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Review

A Review of Battery Energy Storage Optimization in the Built Environment

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Abstract: The increasing adoption of renewable energy sources necessitates efficient energy storage solutions, with buildings emerging as critical nodes in residential energy systems. This review synthesizes state-of-the-art research on the role of batteries in residential settings, emphasizing their diverse applications, such as energy storage for photovoltaic systems, peak shaving, load shifting, demand response, and backup power. Distinct from prior review studies, our work provides a structured framework categorizing battery applications, spanning individual use, shared systems, and energy communities, and examines modeling techniques like State of Charge estimation and degradation analysis. Highlighting the integration of batteries with renewable infrastructures, we explore multi-objective optimization strategies and hierarchical decomposition methods for effective battery utilization. The findings underscore that advanced battery management systems and technological innovations are aimed at extending battery life and enhancing efficiency. Finally, we identify critical knowledge gaps and propose directions for future research, with a focus on scaling battery applications to meet operational, economic, and environmental objectives. By bridging theoretical insights with practical applications, this review contributes to advancing the understanding and optimization of residential energy storage systems within the energy transition.

Keywords: battery energy storage systems (BESSs); residential buildings; renewable energy integration; peak shaving; self-consumption optimization; multi-objective optimization (MOO); state of charge (SoC); battery degradation; energy communities; second-life batteries (SLBs)

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1. Introduction

1.1. Context: Batteries in the Built Environment

Battery energy storage systems (BESSs) are at the forefront of the global transition to renewable energy and decarbonized urban environments. As cities strive to reduce greenhouse gas emissions and enhance energy resilience, batteries have emerged as a crucial component for integrating renewable energy sources such as solar photovoltaic (PV) systems into the built environment [1,2]. They enable energy storage, grid stability, and load management, addressing both local and national energy challenges [3].

In residential buildings, batteries can play a transformative role by facilitating self-consumption, reducing peak demand, and providing backup power during outages [4]. Besides homes, batteries support broader urban systems, enabling microgrids, energy sharing, and congestion management [5]. In addition to residential applications, industrial and large commercial battery storage systems provide critical services at a higher scale. These batteries support large-scale energy consumers by participating in frequency regulation, reserve power, and demand-side response programs, reducing operational costs while enhancing grid flexibility [6]. Their larger capacities allow them to contribute to national grid stability and balancing mechanisms, distinguishing them from smaller residential systems [7].

However, integrating batteries in the built environment comes with significant challenges. Issues such as battery degradation, scalability, and grid compatibility need to be addressed to maximize their potential. Battery modeling, optimization, and management are essential to overcome these challenges, ensuring their sustainability and economic viability. Figure 1 illustrates the many aspects of residential BESSs.

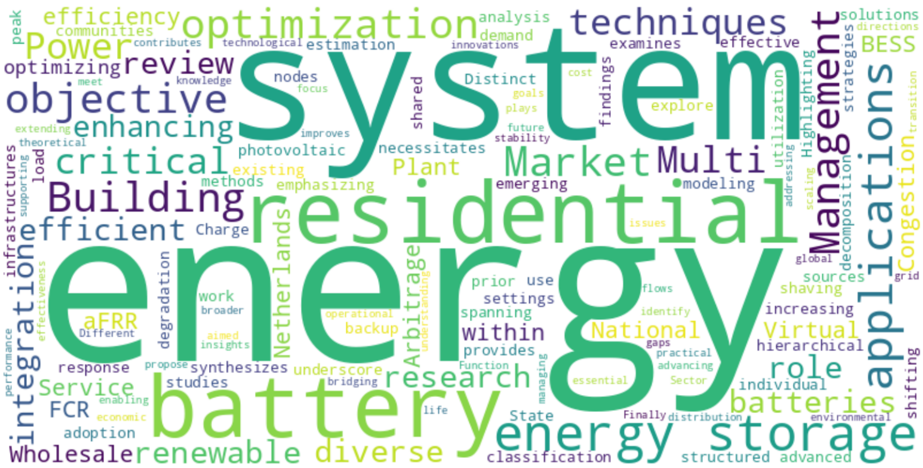

Figure 1. Word cloud created by the authors using Wordle.net, based on the text of this manuscript [8].

1.2. Objectives and Motivation

This review aims to provide a comprehensive analysis of the role of batteries in the built environment, focusing on their applications in residential buildings and urban systems. While factors such as material scarcity, market price fluctuations, and accessibility of BESSs influence their adoption, these aspects are beyond the scope of this review which focuses on the following:

- Types of batteries used in residential and urban settings and their suitability for various applications;
- Applications, including national grid services (e.g., grid frequency regulation, reserve power) and local services (e.g., peak shaving, microgrids);
- Challenges related to battery degradation, economic and technical barriers, and environmental sustainability, including second-life batteries;
- Optimization techniques and models that enhance battery performance and lifespan, tailored for diverse purposes.

By synthesizing the recent literature, this review identifies critical knowledge gaps and proposes areas for future research, particularly related to the role of batteries in urban flexibility and energy hubs. Several strategies have emerged to address the challenges associated with integrating batteries into the built environment. These include the deployment of battery energy management systems (BEMSs) for improving efficiency and longevity [9], the use of predictive control and optimization techniques [10], and new business models that enable self-consumption and participation in flexibility markets [11]. Regulatory initiatives and incentive schemes, especially within the European context, have also contributed to more favorable conditions for battery deployment in buildings [12]. However, many of these approaches remain fragmented or limited in scope. A comprehensive synthesis is needed to assess their effectiveness, identify persisting limitations, and guide future research and development.

1.3. Scope and Boundaries of the Review

This study examines BESSs in the European energy system, following the harmonized role model established by the European Network of Transmission System Operators for Electricity (ENTSO-E) [13]. By adopting a European market perspective, this review ensures consistency in definitions and services while acknowledging variations in market structures, regulatory frameworks, and terminology across different regions. We adhere to ENTSO-E's standardization, which categorizes electricity market roles and services uniformly across European transmission and distribution networks.

This review considers battery applications within the built environment, encompassing residential, commercial, and industrial complexes. Batteries are integrated into buildings, energy hubs, and industrial facilities, supporting both local energy flexibility and national grid services. Residential BESSs primarily enhance self-consumption, peak shaving, and local flexibility within households and apartment buildings. In contrast, commercial and industrial-scale battery storage plays a crucial role in both local and national services. At the local level, these systems enhance self-consumption, peak shaving, back-up power, and congestion management within industrial complexes and commercial facilities. At the national level, they contribute to grid-balancing mechanisms such as frequency regulation, reserve power, and demand-side response, ensuring transmission and distribution network stability while optimizing energy costs for large consumers. Additionally, commercial and industrial batteries can participate in wholesale energy markets, engaging in day-ahead and intra-day trading to maximize revenue opportunities and support market efficiency.

While this study focuses on the system-level deployment, operation, and optimization of BESSs, it does not address the chemical and electrochemical aspects of battery technology. While advancements in battery chemistry and materials science are essential for long-term adoption, this review focuses on the economic, regulatory, and technical aspects of integrating BESSs into urban energy systems, commercial facilities, and industrial sites.

At the European level, BESSs deployment follows a harmonized regulatory framework under ENTSO-E, ensuring standardized definitions of grid services across member states. However, congestion management and flexibility markets vary significantly across national electricity networks. Within this broader context, the Netherlands serves as a key case study, given its high penetration of distributed renewable energy technologies and increasing reliance on local flexibility mechanisms. To address rising grid congestion, Dutch system operators have developed GOPACS [14] (Grid Operators Platform for Congestion Solutions), a market-based congestion management platform that enables distributed energy resources (DERs), including BESSs, to offer flexibility services and mitigate grid bottlenecks. Originally designed for transmission-level congestion relief, GOPACS has evolved to include distribution network congestion management, further integrating decentralized energy storage solutions into the flexibility market.

By analyzing the European regulatory framework and standardized market structures, including the Dutch case study, this review provides a structured assessment of how BESSs contribute to local and national energy systems in the Dutch market specifically. The defined scope ensures clarity and relevance within a regulatory and operational framework while reducing ambiguity arising from varying international market designs.

Several reviews have previously addressed battery degradation, optimization, or applications in the built environment. However, compared to the existing literature, our work differentiates itself by focusing specifically on stationary batteries in residential and commercial buildings, combining degradation modeling and multi-objective optimization (MOO). Unlike reviews that primarily focus on electric vehicles or thermal management (e.g., Xue [15], Afzal and Ramis [16]), or address battery applications at a broader system level without detailed treatment of degradation (e.g., Lampropoulos et al. [2], Yang et al. [17]), this review uniquely synthesizes both degradation and optimization perspectives in the context of the built environment.

The methodology for selecting and reviewing the relevant literature is outlined in the following subsection.

1.4. Literature Search Methodology

A structured literature search was conducted to ensure a comprehensive and relevant review of the field. The databases Scopus, Web of Science, and IEEE Xplore were systematically searched. The search strategy combined keywords such as “battery energy storage system”, ”BESS”, “residential batteries”, “built environment”, “degradation modeling”, ”battery optimization”, “peak-shaving”, “self-consumption”, and “grid services”. Articles published between 2010 and 2024 were considered to capture recent developments while including foundational studies. The inclusion criteria were peer-reviewed journal articles, conference proceedings, and major review papers focused on stationary battery systems integrated into residential, commercial, and industrial buildings. Studies focusing solely on electric vehicles or purely rural off-grid systems were excluded, while microgrid and backup power applications within the built environment were included. Reference lists of key articles were also examined to identify additional relevant sources through backward snowballing.

1.5. Structure of the Paper

This paper progresses logically from an overview of battery systems to their applications and challenges in the built environment. Section 2 provides a foundational understanding of battery types and their general applications. Section 3 explores the applications of batteries, distinguishing between national and local services. Section 4 highlights the challenges of integrating batteries into residential and urban systems, focusing on degradation, economic barriers, and environmental considerations. Sections 5 and 6 examine state-of-the-art optimization techniques and their purposes, including models for specific applications and objectives such as economic and environmental optimization. This paper continues with a discussion of findings in Section 7, and concludes with Section 8, including implications for policymakers and relevant stakeholders, and recommendations for future research.

2. Overview of Battery Systems

Batteries deployed in residential energy systems must meet specific requirements, such as (fire) safety, scalability, efficiency, and cost-effectiveness [18]. Table 1 compares several battery types used. The most commonly used type of battery in the residential sector is the lithium–ion battery. Each battery type presents unique advantages and limitations that influence its suitability for specific residential applications, such as peak shaving, self-consumption, or backup power. The choice of battery often depends on factors like system cost, efficiency, safety, and expected life cycle performance.

Table 1. Overview of battery types and their characteristics.

Type	Energy Density (Wh/kg)	Roundtrip Efficiency (%)	Cost-Effectiveness	Cycle Life (Slow/Normal–Fast Charging)	References
Lithium–Ion (NMC, NCA)	100–265	90–95	High (++)	2000–5000/1500–3500	[19–21]
Lithium Iron Phosphate (LFP)	80–160	90–94	High (++)	3000–10,000/2000–6000	[22–24]
Lead–Acid	30–50	70–85	Low (−)	500–1500/300–800	[25,26]
Nickel Cadmium (NiCd)	40–60	70–75	Moderate (+)	1000–2500/800–1500	[27,28]
Nickel Metal Hydride (NiMH)	60–120	60–70	Moderate (+)	500–1200/300–800	[29,30]
Flow Batteries (Vanadium Redox, Zinc-Bromine)	15–70	65–85	Moderate (+)	10,000–20,000/8000–15,000	[31–33]

The symbols (++/+/−) indicate relative cost-effectiveness among battery types: (++) = High, (+) = Moderate, (−) = Low.

2.1. Lithium–Ion Batteries

Lithium–ion batteries are the most widely used energy storage solution in residential settings due to their high energy density, efficiency, and long cycle life [34,35]. They have become the backbone of residential energy systems where performance, compactness, and reliability are critical. This subsection delves into the characteristics, advantages, and recent trends in lithium–ion battery deployment, particularly in the residential sector. Lithium–ion batteries provide several advantages over other battery chemistries, making them a preferred choice for residential energy storage solutions. One of their key benefits is their high energy density, offering an energy-to-weight ratio of 100–265 Wh/kg [20], which allows for compact installations that are well-suited for residential environments. Additionally, lithium–ion batteries are known for their high efficiency, with round-trip efficiencies often exceeding 90% [36], minimizing energy losses and making them ideal for self-consumption and energy-saving applications. Their longevity is another significant advantage, as they typically offer a lifespan of 10–15 years [37], in another word around 3000 to 5000 charge–discharge cycles depending on factors such as depth of discharge (DoD), temperature, and operating conditions [37], also depending on usage patterns and maintenance, ensuring reliability and cost-effectiveness for long-term energy projects. Moreover, their fast charging and discharging capabilities make them highly suitable for dynamic applications such as peak shaving and frequency regulation [38], where rapid response times are crucial. These combined characteristics position lithium–ion batteries as an efficient, durable, and versatile energy storage solution for modern residential applications.

2.2. Lithium Iron Phosphate (LFP) Batteries

Lithium iron phosphate (LFP) batteries, a well-established subtype of lithium–ion batteries, have seen growing adoption in residential energy storage applications due to their distinct advantages in terms of safety, longevity, and cost-effectiveness. One of the primary advantages of LFP batteries is their enhanced safety, which stems from their superior thermal and chemical stability. Unlike other lithium–ion chemistries, LFP batteries exhibit a lower risk of thermal runaway, a hazardous condition that can lead to fire or explosion, making them particularly suitable for residential environments [39]. Their improved thermal stability enables them to operate under a wide range of temperatures with minimal risk, providing homeowners with a safer energy storage solution.

Another key benefit of LFP batteries is their longer cycle life, which refers to their ability to endure a higher number of charge–discharge cycles before significant capacity degradation occurs. Studies have shown that LFP batteries can achieve thousands of cycles, often exceeding 2000–5000 cycles under standard operating conditions, making them a durable and cost-effective choice for long-term energy storage needs [20]. This longevity is particularly beneficial for residential applications where batteries are cycled daily as part of solar energy systems.

Despite having a relatively lower energy density compared to other lithium–ion chemistries, LFP batteries offer notable cost-effectiveness. The materials used in LFP batteries (iron and phosphate) are more abundant and less expensive than the cobalt and nickel used in other lithium–ion technologies. This contributes to lower production costs and, ultimately, a more affordable energy storage solution for homeowners [40]. The reduced costs, coupled with their long lifespan, make LFP batteries an attractive choice for residential applications seeking a balance between performance and affordability.

LFP batteries provide an optimal solution for residential energy storage, offering a combination of safety, longevity, and cost benefits that make them a compelling alternative to traditional lithium–ion chemistries. Unlike Nickel Manganese Cobalt (NMC) and Nickel Cobalt Aluminum (NCA) batteries, which contain toxic metals such as cobalt and nickel, LFP batteries utilize iron and phosphate, both of which are non-toxic and more environmentally benign.

Cobalt exposure has been linked to significant health risks, including respiratory issues and cardiovascular diseases due to its bioaccumulation and toxicity during extraction, production, and disposal [41]. Similarly, nickel compounds are classified as carcinogenic and have been associated with skin allergies and increased cancer risks upon prolonged exposure [42]. Lead–acid batteries, though widely used, pose additional environmental hazards due to the high toxicity of lead, which can contaminate soil and water sources, causing severe neurological and developmental health issues [43].

By eliminating the use of cobalt, nickel, and lead, LFP batteries significantly reduce both human health risks and environmental damage, making them a safer and more sustainable choice for energy storage applications.

2.3. Other Battery Types

2.3.1. Lead–Acid Batteries [25]

Traditionally used in off-grid and backup systems, lead–acid batteries are less expensive but have a lower energy density, typically ranging from 30 to 50 Wh/kg [26], compared to lithium–ion batteries, which range from 100 to 265 Wh/kg [19]. They also have a shorter lifespan but remain viable for cost-sensitive applications or systems where their limitations can be managed effectively.

2.3.2. Nickel-Based Batteries [27,28]

Although less common, nickel–cadmium (NiCd) and nickel–metal hydride (NiMH) batteries are used in niche applications. NiCd batteries are particularly useful in aerospace, industrial backup systems, and power tools due to their durability and ability to withstand extreme temperatures [44]. In the energy sector, NiCd batteries are also employed in remote microgrids and emergency power systems where reliability under harsh environmental conditions is critical [45].

NiMH batteries, in particular, are valued for their safety and moderate performance characteristics, making them suitable for hybrid electric vehicles (HEVs), medical devices, and portable electronics [44]. Additionally, NiMH batteries have been explored for grid stabilization and renewable energy storage in small scales, where their longer cycle life compared to lead–acid batteries provides an advantage in load balancing and demand-side management.

2.3.3. Flow Batteries

Flow batteries, such as vanadium redox flow batteries, are emerging as a promising option for residential and small-scale energy storage. They offer scalability, long cycle life, and safety advantages but are less compact and have a higher upfront cost compared to lithium–ion batteries.

3. Applications of Batteries in the Built Environment

BESSs play a vital role in the contemporary electrical market by boosting flexibility, bolstering grid stability, and optimizing energy utilization across various scales [46]. Batteries perform several functions, including supplementary services like frequency regulation and reserve power, as well as energy management in buildings and communities [47]. Ancillary services cover functions that support grid stability and balance, including frequency containment reserve (FCR), automatic frequency restoration reserve (aFRR), and manual frequency restoration reserve (mFRR). In addition to these services, batteries are progressively utilized to minimize energy losses, assist in congestion management, and enable the integration of renewable energy through balancing methods [17]. This section systematically categorizes various uses, first with batteries' function in supplementary services and subsequently concentrating on their influence on national and local energy networks. This strategy delineates how battery storage facilitates extensive grid operations while also offering direct advantages at the community and building levels through self-consumption optimization, peak shaving, and energy arbitrage.

3.1. Adoption Trends and Use Cases

The widespread adoption of lithium–ion batteries in residential energy systems within the built environment is primarily driven by their ability to integrate seamlessly with renewable energy sources, particularly solar photovoltaic (PV) systems. These batteries offer a versatile and efficient solution to energy storage challenges, enabling homeowners to optimize their energy usage, enhance grid independence, and contribute to a more sustainable energy ecosystem [48,49]. The increasing affordability, improved energy density, and extended lifespan of lithium–ion batteries further contribute to their growing popularity in residential applications [50]. Some of the most common use cases of lithium–ion batteries in residential settings include:

- **Self-Consumption Maximization:** One of the primary drivers for the adoption of lithium–ion batteries is their ability to store surplus PV energy generated during peak sunlight hours. This stored energy can be utilized during periods of low or no solar generation, such as nighttime or cloudy days, allowing homeowners to maximize their self-sufficiency [51]. While reducing reliance on grid electricity can lead to cost savings, the actual economic benefits depend on several factors, including electricity pricing structures, available subsidies, battery system costs, and local regulations [52,53]. Studies have shown that, in regions with high electricity prices and favorable policies (e.g., Germany, Australia, and California), homeowners can achieve a faster return on investment through battery storage [54]. However, in areas where net metering allows homeowners to sell excess PV electricity back to the grid at competitive rates, the financial case for batteries is weaker due to the lower economic incentive for self-consumption [55].

  Additionally, advancements in battery management systems (BMSs) enable intelligent scheduling and optimized charging and discharging cycles to further enhance self-consumption efficiency [56]. However, payback periods for residential battery storage can still range from 6 to 15 years, depending on grid tariffs, system costs, and financial incentives [57]. As a result, while battery storage can enhance energy independence, its financial viability requires detailed economic analysis.

- **Peak Shaving:** Lithium–ion batteries are widely utilized to perform peak shaving, a technique that involves discharging stored energy during periods of high electricity demand when utility rates are at their highest. In the context of time-of-use (TOU) tariffs, this typically refers to periods with elevated electricity prices, such as late afternoons and evenings [58]. However, in some countries, peak electricity costs are determined by maximum demand tariffs, which charge consumers based on their highest power usage within a billing cycle rather than a fixed peak period [59]. In such cases, peak shaving strategies are adapted to reduce the highest recorded power draw, minimizing demand charges rather than responding to fixed TOU price variations. This strategy not only helps homeowners avoid expensive peak-hour tariffs but also alleviates stress on the local electrical grid, enhancing overall grid stability and reliability. For instance, in regions with time-of-use (TOU) pricing structures, batteries can be programmed to discharge during peak periods and recharge during off-peak hours, ensuring cost-effectiveness and efficient energy utilization [60]. Furthermore, the increasing deployment of dynamic pricing contracts, which enable prices of power to fluctuate according to real-time grid conditions and wholesale market prices, strengthens the flexibility that battery systems give [61]. Both of these factors contribute to the overall flexibility of battery systems. By responding to price signals, batteries can optimize charging and discharging schedules to minimize electricity costs, participate in demand response programs, and improve the financial viability of battery storage systems.
- **Backup Power:** In areas prone to power outages, unreliable grid infrastructure, or natural disasters, lithium–ion batteries can serve as a dependable backup power source [62]. They provide a seamless transition to stored energy during grid failures, ensuring the uninterrupted operation of essential household appliances and critical loads such as refrigerators, medical devices, and communication systems. Unlike traditional backup generators, lithium–ion battery systems offer a silent, emission-free, and maintenance-friendly alternative, making them a preferred choice for residential backup power solutions [63].

Overall, the adoption of lithium–ion batteries in residential applications within the built environment is set to grow further, driven by technological advancements, decreasing costs, and increasing consumer awareness of sustainable energy solutions. As energy storage solutions continue to evolve, homeowners are expected to play an active role in energy management, benefiting from greater control, financial savings, and environmental contributions [64].

3.2. Real-World Examples

Major manufacturers and companies have embraced lithium–ion technologies for residential energy systems, offering a range of solutions tailored to different market needs and applications. For example, companies such as Tesla (Powerwall), Huawei (FusionSolar Smart PV Energy Storage), and LG Energy Solution (RESU Series) provide integrated battery storage solutions optimized for self-consumption, backup power, and grid interaction [65–67] (see also Table 2).

- **Tesla Powerwall** [68]: A globally popular lithium–ion battery solution, Tesla's Powerwall provides seamless integration with solar energy systems and smart energy management features. Recent models utilize LFP chemistry, known for enhanced safety, longer cycle life, and higher thermal stability, making them ideal for residential use.

- **iwell and Friday Energy (Netherlands)** [69,70]: These companies are leading Dutch companies deploying LFP-based battery solutions in urban housing projects to enhance self-consumption and increase grid flexibility. Customized solutions for densely inhabited areas with space constraints enable the storage of excess solar energy within buildings, permitting discharge at peak demand, thus reducing electricity costs and dependence on the grid. Both companies incorporate their storage systems into demand–response programs, offering services including peak shaving, load balancing, and congestion management. Iwell focuses on intelligent storage solutions that facilitate real-time energy optimization. In contrast, Friday Energy provides modular battery systems integrated with digital platforms for predictive dispatching and grid-supporting services, including frequency regulation and voltage control.
- **Sonnen** [71]: A German manufacturer offering modular residential storage solutions across Europe. Sonnen's systems incorporate artificial intelligence (AI) algorithms for predictive energy management, enabling users to achieve higher levels of energy autonomy and participation in virtual power plants (VPPs).
- **LG Chem RESU** [72]: Known for high energy density and compact design, LG Chem provides residential batteries with smart control capabilities, facilitating energy independence and peak shaving applications. These systems are widely adopted in both on-grid and off-grid environments.

Table 2. Comparison of major residential battery storage solutions.

Company	Technology	Capacity (kWh)	Efficiency	Market Reach
Tesla	LFP	14	90%	Global
Sonnen	NMC	10	85%	Europe
LG Chem	NMC	3.3	95%	Global
iWell	LFP	35	85%	Netherlands
Friday Energy	LFP	100	85%	Netherlands

3.3. Future Perspectives

Studies analyzing battery deployments highlight key performance indicators such as round-trip efficiency, depth of discharge (DoD), lifecycle costs, and integration with renewable energy sources. A comparative analysis of over 40 studies [73,74] has revealed that lithium–ion batteries, particularly LFP chemistry, offer superior longevity, higher thermal stability, and improved safety compared to other battery chemistries such as nickel manganese cobalt (NMC).

Table 3 summarizes key studies in battery research, highlighting their perspectives on various battery technologies and their potential future impact. The continued innovation in lithium–ion technology is expected to enhance battery performance in multiple dimensions, including higher energy density, longer cycle life, and improved thermal stability. Furthermore, advancements in solid-state lithium batteries and alternative chemistries, such as sodium–ion and silicon anode technologies, are being explored to address existing limitations in cost and material availability while broadening the applicability of battery storage in residential, commercial, and grid-scale energy systems.

Emerging Battery Technologies

Solid-state batteries and sodium–ion batteries represent promising alternatives to current lithium–ion chemistries [75]. Solid-state batteries are being developed for their enhanced safety (non-flammable solid electrolytes), high energy density, and longer lifespan traits particularly valuable in residential environments where safety and compactness are priorities [76]. Sodium–ion batteries offer a low-cost, resource-abundant option that reduces reliance on critical materials like lithium and cobalt, and recent prototypes have shown improved cycle life and performance [77]. However, challenges such as limited commercialization, lower energy density (for sodium–ion), and high manufacturing costs (for solid-state) must still be addressed. If successfully scaled, these technologies could expand battery deployment in the built environment by offering safer, cheaper, and more sustainable storage options.

Table 3. Overview of different studies on emerging battery technologies.

References	Battery Type	Application	Key Findings
[50]	Lithium–Ion	Residential storage, EVs, Grid-scale storage	High energy density, long cycle life, high efficiency. Ageing effects and safety concerns still need improvement.
[78]	Lithium Iron Phosphate	Residential, Commercial, Industrial Storage	Improved thermal stability, longer cycle life, and enhanced safety, lower energy density. Used in stationary storage and EVs.
[79]	Lead–Acid	Backup power, UPS, Industrial applications	Low-cost but limited cycle life, low energy density. Environmental concerns due to lead content.
[80]	Nickel–Cadmium	Aviation, Industrial backup systems	High durability and resistance to extreme conditions but contains toxic cadmium. Disposal is a challenge. Superseded by newer technologies.
[80,81]	Nickel Metal Hydride	Hybrid Vehicles, Consumer Electronics	Better energy density than lead–acid, widely used in older hybrid vehicles. Lower performance compared to lithium–ion.
[82]	Flow batteries (Vanadium Redox, Zinc–Bromine)	Large-scale grid storage, Renewable energy integration	Capable of decoupling power and energy capacity, excellent for long-duration storage. Lower energy density and high upfront costs.

While the use cases of lithium-based batteries have been described above, i.e., peak shaving, backup power, and increased self-consumption, they in principle hold for any type of battery technology.

Furthermore, batteries play a crucial role in maintaining grid stability and enhancing operational efficiency through a variety of grid support services. One key application is frequency regulation, where batteries help stabilize grid frequency by responding to deviations in real time. They provide essential ancillary services such as FCR, aFRR, and mFRR, which are critical for preventing frequency excursions and ensuring reliable grid operation [83]. Unlike traditional power plants, batteries can respond almost instantaneously to frequency deviations, making them highly effective in fast-acting frequency regulation. Additionally, batteries serve as a flexible source of reserve power, offering rapid response capabilities to mitigate sudden imbalances in supply or demand caused by unexpected events, such as generator outages or demand surges [84].

Another important grid support service provided by batteries is energy arbitrage, where batteries buy electricity from the grid during periods of low prices and discharge it back into the grid when prices are high. This not only generates economic returns but also supports grid efficiency by smoothing demand and supply curves [85]. Through advanced energy management systems and real-time market participation, batteries optimize energy arbitrage by forecasting electricity prices and adjusting their charge–discharge cycles accordingly [86]. Collectively, these grid support applications contribute to the economic viability of battery storage systems while enhancing grid reliability, stability, and flexibility.

Batteries are a key component in addressing the intermittency and variability of renewable energy sources, thereby enabling their broader adoption in modern power systems. One of the key applications is smoothing variability, where batteries mitigate fluctuations in solar and wind power generation. By storing surplus energy during periods of high renewable production and discharging it during low production, batteries ensure a more stable and predictable energy supply [51]. This capability enhances grid reliability and facilitates the integration of higher shares of intermittent renewables, reducing the need for conventional backup generation. Additionally, batteries support energy sharing within local communities or energy hubs, where surplus energy generated by one participant can be stored and redistributed to others in need. This promotes decentralized energy systems, improves local energy resilience, and fosters collaborative energy management [87].

Furthermore, batteries contribute to congestion management by alleviating transmission and distribution constraints. During periods of excess renewable generation, batteries can store energy locally, preventing overloads in the grid infrastructure. When demand increases or grid congestion subsides, this stored energy can be redistributed efficiently, improving overall grid performance and reducing curtailment of renewable sources [88]. By providing these services, batteries play a critical role in enhancing the economic and operational viability of renewable energy systems while supporting the transition toward a more sustainable and resilient energy future.

3.4. National Services

At the national level, batteries provide essential services to support large-scale energy systems, ensuring grid stability, enhancing operational resilience, and enabling the efficient integration of renewable energy sources into the electricity grid. As energy systems evolve to accommodate increasing shares of intermittent renewable generation, batteries have become indispensable for balancing supply and demand while maintaining the reliability of the power grid.

One of the most critical services batteries provide is frequency regulation, where they stabilize grid frequency by responding to real-time deviations between electricity supply and demand. By participating in ancillary services markets, batteries offer highly responsive solutions, including FCR, aFRR, and mFRR, as described earlier. FCR ensures immediate stabilization within seconds, preventing frequency deviations from escalating into grid instability. Meanwhile, aFRR and mFRR restore frequency to nominal levels over a longer timeframe, providing sustained corrections during extended disturbances.

In contrast to conventional systems that rely on slower thermal or gas-fired power plants, batteries can dispatch their stored energy within milliseconds, offering precise and efficient frequency control. Their rapid response capabilities provide them with a particular effectiveness in handling short-term imbalances, improving overall grid resilience.

Batteries act as a rapid-response reserve power source, capable of addressing unexpected fluctuations in supply and demand. During unplanned events, such as generator outages, transmission line failures, or sudden surges in demand, batteries inject or absorb power almost instantaneously to balance the system. This capability is especially valuable during extreme weather events, which are becoming more frequent due to climate change, as batteries provide a buffer against grid disruptions. Furthermore, batteries reduce dependence on spinning reserves, which are traditionally maintained by fossil-fuel power plants operating below full capacity. By displacing these carbon-intensive systems, batteries not only enhance grid reliability but also contribute to decarbonization. Their ability to support grid operations in islanded or microgrid configurations further bolsters national energy security, ensuring uninterrupted supply during emergencies.

Batteries play a crucial role in contemporary demand–response strategies, enabling dynamic energy management through the adjustment of consumption patterns in response to grid conditions. Charging during times of low demand—when electricity prices and grid stress are at their lowest—and discharging during peak times helps to ease the burden on the grid and postpone expensive infrastructure improvements. At the national level, aggregated battery systems, structured as VPPs, facilitate extensive demand-side flexibility. These systems engage with grid operators in real time to dynamically modify energy consumption and battery dispatch, enabling distributed assets to take part in ancillary service markets and energy arbitrage.

VPPs aggregate distributed batteries and other flexible resources to provide grid stabilization, improve demand-side adaptability, and participate in electricity markets. They enable small-scale battery proprietors to participate in services such as FCR, aFRR, and energy arbitrage, which generally impose considerable entry hurdles (e.g., the minimum power requirement for FCR). By aggregating various small-scale energy storage systems, virtual power plants establish a simulated large-scale resource, enhancing access to wholesale and balancing markets. Nonetheless, obstacles persist in enhancing battery dispatch by considering degradation, market dynamics, and regulatory limitations, necessitating advanced control algorithms and real-time forecasting to guarantee optimal performance.

The variety of renewable energy sources, such as wind and solar power, poses significant challenges to grid stability. Batteries address this issue by storing surplus energy during periods of high renewable generation—e.g., sunny afternoons or windy nights—and discharging it when renewable output is insufficient to meet demand. This capability ensures a consistent and reliable energy supply, even during periods of low renewable generation, such as cloudy days or calm weather. In addition to short-term balancing, batteries are increasingly used for medium-term and seasonal storage, helping to address prolonged periods of renewable energy deficits. For instance, energy stored during summer months with high solar output can be utilized during winter months when solar generation is lower. By minimizing renewable energy curtailment and reducing reliance on fossil fuel-based peaking plants, batteries maximize the value and efficiency of renewable resources. Furthermore, their deployment facilitates the creation of renewable energy trading markets, where excess energy can be stored and dispatched economically, contributing to grid stability and fostering investment in renewable technologies.

Beyond managing energy supply and demand, batteries provide voltage regulation and reactive power support at the national level. By injecting or absorbing reactive power, batteries help maintain voltage levels within acceptable limits across the grid. This service is particularly crucial in systems with high penetration of renewable energy, as fluctuations in generation and load can cause voltage instability. Batteries equipped with advanced inverters can also mitigate power quality issues, such as harmonic distortion, ensuring that electricity delivered to consumers meets regulatory standards. These capabilities make batteries an essential component of grid modernization efforts, supporting the integration of renewable energy and distributed energy resources.

Additionally, batteries contribute to grid resilience by offering black start capabilities, which are crucial for resuming operations following an extensive outage. Batteries are capable of providing immediate power to energize gearbox lines and resume critical infrastructure, in contrast to traditional black start units, which frequently necessitate fuel and time to initiate. This swift response capability not only mitigates economic losses and disruptions during large-scale outages, but also reduces downtime.

3.5. Local Services

On a local scale, batteries serve communities, neighborhoods, and individual buildings, promoting energy efficiency, resilience, and sustainability through multiple key services.

By discharging stored energy during periods of high electricity demand, batteries reduce the peak load on the grid. This reduces electricity costs by lowering demand charges and taking advantage of time-of-use pricing [89]. Additionally, this peak shaving alleviates the stress on local distribution networks, delaying infrastructure upgrades and reducing the risk of blackouts during peak hours [90]. In densely populated urban areas, where peak load issues are prevalent, BESSs significantly contribute to grid reliability and operational flexibility.

Batteries enhance the self-consumption of locally generated renewable energy, particularly in buildings with solar PV systems. By storing excess PV generation during the day and discharging it in the evening or during periods of low sunlight, batteries increase energy independence and reduce reliance on the central grid [51]. This not only helps households and businesses lower their energy bills but also reduces grid feed-in fluctuations, stabilizing the local energy network. Advanced energy management systems (EMSs) optimize self-consumption by predicting demand and generation, ensuring batteries are charged and discharged at optimal times [91].

Batteries are integral to microgrid operations, offering energy storage and management capabilities. Microgrids, which can operate independently from the main grid, rely on batteries to balance generation and consumption, ensuring stable energy supply during outages or when isolated from the main grid [92]. Furthermore, batteries in microgrids enable higher integration of intermittent renewable energy sources, such as wind and solar, by smoothing output fluctuations and providing ancillary services, such as frequency regulation and voltage support [93]. This makes batteries a crucial component in decentralized energy systems and islanded operations.

Energy hubs provide an advanced approach for the integration of various energy carriers, such as electricity, heat, and gas, within a coordinated optimization framework, alongside microgrids. Batteries, alongside other distributed energy resources, are utilized by these centers to enhance energy flows, thus improving local resilience and adaptation. Energy hubs can enhance self-consumption, enable load balancing, and diminish reliance on centralized grid infrastructure by amalgamating storage with demand-side flexibility. Their benefits are especially significant in metropolitan settings, where energy requirements fluctuate rapidly, requiring adaptive management solutions to enhance cost-effectiveness and efficiency.

Within energy communities, batteries facilitate energy sharing among users, promoting efficient energy use and reducing collective costs. Urban energy sharing is particularly relevant in shared residential complexes, where individual PV systems may not be sufficient to meet demand at all times. Batteries store excess generation from one user and supply it to another when needed, creating a more balanced and efficient energy ecosystem [94]. In urban districts with high renewable energy penetration, such shared battery systems can improve overall energy efficiency, reduce peak demand collectively, and lower energy costs through cooperative energy management [94].

3.6. Congestion Management Across Scales

Congestion management is a critical issue in energy systems, especially in urban environments with dense populations, high energy demands, and high renewable generation. Batteries play a pivotal role in alleviating congestion at both local and national levels.

Batteries reduce congestion in distribution networks by storing energy during periods of low demand and discharging it when local demand spikes. This ensures the smooth operation of neighborhood-level energy systems and reduces the need for costly grid upgrades. On a national level batteries assist in managing transmission congestion by storing excess energy near generation sites (e.g., wind farms) and redistributing it during high demand. This helps optimize the use of existing infrastructure and reduces transmission bottlenecks. The interplay between local and national services enhances overall system efficiency. Batteries deployed in urban environments can provide services to the national grid during periods of low local demand, creating a dynamic and integrated energy system.

For example, the Dutch power infrastructure is experiencing increased strain due to electrification and the increasing use of renewable energy sources. A recent example of congestion management in the Netherlands is GOPACS (Grid Operators Platform for Congestion Solutions) [95], a cooperative initiative established by the Dutch transmission system operator (TSO) TenneT and regional distribution system operators (DSOs), such as Stedin, Enexis, Liander, and Westland Infra [96]. Originally intended to alleviate congestion at the high-voltage transmission level, GOPACS has developed to tackle rising congestion issues at the distribution level, facilitating cooperation between the TSO and DSOs. In contrast to conventional grid reinforcements, GOPACS offers a market-oriented congestion management approach, allowing flexibility providers, including battery storage operators and demand-side response participants, to deliver grid relief services in areas of constraint. GOPACS improves grid efficiency, minimizes renewable energy curtailment, and optimizes available capacity through the utilization of decentralized energy resources, without necessitating rapid physical infrastructure enhancements [97].

A summary of battery storage applications across different scales in the built environment, including grid services such as congestion management, is provided in Table 4.

Table 4. Summary of battery energy storage applications across different scales in the built environment, highlighting key services and their objectives.

Application Scale	Services/Applications	Description/Objective
National Grid Services [98]	• Frequency Regulation • Reserve Power • Energy Arbitrage	Support grid stability and energy market operations. Mitigate frequency deviations and participate in energy trading.
Local Grid Services [95,99]	• Congestion Management • Energy Communities • Microgrids	Improve local grid flexibility. Enable energy sharing within communities and operate islanded systems.
Building Level Applications [96,97]	• Self-Consumption • Peak Shaving • Backup Power	Optimize building energy use, reduce grid dependence, lower peak demand charges, and provide backup during outages.

4. Challenges Integrating Batteries in Residential Sector

The deployment of batteries in residential settings presents a range of challenges that must be addressed to maximize their potential benefits. These challenges span economic, technical, and environmental domains, each posing significant barriers to widespread adoption and optimal performance.

4.1. Economic Barriers

The substantial upfront investments (capital expenditures (CAPEX)) linked to battery storage systems continue to pose a major barrier to their extensive use in residential environments. This initial expense is associated with acquiring and installing battery systems, encompassing the cost of the battery, inverters, control systems, and professional installation services.

In addition, operational and maintenance expenses (OPEX) further contribute to financial strain, particularly in long-term ownership. Batteries require regular software updates, hardware assessments, and eventual cell replacements to maintain efficiency and reliability. For instance, Dufo-López and Bernal-Agustín [100] estimate that the O&M costs for grid-connected battery systems can represent approximately 1–2% of the initial investment per year, factoring in periodic maintenance and degradation-related replacements. These persistent expenses may deter investment, especially for homeowners without technical expertise or access to cost-effective maintenance providers.

A significant difficulty is scalability, particularly in extensive residential complexes or energy villages. As systems expand, expenses may rise considerably, rendering affordability challenging without sacrificing performance. While larger installations may leverage economies of scale, the overall financial feasibility remains ambiguous—particularly when incorporating many battery units into a cohesive system.

Moreover, insufficient financial incentives impede extensive residential adoption. Government subsidies, tax credits, and market-driven incentives can significantly enhance the return on investment (ROI) for battery systems; nevertheless, these mechanisms frequently exhibit inconsistency across different locations. In the absence of permanent incentives, homeowners exhibit reluctance to engage in battery storage, especially when competing alternatives, such as net metering, offer more economical methods for managing surplus solar energy. Therefore, overcoming these economic obstacles necessitates a combination of cost reductions, supportive regulations, and creative financing models to enhance the financial appeal of residential battery storage solutions. As summarized in Table 5, multiple studies highlight the financial constraints and policy challenges influencing residential BESS adoption, emphasizing the role of subsidies, long-term incentives, and innovative financing models in improving economic viability.

Table 5. Selected studies on economic barriers and viability of residential battery storage.

Reference	Focus	Main Findings	Region/Context
[101]	High Upfront Investment Costs	Initial CAPEX prevents EU home battery adoption. Subsidies in Germany and Italy shorten payback timeframes to 7–10 years, but regulatory frameworks and electricity pricing patterns determine financial sustainability.	Germany, Italy

Table 5. *Cont.*

Reference	Focus	Main Findings	Region/Context
[102]	Policy and Financial Incentives	40–45% of homeowners could install PV + BESS by 2030 under favorable financial policies. Uncertainty in long-term policy commitments acts as a barrier, as short-term incentives may not provide sufficient confidence for widespread adoption.	Italy
[103]	Economic and Regulatory Challenges	Economic challenges in scaling up storage solutions, particularly within the residential and commercial sectors. The study emphasizes the need for policy adjustments to facilitate BESS integration in local and national markets.	The Netherlands
[104]	Investment Uncertainty	High capital expenditure (CAPEX) is a critical barrier to energy storage deployment; it emphasizes that policy frameworks and long-term incentives are necessary to mitigate financial risks for investors.	Germany, UK
[105]	High Cycle Cost and Market Design	Identifies high battery wear costs as a key barrier to the economic viability of grid-connected battery storage in Spain. Battery utilization for energy arbitrage remains low unless cycle costs fall below EUR 15/MWh. Highlights market design limitations that hinder profitability.	Spain
[106]	High Grid Integration Costs	The economic viability of residential BESSs is impacted by high grid integration costs. Without proper market mechanisms, the financial burden of battery deployment is shifted to consumers, limiting widespread adoption.	France
[107,108]	Upfront Cost Analysis	Identified battery CAPEX and installation fees as prime barriers; found that government rebates reduce payback period by 40%.	Residential PV-battery in the UK
[109]	Financing Models	Compared leasing vs. outright purchase; concluded leasing can boost adoption rates in lower-income households.	Germany
[110]	Maintenance Expenses	High replacement costs in Life Cycle Cost (LCC) deter adoption unless covered by warranties or service contracts.	Worldwide
[111]	Economies of Scale	Demonstrated that communal battery ownership in multi-apartment complexes enhances self-sufficiency, reducing grid dependence by over 60% through shared solar and battery configurations.	Australia

Table 5. *Cont.*

Reference	Focus	Main Findings	Region/Context
[112]	Policy Incentives	Long-term tax credits (5+ years) significantly enhance investment attractiveness and market stability, while short-lived incentives create uncertainty and have minimal impact on adoption rates.	USA
[113]	Operational Cost Studies	Highlights that ongoing operational and maintenance costs, including software upgrades and professional maintenance, are significant considerations for BESS projects; recommends extended supplier warranties or maintenance agreements to manage these expenses.	USA
[114]	Net Metering Alternatives	Discussed that recent changes in California's net metering policy reduce export compensation, diminishing ROI for solar-only systems; integrating battery storage with time-of-use rates can enhance investment returns.	USA
[115]	Cost-Benefit Tradeoff	Analyzed various tariff structures; found that high fixed charges in traditional tariffs discourage battery adoption, while time-of-use rates with significant price differentials can enhance investment attractiveness.	Brazil
[116]	Scalability Concerns	Found that community-scale battery storage in residential areas lowers per-unit costs but requires high initial capital and strong local coordination.	UK
[117]	Innovative Financing	Demonstrated that green loans can improve the payback period of integrated solar PV and battery storage projects by bundling costs.	Chile

4.2. Technical Challenges

Technical hurdles impact the efficiency, reliability, and integration of batteries into residential energy systems. These challenges span several aspects, including performance, economics, security concerns, and practical deployment barriers such as permitting, fire safety codes, and spatial constraints, particularly in dense urban areas. Together, these factors influence the large-scale deployment and adoption of residential energy storage solutions.

- **Battery Degradation**: Lithium–ion batteries degrade over time due to continuous charge–discharge cycles, temperature fluctuations, and depth of discharge. This degradation affects capacity retention and overall system efficiency, necessitating the development of advanced battery management systems to monitor and optimize battery health [118,119]. Studies suggest that using smart charging techniques and efficient heat management systems could help to slow down degradation. Cycle life has been shown to be significantly extended by adaptive charging algorithms limiting charging to 80% SoC during typical use. Liquid cooling and phase-change materials are two examples of temperature control methods that maintain optimal operating temperatures and reduce capacity degradation resulting from thermal stress. Dynamic charge–discharge control is another useful method whereby batteries are charged and drained at low C-rates (the rate at which a battery (dis-)charges relative to its maximum capacity) under normal conditions to reduce stress. Rest periods let the batteries stay dormant between active cycles, therefore reducing the generation of solid electrolyte interface (SEI) layers, which are essential in deterioration processes. These technologies together increase battery lifetime, hence increasing the economic viability of energy storage systems.

- **Thermal Management**: Batteries generate heat during operation, which, if not properly managed, can lead to thermal runaway, reducing lifespan and posing safety risks. Effective cooling and heat dissipation techniques, such as liquid cooling and phase change materials, are crucial for maintaining optimal battery performance [120,121]. Advances in thermal modeling and real-time monitoring are improving the safety and efficiency of residential storage systems.
- **Grid Compatibility**: Integrating battery storage with residential grids presents challenges related to voltage fluctuations, phase imbalances, and frequency regulation. Smart inverters and advanced power electronics are necessary to ensure seamless operation within the grid, while adherence to grid codes and standards remains essential [122,123].
- **Cybersecurity Risks**: The integration of smart battery systems with IoT and cloud platforms increases exposure to cyber threats. Potential risks include unauthorized access, data breaches, and grid disruptions. Implementing robust cybersecurity measures, such as encryption protocols and intrusion detection systems is crucial to ensuring the security and privacy of residential energy storage networks [124,125].

An overview of these key technical challenges in residential battery systems, along with their impacts and supporting references, is provided in Table 6.

Table 6. Technical challenges in residential energy storage.

Challenge	Impact	References
Battery Degradation	Reduced capacity over time	[118,119]
Thermal Management	Safety and efficiency issues	[120,121]
Grid Compatibility	Voltage/frequency stability	[122,126]
Cybersecurity Risks	Potential cyber attacks	[124,125]

Degradation Models and Lifecycle

Battery degradation is influenced by various chemical and mechanical ageing processes, primarily capacity fade and increased internal resistance, both of which impact the economic feasibility and operational efficiency of energy storage systems. The main degradation mechanisms include calendar ageing, which occurs due to side reactions during periods of inactivity, and cyclic ageing, which is caused by repeated charge–discharge cycles, typically linked to the depth of discharge (DoD) and temperature conditions. Various methodologies have been proposed for accurately modeling degradation, encompassing empirical, semi-empirical, electrochemical, and data-driven approaches. Empirical methods, as demonstrated by [127], utilize actual battery test data and typically employ Wöhler S–N (cyclic stress versus number of cycles to failure) curves [128] or piecewise-linear cycle-based formulations to forecast lifespan across different operational conditions. These models are widely utilized in battery scheduling and optimization for self-consumption, peak shaving, and grid ancillary services, as they balance accuracy with computational efficiency. Electrochemical models, including pseudo-two-dimensional (P2D) models and single-particle models, offer enhanced accuracy through the simulation of ion transport and the development of solid electrolyte interfaces. However, due to their significant computational cost, they are impractical for large-scale optimizations. Semi-empirical models incorporate stress components that depend on DoD and temperature while maintaining manageable complexity, making them suitable for system-level analyses. Machine learning and data-driven methodologies have markedly enhanced the accuracy of battery degradation predictions through the analysis of historical usage patterns. These models acknowledge nonlinear ageing trends instead of depending on explicit electrochemical equations, providing important insights into optimal operating strategies for prolonging battery lifespan. Geerts et al. [129] utilized a capacity loss model to integrate degradation costs into optimization, taking into account the effects of charge rate, SoC, and DoD. The study demonstrated that delaying charging reduces degradation by lowering root mean square (RMS) voltage, thus extending battery life. Degradation models are crucial for optimizing the implementation of energy storage in self-consumption, peak shaving, and grid services, while ensuring economic feasibility.

4.3. Environmental Considerations

BESSs offer substantial advantages in the integration of renewable energy and the mitigation of reliance on fossil fuel-based power generation; yet, their implementation presents environmental challenges. A primary issue is end-of-life (EOL) management, as inadequate disposal of batteries may result in harmful leaks, soil contamination, and water pollution [130]. Moreover, inadequate recycling infrastructure hinders material recovery, intensifying resource scarcity and amplifying the environmental impact of battery manufacturing.

The production of lithium–ion batteries is energy-intensive, requiring the extraction and purification of raw materials including lithium, cobalt, and nickel [131]. Mining activities lead to deforestation, water contamination, and greenhouse gas emissions. The dependence on cobalt specifically presents ethical and environmental problems due to the ecological deterioration and human rights violations linked to its extraction. Minimizing reliance on scarce or detrimental elements by advancements in battery chemistry—such as cobalt-free or sodium–ion alternatives—can alleviate these adverse impacts and enhance the sustainability of BESSs.

A highly promising approach to mitigate battery waste is the repurposing of second-life batteries (SLBs) [132]. Post-retirement from electric vehicle (EV) applications, batteries frequently maintain adequate capacity, typically about 80% of the initial capacity, for less rigorous stationary storage uses. This study offers an extensive analysis of the technological and economic dimensions of SLBs, emphasizing their potential for implementation in energy storage applications, including grid support, domestic backup power, and off-grid electrification. The lack of deterioration models especially designed for SLBs constitutes a significant research gap. In contrast to fresh batteries, SLBs have considerable cell-to-cell variability stemming from diverse usage histories, necessitating sophisticated categorization techniques to guarantee safety and performance. This review advocates a hybrid methodology that integrates physics-based theories with data-driven techniques to create explainable and generalizable deterioration models, hence improving SLB reliability. This paper also examines regrouping criteria to handle these variances, offering a framework for enhancing categorization techniques and optimizing battery repurposing.

From an economic perspective, SLBs provide a cost-effective approach to extending battery performance while reducing the demand for raw materials and minimizing electronic waste generation. Profitable applications include peak shaving, renewable energy storage, and microgrid integration, where reduced energy and power needs align with the lower effectiveness of SLBs. The evaluation examines advancements in power electronics technologies, such as high-efficiency energy conversion, active equalization, and systems that enhance reliability, all aimed at improving SLB performance. These advancements significantly improve the circular economy of energy storage systems, strengthening sustainability while maximizing economic value [133].

The shift towards a sustainable battery lifecycle necessitates a comprehensive strategy, including enhanced recycling techniques, alternative chemistries, second-life applications, and regulatory measures that promote circular economy concepts. Securing the enduring sustainability of battery storage systems requires ongoing investment in research, regulatory coherence, and the advancement of scalable technologies that support both first- and second-life battery applications.

4.4. Practical Deployment Barriers in Urban Areas

In addition to economic, technical, and environmental challenges, practical deployment barriers also hinder the adoption of residential BESSs, particularly in dense European urban areas.

First, regulatory hurdles such as permitting and fire safety codes present significant obstacles. Battery installations must comply with strict fire protection standards, such as IEC 62933 [134], NFPA 855 [135], and national regulations, particularly under European building and safety regulations, which often mandate specific distances from buildings, fire-resistant enclosures, and detailed risk assessments [136]. In urban settings where space is limited, complying with these requirements can be challenging or even prohibitive, especially in older buildings not designed for energy storage retrofits [137].

Second, space constraints in high-density residential environments pose limitations on battery size and placement [138]. Rooftops and utility rooms are often already occupied by other critical infrastructure, leaving insufficient room for battery systems. Innovative solutions such as modular battery designs, integrated systems within building facades, or underground installations are being explored to address these spatial challenges [139].

Moreover, urban planning regulations sometimes restrict the visible alteration of building exteriors, particularly in heritage zones, further complicating BESS deployment [140]. Approval processes can be lengthy and costly, discouraging residential customers and building owners from pursuing installations [141].

Finally, insurance and liability considerations have emerged as practical barriers [142]. Insurance premiums for buildings with battery systems may increase due to perceived fire risks, and unclear responsibilities between property owners, tenants, and system operators can deter installations.

Addressing these barriers will require updated building codes, streamlined permitting processes, better coordination between energy and urban planning policies, and increased public awareness about the safety and benefits of modern BESS technologies.

5. Optimization Techniques

In this section, we review state-of-the-art optimization techniques used in battery modeling and simulation for residential applications. Optimization enhances battery performance, extends lifetime, and minimizes costs. This section covers modeling scales from cell-level to system-level optimizations, emphasizing accurate simulations to predict and improve battery operations. An overview of the optimization framework, illustrating the relationship between optimization objectives, methods, and application levels in the built environment, is provided in Figure 2.

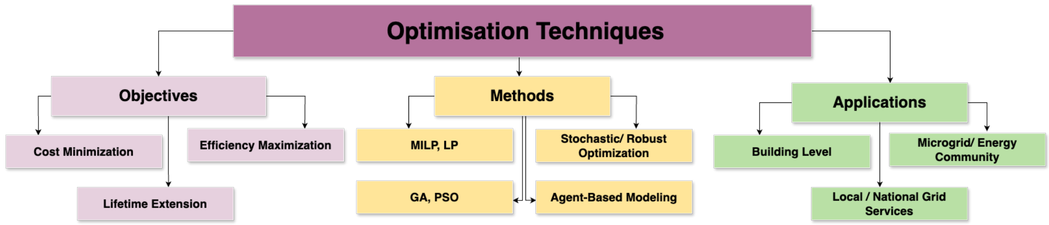

Figure 2. Optimization framework of battery energy storage systems in the built environment.

5.1. System-Level Modeling

System-level modeling and optimization are crucial for integrating batteries with other residential energy systems, such as PV panels, EVs, and grid infrastructure. This level of modeling aims to enhance energy management, optimize grid interactions, and improve the resilience of distributed energy resources in residential and commercial settings. System-level optimization considers both the operational efficiency of the battery and its role in reducing energy costs, balancing loads, and managing demand within larger energy networks.

System-level optimization has become increasingly significant as residential energy systems shift towards distributed generation, where batteries are used alongside renewable energy sources like PV panels. By facilitating effective energy storage and load management, system-level models help improve the sustainability and economics of energy use in residential settings.

The following key approaches can be identified:

- **Mixed-Integer Linear Programming (MILP):** MILP is commonly used for optimizing energy distribution, scheduling, and operation of battery storage in residential applications. It is particularly effective in incorporating constraints like time-of-use tariffs, peak shaving, and load shifting. MILP models allow for the precise allocation of energy storage and dispatch, balancing energy supply with household demand to minimize costs and reduce dependency on the grid. For example, Lu et al. (2020) demonstrated the application of MILP to optimize battery storage for residential PV systems, incorporating variable pricing to enhance savings and reduce peak loads [143]. Additionally, MILP can address the stochastic nature of PV generation by accounting for uncertainties in solar power generation and user demand [144].
- **Agent-Based Modeling (ABM):** ABM simulates the behaviors and interactions of individual components (agents) within a system, such as batteries, PV systems, and household appliances. This approach is especially valuable for studying the effects of large-scale deployment, demand response, and user behaviors in residential settings. ABM enables the analysis of grid interactions with multiple distributed storage units, providing insights into network stability, energy flows, and local energy markets. Zhou et al. (2023) applied ABM to simulate energy trading within a residential community equipped with battery storage, highlighting the potential for community-based energy markets to enhance grid resilience and reduce costs [145]. Other studies have used ABM to examine the impact of battery storage on load balancing and grid congestion in distributed systems [146].
- **Dynamic Programming (DP):** DP is a recursive optimization technique useful for managing the sequential decision-making involved in battery charging and discharging, especially when integrated with PV and grid systems. DP is beneficial for scenarios requiring multi-period optimization, allowing for a balanced approach to maximize battery utilization while minimizing costs over time. Studies have shown that DP can be effective in optimizing battery energy management systems (BMS) for residen-

tial PV setups by managing fluctuations in energy supply and demand throughout the day [147].

- **Stochastic Optimization and Robust Control Models:** Due to the inherent uncertainties in renewable generation and user demand, stochastic models are increasingly employed to ensure reliable system operation under variable conditions. Stochastic optimization approaches, such as chance-constrained programming, consider uncertainty in PV generation and user consumption patterns to optimize battery operation, ensuring resilience under fluctuating conditions. Robust control models, on the other hand, focus on ensuring performance under worst-case scenarios, making them valuable for grid-interconnected batteries that require stable operation. Kaffash et al. [148] used stochastic programming to optimize a residential battery system, demonstrating improved reliability and cost-effectiveness in the face of renewable generation variability.
- **Hybrid Modeling Approaches:** Combining different modeling techniques can yield more comprehensive results by capturing both deterministic and probabilistic elements in battery optimization. For instance, integrating MILP with stochastic optimization allows for flexibility in energy dispatch while accommodating uncertainty. Hybrid approaches are valuable for complex scenarios where batteries interact with both grid and renewable resources, as well as in environments where demand response is encouraged [149].

5.2. Multi-Scale Modeling

In order to optimize battery performance across various scales, from individual cell dynamics to entire battery systems, multi-scale modeling and co-simulation techniques are fundamental. By connecting cell-level, module-level, and system-level simulations, these methods offer a thorough comprehension of battery behavior. Multi-scale modeling and co-simulation facilitate the assessment of the impact of individual cell behaviors on the overall performance, efficiency, thermal stability, and degradation of batteries in real-world applications by connecting detailed cell models with larger system-level models. This method is particularly advantageous for applications that necessitate the coordination of computational efficiency and high-resolution insights.

The following key approaches can be identified:

- **Co-Simulation Platforms:** Co-simulation involves the simultaneous execution of multiple simulation models that represent different aspects of battery performance, such as thermal, electrical, and electrochemical processes. By linking these models, co-simulation provides a holistic view of battery behavior under various operational conditions. Yuan et al. [150] developed a co-simulation platform to integrate thermal and electrochemical models for lithium–ion batteries, enabling a real-time assessment of thermal runaway risks during high-load conditions. This approach allows engineers to predict temperature gradients and prevent overheating by actively adjusting the cooling system based on electrochemical feedback. Co-simulation is particularly beneficial for EV applications, where balancing power demand and thermal stability is crucial.
- **Multi-Scale Modeling Techniques:** Multi-scale models are hierarchical simulations that amalgamate intricate cellular data with systemic dynamics. Multi-scale modeling utilizes data from lower-level models (such as cell and module levels) to enhance higher-level optimizations (such as system-level energy management), resulting in more precise forecasts of battery performance. Rašić et al. [151] presented a multi-scale methodology that integrated cell degradation models with a system-level model for electric vehicle applications, elucidating the impact of individual cell ageing

on the overall efficiency of the battery pack. Hierarchical models are crucial for comprehending how microscopic alterations in cell chemistry influence macroscopic attributes such as cycle life, capacity, and temperature management within the entire battery system.

- **Reduced-Order Modeling (ROM):** ROM techniques are employed to simplify complex cell-level models into computationally efficient forms, making them suitable for integration into larger system models. ROM is especially useful for real-time applications where computational speed is critical, such as BMS in EVs and grid storage applications. By approximating the key behaviors of detailed electrochemical models, ROM techniques enable the rapid simulation of battery systems without sacrificing accuracy. For instance, models based on lumped-parameter or equivalent circuit representations have been successfully implemented in BMS for large battery packs, significantly reducing computation time while preserving accuracy [152].
- **Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD) Integration:** FEA and CFD models are used to study the mechanical and thermal characteristics of batteries, respectively. When integrated within a multi-scale co-simulation framework, FEA and CFD can simulate the impact of mechanical stresses and temperature distribution on battery cells and modules. FEA is particularly useful for analyzing stress distributions in battery materials, which can affect battery life and performance under various operating conditions. CFD models, on the other hand, focus on fluid flow and heat transfer, which are crucial for thermal management in battery packs. Integrated FEA-CFD models help optimize cooling strategies by providing insights into how heat is dissipated throughout the battery system, ensuring thermal stability under different load conditions [153].
- **Machine Learning-Assisted Multi-Scale Models:** Machine learning (ML) techniques are increasingly being incorporated into multi-scale models to enhance predictive accuracy and computational efficiency. ML algorithms, such as neural networks, can be trained to emulate complex physical processes, reducing the need for detailed simulations at every scale. By using ML models to approximate fine-scale behaviors, multi-scale models can achieve faster computation while retaining predictive power. Nozarijouybari and Fathy [154] developed a machine learning-assisted multi-scale model to predict battery degradation patterns in real time, enabling more accurate life cycle predictions for grid-connected storage systems. ML-based approaches are particularly valuable in applications requiring rapid, real-time decision-making, such as load balancing in microgrid systems.

Hierarchical Decomposition Methods

Hierarchical decomposition structures battery optimization across multiple levels, ensuring scalability and computational feasibility. Decomposition techniques can be classified into the following:

- **Time-Based Decomposition:** Time-based decomposition segments optimization into distinct time horizons, such as day-ahead scheduling, intra-hour adjustments, and real-time control. Lampropoulos et al. (2015) proposed a hierarchical predictive control scheme that employs a three-level scheduling framework [155]:
  - *Day-ahead scheduling* optimizes battery participation in energy markets [156].
  - *Intra-hour adjustments* refine battery dispatch based on updated forecasts.
  - *Real-time control* ensures stability by responding dynamically to deviations.

  Further supporting time-based decomposition, Schram et al. examined the effects of optimal battery sizing for self-consumption, showcasing how time-dependent control strategies enhance both peak shaving and energy arbitrage [157].

- **Mode of Operation Decomposition:** This perspective classifies the operational modes of the power system based on its real-time needs and constraints. Lampropoulos et al. [158] propose a hierarchical framework that identifies three primary modes of system operation: a normal mode, where assets like batteries operate based on market signals and internal objectives; a congestion management mode, triggered by local grid constraints requiring flexibility procurement by DSOs; and a system balancing mode, where flexibility is used to resolve imbalances at the transmission level. Schram et al. highlighted the trade-offs between economic and environmental objectives in community energy storage (CES) [159]. Lampropoulos et al. further proposed a hierarchical structure to manage flexibility services at both transmission and distribution levels, supporting the integration of distributed energy resources.
- **Level-Based Decomposition:** Level-based decomposition structures optimization across different operational layers:
  - *Individual Level:* Households optimize battery operation for self-consumption and demand charge management.
  - *Community Level:* Aggregated batteries in community energy storage setups provide localized flexibility [160].
  - *System-Wide Level:* Large-scale energy storage systems interact with wholesale markets and grid operators.

The integration of **multi-scale modeling techniques with hierarchical decomposition** ensures effective battery optimization for high-resolution performance analysis, real-time control, and long-term sustainability. These methodologies enable better integration of energy storage into applications ranging from household self-consumption to large-scale grid stability.

5.3. Optimization Algorithms in Battery Modeling

Optimization algorithms are critical in enhancing various aspects of battery performance, including thermal management, energy efficiency, cycle life, and operational cost-effectiveness. These algorithms help overcome the inherent challenges in battery systems, such as non-linear behavior, multi-modal optimization landscapes, and complex interactions within battery packs. This section presents a comprehensive overview of optimization algorithms commonly applied in battery modeling, highlighting their applications, strengths, and limitations.

Popular algorithms and their applications are (see also Table 7):

- **Genetic Algorithms (GAs):** GAs are powerful evolutionary algorithms that mimic the process of natural selection to solve optimization problems. They are particularly useful for non-linear and complex systems, where traditional optimization techniques may struggle. In battery modeling, GAs have been extensively applied to optimize thermal management systems, such as improving heat dissipation structures and optimizing cooling strategies to maintain thermal uniformity across battery packs. For instance, Afzal and Ramis [16] demonstrated the effectiveness of GAs in optimizing the layout and cooling strategies for battery modules in electric vehicles, achieving significant thermal uniformity and cost reductions.
- **Particle Swarm Optimization (PSO):** Inspired by social behaviors observed in nature, PSO is an algorithm based on the movement and intelligence of swarms. PSO is advantageous in battery systems for SoC estimation and power load balancing. Dai et al. applied PSO in a hybrid energy system, integrating batteries and other renewable energy sources [161]. Their results indicated that PSO could effectively reduce energy costs and improve power load distribution by optimizing the battery's

charge and discharge cycles. PSO is especially beneficial for large-scale applications, where battery systems are deployed in tandem with renewable energy sources in residential or grid-level scenarios.

- **Simulated Annealing (SA):** SA is a probabilistic technique that mimics the annealing process in metallurgy, where materials are slowly cooled to remove defects. This algorithm is particularly valuable in large solution spaces, where it can help avoid local minima and find near-global optimal solutions. Luo et al. [162] demonstrated the use of SA to optimize battery pack configuration, focusing on lithium–ion and nickel-metal hydride cells. Their study showed that SA could improve energy efficiency and reduce costs in battery pack design, especially in configurations requiring large-scale simulations.
- **Gradient-Based Methods:** Gradient-based methods are traditional optimization techniques that rely on the gradient of a function to guide the optimization process. These methods are efficient in continuous optimization problems but can face challenges in the highly non-linear and multi-modal landscapes typical of battery systems. Zhao et al. [163] applied gradient-based optimization for predictive maintenance in lithium–ion batteries, focusing on the estimation of degradation rates and cycle life. Although effective for relatively simpler models, gradient-based methods may not be ideal for complex battery applications due to the risk of becoming trapped in local minima.
- **Ant Colony Optimization (ACO):** ACO is inspired by the foraging behavior of ants, where ants communicate indirectly by leaving pheromones to mark paths. In battery systems, ACO has been applied to optimize charging and discharging patterns to extend battery life and minimize degradation. Muslimin et al. [164] utilized ACO to develop optimized charging strategies for smart grids, integrating residential battery storage systems. Their work showed that ACO could effectively extend battery life by optimizing the charge–discharge cycle, reducing degradation, and enhancing battery sustainability.
- **Differential Evolution (DE):** DE is an optimization algorithm particularly suitable for multi-objective scenarios, where trade-offs between multiple goals must be managed. Ref. [165] used DE in a study focused on optimizing thermal management and extending cycle life in lithium–ion battery packs. By optimizing thermal stability and balancing the charge–discharge rates, DE was shown to be effective in reducing temperature gradients within the battery pack, thus enhancing cycle life and overall performance [166]. DE is beneficial for applications where the balance between thermal management and energy efficiency is critical.
- **Artificial Neural Networks (ANNs) in Optimization:** ANNs, when combined with other optimization algorithms such as GA or PSO, are becoming increasingly popular for predicting and optimizing battery state-of-health (SoH), remaining useful life (RUL), and degradation rates. Fan et al. [167] developed a hybrid ANN-GA model to accurately predict battery health metrics and optimize battery maintenance schedules. The model leveraged large datasets to improve prediction accuracy, making it suitable for applications in battery monitoring and predictive maintenance. ANN models are particularly useful for applications that require real-time data processing and predictive analytics.

Table 7. Overview of optimization algorithms in battery modeling.

Algorithm	Application Sector	Battery Type	Cell Type	Optimization Criteria	References
Genetic Algorithm (GA)	Industrial	Lithium–ion	Prismatic, cylindrical	Thermal uniformity, cost reduction	[16]
Particle Swarm Optimization (PSO)	Microgrid	Lithium–ion, lead–acid	Cylindrical	Cost minimization, energy balance	[161]
Simulated Annealing (SA)	Industrial	Nickel–metal hydride, lithium–ion	Prismatic	Energy efficiency, cost minimization	[162]
Gradient-Based Methods	Residential	Lithium–ion	Pouch	Battery health, cycle life	[163]
Ant Colony Optimization (ACO)	Grid	Lithium–ion, flow batteries	Cylindrical	Degradation minimization, life extension	[164]
Differential Evolution (DE)	Residential	Lithium–ion	Prismatic	Cycle life, thermal stability	[166]
Artificial Neural Networks (ANNs)	Home	Lithium–ion	Prismatic, pouch	Accuracy, longevity prediction	[167]

Each algorithm offers distinct benefits, with specific applications tailored to the unique demands of battery systems in residential, automotive, and grid-level energy applications. The choice of algorithm depends on the desired optimization criteria—such as thermal stability, energy efficiency, cycle life, or cost reduction—and on the complexity of the battery model. While these algorithms have demonstrated substantial effectiveness in simulation-based studies and offline optimization tasks, their real-time application in practical systems presents notable challenges [168]. Many metaheuristic algorithms, such as GA, PSO, and SA, are computationally intensive and require multiple iterations to converge, which limits their direct use in fast-responding or real-time control environments [169]. This issue is particularly pronounced in large-scale distributed energy storage systems (DESSs), where coordinated control, responsiveness, and communication constraints must be considered [170]. As a result, practical implementations often rely on hybrid approaches, combining heuristic algorithms with rule-based control or using simplified models and rolling-horizon techniques. Model Predictive Control (MPC) is increasingly adopted in operational settings due to its ability to incorporate system constraints and operate within real-time horizons [171]. Furthermore, control strategies based on hierarchical or decentralized architectures are increasingly being explored to enable real-time responsiveness at the local level, while ensuring coordinated operation across distributed storage systems [172].

5.4. Different Models for Different Purposes

5.4.1. Models for National Services

Residential energy storage systems (RESSs) can provide various ancillary services to the national grid, improving stability, efficiency, and economic benefits. Several optimization models have been proposed to harness these services effectively, focusing on frequency control, energy arbitrage, and congestion management, as seen in Table 8. FCR is a critical service that ensures grid frequency stability by balancing supply and demand fluctuations. Optimization models for FCR participation typically focus on minimizing degradation costs of the battery while maximizing revenue. Studies have demonstrated that RESSs can be effectively utilized for FCR provision, achieving economic feasibility and technical reliability [173–175]. aFRR assists in restoring the grid frequency to its nominal value by adjusting the power output of energy storage systems in response to grid operator signals. Optimization models for aFRR participation consider dynamic constraints, battery state of health, and revenue maximization. Research has shown the potential of residential storage in providing cost-effective aFRR services [99,176,177].

Congestion management aims to alleviate grid bottlenecks by optimizing energy storage deployment at a local level. For example, the GOPACS platform in the Netherlands [95] serves as an example where market-based congestion management mechanisms have been integrated with residential storage participation. Models developed for this purpose optimize the spatial and temporal distribution of stored energy to minimize congestion costs [98,99,178]. Sahoo et al. [99] proposed an optimal scheduling framework for residential storage systems participating in congestion management markets. Their findings emphasized the economic feasibility of residential storage participation, showing significant reductions in operational costs while enhancing grid flexibility. They applied stochastic optimization techniques to account for uncertainties in load demand and renewable generation. Wang et al. [98] investigated the role of frequency regulation in congestion management by utilizing residential battery storage to provide flexible energy solutions. Their study demonstrated the effectiveness of a MOO approach in balancing frequency stability with congestion reduction, particularly in highly renewable energy penetration scenarios. Zorzano et al. [178] analyzed the techno-economic aspects of integrating distributed energy resources within congestion management schemes. Their work provided insights into the trade-offs between capital investment and operational benefits, concluding that regulatory support is crucial for widespread adoption.

The Dutch energy market provides a unique landscape for residential storage optimization, with increasing penetration of renewable energy sources and a strong emphasis on demand-side flexibility. Initiatives such as GOPACS highlight the country's commitment to leveraging distributed energy resources to enhance grid resilience and reduce operational costs.

Table 8. Summary of different optimization models for national services.

Service	Objective	Optimization Method	Key References
FCR	Frequency stability	Mixed-integer programming	[173,174]
aFRR	Frequency restoration	Dynamic programming	[176,177]
Congestion management	Grid congestion reduction	Stochastic optimization	[98,99]

While these models offer promising approaches to optimizing RESSs for national grid services, several challenges remain. These include uncertainties in market prices, regulatory barriers, and the need for advanced control algorithms to handle complex grid interactions. Additionally, battery ageing and degradation over extended periods present a challenge to cost-effectiveness, requiring strategic charging and discharging cycles to maximize lifespan. Another critical aspect is the economic viability of RESS participation in ancillary markets, as incentives and policies differ across regions, influencing investment decisions. The integration of RESSs with other distributed energy resources (DERs), such as PV systems, can further enhance system efficiency but requires sophisticated coordination strategies. Future research should focus on the integration of machine learning techniques and robust optimization to enhance the adaptability and effectiveness of RESS participation in national services. Developing standardized frameworks and regulatory guidelines to support the widespread adoption of RESSs can significantly contribute to achieving grid reliability and sustainability goals.

5.4.2. Models for Local Services

Batteries in local energy systems can be optimized using multi-objective formulations that reduce peak demand and enhance self-consumption of on-site renewable energy sources. These objectives are typically included into linear or mixed-integer linear programming models, which address restrictions including battery capacity, state-of-charge, and time-dependent load and generation profiles. By optimizing peak–demand reduction and self-consumption, users can diminish demand charges and enhance dependence on locally produced energy, resulting in cost savings and augmented system resilience. Alongside these operational and economic objectives, limiting battery degradation may function as a tertiary goal, safeguarding against the premature reduction in the battery's lifespan due to frequent cycling. Incorporating degradation models into the optimization process produces more realistic results, averting excessively aggressive charge–discharge procedures that undermine long-term system performance. Here, we discuss the specific treatment of degradation modeling and its parameterization. This multi-objective strategy guarantees a strong equilibrium among cost efficiency, operational dependability, and asset durability.

Alongside linear and mixed-integer linear programming, various other modeling methodologies are utilized to encapsulate the intricacies of local services, including peak-shaving and self-consumption (see also Table 9). Dynamic programming (DP) methods are employed to address sequential decision-making within uncertainty, rendering them particularly appropriate for environments characterized by variable demand or renewable generation [179]. Agent-based models replicate the behaviors and interactions of many stakeholders—such as prosumers, batteries, and grid operators—enabling researchers to examine decentralized control mechanisms and local energy markets. Heuristic or metaheuristic techniques (e.g., evolutionary algorithms, particle swarm optimization) are favored for larger-scale or more intricate situations wherein linear problem formulations may become unmanageable. Certain researchers select resilient or stochastic optimization frameworks to address uncertainty in predicting solar irradiance or future electricity prices, thereby ensuring that solutions stay viable under fluctuating conditions. Data-driven models utilizing machine learning approaches are particularly adept at enhancing predictions of demand and photovoltaic generation, integrating these forecasts into optimization procedures for improved battery scheduling accuracy. These diverse modeling paradigms provide various analytical perspectives and computational instruments for the efficient management of local energy systems, each presenting distinct trade-offs regarding complexity, scalability, and solution optimality.

Table 9. Overview of different modeling approaches for local battery services.

Reference	Model	Main Findings	Application
[180]	Dynamic Programming	Demonstrated cost-optimal battery dispatch strategies under uncertain PV generation and load, achieving reduction in grid electricity costs and CO_2 emissions	Peak shaving, self-consumption
[181]	Multi-Objective MILP	Balanced demand-charge reduction with maximizing PV usage; included battery aging constraints for more realistic operations	Peak shaving, self-consumption
[182]	Genetic Algorithm	Efficient solution for large-scale prosumer networks; reduced peak demand by 20% and improved local PV utilization	Community-scale peak shaving
[183]	Agent-Based Modeling	Analyzed decentralized battery control among multiple prosumers; found improved load balancing with minimal central coordination	Microgrids, local energy markets
[184]	Robust Optimization	Ensured reliable scheduling under worst-case PV/load deviations; peak demand decreased by up to 25% in simulations	Industrial peak shaving
[185]	Particle Swarm Optimization	Fast convergence for real-time battery scheduling; highlighted synergy between EV charging and stationary storage	Residential load management
[186]	Stochastic Optimization	Incorporated probabilistic solar and load forecasts; improved expected energy savings compared to deterministic methods	Self-consumption, peak shaving
[187]	Model Predictive Control	Achieved near-real-time control of battery operation; effectively minimized peak demand under dynamic tariffs	Commercial building load shifting
[188]	Mixed-Integer Linear Programming	Optimized battery and HVAC systems jointly; notable cost savings under time-of-use pricing	Peak shaving, building energy management
[189]	MOO	Proposed Pareto-optimal solutions balancing cost and grid impact; indicated trade-offs between battery cycling and peak reduction	Residential storage integration

5.4.3. Incorporating Degradation Models

Numerous battery deterioration models have been introduced in the literature, each balancing computational complexity with accuracy in depicting real-world ageing. Fundamentally, constant per-cycle or linear cycle-count methodologies regard each discharge cycle as imparting a fixed percentage of wear—an assumption that overlooks DoD, temperature, and additional variables, potentially leading to inaccurate assessments of capacity degradation. Calendar-plus-cycle formulations enhance this by considering time-dependent degradation during idle intervals, which may be exacerbated by elevated states of charge or increased temperatures. Additional semi-empirical methodologies—frequently based on laboratory data—incorporate dependencies on DoD, temperature, and current rate; for instance, Wöhler-based (S–N) curves correlate partial cycles with DoD-dependent fatigue. Brinkel et al. [127] illustrate this methodology by employing curve-fitting with empirical parameters b and m, subsequently converting the outcome into piecewise-linear segments for enhanced integration into optimization. In contrast, physics-based (pseudo-two-dimensional or single-particle) models offer detailed insights into side reactions and solid electrolyte interface development; nevertheless, they are generally too computationally demanding for large-scale scheduling. Simultaneously, empirical and data-driven models encompass regression-based techniques that directly correlate cycle life with laboratory data, as well as machine learning frameworks that forecast capacity degradation absent conventional electrochemical equations. Due to the intricacies of battery utilization in peak shaving, self-consumption, and grid ancillary services, most large-scale optimization frameworks prefer DoD-sensitive, cycle-based, or piecewise methodologies, attaining a pragmatic balance between realism and practicalities. In Table 10, an overview of different battery degradation models used in optimizations techniques is presented.

Table 10. Overview of different battery degradation models used in optimization.

Reference	Model	Main Findings	Application
[190]	Linear	Developed a linear optimization model incorporating battery degradation to maximize revenue and minimize wear; demonstrated improved economic outcomes in energy trading applications.	Grid-scale energy trading
[191]	Diagnostic Model	Provided a comprehensive review of degradation mechanisms in lithium–ion batteries, emphasizing the importance of physics-based models for accurate lifetime predictions under various operational conditions.	Battery life cycle analysis
[192]	Semi-Empirical	Developed a semi-empirical ageing model incorporating temperature and state of charge effects; validated with laboratory cycling data for LFP and NMC cells; improved predictive accuracy of capacity fade in optimization.	Automotive li–ion scheduling
[193]	Machine Learning	Developed an attention-based deep neural network trained on operational data to predict battery discharge capacity without explicit electrochemical equations; suitable for real-time battery management systems.	Real-time battery management

Table 10. *Cont.*

Reference	Model	Main Findings	Application
[194]	Calendar-plus-Cycle	Investigated the combined effects of calendar and cyclic ageing; identified optimal partial state-of-charge windows to minimize overall capacity fade in stationary storage applications.	Stationary battery (peak shaving)

In recent years, data-driven approaches for real-time battery degradation prediction have gained significant traction, particularly in the context of smart battery management systems (BMSs) [195]. These methods leverage large volumes of operational data—such as voltage, current, temperature, and state of charge—to predict key degradation indicators like State of Health (SoH) and Remaining Useful Life (RUL) [196]. Techniques including artificial neural networks (ANNs), recurrent neural networks (RNNs), support vector machines (SVMs), and gradient boosting (e.g., XGBoost) are being developed to model complex, nonlinear degradation patterns without relying on first-principle equations [195]. When integrated into modern BMSs, these models support real-time decision-making and predictive maintenance, enabling dynamic adaptation of charge/discharge strategies to extend battery lifespan and reduce failure risk [197]. As computational resources become more accessible, data-driven degradation forecasting is expected to become standard in both residential and grid-scale battery systems [198].

6. Different Optimization Objectives for Different Purposes

The integration of BESSs in residential buildings involves optimizing their utilization to achieve specific objectives. These objectives can be categorized into economic, environmental, and operational goals, often requiring MOO approaches to address competing priorities effectively. This section elaborates on the distinct optimization objectives and discusses their implications for residential energy storage systems.

6.1. Economic Objectives:

Cost minimization and ROI optimization are critical drivers for residential BESS adoption. The economic viability of these systems depends on reducing initial investment costs, operational expenses, and maximizing revenue generation opportunities. Strategies include (Table 11):

- **Self-consumption optimization:** Enhancing the utilization of on-site renewable energy production, such as PV systems, to reduce dependency on grid electricity and associated costs [49].
- **Peak shaving:** Minimizing demand charges by flattening load profiles during peak periods [199].
- **Participation in demand response programs:** Leveraging battery storage to capitalize on time-of-use tariffs and incentives offered by grid operators [200].

Economic objectives often require advanced financial modeling to account for factors such as battery degradation, energy market dynamics, and policy incentives. Techniques like net present value (NPV) analysis and levelized cost of storage (LCOS) are commonly employed for evaluating ROI [201].

Table 11. Economic strategies for residential BESSs.

Strategy	Description	Potential Economic Impact
Self-consumption optimization	Enhancing the use of on-site renewable energy to reduce grid dependency.	Increases self-consumption rates, leading to significant electricity bill savings [49].
Peak shaving	Reducing demand charges by discharging stored energy during peak periods.	Potential reduction in peak demand charges, resulting in lower overall electricity costs [199].
Demand response participation	Adjusting energy usage based on grid signals to benefit from time-of-use tariffs and incentives.	Provides additional revenue streams, enhancing ROI through compensation for grid services [200].

6.2. Environmental Objectives:

The environmental benefits of residential BESSs are integral to their adoption, aligning with global sustainability goals. Key considerations include (see also Table 12):

- **Reduction in Greenhouse Gas Emissions:** By maximizing the use of renewable energy and minimizing reliance on fossil-fuel-based grid power, residential BESSs can significantly lower carbon footprints. For instance, storing excess solar energy during peak production times and utilizing it during periods of high demand reduces the need for electricity generated from fossil fuels, thereby decreasing greenhouse gas emissions [202].
- **Life Cycle Sustainability:** Considering the environmental impacts of battery production, use, and end-of-life management is crucial. Life Cycle Assessments (LCAs) of residential PV and battery storage systems reveal that, while the production phase contributes to environmental impacts, the operational phase offers substantial benefits by offsetting emissions through renewable energy utilization. Effective recycling and repurposing strategies further enhance life cycle sustainability [203].
- **Facilitating Renewable Energy Integration:** Residential BESSs mitigate the variability of renewable generation by storing excess energy and supplying it when needed. This capability enhances grid stability and supports the broader integration of renewable energy sources into the energy mix, promoting a more resilient and sustainable energy infrastructure [204].

To evaluate environmental objectives, several metrics are commonly analyzed:

- **Carbon Footprint:** Measures the total greenhouse gas emissions directly and indirectly associated with the BESS throughout its life cycle. Studies indicate that residential BESSs, when combined with PV systems, can significantly reduce household carbon footprints by decreasing reliance on grid electricity generated from fossil fuels [203].
- **Energy Payback Time (EPBT):** Represents the time required for the system to generate the amount of energy equivalent to that consumed during its production. Shorter EPBTs indicate more efficient systems. Research shows that integrating BESSs with PV systems can improve EPBT by enabling higher self-consumption rates of renewable energy [205].
- **Material Recycling Efficiency:** Assesses the effectiveness of recycling processes in recovering valuable materials from decommissioned batteries. High recycling efficiency reduces the environmental impact of raw material extraction and processing. Advances in recycling technologies are improving the sustainability of BESSs by enabling the recovery of critical materials such as lithium and cobalt [203].

Table 12. Environmental metrics for residential BESSs.

Metric	Description	Reference
Carbon Footprint	Total greenhouse gas emissions over the system's lifecycle.	[203]
Energy Payback Time (EPBT)	Time required to generate energy equivalent to that consumed during production.	[205]
Material Recycling Efficiency	Effectiveness of recycling processes in recovering valuable materials.	[203]

In conclusion, residential BESSs offer substantial environmental benefits by reducing greenhouse gas emissions, enhancing life cycle sustainability, and facilitating the integration of renewable energy sources. Evaluating these systems through metrics such as carbon footprint, energy payback time, and material recycling efficiency provides a comprehensive understanding of their environmental impact and supports informed decision-making for sustainable energy solutions.

6.3. Operational Objectives

The operational efficiency and reliability of BESSs are important for their practical deployment in residential settings. Key operational goals include the following:

- **SoC Management:** Ensuring optimal SoC levels is essential to balance energy availability and battery longevity. Effective SoC management prevents overcharging and deep discharging, both of which can degrade battery health. Advanced algorithms and predictive models are employed to maintain SoC within optimal ranges, thereby extending battery lifespan and ensuring energy availability when needed [206].
- **Reliability:** Guaranteeing an uninterrupted energy supply during outages and grid fluctuations is a critical operational objective. BESSs provide backup power, enhancing the resilience of residential energy systems against grid instability. Reliability assessments involve evaluating the system's ability to meet energy demands consistently, considering factors such as battery ageing, environmental conditions, and load variability [207].
- **Grid Interaction:** Facilitating bidirectional energy flows enables BESSs to provide ancillary services such as frequency regulation and load balancing. Effective grid interaction requires sophisticated control strategies to manage energy import and export, ensuring compatibility with grid requirements and maximizing economic benefits through participation in demand response programs [208].

Advanced BMSs play a crucial role in achieving these objectives by leveraging predictive algorithms and real-time monitoring. BMSs oversee various parameters, including temperature, voltage, and current, to optimize performance and prevent failures. The integration of machine learning techniques into BMSs enhances predictive maintenance capabilities, allowing for the anticipation of potential issues before they impact system operation [209].

Furthermore, the operational modes of residential BESSs can significantly impact battery life. Variations in use cases, environmental conditions, and battery chemistries influence degradation rates. For instance, high-frequency cycling associated with certain operational strategies can accelerate wear, reducing overall system longevity. Understanding these factors is crucial for designing robust and efficient BESS deployments that maximize benefits for residential users while ensuring long-term reliability and performance [210].

Proper sizing, placement, and management of BESSs are essential for optimal performance in both individual and shared residential installations. Studies have demonstrated that appropriately sized and strategically placed BESSs can enhance energy efficiency, reduce costs, and improve grid stability. In shared residential settings, coordinated management of BESSs among multiple users can lead to collective benefits, such as increased self-consumption of renewable energy and reduced peak demand [211].

Achieving operational objectives in residential BESS deployment requires a comprehensive approach that encompasses effective SoC management, ensuring reliability, facilitating seamless grid interaction, and understanding the implications of various operational modes on battery life. Advanced BMSs, informed by predictive algorithms and real-time data, are instrumental in realizing these goals, thereby enhancing the efficiency and resilience of residential energy systems.

6.4. Multi-Objective Optimization: Balancing Economic, Environmental, and Operational Goals

Balancing economic, environmental, and operational objectives in residential BESSs often leads to trade-offs, necessitating MOO approaches. These techniques aim to identify optimal solutions that satisfy multiple, often conflicting, criteria simultaneously.

6.4.1. Common MOO Techniques

Several MOO techniques are prevalent in the optimization of BESSs:

- **PSO:** An evolutionary computation technique inspired by the social behavior of birds flocking, used to find optimal solutions by iteratively improving candidate solutions with regard to a given measure of quality. PSO has been applied in sizing BESSs to improve network performance by reducing power loss, voltage deviations, and system costs [212].
- **Non-Dominated Sorting Genetic Algorithm II (NSGA-II):** An evolutionary algorithm that generates a set of Pareto-optimal solutions, facilitating decision-making in complex optimization problems. NSGA-II has been utilized in optimizing hybrid energy storage systems for electric vehicles, considering multiple criteria such as cost and performance [212].
- **Strength Pareto Evolutionary Algorithm 2 (SPEA-2):** An improved version of SPEA that incorporates a fine-grained fitness assignment strategy, density estimation technique, and an enhanced archive truncation method. SPEA-2 has been applied in various power system optimization problems, including the optimal siting of energy storage systems in electric power distribution networks [213].
- **Multi-Objective Differential Evolution (MODE):** A variant of the differential evolution algorithm tailored for multi-objective problems, known for its simplicity and efficiency in handling complex optimization tasks. MODE has been employed in the optimal sizing of photovoltaic and energy storage systems for ultra-fast charging stations of electric vehicles, aiming to minimize costs and emissions [214].

6.4.2. Frequency of Use in Literature

The application of MOO techniques in BESS optimization has significantly evolved over the past five years. This subsection aims to provide a comprehensive overview of the frequency of use of various MOO techniques, highlighting trends and preferences in the recent literature. The analysis is based on a review of 15 peer-reviewed articles published between 2019 and 2024, focusing on different methodologies and their adoption in BESS optimization.

Researchers have extensively explored algorithms such as PSO, NSGA-II, SPEA-2, and MODE. These techniques are favored for their ability to handle the complex, non-linear, and multi-dimensional nature of BESS optimization problems.

The core of MOO application in BESSs lies in its ability to simultaneously optimize multiple conflicting objectives such as cost minimization, efficiency maximization, battery lifespan extension, and energy loss reduction. PSO, for instance, is widely adopted due to its simplicity and fast convergence, making it effective for real-time applications. NSGA-II remains a popular choice because of its strong performance in maintaining solution diversity and efficiently identifying Pareto-optimal fronts. SPEA-2 and MODE are appreciated for their advanced selection mechanisms and robustness in exploring large solution spaces, crucial for dynamic BESS environments.

The distribution of these techniques is presented in Table 13, illustrating their prevalence in recent studies. Notably, PSO and NSGA-II dominate the field due to their robustness and efficiency in converging towards optimal Pareto fronts. SPEA-2 and MODE follow closely, appreciated for their capability to maintain solution diversity and explore large search spaces effectively. Other techniques, while less frequent, provide unique advantages in specific scenarios, contributing to the diversity of approaches in the literature.

Table 13. Frequency of use of MOO techniques in BESS studies (2019–2024).

Optimization Technique	Frequency (%)	Reference
Particle Swarm Optimization (PSO)	30%	[215–217]
Non-Dominated Sorting Genetic Algorithm II (NSGA-II)	25%	[218–220]
Strength Pareto Evolutionary Algorithm 2 (SPEA-2)	20%	[221–223]
Multi-Objective Differential Evolution (MODE)	15%	[224,225]
Other Techniques	10%	[226,227]

The application trends highlighted in this review reflect the growing complexity of BESS optimization tasks in the residential sector and the need for versatile and adaptive algorithms. PSO's dominance indicates a preference for methods that balance computational efficiency with solution quality, particularly in scenarios where quick, real-time decisions are required for household energy management. This is essential in residential applications where energy consumption patterns can be highly variable.

NSGA-II's popularity underscores the importance of maintaining Pareto-optimal solution sets, allowing homeowners and energy managers to make informed decisions when balancing trade-offs between objectives such as cost savings, energy efficiency, and battery lifespan. This capability is particularly valuable in residential settings where financial constraints often influence decision-making.

While SPEA-2 and MODE are less frequently used, their advantages in handling complex optimization landscapes and maintaining diversity make them suitable for specific residential applications. For instance, they are effective in managing energy flows in homes with integrated renewable energy systems, such as solar panels combined with BESSs, where variability in generation and consumption requires flexible optimization strategies.

The presence of other emerging techniques highlights the continuous evolution of MOO applications in the residential sector. These techniques are often tailored to specific needs, such as optimizing battery charge–discharge cycles under dynamic pricing models or improving the resilience of home energy systems against power outages. Overall, the diversity in MOO techniques reflects the varied and dynamic requirements of residential BESS optimization.

7. Results and Discussion

7.1. Battery Technologies and Performance

This section presents the key findings from our comprehensive review of BESSs in residential applications, highlighting their role in supporting renewable energy integration. We analyze the performance and characteristics of various battery technologies, focusing on LFP batteries, due to their growing prominence in residential settings. The discussion delves into their advantages, such as high safety, efficiency, and resilience against cyclic degradation, compared to alternative technologies like flow batteries. Furthermore, we explore the applications of batteries in the built environment, covering energy storage for PV systems, peak shaving, load shifting, demand response, and backup power. The section also examines optimization strategies for enhancing battery utilization, comparing MOO techniques with other approaches, and concludes with practical recommendations for stakeholders and policymakers to support the broader adoption of BESSs in residential energy systems.

A key outcome of this review is the structured classification of battery applications into individual use, shared storage, and energy communities. While individual BESSs primarily aim to enhance self-consumption and peak shaving, shared systems—such as community energy storage (CES) and aggregated multi-building setups—can improve local grid flexibility and cost-sharing mechanisms. The largest-scale application, VPPs, demonstrates how distributed storage can participate in wholesale electricity markets and frequency regulation services. However, a critical gap remains in how these different scales interact dynamically. Future research should focus on multi-level control strategies that allow BESSs to transition between roles, maximizing flexibility and profitability seamlessly. While Table 3 provides an overview of key battery technologies and their applications, a critical review reveals some gaps and areas for improvement. Notably, while lithium–ion batteries are widely adopted for residential, EV, and grid applications, ageing effects and safety concerns remain challenges that require further research [50]. Additionally, LFP batteries offer improved thermal stability and longer cycle life, making them a strong candidate for stationary storage and EV applications, yet their lower energy density limits their broader adoption [78]. Flow batteries, such as vanadium redox and zinc–bromine, have emerged as promising technologies for long-duration energy storage, particularly for large-scale grid applications [82]. These batteries offer the advantage of decoupling power and energy capacity, making them highly suitable for renewable energy integration, though their higher upfront costs remain a barrier. The environmental impact of lead–acid and nickel–based batteries continues to be a concern. Lead–acid technology, despite its low cost, poses environmental risks due to lead content and limited cycle life [79]. Similarly, nickel–cadmium (NiCd) batteries, once widely used in industrial and aviation applications, contain toxic cadmium, which complicates disposal and limits their sustainability [80]. Nickel–metal hydride (NiMH) batteries, while still found in hybrid vehicles and consumer electronics, exhibit lower performance compared to lithium–ion and have gradually been replaced in newer automotive applications [80,81]. These aspects highlight the need for continued research into safer, more sustainable energy storage alternatives.

The integration of renewable energy sources into residential energy systems has increased the demand for efficient and reliable battery storage solutions. Among the available technologies, LFP batteries stand out as the most commonly deployed due to their superior safety profile, long cycle life, and stable thermal performance [22,228]. LFP batteries have high thermal stability and reduced risk of thermal runaway compared to other lithium–ion chemistries, making them particularly suitable for residential environments where safety is paramount. In addition, their excellent cycle life and consistent performance under varying load conditions enhance their cost-effectiveness over the long term. Lithium–ion batteries, particularly those based on LFP chemistry, offer a compelling combination of high energy density, efficiency, and longevity. With an energy density range of 80–160 Wh/kg [22], they support compact installations ideal for residential spaces. Their round-trip efficiency often exceeds 90% [36], minimizing energy losses and maximizing the benefits of self-consumption from renewable sources. The extended cycle life, typically spanning over 4000 cycles [37], reduces the frequency of replacements, contributing to lower life cycle costs. Furthermore, their rapid charge–discharge capabilities make them well-suited for dynamic grid support applications such as demand response and frequency regulation [38]. Despite the presence of other battery types such as flow batteries, which have garnered attention for large-scale energy storage due to their scalability and decoupled energy-power design [31,32], their adoption in residential applications is limited due to challenges like low energy density, high system complexity, and substantial installation costs. Their relatively low energy density (15–70 Wh/kg) necessitates larger physical installations, which are impractical for most residential environments. Additionally, the complexity of their system components, such as pumps and electrolyte management systems, increases both the initial capital expenditure and ongoing maintenance costs. Efficiency losses during energy conversion and the limited availability of cost-effective materials further hinder their competitiveness against lithium–ion technologies. The choice of LFP-based lithium–ion batteries is further justified by their superior resistance to cyclic degradation, a critical factor in residential energy storage applications. In contrast to other chemistries that experience significant capacity fade over time, LFP batteries maintain structural integrity and electrochemical performance across extensive charge–discharge cycles [228]. This durability not only extends the battery lifespan but also enhances the reliability of the energy supply, aligning with the operational demands of residential energy systems. The combination of high safety standards, cost-effectiveness, and resilience against cyclic degradation strategically underscores the preference for LFP batteries in the context of renewable energy integration within residential infrastructures.

7.2. Optimization Methods for Residential BESS

Balancing economic, environmental, and operational objectives in residential BESSs often requires the application of MOO techniques. These approaches aim to identify optimal solutions that satisfy multiple, often conflicting, criteria simultaneously, such as cost minimization, energy efficiency, and battery lifespan. Multi-objective functions, such as those implemented through PSO, NSGA-II, SPEA-2, and MODE, are widely used in optimizing BESS performance. PSO offers the advantage of simplicity and fast convergence, making it suitable for real-time residential energy management scenarios [212]. In contrast, NSGA-II is effective in generating diverse Pareto-optimal solutions, supporting decision-making when trade-offs are necessary between financial savings and energy sustainability [212]. SPEA-2 and MODE provide enhanced capabilities for managing complex optimization landscapes, particularly in homes integrating renewable energy systems where energy generation and consumption are highly variable [213,214]. Despite their advantages, these techniques face challenges such as computational complexity, sensitivity to parameter tuning, and the need for large datasets for accurate modeling. Comparing these with single-objective optimization methods, MOO techniques offer superior flexibility but at the cost of increased computational demands. Overall, the selection of an appropriate optimization strategy should be based on the specific objectives, system constraints, and computational resources available.

7.3. Integration of BESSs into Local and National Energy Systems

Battery storage within the built environment contributes significantly to both local and national energy systems by enhancing grid stability, providing economic advantages, and facilitating the integration of renewable energy sources [229–231]. Global studies provide important new perspectives for raising BESSs' economic feasibility in Europe. Extended tax incentives in the United States have greatly encouraged the acceptance of battery energy storage systems, therefore lowering investment uncertainty and improving market stability [112]. Studies show that temporary incentives do not inspire enough confidence for general acceptance, which emphasizes the need of lasting policy frameworks in Europe [102]. Green loans for PV+BESS projects implemented in Chile have considerably improved payback times, offering a possible structure for European financial institutions to create similar systems aiming at reducing high initial costs [117]. Studies on the Spanish power market reveal that substantial battery degradation costs and structural limitations within the market impede the economic viability of home battery energy storage systems. This indicates that EU policymakers ought to consider alterations to market structures to ensure fair remuneration for battery flexibility services [105]. In France, the costs associated with grid connectivity represent a significant economic barrier, imposing financial burdens on customers and impeding adoption [106]. This underscores the need to revise EU regulatory frameworks to enhance grid access for distributed storage. Optimization models play a pivotal role in maximizing these benefits, ensuring that storage assets are utilized efficiently across diverse applications. At the national level, batteries support ancillary services such as FCR, aFRR, and mFRR, offering rapid response capabilities that traditional power plants cannot achieve. To overcome market entry barriers, VPPs aggregate distributed battery systems and other flexible energy assets, enabling small-scale battery owners to participate in ancillary services and electricity markets that typically impose high entry barriers, such as the 1 MW minimum for FCR participation. By pooling decentralized storage capacities, VPPs enhance grid flexibility while unlocking additional revenue streams for residential and commercial battery owners. However, their operational success depends on regulatory alignment, advanced control algorithms, and real-time coordination between distributed assets. In wholesale energy markets, batteries enable energy arbitrage, capitalizing on price fluctuations to maximize profits. Nevertheless, price volatility and regulatory uncertainties pose challenges for accurate price forecasting and charge–discharge scheduling.

On a local scale, battery systems are integral for peak shaving and enhancing the self-consumption of renewable energy. These applications are impacted by regional regulatory frameworks, tariff structures, and net metering policies, all of which affect the economic feasibility and operational strategies of battery deployment. In urban areas, where grid congestion is a growing concern, batteries contribute to congestion management by providing localized energy flexibility, reducing the risk of overloading distribution networks. in the Netherlands, initiatives like GOPACS support this function by enabling distributed energy resources to participate in flexibility markets, although challenges related to market liquidity and financial viability remain. Energy Hubs further expand the role of batteries in local energy management by integrating multiple energy carriers—such as electricity, heat, and gas—within a unified optimization framework. This approach enhances the efficiency of local energy flows, facilitating demand-side management and energy sharing among interconnected users. By using sector coupling, Energy Hubs reduce reliance on centralized grid infrastructure and enhance system resilience. Moreover, the implementation of Energy Hubs requires significant investment in advanced energy management systems (EMSs) and regulatory frameworks that facilitate sector coupling and coordinated dispatch of different energy vectors.

7.4. Advanced Battery Management and Second-Life Applications

In addition to optimizing battery operations, developments in BMSs play a crucial role in extending battery lifespan and improving efficiency. Traditional BMS implementations rely on rule-based charge–discharge strategies, whereas recent innovations incorporate machine learning (ML) and predictive analytics to dynamically adjust operating parameters. ML-driven BMSs can anticipate battery ageing patterns, adjust cycling behavior, and minimize degradation effects in real time. Additionally, the repurposing of second-life batteries from electric vehicles (EVs) into stationary storage offers a sustainable solution for cost-effective energy storage. However, one of the key challenges in second-life battery adoption is the lack of standardized degradation models, making it difficult to predict the remaining useful life (RUL). Future research should focus on adaptive degradation modeling techniques to improve reliability and integration into residential and community energy systems.

7.5. Hierarchical Control and Energy Communities

The integration of hierarchical decomposition into battery optimization provides a structured framework for balancing these competing applications. By breaking down battery management into time-based, mode-based, and level-based layers, these methods enhance computational efficiency and operational adaptability. This structured approach allows batteries to dynamically switch between different services such as self-consumption enhancement, peak shaving, and grid flexibility depending on economic incentives, market prices, and grid constraints.

Several studies, such as those by [2], demonstrate that applying hierarchical control strategies can significantly improve battery profitability and system resilience, particularly in community energy storage (CES) and VPP configurations. This approach ensures that energy storage assets are utilized optimally across different market and local grid conditions, minimizing unnecessary cycling and degradation while maximizing economic returns.

Addressing the environmental footprint requires advances in battery chemistries that reduce reliance on rare or harmful materials, such as cobalt. In addition, the second-life batteries (SLBs) present a sustainable approach to battery reuse, mitigating both waste and extending battery lifespan. With the repurposing of the retired EV batteries for stationary storage or less demanding applications, SLBs contribute to resource efficiency and circular economy principles.

The scalability of battery storage solutions from single households to large-scale energy communities requires adaptive control mechanisms that can coordinate multiple storage assets under varying market conditions. CES projects have shown potential for reducing energy costs and increasing self-consumption, but their adoption is often hindered by regulatory and financial barriers. One approach to overcoming these barriers is hierarchical control strategies, where decision-making is distributed across individual, community, and system-wide levels. Furthermore, peer-to-peer (P2P) energy trading within energy communities could enable direct transactions between prosumers, further incentivizing local energy exchange. Research should focus on scalable optimization models that integrate BESS scheduling, P2P trading, and grid support services, ensuring that community-scale storage operates efficiently in dynamic energy markets.

7.6. Trade-Offs and Policy Recommendations

Despite these advantages, trade-offs must be considered when deploying batteries across multiple applications. For instance, a battery dedicated to frequency regulation may not simultaneously support peak shaving or self-consumption, limiting its financial returns for residential users. Additionally, frequent cycling in energy arbitrage can accelerate battery degradation, affecting long-term cost-effectiveness. The complexity of managing these competing priorities underscores the importance of MOO frameworks, which can balance technical performance with economic outcomes. Ultimately, the successful integration of battery storage in the built environment depends on well-structured market mechanisms, supportive regulatory policies, and advanced optimization strategies that enhance both technical efficiency and economic sustainability.

Stakeholders and policymakers should prioritize incentives and funding for the deployment of LFP-based energy storage systems in residential sectors due to their safety and cost-effectiveness. Encouraging research and development in battery management systems can further enhance the efficiency and lifespan of these technologies. Standardized safety requirements will also encourage wider usage while guaranteeing safe energy storage methods. Moreover, policymakers should consider implementing dynamic pricing models and demand response programs to incentivize residential energy storage usage, enhancing grid stability and reducing peak load pressures. Investments in educational campaigns can also raise awareness among consumers about the benefits of residential BESSs, fostering greater acceptance and adoption. Furthermore, stakeholders can promote public–private partnerships to accelerate technological advancements, infrastructure development, and the integration of BESSs into smart grid initiatives. In addition to regulatory support and market mechanisms, advancing battery optimization methodologies through multi-scale modeling and hierarchical decomposition is key to ensuring the long-term viability of BESSs. To further improve real-time optimization, future research should explore hybrid approaches that combine data-driven forecasting with structured decomposition techniques. Additionally, the development of machine learning-enhanced hierarchical control models could improve the responsiveness of residential and community battery systems, allowing for smarter, more autonomous grid interactions.

8. Conclusions

This analysis highlights the critical role of BESSs in facilitating the incorporation of renewable energy sources in residential settings. The analysis recognizes LFP batteries as a very promising technology due to their safety, high efficiency, prolonged cycle life, and improved resistance to cyclic deterioration. LFP batteries show notable thermal stability, thereby decreasing the risk of thermal runaway, an essential safety factor for residential use. Their high round-trip efficiency and prolonged operational lifespan significantly improve cost savings over time, making them a financially viable option for homeowners and energy communities. Additionally, their rapid charge–discharge capabilities facilitate dynamic grid applications, such as demand response and peak shaving, which enhance grid stability. Alternative technologies like flow batteries offer scalability advantages for large-scale applications; however, their inherent limitations—specifically lower energy density, greater system complexity, and higher costs—hinder their practicality for residential use.

This study emphasizes the importance of optimization models in improving the efficiency and cost-effectiveness of BESSs. Multi-objective optimization approaches, including PSO, NSGA-II, SPEA-2, and MODE, enable the simultaneous evaluation of many criteria, such as economic returns, energy efficiency, and environmental sustainability. These techniques enable the creation of Pareto-optimal solutions, offering decision-makers a range of options that balance trade-offs among competing objectives. NSGA-II facilitates strategic decision-making by balancing economic performance with environmental benefits, whereas PSO is suitable for real-time management applications due to its rapid convergence. The adaptability of these models enables customization for specific residential energy scenarios, accommodating diverse consumption patterns and renewable energy inputs. Challenges such as computational complexity and the necessity for precise data inputs notwithstanding, the implementation of multi-objective optimization markedly improves the strategic deployment and operational efficiency of BESSs. The integration of advanced optimization modeling with BESS deployment is essential for enhancing technical performance and advancing sustainability and resilience objectives in contemporary energy systems.

Despite advancements in BESS control strategies, several critical research gaps remain. First, there is an urgent need for standardized degradation models to accurately assess the lifespan of second-life batteries. Second, while hierarchical decomposition and multi-scale modeling have been successfully demonstrated in simulation environments, real-world field trials remain limited. Finally, regulatory challenges continue to restrict small-scale energy storage participation in ancillary services and market-based flexibility programs. Future research should focus on real-world pilot projects that validate the technical, economic, and policy implications of hierarchical battery optimization, enabling scalable and economically viable BESS integration.

Beyond conventional optimization models, the inclusion of hierarchical decomposition techniques in battery energy storage management enables a more structured approach to scheduling, market participation, and flexibility provision. By segmenting battery operations into time-based, mode-based, and level-based layers, these frameworks ensure that energy storage assets operate efficiently across individual, community, and system-wide levels.

The effectiveness of MOO techniques in battery scheduling is further enhanced when integrated with hierarchical control frameworks. Recent studies have demonstrated that combining real-time forecasting with structured decision-making layers significantly improves BESS profitability, self-consumption rates, and flexibility service provision. Future advancements in hybrid AI-driven optimization methods will be crucial in ensuring the real-time adaptability of BESSs across multiple operational levels.

Additionally, this review highlights the significant role of battery storage in the built environment, contributing to both local and national energy systems. BESSs enhance grid stability, support ancillary services such as frequency regulation, and allow for services like energy arbitrage in the day ahead market, thus improving the efficiency and reliability of modern power grids. At the national level, VPPs aggregate distributed battery systems and other flexible energy assets, enabling small-scale battery owners to participate in ancillary services and electricity markets that typically impose high entry barriers, such as the minimum power requirements for FCR participation. By pooling decentralized storage capacities, VPPs enhance grid flexibility while unlocking additional revenue streams for residential and commercial battery owners. At the local level, BESSs play a crucial role in peak shaving and self-consumption optimization, reducing grid dependency and lowering electricity costs for residential users. Energy hubs further extend this concept by integrating multiple energy carriers—such as electricity, heat, and gas—within a unified optimization framework. These hubs enhance the efficiency of local energy flows, enabling advanced demand-side management and facilitating energy sharing among connected users. However, the trade-offs between applications—such as the choice between frequency regulation and self-consumption—underscore the need for advanced scheduling strategies and MOO models to balance technical efficiency with economic viability.

Future research should focus on integrating data-driven forecasting methods with hierarchical decomposition techniques to further refine real-time battery optimization strategies. Additionally, the development of hybrid approaches that combine AI-enhanced predictive models with structured decomposition methods will be critical in advancing smart battery management systems. These innovations will enable residential, community, and system-wide batteries to interact more effectively with emerging energy markets, ensuring that BESSs not only support self-consumption and peak shaving but also actively participate in grid-balancing and other ancillary services.

Moreover, Digital Twin technologies are expected to play a pivotal role in advancing BESS management [232]. By creating dynamic virtual replicas of batteries and energy hubs, Digital Twins enable real-time monitoring, predictive diagnostics, and optimization across multiple operational layers. Their integration with hierarchical control architectures and AI-driven forecasting methods can significantly enhance the adaptability, resilience, and economic performance of BESSs in the built environment [233]. Future research should explore the deployment of Digital Twins to facilitate smarter battery operation, particularly in applications related to congestion management, flexibility services, and energy community optimization.

While advancements in battery optimization continue, their effective application largely depends on supportive regulatory frameworks and market incentives. To facilitate the widespread adoption of BESSs in the built environment, policymakers should consider the following:

- Establish financial incentives for second-life battery repurposing, promoting sustainability and cost reduction;
- Define clear regulatory pathways for small-scale battery participation in flexibility markets to enhance grid stability;
- Encourage investment in smart BMS technology that integrates predictive analytics and adaptive control mechanism;
- Support the development of VPP models that enable distributed storage to access wholesale electricity and balancing markets.

Aligning regulatory policies with technological advancements can facilitate the full realization of the potential of BESSs, thereby promoting a more resilient and sustainable energy framework. The successful integration of BESSs relies on supportive legislative frameworks, flexible pricing mechanisms, and structured market conditions that promote operational efficiency and sustainability over time.

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Abbreviations

The following abbreviations are used in this manuscript:

BESS	Battery Energy Storage Systems
BMS	Battery Management System
LCC	Life Cycle Cost

ENTSO-E	European Network of Transmission System Operators for Electricity
MOO	Multi-Objective Optimization
PSO	Particle Swarm Optimization
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
SPEA-2	Strength Pareto Evolutionary Algorithm 2
MODE	Multi-Objective Differential Evolution
FCR	Frequency Containment Reserve
aFRR	Automatic Frequency Restoration Reserve
mFRR	Manual Frequency Restoration Reserve
LFP	Lithium Iron Phosphate
GOPACS	Grid Operators Platform for Congestion Solutions
SoC	State of Charge
SLBs	Second-Life Batteries

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