IEEE Open Journal of
Industry Applications

Received 3 July 2025; revised 21 November 2025 and 15 December 2025; accepted 23 January 2026. Date of publication 28 January 2026; date of current version 10 February 2026.

Digital Object Identifier 10.1109/OJIA.2026.3658824

State-of-the-Art of Hybrid Energy Storage Systems for Electric Vehicles

ANDRIJA ALEKSIC, CRISTINA TERLIZZI (Member, IEEE), AND STEFANO BIFARETTI (Senior Member, IEEE)

[1]University of Rome "Tor Vergata," 00133 Rome, Italy

CORRESPONDING AUTHOR: CRISTINA TERLIZZI (e-mail: cristina.terlizzi@uniroma2.it).

ABSTRACT This article offers a critical review of recent advances in hybrid energy storage systems (HESS) for electric vehicles, emphasizing architectures that integrate supercapacitors and lithium-ion batteries to overcome the limitations of current energy storage technologies. The review examines the essential role of power electronic converters in managing energy flow and improving system performance. It also discusses modeling approaches and the development of advanced energy management strategies. Modern topics, such as the integration of artificial intelligence and digital twin models, are explored for their potential to enhance system efficiency and reliability through health monitoring and predictive maintenance. The review also considers some alternative HESS applications beyond the conventional automotive realm, offering insights into the potential design ideas for high-performance, sustainable transportation systems. Finally, future research directions are proposed to help academia and industry identify the main pathways for improving the next generation of electric vehicles.

INDEX TERMS Artificial intelligence (AI), battery, DC–DC converters, digital twins, energy management system (EMS), hybrid energy storage systems (HESS), supercapacitor.

NOMENCLATURE

A-HEST	Active hybrid energy storage topology.
ATC	Active thermal control.
ASIC	Application specific integrated circuits.
AI	Artificial intelligence.
BPHM	Battery prognostics and health management.
BESS	Battery-only energy storage system.
CAPEX	Capital expenditures.
DBN	Deep belief networks.
DL	Deep learning.
DNN	Deep neural networks.
DRL	Deep reinforcement learning.
DOD	Depth-of-discharge.
DWT	Discrete wavelet transform.
DAB	Dual active bridge.
DP	Dynamic programming.
EDLC	Electric double-layer capacitors.
EV	Electric vehicles.
EMI	Electromagnetic interference.
EMS	Energy management system.
ESS	Energy storage system.
FMEA	Failure modes and effects analysis.
FPGA	Field programmable gate arrays.
GRU	Gated recurrent units.
GAN	Generative adversarial networks.
GPU	Graphics processing unit.
G2V	Grid to vehicle.
HVAC	Heating, ventilation, and air conditioning.
HCP	High current path.
HE	High-energy.
HP	High-power.
HWDC	Highway and driving cycle.
HEV	Hybrid electric vehicle.
HESS	Hybrid energy storage systems.
ILPF	Improved low-pass filter.
IUDC	Indian urban drive cycle.
IoV	Internet of Vehicles.
LiB	Lithium-ion battery.
LiC	Lithium-ion supercapacitor.
LTSM	Long short-term memory.

LCP	Low current path.
ML	Machine learning.
MPPT	Maximum power point tracking.
MRMR	Max-relevance and min-redundancy.
MAE	Mean average error.
MTBF	Mean time between failures.
MTTR	Mean time to repair.
MLP	Multilayer perceptron.
MIMO	Multiple-input multiple-output.
MRA	Multiresolution analysis.
NM	Nelder–Mead.
NN	Neural network.
NPC	Neutral-point clamped.
NEDC	New European Driving Cycle.
OPEX	Operating and maintenance expenditure.
PSO	Particle swarm optimization.
P-HEST	Passive hybrid energy storage topology.
PSM	Phase-shift modulation.
PV	Photovoltaic.
PEV	Plug-in electric vehicle.
PE	Power electronic.
PRISMA	Preferred reporting items for systematic reviews and meta-analyses.
PV2G	PV to grid.
PV2V	PV to vehicle.
RNN	Recurrent neural network.
RL	Reinforcement learning.
RES	Renewable energy sources.
RMSE	Root mean square error.
SA-HEST	Semiactive hybrid energy storage topology.
SIMO	Single-input multiple-output.
SISO	Single-input single-output.
SPDT	Single-pole double-throw.
SiB	Sodium-ion battery.
SOC	State of charge.
SOH	State of health.
SC	Supercapacitors.
TCN	Temporal convolutional networks.
TPU	Tensor processing unit.
UGF	Universal generating function.
UDDS	Urban dynamometer driving schedule.
V2G	Vehicle to grid.
WLTP	Worldwide harmonized light vehicles test procedure.
ZTE-EV	Zero tailpipe emission electric vehicles.
ZVS	Zero-voltage switching.

I. INTRODUCTION

Transportation plays a crucial role in modern society, connecting people and goods. However, its reliance on fossil fuels poses significant environmental challenges. The combustion of gasoline and diesel fuels releases substantial greenhouse gas emissions, which are major contributors to climate change and urban air pollution [1], [2]. These emissions include health-threatening carcinogens, degrade air quality, and increase health risks [3]. Essentially, excessive dependence on fossil fuels demands a fundamental shift to sustainable, low-emission, and environmentally friendly transportation alternatives.

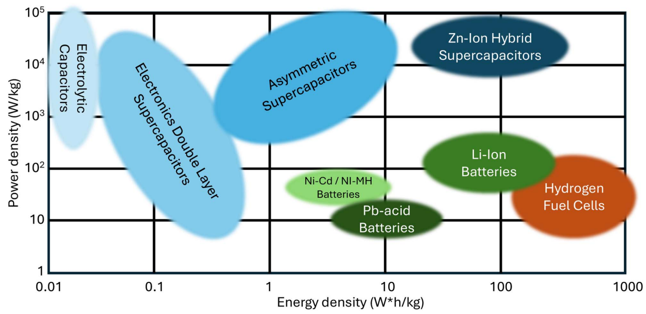

FIGURE 1. Ragone plot for different energy storage units, synthesized with reference to [12] and [13].

Hybridization, which combines internal combustion engines with electric motors, offers modest improvement, since it still relies heavily on fossil fuels and does not fully address the underlying environmental concerns [4], [5]. A more effective solution lies in the widespread adoption of zero tailpipe emission electric vehicles (ZTE EVs or simply EVs). EVs eliminate the direct need for fossil fuels to power vehicles, relying instead on electricity to power their motors. The transition toward large-scale electric transportation requires advanced battery technologies with higher power density and longer cycle life to address existing adoption challenges. More importantly, it requires the systematic development of charging infrastructure and robust electrical grids, as shown in [6] and [7].

On the other hand, a promising approach to enhance EV performance, reducing costs, and prolonging battery life involves hybridizing two distinct electric energy storage technologies: a power-dense system (such as supercapacitors, or SCs) and an energy-dense system (such as lithium-ion batteries, or LiBs). Several studies in the literature explain and analyze the operating principles of these individual energy storage systems (ESS). Concerning LiBs, Armand et al. [8] provide a comprehensive review of LiB technology, highlighting its current advancements and prospects. They discuss recent developments in electrode materials, electrolytes, and cell design, while also addressing challenges related to sustainability. Furthermore, Li et al. [9] review emerging technologies for treating spent LiBs, focusing on methods that improve material recovery while reducing environmental and health impacts. In parallel, research on SCs has seen substantial progress, with numerous recent reviews. For instance, Czagany et al. [10] focus on the critical role of electrode and electrolyte materials, including carbon-based substances, polymers, and metal compounds, in enhancing performance metrics like energy capacity and cycling stability. The work in [11] provides a broader analysis of SC technology, addressing its challenges (such as energy density limitations) and applications in renewable energy systems.

Fig. 1 shows a Ragone plot which compares different individual energy storage units, with respect to their energy density in W∗h/kg (x-axis) and power density in W/kg (y-axis). The aforementioned hybrid configuration integrates the complementary strengths of both energy storage solutions, potentially leading to improved vehicle dynamics, faster charging times, extended range, and longer cycle life of the entire system. These effects are described in more detail and proven by the authors in [14], [15], and [16].

In addition to the energy storage technologies themselves, effective power management is integral to the success of the electrification process. This management is enabled by power electronic (PE) converters that regulate power flow within the vehicle's electrical system. Their overview and detailed analysis of the roles they play can be found in [17], [18], and [19].

The rapid global growth of EV fleets is progressively revealing the limitations of battery-only ESS in terms of power density, durability under highly dynamic loading, and associated stress on the charging infrastructure, thereby making updated and focused examination of modern energy storage solutions both necessary and timely. Accordingly, this article presents a thorough and methodical overview of advancements in hybrid energy storage systems (HESS) for EVs. It encompasses various system configurations, PE converter topologies, and energy management systems (EMS), while incorporating critical elements such as artificial intelligence (AI), digital twin technologies, and reliability considerations. This article explicitly addresses the integration of these components, bridging the gap between them. Moreover, it moves beyond conventional surveys by identifying unresolved challenges, formulating structured directions for future research, and reasoning hypotheses on how rapidly evolving HESS and PE systems are likely to shape the forthcoming generation of EVs. The review begins with a section focused on the configurations and design of HESS, highlighting the pivotal role of single-input single-output/multiple-output (SISO/SIMO) and multiport converters in the operation of these systems. It also provides an overview of EMS for HESS, examining advanced algorithms and strategies designed to optimize energy utilization, minimize losses, and ensure the safe and reliable operation of the system. The subsequent section consists of a discussion on reliability aspects, the integration of digital twin models, and the application of AI, which is a modern area of significant interest. The penultimate section will illustrate an exploration of niche and alternative HESS systems, somewhat beyond the conventional automotive domain, recognizing that insights gained from these broader applications can significantly impact the development of automotive HESS. To conclude this review, a comprehensive discussion will be provided to synthesize the key findings and highlight promising directions and emerging trends for future research.

II. CONFIGURATION AND DESIGN CASES

A. BASIC CONFIGURATIONS

The type of HESS configuration has a significant influence on its overall performance [20]. To maximize HESS efficiency, a design that exploits the strengths and mitigates the weaknesses of each component is required. Specifically,

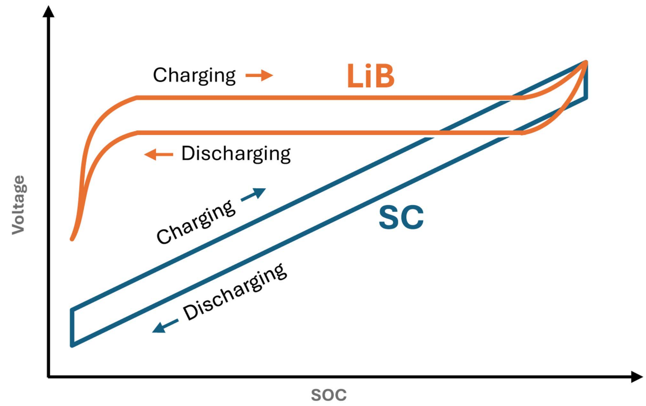

FIGURE 2. Charging and discharging profiles of HP (SC, blue line) and HE (LiB, orange line) devices – voltage in [V] vs SOC in [%], synthesized with reference to [21].

the high-energy (HE) storage capacity of LiBs should be combined effectively with the high-power (HP) density of SCs, typically electric double-layer capacitors (EDLCs) and/or lithium-ion SCs (LiCs), also known as hybrid SCs. Furthermore, the state of charge (SOC) of both LiBs and SCs is a crucial factor, as it determines their usable power capacity, voltage range, and permissible charge/discharge current limits (as illustrated conceptually in Fig. 2). The duration of power pulses handled by the HESS also needs careful consideration in the design process.

There are several papers in the literature that examine battery structure, connections, and cell balancing techniques in depth. Two recent reviews of cell balancing methods can be found in [22] and [23], while some novel approaches can be found in [24], [25], [26], and [27]. The main takeaway is that battery storage modules are composed of many smaller cells of the same type and chemistry. Although the hard wiring of identical storage elements is straightforward, it permits only a limited range of interconnection configurations. Scientific literature also investigates reconfigurable topologies on the cell level and module level. More details about reconfigurable battery techniques can be found in [28] and [29]. Furthermore, Huang et al. [30] present an interesting concept of reconfigurable LiB-SC HESS with active cell balancing. Similar concepts can be used on the topic of a transition from a single capacitor cell to an SC module [31].

In contrast to the hard wiring of battery and capacitor storage elements, which have the same cell chemistry, combining modules of these individual ESS offers a variety of connection topologies for the purposes of HESS. The topologies examined in scientific literature can be classified as follows.

1) Passive hybrid energy storage topology (P-HEST).
2) Semiactive hybrid energy storage topology (SA-HEST).
3) Active hybrid energy storage topology (A-HEST).

P-HEST (shown in Fig. 3) represents the most straightforward and cost-effective form of hybridization, achieved by the direct parallel connection of two different ESS technologies, without the use of an intermediary PE converter. The load

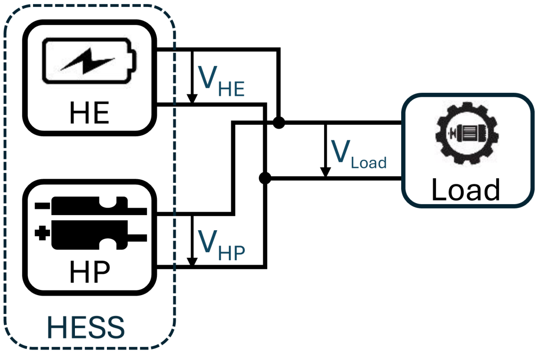

FIGURE 3. P-HESS topology.

voltage (V_{Load}) is identical to the voltage of the two energy storage devices (V_{HE} and V_{HP}). The voltage window of both individual ESS must therefore match the load requirements, as can sometimes be found in satellites with an unregulated DC-bus [32], but presents quite an unusual occurrence in automotive powertrains. Passive hybridization is used to reduce battery stress primarily by diverting high-current transients and rapid power bursts to the SC, thus minimizing current peaks, thermal stress, and voltage fluctuations. This approach extends battery lifetime and reliability by ensuring the battery experiences steadier, monotonic, and low-power cycling. Fundamentally, the HP device connected in parallel functions as a low-pass filter for the HE system, as it smooths and averages rapid current changes. Despite its simplicity and low cost, P-HEST exhibits unsatisfactory energy performance [33].

To optimize the operation of individual energy storage devices within HESS, decoupling is necessary and is typically achieved using DC–DC converters. This approach defines A-HESTs, which can be further categorized based on the number of decoupled energy storage units. Partially decoupled configurations, also known as SA-HESTs, employ a single DC–DC converter. Conversely, fully decoupled configurations, or FA-HESTs, utilize one DC–DC converter for each ESS element [34].

SA-HEST is composed of two (or more) different energy storage devices, some of which are decoupled. Although the use of a converter requires extra costs and installation space, this topology class has several advantages. In particular, the decoupled energy storage element can be operated optimally based on its charge and discharge characteristics. Depending on the device chosen to be decoupled by DC–DC converter, SA-HEST can be subdivided into HE SA-HEST [Fig. 4(a)], HP SA-HEST [Fig. 4(b)], or parallel SA-HEST [Fig. 4(c)]. Further analysis of these subcategories can be found in [35].

Regarding FA-HEST, every energy storage unit is decoupled, usually by bidirectional DC–DC converters, permitting a full regulation of the load voltage. System losses are higher than those from SA-HEST. Furthermore, the larger number of DC–DC converters implies extra weight and cost, and additional installation space for PE. Even though the complexity of HESS increases with each additional DC–DC converter,

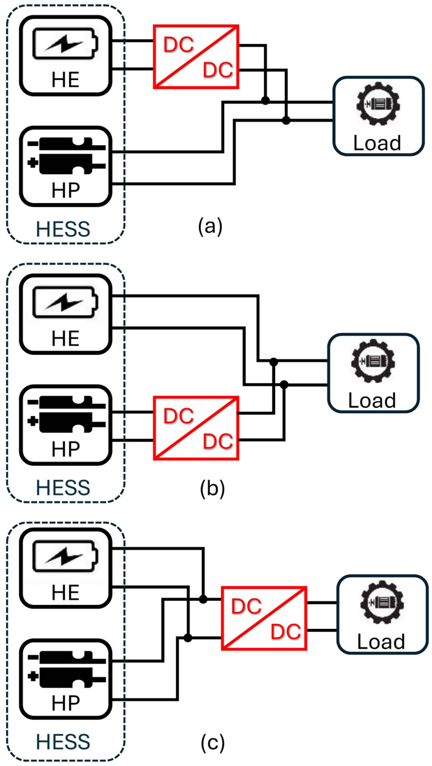

FIGURE 4. SA-HESS topologies: DC–DC converter positioned between the load and the (a) HE source, (b) HP source, or (c) both HE and HP sources connected in parallel. (a) High-Energy HEST. (b) High-Power HEST. (c) Parallel HEST.

this topology class has certain advantages. If a suitable control strategy is used, FA-HESS allows every energy storage unit to be operated in the most optimal window based on its charge and discharge characteristics. This high degree of controllability provides the advantage of individually (and correspondingly) assigning the power requirements to each energy storage device, improving the response performance of the whole storage system and its useful life. Similarly to the SA solution, literature suggests three subcategories of FA-HEST, which are cascade HE FA-HEST [Fig. 5(a)], cascade HP FA-HEST [Fig. 5(b)] and parallel FA-HEST [Fig. 5(c)]. Further analysis of these subcategories can be found in [36].

B. DESIGN CASES

The SA-HESS configuration offers a strong balance between performance and cost, making it a popular choice and the most intensively widespread topology in existing research.

Recent studies on SA-HESS for EVs, although sharing the same goals of minimizing battery degradation and enhancing cost-effectiveness, vary in proposed approaches. Their methodologies span from experimental prototypes with advanced converter designs to computational optimization frameworks, each offering different balances between practical validation, control strategy complexity, and theoretical innovation.

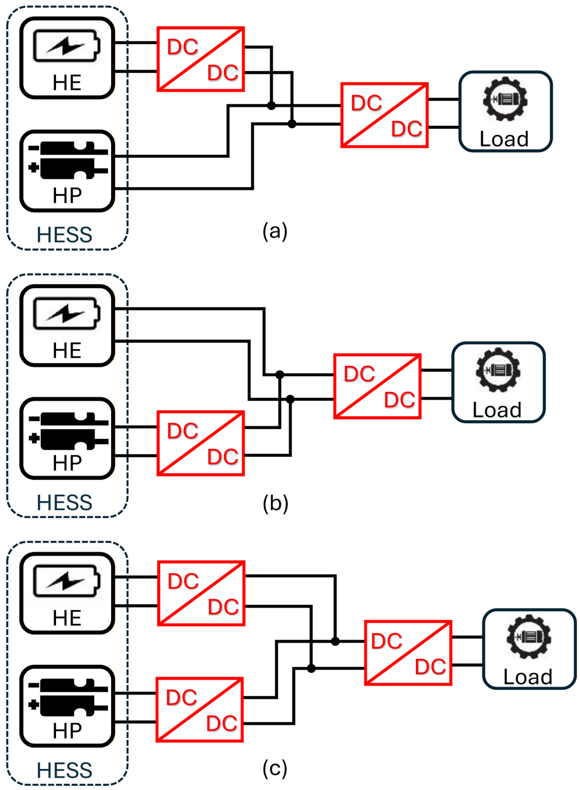

FIGURE 5. **FA-HES topologies: one DC–DC converter connected between the load and the DC link, while a second converter is positioned between the DC link and the (a) HE source, (b) HP source, or (c) both sources, each interfaced through its own dedicated converter in a parallel configuration. (a) High-Energy HEST. (b) High-Power HEST. (c) Parallel HEST.**

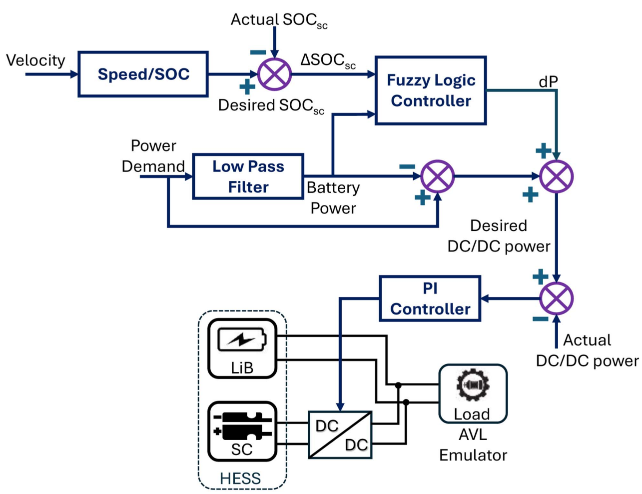

FIGURE 6. **Schematic diagram of the system proposed in [37].**

A common thread in [37] and [38] is the adoption of partially decoupled topologies. For instance, Zhang and Li [37] validated a 30 kW experimental platform based on HP SA-HEST, using a fuzzy logic-based control strategy (shown in Fig. 6). The authors presented 30–57% reductions in battery capacity fade (compared to battery-only ESS, or BESS), different across driving cycles (New European Driving Cycle - NEDC, Highway and Driving Cycle - HWDC, and Indian Urban Drive Cycle - IUDC). On the other hand, Zhuge and Kazerani [38] presented the HE SA-HEST configuration, with an interleaved converter design to reduce current ripple and system weight, coupled with a power management algorithm that limits battery stress through dynamic current and voltage regulation.

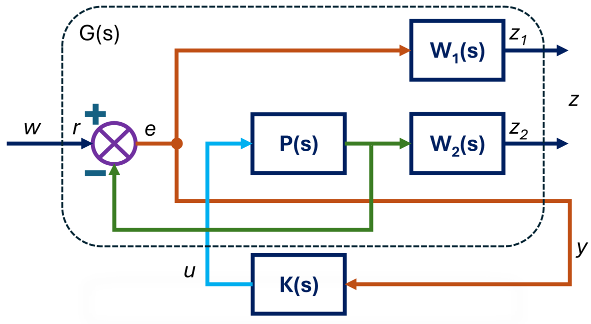

FIGURE 7. **H$_\infty$ weighted mixed-sensitivity design, from [40], where P(s): plant model, K(s): controller, W$_1$(s) and W$_2$(s): weighted functions, G(s): augmented plant for P(s).**

Continuing, Shen et al. [39] proposed a partially decoupled topology where SC is used to absorb high current peaks. Furthermore, the authors adopted a computationally rigorous approach, integrating a coupled electro-thermal battery degradation model, incorporating depth-of-discharge (DoD) and cycle count, with a multiobjective genetic algorithm to optimize HESS sizing. This framework demonstrated a 28–32% reduction in battery degradation over simulated driving cycles (Worldwide Harmonized Light Vehicles Test Procedure - WLTP, and Urban Dynamometer Driving Schedule - UDDS), alongside a 22% lower total ownership cost over eight years despite a 15% higher initial investment. While the authors in [37] and [38] prioritized experimental validation and practical implementation, such as focus on converter efficiency [37] and aging cost quantification [38], the work in [39] showed theoretical innovation with dynamic programming (DP) for real-time power allocation and lithium plating risk mitigation. All studies converged on the economic viability of HESS, although they differ in control strategies. They also identified unresolved challenges such as temperature-dependent aging dynamics and converter efficiency optimization under real-world load variability.

Bai et al. [40] investigated a parallel SA-HESS, made of LiB and SC, integrated by a four-quadrant DC–DC converter. Their research emphasized power flow management for EV applications. They designed an H$_\infty$ (H-infinity) robust control strategy translated to a weighted mixed-sensitivity problem, as shown in Fig. 7 block diagram to ensure that the SC handles HP transients, while the battery supplies nonfluctuating or monotonic power output.

This decoupling of power responsibilities minimized the high current peaks experienced by the battery, which are known to accelerate its degradation (as confirmed in [41]).

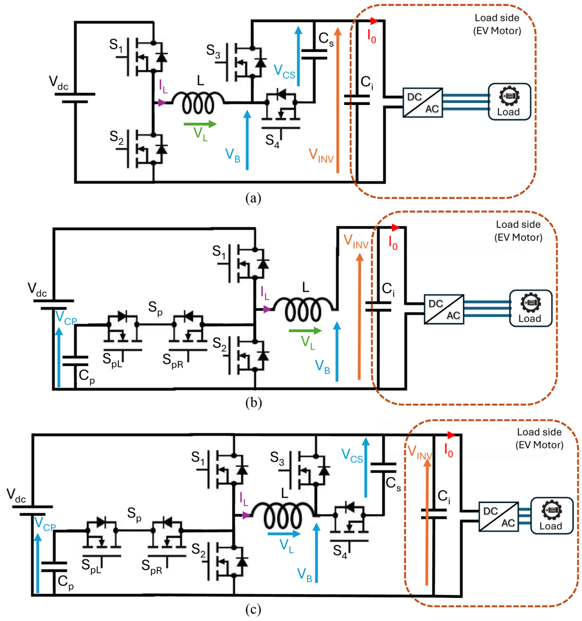

FIGURE 8. **LIC-based system topologies presented in [42]. (a) Series LIC topology. (b) Parallel LIC topology. (c) Series/Parallel LIC topology.**

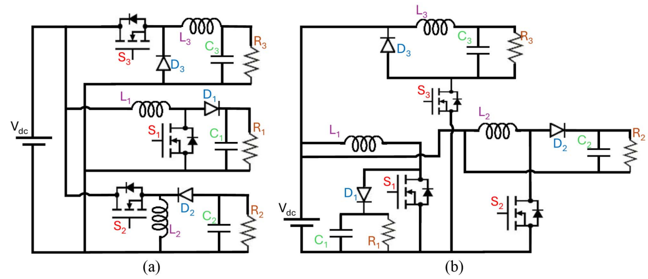

FIGURE 9. **(a) Conventional SIMO design topology. (b) Novel SIMO design topology proposed in [44].**

Experimental validation on a 20 kW prototype in a 1530 kg EV demonstrated significant improvements. During acceleration, the hybrid system reduced battery peak currents by 25% by offloading high-power demands to the SC. Furthermore, Sayed et al. [42] explored a similar concept (HE FA-HESS) but with series and parallel LiCs, managed by a bidirectional DC–DC converter, positioned between the main battery and the motor drive inverter. They investigated three LiC configurations: series, parallel, and a combined series/parallel, shown in Fig. 8(a), (b), and (c), respectively.

Their primary focus was on leveraging the HP density and fast charging capabilities of LiCs to enhance energy recovery during braking and reduce battery stress during acceleration. The proposed system aimed to control the LiC voltages within permissible limits (2.2–3.8 V per cell) during charge and discharge cycles. Maintaining these voltage limits is crucial for ensuring the long-term health and reliable operation of LiCs. Moreover, the converter regulates the DC voltage at the inverter input, contributing to reduced switching losses and improved efficiency. Simulations and a 1 kW, 48 V prototype (although with power levels lower than usually found in real-world EV applications) validated the effectiveness of the proposed series/parallel LiC topology, demonstrating improved regenerative braking performance, reduced battery current fluctuations and peaks during dynamic load changes compared to systems without LiCs.

Kuperman [43] presented an SA-HESS combining a LiB and SC, but, in contrast to [37], [38], and [39], the pulsed load was the targeted application. The system utilized a non-inverting buck-boost DC–DC converter to interface the SC with the load, enabling active control of energy flow. The core concept was to decouple the LiB current from the dynamic load variations. Their control strategy, based on a capacitance-emulating method, aimed to make the SC behave like a "large capacitor filter," effectively absorbing the high-power load demand spikes of the pulsed load without directly measuring the load current. This sensor-less control approach simplifies the system architecture and reduces the complexity of the control algorithm. The battery was tasked with providing a relatively constant and monotonic current, equal to the average load current, while SC, managed by the DC–DC converter, handled the pulsed current demands, providing peak power and absorbing regenerative energy during load variations. Simulations and experimental results validated the system's performance, demonstrating its ability to maintain a stable battery current, independent of the load's dynamic behavior. They also showed that the battery current was insensitive to the SC's size, with the SC primarily influencing the load voltage.

Moving on, Dhananjaya et al. [44] proposed a new SIMO DC–DC converter topology (Fig. 9), aimed to efficiently provide multiple voltage levels (boost, buck-boost, and buck) required by various EV subsystems, such as the traction motor drive, lighting, auxiliary systems, and battery charging. Conventional single inductor multioutput converters often suffer from cross-regulation issues, imposing constraints on duty cycles and inductor current relationships, which limit their operational flexibility and complicated control. The proposed topology addresses these challenges by using three independently controlled switches and corresponding LC pairs, ensuring that the energy stored in each inductor is confined to its respective load during switching. This design enables each output to be regulated independently without mutual interference. The topology has been validated through both simulations and a 200 W experimental prototype, achieving output voltages of 100 V (boost), 50 V (buck-boost), and 25 V (buck) from a 50 V input and confirming the converter's ability to maintain output voltage stability under dynamic load and input variations. The system achieves high efficiency ($> 95\%$) across a range of duty cycles and output power levels. Even though the system has been tested with power levels usually lower than those found in modern EVs, comparative evaluation with existing single inductor multioutput converters shows that the proposed design offers low control complexity, high-power density, and most importantly, complete elimination of cross-regulation.

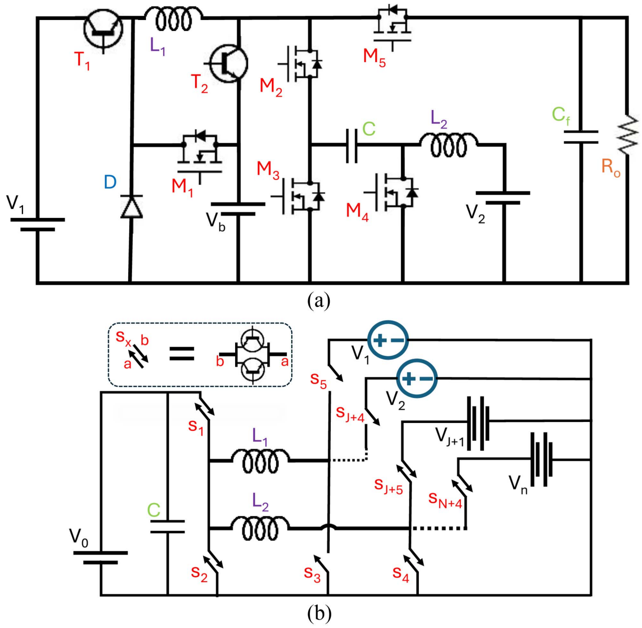

FIGURE 10. Configuration proposed in (a) [45] and (b) [46].

C. MULTIPORT TOPOLOGIES

This section transitions to an examination of multiport converter architectures, which expand system flexibility through integrated power management across diverse energy sources and loads. A classification based on isolation characteristics (isolated vs. nonisolated) and on the specific functionalities integrated in the converter has been considered. These multiport configurations introduce advanced control paradigms and topological innovations to address the growing complexity of modern HESS applications. Several recent studies have explored innovative multiport DC–DC converter topologies for integrating HESS into EVs, aiming to efficiently manage power flow between diverse energy sources, while addressing challenges related to size, cost, and efficiency.

Non-isolated multiport converters offer the advantage of simpler topologies with fewer components, leading to potentially lower cost and higher battery current.

To begin with, the triple-input bidirectional converter proposed by Jalilzadeh and Rostami [45] employed two unidirectional ports for SC or Renewable Energy Sources (RES), like Photovoltaic (PV) and fuel cells, and one bidirectional battery port. The DC link enables flexible power transfer across eight operating scenarios, including energy return in buck mode and independent simultaneous power transfer. The non-isolated multiport converter in [46] also integrated multiple energy sources and storage systems, but employed a clustered input structure with unidirectional switches for RESs and bidirectional switches for LiB, allowing simultaneous energy transfer from multiple sources of varying voltage levels to the DC link. A key distinction is that the triple-input converter from [45] [Fig. 10(a)] uses seven switches, one diode, two inductors, and two capacitors, ensuring lower voltage stress and a compact component count, whereas the multiport converter

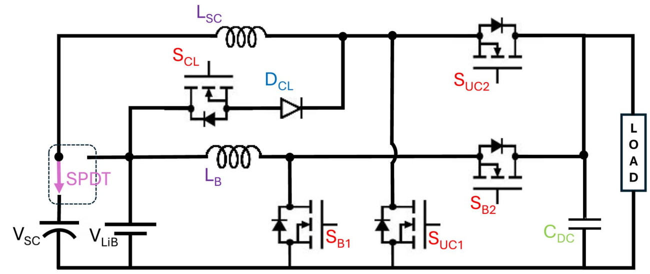

FIGURE 11. SPDT multiport converter configuration proposed in [47].

from [46] [Fig. 10(b)] maintains a fixed two-inductor structure, reducing complexity and enabling easy scalability with minimal modifications, as observed in Fig. 10. Triple-input design from [45] benefits from common grounding, enhancing safety and electromagnetic interference (EMI) reduction with efficiency peak equal to 95%. However, its design may require further optimization in input current continuity or soft switching. On the other hand, the multiport converter from [46] features an H-bridge topology with reverse-blocking and fully controllable bidirectional switches, supporting over twenty operating modes, including intercluster power transfer. Despite its flexibility, it may face challenges related to EMI due to its switching architecture.

Furthermore, the work in [47] presented a two-input, one-output nonisolated converter with a unique single-pole double-throw (SPDT) switch, illustrated in Fig. 11.

The SPDT switch was the core innovation, since it allowed flexible allocation of either the battery or SC to the high current path (HCP), optimizing utilization based on operational needs. During HP demands, the SC can be connected to the HCP, while the battery provides sustained (monotonic) energy through the lower current path (LCP). This dynamic reconfiguration enables seven distinct operating modes, each tailored to specific EV driving scenario, including modes where both battery and SC contribute to the load, modes for SC charging, and regenerative braking modes: mode 1 - battery to load; mode 2 - battery and SC to load; mode 3 - battery to load via HCP; mode 4 - battery to load and SC charging; mode 5 - load to SC; mode 6 - load to SC and battery; mode 7 - load to battery via HCP. The supervisory control scheme, shown in Fig. 12, monitors load power, SC voltage, and battery voltage thresholds to govern transitions between these modes.

Experimental validation on a scaled-down prototype confirmed the converter's dynamic flexibility and the effectiveness of the proposed control strategy. However, as the experiments were limited to low-power conditions, their applicability to EVs remains uncertain. Moreover, while the control strategy can manage seven operational modes, its complexity may pose challenges for real-world implementation, specifically regarding potential computational burden. To fully assess its practicality for EV applications, further validation under higher power levels and real-world implementation of the proposed control strategy are necessary.

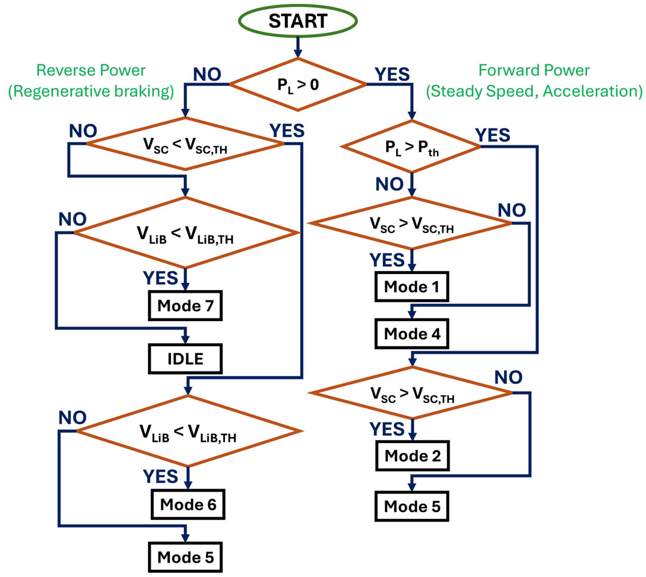

FIGURE 12. Flowchart for supervisory power control scheme, proposed in [47].

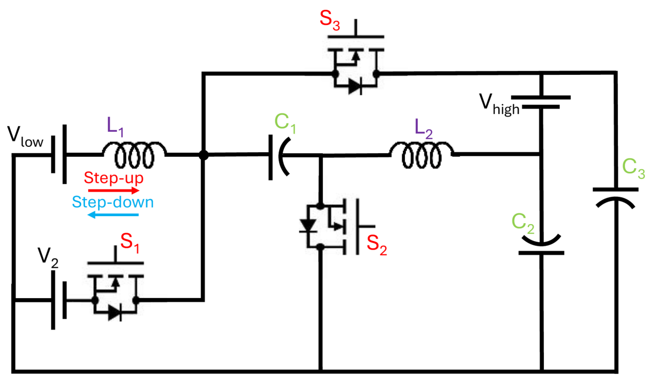

FIGURE 13. Topology proposed in [48].

The work in [48] also focused on a nonisolated three-port bidirectional converter for EV purposes, with a simplified topology, enabling simultaneous power flow from two independent input sources. This design used only three switches, two inductors, and three capacitors, achieving both step-up and step-down operation with bidirectional power flow across all ports. The proposed configuration can be seen in Fig. 13. A key feature is the ability for the output port to receive power from two independent input sources, simultaneously, in both step-up and step-down modes. Detailed steady-state analysis, along with equations for voltage gain and component currents, is provided by the authors. A dual-loop control system is designed based on a small-signal model and validated through a 120 W step-up and 30 W step-down experimental prototype. While this design offers flexibility and reduced component count, the experimental validation is limited to lower power levels, and its suitability for EV applications needs further investigation.

The final nonisolated topology presented in this review is [49], and it is designed to support bidirectional and simultaneous power transfer in a noninverting buck-boost configuration, like the system in [48]. This multi-input converter minimizes component count by using only one inductor and a single bidirectional switch per input port, reducing redundancy and simplifying design scalability. During simultaneous power transfer from the sources to the DC bus, the effect of different input voltages on the output voltage does not solely depend on the duty cycles but also on the effective duty cycle of the other input sources. Thus, the gain relationship of a multi-input converter, capable of simultaneous power transfer from the inputs, is best defined as a voltage transformation factor (V_{TR}, as in [49])

$$V_{TR} = \frac{V_0}{\sum_{i=1}^{N} D(i)_{eff}\, V_i} = \frac{1}{1 - \sum_{i=1}^{N} D(i)_{eff}} \tag{1}$$

where $\sum_{i=1}^{N} D(i)_{eff}$is the sum of the input voltages scaled by the ON time of their respective switches, the conventional reasoning for the gain relationships of the basic single input converters cannot be applied in this case.

Unlike traditional multi-input converters that require complex multiple-input multiple-output (MIMO) controllers, the authors employed a SISO control scheme in this design, significantly simplifying implementation and reducing overall computational load. The converter was tested up to 5 kW with switching frequencies in the range of 20–150 kHz (to showcase the capabilities of the proposed system to operate efficiently in a wide range of switching frequencies), achieving a peak efficiency of 96% at 150 kHz and 91% at 20 kHz under a 2.5 kW load. Compared to existing multi-input converters, the design proposed in [49] offers higher efficiency, lower component count (2N+4 vs. 5N+5 for some similar alternatives), and the unique ability to support simultaneous buck-boost power flow. All of which makes it particularly suited for applications in EV, but also potentially for microgrids and RES.

In contrast, Kurm and Agarwal [50] explored an isolated multiport converter based on a current-fed Dual Active Bridge (DAB) topology. DAB converters, particularly the current-fed variant, offer important advantages, such as galvanic isolation for safety and reduced input current ripple, which is crucial for extending battery lifespan. Unlike voltage-fed DABs, which control the voltage applied to the transformer primary and suffer from high input current ripple, the current-fed DAB controls the current injected into the transformer primary, significantly minimizing this ripple. This is achieved using an inductor and switches on the primary side to create a current source. The current-fed DAB also improves efficiency by enabling soft switching (zero-voltage switching, ZVS) and allowing increased power density due to higher switching frequency capabilities, which is particularly well-suited for HP EV applications. The converter proposed in [50], illustrated in Fig. 14, integrates four ports: a DC charging port for simplified charging (port 1), a battery port with controlled

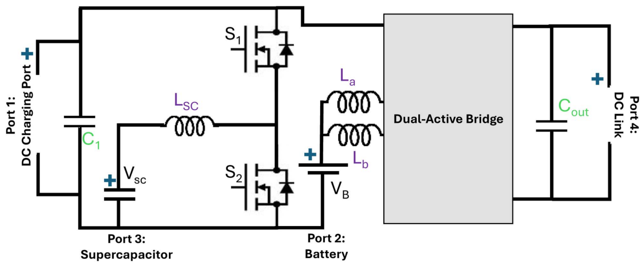

FIGURE 14. **Novel 4-port DAB proposed in [50].**

current to prevent power surges (port 2), a SC port for managing transient power demands (port 3) and a DC link port for connection to the EV's drive inverter (port 4).

The authors proposed the following three different operation modes.

1) Driving operation mode is a standard mode where the battery delivers base current to the motor, and all the sudden peaks are covered by SC. Also, in this mode, power from the battery can be used to recharge SC.
2) Braking operation mode describes EV's behavior under regenerative braking condition; the battery is charged monotonically, while all the sudden peaks in regeneration current are absorbed by SC. The DAB converter operates in a negative power transfer region to send the regenerated power to HESS, thereby preventing overvoltage at the DC link.
3) Charging operation mode represents the mode when the battery is charged by taking power from the DC charging port.

The battery is charged at a regulated current by behaving like an interleaved buck converter with reduced current battery ripple. A separate charger is not required using the proposed MIMO converter, since it performs the task of the on-board DC charger as well, which can significantly reduce EV size and weight. The control strategy involves a combination of PWM and phase-shift control, where the phase shift between the primary and secondary side voltages of the DAB transformer controls the power flow. The battery current is controlled using a closed-loop control scheme, with a reference current derived from the load demand. The SC voltage is also regulated using a separate control loop. To conclude, this multifunctional converter not only manages power between the HESS components and the drive system but also integrates the functionality of an onboard DC charger, reducing component number and cost.

Table 1 summarizes the main characteristics related to all the topologies analyzed in this section.

III. DIGITAL TWINS, AI, AND RELIABILITY CONSIDERATIONS IN HESS

Historically, vehicle manufacturers have predominantly relied on single energy storage units and conventional PE devices. While such solutions are consolidated, they are now approaching the limits of their capabilities regarding energy density, dynamic response, and efficiency, making them insufficient for emerging high-performance EV demands. Modern requirements, such as reducing range anxiety, supporting higher power peaks, and slowing battery degradation, need novel solutions. Characteristics of conventional batteries impose fundamental restrictions on further enhancements in charge-discharge efficiency, thermal stability, and operational lifespan. Similarly, conventional PE interfaces exhibit reduced efficiency under fluctuating load conditions and are less capable of managing complex multisource systems effectively. Consequently, the shift toward HESS configurations and intelligent EMS frameworks is becoming crucial in meeting the dynamic performance and reliability requirements of modern EVs [51], [52], [53], [54].

This raises the question of whether further enhancements can be introduced to advance state-of-the-art systems and extend their capabilities. Are there some techniques that can aid and enhance properties of systems that industry and academia find reliable, but are not yet ready to get rid of? The answer to this question lies in the use of digital twins and AI technology. Digital twins, defined as high-fidelity and time-variant virtual replicas of physical systems (as per [55]), facilitate real-time monitoring, simulation, and diagnostic capabilities by dynamically modeling electrothermal and aging properties. With appropriate updates and measurements, digital twins are becoming crucial in the development and maintenance of modern systems [56]. On the other hand, the expansion of AI is a realm that has affected every sphere of modern-day life. AI encompasses a broad field of computational methodologies aimed at enabling systems to simulate intelligent behavior. Within this domain, Machine Learning (ML) is a branch of AI focused on data-driven learning processes, while deep learning (DL) refers specifically to ML approaches based on deep neural network (DNN) architectures to model complex patterns and representations in data [57]. These techniques have been employed to try to further improve modern systems, prolong their life, and potentially increase the number of their use cases. Use cases for AI in modern industry are explored in [58], [59], [60], and [61]. Moving to more specialized applications, the work in [62] concentrated on big data analysis in the maritime industry, while in [63], the authors focused on how AI affects the transportation industry. An interesting paper is proposed in [64], about the impact of explainable AI models and how they are leading the technological world from Industry 4.0 toward Industry 5.0.

In "The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail" [65], Clayton M. Christensen famously said, "Historically, disruptive technologies involve no new technologies; rather, they consist of components built around proven technologies and put together in a novel product architecture that offers the customer a set of attributes never before available." Merging digital twin technology and AI represents a disruptive paradigm shift in the management and optimization of HESS, but also systems in general. The integration of AI, particularly ML, DL, and NNs, empowers the potential of digital twins with advanced

TABLE 1. HESS Topology Summary Table

Ref.	Topology type	Key features	Control strategy	Experiments/ simulations results	Challenges	Application focus
[37]	Partially decoupled (bidirectional HE DC–DC converter)	SC direct to DC bus, battery via bidirectional DC–DC	Fuzzy logic	30%–57% battery capacity fade reduction (30 kW platform)	Temperature-dependent aging effects need consideration	Battery degradation reduction
[38]	Partially decoupled (interleaved converter for battery)	Interleaved converter for reduced ripple, dynamic current/voltage regulation	Power Management Algorithm	Focus on converter efficiency and aging cost quantification	Developing control strategy that balances real-time power demands to reduce battery stress, while simultaneously optimizing converter efficiency and aging costs for enhanced system durability and performance	Reduced battery stress
[39]	Partially decoupled	Electro-thermal degradation model, multi-objective genetic algorithm for sizing, dynamic programming for control	Rule-based hysteresis, frequency-domain transient	28%–32% battery degradation reduction, 22% lower total ownership cost (simulated)	Higher initial investment	HESS sizing and battery degradation minimization
[40]	Four-quadrant DC–DC converter for battery & SC	Both SC & battery via four-quadrant converter, H∞ robust control	H∞ Robust Control (weighted mix-sensitivity)	25% reduction in battery peak current, efficient regenerative braking (20 kW prototype)	High computational load demand	Power flow management during acceleration and braking
[42]	LIC-based HESS with bidirectional DC-DC	Series/parallel LICs managed by bidirectional converter, DC bus voltage regulation	Conventional voltage and current feedback control scheme	Improved regenerative braking, reduced battery current fluctuations (1 kW 48 V lab prototype)	Precise control strategies needed for maintaining voltage limits for LiCs	Enhanced energy recovery and reduced battery stress
[43]	SA-HESS with non-inverting buck-boost (SC interface)	Capacitance-emulating control, sensor-less control, decoupled battery current from pulsed load	Capacitance-Emulating	Stable battery current independent of load dynamics (experimental)	Challenges in stability and performance validated only under pulsed and dynamic load profiles	Pulsed load applications
[44]	SIMO DC–DC converter	Single switch boost converter, multi-winding transformer, galvanic isolation for outputs	PI-Based closed-loop control	Up to 95% efficiency (simulated)	Not directly analyzed for SA-HESS topology	Efficient power conversion for multiple EV subsystems
[45]	Triple-input bidirectional converter	Two unidirectional ports (SC/Renewables), one bidirectional battery port, common grounding	Flexible power transfer (8 scenarios), common grounding	95% peak efficiency (Scenario 6)	Optimizing input current continuity and soft switching to ensure reliable power flow while minimizing complexity and cost	Integrated power management with multiple sources
[46]	Clustered input non-isolated multiport converter	Clustered input structure, unidirectional/bidirectional switches, H-bridge topology, easy scalability	Complex switching control (over 20 modes)	Simultaneous energy transfer from multiple sources	Potential EMI issues	Flexible integration of diverse energy sources
[47]	Two-input, One-output converter with SPDT switch	SPDT switch for dynamic allocation to high current path, seven operating modes	Supervisory control based on load power and voltage thresholds	Dynamic flexibility demonstrated (scaled-down prototype)	Complex control strategy implementation	Optimized utilization of battery and SC based on driving scenarios
[48]	Three-port bidirectional converter	Simplified topology (3 switches), simultaneous power flow from two inputs, bidirectional across all ports	Dual-loop control based on small-signal model	120 W step-up, 30 W step-down (experimental)	Experimental validation at low power levels, suitability for EV needs further investigation	Simultaneous power flow and bidirectional energy transfer
[49]	V_{TR}-based multi-input converter	Single inductor per input, single bidirectional switch per input, novel V_{TR}, SISO control	V_{TR}-based SISO control	96% peak efficiency at 150 kHz (5 kW load)	Achieving simultaneous power transfer with minimal components requires careful management of voltage transformation, as conventional gain reasoning no longer applies	High efficiency, low component count, simultaneous buck-boost for EV and other applications
[50]	Current-fed DAB	Galvanic isolation, reduced input current ripple, integrates DC charger, three operating modes (driving, braking, charging)	Combination of PWM and phase-shift control, closed-loop for battery current and SC voltage	Efficient power management and energy recovery (prototype not specified)	Challenges in integrating multiple operating modes and control schemes for EV applications	High-power EV applications, integrated charging functionality

analytical and predictive functionalities. This combination further enables the development of adaptive and dynamic control strategies that respond to fluctuating and variable load profiles and environmental interchanging conditions. Moreover, Reinforcement Learning (RL) frameworks have been successfully applied to optimize charge/discharge cycling, while digital twin platforms coupled with predictive analytics have demonstrated the capacity to anticipate and prevent risks through anomaly forecasting. This "cooperation," which not only improves operational efficiency but also extends system lifespan and usability while reducing operational costs, is extensively examined in [66], [67], and [68], revealing its considerable potential and offering practical insights.

A. DIGITAL TWINS

To begin with, Semeraro et al. [69] presented a very thorough analysis of the integration of digital twin technology in BESS, highlighting its potential for improving system efficiency, real-time monitoring, and fault detection. They have reviewed various digital twin architectures and functionalities, such as parameter estimation and optimization, temperature control, and predictive maintenance, and have identified a general schematic of digital twins. Furthermore, they have employed formal concept analysis to identify trends and gaps in current research, revealing that most studies focus on LiBs and the physical layer of digital twins, while aspects like Pb-acid batteries and the integration of the other two architectural layers (network and computing) remain underexplored. There are several papers in the literature that examine the same topic, but from different points of view. For example, Wu et al. [70] provide a top-down perspective on the fusion of physics-based battery models, real-world data, and AI, presenting a structured framework for the smart management of batteries in applications like EVs. It stresses the integration of multiscale modeling for battery behavior, advanced data analytics, and ML to enable predictive maintenance and onboard decision-making for reliable battery management. Furthermore, Wang et al. [71] provided a comprehensive academic review, systematically integrating the DT concept for battery health prognosis by introducing a four-layer conceptual framework.

- Physical layer.
- Data and communication layer.
- Virtual model layer.
- Twin service layer.

The virtual model layer incorporates advanced hybrid approaches, including CNNs and LSTM networks, to achieve superior predictive accuracy for indicators like SOC, SOH, and remaining useful life.

To conclude, unlike [70], [71] provides a detailed analysis of diagnostic methodologies and identifies key research gaps in uncertainty quantification and predictive analytics. Comparatively, the perspective from [70] is broad and systematic, emphasizing foundational frameworks for digital twin fusion, making these two papers complementary in scope and depth for understanding battery digital twin technology.

In the literature, it can be noticed that only battery digital twins have been investigated, and therefore, this reveals one more gap: digital twins for SCs and HESS, in general. These domains represent a significant unexplored potential within HESS research, which is anticipated to be addressed soon, so as to have a better understanding of how these systems and components behave in the long term and, consequently, what further steps are needed in their improvement.

The rationale for developing digital twin models of SCs lies in their performance degradation, which results from electrode material deterioration, electrolyte instability, and current collector corrosion [72], [73]. These degradation parameters cannot be measured directly; therefore, a proposed solution is building SC digital twin models, which will enable continuous real-time monitoring and predictive analytics.

More broadly, digital twins for HESS create detailed virtual replicas of the entire system, enabling advanced monitoring, simulation, and diagnostics of both batteries and SCs, with the potential to also include PE converters. These digital models make it possible to optimize system performance, spot faults early, and support informed decision-making, even in interchangeable conditions. Developing a digital twin framework for all parts of HESS is therefore crucial for improving predictive maintenance, reliability, and supporting better long-term management. A conceptual diagram about the HESS digital twin framework, with AI integration, can be found in Fig. 15. Interconnection between the physical and cyber-physical domains establishes a continuous exchange of information, allowing the real-time operational parameters of the physical system to be transmitted to the digital twin. Within the virtual environment, these parameters are systematically compared with the corresponding values of the digital twin, enabling the identification of deviations or inconsistencies between the real and virtual representations. Beyond this comparative process, the digital twin can employ dedicated internal estimation algorithms to refine model accuracy by deriving updated parameters that reflect the evolving state of the physical system. Furthermore, digital twin architecture can integrate information provided by an external supervisory framework, capable of executing advanced AI procedures, thereby enhancing system adaptability, predictive capabilities, and overall decision-making performance. This system has some resemblance to observer systems, commonly found in Control System Theory.

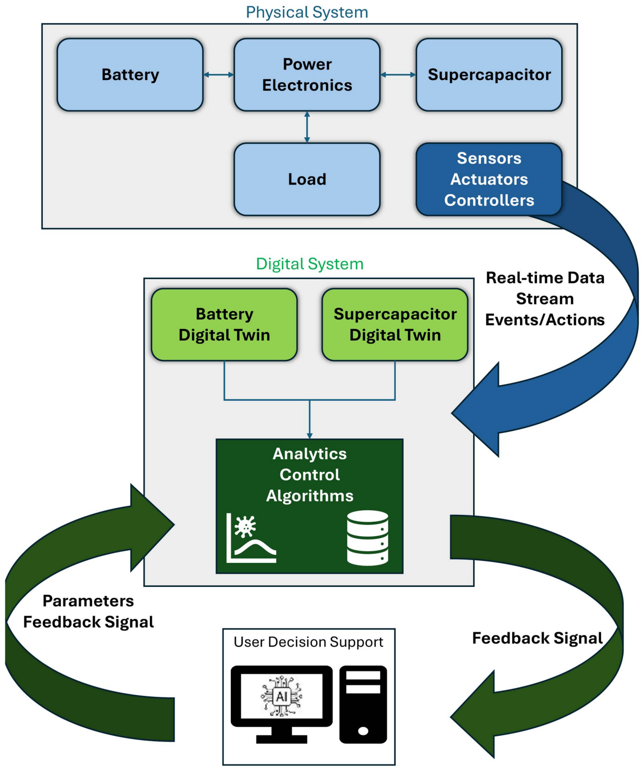

FIGURE 15. HESS digital twin conceptual diagram, with AI integration.

B. AI INTEGRATION

Advances in digital twin technology, mentioned in the previous part of this section, lay the foundation for increasingly intelligent and adaptive management of ESS in EVs. Building upon these developments, the following subsection examines current trends in AI-integration within ESS, highlighting potential synergies with the digital twin framework.

To begin with, the article [74] provides a thorough and forward-looking analysis of how AI is reshaping ESS in EVs, emphasizing both technological advancements and practical benefits for modern mobility. It outlines key factors, such as battery efficiency, degradation, and power management, and discusses how AI-driven solutions notably enhance battery systems, improve power quality, optimize charging cycles, and facilitate integration of RES with EV charging infrastructure. The central role of ML, NN, and statistical models in enabling SOC and state-of-health (SOH) predictions, supporting more precise and adaptive energy management, has been highlighted. DL architectures are recognized for their ability to model complex nonlinear behaviors in battery aging and energy demand, while RL is presented as a promising control strategy for real-time, adaptive energy management in HESS, though it is not yet commonly used for SOC or SOH prediction. The article ultimately identifies ongoing research gaps, including the need for standardized AI frameworks and improved integration of AI in HESS. A study on a very similar topic has been presented in [75], where the authors have presented AI integration trends in modern EMS, for EV purposes. They used PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) methodology to identify 46 most relevant papers from standard academic databases. Their study reports significant advancements in EMS optimization, route planning, energy demand forecasting, and real-time adaptation to interchangeable driving conditions through advanced dynamic control algorithms. Additionally, this article explores AI's role in fault-diagnosis, predictive maintenance of electric propulsion systems and batteries, and personalized driving experiences based on driver preferences and environmental factors. The authors went one step further than others and explored AI's role regarding security and cybersecurity threats in EV's EMS. Their findings emphasized the need for further development on these topics, to overcome current challenges and optimize practical applications, but also make them industrially acceptable and financially viable.

Continuing, Zhang et al. [76] presented a comprehensive review of DL techniques for LiB SOC estimations in EVs. The authors have examined technical processes, common public datasets, and the NN used, as well as the structural characteristics and advantages and disadvantages of LiB SOC estimation in DL methods. This article addressed the limitations of traditional SOC estimation methods, such as model-driven approaches (electrochemical models and equivalent circuit models) and conventional data-driven techniques (filtering algorithms and traditional ML), which often suffer from high computational costs, interpretability issues, or limited accuracy ranges. The authors systematically dissected the DL-based SOC estimation pipeline, which consists of five stages: data collection (under standardized driving cycles), preprocessing (data cleaning and normalization), feature engineering, model training, and performance evaluation using standard error-metrics. Publicly available datasets from institutions such as NASA, MIT, and Toyota were utilized. These datasets typically include parameters such as voltage, current, temperature, capacity, and cycle life under various driving conditions and temperatures. The authors categorized DL architectures into the following three main groups.

1) Single-structure networks:
   a) Deep neural networks (DNN)
   b) Temporal convolutional networks (1D-CNN and TCN)
   c) Long short-term memory (LTSM) and gated recurrent units (GRU)
2) Hybrid architectures
3) Trans-structure models:
   a) Transfer learning
   b) Transformer-based models

This article was concluded by identifying key challenges, such as the need for high-quality labeled datasets, computational resource demands, and limited interpretability of DL models. The authors also suggested future research directions, including the integration of domain knowledge into DL frameworks, real-time deployment in embedded systems, and enhancing model robustness against noise and temperature variation.

In the following part, specific papers about the ways of using ML and DL in EV applications are analyzed. First, the research article in [77] explores the application of ML, particularly RL, to optimize energy management in HESS for hybrid EVs (HEVs) and EVs. Traditional rule-based EMS are criticized for their rigidity in dynamic driving conditions, prompting the authors to propose adaptive ML-driven

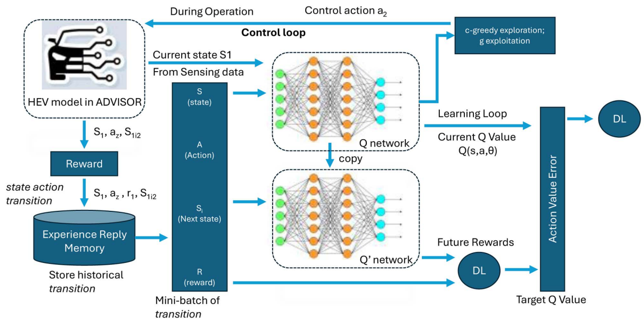

FIGURE 16. DRL-based control framework, proposed in [77].

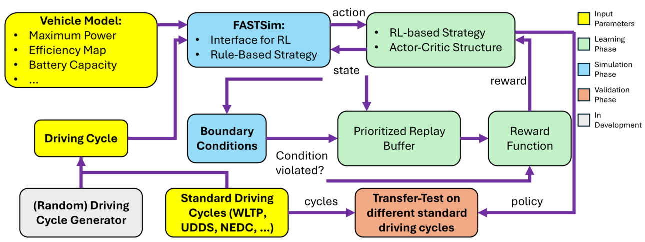

FIGURE 17. Training RL-based framework for HEV driving strategies using FASTSim, proposed in [78].

strategies. This article evaluates RL algorithms, including Q-learning and deep reinforcement learning (DRL), and hybrid approaches combining RL with predictive models or NN to try to solve energy management challenges, such as balancing power distribution among multiple sources while minimizing costs like fuel consumption (in HEVs) and battery degradation. A key innovative proposal involves a DRL-based framework, schematically represented in Fig. 16, with dual NN (transaction and nontransaction modes), tested across six strategies.

However, factors like the substantial computational load required for real-time processing and the large volumes of data needed for training continue to impede practical implementation. Contrary to many other potential solutions proposed in the literature, the authors have proposed future integration with intelligent transportation systems in smart cities to enhance data accessibility and push for real-world validation of these strategies. In addition, Wu et al. [78] also explore the usage of RL in EMS for HEVs, but they introduce a novel framework that integrates RL technique with the open-source FASTSim simulation tool, embedding boundary constraints (speed adherence and battery SOC) into the reward function, enhancing learning efficiency through prioritized experience replay and Monte Carlo dropout methods, so to mitigate overfitting. The proposed schematic framework for network training is shown in Fig. 17. Addressing the limitations of proprietary and rigid rule-based systems, the authors propose a flexible RL-driven approach that adapts to dynamic driving conditions. Experiments on HEVs (BMW i3 and Toyota Prius) demonstrate significant energy consumption reductions (BMW i3's consumption dropped from 7.65 to 2.92 kWh after 10 training episodes, outperforming rule-based strategies at 3.07 kWh). The framework's transferability was validated across diverse driving cycles (WLTP and UDDS), though challenges emerged in aggressive scenarios, due to simplified efficiency models in FASTSim. Other limitations are related to simplified SOC references. To conclude, this approach offers a scalable and, more importantly, open-source solution for advancing HEV energy efficiency in varied driving conditions, with a caveat of needing more viable and precise models.

Continuing with a similar methodology, Chu et al. [79] explore the integration of RL algorithms for advanced temperature control of PE within EVs, aiming to extend component lifetime and enhance system reliability. The authors present a predictive, data-driven framework employing RL to dynamically optimize device thermal profiles under varying operating conditions, considering thermal stress and degradation models for critical components like IGBTs and MOSFETs. The methodology leverages real-time temperature and operational data to train RL agents, which adaptively adjust control parameters of thermal management systems, balancing immediate thermal needs with long-term degradation minimization. Experimental results on testbench setups demonstrate improved temperature regulation, reduced peak thermal excursions, and a measurable extension of device service life compared to conventional PID-based approaches (2.8x better energy efficiency, while achieving a better lifetime extension by up to 63%). This article highlights how combining RL with lifetime prediction models enables smarter, self-optimizing control strategies crucial for reliability and efficiency in PE for EVs. However, this methodology suffers from the standard problems related to using RL, such as the need for extensive representative training data, and even more importantly, computational challenges for real-time embedded automotive applications. Additionally, transfer from simulated training environments to actual vehicle hardware remains challenging due to unmodeled vehicle dynamics and sensor inaccuracies, requiring extensive validation in diverse real-world driving scenarios before practical industrial adoption.

The last paper to be mentioned in this part is on the topic of SOC estimation using DL techniques. Lin [80] presented a novel DL-based framework for accurately estimating the SOC in LiBs for EVs, addressing key limitations of traditional estimation methods. Unlike previous approaches that primarily relied on laboratory data or simplistic modeling assumptions, this study utilized comprehensive real-world driving data collected from a BMW i3, under both summer and winter conditions (batteries present significantly different characteristics in cold and warm environments, as shown in [81]). The proposed model integrates 24 environmental, vehicular, and battery-related features, such as temperature, elevation, vehicle speed, throttle input, battery voltage/current, and cabin temperature, into a multilayer perceptron (MLP) DNN, with three hidden layers (shown in Fig. 18).

Feature selection was conducted using the Max-Relevance and Min-Redundancy (MRMR) algorithm to enhance training efficiency and accuracy. The study emphasized the advantage

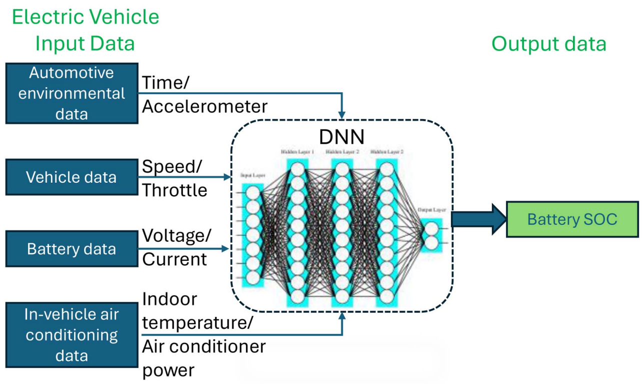

FIGURE 18. Block diagram of DNN methodology presented in [80].

of using real-world data over synthetic datasets, ensuring better generalization and adaptability across diverse operating scenarios. Comparative experiments with traditional robust regression models reveal the DNN's superior performance: across summer tests, achieving Root Mean Square Error (RMSE) equal to 0.84 and Mean Average Error (MAE) of 0.62, while robust regression yielded an RMSE above 2. Winter conditions presented a greater challenge due to environmental variability, yet the DNN maintained an RMSE of 2.36 and MAE of 1.67, significantly outperforming robust regression, which showed RMSE values above 5.6 and MAE nearing 3.9. This article further discusses training dynamics, including the use of backpropagation through time and adaptive learning rate strategies based on error gradient behavior. It justifies the eventual use of feedforward MLPs over recurrent-NN (RNN), noting that sequence modeling added little value for the given SOC estimation task. The authors stated that DL-based SOC estimation is a huge leap forward in terms of more accurate and reliable EV battery management systems, reducing range anxiety and supporting sustainable transportation initiatives. On the other hand, this work may be limited by its reliance on feed-forward DNNs, omitting sequence-based models like LSTM RNN despite the temporal nature of driving data, and by high computational demands that obstruct real-time validation on physical hardware. Additionally, the model's performance and generalizability are constrained by testing a single EV model in a specific geographic region only.

In [69], the authors offered a detailed review of digital twin applications in BESS, while comprehensive summary tables for AI integration into ESS for EVs can be found in [74], [75], and [76]. The summary of the individual papers discussed solely in this review is presented in Table 2.

C. RELIABILITY CONSIDERATIONS

While AI and digital twin technologies offer promising capabilities, ensuring system reliability is equally essential for robust (H)ESS operation, as extending the lifespan of EVs is of both economic and environmental importance. Using vehicles for longer periods helps owners save money by reducing the need for costly battery replacements. More importantly,

TABLE 2. ML and AI in (H)ESS Summary Table

Ref.	Focus	Method	Innovation	Advantages	Limitations
[77]	Energy management	DRL-based framework with dual NN	Hybrid RL approaches (e.g., DRL, Q-learning), integration with ITS, six strategy tests	Adaptive to dynamic driving, fuel/battery efficiency, real-world data potential	High computational demands, large training data requirements, no validation on experimental rigs
[78]	Energy management	RL integrated with FASTSim, enhanced reward design	Prioritized experience replay, Monte Carlo dropout, SOC/speed constraints	Energy savings, flexible, open source	Performance drops in aggressive driving, simplified FASTSim models, SOC limitations
[79]	Thermal management	Predictive, data-driven RL framework optimizing thermal profiles using stress and degradation models	Real-time RL agent adapts control using operational data for lifetime extension	Improved regulation, reduced thermal peaks, increased energy efficiency, prolonged device life	Requires extensive training data, high computational demand, and faces transferability issues to real hardware
[80]	SOC estimation	MLP-DNN	Extensive real-world SOC estimation with DNN, integrating 24 real-world driving parameters	Significantly lower error-metrics than robust regression, Practical deployment potential	No LSTM or sequence models; high resource demands; no hardware validation; region specific

it lowers environmental harm by decreasing the frequency of battery disposal, which is a process known to release toxic materials and pollutants harmful to soil, water, and air quality [82], [83]. Digital twin technology is a promising tool in this area since it allows to simulate accelerated degradation and the prediction of faults with greater speed and safety.

Yan et al. [84] provided an extensive literature review summarizing the reliability assessment methodologies for ESS, including HESS configurations. It highlights that ESS reliability is a multidimensional concept, encompassing factors such as availability, dependability, maintainability, and durability. These aspects are evaluated using metrics such as mean time between failures (MTBF) and mean time to repair (MTTR). Technical modeling covers topics from simplistic two-state operational/fault representations to rigorous multistate models designed to capture degradation, partial functionality, and general aging effects, particularly critical for HESS component-level analysis, like battery SOH fading and cycle life losses. These multistate stochastic processes are often implemented using Markov chains to model state transitions and the universal generating function (UGF) methodology for calculating overall system performance distribution across numerous states. Reliability quantification leverages advanced probabilistic methods, notably Monte Carlo simulations and statistical inference from empirical failure data, supplemented by qualitative approaches like failure modes and effects analysis (FMEA). Reliability challenges for HESS include high variability due to intensive charge-discharge cycling, the complexity of SOC management, and complex interdependency between components. Consequently, future research must focus on leveraging AI and digital twins to enable predictive reliability modeling and sophisticated maintenance strategies.

Moreover, Liu et al. [85] present a systematic review of SC lifetime models and reliability-oriented design for ESS, including HESS configurations. Technical details cover so-called "physics-of-failure" mechanisms, such as electrode chemical reactions and solvent decomposition, where solid and gaseous products block SC porosity and increase cell pressure, causing capacitance loss and a rise in equivalent series resistance (ESR). Critical stressors, such as operating temperature, voltage, and current, accelerate the aging of SC. In this article, the authors specify that a 10 °C increase in temperature or a 0.2 V increase in voltage typically halves the lifetime of SC, with scaling parameters for model fitting based on empirical tests. Lifetime models for SCs use Arrhenius-type and Eyring-type functions to express dependence on temperature, voltage, and current. This article explores a reliability-oriented design workflow for HESS, emphasizing the use of realistic mission profiles over datasheet ratings, the incorporation of multiobjective optimization (reliability, robustness, cost, and size), and feedback loops in system-level design based on lifetime prediction. To conclude, the authors identify the following three key areas that must be prioritized to achieve enhanced reliability and design optimization.

1) Establishing lifetime models centered on failure mechanisms.
2) Advancing thermal modeling at the system level.
3) Accumulating substantial operational data.

Shifting the discussion to the reliability of PE devices, Ibrahim et al. [86] offered a detailed and systematic examination of active thermal control (ATC) strategy, organizing current advances into device-level, converter-level, and system-level methodologies. The article emphasized that ATC significantly enhances the reliability and lifespan of PE converters by dynamically managing thermal stress and mitigating temperature-induced degradation of semiconductor components. Experimental demonstrations in IGBT modules show that regulating the junction temperature during fault conditions keeps it below 110 °C, thereby avoiding critical thermal stress and premature aging. Quantitative results indicate that ATC strategies can reduce junction temperature swings by up to 32 °C compared to uncontrolled cycling, where swings of 37 °C are typical in comparable modules. Furthermore, adaptive control using switching frequency and current limiting was shown to maintain operational stability during transient faults, effectively controlling fluctuations and maximizing the silicon's usable temperature window. This article concludes that modern ATC strategies allow for operational thermal ranges well below typical critical limits. Junction temperatures were consistently observed to remain below 120 °C during real-time control experiments, indicating significant improvements in both reliability and safety for PE systems in demanding automotive, industrial, and renewable energy applications. These advancements are especially important for the development of digital twin frameworks and the optimization of thermal management in HESS for EVs. They provide crucial data and modeling approaches necessary to more accurately simulate, predict, and manage the thermal behavior, reliability, and lifespan of these systems under real-world operating conditions.

Cheng et al. [87] investigated the operational reliability of BESS by developing a LiB lifetime degradation model that combines empirical observations with mathematical descriptions. The authors divided the battery aging process into phases, starting with rapid degradation during the formation of the solid electrolyte interphase, followed by a steady aging phase, and ending with accelerated capacity loss near the battery's end of life. Degradation rate is considered to be a function of several key stress factors, such as temperature (T), SOC, DOD, and aging duration (t). The model expresses capacity fade as: $Q_{loss}(t) = f(T,\ SOC, DOD, t),\ \ Q_{loss}$ being quantified lost capacity as a function of operational and environmental variables. To quantify system-level reliability, the authors used the UGF method, which allows the probabilistic modeling of systems composed of batteries that may have different health states. Each battery cell in the system is assigned a probabilistic SOH, and the combined reliability of the storage system is calculated by aggregating the states of all cells, considering both series and parallel configurations. The reliability importance index (RI_i) is updated continuously as cells age and as the system operates under varying conditions. The model also supports thresholds for SOH lower than the conventional 80%, which extends useful life for aging batteries, although the point about practical usability must be raised (whether these degraded cells can provide a meaningful amount of energy to the system). A significant innovation in this article is the weak-link analysis, where the impact of each cell on the entire storage system's reliability is measured using both state-based and change-based reliability importance indices. The state-based index evaluates the sensitivity of system reliability to the current condition of each cell, while the state-change-based index assesses how system reliability changes as a result of cell SOH degradation over time.

These indices are combined using an entropy-weighting method ($RI_i = \omega_1 * SORI_i * \omega_2 * SCORI_i$, where SORI and SCORI denote state-oriented and state-change-oriented reliability importance and $\omega_1,\ \ \omega_2$ are weights determined by entropy analysis) to provide a comprehensive reliability importance index score for each cell. The proposed framework not only highlights which cells are the weakest links but also informs intervention strategies to extend system lifetime. Case studies with real operating data illustrate that reliability is affected by nonuniform aging and varying operational stresses at the cell level, confirming the practical value of this model for HESS in EVs. The result is a robust, quantitative framework that integrates battery degradation modeling with probabilistic reliability assessment, offering actionable metrics to manufacturers seeking to maximize system longevity and reliability.

To conclude, this section has presented papers of significant interest and impact, regarding AI and digital twins in HESS. Moreover, reliability considerations have been discussed based on the available literature. This section aims to bridge the three topics, encouraging future studies to explore their integration. The authors believe that these domains are inherently interconnected and should be examined through a cohesive research perspective.

IV. ALTERNATIVE AND NICHE CASES IN LITERATURE

The final section of this review will take into consideration papers with topics related to HESS, but that somewhat expand the above conventional EV applications, venturing into alternative and niche domains, as well as nonconventional control and energy management methods. However, ideas presented hereafter provide a wider insight into HESS and can potentially expand the perception of HESS for new EVs. In other words, the following articles can hypothetically help readers to think outside the box. Although numerous publications introduce novel ideas, this review focuses on selected papers that demonstrate unique concepts and clear perspectives.

To begin with, Barcellona et al. [88] presented a critical demonstration that P-HESS, which pairs LiB with SC, significantly improves EV performance in subzero conditions where conventional LiBs alone are inadequate. This article reported that at temperatures below −10 °C, LiBs lose a substantial portion of their available capacity (down to 30%–50%), and at −40 °C, this falls to as little as 5%. Furthermore, their internal resistance also rises by a factor of ten at −20 °C, compared to room temperature. In contrast, SCs maintain high power and stable performance even at −40 °C, and thus, when configured in a P-HESS, are able to deliver the high currents needed for cold starts and acceleration when the battery is not. Experimentally, this article demonstrates that at −20 °C, EVs such as the Toyota Rav4 and Renault Zoe are unable to start using only LiBs. However, with the addition of a passive HESS, these vehicles are able to achieve ranges of 7.9 km for the Toyota Rav4 and several kilometers for the Renault Zoe. Very similar results were seen for the Volkswagen e-Golf. At −10 °C, range increases are substantial, going from 53.5 km (LiB only) to 86.4 km (HESS; +61.5%), for the Toyota Rav4, and from 9.4 km (LiB only) to 20.4 km (HESS; +116%) for the Renault Zoe. In the case of Volkswagen Golf, the range increases by 369%, and for the Zoe (alternative drive cycle), by 794% with HESS. At room temperature (20 °C), the difference between systems is negligible. The authors conclude that P-HESS offers a simple, robust, and cost-effective solution for reliable EV operation in cold climates. In the end, the authors justify putting this article in this section due to the fact that P-HESS, even though offering notable benefits, is not widely adopted in industry or extensively documented in the literature, largely due to the drawbacks discussed in Section II. Nonetheless, this study underscores the importance of hybridization in EV ESS, as batteries alone are unable to adequately address the diverse range of operating and temperature conditions encountered by modern vehicles. Additionally, this research is among the very few that examine the behavior of HESS across multiple temperature scenarios.

Continuing, a similar consideration has been addressed in [89]. Namely, the authors have stated that "Li-ion batteries are adversely affected by subzero temperatures. At −20 °C, the EV's driving range is reduced significantly to half its capacity compared to that at 20 °C, meaning that it is important to maintain a suitable temperature for battery operation," as confirmed by [90] also. Furthermore, the harmful effects of charging batteries at subzero temperatures have

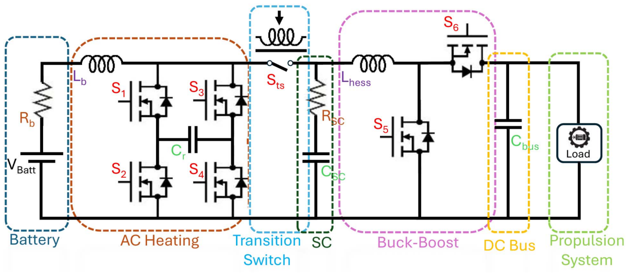

FIGURE 19. **HESS system proposed in [89].**

been highlighted, as also mentioned in [81]. The research in [89] introduces an integrated HESS for EVs, designed to address LiBs performance degradation in cold environments while efficiently managing power demands.

The proposed system, shown in Fig. 19, combines a bidirectional half-bridge converter with a resonant network to enable two critical features: enabling an internal battery heating and a dynamic power distribution between the battery and SCs. At subzero temperatures, the converter operates in heating mode, utilizing a resonant circuit to generate high-frequency (HF) current within the battery, leveraging its internal resistance to produce uniform heat without external heating elements, which usually dissipate a large amount of energy. This method raises battery temperature at a rate of 1 °C per minute (from −20 °C to +5.3 °C in 5 min) while avoiding lithium plating risks through frequency optimization. During normal operation, the same resonant components switch to power transfer mode, where the converter intelligently distributes power demands. In this mode, SCs handle high-frequency transient loads, such as acceleration and regenerative braking, due to their rapid response capabilities, while the battery supplies a steady, low-frequency base current. This approach significantly reduces stress on the battery, thereby extending its lifespan. A frequency-domain design approach (Discrete Fourier Transform analysis) optimizes component parameters, such as inductor sizing, to align with driving cycle power profiles, ensuring efficient energy distribution. Experimental validation on a 1 kW prototype (48 V LiB, 48 V SCs) demonstrated seamless mode transitions, soft switching for reduced losses, and effective load management, with SCs absorbing up to 90% of transient currents during dynamic driving cycles. All the abovementioned properties make this system particularly suitable for EVs operating at extreme temperatures. Integrating HESS with smart thermal management in EVs, as done in this article, can significantly improve performance and safety and decrease one of the main modern EV-related problems, which is range anxiety. By improving reliability in harsh climates and ensuring consistent operation in real-world conditions, such innovations make EVs more practical for widespread adoption.

Mesbahi et al. [91] presented an unconventional electrothermal-aging model for HESS, integrating a 40 Ah LiB and 350 F SC, with an equivalent circuit capturing

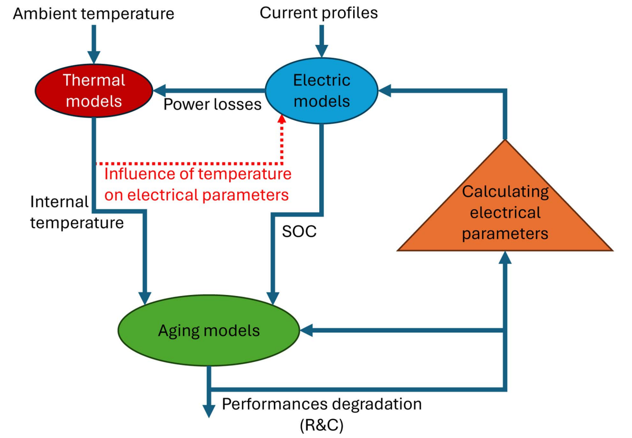

FIGURE 20. **Advanced electrothermal-aging HESS model, proposed in [91].**

battery transient behavior (Fig. 20). This type of model enables joint prediction of both electrical performance and thermal evolution. The thermal model predicts temperature rise (up to 44 °C under 60 A pulses), and an aging model forecasts capacity fade and resistance increase with less than 1% error over 3600 cycles. This study emphasized degradation prediction, using hybrid PSO–NM (Nelder–Mead) optimization for accurate parameter identification. Cycle conditions, including current rate and temperature profile, were based on standard EV duty cycles, which may not capture all the stresses encountered in real-world operation. The parameter identification process relied on simulated or laboratory datasets rather than continuous in-field EV operation. Even though the model shows promise in controlled environments, its real-world applicability remains to be confirmed, as experimental validation under actual operational conditions is still lacking, and practical effects on long-term reliability and performance may differ from simulation-based predictions.

Some studies prioritize innovative approaches to energy management, focusing on sophisticated control strategies and models, rather than hardware configuration. To begin with, Maghfiroh et al. [92] introduced an improved low-pass filter (ILPF) energy management strategy for LiB-SC HESS. To improve adaptability under diverse driving conditions by dividing the load into high-frequency (covered by SC) and low-frequency (covered by battery) parts, they proposed an improved method, which optimized the cut-off frequency and mitigated phase shift effects. Using particle swarm optimization (PSO), the study determines the optimal sizing of the battery and SC, alongside a 5 kW bidirectional DC–DC converter. The ILPF method enhances travel distance by a significant 8% in UDDS and 6.5% in WLTC, outperforming traditional low-pass filters and fuzzy logic controllers by reducing unnecessary energy exchange, thus minimizing losses in the DC–DC converter (95% efficiency). However, its highway performance is limited due to inadequate SC utilization, suggesting the need for predictive power allocation strategies.

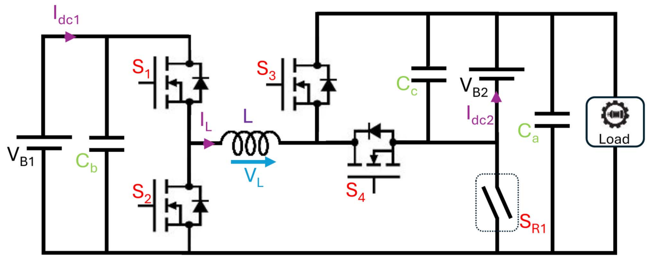

FIGURE 21. Hybrid battery system proposed in [93].

In addition to mainstream developments, a subset of research has pursued notably niche architectures, presenting innovative and less conventional ideas for system integration and hardware design. These works put forth unique configurations and components, contributing fresh perspectives and potential advancements beyond standard practices found in HESS-related literature.

Starting from the system-level approach, Sayed et al. [93] present an interesting system, designed to optimize power delivery and regenerative braking, particularly micro-EV solutions like electric motorcycles and scooters. The system integrates two LiBs: a HE (or high capacity) main battery with low power capability and a HP sub-battery with low capacity (30%–60% of the main battery). As shown in Fig. 21, such batteries are connected via two bidirectional DC–DC converters, sharing a common inductor, which allows flexible energy distribution.

The system employs four operational modes for power delivery and regeneration: main battery-only mode, sub-battery-only mode, series mode, and parallel mode, ensuring adaptive power management. Simulation results and a laboratory prototype confirm significant efficiency improvements, with sub-battery support reducing the main battery current by 65% during acceleration and 70% during regenerative braking, which gives a benefit of lowering heat generation and extending battery lifespan. Additionally, switching losses in the inverter are minimized (therefore increasing the system's efficiency) by dynamically adjusting the input DC voltage based on motor speed. The bidirectional switch enables SOC balancing during idle periods, further optimizing performance. Experimental results show that sub-battery integration significantly reduces peak current stress on the main battery, preventing thermal runaway and power loss, which is critical for sustained EV operation. However, these efficiency improvements were validated primarily through simulations and laboratory prototypes; thus, the results may overlook important factors present during actual driving and typical EV operation.

Alternatively, Yamanaka et al. [94] strictly focused on regenerative braking, employing a bidirectional DC–DC converter and two SCs to store energy before transferring it to the battery, thus mitigating regenerative current stress and inverter losses. Unlike [92], which prioritizes real-time power distribution, this approach dynamically adjusts inverter input voltage based on motor speed, enhancing efficiency at 400 W power levels by shifting from battery reliance to SC supply, effectively reducing battery cycling (degradation) and energy losses. Even though power levels are lower than expected in the EV case, the system clearly offers potential. However, it is crucial to conduct thorough scalability testing in real-world EV scenarios to fully validate its performance across different power demands and operational conditions.

Instead of just two of the mentioned individual units, a novel idea of HESS for EVs, integrating LiBs, EDLC (SC), and LiCs, through a multiple-input DC–DC converter has been presented in [95]. The system addresses limitations of conventional LiB-EDLC or LiB-LiC hybrids by combining EDLCs (high-power density) and LiCs (higher energy density than EDLCs, but lower cost than LiBs) in parallel, reducing multiport converter complexity from three-input to two-input topology. This configuration minimizes resource usage (fewer MOSFETs, snubbers, and drivers) while optimizing power distribution. In this case, EDLC will handle high transient loads (acceleration and deceleration), LiCs will manage moderate sustained demands, and LIBs will supply base current/power, thereby reducing battery straining and consequently extending lifespan. Key innovations include trickle charging (a method of charging a device by supplying a small, continuous amount of current) for component longevity, downsized LIBs for reduced weight/volume, and a control strategy that prioritizes the usage of SCs during regenerative braking. Validated via simulations and experimental EV load profiles, the system outperformed conventional HESS in normalized metrics, achieving a specific power of 12.59 kW/kg compared to 7.83 kW/kg for battery-SC, thus confirming reduced battery degradation and enhanced energy efficiency. Experimental validation, even if in a reduced scale (150 W prototype), demonstrated an improved transient response and provided valuable insights into system dynamics, but the system upscaling remains in question and needs further analysis.

In terms of hardware design contributions, Ebadpour [96] proposed a low-cost, HP multiport isolated DC–DC converter for plug-in electric vehicles (PEVs). This converter integrates PV systems, vehicle batteries, and the power grid, enabling bidirectional energy transfer across various operating scenarios, including PV-to-vehicle (PV2V), PV-to-grid (PV2G), grid-to-vehicle (G2V), and vehicle-to-grid (V2G). The proposed topology utilizes a CLLLC resonant converter, reducing switching device count and leveraging the leakage inductance of an integrated three-winding transformer, thus eliminating the need for additional resonant inductors and minimizing current stress. The converter operates with a unified MIMO controller (shown in Fig. 22), ensuring optimal power management and maximum power point tracking (MPPT) for PV integration while enabling bidirectional energy flow. The dual-output charging strategy enhances efficiency and extends the operating voltage range, allowing vehicle batteries to be

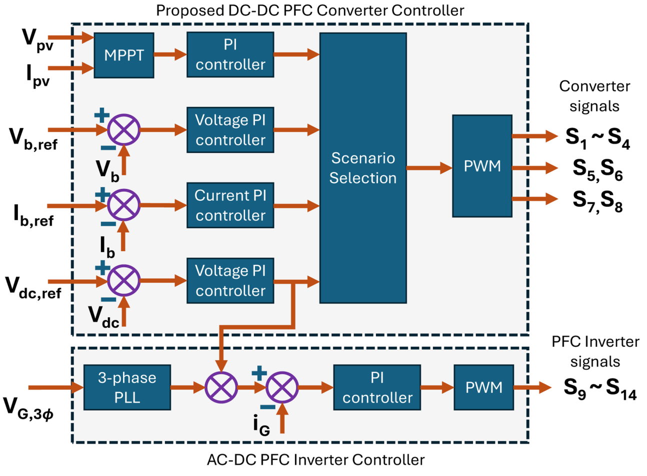

FIGURE 22. Integrated MIMO control diagram of the converter proposed in [96].

charged either solely by PV systems or through a combination of PV and grid power. The system's control methodology prioritizes standalone PV charging, automatically switching to grid-assisted modes when necessary. The authors highlighted the superiority of the proposed topology over conventional phase-shifted and LLC resonant converters because it offers reduced component count, improved efficiency, and better reliability.

Cao and Emadi [97] introduced a novel LiB-SC HESS that minimizes the need for large DC–DC converters by using a compact converter functioning as an energy pump to ensure the SC voltage remains above the battery voltage, enabling the SC to handle peak loads. This approach contrasts with the one in [92] since it focuses on sustained SC utilization rather than transient peak assistance, achieving enhanced vehicle drivability at a wider temperature range, while utilizing 75% of SC energy, as shown in simulations and experiments. Furthermore, this approach shows improved battery life due to lower operational stresses.

Similarly, Suresh et al. [98] proposed a novel four-port nonisolated converter, tailored for LiB-PV HESS, with a remarkably low component count, achieving simultaneous buck and boost functionalities with only three active switches. This simplified topology, using a clever arrangement of coupled inductors and switches, enhanced reliability and reduced cost. The converter operates in five distinct states, handling power flow from a PV panel and battery to the load, as well as regenerative braking. Small-signal models are derived for each state, facilitating control design, and a hardware prototype validates the converter's performance, demonstrating high peak efficiencies (around 98%). However, the limited number of switches might restrict the flexibility in managing more complex power flow scenarios compared to the dynamically reconfigurable approach in [47], for example. Nonetheless, this topology provides an interesting idea worth exploring further, reworking it for LiBs-SC HESS.

On the other hand, in [99], even though the authors focus on single-phase grid-connected HESS, an interesting idea can be found. Namely, they introduce an interleaved boost inverter-based design that reduces current sensor requirements while maintaining phase-shifted PWM control. Using only two current sensors and applying sampling manipulation, four inductor currents are then reconstructed. This method lowers system complexity and cost, while reducing high-frequency ripple by 50%, outperforming conventional HESS in minimizing switching-induced losses. HESS with reduced current sensors can lower costs and system complexity in EVs. However, its practical application can face challenges in current reconstruction accuracy, control complexity, environmental reliability, and fault detection, all of which require extensive testing and rigorous system design.

Pelosi et al. [100] introduced a rigorous and computationally efficient method for the real-time assessment and monitoring of sodium-ion battery (SiB) SOH, also proposing SiBs as a sustainable and cost-effective alternative, which can be an efficient alternative to address potential global lithium shortages [101]. The authors have recognized that conventional methods for SOH estimation often lack computational power for complex data-driven models or suffer from poor accuracy from simple methods like coulombic counting during limited cycles. The authors propose a procedure based on the discrete wavelet transform (DWT). The proposed technique, which employs multiresolution analysis (MRA), is uniquely suited to analyze the nonstationary voltage signal acquired during vehicular operation, capturing both time and frequency information. Specifically, the DWT decomposes the signal into approximation coefficients, which quantify the signal's "energetic content" and decrease as capacity fades, and detail coefficients, which reflect high-frequency transients associated with increasing internal resistance due to aging. After aggressive accelerated aging tests on Tycorun 18650 SiB cells using, at varying temperatures (0 °C, 20 °C, and 30 °C), an empirical correlation was derived to link these DWT coefficients to capacity fading ((2) as in [100])

$$C_{fade}\left(A, D_{1,4}, N\right) = a\frac{A_0}{A_i}e^{-\left(b\frac{N_i^C}{A_i}\frac{\sum_i \Delta_i}{\sum_{n=1}^{4} D_{n,0}}\right)} * 100\,(\%)\,. \quad (2)$$

The procedure achieved an impressive RMSE of 1.18% between the assessed and measured values by correlating the DWT's detail and approximation coefficients with the number of cycles. Significantly, the SiB cells demonstrated a much greater tolerance to cycling than comparable LiB cells, reaching the 80% SOH threshold at the 540th cycle compared to the LiB cell's 240th cycle, highlighting SiB's suitability for high-cycle applications. Furthermore, while low temperatures increase internal resistance and affect performance, the SiB cell exhibited a slightly reduced capacity decrease at 0 °C (a −19.6% reduction versus 20 °C) compared to LiB technology (a −22.5% reduction).

Finally, an overview of onboard ESS for railway applications, found in [102], will be presented. The review explains that electrification of railways is expanding globally to address emissions targets, yet full electrification via catenaries remains costly and impractical in many regions, making onboard energy storage devices (OESDs) a crucial solution for nonelectrified or partially electrified segments. The authors discussed core functions of OESDs, such as peak power assistance during acceleration, regenerative braking energy recovery, enabling first/last-mile and catenary-free operation, providing emergency or backup power, and smoothing load profiles to reduce grid or system stress. Key technologies reviewed include:

1) SC, which are valued for their HP density and rapid charging in urban and metro contexts
2) LiBs of various subchemistries selected for urban, regional, and backup operations
3) Hybrid configurations combining LiBs and SC for optimized performance and lifespan
4) Hydrogen fuel cells, for longer-range applications, since they offer high gravimetric energy density and rapid refueling (although with lower system efficiency than batteries).

The review highlighted the importance of power conversion architectures, specifically noting that nonisolated bidirectional buck–boost converters are a conventional choice and critical for the effective integration and management of OESDs within the train power system. On a more interesting note, the authors include a range of real-world case studies, including SC-equipped trams in China and Spain, and hybrid battery/fuel-cell regional trains in Germany and Japan, demonstrating both new and retrofitted[1] systems. Establishing a similarity between EV ESS, it can be noted that the same fundamental enabling technologies are prominent in both fields, driven by similar motivations such as sustainability, efficiency, grid independence, and operational flexibility. Furthermore, both industries face comparable engineering challenges around EMS, safety, reliability, and bidirectional power conversion. In conclusion, technical advancements and hybridization strategies developed for railway OESDs have significant relevance for EV ESS (and vice versa), and ongoing innovation in architecture and energy management is mutually beneficial for the advancement of both the railway and EV sectors.

As a summary of the main key innovation features found for niche applications, a categorical listing can be found in Table 3.

To conclude this section, a brief but relevant view about the economic analysis of HESS will be provided. Song et al. [103] investigated the effectiveness of a LiB-SC HESS for EVs, focusing on optimizing SC sizing and EMS while considering battery prices and temperature variations as the key points. The case study, conceptually illustrated in Fig. 23, suggests that, while declining LiB costs may reduce the initial cost-effectiveness of HESS, it remains beneficial in reducing battery degradation and overall operational expenses.

1. Adding new properties to already existing systems.

TABLE 3. Niche Applications Summarization Table

Ref.	Key Innovations/focus	Purpose
[88]	P-HESS for subzero temperatures	Proof of concept regarding SC use in HESS for low temperatures
[89]	HESS for cold environments	Warm battery to optimal temperature before use
[91]	Electrothermal-aging model	HESS degradation prediction
[92]	Improved Low-Pass Filter (ILPF)	EMS based on load division
[93]	Hybrid battery system for micro-EVs	HE battery coupled with HP battery, instead of SC
[94]	HESS with battery and 2 SCs	2 SCs store regenerated energy, reducing stress on the battery
[95]	HESS for EVs, integrating LiBs, EDLC (SC), and LiCs	Minimize strain on components and system cost
[96]	Multiport isolated DC–DC converter, integrating PV systems, vehicle batteries, and the power grid	Compact solution for incorporating multiple energy sources
[97]	LiB-SC HESS with converter acting as energy pump	Maintain SC voltage above battery voltage, enabling the SC to handle peak loads
[98]	Four-Port Nonisolated Converter with low component count (3 switches), simultaneous buck/boost, coupled inductors	Power flow management in LiB-PV HESS, with potential adaptation to LiB-SC
[99]	Interleaved boost inverter-based HESS, with lower sensor count	Reduce system component count
[100]	Discrete Wavelet Transform procedure, employing Multiresolution Analysis, to analyze voltage signals acquired during vehicular operation	Real-time assessment and monitoring of SiB SOH

Considering Table 4, the authors calculated the total ownership costs over a 10-year period by adding the projected capital costs, electricity costs, and battery replacement costs. They compared these costs at three different points during the 10 years. The results show that using HESS reduces total ownership costs by 12% to 25% over ten years, compared to traditional BESS.

The authors also found that the optimal SC size remains stable across different battery prices and temperatures. This stability may reflect limitations in sizing methodologies, which often rely on rule-based or static approaches. By incorporating adaptive algorithms,[2] such as RL and multiobjective optimization, future studies can better account for dynamic driving patterns, temperature fluctuations, system aging, and potentially even evolving market conditions.

That being said, the authors in [104] went even further and addressed the limitation mentioned in [103] from a slightly different angle. They proposed an optimal sizing of SCs in battery-SC HESS to enhance cost-effectiveness and sustainability, but by retrofitting existing BESS. They developed a

2. “Battery replacement cost (k$)” in table 4.

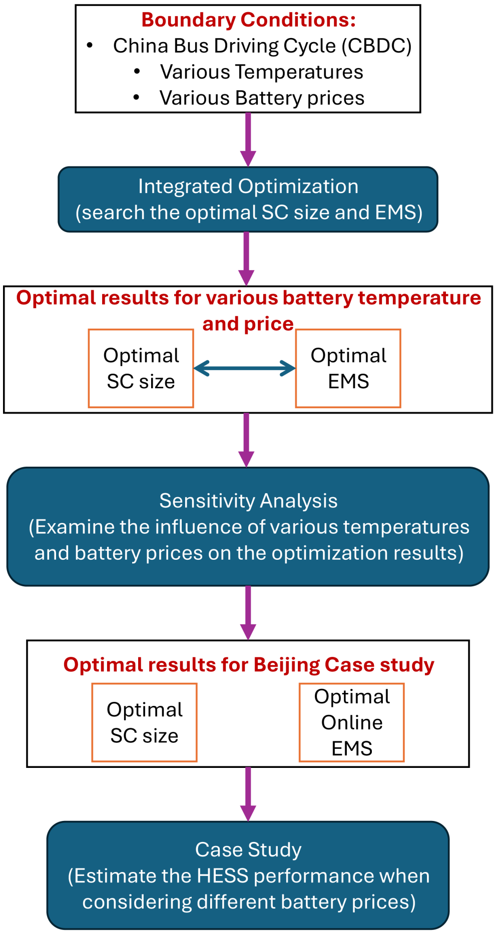

FIGURE 23. Case study process from [103].

TABLE 4. HESS and BESS Cost Over 10-Year Operation in Beijing (2018–2028)

Type	*HESS*			*BESS*		
Year	2018	2023	2028	2018	2023	2028
Battery price ($/kWh)	257	200	143	257	200	143
Capital cost (k$)	49.2	41.7	34.1	29.8	23.2	16.5
Electricity cost (k$)	56.4	56.4	56.4	53.2	53.2	53.2
Battery replacement cost (k$)*	0	0	0	59.5	46.3	33.1
Total cost (k$)	105.6	98.1	90.5	142.5	122.7	102.8

*Authors presented these numbers, but they do not seem realistic since the battery fading, even if significantly reduced by SC, cannot be evaluated as null.

life cycle optimization model that integrates capital expenditures (CAPEX), operating and maintenance (OPEX) costs, and environmental impacts. A novel battery equivalent circuit model, combining Thevenin and RC model elements, improves voltage prediction accuracy by 10% compared to traditional RC models, with minimal computational overhead, thereby reducing resource needs. The proposed HESS framework incorporates state-space models for both battery and SC dynamics, considering constraints on terminal voltages (battery: 2.5–3.65 V/cell; SC: 2.5–5 V/cell), current limits, and power balance. This article presents case studies and demonstrates that optimally sized SCs (five parallel strings) reduce life-cycle cost (LCC) by 2% over five years, primarily by extending battery lifespan (4% increase) and reducing replacements, while lowering manufacturing and operational energy consumption and CO_2-equivalent emissions all by 5.2%. Key technical parameters include battery degradation models for calendar aging (dependent on temperature and SOC) and cycle aging (accelerated by high current rates), SC lifespan estimation based on voltage and temperature, and converter efficiency curves. The optimization framework minimizes LCC by balancing SC capital costs against savings from reduced battery degradation and HVAC energy losses. In the end, it can be concluded that percentage savings are modest. The authors also acknowledge the persisting challenges of ensuring stability in relation to economic uncertainties and achieving effective real-time control. One way to address these limitations is to enhance the optimization model by integrating stochastic programming or frameworks that account for uncertainties in economic parameters and operational conditions. Potential use of AI-driven EMS will increase system resilience to fluctuating costs and degradation profiles, ensuring sustained LCC benefits. Also, periodic reoptimization based on real-world market dynamics data will enable continuous adjustment of sizing and control methodologies. The importance of holistic techno-economic-environmental assessments in HESS design is pointed out in this article, advocating for future integration of sustainability and cost metrics into design and optimization models.

In contrast to standard HESS literature, this section highlighted a range of unconventional modeling and simulation methodologies that challenge traditional frameworks and encourage creative thinking in the field of energy storage. These approaches, which include novel hybrid architectures, advanced control strategies, and integrated optimization techniques, are rarely seen in mainstream HESS research but show promise of helping to overcome the persistent challenges EVs face today. By stepping outside of familiar paradigms, the methods discussed in this section aim to inspire exploration of alternative solutions and drive the development of innovative out-of-the-loop HESS concepts.

V. DISCUSSION

Recent developments in HESS research have significantly enhanced the integration of LiBs with SCs, addressing longstanding challenges in EVs such as range anxiety, battery degradation, and dynamic response. Innovative converter topologies and advanced control strategies are driving these improvements. However, a common limitation found in the studies reviewed in this article is the substantial reliance on simulation models and laboratory testing environments. While useful, these approaches only partially reflect the complexities of real-world conditions experienced during actual vehicle operation. This gap highlights the need for more extensive empirical validation to ensure the accuracy and applicability of the findings in practical settings.

Furthermore, AI-powered EMS and digital twin technologies have emerged as promising solutions for adaptive control and predictive maintenance in HESS applications. By employing DL for degradation modeling and RL for adaptive energy dispatch, these frameworks can monitor both LiB and SC in real time, predicting faults and supporting data-driven maintenance decisions. Still, the industrial application of these technologies faces notable obstacles, including limited experimental validation, the absence of standardized frameworks, and a lack of large-scale, high-quality datasets that represent diverse operational conditions. To address these shortcomings and properly showcase the value of AI and digital twin integration in HESS, it is essential to utilize universally accepted metrics. Energy distribution effectiveness should be assessed with clear indicators, such as round-trip efficiency (which measures the proportion of energy successfully discharged compared to charged). Peak power smoothing by SCs and load following accuracy (defined as the deviation between target and achieved power sharing) are equally important. For fault prediction, relevant measures should include the true positive rate for correctly identifying faults and the false positive rate to minimize unnecessary interventions. Implementation of these metrics within digital twin and AI frameworks will enable direct comparison of algorithmic performance in both simulated and real-world conditions, thus promoting more rigorous and consistent reporting standards across studies.

An additional critical issue, which is currently under-investigated in literature, is related to the computational burden for on-board controllers executing advanced control algorithms. Modern vehicles frequently encounter limited computing power, since the processors and microcontrollers are still improving in performance. This is even more challenging when computationally intensive AI methods, like DL and DRL, are required [105]. Comparatively, DRL algorithms often have high computational complexity and can require between 100–500 ms per decision, creating a risk of poor responsiveness for critical applications compared to simpler methods like Fuzzy Logic (which operates at < 10 ms) [106]. This high demand poses real-time feasibility issues because numerous vehicle subsystems need real-time responsiveness. Currently, the integration of real-time data streaming and processing functionalities into vehicle software is not yet fully realized; therefore, major big data analytics is often relegated to cloud-based environments, directly increasing the response time of the system. To mitigate these issues and ensure necessary low-latency performance, on-board systems often rely on edge-computing methodologies where the vehicle's hardware manages initial data processing and decision-making, therefore eliminating communication delays with remote servers. Achieving real-time performance often necessitates the use of advanced hardware accelerators like Graphics Processing Units (GPUs), Tensor Processing Units (TPUs), Field Programmable Gate Arrays (FPGAs), or even Application-Specific Integrated Circuits (ASICs), for critical occurrences. Additionally, engineers must optimize AI algorithms by employing lightweight NNs, hybrid models, or model compression techniques (like pruning or quantization) to reduce computational burden. In this way, a balance between accuracy, processing burden, and energy usage can be achieved [107].

On the other side, despite intense focus on digital twin models for batteries, current research has paid very little attention to developing these frameworks for SCs or for HESS as integrated systems. This is a notable gap since SCs have distinct degradation patterns, not easily measured with conventional techniques. Advanced digital twin technologies offer the means to address these issues by enabling continuous, real-time assessment of the state and the health of each storage component inside HESS. Only with comprehensive models that account for thermal effects and aging processes in both batteries and SCs can HESS performance and lifespan under real-world conditions be fully optimized.

Moreover, considerable research gaps regarding the empirical validation of HESS designs in the context of varying ambient temperatures and aging still remain. Both batteries and SCs display pronounced sensitivity to temperature shifts and long-term aging, and yet real-world comparative studies and field data remain scarce. The PE components central to HESS operation are prone to accelerated wear and instability under thermal stress and sustained high temperatures. Recent studies have demonstrated that approaches such as accelerated aging simulations, ATC, and AI-based predictive algorithms can suppress degradation and extend device life [108]. However, these methods are infrequently adopted in practical design.

Looking ahead, future research efforts should focus on robust, field-based testing protocols that incorporate diverse operational environments and loading conditions, alongside fully integrated digital twins capable of adaptive monitoring and predictive optimization for the whole HESS. Through the adoption of advanced electro-thermal modeling, real-time SOC and SOH monitoring, and standardized evaluation frameworks, the field can progress toward the reliable and efficient integration of data-driven and AI-enabled tools in HESS management. Such approaches will be essential for achieving high reliability and scalability for EVs and potentially provide a final and decisive step toward global mass adoption. However, demonstrating their effectiveness requires thorough validation under real-world and diverse vehicle operating conditions.

To conclude, Fig. 24 offers a clear visual summary of the main achievements, open challenges, and future perspectives in HESS research. At the top, major progress in critical areas, such as new converter designs, advanced control methods, and the adoption of AI and digital twin technologies, which together have enabled smarter and more reliable HESS operation, has been highlighted. The middle part of the diagram points out unresolved issues that are still holding back

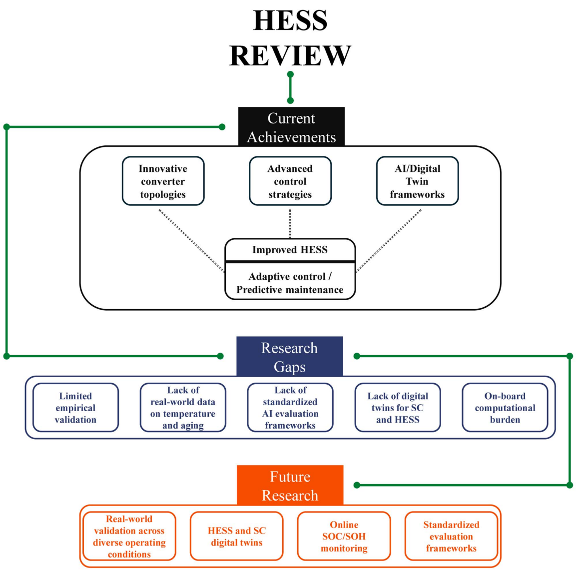

FIGURE 24. Graphical summary framework.

the field, including the need for more real-world validation, better data on how systems perform over time and under different conditions, widely accepted methods for evaluating new AI approaches, and powerful enough on-board processors. It also highlights the lack of practical digital twin SCs and HESS models on a system level. Looking ahead, the framework outlines several key areas for future research, as identified by the authors. These include conducting real-world validation of systems, developing digital twins for both individual components and the entire system, advancing on-line SOC and SOH monitoring techniques, and establishing standardized methodologies to assess the impact of AI technologies.

VI. CONCLUSION

This article has offered a thorough review of the current state-of-the-art of HESS for EV applications, covering configurations, control strategies, and simulation-based analyses, critically classifying and assessing both traditional and emerging solutions and their feasibility for wide-scale deployment under real-world constraints. Additionally, it has examined the role of AI and the emerging applications of digital twins in HESS frameworks. The increasingly popular topic of reliability has also been investigated. The discourse was extended to include alternative applications and to highlight principles that could potentially be adapted for LiB-SC HESS. Effective summary tables, including relevant information on every covered HESS aspect, are provided to help readers identify the key elements of the selected literature. In the end, a critical discussion has been provided in order to summarize key findings and add propositions for the following steps in the development of this topic.

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