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Review Article

A Review of Health-Aware Modeling and Control Strategies for Battery Energy Storage Systems

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Abstract

Battery Energy Storage Systems (BESS) are critical enablers of modern power systems, supporting renewable energy integration, grid stability, and flexible energy management. However, battery degradation, safety risks, and high lifecycle costs remain major barriers to their long-term economic viability. In response, health-aware modeling and control strategies have emerged as a key paradigm for explicitly embedding battery aging and health considerations into system-level decision-making. This review provides a structured and integrative synthesis of state-of-the-art health-aware approaches for BESS, with a particular emphasis on how degradation knowledge is translated into modeling, control, and energy management frameworks. First, fundamental battery degradation mechanisms and key health indicators are reviewed to establish a unified physical and operational foundation. Electrochemical, equivalent-circuit, data-driven, and hybrid battery models are then critically compared based on their ability to capture aging dynamics, computational tractability, and suitability for real-time applications.

Subsequently, health-aware control strategies including rule-based methods, model predictive control, optimization-based energy management, and learning-based approaches are systematically analyzed, highlighting trade-offs between performance, battery lifetime, and implementation complexity. Practical applications in grid-connected systems, micro-grids, electric vehicles, and second-life BESS are discussed to demonstrate real-world relevance. Distinct from existing surveys, this review emphasizes the coupling between modeling fidelity and control design, and explicitly frames battery health as a unifying optimization objective rather than a secondary constraint. Finally, open research challenges and future directions are identified, including scalability, uncertainty management, real-time deployment, and the integration of health, safety, and economic objectives. This work aims to serve as a comprehensive reference for researchers and practitioners developing sustainable, reliable, and health-aware BESS solutions.

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1. Introduction

Battery Energy Storage Systems (BESS) have become a cornerstone of modern power systems, enabling renewable energy integration, enhancing grid flexibility, and improving system reliability. As power systems transition toward higher penetrations of intermittent renewable energy sources such as wind and solar, BESS provide essential services including frequency regulation, peak shaving, voltage support, and energy arbitrage. Their rapid response capability and modular deployment make them indispensable assets in both grid-connected and islanded operation modes [1].

Despite these advantages, the widespread adoption of BESS is significantly constrained by battery degradation, safety concerns, and high lifecycle costs. Battery aging, driven by complex electrochemical and thermal processes, leads to capacity fade, internal resistance growth, and increased risk of failure over time [2]. These degradation mechanisms are strongly influenced by operational conditions such as temperature, depth of discharge, charge–discharge rates, and state-of-charge (SOC) operating windows [3]. As a result, improper operation can substantially reduce battery lifetime and economic viability while raising safety risks.

Conventional battery modeling and control strategies primarily focus on short-term performance objectives, such as power tracking or energy efficiency, often neglecting long-term health considerations. Simplified models with fixed parameters and health-agnostic control schemes fail to capture degradation dynamics, leading to suboptimal or even damaging operational decisions. This disconnect between control objectives and battery health has motivated the development of health-aware modeling and control paradigms [4].

Health-aware approaches explicitly incorporate battery degradation mechanisms, health indicators, and aging dynamics into system models and control algorithms [5]. By integrating metrics such as State of Health (SOH) or degradation cost into decision-making processes, these methods aim to balance performance, safety, and lifetime optimization [6]. Recent advances in physics-based modeling, data-driven techniques, and optimization-based control have accelerated progress in this area.

This review provides a comprehensive overview of health-aware modeling and control strategies for BESS. The main contributions include: (i) a structured taxonomy of health-aware battery modeling approaches, (ii) a critical review of control strategies that explicitly account for battery health, and (iii) an identification of key challenges and open research directions. The remainder of this paper is organized to first discuss degradation mechanisms and health indicators, followed by modeling approaches, control strategies, applications, and future research opportunities. To provide a unified perspective on the scope of this review, Figure 1 presents a conceptual taxonomy of health-aware modeling and control for battery energy storage systems.

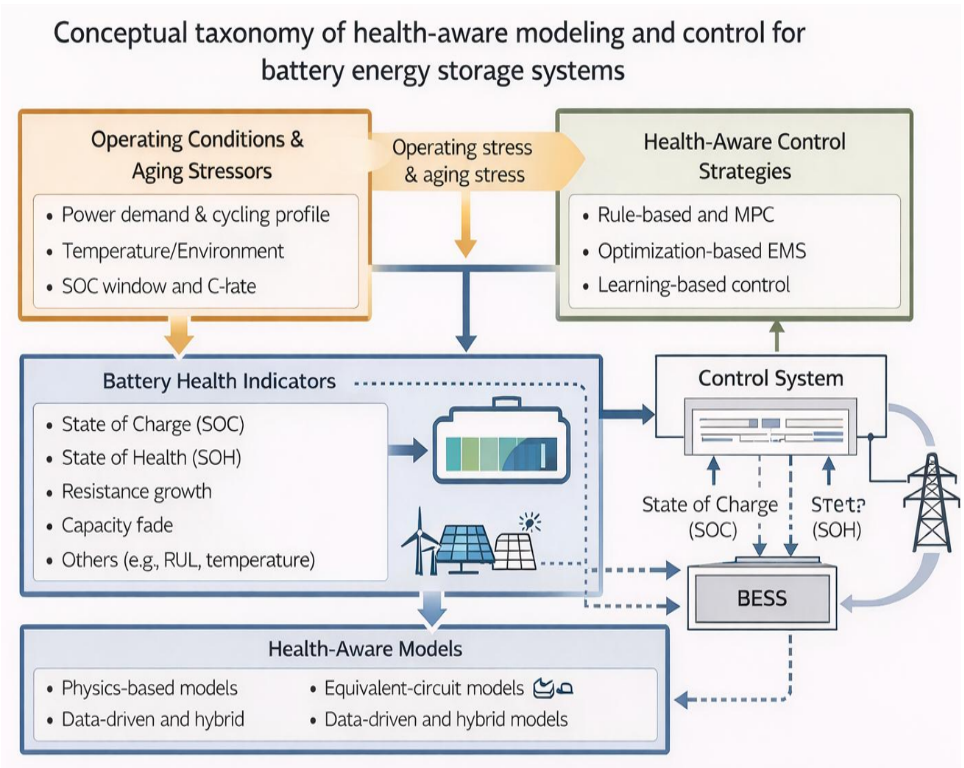

Figure 1: Conceptual taxonomy of health-aware modeling and control for battery energy storage systems

Figure1 Conceptual taxonomy of health-aware modeling and control for battery energy storage systems, illustrating the closed-loop interaction between operating conditions and aging stressors, battery health indicators, degradation-aware modeling approaches, and health-aware control and energy management strategies.

To develop effective health-aware modeling and control strategies, it is first necessary to understand the underlying physical processes that govern battery aging and performance deterioration. Battery degradation arises from complex electrochemical, thermal, and mechanical To develop effective health-aware modeling and control strategies, it is first necessary to understand the underlying physical processes that govern battery aging and performance deterioration. Battery degradation arises from complex electrochemical, thermal, and mechanical interactions that evolve over time and operating conditions. This section therefore establishes the foundational concepts of battery degradation mechanisms and health indicators, which form the basis for the modeling and control approaches reviewed in subsequent sections.

2. Battery Degradation Mechanisms and Health Indicators

2.1. Battery Degradation Mechanisms

Battery degradation is an inevitable process resulting from complex and interrelated electrochemical, thermal, and mechanical phenomena occurring during storage and operation. These degradation processes are commonly categorized into calendar aging and cycle aging, depending on whether degradation occurs during rest or active charge–discharge cycling [7].

Calendar aging refers to performance deterioration that takes place even when the battery is not in active use. It is primarily driven by time, temperature, and state-of-charge (SOC) conditions. Prolonged exposure to high SOC levels and elevated temperatures accelerates side reactions such as electrolyte decomposition and solid–electrolyte interphase (SEI) layer growth, leading to irreversible capacity loss. Calendar aging is particularly relevant for a stationary BESS that may remain idle for extended periods [8].

Cycle aging, in contrast, is associated with repeated charge–discharge cycles and is strongly influenced by operational stress factors. Key contributors include lithium plating, active material loss, electrode particle cracking, and continuous SEI layer thickening. The severity of cycle aging depends on factors such as depth of discharge (DoD), charge and discharge rates (C-rate), and cycling frequency. Deep cycling and high C-rates significantly increase mechanical and thermal stress, accelerating degradation [9].

Temperature plays a critical role in both calendar and cycle aging. Elevated temperatures intensify chemical reaction rates, while low temperatures increase internal resistance and promote lithium plating during charging. Similarly, the SOC operating window has a pronounced effect on aging behavior, with extreme SOC levels (near full charge or deep discharge) exacerbating degradation mechanisms. Consequently, the interaction among temperature, DoD, C-rate, and SOC window defines the overall degradation trajectory of a battery and must be carefully managed in health-aware control strategies [10].

2.2. Battery Health Metrics and Indicators

To quantify and monitor battery degradation, several health metrics and indicators are commonly employed. State of Health (SOH) is the most widely used metric, typically defined as the ratio of the current battery capacity to its nominal or rated capacity. SOH provides a high-level measure of degradation and is often used as a threshold for end-of-life determination [5].

Remaining Useful Life (RUL) estimates the time or number of cycles a battery can continue to operate before reaching a predefined failure criterion. RUL prediction is essential for maintenance planning and lifetime-aware control [11]. Additionally, internal resistance growth serves as a key indicator of power capability degradation, directly affecting efficiency, thermal behavior, and safety. Finally, capacity fade and power fade quantify the loss of energy storage and deliverable power, respectively, and are fundamental indicators for assessing long-term BESS performance and reliability [12].

While degradation mechanisms and health indicators provide essential insight into battery aging, their practical use in control and energy management requires suitable mathematical representations. Health-aware battery models serve as the critical link between physical degradation processes and actionable control decisions. Building on the degradation phenomena outlined in the previous section, this section reviews and compares electrochemical, equivalent-circuit, data-driven, and hybrid modeling approaches with respect to their ability to capture aging dynamics and support real-time BESS operation.

3. Health-Aware Battery Modeling Approaches

Health-aware battery modeling forms the foundation for degradation-conscious control and energy management of Battery Energy Storage Systems (BESS). Unlike conventional models that assume fixed parameters and neglect aging effects, health-aware models explicitly capture degradation dynamics, enabling more accurate prediction of long-term performance and informed decision-making. This section reviews and critically compares electrochemical, equivalent circuit, and data-driven modeling approaches with an emphasis on their ability to incorporate battery health [4, 13].

3.1. Electrochemical and Physics-Based Models

Electrochemical and physics-based models offer the most detailed representation of battery behavior by explicitly describing internal transport and reaction mechanisms. Among these, the pseudo-two-dimensional (P2D) model is widely regarded as the most comprehensive framework, as it captures lithium-ion diffusion in solid particles, electrolyte transport, and electrochemical reactions across electrodes [14]. Health-aware extensions of P2D models embed degradation mechanisms such as solid–electrolyte interphase (SEI) layer growth, lithium plating, and active material loss, enabling high-fidelity aging prediction under diverse operating conditions [15].

To reduce computational burden, Single-Particle Models (SPM) and their enhanced variants (SPMe) approximate each electrode as a single representative particle while retaining essential electrochemical dynamics. Health parameters such as diffusion coefficients, reaction rate constants, and loss of cyclable lithium can be integrated into these models to represent aging effects. Compared to P2D models, SPM-based approaches offer a favorable balance between accuracy and complexity, making them attractive for control-oriented applications [16].

Despite their strong physical interpretability and predictive accuracy, physics-based models face limitations in real-time BESS applications. Their high computational cost, parameter identification challenges, and sensitivity to modeling assumptions restrict scalability, particularly for large battery packs. Consequently, their direct use in online control is often impractical, motivating simplified or reduced-order alternatives.

3.2. Equivalent Circuit Models with Degradation Awareness

Equivalent Circuit Models (ECMs) are among the most widely adopted modeling approaches in industrial BESS applications due to their simplicity and computational efficiency. Common structures include RC networks and Thevenin-based models, which approximate battery dynamics using combinations of resistors, capacitors, and voltage sources. Traditionally, ECM parameters are assumed constant; however, health-aware extensions allow these parameters to vary as functions of aging and operating conditions [17].

Degradation awareness in ECMs is typically achieved through aging-dependent parameter identification, where changes in internal resistance, capacitance, and open-circuit voltage are correlated with SOH or cycle count. Offline identification methods rely on periodic characterization tests, while online approaches update parameters in real time using estimation techniques such as recursive least squares or Kalman filtering. Online adaptation is particularly valuable for BESS operating under varying environmental and load conditions, as it enables continuous tracking of degradation [18].

While ECMs lack the physical depth of electrochemical models, their low computational cost and ease of implementation make them highly suitable for real-time control and large-scale deployment. However, their reduced physical interpretability limits their ability to extrapolate degradation behavior beyond trained or identified operating regimes.

3.3. Data-Driven and Hybrid Health-Aware Models

Recent advances in data availability and computational intelligence have driven growing interest in data-driven battery modeling approaches. Machine learning techniques such as neural networks (NNs), Gaussian processes (GPs), and long short-term memory (LSTM) networks are increasingly used to model nonlinear battery behavior and predict health indicators such as SOH and RUL. These methods can capture complex degradation patterns directly from operational data without explicit physical assumptions [19].

Hybrid and physics-informed machine learning models aim to combine the strengths of data-driven flexibility and physics-based interpretability. By embedding physical constraints or simplified electrochemical relationships into learning architectures, these models improve generalization, robustness, and trustworthiness. Such approaches are particularly promising for health-aware control, where prediction accuracy and safety are critical [20].

Nevertheless, data-driven models face notable challenges, including dependence on large, high-quality datasets, limited interpretability, and concerns regarding robustness under unseen operating conditions. Additionally, computational requirements and training complexity may hinder real-time deployment in resource-constrained BESS controllers.

3.4. Comparative Summary

In summary, electrochemical models offer high accuracy and physical insight but suffer from computational complexity, limiting real-time applicability. ECMs provide computational efficiency and scalability, making them well-suited for online control, albeit at the expense of physical fidelity. Data-driven and hybrid models deliver strong predictive capability but raise concerns regarding interpretability and reliability [5]. The choice of health-aware modeling approach, therefore, depends on application requirements, available data, and the trade-off between accuracy, complexity, and scalability in large BESS deployments. To facilitate a systematic comparison, Table 1 summarizes the main health-aware battery modeling approaches and highlights the trade-offs among modeling accuracy, computational complexity, physical interpretability, and suitability for real-time BESS control [21].

Accurate health-aware models alone are insufficient to extend battery lifetime unless their information is systematically incorporated into operational decision-making. Control strategies determine how battery systems are dispatched, constrained, and optimized under dynamic grid and load conditions. Leveraging the modeling frameworks discussed in the previous section, this section examines health-aware control strategies that explicitly integrate battery aging considerations into real-time control and energy management.

4. Health-Aware Control Strategies for Battery Energy Storage Systems

Health-aware control strategies aim to explicitly integrate battery degradation considerations into the operational decision-making of BESS. Unlike conventional control approaches that prioritize short-term performance or economic objectives, health-aware strategies seek to balance system-level requirements with long-term battery reliability, safety, and lifetime optimization. This section reviews major classes of control strategies and critically examines their effectiveness, complexity, and applicability [27].

4.1. Rule-Based and Heuristic Health-Conscious Control

Rule-based and heuristic control strategies represent the earliest and most widely implemented form of health-aware control in BESS. These approaches rely on predefined operational rules designed to mitigate degradation by avoiding harmful operating conditions. Common examples include SOC window management, where the battery is operated within conservative SOC limits to reduce stress associated with overcharging and deep discharging. Similarly, temperature-aware power limiting strategies restrict charge and discharge power when battery temperature exceeds safe thresholds, thereby reducing thermal aging and safety risks [28].

The primary advantages of rule-based methods lie in their simplicity, transparency, and low computational requirements, making them attractive for industrial applications. However, these approaches are inherently conservative and suboptimal, as they do not explicitly quantify degradation or adapt to changing operating conditions. As a result, they often sacrifice performance or economic efficiency and lack the flexibility required for complex, multi-objective BESS applications [29].

4.2. Model Predictive Control with Battery Health Constraints

Model Predictive Control (MPC) has emerged as a powerful framework for health-aware BESS control due to its ability to systematically handle constraints and optimize future behavior over a prediction horizon. In health-aware MPC, battery degradation is incorporated either through explicit degradation models or surrogate health indicators embedded in the cost function. Health-aware cost functions typically penalize aggressive charging, high C-rates, deep cycling, or operation at extreme SOC and temperature levels, thereby discouraging actions that accelerate aging [30, 31].

In addition to cost-function design, degradation-aware constraints play a central role in MPC formulations. These constraints may limit SOC ranges, temperature evolution, or cumulative degradation metrics, ensuring safe and health-conscious operation. Multi-objective MPC

Table 1: Comparison of Health-Aware Battery Modeling Approaches for BESS

Modeling Approach	Degradation Representation	Accuracy	Computational Complexity	Physical Interpretability	Real-time Control Suitability	Scalability to Large BESS	Typical Use Cases
Electrochemical (P2D) [18]	Explicit modeling of SEI growth, lithium plating, and active material loss	Very High	Very High	Very High	Low	Low	Offline aging analysis, design studies, benchmark modeling
Reduced Electrochemical (SPM/SPMe) [6, 22]	Lumped degradation parameters (e.g., loss of cyclable lithium, diffusion decay)	High	Medium	High	Medium	Medium	Control-oriented modeling, health-aware MPC
Equivalent Circuit Models (ECM) [23]	Aging-dependent resistance, capacitance and OCV drift linked to SOH	Medium	Low	Low–Medium	High	High	Real-time control, BMS implementation, large-scale BESS
Data-Driven Models (NN, GP, LSTM) [24]	Implicit degradation learning from historica data (SOH/RUL prediction)	High (data-dependent)	Medium–High	Low	Medium	High	Health estimation, lifetime prediction, EMS support
Hybrid / Physics-Informed Models [25, 26]	A combination of physical degradation laws and data-driven correction	High	Medium	Medium–High	Medium	Medium –High	Health-aware control, digital twins, adaptive EMS

frameworks explicitly balance competing objectives, such as tracking power references, minimizing operational costs, and reducing battery aging. Pareto-based or weighted-sum approaches are commonly employed to manage these trade-offs [32].

For large-scale BESS, both centralized and distributed MPC architectures have been explored. Centralized MPC provides globally optimal solutions but faces scalability and computational challenges. Distributed MPC, on the other hand, decomposes the control problem across battery modules or subsystems, improving scalability and fault tolerance at the cost of increased coordination complexity. Despite their effectiveness, MPC-based strategies require accurate models and sufficient computational resources, which may limit real-time implementation in some applications [33].

4.3. Optimization-Based Energy Management with Health Consideration

Beyond real-time control, health-aware optimization-based energy management strategies focus on long-term operational planning and dispatch decisions for BESS. These approaches typically formulate optimization problems that explicitly account for battery lifetime degradation as a cost or constraint. Lifetime-aware dispatch strategies quantify degradation in economic terms, enabling direct comparison between immediate operational benefits and long-term health costs.

A key challenge in this context is managing the trade-off between economic objectives and battery health preservation. For instance, aggressive participation in energy arbitrage or frequency regulation markets may yield higher short-term revenue but significantly accelerate degradation. Health-aware optimization frameworks address this trade-off by limiting cycling intensity or assigning degradation-dependent costs to battery usage [16, 34].

Such strategies have been widely applied to grid services, including frequency regulation, peak shaving, renewable smoothing, and microgrid energy management. By incorporating health considerations, these methods improve the economic sustainability and reliability of BESS over their full lifecycle. However, their effectiveness depends heavily on the accuracy of degradation models and forecasts of market conditions and system demand.

4.4. Learning-Based and Adaptive Control Approaches

Learning-based and adaptive control strategies have gained increasing attention as promising solutions for health-aware BESS operation in uncertain and dynamic environments. Reinforcement learning (RL) approaches, in particular, enable controllers to learn optimal policies through interaction with the system. Health awareness is introduced by incorporating degradation penalties, SOH-based rewards, or lifetime constraints into the learning objective, encouraging policies that balance performance and aging [25, 35].

Adaptive control strategies leverage online SOH estimation to dynamically adjust control parameters in response to changing battery conditions. By continuously updating model parameters or control gains, these methods enhance robustness to aging and environmental variations. Learning-based approaches are especially attractive for complex systems where explicit modeling is difficult [5].

Despite their potential, safety and robustness remain critical concerns. RL-based controllers may explore unsafe actions during training, and learned policies can be sensitive to unmodeled conditions or data bias. Ensuring safe exploration, constraint satisfaction, and interpretability is therefore essential before such approaches can be widely deployed in real-world BESS applications.

4.5. Comparative Analysis of Control Strategies

Overall, rule-based methods offer simplicity but limited optimality, MPC provides systematic and flexible health integration at a higher computational cost, optimization-based energy management enables lifetime-aware planning, and learning-based approaches promise adaptability but face safety challenges. Selecting an appropriate health-aware control strategy depends on application requirements, system scale, and available computational and modeling resources [36]. Table 2 provides a comparative analysis of health-aware control strategies for BESS, highlighting differences in health integration mechanisms, computational requirements, and practical applicability. Michailidis et al [31] To highlight the inherent trade-offs in battery operation, Figure 2 conceptually illustrates the relationship between operational performance and battery degradation under different control strategies.

Table 2: Comparative Analysis of Health-Aware Control Strategies for Battery Energy Storage Systems

Control Strategy	Health Integration Mechanism	Key Advantages	Main Limitations	Computational Demand	Implementation Maturity	Typical Applications
Rule-Based / Heuristic [28]	Fixed SOC windows, temperature thresholds, and power limits	Simple, transparent, low cost	Conservative, suboptimal, non-adaptive	Very Low	High (industrial practice)	BMS protection, basic grid services
Model Predictive Control Model Predictive (MPC) [37]	Degradation-aware cost functions and constraints (SOC, C-rate, temperature SOH)	Systemati multi-objective optimization, constraint handling	Model dependency, computational burden	High	Medium	Grid-connected BESS, frequency regulation
Optimization-Based Energ Management [36]	Lifetime degradation is modeled as an economic cost or constraint	Explicit economic–health trade-off, long-term planning	Forecast uncertainty, offline tuning	Medium	Medium	Energy arbitrage, peak shaving microgrids
Learning-Based Control (RL) [38]	Degradation penalties and SOH-aware reward functions	Adaptive, model-free, handles nonlinearities	Safety concerns, data-intensive, and limited interpretability	High	Low–Medium	Complex EMS, uncertain environments
Adaptive / Hybrid Control [39]	Online SOH estimation with parameter or gain adaptation	Robust to aging and uncertainty	Estimation errors, design complexity	Medium	Medium	Aging-aware BESS, second-life systems

The comparison reveals that advanced control strategies, while offering superior performance–health trade-offs, face increasing challenges in computational complexity and practical deployment.

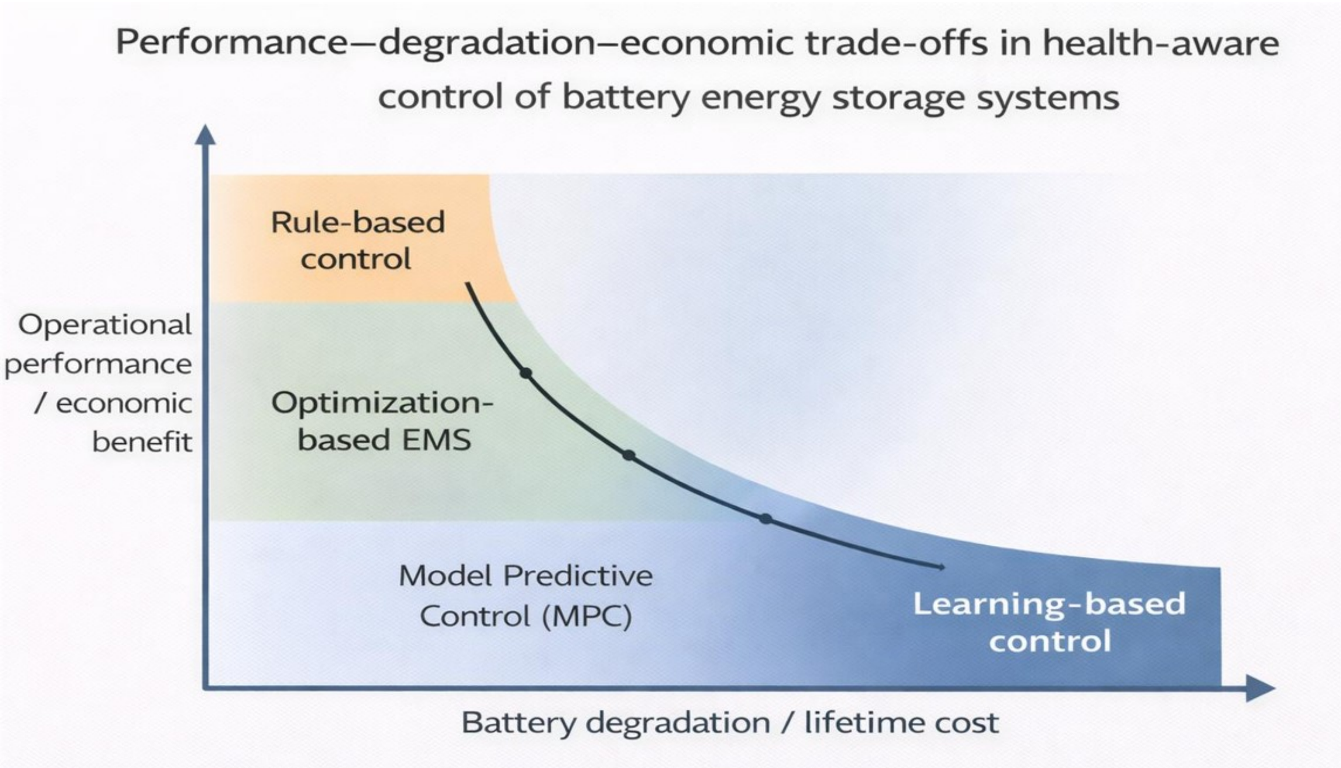

Figure 2: Performance–degradation–economic trade-offs in health-aware control of battery energy storage systems

Conceptual illustration of the trade-off between operational performance and battery degradation for different control strategies in battery energy storage systems, highlighting the role of health-aware control in balancing economic benefits and battery lifetime.

This trade-off motivates the integration of battery health awareness into control and energy management strategies, as discussed in the following application scenarios. The effectiveness of health-aware modeling and control strategies ultimately depends on their performance in practical deployment scenarios. Beyond theoretical formulation, real-world applications introduce additional constraints related to uncertainty, scalability, and economic objectives. This section, therefore, reviews representative applications and case studies to illustrate how health-aware approaches have been implemented across grid-connected BESS, microgrids, electric vehicles, and second-life battery systems.

5. Applications and Case Studies

Health-aware modeling and control strategies have been increasingly adopted in practical BESS applications to enhance reliability, economic performance, and asset longevity. This section highlights representative application domains where health-aware approaches demonstrate clear advantages over conventional methods.

5.1. Grid-Connected Battery Energy Storage System Applications

In grid-connected environments, BESS play a vital role in facilitating large-scale renewable energy integration. Health-aware control strategies enable batteries to smooth power fluctuations from wind and solar generation while limiting excessive cycling and high C-rate operation that accelerate degradation. By incorporating degradation-aware constraints and cost functions, these systems can achieve a balance between renewable power utilization and battery lifetime preservation [34, 40].

Frequency regulation is another prominent application where health-aware control has proven effective. While fast response and frequent cycling are required to maintain grid stability, health-aware strategies moderate control actions by accounting for cumulative degradation costs. This approach allows BESS to provide ancillary services without disproportionately reducing battery lifespan. Model predictive and optimization-based control frameworks are particularly well-suited for this application due to their ability to anticipate future regulation demands and manage trade-offs in real time [41].

Microgrids represent a complex operational context where BESS must coordinate with renewable generators, loads, and other storage assets.[42]. Health-aware energy management in microgrids improves resilience and reduces maintenance costs by adapting operational strategies based on battery health. Case studies have shown that incorporating SOH-aware dispatch decisions can significantly extend battery lifetime while maintaining a reliable power supply during islanded operation and grid disturbances.

5.2. Electric Vehicle and Second-Life BESS Applications

Health-aware control is equally important in electric vehicle (EV)–related applications and second-life battery systems. Vehicle-to-grid (V2G) schemes allow EV batteries to provide grid services such as peak shaving and frequency support. However, uncontrolled V2G participation can accelerate battery degradation and negatively impact user satisfaction. Health-aware control frameworks address this issue by limiting participation based on SOH, user preferences, and degradation costs, ensuring a fair balance between grid support and battery longevity.

Second-life BESS, formed by repurposing retired EV batteries for stationary applications, presents unique challenges due to significant health heterogeneity among battery modules. Variations in capacity, internal resistance, and aging history complicate modeling and control. Health-aware strategies that incorporate module-level SOH estimation and adaptive power allocation have demonstrated improved performance and safety in such systems. These applications highlight the critical role of health-aware modeling and control in maximizing the value of batteries across multiple life cycles [43].

Although existing applications demonstrate the potential of health-aware BESS operation, several limitations and unresolved issues remain that hinder widespread adoption. Identifying these gaps is essential for guiding future research and technology development. Accordingly, the following section discusses key challenges, open research questions, and emerging directions in health-aware modeling and control of battery energy storage systems.

6. Challenges, Open Issues, and Future Research Directions

Despite significant progress in health-aware modeling and control of Battery Energy Storage Systems, several challenges remain that limit widespread deployment and practical impact. One major issue is model uncertainty and parameter drift caused by aging, environmental variations, and manufacturing inconsistencies. Even health-aware models may lose accuracy over time if parameters are not continuously updated, which can degrade control performance and compromise reliability.

Scalability is another critical challenge, particularly for large battery packs composed of hundreds or thousands of cells. Capturing cell-to-cell variations and health heterogeneity while maintaining manageable computational complexity remains an open problem. Simplified models may overlook critical degradation dynamics, whereas high-fidelity models are often impractical for large-scale real-time applications [44].

Real-time implementation constraints, including limited computational resources, communication delays, and measurement noise, further complicate the deployment of advanced health-aware control strategies. Approaches such as model predictive control and learning-based methods require efficient algorithms and robust estimation techniques to ensure feasibility under strict timing requirements.

The effectiveness of data-driven and hybrid approaches is strongly influenced by data availability and standardization. A lack of high-quality, labeled degradation data and standardized testing protocols hinders model generalization and fair comparison across studies. Improved data sharing frameworks and benchmarking practices are therefore essential.

Future research must also address the integration of safety, health, and economic objectives within unified control frameworks. Aging, thermal runaway risks, and economic performance are tightly coupled, yet often treated separately. Emerging trends such as digital twins and AI-assisted control offer promising directions by enabling real-time health monitoring, predictive maintenance, and adaptive decision-making. These advancements have the potential to significantly enhance the reliability, sustainability, and economic viability of next-generation BESS [45, 46].

In light of the reviewed modeling approaches, control strategies, applications, and remaining challenges, a consolidated synthesis is required to contextualize the current state of the field and its future trajectory. The concluding section summarizes the key insights of this review and highlights the implications for the design and operation of next-generation health-aware BESS.

7. Conclusion

This review has presented a comprehensive synthesis of health-aware modeling and control strategies for Battery Energy Storage Systems (BESS), highlighting their critical role in improving system reliability, safety, and lifecycle performance in modern power systems. Electrochemical, equivalent-circuit, data-driven, and hybrid modeling approaches were examined alongside a broad spectrum of control strategies ranging from rule-based methods to optimization-based, predictive, and learning-driven frameworks. A central insight of this review is that explicitly embedding battery health into modeling and control enables a principled trade-off between short-term operational performance and long-term degradation, which is essential for the sustainable deployment of BESS.

Despite substantial progress, several open research challenges remain. Model uncertainty and parameter drift caused by aging, environmental variability, and manufacturing heterogeneity continue to limit long-term prediction accuracy, underscoring the need for adaptive and self-updating health-aware models. Scalability remains a major obstacle for large-scale BESS, where capturing cell-to-cell and module-level health heterogeneity must be balanced against computational feasibility. Real-time implementation constraints, including limited computational resources, communication delays, and measurement noise, further complicate the deployment of advanced control strategies such as model predictive control and learning-based approaches.

In addition, data availability and standardization pose critical challenges for data-driven and hybrid methods. The lack of large, high-quality, and standardized degradation datasets hampers model generalization, benchmarking, and reproducibility. Ensuring safety, robustness, and interpretability in learning-based control, particularly under unseen operating conditions, remains an open and pressing issue for real-world adoption.

Future research should therefore prioritize unified frameworks that jointly integrate health, safety, and economic objectives, rather than treating them in isolation. Emerging directions such as digital twins, physics-informed machine learning, and AI-assisted adaptive control offer promising pathways for real-time health monitoring, predictive maintenance, and lifetime-aware decision-making. Addressing these challenges will be essential to unlocking the full potential of BESS as resilient, economically viable, and sustainable assets in next-generation power systems.

Article Information

Disclaimer (Artificial Intelligence): The author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.), and text-to-image generators have been used during writing or editing of manuscripts.

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