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Modeling, control and safety of hybrid energy storage systems in microgrids☆

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ABSTRACT

The rapid growth of renewable energy sources (RESs) has introduced significant uncertainty and instability to the operation of smart microgrids. To address these challenges, energy storage systems (ESSs) have become essential, as they can effectively mitigate the impact of the fluctuations of RESs. However, ESSs consisting of single-type energy storage devices face limitations in meeting the various requirements of microgrid applications. A hybrid energy storage system (HESS) that integrates multiple types of ESSs offers a popular solution by exploiting their complementary characteristics. This article provides a comprehensive review of the state-of-the-art technologies of HESSs, covering their types, modeling methods, control strategies, and particularly, the safety considerations that have often been overlooked in the existing review papers. The pros and cons of the existing works across these four dimensions are also critically analyzed. Finally, future trends and potential directions are highlighted to carry out further research and the practical implementation of HESS technologies.

1. Introduction

As the concept of carbon neutrality gains wide recognition and support from countries around the world, renewable energy sources (RESs), including solar photovoltaic, wind, hydro, and geothermal, have attracted increasing attention for their ability to provide a sustainable and clean power supply [1]. To fully leverage these advantages, it is significant and urgent to develop microgrid technologies, which have the capability to convert, store, and supply high-quality electrical power [2]. The energy storage system (ESS) is an important component in a microgrid, which contributes to RES integration by flattening power fluctuations, improving power quality, and enhancing system stability [3].

ESSs have been widely used for decades with continuous improvement over time. According to different power and energy characteristics, ESSs can be divided into high energy-density storage (HES) devices and high power-density storage (HPS) devices, as shown in Fig. 1. HES devices can store relatively large amounts of energy to guarantee long-term energy consumption in the form of mechanical (compressed air), chemical (hydrogen storage), electrochemical (batteries and fuel cells), or thermal processes. However, the main disadvantages of HES devices are the relatively short cycling life and slow response speed. HPS devices, known for their fast dynamics, store electrical power mainly in the form of mechanical (flywheel), electrochemical (supercapacitor), and magnetic energy (superconducting magnetic energy storage, SMES). However, HPS devices are not suitable for long-term discharge [4]. A hybrid energy storage system (HESS), which combines HESs and HPSs, offers a promising solution to address these limitations by leveraging and maximizing the advantages of both technologies [5]. Consequently, HESSs can be integrated with RESs in microgrids to regulate DC bus voltage and enable more economical operation. A general AC/DC microgrid with HESS is shown in Fig. 2. In Fig. 2, a unity grid, distributed energy resources (DERs), and AC loads are connected to the AC bus. HESS, DC loads, and renewable energy generation are connected to the

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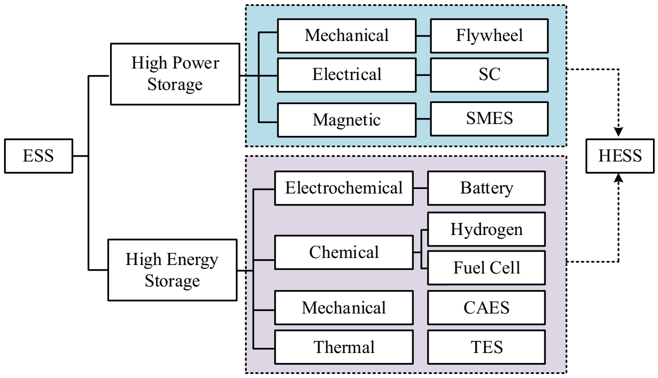

Fig. 1. Classification of ESSs and potential components of HESSs.

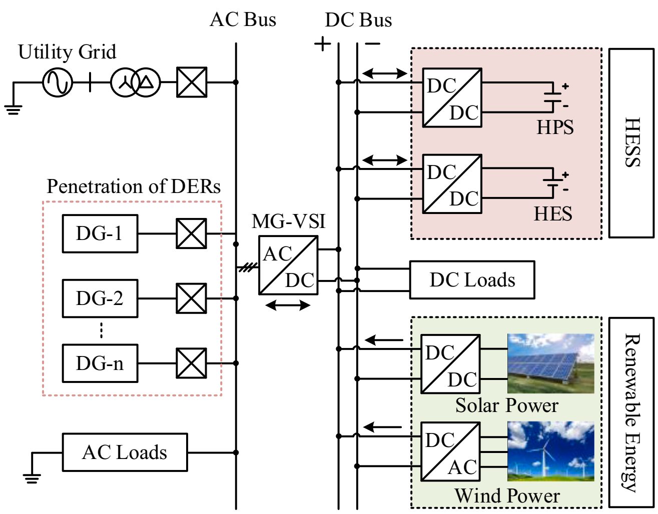

Fig. 2. Topology of a general AC/DC microgrid with HESS.

DC bus. The AC bus and DC bus are tied by the bi-directional interlinking converter.

With the rapid development of materials science and chemistry, many novel ESSs have been reported recently, which show great potential as components of HESSs. For example, all-solid-state batteries, considered to be one of the next-generation technologies of lithium-ion batteries, are discussed in [6], thermal energy storage technique is reported in [7], and the recent progress in the capture air energy storage (CAES) technique is reviewed in [8]. To fully exploit the potential and unique characteristics of different ESSs, accurate modeling technologies are essential. In particular, data-driven and artificial intelligence (AI) technologies have enabled the extraction of key features from extensive operational data, improving the accuracy of ESS modeling [9]. On the other hand, advances in control theory have facilitated the application of advanced control technologies, such as model predictive control (MPC) [10] and sliding mode control (SMC) [11], to HESSs.

However, the integration of multiple ESS technologies into a microgrid system presents several challenges. These include the complexity of managing the interactions between different ESSs, ensuring the reliability and stability of the system under varying operational conditions, and addressing the efficiency of energy conversion and storage. Moreover, the lack of standardized protocols and interfaces for HESSs, along with the need for advanced real-time monitoring and control systems, further complicates their practical implementation.

Motivated by the rapid progress and associated issues, this paper presents a comprehensive review of HESSs for microgrid applications, focusing on types, modeling, control, and safety. Unlike existing surveys that mainly focus on power electronic topologies and control strategies in [12,13], this review covers a broader spectrum of HESS configurations, summarizes a three-tier taxonomy of modeling approaches, and structures the modeling, control, and safety discussions as an integrated framework. The unresolved challenges and corresponding potential research directions are also discussed for future investigations.

2. Type of HESS

Relying on a single energy storage technology often forces a compromise between HES and HPS. The fundamental premise of a HESS is to create a synergistic storage system capable of handling power fluctuations across multiple timescales in microgrids. Driven by the rapid advancements in materials science and chemistry, the toolkit of available ESS components has expanded significantly in recent years. Consequently, selecting and pairing the most appropriate storage technologies is the crucial first step in overcoming the broader integration, efficiency, and management challenges of microgrid applications. To provide a clear overview of this expanding landscape, this section categorizes and reviews various HESS configurations. It explores both the conventional combinations those have formed the widely adopted HESS in current microgrid deployments, as well as emerging HESS architectures which offer promising site-specific solutions for the future [14–30].

2.1. Conventional HESS

Conventional HESSs represent the most mature researched and widely deployed configurations in contemporary microgrid applications. These systems fundamentally rely on well-established storage technologies. By pairing a primary HES device with a secondary HPS counterpart, conventional HESS architectures successfully bridge the gap between long-term energy provision and rapid dynamic response. This proven synergy is critical for mitigating the inherent intermittency of renewable energy sources, ensuring stable bus voltages, and improving overall power quality within the microgrid. To provide a comprehensive overview of these foundational architectures, this paper will elaborate on the following aspects: A. HESS Based on Batteries, B. HESS Based on SMES, and C. HESS Based on Fuel Cell/Hydrogen Storage.

A. HESS based on batteries

As one of the most common types of HESSs, battery-based HESS has been widely investigated [14–17]. For example, in a battery-flywheel HESS, two control strategies are designed for splitting power between the battery and flywheel in order to flatten the power fluctuation and reduce the power loss, respectively [15]. It is noteworthy that flow batteries, with liquid electrolytes stored in the external storage tanks and circulated by the pump, are a potential replacement for the lithium-ion battery in HESS for microgrid applications due to their advantages of long cycle life, high safety, and good charge-discharge characteristics [16]. Behera et al. [17] proposed HESS, integrating a hydrogen/bromine redox flow battery (RFB), supercapacitor, and photovoltaics (PV) with a resilient controller.

B. HESS based on SMES

SMES is a potential type of HPS technique, which utilizes the properties of superconducting materials to store electrical energy in the form of a magnetic field [18,19]. Jacques et al. [18] contributed to the performance improvement of a PV/wind DC microgrid by integrating a hybrid SMES/battery energy storage unit, applying a coordinated fuzzy logic control and PI controller strategy to effectively manage energy exchange, smooth power fluctuations, and maintain stable bus voltage and load profile under various disturbances. Liu et al. [19] designed a battery-SMES HESS with the optimal control strategy to improve the economy and stability of microgrid operation by optimizing the capacity allocation and output of HESS.

C. HESS based on fuel cell/hydrogen storage

Various hybrid battery-fuel cell HESSs with energy management are reported in [20–22]. Alharbi et al. [20] proposed an optimized energy management and control strategy for a DC microgrid with PV, and a hybrid fuel cell-battery-supercapacitor storage system, developing a novel Beluga Whale Optimization-based strategy to efficiently allocate the load among components and to improve system efficiency while reducing hydrogen consumption. Belkhier et al. [21] proposed a novel design and adaptive coordinated energy management strategy for a microgrid integrating tidal, wind, PV, and hybrid fuel cell-battery storage, utilizing a fuzzy logic modified super twisting algorithm to optimize system operation, ensure service continuity, and smooth power output.

2.2. Other HESS

While the conventional HESS configurations provide a reliable and well-established foundation for microgrid operations, their reliance on electrochemical and magnetic processes can sometimes be constrained by scaling costs, lifecycle degradation, and specific environmental limitations. As microgrids evolve to manage larger energy capacities and integrate more deeply with local infrastructure, there is a growing need to explore alternative storage mechanisms. To address these evolving demands, researchers are increasingly investigating emerging HESS architectures which leverage large-scale mechanical and thermal processes. These alternative systems offer unique advantages, such as extended storage durations, massive capacity scaling, and the ability to repurpose local geographic or thermal assets. To highlight the potential of these innovative architectures, this paper will discuss the following key perspectives: A. HESS based on CAES and B. TES-Based HESS.

A. HESS based on CAES

In the charging phase of CAES, energy is usually captured, compressed, and stored in an underground cavern. During the discharging phase, compressed air is withdrawn from storage, mixed with fuel and combusted, then expanded through a turbine to drive a generator, thereby converting the stored energy into electricity [23,24]. Naghibi et al. [23] proposed an economic energy scheduling and flexibility regulation framework for multi-microgrids containing non-renewable/renewable units and a battery-CAES HESS, utilizing a hybrid grey wolf-red panda optimizer and an unscented transformation model to minimize energy cost and loss while enhancing system safety. Bartela et al. [24] proposed a novel HESS combining CAES and hydrogen as energy carriers, utilizing thermal integration to achieve efficient large-scale energy storage with a competitive efficiency, as demonstrated through thermodynamic assessment and comparison with pure hydrogen and other reference systems. The thermodynamics of the hybrid CAES-hydrogen system is analyzed in [25]. Sensitivity analysis indicates that the outlet temperature of the hydrogen combustor and specific energy consumption of the water electrolysis hydrogen generator are key influencing factors of system performance. Hybrid hydrogen-fueled CAES and PEM electrolyzer are assessed in [26], where the PEM electrolyzer is employed to smooth out long-duration time-scale fluctuation, while hydrogen-fueled CAES is used to settle the remaining time-scale fluctuations. The proposed HESS has relatively higher power supply reliability than any single energy storage unit.

B. TES-Based HESS

In the charging phase of thermal energy storage (TES), thermal energy can be stored in well-insulated phase change materials as internal energy, and the process is reversed during discharging. TES has been widely integrated with solar power generation [27] and cooling systems [28]. Guo et al. [29] developed a hybrid battery-TES system with the optimal planning method to improve the economy and prolong the second-life battery service life. Wang et al. [30] compared the integrated energy efficiency and carbon emissions of hybrid hydrogen-heat, hydrogen ESS, and hybrid battery-heat schemes, and the result showed the superiority of the hybrid hydrogen-heat system over the other two types. A hybrid TES-hydrogen system is proposed in [31] to extend operational hours of the electrolyzer during the night time, levelized cost of hydrogen is further minimized. Despite potential reductions in the price of TES, large-scale TES in the hydrogen generation system is still not cost-effective.

2.3. Comparison of different types of HESSs

To provide a comprehensive understanding of the aforementioned HESS configurations within a microgrid context, it is crucial to evaluate their qualitative differences. Microgrids present unique operational environments characterized by spatial limitations, specific localized demands, and the critical need for cost-effective resilience. Table 1 summarizes the comparison of various HESS configurations regarding cost, efficiency, complexity, and specific implementation constraints.

A critical evaluation of these HESS configurations reveals that no single combination offers a universal solution for microgrid applications, as each presents distinct trade-offs between performance metrics and practical feasibility. From the perspective of economic viability and energy conversion efficiency, battery-based HESSs coupled with supercapacitors or flywheels remain the most commercially mature options, offering high overall efficiency and moderate capital costs. Conversely, systems integrating SMES, despite possessing exceptional efficiency and fast dynamic responses, are severely constrained by their prohibitive capital costs and the necessity for extreme cryogenic cooling. When long-term or seasonal energy storage is required, hybrid configurations utilizing fuel cells or hydrogen become attractive. However, their widespread adoption is predominantly hindered by relatively low round-trip efficiency and high initial investments.

Beyond cost and efficiency, the physical deployment of emerging HESS technologies in microgrids is frequently impeded by implementation barriers and site-specific constraints. For example, while CAES provides a promising avenue for large-scale energy shifting, its absolute reliance on specific geological formations, such as underground caverns, makes it impractical for typical commercial or residential microgrids with limited space. Similarly, the economic and operational viability of TES-integrated HESS heavily depends on the existence of localized heating or cooling demands, and TES loses its operational advantage in a purely electrical microgrid without such coupled thermal requirements. Even for geographically flexible systems, HESS integration introduces distinct feasibility challenges. For battery-supercapacitor combinations, energy management systems must constantly mitigate the asymmetric degradation caused by continuous high-frequency cycling. Meanwhile, the control complexity significantly escalates for hydrogen-based HESSs, because the system must coordinately optimize components operating across different thermodynamic and electrochemical domains while strictly adhering to safety protocols for hydrogen storage in localized environments.

2.4. Future trends

Based on the aforementioned discussion, lithium-ion batteries are still the most common type used in HESS because they are well-developed and easy to manage [14–16,18]- [24,29,30]. However, relying too much on lithium-ion batteries creates a major problem, that is, existing works lack good ways to combine them effectively with newer types of storage technologies that work very differently. The advent of novel technologies, such as solid-state batteries, sodium-ion batteries, and liquid-metal batteries, promises enhanced performance

Table 1
Comparison of Different HESS Configurations in Microgrid Applications.

Reference	HESS Configuration	Capital Cost	Overall Efficiency	Control Complexity	Geographic / Site Constraints	Primary Implementation Barriers in Microgrids
[14–17]	Battery + Supercapacitor / Flywheel	Medium	High	Medium	Low	1. Asymmetric aging; 2. Continuous cycle stress; 3. Limited long-term energy capacity.
[18,19]	Battery + SMES	Very High	High	High	Low	1. Prohibitive costs of superconducting materials; 2. Extreme cryogenic cooling requirements.
[20–22]	Battery + Fuel Cell / Hydrogen	High	Low to Medium	High	Low (but requires safe storage)	1. Low round-trip efficiency; 2. Complex multi-domain energy management; 3. Strict safety protocols.
[23,24]	Battery + CAES	High	Medium	Medium	Very High	1. Absolute reliance on specific geological formations; 2. Scaling down issues.
[27–30]	Battery + TES	Medium	Medium to High	Medium	High	1. Requires localized heating/cooling demands for optimal viability; 2. Thermal energy leakage.

metrics at the device level. However, their effective integration into microgrid-scale HESS introduces new challenges, particularly in dynamic response coordination under intermittent renewable generation, lifecycle degradation synchronization under frequent charge/discharge cycles, and safety redefinition within spatially constrained microgrid environments. For instance, while the multi-timescale energy management system proposed in [32] addresses component-level response heterogeneity, its underlying optimization architecture, real-time interoperability under microgrid disturbances, and scalability to diverse distributed technology mixes remain insufficiently studied in microgrid applications.

Furthermore, existing planning models frequently assume uniform aging, but in practice, the frequent and high-depth cycling required for microgrid stability affects components through fairly different mechanisms, such as the chemical degradation of batteries versus the mechanical wear in CAES or thermal stress in TES. Developing co-optimized capacity allocation models that account for these asymmetric aging trajectories is essential to prevent a single weakest link from prematurely compromising the entire HESS investment. Finally, current microgrid-scale HESS configurations remain overly generic and inadequately adapted to local environmental and geographic constraints. Future studies are suggested to prioritize integrated systemic optimization driven by local datasets, where the HESS composition is dictated not just by cost, but by site-specific factors such as underground cavern availability for CAES or local thermal demands for TES. This evolution from a descriptive selection to a deeply coupled and site-specific structural design will be the cornerstone of next-generation resilient microgrids.

To make these directions more actionable, two research frameworks are introduced. For degradation-synchronized planning, a multi-objective co-optimization framework should be formulated that integrates capacity design with degradation-aware energy management, explicitly quantifying the asymmetric cycling aging of batteries, CAES, and TES components. For site-specific design, representative operating and tail scenarios derived from local datasets should be systematically used for testing and validation, ensuring that geographic constraints such as cavern availability and local heat-demand profiles are embedded directly into the HESS design process.

3. Modeling of HESS

The landscape of HESS encompasses a diverse and complex array of technologies, ranging from conventional battery-SMES pairings to emerging mechanical and thermal configurations like CAES and TES. Integrating these heterogeneous components into a cohesive microgrid system presents a significant operational challenge. To safely manage their interactions, optimize energy dispatch, and fully exploit their complementary characteristics, highly accurate and adaptable modeling technologies are imperative. To address the multifaceted nature of these hybrid systems, advanced modeling methods for HESS have evolved accordingly. This section reviews the major advanced modeling methodologies for HESS, encompassing mechanistic (physics-based), data-driven, and mechanism-data fusion approaches, outlining their fundamental principles.

3.1. Mechanistic modeling

Mechanistic modeling serves as the foundational approach for understanding and simulating the dynamic behaviours of HESS components. By translating complex internal physical and electrochemical processes into mathematical equations, these methods provide a transparent “white-box” representation of energy storage devices. Within this domain, the Equivalent Circuit Model (ECM) is particularly prominent, which simplifies intricate physicochemical reactions into intuitive combinations of standard electrical components. This abstraction is widely adopted in related research fields because it retains a clear physical meaning. Moreover, it only requires relatively low computational overhead and offers ease of parameter identification for mathematical analysis and control system design. To systematically explore the fundamental architectures and recent advancements in this area, this manuscript will elaborate on this category from the following key perspectives: A. Thevenin ECM and B. Fractional-order Modeling.

A. Thevenin ECM

Using the battery as an example, the most basic form of a Thevenin ECM is shown in Fig. 3. This model consists of a series resistor and an RC parallel network designed to predict the battery's response to transient load events at a given state of charge (SOC). The electrical behaviours of the Thevenin ECM can be generally expressed as:

$$\begin{cases} \dot{U}_1 = -\dfrac{1}{R_1 C_1}U_1 + \dfrac{1}{C_1}I_b \\ U_b = U_{oc} - I_b R_0 - \sum\limits_{i=1}^{n} U_i \end{cases} \tag{1}$$

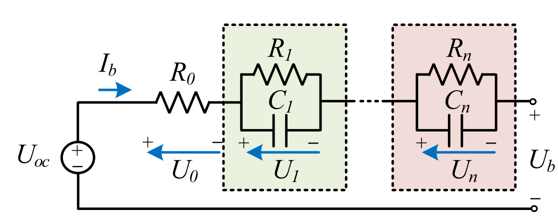

Fig. 3. Diagram of nth-order Thevenin ECM.

where n is the number of the parallel RC units in the ECM. The polarization characteristics of the battery are particularly considered by the parallel RC units. In practice, the number of RC units is determined by the required accuracy, sampling bandwidth, and fitting performance. EIS-based comparisons indicate that a single RC ECM typically matches measured impedance only over a mid-frequency band (approximately 1 Hz–10 kHz), while two to three RC units are needed to extend the fit toward the mHz decade. Usually, a single RC unit is sufficient for the early-stage HESS simulation. Furthermore, when the modeling accuracy fails to meet the requirements and the sampling bandwidth is sufficient while the model is not overfitted [33], a higher-order model can be developed.

The electrolyzer is another important component of HESS, often simulated using the mechanistic modeling method. As shown in Fig. 4, Hossain et al. [34] introduced a simplified first-order ECM, where only a single loop is used to describe the anodic and cathodic dynamics of the electrolyzer. This model incorporates double-layer charge effects to capture its influence on dynamics. However, these models only focus on the electrolysis stage, and the start-up and turn-off stages are ignored in the modeling process. To address this limitation, a multi-timescale ECM was proposed in [35], which simulates the stable electrical characteristics of electrolyzers under both voltage- and current-controlled modes. This model accurately represents dynamic characteristics during the start-up, electrolysis, and turn-off stages. In order to improve the estimation accuracy of electrode impedance during operation, Wang et al. [36] proposed a comprehensive ECM of electrolyzer considering the double-layer capacitance and electro-thermal characteristics. This advanced model provides a more detailed representation of the electrolyzer's dynamic and thermal behaviour.

B. Fractional-order modeling

Fractional-order modeling (FOM) is developed from the Thevenin ECM by introducing constant phase elements (CPEs), and the model parameters are identified by fitting the electrochemical impedance spectroscopy (EIS) in order to address the limitations of the ideal capacitor in ECMs [37]. The inclusion of CPEs allows FOM to more accurately simulate the double layers on the electrode compared with the ideal capacitors in conventional ECMs, thereby improving model accuracy, which is given as:

$$Z(s) = \frac{1}{Cs^{\alpha}} \tag{2}$$

where Z is a complex impedance, C is a constant representing the main capacitive effect, s is a complex variable, and $0 < \alpha < 1$. The voltage dynamics of RC branches can be expressed as:

$$\mathrm{D}^{\alpha} U_{CPEi}(t) = -\frac{1}{R_1 C_1} U_{CPEi}(t) + \frac{1}{C_1} I_o(t) \tag{3}$$

where D^{α} denotes the fractional differential operator with respect to time. Then, the Kirchhoff's voltage law is adopted to obtain the terminal voltage, as follows:

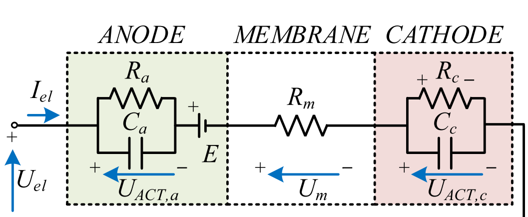

Fig. 4. ECM of an electrolyzer.

$$U_b = U_{oc} - I_b R_0 - \sum_{i=1}^{n} U_{CPEi} \tag{4}$$

Recently, FOM has attracted significant research attention in the modeling of energy storage devices [38,39]. In [38], a partial-adaptive FOM was constructed by combining offline and online parameter identification techniques, which enables the mitigation of model mismatch issues and the effective interpretation of battery dynamics across different timescales. Moreover, a fractional-order multi-model system was proposed in [39] by incorporating sub-models in different temperatures, and the sub-model coefficients are fine-tuned online via a regularized moving-horizon estimation algorithm with temperature embedding. Beyond model accuracy, practical deployment of FOM has also been demonstrated in embedded and real-time environments. An embedded implementation of a fractional-order cell model for internal resistance estimation is reported in [40], achieving very low computational cost by combining float- and fixed-point arithmetic. Furthermore, experimental evaluation of FOM for microgrid frequency control is validated on a real-time OPAL-RT hardware-in-the-loop platform in [41].

3.2. Data-driven modeling

While the mechanistic approaches provide excellent physical interpretability and are highly effective when internal processes are well-understood, they face significant limitations in practical HESS applications. Specifically, deriving precise mathematical equations and tracking dynamically changing parameters for complex, multi-physics systems under highly variable microgrid conditions can be exceptionally challenging and computationally expensive. To overcome these limitations, research has increasingly shifted toward data-driven modeling. Supported by rapid advancements in sensing technology, high-resolution operational data can now be efficiently collected. Parallel developments in machine learning and artificial intelligence provide powerful tools to analyze these massive datasets, allowing researchers to map highly non-linear relationships without relying on explicitly defined physical equations. This approach, driven by data analysis, effectively complements traditional mechanistic methods by offering superior adaptability and high accuracy in state estimation and degradation prediction. To systematically review the prominent algorithms applied in this domain, this paper will go through the following key perspectives in detail: A. Gaussian Process Regression, B. Random Forest Regression, and C. Deep Neural Network.

A. Gaussian process regression

Gaussian process (GP) regression assumes system model to take the form of $y = f(x) + \varepsilon$, where $f(x)$ represents a latent function and $\varepsilon \sim \mathscr{N}(0, \sigma_n^2)$ is an independent and identically distributed noise contribution. A GP prior on the latent function is designed as:

$$f(x) \sim GP(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')) \tag{5}$$

Given a labelled training set $\mathscr{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N_D}$, the predictive distribution for a test input can be obtained from the conditional Gaussian distribution,

$$p(\boldsymbol{y}^* | X^*, X, \boldsymbol{y}) = (\boldsymbol{y}^* | \boldsymbol{m}^*, \sigma^*) \tag{6}$$

where closed-form mean $\boldsymbol{m}^*$ and variance σ^* are determined as:

$$\mathbf{m}^* = \mathbf{K}(X, X^*)^T \mathbf{K}(X, X)^{-1} y \tag{7}$$

$$\sigma^* = \mathbf{K}(X^*, X^*) - \mathbf{K}(X, X^*)^T \mathbf{K}(X, X)^{-1} \mathbf{K}(X, X^*) \tag{8}$$

This enables GP regression to provide both point predictions and uncertainty quantification for SOC or SOH estimation, which is advantageous for modeling of HESS.

In [42], a Gaussian process (GP) model was employed for battery capacity estimation. This method addresses the challenges of differentiating voltage-time data while also ensuring voltage measurements encompass the peaks in IC/DV curves, achieved by smoothing the voltage curve. The Savitzky-Golay filter is applied to improve the ratio of signal to noise. To improve model accuracy, a deep GP model was proposed in [43] by adopting the multilayer GP. Consequently, the predicted result is shown to be robust against different selections of kernel functions and scales of training data. In addition, a hybrid modeling method with uncertainty quantification is proposed in [44], where a Kalman filter-based state tracking process transforms the battery degradation trend into a function of its virtual degradation rate and acceleration. Then, the battery degradation is predicted iteratively using a GP regression strategy with multistep predictions and moving sliding windows.

B. Random forest regression

Random forest regression (RFR) is developed using the input vector $X = [x_1, x_2, \cdots, x_n]$ to build a forest. A set of m trees $\{T_1, T_2, \cdots, T_m\}$ is used inside the forest, thus, the output value of each tree can be represented as $y_k(\mathbf{X}) = T_k(\mathbf{X})$, where $k = 1,2,\cdots,m$. The prediction output of RFR can be obtained by calculating the average of the outputs of all trees:

$$y_p(\mathbf{X}) = \frac{1}{k}\sum_{k=1}^{m} y_k(\mathbf{X}) \tag{9}$$

In [45], the RFR technique with an optimization approach is proposed by adopting a differential search algorithm to determine the optimal values of trees and leaves in the RLR model, eliminating the need for an exhaustive trial-and-error process. Another optimized RFR model was developed in [46], where Harris Hawks Optimization is employed for hyperparameter tuning, and sensor fusion is applied to extract more meaningful features from the data, thereby further enhancing the model's accuracy.

C. Deep neural network

Deep learning technology provides an effective means to directly extract useful features from raw input data, which serves as a foundation for various modeling tasks using different neural network architectures. DNNs have found widespread application in modeling tasks, with various architectures such as convolution neural networks (CNN), long short-term memory (LSTM), gated recurrent unit (GRU), transformer networks, etc. A general DNN-based modeling method is illustrated in Fig. 5, where the output of each layer can be expressed as follows:

$$\mathbf{y} = A(\mathbf{W}\mathbf{x} + \mathbf{b}), \mathbf{W} \in \mathbb{R}^{m\times k}, \mathbf{x} \in \mathbb{R}^{k\times 1}, \mathbf{b} \in \mathbb{R}^{m\times 1} \tag{10}$$

An auto-CNN-LSTM model was proposed in [47], where a CNN is used for data augmentation and feature extraction, and LSTM is employed to process time series data, which are then combined with the feature map and normalized. Furthermore, in [48], the data-model interactive approach incorporated a temporal attention-based bidirectional-GRU that assigns a self-learned weight to each time instance. In [49], a temporal transformer-based sequence network was designed to fully utilize temporal dimensional information. The temporal transformer encodes the temporal features, and the resulting features are further fed into an attention-guided feature fusion module to enable interaction across different dimensions.

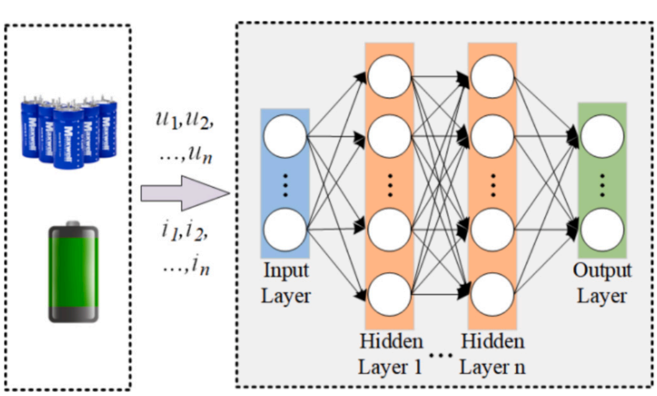

Fig. 5. Diagram of DNN-based modeling method.

3.3. Mechanism-data fusion modeling

While the purely data-driven methods excel at extracting complex, non-linear features from massive operational datasets, their inherent "black-box" nature often limits their physical interpretability and generalization capabilities when facing unexpected microgrid conditions. Conversely, the purely mechanistic models provide strict physical boundaries and clear interpretability, but they frequently struggle to adapt to real-time parameter degradation and unmodeled external disturbances. To bridge this critical gap, Mechanism-Data Fusion Modeling has emerged as an advanced paradigm.

These fusion methods systematically utilize the complementary advantages of both physics-based and data-driven approaches. By embedding known physical laws, electrochemical equations, or equivalent circuit features directly into machine learning architectures, these hybrid models offer significantly improved adaptability, computational efficiency, and robustness. They ensure that AI predictions are not only accurate but also physically feasible. To illustrate the evolution and application of this cutting-edge approach, this section investigates various prominent fusion frameworks, including coupled ECM-AI modules, high-precision Digital Twin (DT) technologies, and Physics-Informed Neural Networks (PINNs).

In [50], an open-circuit voltage (OCV) model was developed to extract the OCV curves, incremental capacity curves, and their associated feature-of-interest. The extracted features are further fused for SOH estimation through an ANN. In [51], a coupling module based on modified adaptive boosting was applied to integrate the advantages of multiple LSTM-based ECMs. In contrast, the work in [52] proposed a fractional-order ECM incorporating two CPEs and a Warburg component to better describe battery impedance characteristics, alongside a random forest regression method to model the OCV-SOC relationship across varying temperatures. A generative adversarial network (GAN) model was used for the battery calendar aging forecasting, where the electrochemical knowledge of the battery is used as the guidelines for designing the GAN conditioner [53].

DT modeling is a promising solution for high-precision modeling of complex systems [54]. A general DT structure is shown in Fig. 6. In [55], the authors proposed a DT-based real-time SOH estimation model established based on a variable cycling data synchronization approach, a time-attention state estimation algorithm, and a future data reconstruction strategy. In [56], an extended Thevenin model-based cloud DT was developed for battery management systems, which provides useful internal information of battery packs, with H-infinity and PSO algorithms applied for SOC and SOH estimation.

PINN is another powerful modeling method that integrates extra information derived from partial differential equations (PDEs) that govern specific physical processes. By leveraging the underlying physical laws, PINNs enhance the prediction capabilities of DNNs. A representative PINN-based modeling method is illustrated in Fig. 7. Wu et al. [57] proposed a PINN method to estimate battery parameters through the single particle model. Nascimento et al. [58] proposed a hybrid PINN model that integrates a reduced-order model (based on Nernst and Butler–Volmer equations) to represent overall battery discharge, a multilayer perceptron to capture non-ideal voltage, and an ensemble of variational Bayesian multilayer perceptrons to model time-dependent

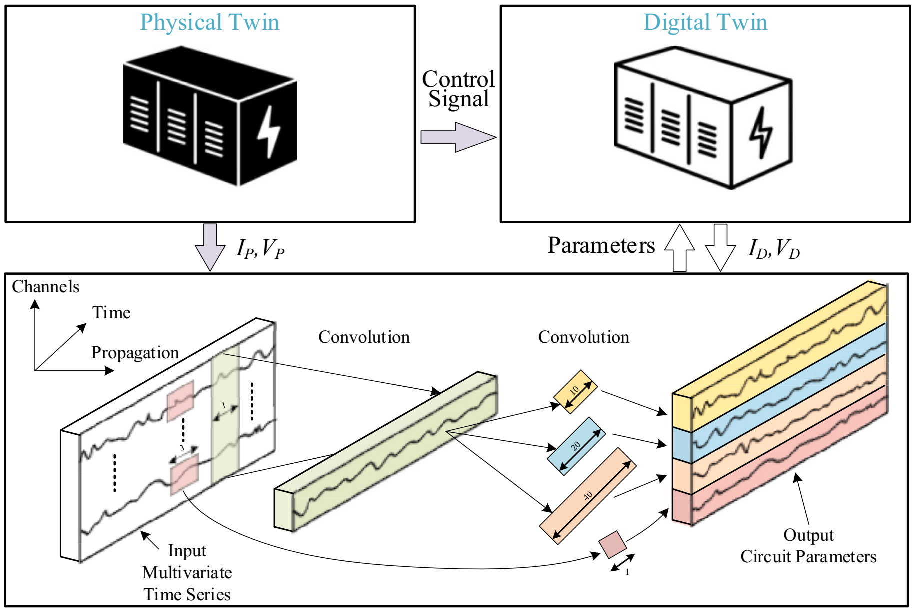

Fig. 6. Diagram of DT modeling method.

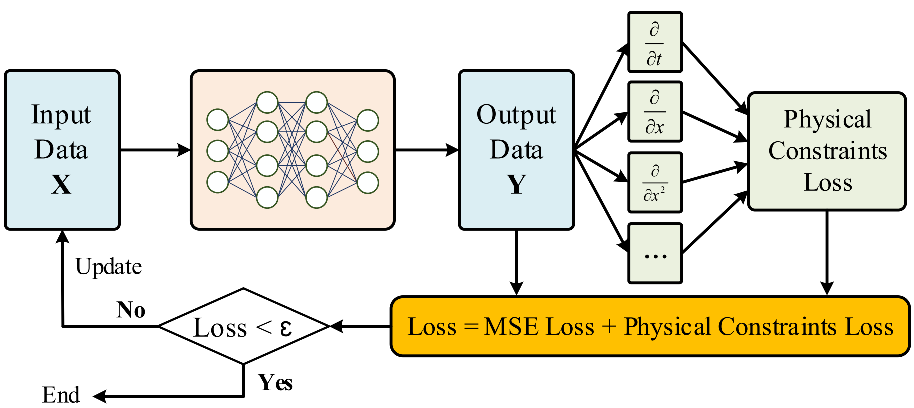

Fig. 7. Diagram of PINN-based modeling method.

internal resistance and available Li-ions, thereby predicting battery voltage and capacity. To improve the PINN model, a physics-informed composite network consisting of four DNNs is presented in [59]. Recent work [60] demonstrated that NN can be readily integrated with a high-fidelity partial differential-algebraic equation-based pseudo-two-dimensional (P2D) model of Li-ion batteries, and the resulting model-integrated NN (MINN) is shown to be capable of providing fast model solutions under a wide range of operating conditions.

3.4. Comparison of different modeling methods of HESSs

To effectively implement energy management and control strategies in microgrids, selecting an appropriate HESS modeling method is critical. Microgrid controllers typically operate under strict constraints regarding computational resources, real-time responsiveness, and system stability under highly volatile renewable energy generation. Table 2 provides a comparison of the aforementioned modeling techniques, highlighting the fundamental trade-offs among accuracy, computational efficiency, complexity, and data dependency.

A critical evaluation of these modeling methodologies reveals a persistent tension between physical interpretability, computational burden, and predictive accuracy within microgrid environments. Conventional mechanistic models, particularly standard Thevenin ECMs, remain the industry standard for baseline control due to their exceptional computational efficiency and explicit physical meaning. To ensure that ECM parameters retain valid physical meanings in practice, three aspects of parameter identification require careful attention. First, physical bounds such as $R > 0$ and $C > 0$ should be enforced as hard

Table 2
Comparison of Different HESS Modeling Methods in Microgrid Applications.

Reference	Modeling Approach	Accuracy & Fidelity	Computational Efficiency	Interpretability	Data Dependency
[30–32]	Mechanistic: Thevenin ECM	Low to Medium	Very High	High (White-box)	Low
[33–35]	Mechanistic: Fractional-order (FOM)	Medium to High	Medium	High (White-box)	Low
[36–43]	Pure Data-Driven (GP regression, RFR, DNN)	High	Low (Training) / High (Inference)	Low (Black-box)	Very High
[44]- [47,51–54]	Mechanism-Data Fusion (PINN)	Very High	Medium to Low	Medium (Grey-box)	Medium
[48–50]	Digital Twin	Very High	Low (Requires Edge/Cloud)	High	Very High

constraints to prevent physically meaningless solutions [61]. Second, model order should be selected judiciously, as excessively high RC orders can cause parameter degeneracy and absorb measurement noise [62]. Third, structural identifiability analysis should be conducted to verify that each parameter is uniquely recoverable from the available data. Without this check, parameters in higher-order ECMs tend to overcompensate for one another and lose their physical uniqueness [63]. However, their simplified nature frequently fails to capture the intricate multi-physics degradation induced by the highly stochastic charge/discharge cycles typical in microgrids. While advancing to FOM improves fidelity, it introduces complex mathematical operators that are often computationally prohibitive for real-time execution on standard embedded edge devices.

Conversely, pure data-driven approaches bypass the need to explicitly map complex internal electrochemical phenomena, achieving high accuracy provided high-quality training data are abundant. Nevertheless, their inherent "black-box" nature presents a severe implementation barrier for resilient microgrids. When a microgrid operates under unprecedented conditions, such as extreme weather events or sudden topological faults, purely data-driven models may extrapolate unreliably, potentially leading to control failures. Specifically, RFR fundamentally cannot extrapolate beyond the boundaries of its training data, leading to systematic errors under advanced aging conditions. Standard DNNs may yield overconfident but erroneous estimations under distributional shift, though transfer learning and domain adaptation have been shown to substantially improve cross-condition generalization with minimal retraining data [64]. GPR offers a partial remedy through its inherent uncertainty quantification, providing an interpretable reliability indicator for the microgrid management system [65]. For RFR, extracting physics-informed relative features rather than raw sensor measurements has been demonstrated to improve robustness against sensor drift and aging-induced distributional shift [66]. To solve the above issues, mechanism-data fusion paradigms, including PINNs and Digital Twins, are rapidly emerging as the most promising solutions. By embedding thermodynamic and electrochemical laws into neural network architectures, these models constrain predictions within physically plausible boundaries. Despite their theoretical superiority, the practical deployment of these fusion models in decentralized microgrids is currently hindered by the necessity for costly cloud and edge computing infrastructures, strict requirements for real-time data, and the complexities associated with co-optimizing physical and data-driven loss functions.

3.5. Future trends

HESS involves interactions across multiple physical domains, such as electrochemistry, thermodynamics, electromagnetics, and mechanics. However, current modeling approaches often remain confined to a single domain, which is incapable of capturing the diverse dynamic interactions critical for microgrids' stability and safety. Furthermore, a more profound issue is the static parameter assumption prevalent in existing models. In fact, parameters are intrinsically dynamic, varying with SOC, SOH, and ambient conditions. This gap renders many high-fidelity models inaccurate in practice, underscoring the urgent need for adaptive models with embedded real-time parameter identification, particularly for the fluctuating operational situations in microgrids.

While data-driven methods [47–49] are increasingly applied, their "black-box" nature and poor generalizability under shifting operational regimes limit their reliability for safety-critical microgrid control. The future modeling lies in mechanism-data fusion, such as DT and PINN, which offers a promising path by embedding physical laws into learning architectures and enhances interpretability and robustness against parameter variations. On the other hand, as HESS models grow in complexity to incorporate multi-physics dynamics, adaptive parameters, and hybrid AI mechanisms, computational tractability becomes a key bottleneck for real-time microgrid management. Future research must explicitly address this accuracy-computation trade-off, developing hierarchical or reduced-order modeling strategies that preserve essential dynamics for control assessment without prohibitive computational cost [67]. Furthermore, the absence of standardized benchmarks and publicly available datasets collected under representative microgrid conditions makes it difficult to fairly evaluate and compare different modeling approaches.

To make the aforementioned future trends more feasible, four research frameworks are discussed. For multi-physics modeling, co-simulation frameworks with clearly defined coupling interfaces, such as electric power exchange and heat flux, should be established to enable systematic cross-domain validation. For adaptive parameter identification, online update mechanisms incorporating physics-informed constraints should be implemented, with PINN-based and DT-based methods serving as promising candidates given their superiority in industrial process control applications [68–70]. For reduced-order real-time modeling, future work should systematically benchmark sampling rate, computation budget, and model accuracy across different control timescales to ensure practical implementation. For standardized benchmarking, publicly available HESS datasets with unified test protocols covering multi-component interactions and long-term aging under representative microgrid conditions should be developed to enable rigorous cross-method comparison.

4. Control strategies

Building upon the high-fidelity modeling techniques, which accurately capture the multi-physics and non-linear dynamics of heterogeneous storage devices, the next critical step is active system management. While accurate mathematical representation is foundational, it is the control framework that translates these models into practical performance. The operation of HESS within a microgrid is complex, as the widespread adoption of RESs and non-linear loads introduces severe power fluctuations and transient disturbances. To safely manage the interacting dynamics of the models, the applied control strategies must exhibit exceptionally fast response, high reliability, and strong robustness. Conventional linear controllers, such as standard PID, typically lack the bandwidth and adaptability to handle these non-linearities or to fully leverage the detailed system states captured by advanced models. Therefore, the implementation of advanced control architectures is imperative. In this section, rule-based, optimization-based, and hybrid control approaches are reviewed, outlining their basic operation principles and how they address the challenges posed by HESS applications.

4.1. Rule-based control

Rule-based control strategies are fundamental and highly effective approaches for managing the dynamics of HESS. Unlike conventional linear controllers, these methods are designed around predefined mathematical rules, structural boundaries, or dynamics governed by state errors that force the system to follow a desired trajectory, regardless of external perturbations. In the context of microgrids, HESS converters must constantly manage varying renewable energy inputs, fluctuating loads, and internal parameter variations. By systematically addressing system non-linearities through techniques like defined sliding surfaces, cascaded virtual control laws, or real-time disturbance observation, these methods ensure reliable power tracking and bus voltage stability. To provide a comprehensive understanding of these robust methodologies, this paper will discuss the following three control methods in detail: A. Sliding Mode Control, B. Backstepping Control, and C. Active Disturbance Rejection Control.

A. Sliding mode control

SMC is a robust, variable structure nonlinear control technique that is highly favoured in both industry and academia due to its simplicity and ease of implementation. The core concept of SMC involves designing a control law that drives the system state to reach and maintain a predefined sliding mode surface, which corresponds to the desired system dynamics defined by the designer [71]. For a simple first-order system, the design procedure of SMC can be described as follows:

$$\begin{cases} e = x - x^* \\ u = 0.5[1 + \mathrm{sign}(s)] \end{cases} \tag{11}$$

where s is the sliding surface, and it can be calculated with a proportional form as $s = Ke$ and K represents the sliding coefficient to be designed. u is the system input signal.

In [72], an SMC-based method utilizing a hyperbolic tangent function was proposed for HESS to overcome the chattering problem caused by highly nonlinear feedback and mitigate oscillations resulting from control delays. Furthermore, in [73], a finite-time SMC method was proposed for the buck converter of HESS, where lumped disturbance estimations were integrated into the designed sliding mode surface to alleviate the impact of mismatched disturbances. The finite-time SMC method was further improved by using coordinate transformation and a second-order sliding mode observer, further enhancing its performance in HESS applications [74].

B. Backstepping control

The backstepping control (BC) method is one of the most efficient nonlinear techniques for HESS, especially when the system can be decomposed into subsystems with cascaded dynamics [75], as shown in Fig. 8. The whole system is stabilized by designing a control law for each subsystem in a step-by-step manner. Bi-directional DC-DC converters, commonly used as the interface for HESS, allow the 2nd-order system model to be transformed into a standard form:

$$\begin{cases} \dot{x}_1 = x_2 + d_1 \\ \dot{x}_2 = v + d_2 \end{cases} \tag{12}$$

where v is the intermediate control law to be designed in the subsequent steps, d_1 and d_2 are uncertainties to be estimated. The coordinate transformation is determined as:

$$\begin{cases} z_1 = x_1 - x_1^* \\ z_2 = x_2 - x_2^* \end{cases} \tag{13}$$

Considering the Lyapunov function $V_1 = 0.5z_1^2$, x_2^* can be designed as:

$$x_2^* = -K_1 z_1 + \dot{x}_1^* - d_1 \tag{14}$$

Considering the Lyapunov function $V_1 = 0.5z_1^2 + 0.5z_2^*$, the intermediate control law can be obtained:

$$v = -K_2 z_2 - d_2 + \ddot{x}_1^* - K_1(z_2 - K_1 z_1) \tag{15}$$

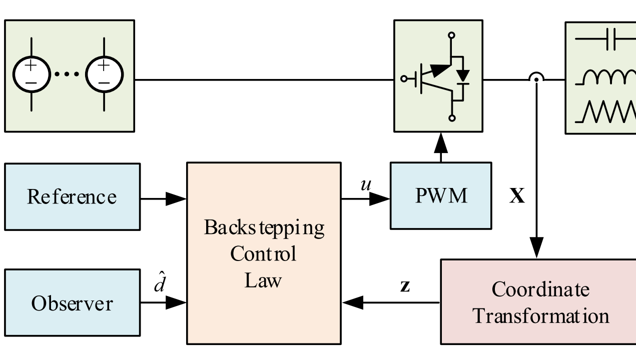

Fig. 8. Diagram of BC implementation.

The input duty ratio of the bidirectional DC-DC converter can be transformed from the intermediate control law as:

$$u = 1 - \left(\frac{E^2}{L} + \frac{2V_{bus}^2}{R^2C} - v\right) \Big/ \left(\frac{EV_{bus}}{L} + \frac{2I_L V_{bus}}{RC}\right) \tag{16}$$

where R, C, and L are nominal circuit parameters. E and $V_{bus}$are input and output voltage, respectively, and I_L is the inductor current.

In [76], to make the estimated disturbance more comprehensive, the effects of both matched and mismatched uncertainties, as well as parameter variations, are simultaneously considered during the HESS modeling phase. In addition, the integration of a second-order differentiator into the virtual control laws further enhances the system's dynamic performance. In [77], an improved BC method was proposed for HESS, where a sliding mode surface and a higher-order sliding mode observer are adopted in the control law to achieve finite-time convergence and fast dynamic response. However, the BC method has the drawback of a high computational burden, which limits its industrial applicability.

C. Active disturbance rejection control

Active disturbance rejection control (ADRC) is a nonlinear control method similar to PID mathematically. As shown in Fig. 9, the ADRC uses an extended state observer (ESO) to estimate system disturbances, which are then compensated in the control law. The ADRC control law can be summarized as:

$$\begin{cases} e_1 = y^* - z_1 \\ u_0 = Ke_1 \\ u^* = (u_0 - z_2)/b_0 \end{cases} \tag{17}$$

where y^* is the reference signal, K and b_0 are the control parameters. z_1 and z_2 are internal states to be estimated by the ESO as follows:

$$\begin{cases} e_2 = z_1 - y \\ \dot{z}_1 = \dot{z}_2 - \beta_1 e_1 + b_0 u^* \\ \dot{z}_2 = -\beta_2 \mathrm{fal}(e_1, \alpha, \delta) \end{cases} \tag{18}$$

where β_1 and β_2 are observer gains. The nonlinear function fal(·) is expressed as:

$$\mathrm{fal}(e_1, \alpha, \delta) = \begin{cases} \frac{e_1}{\delta^{1-\alpha}}, |e_1| \le \delta \\ |e_1|^\alpha \mathrm{sign}(e_1), |e_1| > \delta \end{cases} \tag{19}$$

where $\alpha \in (0, 1)$ is tuneable control parameter related to the convergence of ESO and δ is a small value usually selected equal to the sampling time. In [78], a centralized ADRC method was proposed for HESS in electric vehicles. However, the aforementioned studies related to ADRC only consider resistive loads. In [79], a decentralized ADRC method was proposed for DC microgrid feeding CPLs with a simple control law design while achieving performance comparable to existing large-signal stable methods.

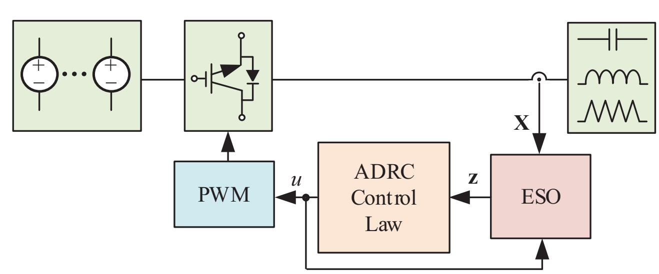

Fig. 9. Diagram of ADRC implementation.

4.2. Optimization-based control

While the rule-based control strategies provide robust and fast transient responses to handle non-linear disturbances, they generally operate reactively and lack the capability to optimize long-term system performance. In modern microgrid applications, controlling HESS is rarely just about maintaining immediate stability. It also involves juggling multiple operational constraints, such as minimizing conversion losses, extending battery lifespan, and optimizing dynamic power sharing. To address these multi-objective requirements, optimization-based control strategies have become increasingly essential. To explore how these predictive algorithms enhance HESS efficiency and robustness, this section reviews two prominent optimization-based methods: model predictive control (MPC) and deadbeat control.

MPC is a powerful control strategy and is widely used in both industry and academia. A general MPC diagram is shown in Fig. 10. It is shown that the key idea of MPC is to predict future behaviours of the controlled system based on a state-space model and compute the optimal control signals by minimizing a cost function [80]. A general cost function is expressed as follows:

$$J=\frac{1}{2}\int_{0}^{T}\left(\|\mathbf{y}^{p}-\mathbf{y}^{*}\|^{2}+\|\mathbf{u}\|^{2}\right)dt \tag{20}$$

where $\mathbf{y}^p$ and $\mathbf{y}^*$ are output predictions and reference outputs relatively, and $\mathbf{u}$ is the input of the controlled system.

MPC predicts system behaviours based on a state-space model, and the duty ratio is generated as the input of the controlled system. Generally, MPC is classified into continuous and discrete types, both of which share similar state-space model forms. Take the discrete system as an example, the state-space model is expressed as:

$$\begin{cases}\mathbf{x}(k+1)=\mathbf{A}\mathbf{x}(k)+\mathbf{B}\mathbf{u}(k)\\ \mathbf{y}^{p}(k+1)=\mathbf{C}\mathbf{x}(k+1)+\mathbf{D}\mathbf{u}(k)\end{cases} \tag{21}$$

where $\mathbf{x}$ and $\mathbf{y}$ represent the instantaneous states and outputs of the controlled system at either the k-th or $(k+1)$-th time instant. $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, and $\mathbf{D}$ represent the system parameter matrices.

A composite MPC-based decentralized dynamic power-sharing strategy is proposed for HESS in [81]. Through transferring the HESS model to a standard feedback model, a coordinate scheme is developed for HESS by integrating MPC and virtual resistance/capacitance droop control. The main goal of HESS control is to maintain the bus voltage balance and reduce the imbalance of supply and demand power. However, with increasing concern about HESS lifespan and power loss, more constraints are considered in MPC to obtain the desired performance. In [82], a multi-objective MPC strategy based on linear parameter-varying HESS models was developed to optimally split the load current, thereby reducing energy losses and battery degradation. Whereas in [83], a dual-layer MPC method was proposed to govern HESS charging/discharging. The primary layer MPC controls converter states, while the secondary layer utilizes predicted currents and optimized signals to forecast dynamic power loss, ultimately generating the power reference to achieve efficient control.

Deadbeat control is another online optimization-based method. The main idea of deadbeat control is to make control signals reach the reference values in one control cycle. Thus, improved robustness can be achieved [83]. In [84], a deadbeat voltage controller is proposed for HESS to achieve fast dynamics, simple design, and high accuracy where the HESS current reference is calculated by an energy conservation equation between inductors and capacitors, as shown in Fig. 11. Furthermore, the power loss of converters is considered in the deadbeat controller's energy equation to improve the accuracy [85].

4.3. Hybrid control method

Rule-based methods deliver robust transient responses, while optimization-based methods manage long-term and multi-objective goals. However, single-type control methods that are only based on rules or optimization may not be able to cope with every aspect of HESS or the complicated operation situations. Therefore, hybrid control methods have been developed to achieve improved performance across multiple aspects. To briefly outline the recent advancements in this area, this paper will elaborate from the following perspectives: A. Hybrid Rule-based Method and B. Hybrid Rule and Optimization Method.

A. Hybrid rule-based method

In [86], an L2 gain disturbance attenuation technique is integrated with passivity-based control to guarantee fast response, high performance, and asymptotic stability. In [87], a dual fuzzy logical controller combined with an MPC scheme is proposed to improve the energy economy and lifespan of HESS, where the input of the fuzzy logical controller is the required power prediction, and the output is the power allocation result.

B. Hybrid rule and optimization method

It is noteworthy that control parameters of rule-based methods can be optimized to further improve control performance. With a reward function defined by the sum of voltage output errors, the study in [88] utilizes a deep deterministic policy gradient (DDPG) reinforcement learning (RL) algorithm to adaptively tune the gains of an ADRC controller, as shown in Fig. 12. Different from tuning the control gains, an adaptive compensator using DDPG is proposed to compensate the control signal of the model-independent controller to improve the robustness and eliminate observer estimation error in [89].

4.4. Comparison of different control methods of HESSs

The implementation of control strategies for HESS in microgrids

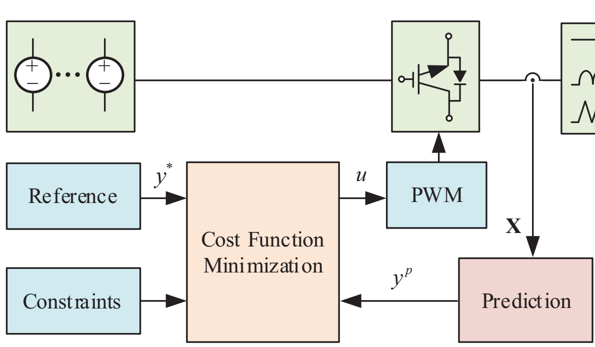

Fig. 10. Diagram of MPC implementation.

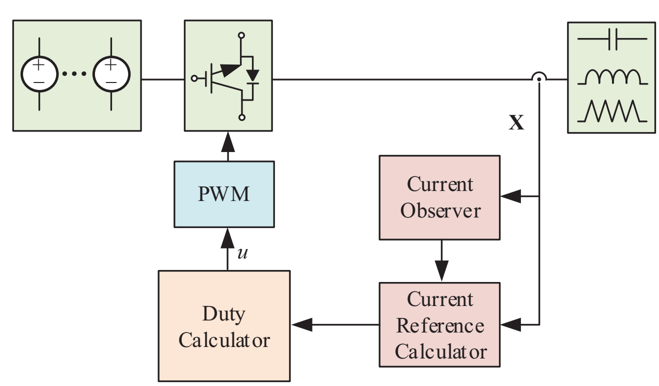

Fig. 11. Diagram of deadbeat control implementation.

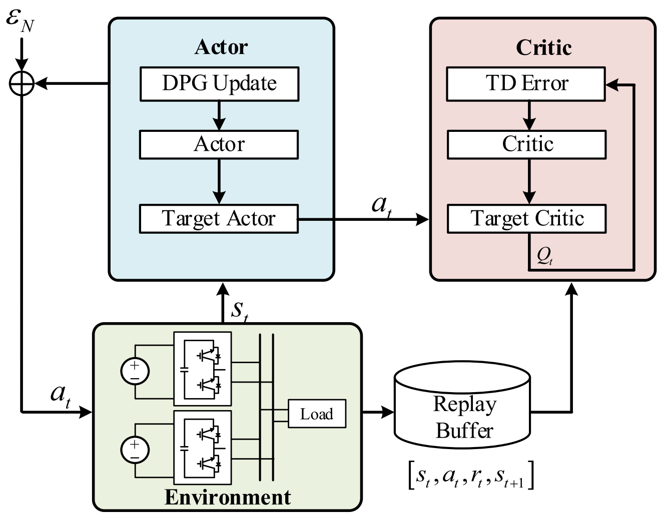

Fig. 12. Diagram of RL implementation.

requires a delicate balance among transient response speed, computational overhead, and resilience against system uncertainties. Unlike the main power grid, microgrids are low-inertia systems susceptible to renewable energy intermittency and sudden load variations. Consequently, selecting an appropriate control scheme is a critical determinant of system stability. Table 3 presents a comparison of the above discussed control strategies, evaluating their complexity, robustness, and reliability.

A critical analysis of these methods reveals trade-offs between theoretical optimality and practical reliability in microgrid deployments. Optimization-based strategies, particularly MPC and deadbeat control, are good at handling multi-objective constraints. However, their reliability is strictly bound to the accuracy of the mathematical models. In a microgrid environment, the intrinsic parameters of HESS components continuously drift due to aging and thermal variations. If the predictive model fails to adapt to these drifts, the control performance deteriorates rapidly. Furthermore, the calculations required by MPC over a receding horizon impose a heavy computational burden on the low-cost digital signal processors (DSPs) typically used in microgrid converters, thereby limiting their application in high-frequency switching scenarios.

In contrast, nonlinear rule-based controllers offer superior robustness against unmodeled dynamics. SMC provides excellent transient tracking with minimal computational effort, yet its inherent chattering phenomenon introduces high-frequency oscillations that can accelerate the degradation of energy storage devices. While BC mitigates some of these oscillatory issues through rigorous Lyapunov-based step-by-step design, its cascaded derivation process becomes mathematically difficult and computationally heavy for complex HESS topologies. Among the rule-based paradigms, ADRC emerges as a highly practical alternative for microgrids with HESS. By actively estimating and compensating for both internal parameter variations and external load disturbances through an extended state observer, ADRC achieves high reliability with low model dependency.

Despite the individual merits of these foundational techniques, the increasing complexity of modern microgrids has catalyzed the development of hybrid and AI-assisted control frameworks. These advanced configurations theoretically leverage the robustness of nonlinear control and the adaptivity of machine learning. Nevertheless, a major implementation barrier persists: AI algorithms, such as reinforcement learning, fundamentally lack rigid mathematical proofs for bounded stability under extreme conditions. Until these hybrid architectures can mathematically guarantee safety during transient events, their deployment will remain restricted to secondary energy management layers rather than the high-frequency converter-level control.

Table 3
Comparison of Different Control Methods for HESSs in Microgrids.

Reference	Control Strategy	Computational & Design Complexity	Robustness to Disturbances	Model Dependency (Reliability)
[56–59]	SMC	Low	High	Low
[60–62]	BC	High	High	Medium
[63–64]	ADRC	Medium	Very High	Very Low
[65–68]	MPC	Very High	Medium to High	Very High
[69–70]	Deadbeat Control	Medium	Medium	Very High
[71–74]	Hybrid / AI-Assisted Control	Very High	Very High	Low to Medium

4.5. *Future trends*

The evolving complexity of microgrids, resulting from high-penetration power electronics and dynamic loads, exposes significant limitations in current HESS control paradigms. Even though the integration of the aforementioned rule-based, optimization-based, and data-driven methods is often proposed, the fusion remains largely conceptual. For example, using an artificial neural network to emulate an MPC controller [90] addresses computational latency but inherits the original model's inaccuracies and offers no interpretability for safety validation. Similarly, while RL promises model-free optimization [91,92], its training inefficiency and lack of safety guarantees during exploration hinder its direct application in real-time HESS operation. One promising direction is the development of physics-informed learning controllers, which adopt known system dynamics as constraints within data-driven models to enhance their interpretability and safety. Furthermore, employing DT environments for extensive offline training and real-time validation of hybrid control strategies can bridge the gap between conceptual proposals and field-ready solutions. This approach ensures that advanced controllers are rigorously tested under a wide range of microgrid contingencies before the deployment of HESS.

Another fundamental flaw of existing works is the prevailing reliance on centralized control architectures [79]. These schemes create failures due to communication reliability and cyber-physical security, which are unacceptable for resilient microgrids. Distributed and decentralized control schemes, enabled by sparse communication networks, offer a compelling alternative by enhancing robustness and enabling plug-and-play functionality. However, the implementation of HESS in microgrids faces several challenges, including the design of consensus protocols that reconcile heterogeneous storage device dynamics, the assurance of stability, and the cybersecurity mechanisms. Key research directions include fault-tolerant control, stability evaluation under delays or packet loss [93], and cybersecurity mechanisms, such as attack detection and diagnosis [94,95].

Three promising research frameworks are introduced to make the aforementioned future directions more actionable. For controller design under non-ideal sources, HESS model dynamics should be explicitly integrated into controller design and stability analysis, considering performance evaluation conducted under intermittent renewable generation and disturbances induced by converters. For safe and explainable learning-based controllers, future work should focus on physics-informed learning frameworks with online safe boundary estimation, providing quantified stability and clear explainability to address the interpretability gap that currently restricts learning-based controllers from converter deployment. For resilient distributed control, future work should develop fault-tolerant consensus protocols and cybersecurity mechanisms that can handle concurrent communication impairments and cyber-attacks, evolving from individual point solutions toward an integrated design of communication, control, and safety.

5. Safety

While the advanced control strategies are vital for managing power flow, optimizing efficiency, and maintaining the electrical stability of a HESS, they inherently operate within the cyber-physical domain. However, even the most robust and adaptive control algorithms cannot eliminate the risks associated with internal hardware defects, chemical aging, or severe environmental abuse. When operational limits are exceeded or when components physically fail, the system transitions from an electrical control problem to a critical physical safety emergency. In recent years, catastrophic failures have frequently been reported, particularly thermal runaway accidents in battery systems, resulting in severe safety hazards and massive economic losses. Given that lithium-ion and other battery technologies remain the foundational components of most HESS configurations, implementing a rigorous physical safety framework is critical for microgrid resilience. Therefore, physical safety is mainly discussed in this section, with an emphasis on early warning systems for thermal runaway and fire suppression strategies.

5.1. Early warning of thermal runaway

Thermal runaway evolution, as illustrated in Fig. 13, is not an instantaneous event but rather a progressive chain reaction. It advances through distinct phases, with each phase exhibiting specific characteristic signals that can be captured and analyzed to prevent catastrophic failure. As shown in the general early warning framework in Fig. 14, an effective diagnostic system typically consists of three sequential stages. Specifically, characteristic signals are first obtained from sensors, and after data pre-processing of these signals, various algorithms can be used to predict thermal runaway. Because the accuracy, reliability, and response time of these predictive algorithms depend fundamentally on the physical or electrical parameters being monitored, existing early warning methods are heavily defined by their target indicators. To comprehensively review the latest technologies in this critical safety domain, this paper will elaborate on the following three methods: A. Temperature-based Method, B. Electrical-Characteristic-Based Method, and C. Other Methods.

A. Temperature-based method

Temperature is a critical indicator in the early warning of thermal runaway in battery systems [96]. The central controller continuously monitors the temperature and issues an early-warning alert once the threshold is exceeded. Thus, the key to a temperature-based method is to obtain accurate temperature measurements and predictions. Xie et al. [97] enhanced internal temperature estimation by integrating a 1-D

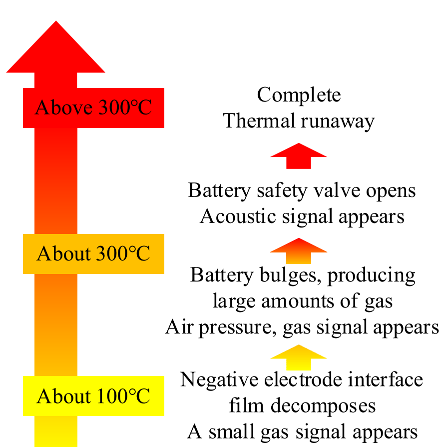

Fig. 13. Simplified diagram of thermal runaway.

model with a dual Kalman filter that concurrently estimates internal resistance and SOC, thereby achieving higher accuracy. Deep learning-based methods can further make temperature estimation more accurate. For example, Li et al. [98] proposed a novel thermal runaway prognosis model for early warning by detecting abnormal heat generation, which integrates LSTM and CNN architectures. The results demonstrated that thermal runaway could be accurately predicted 27 min in advance using their proposed method.

B. Electrical-characteristic-based method

The electrical-characteristic-based methods normally adopt voltage and impedance as two of the most informative and directly measurable indicators.

a) Voltage: Gan et al. [99] devised a two-tier machine-learning strategy for detecting over-discharge, which establishes the residual between measured and predicted voltage as a diagnostic threshold to classify fault severity. Complementing this, Li et al. [100] formulated a diagnostic technique that fuses an LSTM network with an equivalent circuit model, employing modified adaptive boosting to enhance accuracy and a pre-judging module to boost computational efficiency and reliability. Separately, Xiong et al. [101] conceived a novel two-step ECM capable of discriminating between polarization-induced voltage changes and abrupt drops from high current, subsequently deriving an online diagnostic framework for external short circuits in battery packs from this model.

b) Impedance: Impedance serves as a critical battery parameter, varying with factors such as SOC and temperature. It is widely utilized for remaining useful life assessment, state-of-health estimation, performance testing, and abnormality detection [102]. In a related diagnostic study, Lyu et al. [103] observed that the slope of dynamic impedance within the 30–90 Hz frequency band shifts from negative to positive as the cell initiates overcharging. Accordingly, the authors developed a theoretical explanation that can be used as an indicator of overcharge-induced thermal runaway accidents. Li et al. [104] proposed a three-stage thermal runaway warning method using impedance and phase angle, which overcomes the shortcomings of existing warning methods based on traditional signals with reduced time delay and low cost.

C. Other methods

The sound of gas generation is an important indicator of faults and thermal runaway. Lyu et al. [105] introduced an innovative acoustic-based method for battery fault warning and localization, achieving precise cell identification with a maximum error of 0.1 m using just four sensors placed at the corners of the storage cabin. Beyond acoustic signals, gas concentration serves as a key failure indicator. Cai et al. [106] employed a non-dispersive infrared CO_2 sensor to monitor exhaust gases during overcharging, setting the volume-averaged CO_2 concentration in the vent channel as the detection threshold upper limit. Separately, Jin et al. [107] created a highly sensitive detection technique based on H_2 gas produced from reactions between metallic lithium and polymer binders. Capturing this H_2 gas can fully suppress lithium dendrite growth without smoke or fire, offering an effective strategy for early safety warning. Recently, ultrasound has shown the potential as a promising technique for battery condition monitoring. Appleberry et al. [108] devised a detection scheme utilizing ultrasound to identify physical alterations in Li-ion cells under conditions linked to thermal runaway. Despite the high sensitivity and reliability of such ultrasonic alarm methods, their industrial adoption is primarily hindered by sensor size and expense. In a different approach, Zhang et al. [109] created a vision-based algorithm to identify swelling faults within battery packs. This method merges deep learning with image processing to enable high-accuracy detection of incipient internal defects, offering an early-warning function that surpasses the capabilities of standard BMS monitoring. Hou et al. [110] proposed a fault warning and localization

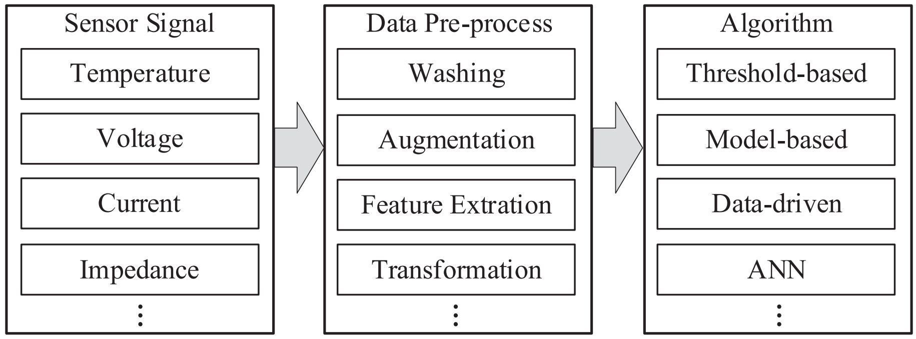

Fig. 14. Diagram of early warning of thermal runaway.

method for lithium-ion batteries by laser signal analysis, which detects and pinpoints thermal runaway through the phase shift of laser beams obstructed by vaporized electrolyte, enabling early intervention before catastrophic failure occurs.

5.2. Fire suppression strategy

While the early warning mechanisms are crucial for detecting precursor anomalies and attempting to halt thermal runaway in its nascent stages, they cannot eliminate the possibility of a catastrophic failure. To effectively manage the fire risks of HESS, a combination of targeted suppression strategies is essential. These approaches address different stages of thermal runaway, from early detection to final containment. Current research focuses on five key directions: precise point-source extinguishing using fire detection tubes, synergistic agent combinations for enhanced effectiveness, intermittent spray techniques for improved cooling, innovative microcapsules for in-situ response, and post-suppression ventilation to prevent secondary hazards. Each method offers specific advantages in speed, efficiency, or system integration. To systematically review the recent developments in active firefighting for microgrid HESS applications, this paper will elaborate on the following key perspectives in detail: A. Fire Detection Tube Technology, B. Collaborative Fire-Extinguishing Method, C. Intermittent Spray, D. Suppression Microcapsule, and E. Ventilation and Explosion Suppression.

A. Fire detection tube technology

The deployment of fire detection tubes enables effective battery fire identification and localized extinguishment, thereby minimizing damage. The mechanism involves the tube fracturing at a predetermined temperature, which allows the pressurized extinguishing agent to be discharged through the opening for precise firefighting [111]. Experimental work by Liu et al. [112] demonstrated that positioning the tube 60 mm above a battery readily achieves successful fire suppression. Battery fire suppression experiments are also conducted in [113] under different water consumption and driving pressure. The results show that the fire detection tube material can respond to the battery's thermal runaway quickly, release extinguishing agents, suppress gas production and combustion, and cool the battery rapidly. Therefore, once the extinguishing material and tube position are set properly, the fire detection tube can detect and suppress the fire effectively.

B. Collaborative fire-extinguishing method

Due to the inherent limitations of individual extinguishing agents, a single agent is often insufficient for effective battery fire suppression, making a multi-agent synergistic formulation a preferable strategy. Zhang et al. [114] developed a novel method combining a gaseous agent with water mist to assess their synergistic effect, finding it superior to any single agent. In parallel, Yao et al. [115] presented an approach integrating $C_6F_{12}O$ with water mist to curb thermal runaway propagation. Their experiments confirmed that $C_6F_{12}O$ coupled with intermittent water mist spraying provided optimal cooling, markedly reduced peak temperature, and delivered the highest level of heat suppression.

C. Intermittent spray

Currently, the intermittent spray technique functions as an active flow control method aimed at enhancing cooling efficiency, a practice frequently employed for heat dissipation in electronic components and thermal management systems [116]. Research in [117] assessed the fire-suppression and cooling capabilities of this technique across various operational modes, concluding that the intermittent strategy delivers a more potent suppression effect than continuous water spray and is highly effective at preventing thermal runaway propagation. In comparison to continuous spray cooling, the intermittent approach offers dual benefits, i.e., it not only prolongs the duration of low-temperature conditions but also significantly mitigates the rate of temperature increase within the battery.

D. Suppression microcapsule

In [118], the authors introduced an in-situ suppression strategy utilizing a self-contained microcapsule extinguishing agent for lithium-ion batteries. This method effectively suppresses flame in ternary batteries while maintaining temperatures below 130 °C. Furthermore, the strategy features autonomous early detection and response at the onset of thermal runaway, enabling it to act directly on the faulty cell within the battery pack and effectively inhibit both the initiation and propagation of thermal runaway. In a complementary development, Guo et al. [119] developed a novel core-shell structured solid-liquid composite fire-extinguishing powder. Results from fire suppression, pyrolysis, and characterization experiments elucidate the physicochemical synergistic inhibition mechanism of the microcapsules, providing effective countermeasures for preventing hydrogen-related safety incidents.

E. Ventilation and explosion suppression

Providing ventilation and explosion prevention measures after extinguishing a battery thermal runaway is crucial for avoiding secondary incidents, ensuring safety, and reducing environmental hazards [120]. Liu et al. [121] investigated the cooling characteristics and combustion inhibition capability of batteries under three typical active control modes for the venting port. Their findings indicate that active vent control effectively retains the cooling energy of the gasified refrigerant, thereby substantially improving the cooling capacity, temperature uniformity, and oxygen suppression effect of emergency spray cooling compared to non-active control. In a separate study, Liu et al. [122] performed thermal runaway experiments in both open and confined environments. The results demonstrate that confined spaces accumulate a greater volume of combustible gases and present a higher risk of deflagration. Additionally, the minimum fresh air renewal rate was calculated to offer quantitative guidance for ventilation, firefighting, and rescue operations. Complementing these experimental studies, Wang et al. [123] introduced a novel multi-scale model that simulates the multiphase processes during battery venting, encompassing the complete chain of chemical reactions and physical transformations in thermal runaway. This model provides new insights for advancing battery thermal safety and venting system design.

F. Synergistic strategy of spray, suppression, and ventilation

While individual fire mitigation techniques exhibit specific advantages, their isolated application is often insufficient for managing the complex, multi-stage hazards of battery thermal runaway. Consequently, a cooperative strategy that dynamically coordinates spray cooling, chemical fire suppression, and active ventilation is essential for comprehensive HESS safety. During the initial temperature anomaly and off-gassing phase, intermittent water spray and localized in-situ suppression should be deployed early to absorb sensible heat and inhibit further cell degradation. Concurrently, active ventilation must operate at a moderate rate to extract early combustible gases without excessively diluting the localized extinguishing agents. As thermal runaway escalates into active combustion, the primary objective shifts to rapid extinguishment. A collaborative multi-agent suppression strategy must be aggressively deployed to smother the fire, during which ventilation must be temporarily restricted to maintain the effective suppressant chemical concentration and prevent oxygen influx. Finally, in the post-suppression phase, intermittent spray is maintained to extract residual deep-seated heat and prevent reignition. Simultaneously, the ventilation system should operate at maximum capacity to exhaust accumulated explosive mixtures, driving the confined environment below the lower flammability limit and ensuring overall safety against secondary deflagration.

5.3. Safety-by-design approaches

Safety-by-design complements early warning and fire suppression by embedding preventive and propagation-resistant measures at the cell, module, system, and site levels. The goal is to reduce both the likelihood and the consequences of thermal runaway in HESS. At the cell level, inherently safer chemistries reduce runaway propensity and the violence of failure. At the module level, recent studies show that properly engineered thermal barriers and interlayers can measurably delay or suppress thermal runaway propagation, such as aerogel felt coupled with flame-retarded PCM [124], and the sensitivity of barrier properties and critical thresholds [125]. Moreover, since sustained high temperature accelerates degradation and can move cells closer to thermal runaway, thermal management system design can be essential for reducing initiation risk and limiting escalation when abnormal heat generation occurs [126]. At the system and site level, safety-by-design requires fault isolation and rapid shutdown, physical segregation from other hazards, and engineered gas management. A recent NREL case study further demonstrates practical site-level measures, including enhanced deflagration venting, increased separation distances, gas detection thresholds at early warning levels, and high ventilation rates [127].

5.4. Future trends

Current safety research for HESS predominantly follows a reactive paradigm, focusing on symptom detection and local suppression [111,116,120]. To achieve safety integration, future efforts are better to shift toward predictive and systemic approaches. In early warning, reliance on fixed thresholds for parameters like temperature or voltage is fundamentally limited, as alarms often trigger only after irreversible internal reactions have begun. Recent innovations have begun to bridge this gap by detecting subtle physical precursors that precede critical electrical or thermal changes, with more advanced techniques such as vision [109] and laser [110]. These examples highlight the critical direction for future research: the development of ultra-early prognostic models that fuse multi-physics mechanisms with real-time data to identify precursor anomalies long before critical thresholds are breached, enabling predictive maintenance rather than last-minute alarms.

Regarding fire suppression, the development of more effective and environmentally benign agents remains important, but a greater challenge lies in designing system-level suppression strategies for heterogeneous storage systems in HESS. Consequently, the critical research gap is the absence of comprehensive, integrated fire suppression frameworks specifically designed for HESS. Future work, therefore, moves beyond technology-specific validation to establish hybrid-oriented protocols. Moreover, the safety of HESS must evolve from a physical concern to a cyber-physical co-design challenge. The integration of IoT and remote control exposes HESS to cyber-attacks, which can directly induce physical safety failures. Therefore, future research works are suggested to develop control frameworks that simultaneously embed physical safety constraints and cybersecurity mechanisms, creating a unified defense-in-depth strategy for next-generation smart microgrids.

Based on the above discussion, three future research frameworks are suggested. For ultra-early warning, future work should develop prognostic models that integrate multi-physics sensing modalities, including mechanical, optical, and acoustic signals, into unified anomaly detection architectures, building upon emerging vision-based [109] and laser-based diagnostic techniques [120] to identify precursor signatures well before conventional threshold-based alarms are triggered. For HESS-level suppression protocols, future studies should establish hybrid-oriented frameworks covering suppression agent compatibility across different ESS types, coupled modeling of heat and gas dispersion and propagation, and device-specific response systems incorporating isolation, shutdown, ventilation, and suppression sequencing. For cyber-physical safety cooperative design, future work should develop unified control frameworks that jointly enforce physical safety constraints and cybersecurity mechanisms, including attack detection, resilient communications, and fault mitigation, where adversarial learning-based frameworks represent a particularly promising research direction.

6. Conclusion

This article provides a comprehensive review of HESS technologies, covering various types, including battery-SC, battery-SMES, battery-CAES, battery-fuel cell, CAES-hydrogen, and RFB-flywheel systems, etc.. For the modeling aspect, conventional mechanism-based, data-driven, and mechanism-data fusion modeling methods are reviewed. In terms of control, advanced rule-based, optimization-based, and hybrid control methods are reviewed. Moreover, the safety of HESS, including early warning and fire suppression strategies, is reviewed. Future trends of the aforementioned aspects are highlighted at the end of the respective section, offering a holistic understanding of HESS development and potential research directions.

Different from other reviews that are limited to the ESS types, characteristics, control, and topologies, this article provides a new perspective to analyze HESS. Thus, the main contribution of this work is that it not only highlights new types of HESSs, advanced modeling methods, and control strategies but also considers the safety issues to give a comprehensive overview of HESS implementation. This review has proposed important and selective suggestions for further development of HESSs in microgrid applications:

1) Considering cost and profit maximization, the type and scale of HESSs should be properly adjusted and planned according to the local conditions. Moreover, research works are required to deeply

explore the characteristics and potentialities of emerging ESS technologies.
2) Mechanism-data fusion modeling, which combines the advantages of mechanism models and data-driven methods, is a promising technology for achieving the accurate modeling of HESS behaviours. However, the balance between the performance and the computation burden should be studied in the future.
3) Rule-based methods and AI-based control methods can be further combined effectively to maximize their advantages for HESS, aiming to improve microgrids' stability and scalability.
4) Ultra-early warning of thermal runaway and predictive maintenance technologies are required to further improve the safety of HESS. Furthermore, cyber-attacks can lead to severe accidents of HESS in microgrids. Adversarial threat models, attack detection, and mitigation strategies should be developed in the future.

CRediT authorship contribution statement

Benfei Wang: Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Xinqiang Tang:** Writing – review & editing, Writing – original draft, Formal analysis. **Zhipeng Li:** Writing – review & editing, Writing – original draft, Resources, Formal analysis, Data curation, Conceptualization. **Xibeng Zhang:** Writing – review & editing, Formal analysis, Conceptualization. **Binyu Xiong:** Writing – review & editing, Formal analysis, Conceptualization. **Yang Li:** Writing – review & editing, Formal analysis, Conceptualization. **Zhongbao Wei:** Writing – review & editing, Formal analysis, Conceptualization. **Qianwen Xu:** Writing – review & editing, Supervision, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

References

[1] D. Gielen, F. Boshell, D. Saygin, M. Bazilian, N. Wagner, R. Gorini, The role of renewable energy in the global energy transformation, Energ. Strat. Rev. 24 (2019) 38–50.
[2] M. Uddin, H. Mo, D. Dong, S. Elsawah, J. Zhu, J.M. Guerrero, Microgrids: a review, outstanding issues and future trends, Energ. Strat. Rev. 49 (2023) 101127.
[3] M.A. Hannan, et al., Battery energy-storage system: a review of technologies, optimization objectives, constraints, approaches, and outstanding issues, J. Energy Storage 42 (2021) 103023.
[4] A.A. Kebede, T. Kalogiannis, J. Van Mierlo, M. Berecibar, A comprehensive review of stationary energy storage devices for large scale renewable energy sources grid integration, Renew. Sust. Energ. Rev. 159 (2022) 112213.
[5] T.B. Nkwanyana, M.W. Siti, Z. Wang, I. Toudjeu, N.T. Mbungu, W. Mulumba, An assessment of hybrid-energy storage systems in the renewable environments, J. Energy Storage 72 (2023) 108307.
[6] R. Yang, et al., Comparative study on the thermal characteristics of solid-state lithium-ion batteries, IEEE Trans. Transportation Electrification 10 (1) (2023) 1541–1557.
[7] I. Sarbu, C. Sebarchievici, A comprehensive review of thermal energy storage, Sustainability 10 (1) (2018) 191.
[8] X. Zhang, et al., Advanced compressed air energy storage systems: fundamentals and applications, Engineering 34 (2024) 246–269.
[9] I.H. Sarker, AI-based modeling: techniques, applications and research issues towards automation, intelligent and smart systems, SN computer science 3 (2) (2022) 158.
[10] X. Zhang, B. Wang, U. Manandhar, H. Beng Gooi, G. Foo, A model predictive current controlled bidirectional three-level DC/DC converter for hybrid energy storage system in DC microgrids, IEEE Trans. Power Electron. 34 (5) (2019) 4025–4030.
[11] A. Jafarian, F. Ferdowsi, Sliding mode control enabled hybrid energy storage system for islanded dc microgrids with pulsing loads, Sustain. Cities Soc. 73 (2021) 103117.
[12] Q. Xu, N. Vafamand, L. Chen, T. Dragičević, L. Xie, F. Blaabjerg, Review on advanced control Technologies for Bidirectional DC/DC converters in DC microgrids, IEEE Journal of Emerging and Selected Topics in Power Electronics 9 (2) (2021) 1205–1221.
[13] E. Mohammadi, M. Alizadeh, M. Asgarimoghaddam, X. Wang, M.G. Simões, A review on application of artificial intelligence techniques in microgrids, IEEE Journal of Emerging and Selected Topics in Industrial Electronics 3 (4) (2022) 878–890.
[14] W. Peng, Q. Chen, U. Manandhar, B. Wang, J. Rodriguez, Event-triggered model predictive control for the inverter of a grid-connected microgrid with a battery-supercapacitor HESS, IEEE Journal of Emerging and Selected Topics in Power Electronics 11 (6) (2023) 5540–5552.
[15] J. Hou, Z. Song, H.F. Hofmann, J. Sun, Control strategy for battery/flywheel hybrid energy storage in electric shipboard microgrids, IEEE Trans. Industrial Informatics 17 (2) (2021) 1089–1099.
[16] Y. Liu, et al., Review on modeling and control of megawatt liquid flow energy storage system, Energy Rep. 9 (2023) 113–123.
[17] M.K. Behera, L.C. Saikia, A novel resilient control of grid-integrated solar PV-hybrid energy storage microgrid for power smoothing and pulse power load accommodation, IEEE Trans. Power Electron. 38 (3) (2023) 3965–3980.
[18] Bouendeu Jean Jacques, et al., Contribution to the improvement of the performances of PV/wind microgrids integrating a hybrid SMES/battery energy storage unit, J. Energy Storage 85 (2024) 111011.
[19] Y. Liu, P. Li, Z. Xing, X. Han, Q. Fu, Z. Jiang, Research on microgrid superconductivity-battery energy storage control strategy based on adaptive dynamic programming, IEEE Trans. Applied Superconductivity 34 (8) (2024) 1–4.
[20] Abdullah G. Alharbi, A.G. Olabi, Hegazy Rezk, Ahmed Fathy, Mohammad Ali Abdelkareem, Optimized energy management and control strategy of photovoltaic/PEM fuel cell/batteries/supercapacitors DC microgrid system, Energy 290 (2024) 130121.
[21] Youcef Belkhier, Adel Oubelaid, Novel design and adaptive coordinated energy management of hybrid fuel-cells/tidal/wind/PV array energy systems with battery storage for microgrids, Energy Storage 6 (1) (2024) e556.
[22] Q. Li, X. Meng, F. Gao, G. Zhang, W. Chen, K. Rajashekara, Reinforcement learning energy Management for Fuel Cell Hybrid Systems: a review, IEEE Ind. Electron. Mag. 17 (4) (2023) 45–54.
[23] A.F. Naghibi, E. Akbari, M. Veisi, et al., Capabilities of battery and compressed air storage in the economic energy scheduling and flexibility regulation of multi-microgrids including non-renewable/renewable units, Sci. Rep. 15 (2025) 24856.
[24] Ł. Bartela, A hybrid energy storage system using compressed air and hydrogen as the energy carrier, Energy 196 (2020) 117088.
[25] R. Cao, Y. Wang, W. Li, H. Ni, Y. Duan, Thermodynamics analysis of a hybrid system based on a combination of hydrogen fueled compressed air energy storage system and water electrolysis hydrogen generator, Int. J. Hydrog. Energy 48 (63) (2023) 24492–24503.
[26] P. Zhao, W. Xu, A. Liu, W. Wu, J. Wang, X. Wang, Assessment the hydrogen-electric coupled energy storage system based on hydrogen-fueled CAES and power-to-gas-to-power device considering multiple time-scale effect and actual operation constraints, Int. J. Hydrog. Energy 48 (25) (2023) 9198–9218.
[27] W. Ding, T. Bauer, Progress in research and development of molten chloride salt technology for next generation concentrated solar power plants, Engineering 7 (3) (2021) 334–347.
[28] H. Faraji, Ç. Yıldız, A. Arshad, M. Arıcı, K. Choukairy, M.E. Alami, Passive thermal management strategy for cooling multiple portable electronic components: hybrid nanoparticles enhanced phase change materials as an innovative solution, J. Energy Storage 70 (2023) 108087.
[29] M. Guo, Y. Mu, H. Jia, Y. Deng, X. Xu, X. Yu, Electric/thermal hybrid energy storage planning for park-level integrated energy systems with second-life battery utilization, Advances in Applied Energy 4 (2021) 100064.
[30] Y. Wang, et al., Synergistic planning of an integrated energy system containing hydrogen storage with the coupled use of electric-thermal energy, Int. J. Hydrog. Energy 48 (40) (2023) 15154–15178.
[31] M. Seitz, H. von Storch, A. Nechache, D. Bauer, Techno economic design of a solid oxide electrolysis system with solar thermal steam supply and thermal energy storage for the generation of renewable hydrogen, Int. J. Hydrog. Energy 42 (42) (2017) 26192–26202.
[32] Z. Wang, B. Du, Y. Li, C. Xie, H. Wang, Y. Huang, P. Meng, Multi-time scale scheduling optimization of integrated energy systems considering seasonal hydrogen utilization and multiple demand responses, Int. J. Hydrog. Energy 67 (2024) 728–749.
[33] M. Schönleber, D. Klotz, E. Ivers-Tiffée, A method for improving the robustness of linear Kramers–Kronig validity tests, Electrochim. Acta 131 (2014) 20–27.
[34] M.B. Hossain, M.R. Islam, K.M. Muttaqi, D. Sutanto, A.P. Agalgaonkar, Dynamic electrical circuit modeling of a proton exchange membrane Electrolyzer for

frequency stability, resiliency, and sensitivity analysis in a power grid, IEEE Trans. Ind. Appl. 59 (6) (2023) 7271–7281.
[35] M. He, et al., A generic equivalent circuit model for PEM electrolyzer with multi-timescale and stages under multi-mode control, Appl. Energy 359 (2024) 122728.
[36] B. Wang, D. Xin, Q. Fu, C. Zhang, A control-oriented comprehensive model of PEM electrolyzer considering double-layer capacitance, International J. Hydrog. Energy 93 (2024) 866–877.
[37] J. Tian, R. Xiong, Q. Yu, Fractional-order model-based incremental capacity analysis for degradation state recognition of Lithium-ion batteries, IEEE Trans. Industrial Electronics 66 (2) (2019) 1576–1584.
[38] R. Guo, W. Shen, Lithium-ion battery state of charge and state of power estimation based on a partial-adaptive fractional-order model in electric vehicles, IEEE Trans. Industrial Electronics 70 (10) (2023) 10123–10133.
[39] R. Guo, C. Hu, W. Shen, An adaptive approach for battery state of charge and state of power co-estimation with a fractional-order multi-model system considering temperatures, IEEE Trans. Intelligent Transportation Systems 24 (12) (2023) 15131–15145.
[40] Y. Bensaad, F. Friedrichs, T. Baumhöfer, M. Eswein, J. Bähr, A. Fill, K.P. Birke, Embedded real-time fractional-order equivalent circuit model for internal resistance estimation of lithium-ion cells, J. Energy Storage 67 (2023). Art. no. 107516.
[41] M. Amir, K. Singh, M. Bashir, Optimal frequency control in renewable-dominated multi-microgrids using an integral filtered derivative tilted controller optimised via salp swarm algorithm, Energy Convers. Manage.: X 29 (2026) 101407.
[42] R.R. Richardson, C.R. Birkl, M.A. Osborne, D.A. Howey, Gaussian process regression for in situ capacity estimation of Lithium-ion batteries, IEEE Trans. Industrial Informatics 15 (1) (2019) 127–138.
[43] J. Zeng, Z. Liang, A deep Gaussian process approach for predictive maintenance, IEEE Trans. Reliability 72 (3) (2023) 916–933.
[44] J. Meng, M. Yue, D. Diallo, A degradation empirical-model-free battery end-of-life prediction framework based on Gaussian process regression and Kalman filter, IEEE Trans. Transportation Electrification 9 (4) (2023) 4898–4908.
[45] M.S. Hossain Lipu, et al., Real-time state of charge estimation of lithium-ion batteries using optimized random forest regression algorithm, IEEE Trans. Intelligent Vehicles 8 (1) (2023) 639–648.
[46] S. Jafari, Y.-C. Byun, Optimizing battery RUL prediction of Lithium-ion batteries based on Harris hawk optimization approach using random Forest and LightGBM, IEEE Access 11 (2023) 87034–87046.
[47] L. Ren, J. Dong, X. Wang, Z. Meng, L. Zhao, M.J. Deen, A data-driven auto-CNN-LSTM prediction model for Lithium-ion battery remaining useful life, IEEE Trans. Industrial Informatics 17 (5) (2021) 3478–3487.
[48] J. Zhang, et al., A data-model interactive remaining useful life prediction approach of lithium-ion batteries based on PF-BiGRU-TSAM, IEEE Trans. Industrial Informatics 20 (2) (2024) 1144–1154.
[49] Z. Bao, J. Nie, H. Lin, K. Gao, Z. He, M. Gao, TTSNet: state-of-charge estimation of Li-ion battery in electrical vehicles with temporal transformer-based sequence network, IEEE Trans. Vehicular Technology 73 (6) (2024) 7838–7851.
[50] X. Bian, Z. Wei, W. Li, J. Pou, D.U. Sauer, L. Liu, State-of-health estimation of Lithium-ion batteries by fusing an open circuit voltage model and incremental capacity analysis, IEEE Trans. Power Electronics 37 (2) (2022) 2226–2236.
[51] D. Li, Z. Zhang, P. Liu, Z. Wang, L. Zhang, Battery fault diagnosis for electric vehicles based on voltage abnormality by combining the long short-term memory neural network and the equivalent circuit model, IEEE Trans. Power Electronics 36 (2) (2021) 1303–1315.
[52] X. Hu, H. Yuan, C. Zou, Z. Li, L. Zhang, Co-estimation of state of charge and state of health for Lithium-ion batteries based on fractional-order Calculus, IEEE Trans. Vehicular Technology 67 (11) (2018) 10319–10329.
[53] T. Hu, H. Ma, H. Sun, K. Liu, Electrochemical-theory-guided modeling of the conditional generative adversarial network for battery calendar aging forecast, IEEE Journal of Emerging and Selected Topics in Power Electronics 11 (1) (2023) 67–77.
[54] H. Chen, Z. Zhang, P. Karamanakos, J. Rodriguez, Digital twin techniques for power electronics-based energy conversion systems: a survey of concepts, application scenarios, future challenges, and trends, IEEE Ind. Electron. Mag. 17 (2) (2023) 20–36.
[55] Y. Qin, A. Arunan, C. Yuen, Digital twin for real-time Li-ion battery state of health estimation with partially discharged cycling data, IEEE Trans. Industrial Informatics 19 (5) (2023) 7247–7257.
[56] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, D.U. Sauer, Digital twin for battery systems: cloud battery management system with online state-of-charge and state-of-health estimation, J. Energy Storage 30 (2020).
[57] B. Wu, B. Zhang, C. Deng, W. Lu, Physics-encoded deep learning in identifying battery parameters without direct knowledge of ground truth, Appl. Energy 321 (119390) (2022).
[58] R.G. Nascimento, M. Corbetta, C.S. Kulkarni, F.A. Viana, Hybrid physics-informed neural networks for lithium-ion battery modeling and prognosis, J. Power Sources 513 (230526) (2021).
[59] B. Wang, Z. Ji, Y. Wang, H. Li, Z. Li, A physics-informed composite network for modeling of electrochemical process of large-scale lithium-ion batteries, IEEE Trans. Industrial Informatics 21 (1) (2025) 287–296.
[60] Y. Huang, C. Zou, Y. Li, T. Wik, MINN: learning the dynamics of differential-algebraic equations and application to battery modeling, IEEE Trans. Pattern Anal. Mach. Intell. 46 (12) (2024) 11331–11344.
[61] J. Sun, Y. Liu, J. Kainz, A comparative study of parameter identification methods for equivalent circuit models for lithium-ion batteries and their application to state of health estimation, J. Energy Storage 114 (Part A) (2025) 115707.
[62] M. Schönleber, D. Klotz, E. Ivers-Tiffée, A method for improving the robustness of linear Kramers–Kronig validity tests, Electrochim. Acta 131 (2014) 20–27.
[63] S.M.M. Alavi, A. Mahdi, S.J. Payne, D.A. Howey, Identifiability of generalized Randles circuit models, IEEE Trans. Control Syst. Technol. 25 (6) (2017) 2112–2120.
[64] Y. Che, Z. Deng, X. Lin, L. Hu, X. Hu, Predictive battery health management with transfer learning and online model correction, IEEE Trans. Veh. Technol. 70 (2) (2021) 1269–1277.
[65] R.R. Richardson, M.A. Osborne, D.A. Howey, Gaussian process regression for forecasting battery state of health, J. Power Sources 357 (2017) 209–219.
[66] G. Wang, Z. Lyu, X. Li, An optimized random forest regression model for Li-ion battery prognostics and health management, Batteries 9 (6) (2023) 332.
[67] Z. Wei, Z. Quan, J. Wu, Y. Li, J. Pou, H. Zhong, Deep deterministic policy gradient-DRL enabled Multiphysics-constrained fast charging of Lithium-ion battery, IEEE Trans. Industrial Electronics 69 (3) (2022) 2588–2598.
[68] Z. Geng, T. Thiringer, In situ key aging parameter determination of a vehicle battery using only CAN signals in commercial vehicles, Appl. Energy 314 (2022) 118932.
[69] ABB, ABB launches new digital application to optimize dry bulk material handling for stockyard operations and beyond, in: ABB News Center (Press release), Zurich, Switzerland, 2019.
[70] M. Geyer, BMW group starts global rollout of NVIDIA Omniverse, in: NVIDIA Blog, 2023.
[71] V. Utkin, Variable structure systems with sliding modes, IEEE Trans. Automatic Control 22 (2) (1977) 212–222.
[72] Y. Huangfu, L. Guo, R. Ma, F. Gao, An advanced robust noise suppression control of bidirectional DC–DC converter for fuel cell electric vehicle, IEEE Trans. Transportation Electrification 5 (4) (2019) 1268–1278.
[73] Z. Wang, S. Li, Q. Li, Discrete-time fast terminal sliding mode control design for DC–DC Buck converters with mismatched disturbances, IEEE Trans. Industrial Informatics 16 (2) (2020) 1204–1213.
[74] N. Sarrafan, J. Zarei, R. Razavi-Far, M. Saif, M.-H. Khooban, A novel on-board DC/DC converter controller feeding uncertain constant power loads, IEEE Journal of Emerging and Selected Topics in Power Electronics 9 (2) (2021) 1233–1240.
[75] Q. Xu, C. Zhang, C. Wen, P. Wang, A novel composite nonlinear controller for stabilization of constant power load in DC microgrid, IEEE Trans. Smart Grid 10 (1) (2019) 752–761.
[76] X. Zhang, Y. Wang, X. Yuan, Y. Shen, Z. Lu, Adaptive dynamic surface control with disturbance observers for battery/supercapacitor-based hybrid energy sources in electric vehicles, IEEE Trans. Transportation Electrification 9 (4) (2023) 5165–5181.
[77] B. Wang, et al., Higher order sliding mode observer based fast composite backstepping control for HESS in DC microgrids, IEEE Trans. Sustain. Energy 15 (3) (2024) 1627–1639.
[78] Y. Han, J. Li, B. Wang, Event-triggered active disturbance rejection control for hybrid energy storage system in electric vehicle, IEEE Trans. Transportation Electrification 9 (1) (2023) 75–86.
[79] Z. Li, B. Wang, L. Xian, M. Zhang, Q. Xu, Decentralized active disturbance rejection control for hybrid energy storage system in DC microgrid, IEEE Trans. Industrial Electronics 71 (11) (2024) 14232–14243.
[80] Q. Xu, Y. Yan, C. Zhang, T. Dragicevic, F. Blaabjerg, An offset-free composite model predictive control strategy for DC/DC Buck converter feeding constant power loads, IEEE Trans. Power Electronics 35 (5) (2020) 5331–5342.
[81] M. Zhang, Q. Xu, C. Zhang, L. Nordström, F. Blaabjerg, Decentralized coordination and stabilization of hybrid energy storage systems in DC microgrids, IEEE Trans. Smart Grid 13 (3) (2022) 1751–1761.
[82] C. Jia, J. Cui, W. Qiao, L. Qu, Real-time model predictive control for battery-supercapacitor hybrid energy storage systems using linear parameter-varying models, IEEE Journal of Emerging and Selected Topics in Power Electronics 11 (1) (2023) 251–263.
[83] X. Zhang, B. Wang, D. Gamage, A. Ukil, Model predictive control based dynamic power loss prediction for hybrid energy storage system in DC microgrids, IEEE Trans. Industrial Electronics 69 (8) (2022) 8080–8090.
[84] B. Wang, U. Manandhar, X. Zhang, H.B. Gooi, A. Ukil, Deadbeat control for hybrid energy storage systems in DC microgrids, IEEE Trans. Sustainable Energy 10 (4) (2019) 1867–1877.
[85] X. Zhang, B. Wang, Y. Zhou, Y. Zhang, A. Ukil, An event-triggered deadbeat control considering dynamic power loss compensation for hybrid energy storage system, IEEE Trans. Industrial Electronics 70 (7) (2023) 6844–6855.
[86] X. Zhang, Z. Lu, X. Yuan, Y. Wang, X. Shen, L2-gain adaptive robust control for hybrid energy storage system in electric vehicles, IEEE Trans. Power Electronics 36 (6) (2021) 7319–7332.
[87] S. Zhou, Z. Chen, D. Huang, T. Lin, Model prediction and rule based energy management strategy for a plug-in hybrid electric vehicle with hybrid energy storage system, IEEE Trans. Power Electronics 36 (5) (2021) 5926–5940.
[88] M. Gheisarnejad, M.H. Khooban, IoT-based DC/DC deep learning power converter control: real-time implementation, IEEE Trans. Power Electronics 35 (12) (2020) 13621–13630.
[89] M. Gheisarnejad, H. Farsizadeh, M.H. Khooban, A novel nonlinear deep reinforcement learning controller for DC–DC power Buck converters, IEEE Trans. Industrial Electronics 68 (8) (2021) 6849–6858.
[90] D. Wang, et al., Model predictive control using artificial neural network for power converters, IEEE Trans. Ind. Electron. 69 (4) (2022) 3689–3699.
[91] J. Ye, H. Guo, B. Wang, X. Zhang, Deep deterministic policy gradient algorithm based reinforcement learning controller for single-inductor multiple-output DC–DC converter, IEEE Trans. Power Electronics 39 (4) (2024) 4078–4090.

[92] X. Zhang, et al., Reinforcement learning based active model variation deadbeat control for energy storage system in DC microgrids with constant power loads, IEEE Trans. Industrial Electronics 73 (2) (2026) 2427–2439.
[93] M. Shi, X. Chen, J. Zhou, Y. Chen, J. Wen, H. He, Distributed optimal control of energy storages in a DC microgrid with communication delay, IEEE Transactions on Smart Grid 11 (3) (2020) 2033–2042.
[94] C. Deng, Y. Wang, C. Wen, Y. Xu, P. Lin, Distributed resilient control for energy storage systems in cyber-physical microgrids, IEEE Trans. Industr. Inform. 17 (2) (2021) 1331–1341.
[95] Z. Lian, C. Guo, F. Wen, C. Deng, P. Lin, Distributed resilient optimal current sharing control for an islanded DC microgrid under DoS attacks, IEEE Transactions on Smart Grid 12 (5) (2021) 4494–4505.
[96] L. Raijmakers, D. Danilov, R. Eichel, P. Notten, A review on various temperature-indication methods for Li-ion batteries, Appl. Energy 240 (2019) 918–945.
[97] Y. Xie, et al., An enhanced online temperature estimation for Lithium-ion batteries, IEEE Trans. Transport. Electrif. 6 (2) (2020) 375–390.
[98] D. Li, et al., Battery thermal runaway fault prognosis in electric vehicles based on abnormal heat generation and deep learning algorithms, IEEE Trans. Power Electron. 37 (7) (2022) 8513–8525.
[99] N. Gan, Z. Sun, Z. Zhang, S. Xu, P. Liu, Z. Qin, Data-driven fault diagnosis of Lithium-ion battery Overdischarge in electric vehicles, IEEE Trans. Power Electronics 37 (4) (2022) 4575–4588.
[100] D. Li, Z. Zhang, P. Liu, Z. Wang, L. Zhang, Battery fault diagnosis for electric vehicles based on voltage abnormality by combining the long short-term memory neural network and the equivalent circuit model, IEEE Trans. Power Electronics 36 (2) (2021) 1303–1315.
[101] R. Xiong, R. Yang, Z. Chen, W. Shen, F. Sun, Online fault diagnosis of external short circuit for Lithium-ion battery pack, IEEE Trans. Industrial Electronics 67 (2) (2020) 1081–1091.
[102] D. Kong, H. Lv, P. Ping, G. Wang, A review of early warning methods of thermal runaway of lithium ion batteries, J. Energy Storage 64 (2023) 107073.
[103] N. Lyu, Y. Jin, R. Xiong, S. Miao, J. Gao, Real-time overcharge warning and early thermal runaway prediction of Li-ion battery by online impedance measurement, IEEE Trans. Industrial Electronics 69 (2) (2022) 1929–1936.
[104] Y. Li, et al., Early warning method for thermal runaway of lithium-ion batteries under thermal abuse condition based on online electrochemical impedance monitoring, J. Energy Chem. 92 (2024) 74–86.
[105] N. Lyu, et al., Fault warning and location in battery energy storage systems via venting acoustic signal, IEEE Journal of Emerging and Selected Topics in Power Electronics 11 (1) (2023) 100–108.
[106] T. Cai, P. Valecha, V. Tran, B. Engle, A. Stefanopoulou, J. Siegel, Detection of Li-ion battery failure and venting with carbon dioxide sensors, eTransportation 7 (2021) 100100.
[107] Y. Jin, et al., Detection of Micro-scale Li dendrite via H2 gas capture for early safety warning, Joule 4 (8) (2020) 1714–1729.
[108] M.C. Appleberry, et al., Avoiding thermal runaway in lithium-ion batteries using ultrasound detection of early failure mechanisms, J. Power Sources 535 (2022) 231423.
[109] Y. Zhang, N. Lyu, L. Jin, N. Wang, Y. Jin, Design of a visual detection algorithm for battery swelling faults inside energy storage lithium-ion battery packs, J. Energy Storage 145 (2026) 119745.
[110] J. Hou, X. Zhu, Y. Song, X. Jiang, N. Lyu, S. Zhang, J. Qiu, Y. Jin, Fault warning and localization for lithium-ion batteries by laser signals, J. Energy Storage 133 (2025) 118044.
[111] F. Khan, Z. Xu, J. Sun, F.M. Khan, A. Ahmed, Y. Zhao, Recent advances in sensors for fire detection, Sensors 22 (9) (2022) 3310.
[112] Y. Liu, Q. Duan, J. Xu, H. Li, J. Sun, Q. Wang, Experimental study on a novel safety strategy of lithium-ion battery integrating fire suppression and rapid cooling, J. Energy Storage 28 (2020) 101185.
[113] X. Cai, et al., Research on the effect of water-based fire detection tubes fire suppression technology on extinguishing lithium-ion battery fire, Fire Sci. Technol. 43 (2) (2024) 210–216.
[114] L. Zhang, et al., Experimental study on the synergistic effect of gas extinguishing agents and water mist on suppressing lithium-ion battery fires, J. Energy Storage 32 (2020) 101801.
[115] Y. Yao, Y. Jiang, F. Chen, Y. Wang, H. Zhou, J. Zhao, Experimental study of the strategy of C6F12O and water mist intermittent spray to suppress lithium-ion batteries thermal runaway propagation, J. Loss Prev. Process Ind. 91 (2024) 105407.
[116] L. Zhang, K. Jin, J. Sun, Q. Wang, A review of fire-extinguishing agents and fire suppression strategies for lithium-ion batteries fire, Fire Technol. 60 (2) (2024) 817–858.
[117] X. Meng, S. Li, W. Fu, Y. Chen, Q. Duan, Q. Wang, Experimental study of intermittent spray cooling on suppression for lithium iron phosphate battery fires, eTransportation 11 (2022) 100142.
[118] Y. Guo, et al., In situ extinguishing mechanism and performance of self-portable microcapsule fire extinguishing agent for lithium-ion batteries, J. Energy Storage 93 (2024) 112393.
[119] X. Guo, et al., Experimental study on suppression of hydrogen jet flame by solid-liquid two-phase composite powders containing core-shell structure, Fuel 371 (2024) 131900.
[120] S. Shahid, M. Agelin-Chaab, A review of thermal runaway prevention and mitigation strategies for lithium-ion batteries, Energy Convers. Manage.: X 16 (2022) 100310.
[121] Y. Liu, Q. Gao, G. Wang, T. Zhang, Y. Zhang, Experimental study on active control of refrigerant emergency spray cooling of thermal abnormal power battery, Appl. Therm. Eng. 182 (2021) 116172.
[122] P. Liu, et al., Experimental study on the thermal runaway and fire behavior of LiNi0.8Co0.1Mn0.1O2 battery in open and confined spaces, Process. Saf. Environ. Prot. 158 (2022) 711–726.
[123] G. Wang, et al., Revealing particle venting of lithium-ion batteries during thermal runaway: a multi-scale model toward multiphase process, eTransportation 16 (2023) 100237.
[124] J. Weng, D. Ouyang, X. Yang, M. Chen, G. Zhang, J. Wang, Alleviation of thermal runaway propagation in thermal management modules using aerogel felt coupled with flame-retarded phase change material, Energ. Conver. Manage. 200 (2019) 112071.
[125] X. Liu, et al., Thermal barrier for preventing battery thermal runaway propagation: sensitivity analysis of parameters and suppression strategy, J. Energy Storage 141 (Part D) (2026) 119501.
[126] P. Dhamodharan, E.J. Manalac, R. Prabakaran, A. Sathishkumar, S.C. Kim, Performance assessment of heat pump-assisted battery chiller cooling system using propane: experimental insights and dynamic simulation, Energ. Conver. Manage. 352 (2026) 121106.
[127] N. Bartlett, A. Cullen, B. Sekulic, K. Smith, White paper on case study of safe installation of second-life energy storage system, NREL, 2026.