Journal of Energy Storage 176 (2026) 123344

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Review article

Thermo-electric storage systems in renewable energy communities: Modeling challenges and perspectives

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ARTICLE INFO

Keywords:
Batteries
Supercapacitors
Electrical storage
Thermal storage
Electric vehicles
Renewable energy communities
Renewables
Phase change materials

ABSTRACT

In this work, a comprehensive review of thermo-electric storage technologies within the context of Renewable Energy Communities (RECs) is presented, focusing on modeling approaches and operational perspectives. The analysis spans over 170 scientific contributions. The study categorizes state-of-the-art into three core domains: thermal energy storage (TESS), electrical storage systems (ESS), and electric mobility. First, the review explores TESS technologies ranging from sensible to latent heat systems emphasizing their critical role in enabling demand-side management and building flexibility to mitigate renewable intermittency. Second, it critically assesses electrical storage modeling, comparing equivalent circuit models for batteries and supercapacitors to identify necessary trade-offs between computational simplicity and accuracy in State-of-Charge (SOC) estimation. Third, the emerging role of Electric Vehicles (EVs) is investigated, highlighting how Vehicle-to-Grid (V2G) protocols transform passive loads into active mobile storage assets, thereby supporting the operational stability and economic viability of the community.

1. Introduction

Buildings account for over 40% of total world energy use [1]. Recently, distributed energy systems have enabled load optimization based on occupants' specific demands. However, traditional systems mainly rely on natural gas, consuming large amounts of fossil fuels. Integrating renewables improves efficiency and cuts emissions, while combining them with storage systems helps stabilize supply and mitigate renewable intermittence [2–5]. A Renewable Energy Community (REC) is a local legal entity where users share electricity from renewable sources. Participation is open and voluntary for individuals, public bodies, and SMEs. The Italian energy services operator (GSE) defined the technical rules for their establishment. RECs aim to promote renewable energy while providing social, environmental, and economic benefits. A December 2023 decree (n. 414) updated rules for self-consumption and RECs. In Italy, RECs receive incentives for shared energy, defined hourly as the minimum between energy withdrawn and injected into the grid. Each plant can have up to 1 MW of peak power, and all members must be connected to the same High-Medium Voltage primary station [6,7]. Recent research on renewable energy communities has focused on optimizing their configurations, particularly member composition and renewable capacity (mainly PV). Belloni et al. [8,9] proposed a co-simulation model for Italian RECs that includes building loads and EV charging. Their tool, *EnergyCommunity.jl*, formulates the problem linearly and accounts for market flexibility through varying tariff schemes. These studies provide detailed analyses of optimal REC sizing, operation, and the impact of EVs on energy flows and profitability [8,9]. This last aspect (electrical mobility) is particularly interesting, especially when analyzed in the context of Italian towns [10]. Pasqui et al. [6] conducted a techno-economic study in Florence to demonstrate the benefits of establishing a REC for multiple stakeholders and to assess the role of storage by comparing three battery management systems (BMS). They developed a smart BMS using real-time REC data, achieving similar self-consumption to battery-free cases while improving grid independence. An optimal BMS based on deterministic demand and production data could further enhance independence and offer better returns for participants.

Studies have also explored energy community models outside Italy,

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https://doi.org/10.1016/j.est.2026.123344
Received 30 January 2026; Received in revised form 7 May 2026; Accepted 27 June 2026

where different regulations apply. Beyond RECs, other forms of cooperation exist in Europe, such as net zero energy (NZE) communities, cooperatives, and consortia [11,12]. A near-zero energy community with hybrid storage was studied in [5], featuring a management strategy that considers the health of electricity and hydrogen storage systems. Liu et al. [13] proposed a similar system integrating electricity, heat, and cold storage to cut emissions and grid interaction. Bartolini et al. [14] analyzed how storage and multigeneration systems enhance renewable self-consumption and link different energy networks in PV-rich residential settings. They showed storage enables local management of high renewable shares, and that hydrogen-based storage can be a viable alternative to batteries, depending on hydrogen availability for CHP engines.

Fan et al. [15] developed a distributed energy system, by combining solar energy with hybrid heat and electricity storage, optimized through a multi-objective algorithm. The system was compared to separate production setups across various community scenarios, including EV integration, and its maximum CO_2 reduction rate was calculated. Another study [16] assessed hybrid fuel cell–based energy networks in terms of reliability, cost, and environmental impact, considering combined heat and power for residential use. Different renewable systems can greatly enhance REC performance, though factors like utility prices and unit costs must be considered for optimal network design.

Parra et al. [17] provided an interdisciplinary review of community energy storage, highlighting its potential and key challenges within the broader energy system. Building on their findings, the following sections will discuss the specific potential of each storage solution. Further studies have explored advanced planning frameworks for RECs, including stochastic multi-objective models for cost-effective renewable resource allocation [18], sequential decision-making approaches integrating refueling stations and hydrogen production [19], and mechanisms for green hydrogen generation in urban energy communities [20].

1.1. Review paper approach and novelties

This section reports the main contents of the present review paper that represents the focus for the systematic review, as illustrated in Fig. 1. It can be observed that both thermal and energy storage systems have been analyzed in terms of their general features and modeling methods. Building applications can be studied when included in RECs, districts or smart grids. One topic worthy of attention is electric vehicle storage: adopting V2G technology offers tangible benefits to RECs by transforming EVs into mobile energy storage units.

In Step 1 the objectives of the study are defined. In Step 2 the methodology for the review is established, and finally in Step 3 the state of the art and trends are described. Widely spread scientific search engines such as Scopus, Science Direct, ResearchGate, and IEEE Explorer are used to search for relevant papers by employing keywords pertinent to the specified objectives. The procedure is as follows: the selection of papers is based on keywords identified in the abstract and title. The abstract is then analyzed to ascertain its relevance, after which the principal features of each paper are identified and classified. Finally, the papers are deeply analyzed in full.

The main keywords used for the research are as follows: electric power system, renewable energy community (REC), smart grids, renewable energy sources (RES), photovoltaics (PV), electric storage, thermal storage, hybrid energy storage systems (HESS), batteries, heating and cooling, electric vehicles (EVs), vehicle-to-grid (V2G), modeling, optimization strategies, algorithm, EU directives, Italian RECs directives. The literature review study focused on the following document types: articles, conference papers, reports, books, and theses.

Papers were included if they addressed at least one of the core topics identified in the objectives (storage modeling, REC operation, or EV integration) and were published in peer-reviewed journals, conference proceedings, or recognized technical reports. Contributions were excluded if they dealt exclusively with generation-side optimization without any storage component, or if they lacked sufficient methodological detail for comparative analysis.

The authors identified over 170 papers, of which approximately 17 articles focus on the state of the art of renewable energy communities. In addition, 46 papers relate to thermal and electrical energy storage technologies, with particular attention to hybrid storage systems. Moreover, around 43 research works examined the effect and importance of storage systems included in RECs and specific case studies were analyzed in depth. Finally, the smart charging of electric vehicles (EVs) inside a REC has been considered (about 27 papers). Besides the standard unidirectional charging protocol, which can anyway be used to differ the EV charging in periods when energy cost is cheaper, the adoption of the V2G technology offers tangible benefits to the REC, transforming EVs into mobile energy storage units capable of storing and

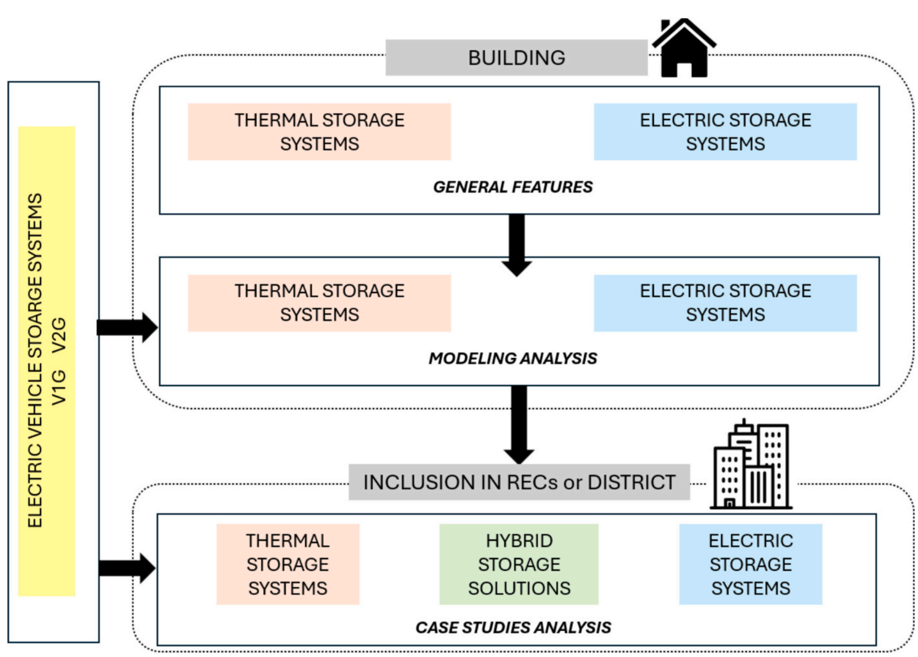

Fig. 1. Schematic representation of the methodology employed in the review analysis and principal interconnection between the system structures.

redistributing energy back during periods of high demand (see Fig. 2).

The novelty of this work lies in its specific focus on the role of storage systems within RECs. It considers not only electrical storage technologies, such as batteries and supercapacitors, but also thermal, hybrid storage systems, and electric vehicles, highlighting their importance and emergent opportunities for designing and managing flexible energy communities. To facilitate the navigation of the mathematical framework and ensure clarity across the numerous expressions presented, a comprehensive nomenclature of the symbols used throughout this work is summarized in Table 1.

The analysis of the existing literature reveals several open challenges that motivate the present review. First, electrical storage technologies in energy communities are mostly studied from a system-level perspective, treating batteries and supercapacitors as ideal energy buffers; the equivalent circuit modeling (ECM) perspective, essential for accurate SOC estimation and real-time control, remains largely disconnected from the REC context. Second, thermal and electrical storage are rarely treated jointly within a REC framework, with most contributions addressing either domain in isolation. Third, supercapacitors receive very limited attention in community-scale reviews, with their ECM modeling confined to automotive or power electronics contexts. Fourth, EV battery models adopted in REC studies are typically simplified energy-balance formulations, overlooking the electrochemical dynamics that govern efficiency and aging, both critical for the economic viability of V2G services. Finally, the Italian regulatory framework for RECs is rarely addressed explicitly in the international literature. The present work fills these gaps by providing an integrated treatment of thermo-electric storage systems within RECs, with emphasis on the modeling approaches that bridge device-level dynamics and community-scale energy management. The structure of the work is as follows. The introduction presents the key studies on RECs and hybrid storage systems, while this subsection outlines the methodology used for the literature review, data analysis, and data selection. Section 2 discusses the role of storage systems, both thermal and electrical. Section 3 examines their modeling, which is central to this review. Section 4 explores how EVs can contribute to RECs, presenting several operational approaches for both unidirectional and bidirectional charging. The paper concludes with final remarks and considerations in Section 5.

Table 1
Summary of defined symbols.

Symbol	Description
R_{ext}	External/contact resistance
R_{sep}	Separator resistance
ω	Frequency
τ	characteristic time constant
Z_p	Impedance of Buller model
C	Full capacitance of Buller model
τ	Time constant of Buller model
C_n	Capacitance of n-th RC cell
R_n	Resistance of n-th RC cell
C_i	Voltage-dependent capacitance in Zubieta model
C_i^0	Constant capacitance coefficient in Zubieta model
C_i^1	Voltage-dependent coefficient in Zubieta model
R_{leak}	Leakage resistance
R_d	Variable resistance
I_{ch}	Charging diffusion current
I_{red}	Redistribution diffusion current
Q	CPE constant
α	CPE exponent ($0 < \alpha < 1$)
V_{oc}	Open-circuit voltage
R_{int}	Internal series resistance
T	Temperature
R_-, R_+	Charge/discharge internal resistances
s_k	State vector at time k
x_k	Input vector at time k
y_k	Output vector at time k
i_k	Battery charge/discharge current at time k
v_k	Battery terminal voltage at time k
C_n	Battery nominal capacity
η_c	Battery Coulombic efficiency
z_k	Battery SOC at time k
K_0, K_1, K_2, K_3, K_4	Parameters of combined model
$V_{s,k}$	Voltage across RC branch at time k
R_s	Resistance of the RC Thevenin model
C_s	Capacitance of the RC Thevenin model
τ_s	RC time constant of the Thevenin model
L_1, L_2	Inductances of RL model
h	Hysteresis voltage state
M	Maximum hysteresis voltage
α_H	Hysteresis tuning coefficient

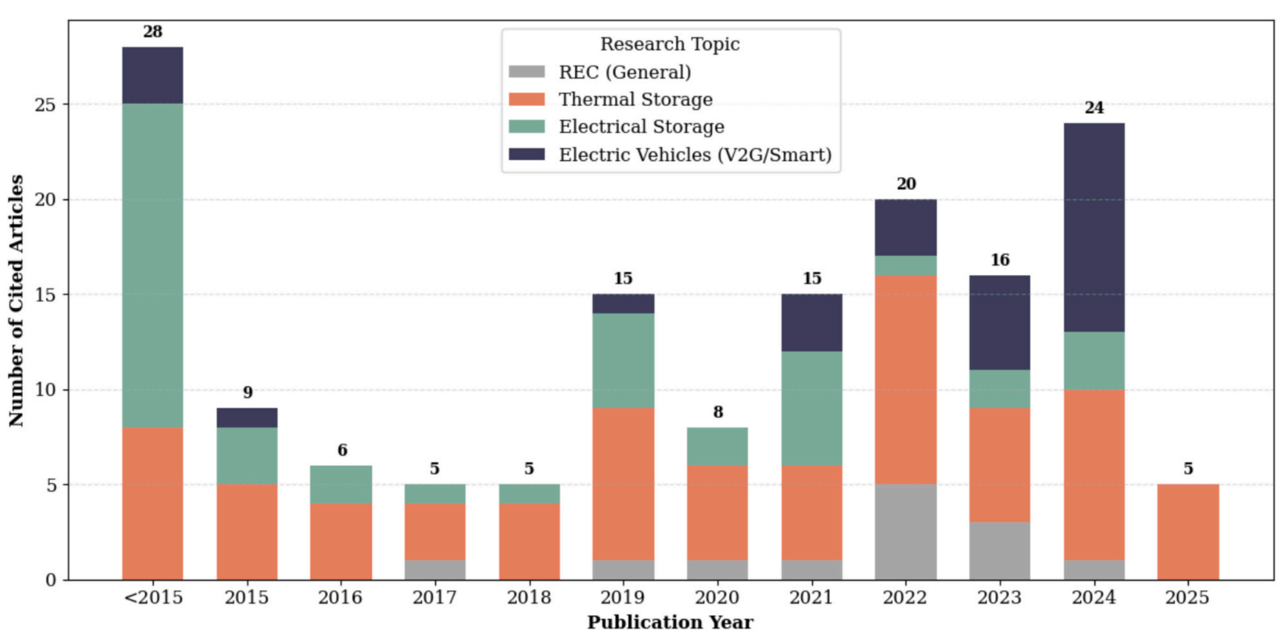

Fig. 2. Temporal distribution of the manuscript analyzed in this review considering the main topics that have been investigated.

2. Storage systems description

2.1. Electrical storage: Technology overview

Electrical storage systems are a critical asset for efficient energy management in a REC, since they enable both peak power shaving and long-term energy balancing. Among the available technologies, batteries and supercapacitors represent the most consolidated solutions, with complementary characteristics. From a physical standpoint, batteries and supercapacitors rely on fundamentally different storage mechanisms. Batteries operate through reversible electrochemical redox reactions occurring within the bulk of the electrode materials, where energy is stored by changing the chemical state of the active species. This diffusion-limited process allows for high energy density but restricts the power rates and cycle life due to mechanical stress. In contrast, supercapacitors (specifically EDLCs) store energy electrostatically through the formation of an electric double layer at the electrode-electrolyte interface. Since no chemical phase changes occur, this surface-based mechanism enables much higher power densities and nearly unlimited cycling, albeit with lower energy storage capacity. Pseudocapacitors and hybrid devices bridge this gap by incorporating fast surface-limited faradaic reactions. For batteries, mature and consolidated technologies include lithium-ion, lead–acid, sodium–sulfur and redox flow [21–24]. Lithium-ion batteries dominate the market due to their high energy density (approx. 150 Wh/kg) and efficiency and progressively decreasing costs, although they are limited in life cycle compared to other storage media. Lead–acid batteries, historically widespread and inexpensive (approx. 100 €/kWh), offer modest energy density (approx. 30 Wh/kg) and short lifetime (approx. 500–1500 cycles), making them mainly suitable for backup or low-cycle applications.

Sodium–sulfur (NaS) batteries operate at high temperature, providing long lifetimes (about 4500 cycles), high energy density (approx. 200 Wh/kg), but at higher economic costs, and most importantly, with demanding thermal management. Finally, redox flow batteries allow the decoupling of energy and power, since the stored energy depends on the electrolyte volume (tank size), while the deliverable power depends on the size of the electrochemical stack. This means that capacity (kWh) can be increased by enlarging the tanks without affecting power, and conversely power (kW) can be increased by adding cell stacks without changing the stored energy. Coupled with practically unlimited cycling capability (>10,000 cycles) and long life the drawbacks lie at the very low energy density (~20 Wh/kg) and relatively high cost (~300 to 500 €/kWh).

Supercapacitors accumulate energy electrostatically or through fast surface reactions, which makes them extremely durable and able of delivering very high specific power. However, such power comes at the cost of a much lower energy density than batteries. As technology, possibly coupled with batteries, supercapacitors are very promising for REC storage [25–28]. Different technologies have been successful:

- EDLCs (Electric Double Layer Capacitors), which rely purely on electrostatic charge separation and achieve excellent cycling capability (more than 10^6 cycles), but very low energy density (5–8 Wh/kg);
- pseudo capacitors, which exploit fast Faradaic reactions at the electrode surface, providing higher energy density (about 10 to 15 Wh/kg), but limited lifetime (5000 to 10,000 cycles);
- hybrid devices (including Li-ion capacitors and so-called “supercabatteries”), which combine capacitive and battery-like electrodes to achieve intermediate characteristics (about 20 to 50 Wh/kg, over 20,000 cycles).

In general, EDLCs are unrivalled for high power density (5 to 10 kW/kg) and cycling, pseudo capacitors provide improved energy storage at the expense of durability, whereas hybrid devices represent a promising compromise. A summary of the technological highlights is given in Table 2.

Table 2
Overview of electrical energy storage tecnologies.

Storage Technology	Energy Density (Wh/kg)	Life Cycles
Li-ion Battery	150	2000–5000
Lead-Acid Battery	30	500–1500
NaS Battery	200	4000–5000
Redox Flow Battery	20	>10,000
EDLC (Supercap)	5–8	>1,000,000
Pseudocapacitor	10–15	5000–10,000
Hybrid SC	20–50	>20,000

2.2. Thermal storage systems analysis

The energy performance and efficiency of a building were introduced by the basic EU legislation to minimize the electrical and thermal energy consumption of buildings [29]. Given the importance of allowing flexibility in RECs, several energy storage technologies have been introduced to improve the reliability of energy, such as batteries, flywheels, thermal systems, etc. The implementation of each technology is contingent on several technical and economic factors [30,31]. Thermal energy storage for homes offers many benefits as it improves indoor comfort by maintaining consistent temperatures, reducing dependence on external energy resources and reducing emissions. Furthermore, it can deliver significant financial savings on energy bills, with research showing reductions in energy consumption of up to 30% in homes fitted with efficient Thermal Energy Storage Systems (TESS) [32].

The three main methods of efficiently storing thermal energy are sensible heat, latent heat, and thermochemical processes. TESS can also be classified according to the source's temperatures: low-temperature storage, such as aquifers, cold ESS, and cryogenic ESS; high-temperature storage, including sensible heat storage (e.g., hot rocks, hot water accumulators, graphite, and concrete); and latent heat storage, which involves phase change materials (PCMs). The application of one technique rather than the other is determined by the advantages and disadvantages of each [32,33].

Sensible heating storage (SHS) systems represent a category within TESS that has been shown to capture and preserve heat by increasing the temperature of a material without inducing a phase transition. This particular, form of TES finds application in a variety of fields, including domestic hot water storage, space heating and cooling, and industrial process heat. Within the field of SHS, heat is accumulated by increasing the temperature of materials (water, molten salts, rocks, concrete, or metals). SHS exhibits efficiencies generally ranging from 70% to 90% [34–36]. The categorization of SHS encompasses two primary classifications, distinguished by the storage medium: liquid-based and solid-based SHS. Among liquids, water is a widely accepted option, due to its abundance, affordability, and high thermal conductivity [37]. It is the preferred storage medium for building applications due to its ubiquity, cost-effectiveness, and capacity to efficiently store heat across a broad temperature range. Other options are molten salts (like sodium nitrate or calcium chloride) that perform well in scenarios demanding high temperatures, whereas organic fluids offer a flexible and high energy density: both of them are more suitable for industrial applications. Solid-based SHS employ materials such as rocks, concrete, or metals as the base for storing heat [38–42]. The advantages are due to their natural abundance and cost effectiveness (such as for rocks), enduring durability, versatility for building applications (the integration of SHS employing concrete can seamlessly blend with building structures, thereby offering an efficient approach to effective space heating and cooling). The use of rocks such as basalt or granite for storage makes these systems notable for large-scale applications. This is because rocks are abundant, cost-effective, and have a high heat capacity. On the other hand, solid SHS present higher ongoing costs for maintenance and operation and they are limited in terms of specific heat capacity and energy storage density when compared to liquid-based SHS. It is difficult to achieve and maintain uniform temperature distributions and it has been demonstrated that storage systems which use solid materials may experience self-discharge, which can result in slow heat loss over time. Another interesting TES is thermocline, which offers a cost-effective solution especially for Concentrating Solar Power (CSP) plants by means of natural thermal stratification. Despite economic advantages, structural integrity is a major concern due to thermal expansion and mechanical stress during cyclic operation [43,44]. Recent studies on multilayer tanks reveal that wall sections exposed to high temperatures can expand by 30.5%, with peak stresses reaching 184.7 MPa [43], which can exceed material yield strengths, potentially leading to plastic deformation and creep damage [43,44]. Optimization research also ams to maximizing exergy efficiency while minimizing environmental impacts through Life Cycle Assessments (LCA): the first leads to tapered tank shapes and reduced volumes, but increasing environmental footprint due to higher pumping energy needs; conversely, environmental issues favor square geometries with lower cumulative energy demand [45]. Successful industrial deployment depends on selecting appropriate filler materials, such as rocks, ceramics, or PCMs, and managing the tank's height-to-diameter ratio to maintain stable thermal stratification throughout its service life [44].

Latent heat storage (LHS) differs from the other thermal energy storage techniques because it can store heat at an almost constant temperature, which is the phase transition temperature of the phase change material (PCM). It also offers a high density of energy storage because the process is characterized by the absorption or release of a significant amount of heat known as the latent heat of fusion or vaporization. LHS systems have the advantage of needing a lower space due to the high energy density, with a consequent reduction in storage volume compared to SHS systems. Furthermore, PCMs exhibit accelerated charging and discharging rates, coupled with diminished sensitivity to temperature fluctuations [46,47]. PCMs can be classified into two distinct categories: organic and inorganic. In the field of building applications, organic PCMs have gained prominence, primarily due to their non-corrosive and non-toxic nature and because the phase transition temperature falls within the human comfort zone [48–50]. Examples of organic PCMs are fatty acids, polyethylene glycol (PEG), and paraffin waxes. Inorganic PCMs include salt, salt hydrates, or metals and have higher thermal conductivity and a greater heat storage capacity per unit volume when compared to organic PCMs. These are particularly beneficial features in cases where effective heat transfer is required, such as in some building's applications [49,51]. PCMs could also be integrated in building construction materials via encapsulation. Advanced encapsulation techniques are now available, such as physical methods, are now available; for example concrete mixtures can be encapsulated with microcapsules containing healing agents to compensate the mechanical performance loss due to the insertion of PCMs [52]. In fact, while PCMs integration improves energy performance, it reduces mechanical strength, especially with high PCM content, but advances in PCM encapsulation techniques could mitigate leakage and improve durability. In concrete the encapsulation method directly affects the material thermal performance and durability. Several methods can be performed: direct, semi-direct, and indirect encapsulation; macroencapsulation; microencapsulation [53]. Each one of these methods shows benefits and challenges in terms of integration, thermal behavior, and structural impact. Integration methods like microencapsulation and also vacuum impregnation seem suitable techniques to encapsulate PCMs in concrete; advances of these techniques are crucial to enhance durability and mechanical properties of concrete with PCMs [54]. In comparison to sensible heat materials, PCM exhibited a superior storage capacity, ranging from 50 to 150 kWh/t, combined with an efficiency level ranging from 75 to 90% [55]. In recent developments, PV panels have been integrated with phase-change materials, with the aim of regulating their operating temperature. This integration showed to enhance the overall performance of the PV plants [56]. The influence of the storage of latent thermal heat within the PCM, and consequently the release of cumulative thermal energy, depends on geographic considerations. The climate conditions, such as the intensity of solar radiation and the ambient temperature, play a pivotal role in determining the release of thermal energy from the PCM [57]. In [58] comprehensive consideration is given to the influence of various climate conditions and employed materials, owing to the promising utilization of PCMs.

Thermochemical storage (TCSS) processes involve the storage of energy through reversible chemical reactions. In these processes, energy is absorbed or released as chemical bonds are broken and reformed, allowing for high energy density storage. This process involves the absorption or release of heat during a chemical transformation, allowing the stored energy to be recovered when it is necessary. The main advantages of this approach are its ability to store energy for long periods without significant losses and its ability to provide long-term storage solutions [32].

The implementation of ESS is an effective procedure for minimizing the fluctuation of the electric energy produced by the renewables. ESSs are required to store excess energy and use it later during periods of peak load demand and this is particularly important in RECs, for obtaining maximum self-consumption and shared energy among the members. The integration of TESS in buildings, encompassing building equipment and building envelopes, has the potential to modify and diminish peak loads, decouple energy demand from its availability, facilitate the integration of renewable energy sources, and provide efficient thermal energy management. TESS functions by storing heat or cold energy during off-peak hours and releasing it during on-peak hours, thereby reducing grid demands and flattening load profiles [59,60]. TESS are integrated with building equipment for demand-side management (DSM), including the following:

- air-conditioning systems [61,62];
- domestic hot water applications [63,64];
- heat pumps [65,66];
- chiller plants [63].

Arteconi et al. [66] investigated the potential of integrating TESS with a heat pump and implementing DSM for residential buildings in Northern Ireland. Results showed that it was possible to achieve good indoor temperature control even when the heat pump was switched off for 3 h during peak periods, with cost savings of around 20–30% from peak demand reduction.

Kamal et al. [67] proposed a novel optimal control strategy for the operation of cold storage facilities within buildings. This strategy had the objective of minimizing annual energy consumption and the subsequent annual energy expenditure. The efficacy of this method is highlighted by its attainment of an annual average energy shifting of 25%–78%, corresponding to a 10%–17% annual cost reduction.

Recently, the integration of TESS with building envelopes for DSM purposes has been also spreading. In [68] the cooling performance of active insulating systems integrated with TESS walls was studied. The results obtained from this research indicated that the heat flux entering the wall could reach up to 80 W/m^2 during discharging, while maintaining a satisfactory dynamic thermal resistance value (R). Another interesting building application is presented in [69,70]: Authors evaluated the use of thermally anisotropic building envelopes combined with TESS for building demand management in various US climates, focusing on peak load reduction, annual energy, and cost savings on the basis of electricity market tariffs.

Among renewables, the most diffused technology to be implemented in RECs is photovoltaic (PV) [71]. The optimization of PV systems integrated in buildings takes into account their overall performance considering not only the electricity production, but also the possibility to exploit the heat stored in these systems by means of TESS. PVs have limited efficiency and lifetime due to high temperatures and limited cooling capabilities, so reducing their operating temperature will improve the overall electricity production. Recently, the combination of solar heating and cooling for domestic applications has been implemented, based on the use of PV combined with heat storage technologies [71]. Operationally, TESS stores excess thermal energy from PV panels by means of storage working fluid for subsequent thermal applications, considering both sensible and latent heat storage [72]. SHS are more diffused for these applications thanks to many advantages such as simplicity, cost-effectiveness, and accessibility for control purposes. Thermal energy can be stored for later release by lowering the temperature of a solid or liquid after it has been raised. The amount of thermal energy stored depends on the mass, temperature difference, and specific heat capacity of the storage medium. Photovoltaic/thermal (PV/T) systems are widely used in many applications and can convert a certain amount of solar radiation into electricity, depending on several operational and design factors, while the rest of the solar energy is partially converted into thermal energy. In addition, the ability to provide both electrical and thermal energy for buildings through PV is useful in cases where accessible space is limited. The use of PV/T systems to provide instantaneous electricity and heat is suitable to allow flexibility conditions in energy demand, and they are effectively and economically well used for both residential and non-residential buildings [73,74]. Another interesting application is presented in [75]: authors modeled and simulated a solar poly-generation system for space heating and cooling with electrical energy storage. The proposed solution included PV/T collectors, a heat pump (HP), an adsorption chiller, and batteries. The suitability of the application of this solution depends on the dynamic thermal loads of the building and the domestic hot water demand.

In the study carried out by Barone et al. [76], the economic affordability of the application of a low-cost innovative water polycrystalline PV/T collector system was examined in a specific case study at the University of Patras (Greece). The PV module in the aluminum box for water heating was constructed with plastic pipes positioned beneath it, with the aim of providing hot water to the building. The PV/T collector was also integrated with a stratified storage tank of hot water, and the system was simulated in different European weather conditions (Naples, Freiburg, and Almeria) to assess the energy savings and the corresponding reduction in terms of CO_2 emissions. The implementation of the PV/T collector in the stratified storage tank resulted in significant energy savings (800–1250 kWh/y) and environmental benefit (avoiding 180–215 kg CO_2 in a year).

Vahidhosseini et al. [77] explored the integration of solar technologies, heat pumps and thermal energy storage systems with a view to reducing building energy demand. To achieve this, the review considered different types of thermal solar collectors. Furthermore, it examined different kinds of thermal energy storage materials. In buildings, the integration of TESS materials with heat pumps has been demonstrated to enhance the efficiency and efficacy of the system to a considerable extent. TESS materials help to store energy generated by solar panels when there is a lot of sunlight. This stored energy is really useful when there is not much sunlight, making sure the heat pump always works well [68]. Beyond specific technological implementations, the European research landscape is increasingly focusing on the systemic integration of these solutions within broader contexts. A notable example is the European project STORIES (Storage Research Infrastructure Eco-System), which explores Hybrid Energy Systems and their application in Renewable Energy Communities. As discussed in recent literature [78], the integration of Hybrid Thermal and Electrical Storage (HTES) represents a crucial frontier for the energy transition. These hybrid configurations allow for balancing the high energy density of thermal storage with the rapid response of electrical systems, providing the flexibility needed to manage the inherent intermittency of renewables at a community scale. This international perspective highlights that the transition toward decarbonized communities relies not just on individual devices, but on the coordinated management of multi-vector storage resources.

Considering the applications of LHS, Allouche et al. [61] conducted a study on the effects of PCM cold storage on a solar-driven air-conditioning system in Tunisia. The study showed that the implementation of cold storage significantly enhanced thermal comfort and ensured the indoor room temperature remained below 26 °C for approximately 95% of the time. An experimental research carried out by Čurpek and Čekon [79] identified the performance of a TES system combined with a ventilated PV façade. Authors studied the influence of solar irradiation and ambient temperature on the PCMs behavior. The findings demonstrated that the impact of implementing PCM on the operational temperature of the rear PVs was substantial at noon under high solar irradiation. Moreover, the release of accumulated thermal energy from PCM for the PV/PCM system was observed to exert a considerable effect at night. In their research, Čurpek and Čekon [80] identified the climate response of latent TESS integrated into a ventilated PV system in Brno, Czechia. The experimental findings demonstrated that the effect of storing and subsequently releasing the thermal latent heat in the PCM depends on climatic parameters, such as the intensity of solar irradiation and the ambient air temperature. Furthermore, it was observed that the release of cumulative thermal energy from the PCM exerts a significant

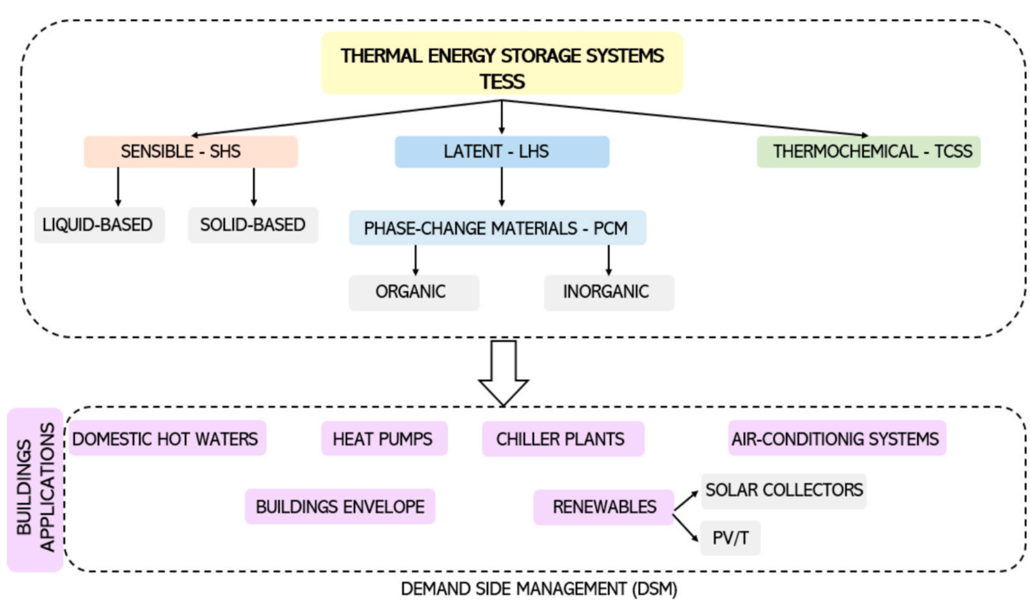

Fig. 3. Schematic representation of different kinds of TESS and their common applications in buildings demand-side management.

Table 3
Summary of the papers considered in this review concerning equivalent circuit modeling of supercapacitors.

Reference	Model	Method and validation	Test conditions	Device characteristics	Model usage
[87]	*Model*: Buller with independent time constants *Order*: integer	*Identification*: EIS, nonlinear optimization *Validation*: comparison between model and measurements used for identification (EIS)	*Charging current*: 0.1 A, 0.5 A, 0.8 A *Frequency range*: 2 mHz ÷ 1 MHz	*Capacity*: 10 F, 400 F *Voltage*: 2.5 V, 2.7 V *Brand*: GoldCap, Ioxus	Generic
[88]	*Model*: Zubieta *Order*: integer	*Identification*: measurements during charge/discharge cycles *Validation*: Hybrid Pulse Power Characterization (HPPC) test, simulating the behavior in automotive applications	*Charging current*: 2 A, 3 A *HPPC cycles*: 10 s charge pulse, 10 s rest period, 10 s discharge pulse	*Capacity*: 100 F *Voltage*: 2.7 V *Brand*: Vinatech	SC bank modeling in automotive applications
[89]	*Model*: simplified Zubieta *Order*: integer	*Identification*: voltage measurements at constant current, analytical parameter calculation *Validation*: comparison between model and measurements used for identification	*Charging current*: 10 A, 33.2 A *Test duration*: 600 s	*Capacity*: 110 F, 200 F, 350 F, 600 F *Voltage*: 2.5 V	Generic
[90]	*Model*: hybrid Buller + Zubieta *Order*: integer	*Identification*: datasheet information, voltage measurements at constant current, analytical parameter calculation *Validation*: comparison with EIS measurements	*Frequency range*: 0.01 ÷ 10^3 Hz *Charging current*: 70 A, 110 A	*Capacity*: 140 F, 150 F *Voltage*: 2.5 V *Application*: portable consumer electronics, automotive subsystems, UPS	Generic
[91]	*Model*: hybrid Buller + Zubieta *Order*: integer	*Identification*: voltage measurements during charge/discharge cycles, parameter fitting using standard nonlinear least squares algorithm *Validation*: comparison between model and measurements used for identification	*Charging current*: 80 A ÷ 130 A	*Capacity*: 3000 F *Voltage*: 2.7 V *Brand*: EATON, Maxwell, LSUC, SPSCAP	Generic
[92]	*Model*: simplified Zubieta *Order*: integer	*Identification*: voltage measurements during charge/discharge cycles, recursive least squares algorithm *Validation*: comparison between model and measurements used for identification	*Charging current*: 120 A	*Capacity*: 3000 F *Voltage*: 2.7 V *Brand*: Maxwell	Generic
[93]	*Model*: simplified Zubieta *Order*: integer	*Identification*: measurements during charge/discharge cycles, segmentation optimization (circuit analysis + recursive least squares) *Validation*: comparison between model and measurements used for identification	*Temperature*: 23 °C *Sampling time*: 2 s *Charging current*: 1 A	*Capacity*: 350 F *Voltage*: 2.7 V *Power density*: 4.2 kW/kg *Energy density*: 5.4 Wh/kg *Brand*: Maxwell	SoC estimation in SC cell modules in backup power of wind turbine pitch systems
[95]	*Model*: Belhachemi with current sources modeling charge diffusion *Order*: integer	*Identification*: voltage measurements at constant current, parameter fitting using nonlinear least squares algorithm *Validation*: measurements during charge/discharge cycles with prolonged resting phases to allow charge redistribution	*Charging current*: 1.5 A, 2.3 A *Test duration*: ~ 1.5 h	*Capacity*: 325 F *Voltage*: 2.7 V	Indicated for modeling long-term supercapacitor dynamics
[96]	*Model*: simplified Zubieta with variable leakage resistor *Order*: integer	*Identification*: voltage measurements at constant current to dimension the two RC branches, heuristic individuation of the time constants during prolonged self-discharge measurements *Validation*: comparison between model and measurements used for identification	*Charging current*: 97 mA *Test duration*: 1500 s (charge + redistribution phases), 2 h (self-discharge phase)	*Capacity*: 22 F *Voltage*: 2.5 V	Long-term SC modeling in self-powered wireless sensor networks
[97]	*Model*: two-branch *Order*: integer	*Identification*: voltage measurements, analytical parameter calculation *Validation*: comparison between model and measurements used for identification	*Test duration*: 4000 s	*Capacity*: 10 F, 2.4 F *Voltage*: 2.7 V, 2.5 V, 2.75 V *Brand*: NessCap, Maxwell, CapXX	Indicated for modeling long-term supercapacitor dynamics
[98]	*Model*: simplified Zubieta with controlled current source *Order*: integer	*Identification*: voltage measurements at constant current, parameter estimation using recursive least squares algorithm *Validation*: measurements during charge/discharge cycles with rest periods	*Charging current*: 15 A *Charge/discharge cycle duration*: ~1200 s	*Capacity*: 350 F *Voltage*: 2.7 V *Power density*: 4600 W/kg *Energy density*: 5.9 Wh/kg *Brand*: SAMWHA	Indicated for modeling long-term supercapacitor dynamics
[100]	*Model*: classical nonideal capacitor *Order*: fractional	*Identification*: step response voltage measurements, parameter fitting using trust region reflective least squares algorithm *Validation*: comparison between model and measurements used for identification	*Test duration*: 30 s *Sampling rate*: 1000 samples/s	*Capacity*: 0.47 F, 1 F, 1.5 F *Voltage*: 5 V *Power density*: 447–1136 W/kg *Energy density*: 0.42–1.10 Wh/kg *Application*: electronics	Generic
[101]	*Model*: Buller *Order*: fractional	*Identification*: voltage/current measurements during charge/discharge cycles, parameter fitting using genetic algorithm + solution refinement with nonlinear least squares algorithm *Validation*: comparison between model and measurements used for identification	*Temperature*: 20 °C *Test duration*: up to 3500 s for dynamic charging/discharging current *Sampling period*: 1 s	*Capacity*: 350 F *Voltage*: 2.7 V *Power density*: 4.2 kW/kg *Energy density*: 5.4 Wh/kg *Application*: UPS, wind turbine pitch control, medical equipment	SOC estimation for electric vehicle HESS
[103]	*Model*: Buller *Order*: comparison	*Identification*: EIS measurements, parameter fitting using genetic algorithm + solution refinement with nonlinear least squares	*Frequency range*: 0.001 Hz ÷ 100 kHz (for fractional model)	*Capacity*: 4000 F *Min/max voltage*: 3 V / 4.2 V	Inclusion of the integer model in time domain simulations

(*continued on next page*)

Table 3 (*continued*)

Reference	Model	Method and validation	Test conditions	Device characteristics	Model usage
	between integer and fractional models	algorithm *Validation*: comparison between model and measurements used for identification	0.1 Hz ÷ 25 kHz (for integer model) 10 points/decade *Temperature*: −20 °C ÷ 50 °C (10 °C steps) *SoC*: 0% ÷ 100% (10% steps)	*Continuous max current*: 5 A *Peak max current*: 10 A	

influence during night-time hours. Finally, the employment of nanoparticles suspended in the base liquids utilized in TESSs has been demonstrated to enhance the performance of thermal systems [81].

In Fig. 3, the more common technologies of TESS, with particular emphasis on those typically employed in building applications and for PVs, are schematically shown.

3. Storage systems modeling

3.1. Electrical storage: Equivalent circuit modeling

This section reviews the main equivalent circuit models used for electrical storage devices, whose lumped parameters often correlate with key state indicators such as SOC and State-of-Health (SOH) and enable system-level time-domain simulation. It presents the main models proposed for supercapacitors (Section 3.1.1) and batteries (Section 3.1.2), starting from basic formulations and then classifying a large set of studies. Each article was examined for its adopted model, parameter-identification method, validation approach, operating conditions, intended applications, and device characteristics. The resulting classifications are summarized in Table 3 (supercapacitors) and Table 4 (batteries).

3.1.1. Supercapacitors models

In the early 1990s, Lai, Levy and Rose [82] proposed one of the first equivalent circuit models for accurate representation of the complex impedance of a supercapacitor. Such model, known as “RC network” model (Fig. 4), emulates the porous electrode structure of supercapacitors by using several RC cells, where each cell is characterized by a different time constant. The model captures the frequency-dependent behavior well, but the high number of parameters makes it impractical for both identification and simulation purposes.

The most straightforward model is the classical non-ideal capacitor model, comprising a capacitor C_{full}, which corresponds to the value of the full capacitance, a leakage resistor R_p and an equivalent series resistance (ESR), accounting for ohmic losses in the supercapacitor electrolyte and contacts. This model is intuitive and easy to identify using basic voltage and current measurements [83].

Buller et al. [84] replaced the single RC cell of the classical model with a more complex impedance Z_p given by the following expression:

$$Z_p(\omega) = \frac{\tau \coth\left(\sqrt{j\omega\tau}\right)}{C\sqrt{j\omega\tau}} \tag{1}$$

where ω is the angular frequency, C is the full capacitance and τ a characteristic time constant. This formulation ensures the correct behavior at both low and high frequencies, with the impedance tending toward $\frac{1}{j\omega C}$ as $\omega \rightarrow 0$. The impedance Z_p is approximated with the equivalent circuit shown in the inset of Fig. 5 where C_n and R_n are given by the following expressions:

$$C_n = \frac{C}{2} \tag{2}$$

$$R_n = \frac{2\tau}{n^2\pi^2 C}$$

The term n in (2) indexes the R_nC_n cells. In [85], the authors claim that ten R_nC_n cells ($N_B = 10$) are sufficient to achieve an accurate representation of the Z_p impedance. The complete Buller equivalent circuit is depicted in Fig. 5. The series inductance L_s is often neglected as it becomes relevant at frequencies higher than the frequency ranges of interest for supercapacitors. It is important to note that, independently on the number of R_nC_n cells included in the model, the number of parameters to be identified to fully define the Buller equivalent circuit is always 4.

Zubieta and Bonert [85] proposed a simplified supercapacitor equivalent circuit, aiming at creating a model of the circuit at time ranges of at least 30 min while retaining low identification complexity. The model introduces a non-linearity in the form of a voltage-dependent capacitive element in one of the RC branches, to account for the EDLC (Electrical Double-Layer Capacitor) effect. The dependency of this capacitance on the applied voltage V_i is non-linear, but can be approximated as:

$$C_i(V_i) = C_i^0 + C_i^1 V_i \tag{3}$$

where C_i^0 is a constant capacitance value and C_i^1 is the coefficient of the voltage-dependent variation. This linear approximation holds in the range of few volts, as proved in [85]. The equivalent circuit resulting from these considerations is depicted in Fig. 6.

Belhachemi et al. [86] proposed an improvement on the Zubieta model by interpreting the supercapacitor as a nonlinear transmission line, separating short-term (nonlinear line) and long-term (RC branches) dynamics, achieving good accuracy at the cost of increased complexity (Fig. 7).

Several later works refine, extend, merge or simplify the models presented so far, as illustrated in the following. In [87], the authors modified the Buller model considering independent R_n and C_n values, allowing for arbitrary relaxation times. Castiglia et al. [88] incorporated initial charges in the Zubieta model and adapted to represent a SC bank of 24 devices connected in series for automotive applications. Faranda et al. [89] proposed a simplified version of the Zubieta model, with only one delayed branch (Fig. 8), introducing one of the simplest models to be identified, which requires only four voltage measurements.

Musolino et al. introduced in [90] a model integrating Zubieta and Buller's. The equivalent circuit resulting from this intuition is depicted in Fig. 9, where C_n and R_n are given by:

$$C_n(V) = \frac{C(V)}{2} \tag{4}$$

$$R_n(V) = \frac{2\tau(V)}{n^2\pi^2 C(V)}$$

The difference between (2) and (4) is that in the second formulation both the full capacitance C and the time constant τ are voltage dependent. In particular, experimentation carried out in [90] confirmed that, similarly

Table 4
Summary of the papers considered in this review concerning equivalent circuit modeling of batteries.

Reference	Model	Method and validation	Test conditions	Device characteristics	Model usage
[110]	*Model*: combined *Equivalent circuit*: Rint	*Model identification*: least-square regression *SOC estimation*: extended Kalman filter, unscented Kalman filter, particle filter *Validation*: experimental measurements	*Characterization and test*: Dynamic Stress Test, Federal Urban Driving Schedule, US06 *Test*: Unknown initial SOC, additional test with 0.87 SOH	*Type*: $LiFePO_4$ *Nominal capacity*: 1.1 Ah *Cutoff voltages (upper/lower)*: 3.6 V/2 V *Max discharge current*: 30 A	SOC estimation, automotive application
[111]	*Model*: combined *Equivalent circuit*: Thevenin	*Model identification*: multi-swarm particle swarm optimization *SOC estimation*: extended Kalman filter, unscented Kalman filter *Validation*: experimental measurements	*Characterization*: Dynamic Stress Test *Test*: Unknown initial SOC (room temperature), current noise (room temperature), varying temperature	*Type*: LiNMC *Nominal capacity*: 1.3 Ah *Nominal voltage*: 3.6 V *Cutoff voltages (upper/lower)*: 4.2 V/2.5 V	SOC estimation, automotive application
[112]	*Model*: comparison of different models (combined, one-state hysteresis) *Equivalent circuit*: Thevenin, with up to 4 RC cells	*Model identification*: genetic algorithm *SOC estimation*: extended Kalman filter *Validation*: experimental measurements	*Characterization and test*: New European Driving Cycle	*Type*: LiNMC *Nominal capacity*: 32.5 Ah *Nominal voltage*: 3.75 V *Cutoff voltages (upper/lower)*: 2.5 V/4.15 V *Max charge current*: 65 A	SOC estimation, generic application
[113]	*Model*: combined *Equivalent circuit*: Thevenin	*Model identification*: genetic algorithm *SOC estimation*; Battery Power-Based Method *Validation*: experimental measurements	*Characterization*: pulse charge/discharge tests *Test*: New European Driving Cycle (Urban Section), field test with Nissan Leaf EV	*Type*: Manganese-oxide *Nominal capacity*: 31.1 Ah *Average voltage*: 3.8 V *Max discharge current*: 240 A	SOC estimation, automotive application
[114]	*Model*: one-state hysteresis *Equivalent circuit*: Thevenin	*Model identification*: particle swarm optimization *Hysteresis estimation*: neural network *SOC estimation*: adaptive extended Kalman filter *Validation*: experimental measurements	*Characterization*: Hybrid Pulse Power Characterization *Test*: New European Driving Cycle, Dynamic Stress Test	*Type*: $LiFePO_4$ *Nominal capacity*: 11 Ah *Nominal voltage*: 3 V *Cutoff voltages (upper/lower)*: 3.6 V/2.5 V	SOC estimation, automotive application
[115]	*Model*: combined *Equivalent circuit*: Thevenin, with 3 RC cells	*Model identification*: least-squares optimization *Validation*: simulations	*Characterization*: underload tests (underload time constants), relaxation tests (relaxation time constants) *Test*: constant current load, drive cycle noisy load	Not available	Equivalent circuit model identification and validation, generic application
[116]	*Equivalent circuit*: 2-branch RL	*Model identification*: nonlinear least-squares optimization *Validation*: experimental measurements	*Characterization*: Hybrid Pulse Power Characterization *Test*: aging test	*Type*: $LiFePO_4$ *Nominal capacity*: 2.5 Ah *Nominal voltage*: 3.2 V *Cutoff voltages (upper/lower)*: 3.65 V/2 V	Equivalent circuit model identification and validation, generic application
[117]	*Model*: zero-state hysteresis *Equivalent circuit*: Rint	*SOC estimation*: combination of neural network and extended Kalman filter	*Characterization and test*: constant-current charge pulses, constant-current discharge pulses	Test battery 1 *Nominal capacity*: 40 Ah *Nominal voltage*: 12 V Test battery 2 *Nominal capacity*: 3.4 Ah *Nominal voltage*: 1.2 V	SOC estimation, automotive application

to what already demonstrated in [85], the dependency on voltage can be approximated as linear in the voltage ranges of interest for supercapacitors as follows:

$$C(V) = C_0 + k_C(V) \tag{5}$$

$$\tau(V) = \tau_0 + k_\tau(V)$$

where C_0 and τ_0 are the values for zero applied voltage and the proportionality factors k_C and k_τ have to be determined experimentally. The tests conducted in [90] show that this equivalent circuit covers frequencies from mHz to tens of kHz, using five Buller cells ($N_B = 5$) and two parallel branches. Parameters are either extracted from the manufacturer's datasheet either estimated through simple measurements performed at constant current.

Faranda and Musolino models are still widely used. For example, in [91], the authors applied a simplified Musolino circuit with experimental validation at charging/discharging currents up to 130 A. The paper in [92] presents a procedure to speed up the identification of the electrical parameters of one-branch and two-branch models of a supercapacitor. The two-branch model is a simplification of the model in [89]. The Faranda model is used also in [93], where the authors study a circuit parameter identification method based on segmentation optimization.

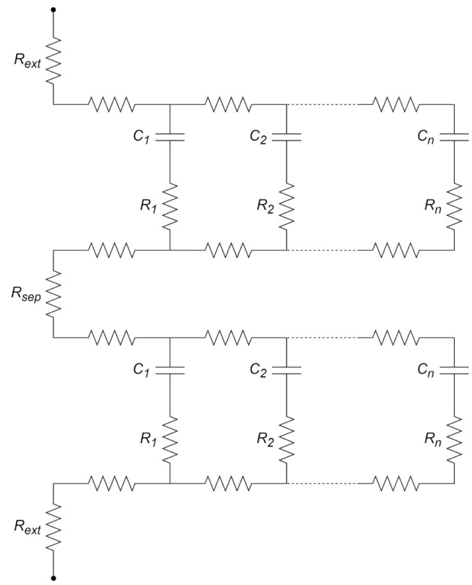

Fig. 4. RC network model. R_{ext} and R_{sep} account for the contacts and separator resistances, respectively.

Long-term voltage decay is due to leakage currents and charge redistribution, not adequately modeled by a single leakage resistor [94]. Torregrossa et al. [95] extended the Zubieta model with two current sources (I_{ch} and I_{red}) to model charging and relaxation transients (Fig. 10).

Zhang and Yang [96] addressed the problem of modeling the self-discharge in the range of few hours by introducing a variable leakage resistance in the Faranda model of Fig. 8. In [97], Sedlakova et al. modeled diffusion dynamics by introducing a variable resistor $R_d(t)$. The resistance increases with time ($R_d(t) \propto \sqrt{t}$), as the probability of diffusion of more carriers decreases with time. The work in [98] proposed a voltage-controlled current source dependent on voltage v and its derivative v', providing a model for long-term behavior (Fig. 11).

All the models proposed so far are integer-order time-domain models. If time-domain representation is not critical, fractional-order models represent a promising alternative for frequency-domain analysis. The asymptotic behavior of Z_p given by (1) in the Buller model is:

$$Z_p(\omega) \sim \frac{1}{j\omega C} \quad (DC) \tag{6}$$

$$Z_p(\omega) \sim \frac{1}{C\sqrt{j\frac{\omega}{\tau}}} \quad (\textit{high frequency})$$

This suggests the use of Constant Phase Elements (CPEs), with the following impedance:

$$Z_{CPE}(\omega) = \frac{1}{Q(j\omega)^{\alpha}} \tag{7}$$

where Q is a constant and $0 < \alpha < 1$.

Equivalent circuits including CPE elements do not differ, topologically, from the models introduced previously [99]. In [100], a simple supercapacitor model is adopted, like the classical non-ideal capacitor model, but replacing the normal capacitor with a CPE. In [101], Wang et al. proposed an equivalent circuit based on the Buller model topology with two RC cells, replacing the capacitors with CPEs, as shown in Fig. 12. (See Fig. 13.)

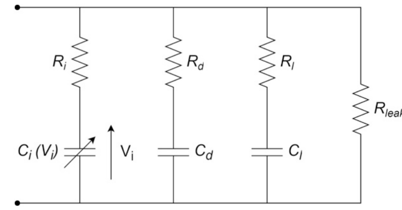

Fig. 6. Zubieta model.

CPEs are known to provide accurate modeling of electrical double layer effects [102]. Studies such as [103] showed that fractional order circuits are generally better at approximating the impedance of a supercapacitor than integer order models, given a comparable number of parameters to be identified, in frequency ranges from mHz to around a hundred kHz. However, fractional order models present two main drawbacks. First, the time-domain representation of CPEs is not trivial, thus inclusion in time-domain simulation of circuits requires considerable mathematical effort [104]. Second, characterization of such models requires long and expensive EIS measurement especially, at low frequency range. The modeling overview given in this section is reported as a summary in Table 3.

Overall, integer-order models such as the Faranda and Musolino variants offer the best trade-off between identification complexity and accuracy for REC applications, where time-domain simulation is the primary requirement. Fractional-order models provide superior frequency-domain accuracy but are impractical for real-time control due to their computational burden. Self-discharge models (e.g. Torregrossa, Zhang) are recommended when long-term energy retention is critical, whereas simpler RC models suffice for short-duration peak-shaving applications.

3.1.2. Batteries models

This section is dedicated to battery modeling, with special emphasis on models related to lithium-ion batteries, as they represent the most widely used technology [21,105,106]. Similarly to the approach adopted for supercapacitors [107], a distinction can be made between integer and fractional order equivalent circuit models. Integer order models are suited for dynamic analyses in time domain, where the objective is to monitor the inner parameters of the device (i.e., SOC, SOH, SOP and SOF) in relation to the values of the equivalent circuit components (e.g., open-circuit voltage or internal resistance).

This review focuses on integer order models only, since fractional order models appear to have less room in applications. All the equivalent circuits presented in the following share the same base structure: an ideal voltage generator or a capacitor represents the open-circuit voltage; different configurations of resistors and capacitors, placed in series or in parallel, account for effects such as ESR, leakage, charge redistribution and terminal voltage relaxation.

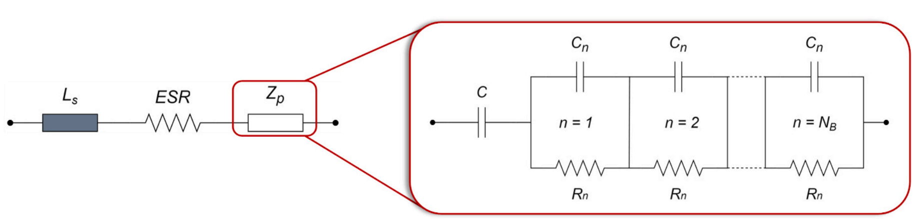

Fig. 5. Buller model (on the left). The inset shows the equivalent circuit approximating the impedance Z_p given by (1) in the Buller model.

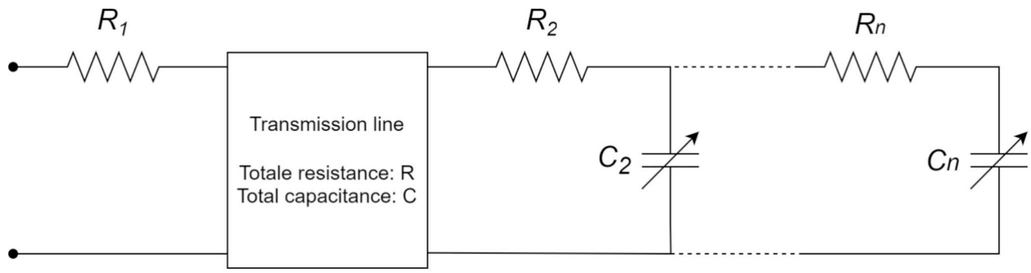

Fig. 7. Belhachemi model.

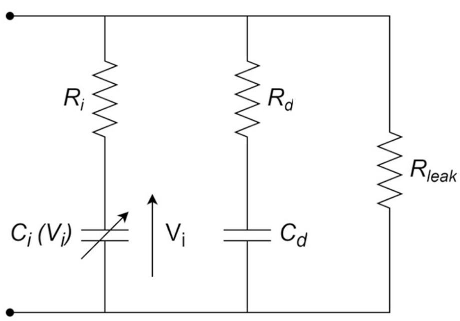

Fig. 8. Faranda model. This equivalent circuit is a simplified version of the Zubieta model (Fig. 6).

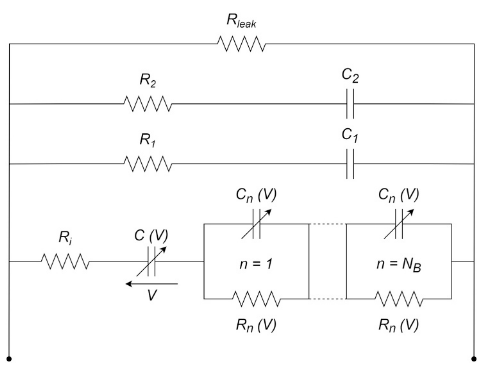

Fig. 9. Musolino hybrid model. This circuit integrates the Buller model (Fig. 5) and the Zubieta model (Fig. 6).

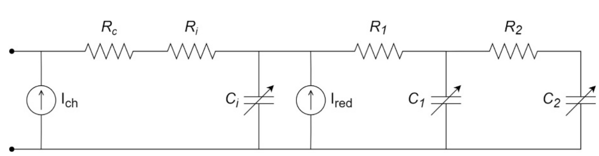

Fig. 10. Torregrossa model proposed in [95]. The current sources account for the supercapacitor charge diffusion effect during charge/discharge (I_{ch}) and redistribution (I_{red}) phases. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

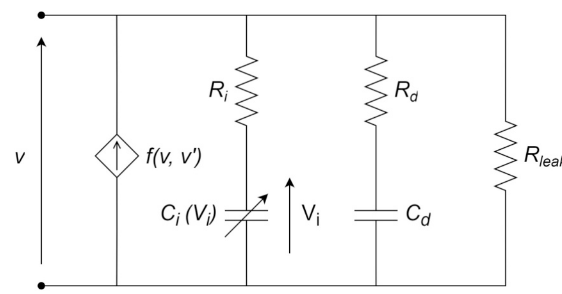

Fig. 11. Equivalent circuit model presented in [98].

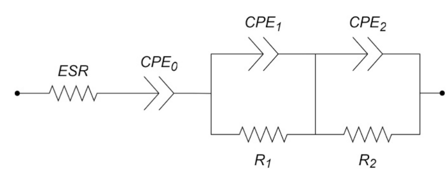

Fig. 12. Fractional order model used in [101].

The simplest model is the so-called R_{int} model, which includes only a voltage generator to model the open-circuit voltage V_{oc} and a series resistance R_{int} representing internal resistance. Both V_{oc} and R_{int} depend on the state of charge and on the temperature, i.e., $V_{oc} = V_{oc}(SOC, T)$ and $R_{int} = R_{int}(SOC, T)$, as indicated in Fig. 13 (a).

As described for instance in [108], following specific measurement procedures, it is possible to obtain the curves linking V_{oc}, SOC and R_{int} for varying operating temperature. Then, using these curves as reference, SOC and R_{int} can be estimated by measuring the temperature and the voltage at the battery terminals. More accurate R_{int} models consider that, in general, the internal resistance is slightly different depending on whether the device is being charged or discharged. In other terms, it can be set:

$R_{int}(SOC, T) = R^{-}(SOC, T)$ during charge

$R_{int}(SOC, T) = R^{+}(SOC, T)$ during discharge

$$R^{-}(SOC, T) \neq R^{+}(SOC, T) \tag{8}$$

This peculiarity is represented in circuits as depicted in Fig. 13 (b), where the diodes are considered to behave as ideal switches [109]. Several attempts have been made to develop a mathematical model able of accurately reproducing the relationship between open-circuit voltage and state of charge. These models are basically used to predict the battery behavior in terms of SOC and V_{oc}, given an initial state of charge and a specific charge/discharge current profile.

To investigate such models, it is useful to introduce the following discretized representation of a generic system:

$$s_{k+1} = f(s_k, x_k) \tag{9}$$

$$y_k = g(s_k, x_k) \tag{10}$$

where s_k is the system state vector, x_k is the system input and y_k is the system output at time instant k. As such, (9) provides the updating rule f for the system state depending on the current state and input, while (10) expresses the relationship g between system state, input variables and output variables. In (9) and (10), we neglected the system noise affecting the state and the measurement noise affecting the output.

Applying this formulation to batteries, the input corresponds to the charge/discharge current i_k, the output is the battery terminal voltage v_k and the state may contain different variables depending on the model. In simpler models, the state vector includes a single variable, corresponding to the SOC. Indicating with C_n the battery nominal capacity in ampere-hours, with η_c the Coulombic efficiency, and with z_k the state of

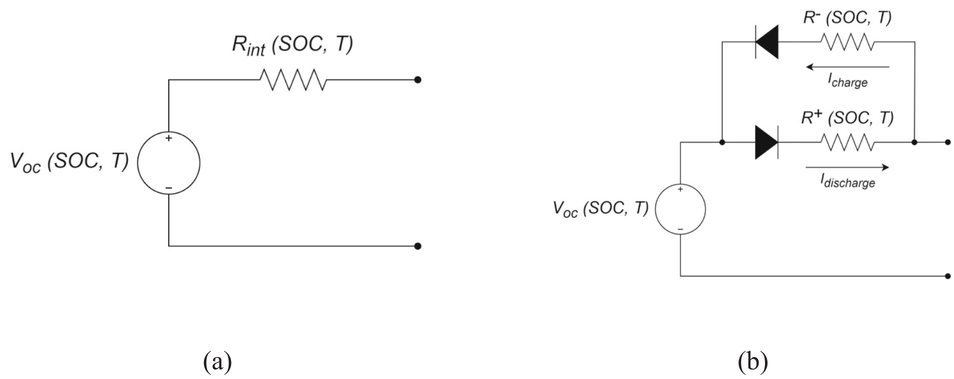

Fig. 13. Classic Rint model (a) and Rint model with different internal resistance values for charge/discharge phases (b).

charge at time instant k, the state updating rule can be expressed by Coulomb counting estimation [109]:

$$z_{k+1} = z_k - \left(\frac{\eta_c \Delta t}{C_n}\right) i_k \tag{11}$$

assuming the current i_k positive for discharge phases and negative for charge phases; Δt is the time interval between the step k and the subsequent $k+1$.

Given eq. (11), various possibilities exist to implement the output relationship given by (10). The "combined model" exploits a combination of three famous models, the Shepherd model, the Unnewehr universal model, and the Nernst model [109], leading to the following formulation:

$$v_k = V_{oc}(z_k) - R_{int} i_k$$

$$V_{oc}(z_k) = K_0 - \frac{K_1}{z_k} - K_2 z_k + K_3 lnln\,(z_k) + K_4 lnln\,(1 - z_k) \tag{12}$$

where K_0, K_1, K_2, K_3 and K_4 are parameters to be identified. In [110] the authors compare three approaches (namely extended Kalman filter, unscented Kalman filter and particle filter) to give an estimation of the state of charge. In [111] a variation of the R_{int} model featuring a RC branch accounting for diffusion and double-layer effects is proposed, as shown in Fig. 14 (a). We refer to this equivalent circuit as the Thevenin model. In this case, the output relationship becomes:

$$v_k = V_{oc}(z_k) - R_{int} i_k - V_{s,k} \tag{13}$$

where $V_{oc}(z_k)$ is still computed as per (12), and $V_{s,k}$ is the voltage across the RC branch at time instant k, given by:

$$V_{s,k} = V_{s,k-1}\, e^{-\frac{\Delta t}{\tau_s}} + R_s i_k \left(1 - e^{-\frac{\Delta t}{\tau_s}}\right) \tag{14}$$

where $\tau_s = R_s C_s$ is the RC branch time constant. The Thevenin equivalent circuit is rather common and adopted in many studies present in the literature [112]– [115]. In some cases, additional RC cells may be added to enhance the representation of battery dynamics, as proposed in [112,115].

A noteworthy alternative to n-order Thevenin circuits is proposed in [116], where RC cells are replaced with RL (resistor-inductor) cells. The authors demonstrate that this formulation, using two RL cells, provides accurate representation of the battery behavior under constant-voltage charging conditions, but with fewer parameters than the corresponding Thevenin model of the same order. Such equivalent circuit, referred to as RL model, is depicted in Fig. 14 (b).

In [109] a hysteresis effect is proposed in terms of a single SOC value associated with two possible open circuit terminal voltages, depending on whether the battery is being charged or discharged. This hysteresis effect, illustrated in Fig. 15, cannot be fully described only by considering different charge/discharge internal resistance values, as per (8). Therefore, the combined model (12) is not able to provide a convincing modeling of the phenomenon.

A simple solution to include hysteresis is the zero-state hysteresis model, which is adopted for example in [117]. This model upgrades the combined model by opportunely adding or subtracting a constant quantity M depending on the charging/discharging state of the device. With this modification, we obtain the following formulation:

$$v_k = V_{oc}(z_k) - R_{int} i_k - j_k M$$

$$V_{oc}(z_k) = K_0 - \frac{K_1}{z_k} - K_2 z_k + K_3 lnln\,(z_k) + K_4 lnln\,(1 - z_k) \tag{15}$$

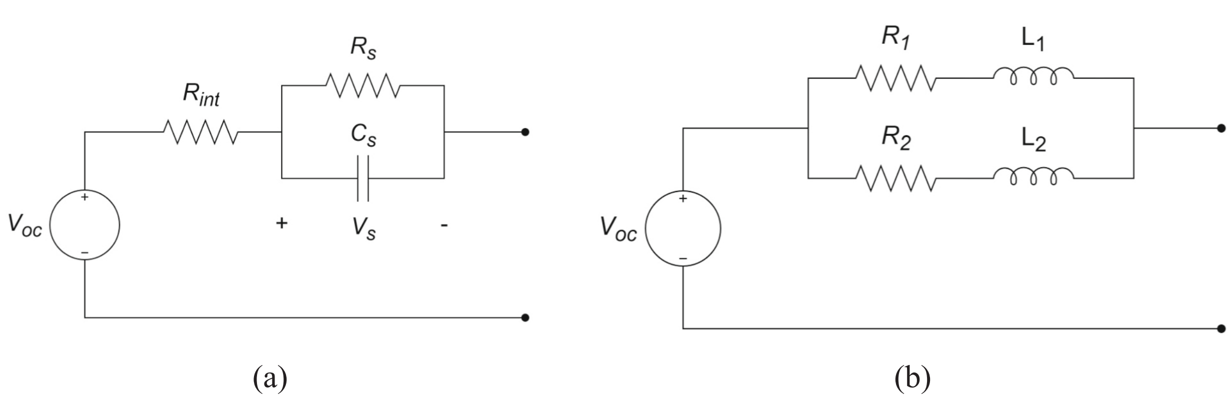

Fig. 14. Thevenin model (a) and RL model proposed in [116] (b).

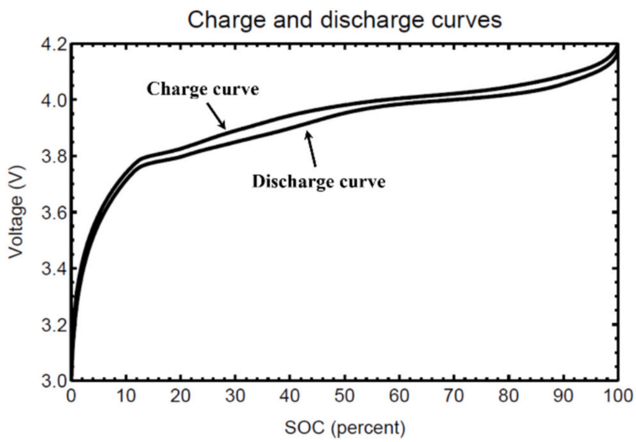

Fig. 15. Hysteresis effect taking place in batteries during charge/discharge. The terminal voltage for charge is the upper curve, for discharge the lower curve. This figure is taken from reference [109].

where j_k can assume the values $+1$ or -1. According to the discussion in [109], the hysteresis component in a lithium-ion cell evolves gradually during charge and discharge processes. However, the zero-state hysteresis model assumes an instantaneous transition between extreme positive and negative values of the hysteresis voltage as soon as the current direction is reversed. This simplification leads to a poor representation of the actual dynamics of the hysteresis effect, making the use of the zero-state hysteresis model in the applications rather limited.

In this regard, a further improvement is achieved by the one-state hysteresis model, which introduces a hysteresis voltage term h as an additional state variable of the system [109]. The evolution of this hysteresis term as a function of SOC and time is described by the following differential equation:

$$\frac{dh(z,t)}{dz} = \alpha_H \, sign(\dot{z}) \, [M(z,\dot{z}) - h(z,t)] \tag{16}$$

where $\dot{z} = \frac{dz}{dt}$; $M(z,\dot{z})$ gives the maximum hysteresis voltage as a function of SOC and its rate of change (M is positive during charge, negative during discharge); α_H is a tuning coefficient. This equation states that the rate of change of the hysteresis voltage depends on the distance from the major hysteresis loop associated to a specific operating condition. Multiplying both sides of (16) by $\dot{z}$, we obtain:

$$\frac{dh(z,t)}{dz}\dot{z} = \alpha \, sign(\dot{z}) \, [M(z,\dot{z}) - h(z,t)]\dot{z} \tag{17}$$

The expression given by (17) can be reformulated considering that $\dot{z} = -\frac{\eta_c}{C_n} i(t)$ and that $\dot{z} \, sign(\dot{z}) = |\dot{z}|$, and indicating $h(z,t)$ as $h(t)$ and $\frac{dh(z,t)}{dt}$ as $\dot{h}(t)$:

$$\dot{h}(t) = -\left|\frac{\eta_c \alpha}{C_n} i(t)\right| h(t) + \left|\frac{\eta_c \alpha}{C_n} i(t)\right| M(z,\dot{z}) \tag{18}$$

Assuming $i(t)$ and $M(z,\dot{z})$ constant over a time step Δt, discretization of (18) leads to the following expression:

$$h_{k+1} = exp\left(-\left|\frac{\eta_c \alpha \Delta t}{C_n} i_k\right|\right) h_k + \left[1 - exp\left(-\left|\frac{\eta_c \alpha \Delta t}{C_n} i_k\right|\right)\right] M(z,\dot{z}) \tag{19}$$

Therefore, combining the SOC updating rule (11) and the hysteresis updating rule (19) in matrix form, and defining $\varepsilon(i_k) = exp\left(-\left|\frac{\eta_c \alpha \Delta t}{C_n} i_k\right|\right)$, the one-state hysteresis model can be written as:

$$[h_{k+1} \; z_{k+1}] = [\varepsilon(i_k) \; 0 \; 0 \; 1][h_k \; z_k] + \left[0 \; [1 - \varepsilon(i_k)] M(z,\dot{z}) - \frac{\eta_c \Delta t}{C_n} \; 0\right][i_k \; 1]$$

$$v_k = V_{oc}(z_k) - R_{int} i_k + h_k \tag{20}$$

The more advanced approaches combine the Thevenin model (13) with the one-state hysteresis model (20), thus providing accurate representation of both double-layer and hysteresis phenomena. The work in [112] provides an interesting comparison of various equivalent circuits and models, testing the one-state hysteresis model in combination with equivalent circuits with up to four RC cells. In [114], a neural network is used to estimate the hysteresis voltage, leading to an enhancement in SOC evaluation accuracy with respect to the no-hysteresis Thevenin model.

Similarly to Table 3, Table 4 summarizes the main features of the papers concerning battery modeling collected in the present review. All the referenced studies share a similar structure:

- they select a mathematical model of the battery with an equivalent circuit;
- identify the model through tests such as Dynamic Stress Test (DST) and Hybrid Pulse Power Characterization (HPPC) combined with optimization algorithms like genetic algorithms (GA) or Particle Swarm Optimization (PSO);
- propose a SOC estimation algorithm (e.g., Kalman filters);
- validate these algorithms using established testing routines such as New European Driving Cycle (NEDC). In nearly all cases, the application domain is automotive.

Among the models reviewed, a Thevenin-based one-state hysteresis formulation represents the most complete integer-order solution for SOC estimation, although it requires a higher parameter-identification effort. Simpler Rint models remain appropriate for community-scale energy balancing when computational speed is prioritized over accuracy. The RL model proposed in [116] offers a promising alternative under constant-voltage charging, although its applicability to dynamic REC operation remains to be demonstrated.

This trade-off is particularly relevant when battery models are embedded in REC-level optimization frameworks. In many community-scale studies, batteries are represented through reduced-order energy-balance models based on a single SOC state, fixed charge/discharge efficiencies, and simplified power constraints. While computationally efficient and suitable for long-horizon scheduling, these formulations cannot reproduce the path-dependent voltage response associated with hysteresis. Consequently, the same SOC may correspond to different terminal voltages and available power depending on the previous charge/discharge history. Neglecting this effect may lead to inaccurate estimates of SOC evolution, round-trip efficiency, and available flexibility, especially under frequent shallow cycling or V2G-oriented operation. Therefore, REC applications requiring dynamic services or battery degradation assessment may benefit from calibrated ECMs, or from hybrid formulations that retain the computational simplicity of reduced-order models while accounting for hysteresis and temperature-dependent effects.

3.2. Thermal storage modeling

The improvement of heating devices and their control strategies can be obtained by simulation model analysis. Thermal energy storage (TESS), which includes phase change materials (PCMs) and ice-based cold storage, helps to shift heating and cooling loads, thereby smoothing out peak demand and enhancing energy flexibility.

The optimal location of the TESS in the building's heating/cooling and power systems strongly depends on the load characteristics of the users and the thermal performance of the equipment. To assess the best behavior of these systems it is useful to develop models able to find the most suitable configurations based on different TES locations and the energy saving effect to be reached [118,119]. Operational strategies can be analyzed using simulation models and optimization problems. In the context of ideal TESS (e.g., ideal sensible heat storage), there is an absence of irreversible losses and, theoretically, the outlet temperature of the working fluid during the discharge process can be considered equivalent to the inlet temperature of the charge process [119]. If a quasi-steady state assumption is considered for SHS, the inlet temperatures of the storage remain constant.

For thermal energy storage, both the charging and discharging processes are in transient states. Despite the non-linearity that occurs in building energy systems, thermal energy storage systems are often manageable as linear problems and are modeled using Mixed Integer Linear Programming (MILP) tools [118].

A perfectly mixed thermal capacity represented by homogeneously distributed internal energy for TESS is not applicable when assessing thermal stratification within storage systems. In general, the treatment of thermal storage as a homogeneous entity precludes the utilization of heat generator or consumer models, given the reliance precise flow and return temperatures for both of them.

In [118], a comparison between capacity and stratification models for TESS was examined: it was found that in the capacity model, the minimum energy content is typically set to a constant value, usually zero. In contrast, the layered storage model allows for the implementation of more accurate limits, such as the required flow temperature based on the building's heating curve. Consequently, the capacity model overrates the system's efficiency, thus underestimating the operating costs.

In the specific case of PCM-TESS, considering them as latent heating storage systems [120,121] there always exist temperature losses due to the TESS heat transfer irreversibility. Nevertheless, the phase change temperature of the PCM can be considered fixed and it is assumed unchanged in many research works [119]. It is considered that the energy storage capacity of the PCM-TESS is sufficient, and that the PCM-TESS could meet the energy balance for one charge and discharge cycle.

In Table 5 a general overview of the main papers related to TESS modeling is presented. The range of temperatures covered by the various applications depends on the type of TESS, ranging from the low-to-medium temperatures typical of buildings and PCMs to the high temperatures characteristic of Concentrated Solar Power (CSP).

The type of thermal storage systems and the characteristics of the proposed models are specified. Some more diffusing modeling approaches are [122,123]:

- black-box models (pure Machine Learning /Deep Learning) that provide accuracy but lack physical insight;
- white-box models (physics-based, e.g., RC-network) are descriptive but require intensive calibration;
- grey-box/hybrid models that combine data-driven flexibility with physical interpretability.

In this context, Artificial Intelligence (AI) and Artificial Neural Networks (ANN) can further optimize the systems' charging and discharging schedules, improving cost efficiency and grid integration [124].

Recent studies have used physics-informed or physically consistent

Table 5
Summary of interesting papers concerning thermal storage modeling.

Reference	Year	Storage features	Models characteristics	Model usage and applications	Temperature range
[128]	2024	Thermal TES + PCM	*Model Predictive Control (MPC) + PCM wallboard, IoT-based*	Building heating system	Medium-low temperature range 19–24 °C
[129]	2019	PCM + HVAC in residential buildings	*Dynamic Programming + PCM, macro-actions*	Building heating system	Medium-low temperature range 18–30 °C
[130]	2022	PCM (latent)	*Physics-Informed Neural Network (PINN) for thermal modeling*	Building	Medium-low temperature range 18–22 °C
[131]	2022	Solar thermal + TES	*Stochastic MPC + PVT & heat pump*	Building	Medium-low temperature range
[132]	2019	Ice storage + large cooling system	*MPC + ANN + genetic algorithm*	District	Medium-low temperature range
[133]	2025	Modeling of PCM integration in buildings	*ANSYS Fluent for finite element analysis*	Building	Medium-low temperature range 24–31 °C
[134]	2023	PV-battery + TES	*Deep reinforcement learning (DRL) (TD3)*	Generic	Medium-low temperature range
[135]	2025	PCM systems	*ML/DL/ANN prediction & control*	Generic, Review	Several level of temperatures (Review Paper)
[136]	2023	TES systems overview	*Techno-economic + PCM/sensible/ hybrid*	Generic, Review	Several level of temperatures (Review Paper)
[137]	2025	Heat Pump	*Stochastic MPC*	Building	Medium-high range (up to 62 °C)
[138]	2022	Water-PCM solar hot water	*ANN predictive model*	Building	Collector: the load temperature is 55 °C and the PCM melting temperature is 28 °C
[139]	2024	PCM in building envelope	*Effective heat capacity & enthalpy models*	Building, Review	Medium-low temperature range 35–39 °C
[140]	2024	PCM-TES general review	*Review PCM applications in buildings and Districts*	Generic, Review	Several level of temperatures (Review Paper)
[141]	2023	PCM-HP coupling	*Review + ANN modeling*	Generic, Review	Several level of temperatures (Review Paper)
[142]	2024	PCM roof slab	*Deep learning (Decision Tree, deep nets)*	Building	Medium-low temperature range
[143]	2019	PCM envelope dynamic NN	*Dynamic NN modeling*	Building	Medium-low temperature range
[144]	2024	HVAC + PCM state prediction	*ANN & Random Forest*	Building heating system	Medium-low temperature range
[125]	2019	thermodynamic model of a water tank	*Computational fluid approach*	Building	Medium-low temperature range
[126]	2016	Comparison of modeling thermal energy storage with electrochemical, chemical and mechanical energy storage technologies	*New proposed modeling methodology in particular for concentrating solar power plants (CSP)*	Generic	Several level of temperatures (Review Paper)
[127]	2024	Numerical models of buried TES in Matlab and Comsol	*Finite element method*	Generic	Several level of temperatures (Review Paper)
[145]	2020	Modeling and dynamic simulation of concentrating solar power plants (CSP)	*Lumped parameter method*	Generic	High temperature range 260–350 °C (CSP)

neural networks (PCNNs), which embed thermal dynamics via constraints or parallel physical modules. Benefits include:
- reliable, physically realistic predictions;
- better generalization than black-box NNs;
- enhanced accuracy (e.g. up to 40% improvement vs. RC models).

Among the literature review, particular interest could be given to [125]: this paper presents a thermodynamic model of a water tank, together with controllers for the processes of charging and discharging energy. The model is based on a computational fluid dynamics approach. The development of this phenomenon is attributed to thermal stratification. It is hypothesized that the hot or cold-water stream, which vertically crosses each tank section, is indicative of heat transfer. This is a non-linear process represented by partial differential equations, which are linearized to obtain a suitable model for control system design. The non-linear model is used in MATLAB/Simulink to design a linear controller of the flow rate of cold and hot water into or out of the tank, so that the energy is used as specified. Another interesting work is presented by Hameer and Van Niekerk [126]: a novel methodology for the comparison of thermal energy storage with electrochemical, chemical and mechanical energy storage technologies is proposed. The authors sought to address the challenge of comparing the charging process of these systems with that of thermal energy storage systems for concentrating solar power plants (CSP). The round-trip efficiency and the leveled cost of energy (LCOE) are the metrics used for the comparison.

Finally, in [127] the authors presented a comparison of detailed large-scale TESS simulation models. The work sets out to compare the implementation of numerical models of buried TES in Matlab and Comsol. It is evident that both tools permit the modeling of the surrounding ground using the finite-element method, whilst the water domain is modeled in a one-dimensional manner.

The COMSOL model has been demonstrated to allow a high level of detail and flexibility, and is thus recommended for TES optimization in a system context. By contrast, the MATLAB model has been developed to a greater degree of simplification, with a particular emphasis on the execution of rapid system simulations. A comparison of the models is conducted in terms of energy flows, temperature stratification and simulation performance. Regarding energy flows, the two models demonstrate a high degree of congruence. Nevertheless, discrepancies in thermal stratification are observed between the two modeling approaches. These observations highlight a broader trade-off in TESS modeling for REC-oriented simulations.

Capacity-based or single-node models are attractive for long-horizon scheduling and MILP-based optimization, since they preserve the overall energy balance while keeping the computational burden low. However, by representing the storage as a homogeneous thermal volume, they may neglect temperature gradients and outlet-temperature dynamics, which determine the actual usability of the stored heat in applications such as heat pumps, solar thermal collectors, domestic hot water systems, and building heating circuits. This simplification can lead to an overestimation of the available thermal flexibility and to biased performance or economic indicators. Stratified or multi-node models provide a more accurate description of charging and discharging processes but require additional parameters and calibration effort. Detailed CFD or finite-element models offer the highest physical fidelity, although their computational cost generally limits their direct use in REC-level optimization. Grey-box and physics-informed models therefore represent a promising compromise, provided that sufficient operational data are available and that the main physical constraints are retained.

4. Electric vehicle storage systems

One of the most significant solutions for mitigating climate change is the adoption of electric vehicles (EV). Contrary to traditional vehicles, EVs are equipped with higher capacity batteries that power electric engines, consequently reducing or avoiding dependence on internal combustion engines. The EV market is broadly divided into hybrid EVs and battery EVs, with adoption rates expected to significantly increase in future years [146]. Hybrid EVs are equipped with both thermal and electric engines, while battery EVs are powered by only electric sources.[1] Typically, electricity storage technology relies on lithium-ion batteries [147], whose capacity ranges from a few to several hundred kWh [148,149].

While technological aspects and modeling of such kinds of batteries have been reported in Sections 2 and 3, respectively, in this section we focus on how the batteries embedded in EVs can provide benefits to a REC.

In their conventional use, batteries inside EVs are charged by an outside source (e.g., the main grid) while they are discharged to provide the power needed for propulsion. So, the presence of EVs is comparable to that of other kinds of loads. However, with the introduction of smart charging protocols [150], EV demand can be managed to better exploit renewable production and promote energy sharing. Charging protocols can be identified as unidirectional or bidirectional. The first case is commonly known as *smart charging* or V1G, while the second one is recognized as *vehicle-to-grid* or V2G [151,152]. Concerning V1G, the charging station is only allowed to control the power flowing from the main grid to the EV. On the other hand, V2G enables the charging station to invert the power flow, hence using the EV battery as temporary energy storage. So, it is apparent that the V2G technology can provide additional services to a REC with respect to the V1G, at the cost of increased charging/discharging cycles and then reduced battery life. In any case, EV batteries are expected to contribute to future energy communities by means of suitable smart charging protocols. In fact, whenever vehicles are plugged into the grid, EV batteries can be operated both as temporary resources or as controllable loads, increasing the energy flexibility inside a REC. Charging station must meet quality criteria to comply with user energy needs and encourage vehicle owners to allow the use of their EVs for the community needs.

In the remainder of this section, a review of contributions describing benefits, solutions, and open challenges of EV smart charging in RECs is reported. Such works are divided on the basis of the assumed charging protocols, i.e., V1G and V2G.

4.1. V1G charging protocol

Several works related to the smart charging of EVs in an energy community aim at minimizing the REC overall cost. In [153], an optimal power flow formulation is used to minimize the community cost on a day-ahead basis. To provide flexibility, the optimizer is allowed to regulate different kinds of controllable loads and EV charging. Specifically, the V1G paradigm is used to perform vehicle charging with the possibility to interrupt the power supply whenever more flexibility is needed. Numerical simulations showed that the proposed approach is capable of reducing peak loads and flattening voltage fluctuations. In [154], an optimization program is formulated to minimize the REC cost by considering the individual costs related to energy supply, energy shared, capacity, and grid usage. The community is composed of prosumers and community chargers, which can provide the charging service to external EVs. The proposed setup assumes the V1G protocol and EVs can contribute to the REC optimal operation by increasing the amount of energy shared in the community system. The formulated setup is able of providing substantial cost savings when energy sharing incentives are introduced.

A flexible energy use regulation system for supply-demand balance of a community micro-grid is proposed in [155]. The objective is to minimize the annual cost of the community operation that comprises investments, equipment, maintenance and environmental indicators.

[1] In this review, we implicitly consider plug-in vehicles only, since the connection to the main grid is essential to provide services to the electricity system and, consequently, to energy communities.

The presence of EV is considered through V1G protocol. Results highlighted that the optimal solution can improve the performance of the system while reducing EV electricity demand during peak hours.

A different framework is employed in [156], where EV charging flexibility is exploited to enhance community performance through demand response (DR) programs (see [157,158] for further investigation on DR). In this setup, the consumption profiles of charging stations change on the basis of DR requests, to help the REC satisfy such requests and receive a reward. A stochastic framework is formulated to handle uncertain variables related to EVs, where the main quantities denoting the charging process (e.g., arrival time, connection time and energy requirements) are modeled through random variables.

A distributed approach for the management of a REC in the presence of EVs is addressed in [159]. Energy profiles are assumed uncertain for the various players, as well as the initial energy stored in the EV batteries. Traditional mono-directional charging is assumed for EVs, where the possibility of differing the charging process helps increase the energy flexibility of the community. This feature is exploited by the devised greedy heuristic procedure which aims at optimizing the mean value of the REC objective and validated through simulations involving small and large-scale energy communities. Different objective functions are considered, as the self-sufficiency maximization or aggregated energy cost.

A REC including an EV rental service has been considered in [160]. Such work is focused on the optimal operation of a community, where REC members are allowed to trade energy exchanges with the community to promote energy sharing. The EV rental service is committed to fulfilling the rental requests incoming each day, and a MILP formulation is presented to optimally provide the request-to-vehicle assignment. The resulting charging schedule allows the community welfare maximization while exploiting reserve services and renewable generation of other members. The obtained community savings are then redistributed among all the REC entities.

The presence of EVs and their related charging techniques is crucial also for the design of an energy community, as reported in [161]. The main goal of this study is to propose an optimization framework to determine the size of renewable generation, EV chargers and electrical storage systems while satisfying the electrical demand and transportation needs. To provide a comprehensive overview of the impact of EV mobility, three kinds of charging stations are considered: uncontrolled chargers, V1G chargers and V2G chargers. The charging station sizing problem is then formulated by taking into account a typical daily profile of EV demand. Depending on the number of vehicles, V1G or V2G are the most preferred options for the optimizer.

4.2. V2G charging protocol

The operation of an energy community usually involves an internal market that allows community members to trade energy in the community. In this framework, a community micro-grid composed of prosumers, consumers, ESSs and EVs is considered in [162]. This work focuses on the definition of a peer-to-peer energy market inside the community, with the aim of reducing the DER influence on the main grid, while maximizing the profit of community members. To reach these goals, a distributed approach is proposed, where the batteries of vehicles are assimilated to the other kinds of storage systems, taking advantage of the V2G technology. In [163], a combinatorial double auction framework is proposed to promote energy sharing among a community of consumers and producers. The presence of EVs is considered through the V2G paradigm, with the constraint that the energy charged at departure must be at least a required amount. The adoption of a double auction market is capable of improving the sustainable behavior of consumers while preserving their privacy. In [164], a new control algorithm for the optimal scheduling of a REC is proposed. Electric vehicles are assumed to work both in V1G and *vehicle-to-building* (V2B). In the latter case, EVs that are parked for a long time can be used as temporary storage systems to provide energy to nearby buildings. The problem is cast as a non-cooperative game and a consensus among EVs and prosumers on prices and exchanged energy is pursued. It is solved through the adoption of a non-cooperative stochastic model predictive control procedure. On the other hand, a peer-to-peer energy market inside a REC is described in [165]. Different technologies for charging/discharging the EVs are considered as V1G, V2G and *vehicle-to-home* (V2H). The proposed energy market aims at shifting electrical loads and exploiting EV batteries to increase the community energy independence and reduce the energy bills. A case study related to an energy community located in England is considered. Results show that exploiting the storage systems of electric vehicles helps achieve the proposed goal, with significant savings especially when the penetration of EVs is massive.

A large penetration of V2G can help increase the resilience of urban microgrids or smart cities in the presence of extreme weather events, like floods and cyclones [166], where fast restoration of power supply after a disaster is of primary importance. In fact, EVs represent the most versatile mobile energy storage solutions, and, through a suitable management mechanism implemented, energy stored in EV batteries can be used to support energy provision after extreme weather disasters [167,168].

The increasing adoption of distributed renewable energy resources and EVs introduces additional challenges concerning grid operation and stability. In this respect, in [169] it is recalled how a high penetration of EVs in the near future can lead to grid stability issues. Thus, controlled EV charging becomes mandatory for stable operation of the grid. An energy community with a high presence of EVs is considered where vehicles are assumed to be charged according to the V2G technology. So, EV storage systems can be used like other electrical storage devices, with the constraint to guarantee the desired battery SOC when required. The proposed methodology allows to evaluate the effectiveness of smart charging to reduce peaks and stabilize the community distribution system. To achieve DSO targets, a local energy community involved in a demand response (DR) program is considered in [170]. In this framework, the objective is to optimally manage the community by a suitable charging/discharging schedule of EVs under the V2G paradigm. The proposed procedures work both in real-time and day-ahead. Electric vehicles involved in V2G are divided on the basis of two different perspectives: performance selection and clustering groups selection. The results obtained by simulations show that a clustering method is more effective for the considered community goals. In [171], a community integrated energy system is considered. Integrated demand response is devised to overcome the issues which arise from the uncertainty in renewable generation. Specifically, demand response of flexible loads is considered, as that provided by the smart charging of EVs. To this purpose, a bi-level dispatching model is proposed, for three different operating modes of the vehicles, namely, charging, discharging and spinning reserve. Simulations of a community located in China are performed, showing that coordinated operations of vehicle batteries can significantly reduce the cost of the REC.

To handle uncertainties affecting the components of RECs, different approaches can be adopted. For instance, in [172] the day-ahead planning problem of a community micro-grid considering different energy carriers is addressed. The objective is focused on minimizing the community cost, comprising energy bought externally, energy bought in the community, community components operation and CO_2 emissions. Concerning EVs, they are considered as temporary storage systems in which the energy charged at departure must be above a prescribed amount. To handle the uncertainty affecting the charging process, arrival and departure times are modeled through Gaussian distributions, while the initial SOC is assumed to follow a long-normal distribution. The overall model is then validated considering winter and summer scenarios. On the other hand, a two-stage optimization approach is proposed in [173] to manage the community operation while considering external stochastic variables. The V2G protocol is considered to

Table 6
Summary of the main features of the research works involving EVs in RECs.

Reference	V1G	V2G	Internal Market	Demand Response	Heterogeneous Energy Carriers	Uncertainty
[153]	✓					
[154]	✓					
[155]	✓				✓	
[156]	✓			✓		✓
[159]	✓					✓
[160]	✓		✓			
[162], [163]		✓	✓			
[164]		✓	✓			✓
[166], [167], [176]		✓				✓
[168]		✓				
[170]		✓		✓		
[171]		✓	✓	✓	✓	✓
[169], [172], [173]		✓			✓	✓
[174]		✓		✓	✓	✓
[176]		✓				✓
[161]	✓	✓				
[165]	✓	✓	✓			
[175]	✓	✓				✓
[177]	✓			✓		

perform EV charging, where the objective is to discharge the least EV batteries and match energy requirements at departure. Moreover, degradation costs have been taken into account to improve battery life. Results have shown that the presence of EVs and storage systems can provide significant cost savings to the community members. To handle uncertainties affecting charging stations, energy demand and renewable production, a stochastic optimization framework is devised in [174]. Specifically, the optimal operation of a multi-energy system is considered. The community is assumed to involve different energy carriers (e.g., electricity, hydrogen and natural gas), considering the possibility to convert generation surplus into other energy sources. In [175], the batteries of an EV fleet are considered as virtual battery resources for a REC, which may allow them to reduce the amount of storage systems needed by the community, with the consequent savings of money for investments. Since the presence and the energy level of a vehicle is stochastic, an estimate of the total battery capacity which can be exploited by the REC is modeled through Markov chains. Both V1G and V2G are considered and different strategies for operating the charging process are simulated and compared.

By employing the flexibility gathered from EV batteries, in [176] a chance-constraint formulation is proposed in order to mitigate the PV forecast uncertainty. In this respect, the storage systems of EVs provide reserves to improve the feasibility of the day-ahead scheduling of the REC.

A summary of the main characteristics of the contributions considered involving EVs inside a REC is reported in Table 6. The table reports the adopted charging protocol (V1G or V2G), the implementation of a community internal market, the presence of demand response mechanisms, and the employment of different kinds of energy carriers (e.g., hydrogen, electricity, thermal energy). The final column highlights whether uncertainty is considered within the respective frameworks.

5. Conclusions

In this work, a systematic review of storage technologies within RECs was presented, analyzing over 170 contributions with a specific focus on modeling strategies for thermal and electrical systems. A comparative summary of the present review with respect to the most closely related works in the literature is provided in Table 7, highlighting the research gaps addressed in this work.

The bibliographic trend analysis highlights a significant acceleration in research output in the 2024–2025 period. Concerning thermal energy storage systems, they offer significant potential for demand-side management by decoupling thermal demand from electrical generation. A modeling gap persists because reduced-order models, although favored for system-level optimization (Section 3.2), often overlook crucial stratification effects in TESS and hysteresis phenomena in battery models (Section 3.1.2). Future research must focus on bridging this gap, potentially leveraging Physics-Informed machine learning approaches. For electrical storage, the trade-off between model fidelity and execution time remains a central challenge. While fractional-order models provide superior accuracy in frequency domain analysis, integer order equivalent circuit models represent the most robust solution for real-time REC management. Furthermore, the analysis suggests that hybrid storage systems (e.g., coupling batteries with supercapacitors) will play an increasingly crucial role in extending system lifespan by buffering power peaks. While the detailed modeling of electrochemical devices might currently appear as an isolated theoretical exercise compared to broad-scale REC studies, it represents a necessary evolution. As RECs transition from simple energy-balancing entities to active providers of grid services using hybrid storage (e.g., batteries combined with supercapacitors), the reliance on simplified energy models will decrease in favor of the multi-physics and electrical models reviewed here. Future

Table 7
Comparative Summary of covered (✓), partially covered (P) and uncovered (X) topics in different reviews.

Reference	Scope	REC	Batteries	SC	TESS/PCM	HESS	V1G	V2G	ECM
[17]	Community energy storage	✓	✓	X	P	P	P	X	X
[14]	Multi-energy storage in local communities	✓	✓	X	P	P	X	X	X
[15]	Distributed energy systems, hybrid storage	✓	✓	X	✓	✓	P	X	X
[8]	Energy communities: building loads & EV	✓	P	X	X	X	✓	P	X
[77]	Solar + heat pump + TES in buildings	X	X	X	✓	P	X	X	X
[107]	Li-ion battery modeling	X	✓	X	X	X	X	X	✓
[103]	Supercapacitor ECM spectroscopy	X	X	✓	X	X	X	X	✓
[78]	Hybrid energy storage systems (book)	P	✓	✓	✓	✓	X	X	P
Present Work	Thermo-electric storage in RECs: modeling & perspectives	✓	✓	✓	✓	✓	✓	✓	✓

research will increasingly require this level of granularity to account for the dynamic voltage-SoC relationships that govern the efficiency and stability of modern energy communities. Lastly, the transition from unidirectional to bidirectional charging is transforming EVs from stochastic loads into active, distributed storage assets. Recent literature emphasizes the need for stochastic optimization methods to handle the uncertainty of EV availability. The primary challenge identified is the definition of robust incentive structures that effectively remunerate users for battery degradation while ensuring grid stability. Although individual storage technologies have reached a high degree of maturity, their coordinated operation within a REC remains an open field of research. The future of REC optimization lies in multidomain simulation frameworks capable of simultaneously managing thermal inertia, electrochemical dynamics, and anthropic analysis of mobility patterns to maximize local self-consumption and grid independence. From an industrial perspective, the technologies reviewed here are progressively transitioning from research prototypes to commercially deployed systems: utility-scale battery storage and heat pump-based TESS are already integrated in several European energy communities, while V2G-capable charging infrastructure is being piloted by major automotive and grid operators. The primary barriers to large-scale adoption remain the high upfront costs of hybrid storage configurations, the lack of standardized communication protocols between devices, and the need for regulatory frameworks that explicitly remunerate flexibility services provided by REC members.

CRediT authorship contribution statement

Elisa Belloni: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cinzia Buratti:** Writing – review & editing, Resources, Project administration, Funding acquisition, Data curation, Conceptualization. **Marco Casini:** Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization. **Matteo Intravaia:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Gabriele Maria Lozito:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Maria Cristina Piccirilli:** Writing – review & editing, Visualization, Supervision, Investigation, Formal analysis, Data curation. **Giovanni Gino Zanvettor:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Cinzia Buratti reports financial support was provided by European Union. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This project was funded by the European Union, Next Generation EU, Mission 4, Component 1, PRIN 2022, Title of the project: "Smart Hybrid Energy Storage Systems for Renewable Energy Communities – SHESS4REC", CUP J53D23000760006.

Data availability

Data will be made available on request.

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