge, safety history, and uncertainty. The practical priority is certifying assets against the requirements of a defined second-life duty [75].

9.6 Repurposing Economics

Second-life economics depends on testing, sorting, remanufacturing, integration, liability, and competing recycling value determine viability. Evaluation should quantify acquisition, testing, yield, warranty, balance-of-system, and residual value.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is selecting applications where avoided new capacity exceeds qualification and integration costs, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [76].

9.7 Recycling Pathways

Storage recycling depends on recovery yield alone cannot capture energy, emissions, water, toxicity, quality, and worker exposure. Evaluation should quantify mass yield, material purity, energy, water, emissions, and safety. The practical priority is comparing routes through consistent lifecycle and product-quality boundaries [77].

9.8 Closed-Loop Reintegration

Closed-loop materials depends on recovered outputs create maximum value only when purity and consistency meet new-product requirements. Evaluation should quantify recovery quality, substitution rate, contamination, yield, and manufacturing performance. The practical priority is linking recyclers with manufacturers through specifications and transparent quality assurance [78].

9.9 Producer Responsibility

Extended producer responsibility depends on unclear ownership and cross-border flows can leave decommissioned assets without accountable recovery. Evaluation should quantify collection, traceability, financing, compliance, exports, and recovery outcomes.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is assigning lifecycle responsibility with enforceable financing and reporting mechanisms, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [21].

9.10 Just Circularity

Equitable circular governance depends on extraction, pollution, unsafe work, and waste may burden communities receiving limited transition benefits. Evaluation should quantify distributional impacts, labour conditions, participation, local value, and remediation. The practical priority is embedding environmental justice within sourcing, siting, operation, and recovery decisions [72, 79].

10. Multiscale Integration and Decision Framework

Storage performance emerges through interactions among materials, cells or components, packs or systems, plants or energy hubs, networks, markets, and regulatory institutions. Optimising one scale independently can transfer costs or risks elsewhere, including higher material intensity, shorter lifetime, network congestion, inadequate capacity, or unrecoverable waste. Material-level electrochemistry, thermal transport, reaction stability, corrosion resistance, and mechanical durability establish boundaries for efficiency, safety, and degradation. Device-level design translates these properties into power, energy, response, controllability, manufacturability, protection, and maintainability. System-level integration adds power electronics, controls, thermal management, balance-of-plant equipment, hybridisation, monitoring, communication, and emergency functions. Plant and microgrid decisions connect storage with renewable production, flexible demand, backup resources, islanding, curtailment, resilience, and local network constraints. Power-system planning then evaluates adequacy, transmission,

distribution, capacity expansion, extreme events, and interactions among geographically distributed storage resources. Market and policy layers determine whether technically valuable services receive bankable revenues, compatible procurement rules, credible standards, and equitable siting processes. The proposed Storage-to-System Evidence Matrix evaluates each pathway through duration, response, service eligibility, efficiency, availability, degradation, safety, and location. Additional dimensions cover climate resilience, digital readiness, circularity, technological maturity, lifecycle cost, revenue certainty, evidence quality, and distributional consequences. Each dimension should receive a confidence grade separating modelled potential from experimentally validated, pilot-demonstrated, and commercially replicated performance. Portfolio selection begins with the system problem, then identifies service requirements, scarcity duration, location, risk tolerance, available infrastructure, and market conditions. Candidate technologies are subsequently screened for technical feasibility before lifecycle cost, safety, circularity, climate, and bankability determine the preferred portfolio. Sensitivity analysis should test renewable profiles, demand growth, discount rates, charging cost, lifetime, extreme events, material prices, regulation, and recovery value. The framework rejects universal rankings because changing any critical boundary can reverse technology preferences without contradicting the underlying evidence. Its purpose is transparent conditional selection that reveals assumptions, trade-offs, uncertainties, and evidence gaps to planners, investors, regulators, and communities.

Table 7 and Figure 11 present a multiscale integration framework connecting energy-storage science, engineering, operation, and governance from materials to electricity markets. At the materials-and-interface level, electrochemical reactivity, thermal transport, degradation resistance, and stability determine foundational performance. Cell, stack, and module design translates these properties into power density, energy density, round-trip efficiency, safety, and reliability. Pack and storage-system integration adds battery management, monitoring, protection, thermal control, fire mitigation, and hybridisation. At plant, microgrid, and energy-hub scales, storage couples renewables, supplies firm capacity, strengthens resilience, and delivers ancillary services. Power-system and market integration then coordinates planning, resource adequacy, revenue stacking, regulation, and capacity valuation. Four cross-cutting enablers—data and diagnostics, control and optimisation, safety and standards, and circularity and lifecycle governance—link every scale bidirectionally. This architecture demonstrates that storage value emerges through optimisation across technical, economic, environmental, and institutional layers, delivering reliable clean power, greater flexibility, lower curtailment, improved asset utilisation, and accelerated net-zero transition.

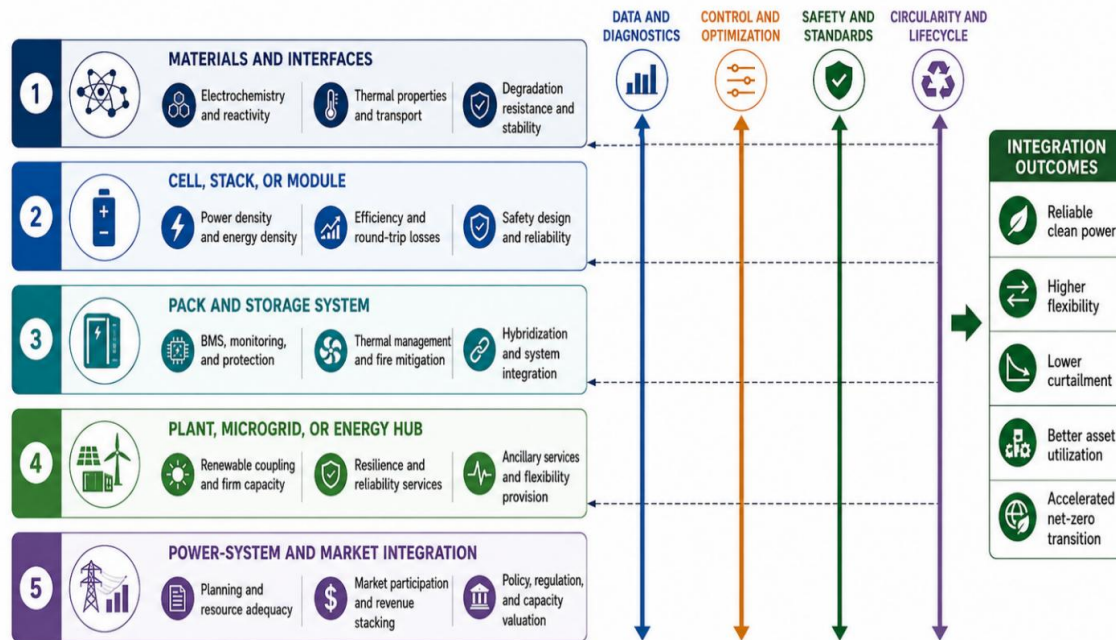


Figure 11. Multiscale integration of energy storage from materials and interfaces through devices, systems, energy hubs, power networks, and markets.

Table 7. Storage-to-System Evidence Matrix for portfolio selection.

Decision dimension	Core indicators	Acceptance test	Evidence requirement	Priority	Decision rule	Reference
Service fit	Response and duration	Meets duty cycle	Activation data	High	Reject if inadequate	[102]
Technical performance	Efficiency and availability	Delivered output	Field or pilot data	High	Apply derating	[103]
Lifetime	Degradation and maintenance	Usable service life	Validated ageing model	High	Monetise replacement	[64]
Risk	Safety and cyber reliability	Residual risk	Failure evidence	High	Require safeguards	[43]
Economics	Cost and revenue certainty	Bankability	Scenario analysis	High	Risk-adjust valuation	[82]
Sustainability	Emissions and circularity	Lifecycle burden	Boundary-consistent LCA	Medium-high	Avoid burden shifting	[78]
Resilience	Climate and scarcity exposure	Critical-service continuity	Stress-test scenarios	High	Portfolio diversification	[104]

10.1 Materials-to-Device Translation

Materials-to-device translation depends on favourable laboratory properties can be diluted by inactive materials, interfaces, manufacturing, and protection requirements. Evaluation should quantify usable density, efficiency, stability, manufacturability, safety, and cost. The practical priority is reporting performance at the scale where system decisions are made [80].

10.2 Device-to-System Integration

Device integration depends on power electronics, cooling, controls, housing, auxiliaries, and redundancy reshape delivered performance. Evaluation should quantify system efficiency, footprint, availability, auxiliary load, and maintainability. The practical priority is evaluating complete storage systems rather than active materials alone [81].

10.3 Hybrid-System Coordination

Hybrid storage coordination depends on technologies with different dynamics, efficiencies, and ageing require stable service allocation. Evaluation should quantify power split, SOC balance, degradation, switching, losses, and reserve. The practical priority is using predictive coordination that preserves complementary roles across timescales [32].

10.4 Plant and Energy Hubs

Energy-hub integration depends on electricity, heat, hydrogen, mobility, and flexible demand share assets and constraints. Evaluation should quantify conversion capacity, energy flows, curtailment, emissions, and service reliability. The practical priority is co-optimising vectors without obscuring conversion losses or infrastructure bottlenecks [2].

10.5 Network Planning

Network-storage co-planning depends on storage can defer infrastructure yet recovery charging and changing flows alter network requirements. Evaluation should quantify congestion, losses, voltage, hosting capacity, reliability, and reinforcement timing. The practical priority is co-optimising storage siting with transmission and distribution investment [82].

10.6 Capacity Expansion

Long-term resource planning depends on technology learning, climate, demand, retirements, and policy create deep uncertainty. Evaluation should quantify capacity mix, adequacy, curtailment, cost, emissions, and stranded assets. The practical priority is testing robust portfolios across multiple plausible futures [83].

10.7 Market Participation

Market-system integration depends on dispatch incentives can diverge from reliability, network, emissions, and lifecycle objectives. Evaluation should quantify revenues, activation, congestion, emissions, degradation, and consumer cost. The practical priority is aligning market signals with measurable system-wide value [2, 84].

10.8 Storage-to-System Evidence Matrix

The SSEM framework depends on technology selection requires simultaneous screening across performance, risk, sustainability, maturity, and confidence. Evaluation should quantify service fit, duration, cost, safety, lifetime, circularity, resilience, and evidence. The practical priority is making trade-offs transparent through conditional thresholds and confidence grades [85].

10.9 Multi-Criteria Decision Analysis

Multi-criteria storage assessment depends on weights can embed hidden stakeholder preferences and produce unstable rankings. Evaluation should quantify criteria definitions, weights, uncertainty, sensitivity, and stakeholder distribution. The practical priority is publishing weighting logic and testing rank stability across perspectives [86, 117].

10.10 Decision Governance

Storage decision governance depends on planning choices distribute costs, risks, land, infrastructure, employment, and environmental burdens. Evaluation should quantify participation, transparency, distribution, accountability, appeal, and monitoring. The practical priority is combining technical evidence with legitimate and inclusive decision processes [80, 81, 87].

11. Strategic Roadmap

Near-term priorities should establish comparable duration definitions, service-specific testing, open operating datasets, safety incident reporting, interoperability, and transparent degradation-aware valuation. Capacity accreditation must reflect scarcity duration, correlated renewable conditions, recovery constraints, and locational deliverability instead of assigning uniform credits to nameplate energy. Commercial demonstrations should publish availability, efficiency, response, cycling, maintenance, climate exposure, safety events, and financial performance using common reporting templates. Standards bodies should harmonise hazard testing while retaining technology-specific requirements for ageing, thermal propagation, pressure integrity, cyber resilience, transport, and decommissioning. Degradation-linked warranties can align manufacturers, owners, optimisers, and financiers when measurement rules, operating envelopes, residual value, and responsibility remain explicit. Digital programmes should prioritise validated state estimation, interpretable prognostics, secure interfaces, edge resilience, uncertainty reporting, and safe fallback operation. Circularity policy should connect producer responsibility, design standards, material passports, second-life certification, recycling infrastructure, and responsible sourcing across jurisdictions. Emerging economies require locally grounded evidence addressing weak networks, high financing costs, tropical climates, skills, repairability, informal recovery, and equitable access to flexibility. Medium-term research should advance bankable LDES portfolios, hybrid controls, climate-informed planning, modular refurbishment, regional recycling, and multi-vector market coordination. Long-term development should enable seasonal storage ecosystems, autonomous but accountable energy hubs, closed-loop materials, and resilience against compound climate and infrastructure disruptions. Roadmap progress should be measured through demonstrated service reliability, declining lifecycle cost, improved safety, reduced material footprint, higher renewable utilisation, and equitable benefits. Research priorities should remain adaptive because technology learning, market reform, climate risk, material supply, and community expectations will change optimal storage portfolios.

Figure 12 synthesises a future research and implementation agenda for energy storage across five interdependent pillars: grid flexibility, long-duration storage, safety and reliability, degradation and lifetime, and circularity and resource stewardship. Grid-focused priorities include co-optimised infrastructure planning, flexibility markets, value stacking, and sector coupling with heat, mobility, and hydrogen. Long-duration pathways require bankable risk mitigation, duration-specific valuation, cost benchmarking, and geographically diverse demonstrations. Safety advancement depends on real-time diagnostics, harmonised standards, early-warning systems, robust architectures, and thermal management. Lifetime optimisation combines chemistry-aware prognostics, degradation-linked warranties, health-aware dispatch, and lifecycle control.



Figure 12. Strategic research roadmap spanning grid flexibility, long-duration storage, safety, degradation, circularity, and system-wide net-zero outcomes.

11.1 Near-Term Evidence Infrastructure

Near-term research infrastructure depends on fragmented definitions and proprietary datasets prevent comparison, validation, and learning from failures. Evaluation should quantify reporting standards, open data, metadata, benchmark tasks, and incident records. The practical priority is building shared evidence foundations before scaling autonomous decision systems [80].

11.2 Demonstration Portfolios

Demonstration strategy depends on single projects cannot reveal reproducibility across climates, markets, duty cycles, and supply chains. Evaluation should quantify replication, operating hours, availability, cost, safety, and independent verification. The practical priority is funding coordinated portfolios with common measurements and transparent outcomes [81].

11.3 Standards Harmonisation

Standards development depends on minimum common requirements must coexist with technology-specific hazards and rapidly changing software. Evaluation should quantify scope, test conditions, ageing, climate, cybersecurity, and conformity. The practical priority is creating modular standards that evolve without weakening essential protections [88].

11.4 Market and Procurement Reform

Procurement reform depends on short contracts and narrow products cannot support capital-intensive long-duration resources or stacked value. Evaluation should quantify contract duration, qualification, settlement, capacity credit, penalties, and risk allocation. The practical priority is procuring verifiable system outcomes through technology-neutral mechanisms [89].

11.5 Finance and Warranties

Storage finance innovation depends on uncertain utilisation, degradation, construction, and revenue require credible measurement and risk sharing. Evaluation should quantify revenue floors, warranties, insurance, contingencies, residual value, and disclosure. The practical priority is allocating risks to parties possessing information and control [90].

11.6 Workforce and Institutional Capacity

Deployment capability depends on scaling requires engineers, operators, responders, regulators, recyclers, financiers, and community institutions. Evaluation should quantify skills, certification, staffing, training, local supply, and knowledge retention.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is investing in regional capabilities alongside physical storage assets, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [83].

11.7 Emerging-Economy Priorities

Emerging-economy deployment depends on high capital costs, weak networks, climate exposure, and limited repair infrastructure change optimal solutions. Evaluation should quantify finance, reliability, maintainability, local value, access, and institutional readiness. The practical priority is developing context-specific portfolios rather than importing assumptions from mature systems [84, 118, 119].

11.8 Long-Term Adaptive Governance

Adaptive storage governance depends on technology learning, climate risk, material markets, and societal expectations will alter priorities. Evaluation should quantify monitoring, review intervals, triggers, scenario updates, and policy learning.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is updating roadmaps through measurable outcomes and transparent adaptive processes, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [85].

12. Conclusions

12.1 Consolidated Technology Finding

Technology selection depends on no single pathway simultaneously maximises response, duration, efficiency, safety, affordability, location freedom, and circular performance. Evaluation should quantify service fit, duration, efficiency, availability, lifecycle cost, risk, and maturity. The practical priority is using complementary portfolios whose composition changes with system boundaries [91].

12.2 Consolidated Governance Finding

Storage governance depends on durable value requires aligned markets, standards, finance, institutions, and community safeguards. Evaluation should quantify revenue certainty, compliance, accountability, participation, learning, and distributional outcomes.

Uncertainty analysis should test technology learning, utilisation, resource availability, climate exposure, financing assumptions, and interactions with neighbouring energy-system assets. The resulting decision priority is coordinating governance reforms with technology demonstrations and infrastructure investment, supported through transparent assumptions, comparable boundaries, field validation, and explicit confidence grading [92].

12.3 Consolidated Research Finding

Future storage research depends on publication growth must yield comparable field evidence, transparent uncertainty, and measurable system outcomes. Evaluation should quantify validation scale, operating hours, availability, incidents, lifecycle effects, and transferability. The practical priority is prioritising decision-relevant evidence that closes deployment and governance gaps [9].

12.4 Actionable Planning Implication

System planners depends on credible portfolios must integrate chronology, network location, extreme events, technology interactions, and uncertain future conditions. Evaluation should quantify adequacy, curtailment, congestion, recovery, lifecycle cost, resilience, and confidence. The practical priority is using transparent scenario ensembles and service-specific acceptance thresholds [78].

12.5 Actionable Deployment Implication

Storage developers depends on successful projects require aligned technical design, warranties, controls, revenue, safety, maintenance, community safeguards, and recovery arrangements. Evaluation should quantify availability, service delivery, incidents, degradation, revenue, environmental performance, and local benefits. The practical priority is treating deployment as a governed lifecycle commitment rather than equipment procurement [89].

Energy storage should be evaluated as a portfolio of service-producing assets rather than a collection of technologies competing through isolated nominal performance indicators. Response speed, duration, cycling, location, climate, network topology, degradation, risk, circularity, digital readiness, and revenue certainty jointly determine suitability.

Fast devices and batteries remain central for regulation and daily balancing, whereas mechanical, thermal, flow-battery, hydrogen, and hybrid pathways address extended scarcity. LDES value depends less on a universal hourly threshold than on the duration, frequency, and system consequence of unmet flexibility or adequacy requirements.

Safety, reliability, and degradation are coupled lifecycle processes that influence availability, economics, environmental burdens, insurance, siting, and public legitimacy. Digital intelligence can improve prediction and control, but benefits require representative data, validated transfer, uncertainty quantification, cybersecurity, interoperability, and safe fallback mechanisms.

Circularity must begin during design and continue through operation, repair, second-life qualification, recycling, material reintegration, and equitable value-chain

governance. The Storage-to-System Evidence Matrix provides a transparent structure for comparing options while distinguishing measured evidence, modelled potential, uncertainty, and local boundary conditions.

The strategic priority is coordinated progress across technology, markets, standards, finance, data, infrastructure, and circular supply chains rather than isolated performance improvement. Such integration can convert storage deployment from capacity accumulation into reliable, affordable, resilient, and materially responsible support for renewable-dominant power systems.

ACKNOWLEDGMENTS

The author acknowledges the use of artificial intelligence tools in the preparation and drafting of this manuscript. All technical content, analyses, data interpretations, and conclusions were authored, reviewed, and finalized by the author, who takes full responsibility for the integrity of the published work.

CONFLICTS OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this paper

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