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Review Article

A Review on Artificial Intelligence Enabled Battery Energy Storage: Fault Diagnosis, Health Estimation and Predictive Optimization

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Abstract

Battery Energy Storage Systems (BESS) are key to improving the reliability, energy efficiency, and flexibility of the contemporary power grid. With their penetration in various applications, including electric vehicles, smart grids, and renewable integration, the safe and secure operation of distributed resources (DRs) becomes more crucial. Traditional Battery Management Systems (BMS) that are usually on rule-based or physics-based models can hardly adapt to various chemistries, operation conditions, and fault scenarios. Approaches based on Artificial Intelligence (AI), such as machine learning (ML) and deep learning (DL), have recently been proposed to provide more promising data-driven options for fault diagnosis, state of health (SoH) estimation, and predictive optimization. This work provides a cutting-edge review of AI deployment in BESSs, which is conceptually classified into three fundamental categories: fault detection and classification, health monitoring and degradation prognosis, and intelligent control and optimization. We discuss the merits and limitations of different AI models, including supervised / unsupervised / hybrid / reinforcement learning, deployment feasibility, interpretability, and data requirements. An analysis of novel techniques, including digital twin modeling, explainable AI, and secure learning frameworks, is also included. Using comparative analysis, taxonomy visualizations, and performance summaries, this review points out the current limitations, standardization issues, and future research directions that are required for industrial-scale deployment. Through capturing the cutting-edge advancements in this field, we hope this work will serve as a guiding reference for the researchers and industry participants to design robust, scalable, and dependable AI-supported battery management systems.

Keywords

Battery Energy Storage Systems (BESS), Artificial Intelligence (AI), Fault Diagnosis, State of Health (SoH) Estimation, Predictive Optimization, Machine Learning in Energy Systems

1. Introduction

1.1. Background

BESS has played a key role in the modern energy system for alleviating the variability of renewable sources, enhancing the stability of the grid, and facilitating energy arbitrage [1]. Among various types of energy storage systems (ESSs), lithium-ion batteries have attracted much attention for their

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high energy density, long cycle life, lightweight and scalability [2, 3]. However, with BESS being deployed on a large scale and increasingly included in vital energy infrastructures, reliability, operational safety, degradation, and optimal energy efficiency are increasingly becoming topics of concern [3, 4].

In order to handle the complexity of these systems, BMSs are used to monitor important parameters like State of Charge (SoC), State of Health (SoH), temperature, and cell balancing [5]. Conventional BMS are rule-based, or use RC (Resistive and Capacitive) equivalent circuit model (ECM) or physics-based models, which are interpretable but lack of generalization capability to different battery chemistries, operational conditions, and fault types [3, 4].

Recent advancements in AI, more specifically in ML and DL, provide new opportunities for designs of data-driven, adaptive, and intelligent battery diagnostics and prognostics. These models have been proven to outperform classical models in tasks like fault detection, SoH estimation, maintenance, and predictive control [3, 6]. Nevertheless, practical deployment challenges impede the implementation of BESS, which needs further investigation.

1.2. Problem Statement

Although AI has been proven efficient in the lab, transferring it to real battery systems faces multiple challenges. These include unlabeled ground-truth fault data, interpretability of the trained model, generalization to unseen environments, integration within existing BMS architectures, and computation cost for real-time performance [7, 8]. Furthermore, research is dispersed, with researches on disconnected issues, battery types, or AI techniques and a lack of a global road map of the potential interactions among these solutions in the BESS ecosystem. These issues impede the safe large-scale deployment of AI-based BESS, especially in critical infrastructures.

1.3. Motivation

It would be highly beneficial to have the state-of-the-art review that not only presents the AI techniques applied in BESS in a survey manner but also organizes them based on their application area, i.e., fault diagnosis, health estimation, maintenance, and predictive optimization. Having a comprehensive vision of such AI applications can help academia and industry to develop robust, scalable and intelligent battery management solutions. In contrast to previous works, this paper combines fault diagnostics, health estimation and optimization in a single framework.

1.4. Research Gaps

We found several gaps in the review of related literature:

1) Narrow-focus reviews: The prior reviews have focused on either battery modelling [3, 4], fault detection [8], or predictive control [9], missing the holistic view.
2) Restricted taxonomies: The majority of work fails to provide a comprehensive taxonomy on AI methods across a variety of battery management tasks.
3) Underexplored generalization and interpretability: Very limited efforts attempt to study how AI models generalize across different chemistries and to provide interpretability in the decision-making process.
4) Lack of uniformity: Datasets, evaluation metrics, as well as benchmarking protocols differ widely among studies.

1.5. Contributions

This paper offers a systematic and thorough summary of AI applications in BESS, and the key contributions of this paper are:

1) A thematic taxonomy of AI approaches for fault diagnosis, health estimation, and predictive optimization, facilitating better cross-comparison.
2) Discussion of data availability, model selection, deployment issues, and evaluation measures.
3) Comparison of various AI algorithms and their trade-offs in performance.
4) Explanation of taxonomy, challenges and research directions.
5) Identify existing challenges and future research directions.

2. Literature Review

2.1. Battery System Fault Diagnosis

Fault detection includes recognition of the presence of abnormal behaviors in batteries such as thermal runaway, overcharge, internal short circuits, and age-induced capacity drop [10]. AI methods for fault detection are generally divided into supervised, unsupervised, and hybrid models.

2.1.1. Supervised Learning Approaches

Supervised learning methods such as Support Vector Machine (SVM), Decision Tree, Random Forest (RF), and Convolutional Neural Network (CNN) have been used to detect faults in BESS using voltage, current, and temperature data [9-11].

Table 1 is the overview of the most effective supervised learning models applied to BESS fault detection, including the source of the dataset and average accuracy under different fault scenarios.

Table 1. *Examples of Supervised Learning Models for Fault Diagnosis for BESS [9, 19].*

Model	Application	Dataset	Reported Accuracy Range
SVM	Fault classification	Lab/Simulation	80-90%
RF	Anomaly detection	Lab/Field Data	85-95%
CNN	Pattern recognition	NASA/Simulated	~90%

2.1.2. Unsupervised and Semi-Supervised Learning

Unsupervised approaches such as Autoencoders, k-Means Clustering and Variational Autoencoders (VAE) have been studied in situations of low labeled data to model the anomaly scores for BESS fault identification [9-11].

Equation 1: Reconstruction Loss (Autoencoder)

$$\mathcal{L}(x, \hat{x}) = \sum_{i=1}^{n} (x_i - \hat{x}_i)^2 \quad (1)$$

Here, x_i: original input data; $\hat{x}_i$: reconstructed output from the Autoencoder; n: total number of features; $\mathcal{L}(x, \hat{x})$: loss function for measuring reconstruction error.

This is helpful to detect abnormal activity as a symptom of faults.

2.1.3. Hybrid Approaches and Feature Extraction

To increase the reliability of AI-based BESS fault diagnosis, some studies integrate physics-based models via so-called grey-box models [25]. Feature engineering using Electrochemical Impedance Spectroscopy (EIS) has also been shown to improve the diagnostic accuracy [10].

A hybrid diagnostic approach, such as the combination of Equivalent Circuit Models (ECM) with Long Short-Term Memory (LSTM) networks, and a CPU thermal fault diagnosis is shown in Figure 1. The ECM models the battery in a physics-based manner in the absence of faults, while the LSTM model sequences of sensor data to detect deviations from their normal trajectories across different operating conditions.

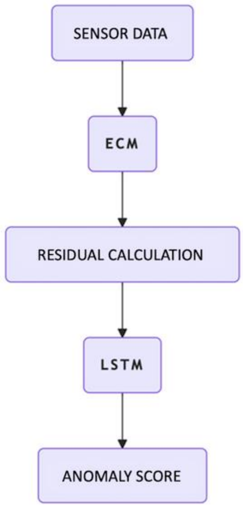

Figure 1. *A hybrid fault diagnosis model that incorporates both ECM for interpretability and LSTM for data-driven anomaly detection on BESS.*

An AI technique taxonomy for BESS is summarized in Figure 2. The taxonomy depends on the learning method employed (supervised, unsupervised, and hybrid) and the target application (fault diagnosis, health estimation, optimization), as well as their computation requirements.

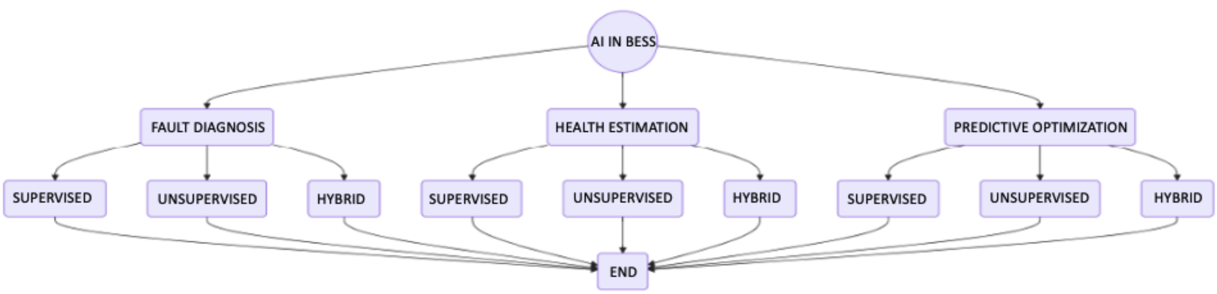

Figure 2. *An AI taxonomy for BESS methods on learning paradigms and application domains.*

The summary overview of fault diagnosis techniques among sensor defects, cyber intrusions, and system-level faults in BESS is provided in Table 2.

Table 2. *An overview of AI methods for fault diagnosis in BESS.*

Technique	Application	Representative Study [Ref]
Neural networks	Sensor-fault & anomaly detection in BESS	RBF network online BESS management [29]
Anomaly detection	Outlier detection in EV/DC-bus/PV charging systems	LOF for DC-bus fault [14]
Cyber intrusion	Detecting cyberattacks on BESS supervisory controllers	ML classifiers for cyberattack detection [14]
Evolutionary opt.	Optimized inference for fault classification	African Buffalo Opt. for BESS fault [33]

2.2. Health Estimation

Estimation of the State of Health (SoH), Remaining Useful Life (RUL), and degradation patterns is evaluated.

2.2.1. State of Health (SoH) Estimation

Recurrent models like RNN, Long Short-Term Memory (LSTM) [9], Gaussian Process Regression (GPR) [10] and Extreme Gradient Boosting (XGBoost) [11] have demonstrated excellent predictive performance in battery systems for data-driven SoH estimation.

Table 3. *Comparative performance of AI model for State of Health (SoH) estimation in benchmarked datasets.*

Paper	Method	RMSE (%)	Dataset
[10]	LSTM	2.3	NASA
[11]	XGBoost	1.8	CALCE

*RMSE: Root Mean Square Error; *CALCE: Center for Advanced Life Cycle Engineering

Table 3 depicts models like LSTM and XGBoost have been successful in predicting the SoH and with high accuracy based on datasets such as NASA, and CALCE. Nonetheless, they have yet to be validated over a broad spectrum of chemistries.

2.2.2. Prediction of The Remaining Useful Life (RUL)

Time-series degradation features and survival models are commonly utilized for RUL prediction. LSTM models on discharge cycles yield good performance on long-term prediction [10].

Equation 2: RUL Function

$$\mathrm{RUL}_t = f(Q_{max} - Q_t) \tag{2}$$

Here, Q_t is the current rating and Q_{max} is the rated capacity.

Whereas SoH estimation models concentrate more on snapshot precision, RUL models yield more longitudinal information, but may come with higher complexity and data requirements.

2.3. Predictive Optimization

Predictive optimization concentrates on the AI application to energy efficiency, load balancing and lifecycle extension.

2.3.1. Model Predictive Control (MPC) and Reinforcement Learning (RL)

AI-enabled MPC and DRL have also been utilized for optimizing charging schedules and temperature control [11-13]. A reinforcement learning control loop for BESS charging optimization is illustrated in Figure 3. The agent observes battery state, acts by selecting controls (e.g., charging rates) and learns to optimize policies for long-term battery health and efficiency rewards.

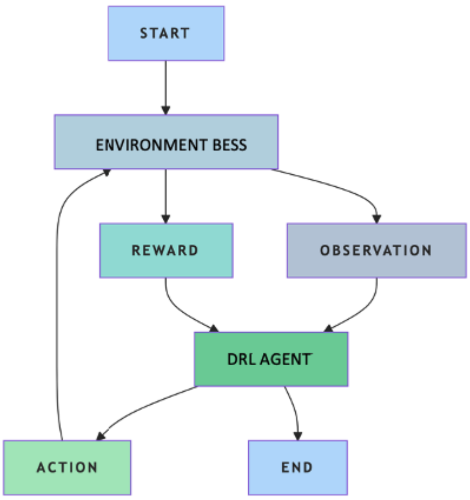

Figure 3. *Deep reinforcement learning (DRL) loop of the adaptive battery charging strategy optimization.*

2.3.2. Multi-Objective Optimization

Trade-off modeling between energy throughput, battery ageing and lifecycle cost was performed using Multi-objective Genetic Algorithms (MOGA) and Particle Swarm Optimization (PSO) in [13].

Table 4 illustrates trade-offs in lifecycle performance, energy efficiency and cost of predictive optimization methods with some popular DRL, MOGA and PSO algorithms.

Table 4. *Predictive Techniques applied in BESS Optimization Application [32].*

Algorithm	Objective	Reported Benefits
Deep Reinforcement Learning (DRL)	Charging and temperature optimization	Improved efficiency and SoH estimation
Multi-Objective Genetic Algorithms (MOGA)	Trade-offs between aging and cost	Better lifecycle management
Particle Swarm Optimization (PSO)	Energy throughput optimization	Enhanced performance under constraints

Equation 3 depicts a generalized RL optimization objective function:

$$\pi^* = \arg\max_{\pi} \mathbb{E}[\textstyle\sum_{t=0}^{T} \gamma^t r(s_t, a_t)] \tag{3}$$

Where π is the policy; π^* is the optimal policy; s_t is the state; $\mathbb{E}$ is the expectation; a_t is the action; γ^t is the discount factor; and r (s_t, a_t) is the reward function.

2.4. Cybersecurity and Data Reliability

The growing interconnectedness of BESS on Large Scale Integration of BESS leads to novel threats [7, 15]. Kharlamova et al. [7, 14] surveyed the data-driven methods for finding cyber-attacks in BESS, which included unsupervised learning-based anomaly detection models.

Lee et al. [15] have shown that detection based on deep learning is capable of reacting almost in real time to spoofing attacks on data. However, the lack of transparency of such models is still a hindrance to regulatory qualification [7].

Equation 4: Anomaly Score Function

$$S = \frac{|x_{real} - x_{pred}|}{\sigma} \tag{4}$$

Where, S is the anomaly score, x_{real} is the observed data, x_{pred} is the AI-predicted value, and σ represents standard deviation.

The cyber-physical architecture of a generic BESS, derived from [14], is shown in Figure 4, which consists of sensors, controllers, AI modules and interconnection paths. AI-based intrusion detection levels are combined to improve data fidelity and block the malicious commands override.

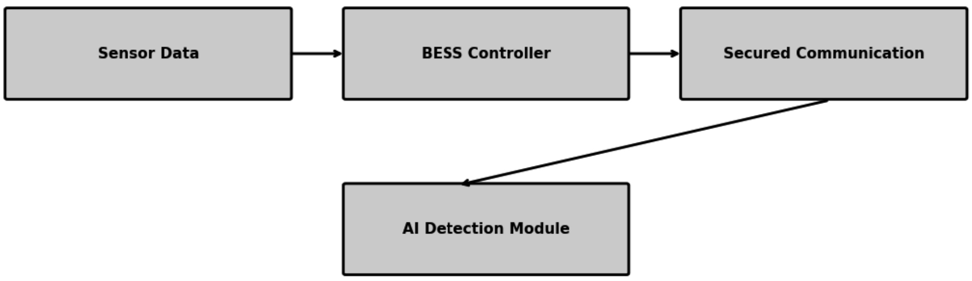

Figure 4. *Cyber-physical structure of BESS with the integrated AI-driven fault detection and cybersecurity layers.*

This underscores the necessity of standards that require cybersecurity considerations of BESS AI solutions.

2.5. BESS Architectures and Digital Twin Modeling

Today, digital twins are an essential tool for real-time simulated monitoring and predictive behavior of BESS. Zhao et al., in [19], proposed a holistic framework for digital twin-based BESS integration for microgrids, encompassing capacity prediction, life-cycle monitoring and fault detection. Zhao et al. [36] suggested the whole process of battery state estimation by means of a digital twin-assisted framework, based on the TCN-LSTM neural network, compared with transfer learning, achieving higher prediction performance and robustness for different battery cases. Their methodology focuses on the possibility of sophisticated neural architectures improving real-time battery health monitoring.

Figure 5 shows the conceptual model of BESS monitoring the digital twin in real time. It consists of a physical battery layer, a data-stream-enabled virtual model, and AI algorithms for predicting system health, performance, and failure of the battery systems.

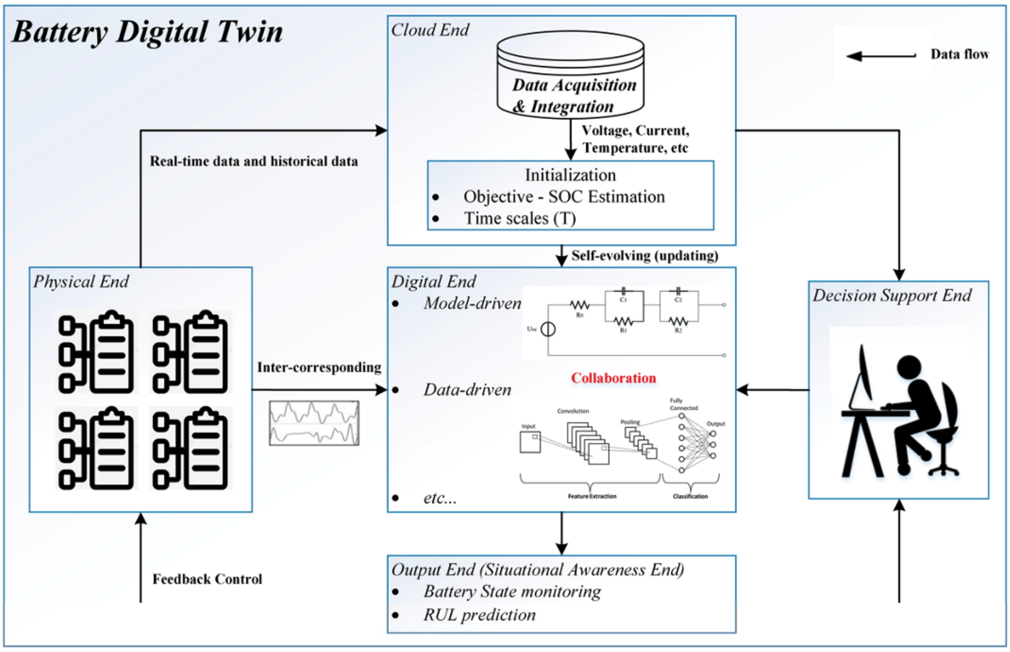

Figure 5. *Digital Twin Architecture for Real-time BESS State Estimation and Predictive Health Diagnostics. [19].*

Equation 5: Battery capacity fade model

$$C(t) = C_0 - k_1 \cdot t - k_2 \cdot \sqrt{t} \tag{5}$$

Where, C(t) is the capacity time, C_0 is initial capacity, k_1, k_2 are degradation coefficient.

Together with AI, these models are often applied in closed-loop digital twin ecosystems that combine the simulation of the physical asset along with its cyber characteristics.

2.6. Integration and Deployment Challenges

While AI provides scalable, field-deployable solutions, it is still hampered by the lack of data available, computational cost, and interpretability requirements [9, 11, 24]. Faunce et al. encourage policy frameworks that incentivize transparency and validation of AI models [16].

Furthermore, Promasa et al. [17] and Parthasarathy et al. [18] suggested the necessity of converging AI tools with grid code and standardization acceleration efforts.

2.7. Summary of Research Trends

This literature review highlights the significant advancement of AI techniques in BESS fault diagnosis, health estimation and optimization. Nevertheless, as Zhao [19] and Dong et al. [20] emphasized that smart battery management has the potential to revolutionize energy storage as long as we take further steps to address challenges in trustworthiness, scalability, and integration.

The distribution of AI applications in BESS is visualized in Figure 6, where the tendency of the supervised learning in fault diagnosis, the time series model in state of health estimation and the reinforcement learning in optimization task is more evident.

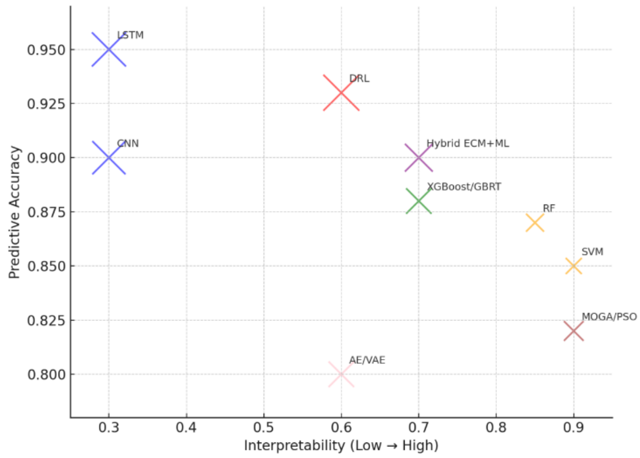

Figure 6. *Mapping of the landscape of AI techniques related to application areas in BESS: diagnosis, estimation, and optimization.*

Table 5 summarizes the AI landscape within three fundamental BESS applications, including common models and benchmark datasets used throughout the literature, along with critical research gaps.

Table 5. *Thematic comparison between dominant AI techniques in BESS, related datasets, and real-world implementation challenges.*

Theme	Dominant Techniques	Common Datasets	Key Challenges
Fault Diagnosis	CNN, RF, AE	NASA, lab-generated	Label scarcity
Health Estimation	LSTM, GPR, XGBoost	CALCE, Oxford	Degradation nonlinearity
Predictive Optimization	DRL, MPC	Simulated	Real-time feasibility

3. Comparative Analysis and Discussion

This work discusses the various systems in which Artificial Intelligence (AI) can be applied to BESS, elaborating on the primary domains of fault diagnosis, health estimation and predictive optimization; each domain of application presents methodological challenges and performance trade-offs. This section briefly guides and critically analyses the present literature review with an emphasis on technical detail, dataset dependence, interpretability, scalability and benchmark considerations.

3.1. Fault Diagnosis Approaches

A common finding throughout the literature is the accuracy-interpretability trade-off. Traditional supervised classifiers, such as the Support Vector Machine (SVM), are robust when trained on small data sizes and small well-engineered feature vector sizes, and often reach 80-90% classification accuracy under laboratory conditions [9]. Nevertheless, they are still limited by the laborious feature extraction and poor scalability involved in handling high-dimensional data [9, 10].

Deep learning approaches, especially those using CNNs and LSTM networks, are good at capturing non-linear relationships from raw voltage/current/temperature measurements [9, 10]. By exploiting NASA datasets, CNN-based multi-class fault detection methods can achieve ~90% accuracy [9, 19], and LSTM-based time-series models are proven to outperform static classifiers in dynamic load conditions [10, 29]. However, while they outperform other models in predictive accuracy, the black-box nature of the model and computational demands cause apprehension toward practicable BMS implementation in real-time [9, 11].

In particular, hybrid frameworks comprising physics-based models like Equivalent Circuit Models (ECM) along with machine learning proved essential to enhance generalization across chemistries and keep some level of interpretability [10, 29]. In related work, by integrating LSTM networks with ECM-derived impedance features, accurate anomaly detection is extended to real-time scenarios regardless of the temperature changes or temperature variations [9, 10, 25]. The probabilistic methods tried so far, like Bayesian inference, introduce uncertainty quantification but are computationally expensive [10, 13].

Benchmarking Gap:

Progress according to reported accuracies varies due to inconsistent datasets, fault scenarios and metrics (e.g., F1-score, ROC-AUC) often making direct comparisons impossible [9, 13, 27]. A standardized benchmarking protocol for BESS fault diagnosis is obviously required with the help of large-scale public datasets (e.g., NASA and CALCE), along with suitable evaluation metrics.

The key fault diagnosis models (interpretability, data requirement, and computation efficiency) are compared in Table 6, which provides guidance for application-oriented deployment.

Table 6. *Comparative assessment in BESS core application domains across AI techniques.*

Application Domain	Dominant AI Techniques	Representative Datasets	Evaluation Metrics	Typical Reported Performance	Computational Complexity	Key References
Fault Diagnosis	SVM, RF, CNN, LSTM, Hybrid (ECM + ML), AE,	NASA [9, 10], CALCE [10], Lab-generated datasets [19, 29]	Accuracy, F1-score, ROC-AUC	SVM: 80-90% (lab/sim) [9], [10]; RF: 85-95%	SVM/RF: Low; CNN/LSTM: High; Hybrid ECM + ML: Medium-High	[9, 10, 19, 29]

Application Domain	Dominant AI Techniques	Representative Datasets	Evaluation Metrics	Typical Reported Performance	Computational Complexity	Key References
	VAE			(lab/field) [9]; CNN: ~90% (NASA) [9], [19]; LSTM: >90% dynamic load [10]		
Health Estimation (SoH)	LSTM, XGBoost, GPR, GBRT	NASA [10], CALCE [11], Oxford [30]	RMSE, MAE, %Error	LSTM: RMSE 2.3% (NASA) [10]; XGBoost: RMSE 1.8% (CALCE) [11]; GPR: RMSE < 3% with uncertainty bounds [10]	LSTM: High; XGBoost/GBRT: Medium; GPR: Medium-High	[9, 10, 11, 30]
Remaining Useful Life (RUL)	LSTM, RNN, Hybrid physics-informed ML	NASA [10], Oxford [30]	RMSE, MAE, Prediction Horizon Accuracy	LSTM: Accurate >200-cycle horizon [10], [30]; Hybrid: Improved cross-condition generalization [10]	LSTM: High; Hybrid: Medium-High	[9, 10, 30]
Predictive Optimization	DRL, MPC, MOGA, PSO	Simulation-based [13, 22, 23], Residential EV/BESS datasets [17]	Energy Efficiency, SoH Retention, Cost Reduction	DRL: Improved charging efficiency & SoH retention [13]; MOGA: Balanced aging/cost trade-off [13]; PSO: Enhanced throughput under constraints [23]	DRL: Very High; MPC: Medium; MOGA/PSO: Low-Medium	[13, 17, 22, 23]
Cybersecurity & Anomaly Detection	Autoencoder, Unsupervised Clustering, ML Classifiers	Simulation/lab cyberattack datasets [7, 14], NASA [15]	Detection Accuracy, False Positive Rate	Deep learning intrusion detection: >95% accuracy [15]; AE-based anomaly detection effective under data spoofing [7]	AE: Medium; Deep learning: High	[7, 14, 15]
Digital Twin Integration	TCN-LSTM, Transfer Learning, Hybrid Models	Microgrid BESS datasets [19, 36]	RMSE, Latency, Adaptability	TCN-LSTM with transfer learning: RMSE < 2% and improved adaptability across conditions [36]	Medium-High	[19, 36]

Overall, the literature points to the fact that, although deep learning offers the most accurate prediction results, hybrid and interpretable solutions are drifting towards state-of-the-art for safety-critical BESS scenarios [10, 11].

3.2. Health Estimation Methods

SoH estimation has often relied on time recurrent models (such as LSTM networks) that can generalize across long-term degradation patterns [9, 10]. LSTM models reduce to root mean square error (RMSE) as low as 2.3% on NASA datasets [10] and GBM methods like XGBoost improve both accuracy (RMSE ~1.8%), and interpretability [11]. Gaussian Process Regression (GPR) has probabilistic outputs with calibrated uncertainty estimates [10], but the scalability to large datasets is bounded.

SoH monitoring is operationally constraining and RUL prediction generalizes the concept by predicting capacity fade trajectories. LSTM models trained on discharge cycles for LFP exhibit excellent long-horizon accuracy [10, 30] but require massive and representative data sets that are often not available for less common chemistries.

Transferability Issue:

A relatively small fraction of models is trained using a single-chemistry dataset [9, 10] and thus generalization to different chemistries or different environmental conditions is limited. Domain adaptation strategies remain underexplored.

3.3. Predictive Optimization Strategies

MPC is a popular choice for rule-constrained optimization, but it has challenges with nonlinear dynamics and long-horizon objectives [13]. In contrast, DRL bypasses these limitations and learns adaptive policies directly from interaction data. These studies model a DRL implementation to optimize charging rate and temperature control, leading to energy throughput and SoH retention improvements over static charging strategies [13, 22].

However, one issue with DRL is that its use of simulation-trained controllers is a potential hurdle to transferability to real systems [13]. Reward function design is a major bottleneck in proper task specification—badly specified goals can lead to unsafe operational behaviors [13, 17]. For example, Multi-Objective Genetic Algorithms (MOGA) [13] and Particle Swarm Optimization (PSO) [23], are more interpretable and computationally lighter, but both require a simplified system model which may no longer be useful in real-time applications [31].

3.4. Data Availability and Benchmarking

Low and heterogeneous data quality are still the main challenges in all fields [9-11]. While the most extensive evaluations in the literature are achieved on NASA and CALCE repositories, their narrow chemistry diversity and lack of rare-fault events may limit generalizability [10]. The small number of studies that release the raw data from the field presents a problem for reproducibility.

Evaluation metrics are also applied inconsistently. For example, some SoH prediction experiments demonstrate the performance only in terms of RMSE, MAE or percentage error without a common baseline [9, 10]. A unified framework for benchmarking that uses well-defined datasets and train-test splits, and defined metrics would be provided.

The major ML models are compared on the predictive task for BESS experiments in Figure 7. To emphasize and guide in practical deployments, we highlight accuracy, interpretability, and computational demand as the main criteria for algorithm selection.

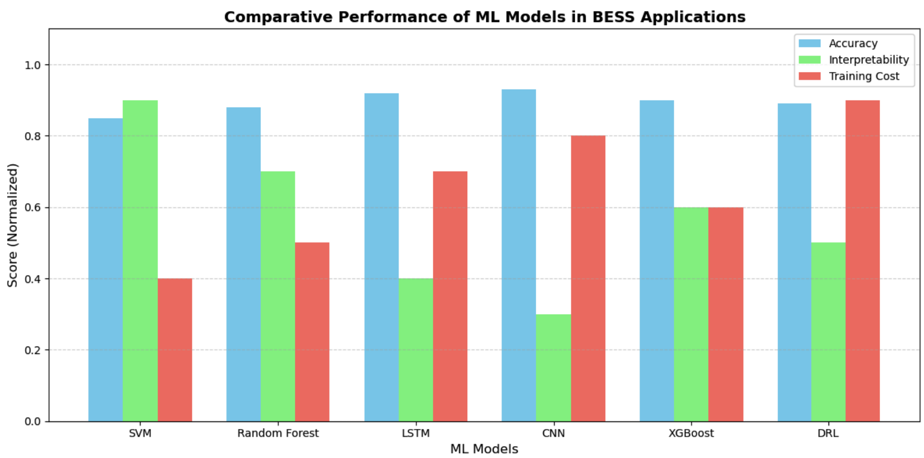

Figure 7. *Comparative analysis of ML models in BESS in terms of accuracy, interpretability and scalability.*

3.5. Interpretability and Deployment Challenges

Interpretability remains the real roadblock to consistent regulation adoption. Tree-based models (RF, GBRT) offer important feature measures while deep neural networks remain a black box [9, 11]. Lastly, Explainable AI (XAI) techniques such as SHAP or LIME have been suggested but so far not really implemented in the real-time BMS [9]. A promising solution is offered by hybrid ECM-ML approaches, which combine physical reasoning with learned representations [10, 29].

However, since the computational resources available for the embedded BMS hardware have limitations on this deployment, works like [28] warn that decision trees have to be optimized and/or models need to be compressed in order to operate close to real-time. State-of-the-art techniques for this challenge include model pruning, quantization, and FPGA acceleration [10, 28].

3.6. Strengths, Limitations and Future Prospects

The cross-domain synthesis is presented in Table 6 and shows three central findings:

1) Performance Leadership:

LSTM and CNN architectures achieve the highest predictive accuracy in both fault detection and health estimation [9, 10, 13], albeit it needs high interpretability for regulatory acceptance.

2) Hybrid Model Promise:

Firstly, it can achieve better generalization by a physics-informed ML approach and secondly, it provides partial transparency, which makes it more for safety-critical deployments [10, 29].

3) Optimization Maturity Gap:

DRL has the advantage of dynamic adaptation, however, these approaches can be less interpretable and mature compared to MOGA/PSO-based approaches, which assumptions hold true under static conditions but don't cope well with stochastic conditions [13, 23].

Future progress depends on:

1) Development of large, heterogeneous, publicly available datasets [9, 10, 20];
2) Lightweight, Interpretable Models for Embedded BMS [28];
3) Benchmarking frameworks for reproducible, cross-study comparison [9, 13];

Contrary to many academic reports that highlight new opportunities of AI in BESS monitoring and control, these observations stress that an integration of accurate prediction, interpretability and feasibility is a necessary framework for real-world industrial-level implementations.

4. Challenges and Open Issues

Artificial intelligence has been used in BESS. However, due to problems and limitations, its development is hindered. The highlights of the discussion are presented in this section.

4.1. Data Scarcity with Labeling Constraints

The major bottlenecks of supervised learning approaches lie in the need for high-quality labeled dataset availability, especially for fault diagnosis and rare failure modes [30, 34]. Most of the published studies use the dataset such as NASA and CALCE, but these datasets are limited in their representation of the range of chemistries, operational conditions (current, voltage), temperature distribution, and usage duty cycles that exist in real-life deployments [9, 10]. It complicates benchmarking and limits the generalizability of models across different battery technologies & applications [10, 11, 13].

The significance of open-access repositories that contain standardized labeling protocols has been given considerable importance in previous reviews, suggesting that without the availability of such data, reproducibility and reliability would not be universal across studies [9, 10].

4.2. Model Interpretability and Trustworthiness

The interpretability issue is still a critical problem for data-driven battery management strategies. While deep learning architectures such as CNNs and LSTM networks offer highly accurate predictions [9, 10], but tend to be black boxes when explaining their predictions. Interpreting this opacity is a real difficulty when it comes to regulatory compliance and operator trust, especially in something so safety-critical as monitoring electric vehicle battery health [9].

For transparency, various explainable AI techniques such as feature attribution methods and visualization frameworks have been suggested but their real-time integration with BMS environments is rare [9, 11]. This trade-off between high predictive power and interpretability is an important area of further research [4].

4.3. Generalization Over Chemistries and Conditions

Most AI models have been trained and tested on one battery chemistry data set or for tightly constrained operating conditions [10, 11]. This limits the ability of these methods to be easily adopted in various cell chemistries, temperatures, and operating conditions [9]. For instance, models learned from lithium-ion data may not transfer effectively to LFP or emerging chemistries because of variations in degradation dynamics and electrical characteristics [10, 25].

Hence, devising generalizable or transferable models and domain adaptation approaches is needed to enhance robustness and dependability in various deployment conditions [10, 13].

4.4. Real-Time Computational Constraints

The deployment of non-linear and complex models (e.g., deep neural networks or reinforcement learning agents) can introduce exceptional computational loads on the embedded BMS hardware [9, 10]. Real-time applications such as fast SoH estimation and dynamic fault detection depend on low-latency inference, which can rarely be achieved by regular microcontrollers [9, 13].

Model compression, quantization, and the use of hardware accelerators (e.g., FPGAs) are promising strategies to address computational efficiency without sacrificing much in terms of prediction accuracy [10, 28].

4.5. Reinforcement Learning Reward Function Design and Validation

Although reinforcement learning (RL) has shown great promise in predictive optimization of charging and cycling strategies, the construction of reward functions that properly capture operational goals is challenging [13]. Incorrectly specified rewards may result in suboptimal or unsafe control policies, which would increase the difficulty of validating and certifying such systems [13].

Moreover, most RL researches are validated in simulation environments [13], whose efficacy under real-world scenarios is uncertain. For this reason, establishing validation pipelines and safety frameworks becomes essential for industrial applications.

4.6. Integration with Existing BMS Architectures

Some AI-enhanced applications are still proof-of-concept oriented, and they have not been fully adopted yet in production-level BMS [10-12]. Challenges include data interface compatibility, interoperability with legacy control systems, safety mechanisms to take over learned policies in case of abnormal behavior, etc. [9, 11].

A hybrid framework involving a combination of physics-based observers and data-driven predictors has been suggested as a possible solution for increasing the robustness of known existing architectures and easing the implementation into existing frameworks [10].

4.7. Cybersecurity and Data Privacy

However, because of the growing dependency between data connectivity and remote monitoring, BESS are now exposed to cybersecurity risks. Here, AI-augmented diagnostic and optimization models themselves can be targeted for adversarial attacks (e.g., in terms of data poisoning or spoofing), potentially endangering both safety and operational continuity [13, 21].

In addition, questions of privacy and data protection are generally unaddressed or unexplored, even though such operational data will often be transmitted across networks. Privacy-preserving AI deployments for BESS applications can potentially benefit from technologies including federated learning [13] and encrypted model training [21].

4.8. Summary of Challenges

The compilation of these challenges synthesizes a complex set of limitations impeding the use of AI in BESS:

1) Data restrictions affect the generalizability and reproducibility.
2) Interpretability compromises trust and regulatory compliance.
3) Computational requirements are beyond the means of most embedded systems.
4) RL-based optimization still has open issues regarding designs and validation of rewards.
5) Cybersecurity and privacy have been neglected compared to other areas of industry.

Solving these challenges will require more than just improved methodologies; it will also be needed an interdisciplinary approach between battery engineers, control theorists, and AI researchers. In summary, to synthesize this complexity, we present a challenge map (Figure 8) which provides an overview of the relative importance of each dimension from our identification of current research trends and on-the-ground deployability up until now.

This Figure 8 is a Radar chart that shows the need for BESS-driven AI in the challenges faced in deploying. This plot displays the aggregated impact and urgency of Data availability, interpretation constraints, Real-time constraints, and Cybersecurity as per the literature.

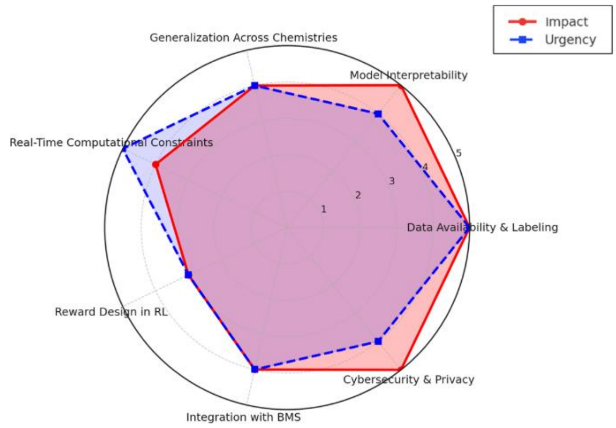

Figure 8. *Radar chart showing the main technical and operational difficulties in deploying AI-enabled BESS.*

5. Future Research Directions

The emergence of AI-aided methods with BESS highlights both the disruptive potential and significant hurdles posed by data-driven technologies. This section presents various solutions to the problems identified in Section 4 and a research roadmap.

5.1. Large-Scale, Standardized Dataset Development

Lack of standardized datasets is one of the biggest bottlenecks to further advancement in this domain. The development of large-scale datasets for benchmarking and cross-study comparisons between different chemistries, operating conditions, and degradation modes is also discussed in future work [9, 10].

To advance this discussion, critical steps such as open-access repositories using standardized protocols for data collection, annotation and publication are essential [16, 20, 26]. Additionally, synthetic data generation (e.g., physics-informed simulations) can be utilized to overcome the problem of the lack of labeled fault data and rare degradation events [10].

To accelerate this effort and promote reproducibility, it is necessary to have collaborative frameworks among academia, industry, and regulatory bodies [9].

5.2. Integrating Explainable AI with Battery Management Systems (BMS)

Because of this widespread concern about model interpretability, it is evident that there is a demand for purpose-built explainable AI (XAI) techniques in BESS applications [9]. Admittedly, some approaches, like feature attribution and visualization frameworks, have demonstrated their importance, but very few of them have been integrated into real-time embedded systems [10].

Instead, future research should investigate lightweight XAI methods that can generate useful explanations for operators while maintaining real-time inference performance [9, 10]. Furthermore, the application of probability concepts in combination with neural networks may improve uncertainty quantification and confidence for safety-critical tasks [11].

5.3. Domain Adaptation and Transfer Learning Across Chemistries

Further study of transfer learning and domain adaptation strategies for BESS applications will be part of a solution to enhance model generalization [10]. For instance, pre-trained models trained with ubiquitous lithium-ion datasets could be fine-tuned from a generic set of chemistries and usage profiles to less well-represented chemistries and unique cycling scenarios by training only on the novel data [10].

Hybrid frameworks that combine physics-informed (PI) models with data-driven components are also a viable direction to improve adaptability in different operational regimes [10, 11].

5.4. Real-Time Lightweight and Quantized Model Deployment

Despite numerous works like [9, 10] have proved that applying complex AI models within embedded BMS environments remains a challenge due to computational constraints (discussed in Section 4.4), Lightweight architecture such as pruning, quantization and knowledge distillation for efficient inference on microcontrollers or edge devices should be considered as the future research direction [11].

More generally, additional research into hardware acceleration (e.g., using FPGAs and domain-specific processors) could provide a much-needed connection between predictive performance and real-time operation and energy efficiency [11].

5.5. Evolution of the Optimization Approach for Lifecycle Management

However, the battery operation still needs to be further optimized, which is a relatively important research direction. Although both reinforcement learning and heuristic optimization methods have shown some promise, they should be applied with caution in safety-motivated domains due to existing concerns around safety, stability, and interpretability [13].

Developers could benefit from hybrid optimization frameworks that blend reinforcement learning with constraint-based control to enable easily understood objectives and safety guarantees in future studies [13]. Moreover, systematic evaluation protocols and simulation-to-reality transfer methods will be required for validating the optimization strategies in industrial applications [11].

5.6. Cyber-Security and Privacy-Preserving Machine Learning

With the increasing connectivity and distributed learning in BESS, cybersecurity and privacy become crucial issues [19]. Future studies should be carried out to develop AI frameworks that are privacy-preserving and secure, such as federated learning encrypted inference [9, 19].

Real-time anomaly detection modules to detect data spoofing and adversarial attacks need to be integrated for maintaining the integrity of the system and operational safety as well [21, 35].

5.7. Co-Design of AI Models and BMS Topologies

Lastly, there is an urgent need to go beyond algorithm-centric development and transition to an integrated co-design of AI models with the BMS architectures [10]. By designing the data pipeline, control hierarchy and hardware capabilities simultaneously, end-to-end reliability can be increased and deployment becomes easier [11].

This co-design methodology should ensure the compliance, documentation and certification frameworks for regulatory purposes with a specific emphasis on designing AI-enabled BMS to meet the requirements of critical applications like electric vehicles and grid-scale storage [20].

5.8. Proposed Unified Framework for AI-Based Bess

The previous review has demonstrated that artificial intelligence (AI) methodologies have been widely used in individual tasks like fault diagnosis [9], health estimation [10] and predictive optimization [13] for battery energy storage systems (BESS). This fragmentation leads to duplicate sensing, passive decision making, and lost opportunities for adaptive optimization across the entire operational cycle [36]. Moreover, some key issues such as real-time learning, cybersecurity and integrated control implementation are very under-researched [7].

Our unified closed-loop AI-BESS framework, consisting of these, is represented in Figure 9 to overcome the above limitations. Its architecture consolidates the functionalities of the state-of-the-art methods into a layered decision-control pipeline:

Monitoring Layer:

The framework contains a multi-sensor data acquisition phase that can measure the voltage, current, temperature and Electrochemical Impedance Spectroscopy (EIS) variables. This can leverage live operational streams and curated benchmark datasets (e.g., NASA, CALCE, Oxford) to facilitate model pre-training and validation. This plays a role in providing downstream AI modules with standardized, high-quality inputs.

Decision and Optimization Layer:

Two parallel analytics modules that are fed by a real-time data feeder:

1) Fault Diagnosis Module - Using system identification and machine learning approaches, such as SVM, RF, CNN, LSTM networks, and hybrid ECM+ML to classify fault type and identify confidence level.
2) Health Estimation Module - Applying LSTM, XGBoost, and Gaussian process regression (GPR) models for SoH & RUL prediction with uncertainty.

Both modules output to a Predictive Optimization Module, where MPC, DRL, MOGA or PSO are used to determine optimal charge/discharge schedules that balance performance, longevity and safety.

Learning and Security Layer:

The loop is completed by a feedback layer, relaying operational results and environmental changes back into the AI models using online learning and transfer learning. It also includes cybersecurity steps and anomaly detection to prevent data poisoning, model tampering or control override attacks.

The framework integrates these layers to create a feedback-driven architecture that provides continuous, adaptive and secured BESS operation across dynamic grid conditions. The design modularity enables step-by-step deployment by operators, integrating the monitoring layer first, followed by the decision-optimization modules and in a final stage, the learning and security functions, which helps in adoption barriers.

Figure 9 illustrates a unified closed-loop AI-BESS architecture which comprises a three-layer architecture: (i) Monitoring Layer for multi-sensor data acquisition and benchmarking; (ii) Decision and Optimization Layer integrating AI-based diagnostics, prognostics, and predictive optimization; and (iii) Learning and Security Layer for continuous adaptation and cyber-resilience. Primary data and control flow directionality are represented with black arrows, while grey arrows correspond to feedback for model retraining and operational refining.

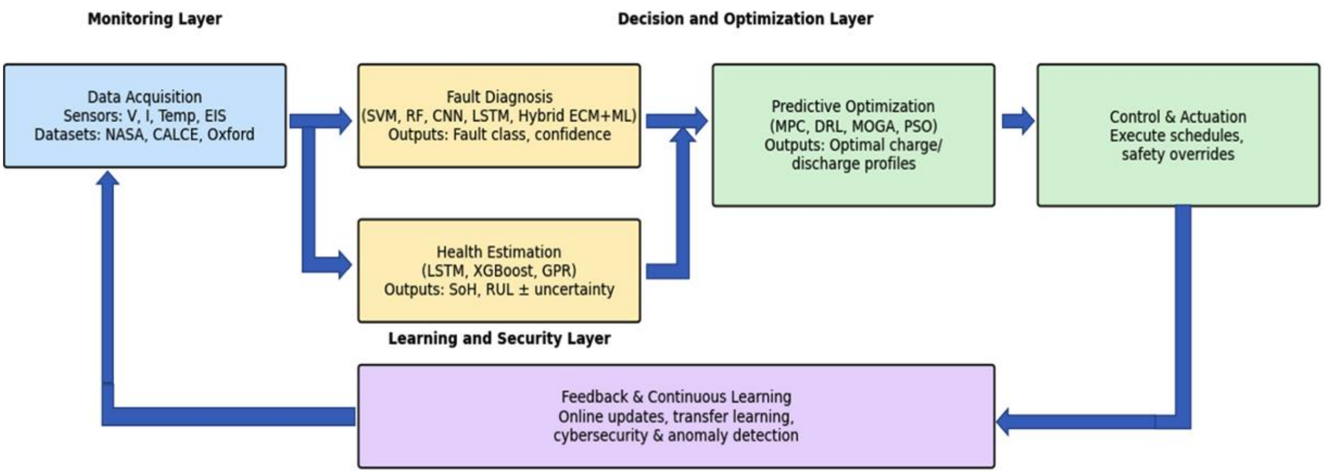

Figure 9*. Unified Closed-Loop AI-BESS Framework.*

This approach directly addresses a unified solution to target the identified gaps (Section 3): (1) End-to-end integration of AI modules and their orchestration, (2) Adaptation to various real-world conditions, and (3) Security-aware design that takes into account system-level constraints.

5.9. Summary of Future Research

To conclude, the development of AI-based BMS requires further investigation in a variety of areas, including:

1) Creating large, quality datasets representing operational diversity
2) Lightweight, interpretable AI frameworks for deployment at the edge
3) Transfer learning and domain adaptation strategies
4) Transparent hybrid optimization strategies
5) Secure, Privacy-Preserving Learning Protocols Execution
6) AI + standard BMS controls (systemic co-design)

Strict adherence to these standards will eventually be needed in order to bridge the gap between experimental research prototypes and large-scale, production-worthy industrial solutions.

6. Conclusion

AI is gaining increasing attention as an enabling technology for advanced BESS, promising to improve fault diagnosis, state estimation, and predictive optimization well beyond what can be achieved by traditional model-based methods. We have now systematically reviewed the latest developments on ML and DL algorithms application to BESS and presented the methodological bases, benchmark results, and deployment issues. It should be noted that, at the feature extraction and temporal pattern recognition level, e.g., LSTM and CNN deep-learning models tend to do significantly better than traditional classifiers, such as SVM or Random Forest, and hybrid techniques that blend physical models with data-driven learning generally can do better in terms of generalization and interpretation [1, 4]. Reinforcement learning can also be applied to optimize the charging strategy to operation [13], but it still has limitations like the lack of standard public datasets [17], the high computational cost [3] and, primarily, the black-box nature of deep neural models [9]. One of the critical efforts to this end is creating large-scale, diverse datasets with better-defined annotation protocols for both lightweight and explicability of the AI framework to fit the real-time requirement of the embedded BMS. Additionally, transfer learning is necessary, as well as robust reinforcement learning policy verification and a safe, privacy-preserving architecture for moving the state of the art from laboratory samples to industry expansions [4, 9, 14, 19]. In short, the full deployment of AI-capable BESS requires a full, systemic approach to solving these issues, in developments and co-design methodologies at system levels, along with testing the practices. This will help researchers and practitioners to accelerate their work to develop scalable, trustworthy intelligent BMS supporting future energy systems for the battery storage to bloom as the third cornerstone of sustainable innovation.

Abbreviations

AI	Artificial Intelligence
AE	Autoencoder
BESS	Battery Energy Storage System
BMS	Battery Management System
CNN	Convolutional Neural Network
DRL	Deep Reinforcement Learning
ECM	Equivalent Circuit Model
LOF	Loss of Function
TCN	Temporal Convolutional Network
SHAP	SHapley Additive Explanations
LIME	Local Interpretable Model-agnostic Explanations
EIS	Electrochemical Impedance Spectroscopy
GA	Genetic Algorithm
GBRT	Gradient Boosting Regression Trees
GPR	Gaussian Process Regression
IoT	Internet of Things
LFP	Lithium Iron Phosphate
LSTM	Long Short-Term Memory
ML	Machine Learning
MOGA	Multi-Objective Genetic Algorithm
MPC	Model Predictive Control
NASA Dataset	NASA Prognostics Center Dataset
PSO	Particle Swarm Optimization
RF	Random Forest
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
SoC	State of Charge
SoH	State of Health
SVM	Support Vector Machine
VAE	Variational Autoencoder
XAI	Explainable Artificial Intelligence
XGBoost	Extreme Gradient Boosting

Author Contributions

Md Rayhan Tanvir is the sole author. The author read and approved the final manuscript.

Ethical Approval

Not applicable. (The present study does not contain any studies with human participants or animal experiments.)

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Availability of Data and Materials

Not applicable. (This is a review article and does not contain any original data. All data discussed in this paper are obtained from published studies, which are cited in the reference list).

Conflicts of Interest

The author declares no conflicts of interest.

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