Review

Hybrid Energy Storage Systems Based on Redox-Flow Batteries: Recent Developments, Challenges, and Future Perspectives

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Abstract: Recently, the appeal of Hybrid Energy Storage Systems (HESSs) has been growing in multiple application fields, such as charging stations, grid services, and microgrids. HESSs consist of an integration of two or more single Energy Storage Systems (ESSs) to combine the benefits of each ESS and improve the overall system performance, e.g., efficiency and lifespan. Most recent studies on HESS mainly focus on power management and coupling between the different ESSs without a particular interest in a specific type of ESS. Over the last decades, Redox-Flow Batteries (RFBs) have received significant attention due to their attractive features, especially for stationary storage applications, and hybridization can improve certain characteristics with respect to short-term duration and peak power availability. Presented in this paper is a comprehensive overview of the main concepts of HESSs based on RFBs. Starting with a brief description and a specification of the Key Performance Indicators (KPIs) of common electrochemical storage technologies suitable for hybridization with RFBs, HESS are classified based on battery-oriented and application-oriented KPIs. Furthermore, an optimal coupling architecture of HESS comprising the combination of an RFB and a Supercapacitor (SC) is proposed and evaluated via numerical simulation. Finally, an in-depth study of Energy Management Systems (EMS) is conducted. The general structure of an EMS as well as possible application scenarios are provided to identify commonly used control and optimization parameters. Therefore, the differentiation in system-oriented and application-oriented parameters is applied to literature data. Afterwards, state-of-the-art EMS optimization techniques are discussed. As an optimal EMS is characterized by the prediction of the system's future behavior and the use of the suitable control technique, a detailed analysis of the previous implemented EMS prediction algorithms and control techniques is carried out. The study summarizes the key aspects and challenges of the electrical hybridization of RFBs and thus gives future perspectives on newly needed optimization and control algorithms for management systems.

Keywords: hybrid energy storage systems; redox-flow batteries; key performance indicators; coupling architecture; energy management system; prediction; control techniques

1. Introduction

In recent years, there has been considerable interest in Energy Storage Systems (ESSs) in many application areas, e.g., electric vehicles and renewable energy (RE) systems. Commonly used ESSs for stationary applications are Lithium-Ion Batteries (LIBs), Lead–Acid Batteries (PbAs), and Pumped Storage hydropower [1]. However, in the last decade, there

has been a rapid rise in the use of Redox-Flow Batteries (RFBs) due to the possibility to independently scale power and energy as well as attractive features, such as low self-discharge, high efficiency, and long life [2,3].

In many applications such as microgrids, a single ESS is insufficient for meeting the important system requirements. Hence, the use of multiple distinct ESSs, also known as Hybrid Energy Storage Systems (HESSs), is needed to benefit from the complementary characteristics of each single ESS. HESSs have received substantial interest over the previous ten years, and research on the major aspects of HESS have been extensively carried out [4–7]. However, only a few studies have focused on HESSs based on RFBs [8,9].

While technological features such as materials, components, or stacking of ESS are being constantly improved, stationary applications require advanced control and management techniques to enable highly adaptable flexibility options in future grids. Management Approaches for ESS should consider multiple decision criteria to optimize the operation and design. Often, these criteria are only based on technical aspects written in the data sheet, while application-oriented criteria are neglected. The technical approach focuses on the storage technology itself and its functionality under different circumstances. The application perspective describes how the storage system should perform and examines the utilization purpose.

As a HESS consists of at least two electrically connected single storage components, both the battery perspective of each component as well as the overall application perspective need to be taken into account to develop advanced control strategies. The combination of battery and application aspects leads to optimized dimensioning of the HESS itself. Figure 1 summarizes the methodology presented in this study. Starting from single storage components (A/B/C...), the evaluation of battery- and application-oriented criteria (step I/II) is performed for single components, and the combination within the HESS results in complementary characteristics and advantages. Moreover, the electrical layout meaning the optimized coupling architectures for single components and design approaches are based on the selected criteria and the storage technologies (step III). In the last step, the evaluation criteria determine the input parameters for the Energy Management structure and optimization in step four.
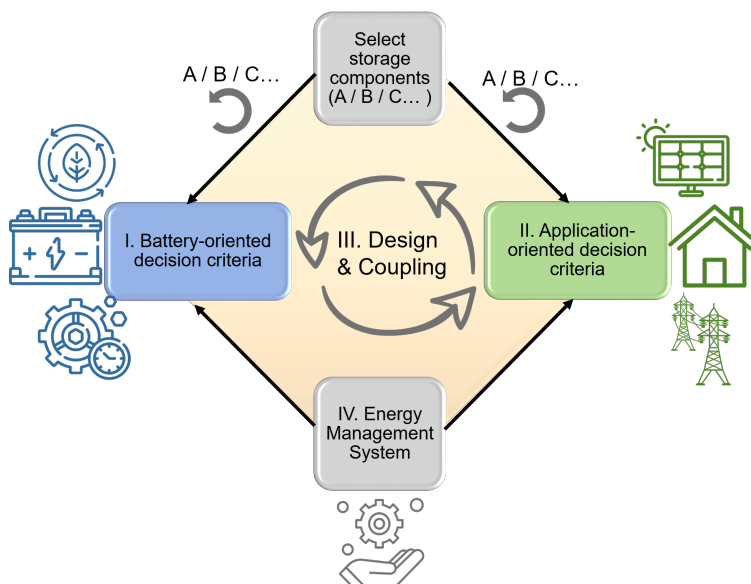
Figure 1. Flow chart of the decision criteria for energy management approaches for HESS.

In this study, the proposed methodology (step one to four) is deeply studied based on literature analysis, and results from two research projects, HyFlow and Open Mobility Electric Infrastructure (OMEI), focusing on the hybridization of RFBs, are evaluated. The goal is to summarize the status quo of recent developments in design and energy management approaches for HESS based on RFB. The presented methodology allows for the

classification of ESSs based on key performance indicators (KPIs) to identify the most suitable candidates for hybridization (Section 2). An optimization strategy to identify optimal electrical coupling architectures is performed using an exemplary HESS with an RFB and an SC from one of the research projects (Section 3). Application scenarios are studied and categorized to identify application-oriented criteria which need to be considered while developing the Energy Management System (EMS) (Section 4.1). The energy management structure, as core control component for all HESSs, will be studied deeply, and newly available optimization and prediction approaches are analyzed for future perspectives (Section 4.2).

2. Evaluation of Key Performance Indicators

KPIs help to characterize the behavior and enable comparison between different storage technologies. They can be classified in battery- and application-oriented KPIs. Materials or components used as well as design approaches, e.g., stacking of single cells influence the technical specifications of a battery, are summarized according to battery-oriented KPIs. For this study, the following KPIs are chosen: energy density in Wh/kg, power density in W/kg, efficiency in %, self-discharge in %/day, and reaction time in s. KPIs can also be formulated based on the application for which the ESS is used or are a result of the application requirements. For the classification approach within this section, the following application-oriented KPIs are used: energy- and power-related costs in EUR/kWh and EUR/kW, lifetime in cycles, shelf life in year, storage duration, design flexibility, ecological impact, and safety.

2.1. Classification of Single Storage Components

A comprehensive overview of existing energy storage technologies and their functionality divided into electrical, mechanical, electrochemical, thermochemical, chemical, and thermal technologies can be found in various publications [7,10–12]. So-called batteries are part of the category electrochemical energy storage technologies and can be further categorized into primary batteries, secondary batteries, fuel cells (FCs), and electrochemical capacitors (SC) [11]. Due to irreversible reactions, primary batteries are mostly not rechargeable and are typically used in small portable applications, e.g., watches or thermostats [11]. Secondary battery cells are based on a reversible electrochemical process and can thus be recharged several times depending on their technical characteristics [11]. The storage technologies investigated within this study are summarized as follows. RFB are used as the core storage component. Most suitable hybridization partners are LIBs, Sodium–Sulfur Batteries (NaSs), and PbAs. Moreover, SCs and Superconducting Magnetic Energy Storage (SMES) are added to the list of investigated technologies, due to their high power density.

2.1.1. Redox-Flow Batteries (RFBs)

In contrast to the other examples of electrochemical storage, RFBs offer independent scalability of energy and power and thus promising storage technology. The first developments were in 1949, and further improvements were patented during the 1970s, which led to the most commercialized Vanadium Redox-Flow Battery (VRFB) found today [2,13–15]. In general, RFBs consist of two half cells with carbon-based high surface electrodes separated by an ion selective membrane, as shown in Figure 2 [2,3]. Commonly, a water-based electrolyte is pumped through the half cells and stored in separated external tanks [2,3]. Typically, up to 40 cells are electrically connected in series using a bipolar stack design, while hydraulic circuits deliver electrolyte parallel to all cells [3,16,17]. In case of the VRFB, the electrolyte is based on a 1.6-molar solution of vanadium ions in sulfuric acid and water [2,18,19]. For the discharging process, a consumer is connected to the electrical circuit. Ideally, V5+ is reduced to V4+ on the cathode, while V2+ is oxidized to V3+ on the anode. In reverse, during the charging process a current source is connected to the electrical circuit, as highlighted in Figure 2, and the electrodes change the roles as cathode and anode [2,18,19].

Besides VRFBs, other types of RFBs are currently in different development or industrialization states [17,20–22]. Ref. [21] provides a comprehensive review of the RFB chemistries. In particular, the substitution of critical raw materials, such as vanadium, with abundant material, led to further developments in the field of Aqueous Organic Redox-Flow Batteries (AORFBs) presented in [20]. Expectations from research and industry are counting on organic molecules to enable a higher voltage range, solubility, and stability while having reduced losses due to crossover-mixing and fast reaction kinetics [20]. A highly ranked scientific review [17,20–24] has already been conducted in the field of RFBs. Thus, our review does not aim to provide a deep overview of RFBs as single storage components but, instead, will focus on aspects of hybridization and control strategies in application-oriented EMSs.
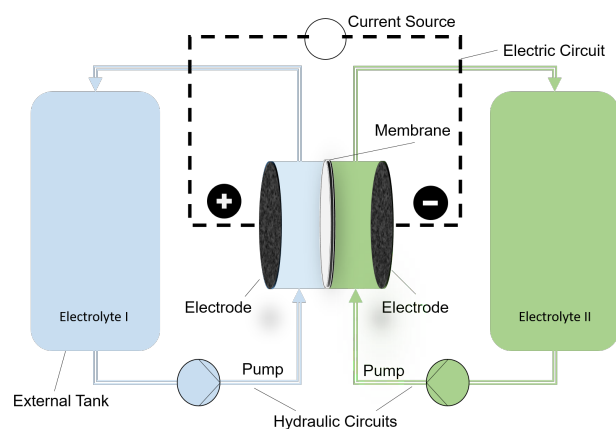
Figure 2. Principle schematic of an RFB cell during charging.

2.1.2. Lithium-Ion Batteries (LIBs)

A LIB is an example of electrochemical storage, based on the rocking chair effect of lithium ions with reversible chemical reactions [25]. It consists of two electrodes, a separator and the electrolyte. The fundamental materials research is due to researchers John B. Goodenough, M. Stanley Whittingham, and Akira Yoshino, who were awarded the Nobel Prize in Chemistry in 2019 for their work [26].

The most commonly used electrode active materials show good hosting characteristics: high storage capability for lithium ions as well as structure stability during intercalation and deintercalation processes [27]. On the cathode side, Lithium–Nickel–Cobalt–Manganese Oxide (NCM) is usually used. It is a complex oxide representing an attempt to combine the advantages of the composed elements. Cobalt shows good electrochemical behavior as well as a positive influence on structure stability, nickel increases the long-term reversibility, whereas manganese is beneficial for costs as well as structure stability [27]. In most cases, the anode consists of a graphite component as hosting material [28].

2.1.3. Sodium–Sulfur Batteries (NaSs)

In contrast to most battery types, NaS technology works at 320 °C instead of ambient conditions. The high temperature is necessary to melt the solid electrodes. The working principle is based on liquid electrodes: sodium on the cathode side and sulfur as the anode. In contrast, the electrolyte is solid and consists of beta-alumina [3]. This material is capable of conducting sodium ions for the battery reaction. Due to the sensitivity of metallic sodium against water, the cell is hermetically sealed as well as thermally insulated to maintain the high temperature [3].

2.1.4. Lead–Acid Batteries (PbAs)

The PbA works in ambient conditions and has a long history. The cathode consists of lead dioxide, whereas the anode is metallic lead. During discharging, lead sulfate is formed at both electrodes. It is nonconducting and insoluble [3]. Nevertheless, this

reaction is reversible, and during the charging process the porous lead dioxide as well as the metallic spongy lead are receded. For the reaction, both electrodes react with the electrolyte composed of sulfuric acid [3].

2.1.5. Supercapacitors (SCs)

Super- or ultracapacitors belong to the category of the electrical or electrochemical double layer capacitors [29]. These systems are composed of two carbon electrodes, a separator (porous membrane), and an electrolyte for the ion conductivity [22]. Due to the high power density and the comparably small energy density, SCs find application where high C-Rates (charging and discharging current related to the capacity) and power systems are required. The disadvantages include a high self-discharge rate and relatively high specific storage costs [29].

2.1.6. Superconducting Magnetic Energy Storage (SMES)

Similar to the SCs, SMES systems are typically listed as a Power Component (PC), due to the high power density. The energy is stored in magnetic form with the help of a coil. The relative high costs, self-discharge rate and the environmental impact of the magnetic field can be identified as the disadvantages of the system [29]. As SMES systems represent an emerging new technology that has not been completely commercialized and, moreover, do not offer advantages over SCs, they are not considered as a hybrid component within this review.

2.1.7. Evaluation of Key Performance Indicators

In Table 1 , the KPIs are applied to the selected storage technologies and subsequently evaluated for their utilization as a HESS component. The storage units are classified by Harvey balls according to their characteristics. Positive characteristics for each KPI are represented by filled balls, negative ones by empty balls, and medium by half-filled balls. For example, high power density is regarded as positive (filled ball), whereas high costs are seen as a negative characteristic (empty ball). For each battery technology, several publications are taken into account [7,10–12,22,29–34].

The collected data are listed, and the average literature values are calculated for each category. In some cases, minimal and maximal values for e.g., efficiency, power density, energy density, self-discharge, or reaction time are listed. For comparison, at the first stage, the average of literature values for minimal and maximal KPIs is calculated. Afterwards, the total average from minimal and maximal values is used for further investigations. The classification, as shown in the table, is then determined in relation to the overall average between all technologies for each category: positive compared to average equals filled balls, negative equals empty ball, and close to average equals half-filled ball. For example, the average power density for all selected batteries based on the named literature is 1001.25 W/kg. For SCs, the literature reveals 3508.33 W/kg, resulting in a filled ball in the table, whereas LIB show 982.92 W/kg, which is close to the overall average represented by a half-filled ball in the table. Average values below 200 W/kg are given by RFB, NaS, and PbA and, thus, represented as empty balls.

In general, high values for energy density, power density, efficiency, lifetime in cycles, shelf life, design flexibility, and safety are seen as positive, whereas low values for energy- and power-related costs, self-discharge, reaction time (low values = fast reaction time), and ecological impact are regarded as good. For storage duration, a wide time window is preferred, from milliseconds to months in the best case. The need for a suitable technology for each time slot leads to the exceptional visualization in the table without Harvey balls but the found storage duration time window.

Table 1. Evaluation of battery- and application-oriented KPIs for different single storage technologies, based on data from [7,10–12,22,29–34].

			LIB	SC	NaS	PbA	RFB
Battery oriented		Energy density in Wh/kg	●	○	●	◑	◑
		Power density in W/kg	◑	●	○	○	○
		Efficiency in %	●	●	◑	○	○
		Self-discharge in %/day	◑	○	○	●	●
		Reaction Time in *s*	◑	●	○	●	○
Application oriented		Cost in EUR/kW	○	●	○	●	◑
		Cost in EUR/kWh	○	○	◑	●	◑
		Lifetime in cycles	◑	●	○	○	●
		Shelf life in years	◑	●	◑	○	◑
		Design Flexibility	○	◑	○	○	●
		Ecologic impact	○	●	◑	○	●
		Safety	○	●	◑	◑	●
		Storage duration	min-days	ms-hour	min-days	min-days	weeks

Legend: ○ = negative characteristics; ◑ = medium characteristics; ● = positive characteristics.

With regard to the types of storage considered, LIBs stand out with high efficiencies of 90% and energy density of 150 Wh/kg [32]. Due to the relatively high power density of 980 W/kg, the batteries have a smaller size, which is suitable for various transportable devices, for stationary applications and for mitigation of power fluctuation applications [29]. The acquisition costs of 1750 EUR/kW, 1700 EUR/kWh, the raw material situation, as well as safety issues impair application [10,28,32].

In contrast to LIBs, RFBs have difficulties with energy and power density with average values of 25 Wh/kg, 143 W/kg for vanadium electrolyte as well as reaction time [32]. The latter depends on whether the pumps are already running or need to be started for a specific power requirement. Nevertheless, there are advantages regarding safety, ecological impact, lifetime of 11,625 cycles on average, and very low self-discharge. Above all, RFBs are characterized by independent scaling of power and energy, which enables an extremely flexible design for different applications. These characteristics make the RFB suitable for stationary storage applications [29].

NaS can be used for grid power quality regulation, voltage regulation, and peak load shifting [7,31]. They have high energy densities of 179 Wh/kg but challenges with self-discharge rates of 10% per day due to the high operating temperatures of up to 300 °C [30]. This goes along with a reduced design flexibility as well as low lifetime of 3469 cycles on average.

These are characteristics that also challenge the PbA. Nevertheless, they are a popular storage choice for power quality and UPS, used in commercial and large-scale energy management applications due to their low cost of 429 EUR/kW and 246/kWh as well as high reliability [30]. However, when comparing the storage type with other batteries, the limited energy/power density of 37 Wh/kg and 193 W/kg as well as relatively low lifetime of 1146 cycles become apparent, especially at low temperatures [30,32]. In addition, the use of lead also results in high maintenance requirements and ecological as well as safety issues regarding toxicity [12,32].

In contrast to battery storage, SCs impress with high efficiency, high power density, and a fast response time of less than 10 milliseconds [10]. Additionally, a lifetime of 228,571 cycles and ecological as well as safety issues are positive aspects of SCs. The main drawbacks of SCs are high energy losses due to self-discharge of 20% per day as well as low energy density of 112 Wh/kg [30,32]. Due to these characteristics, SCs are not

used for large-scale applications but for short-term storage and support [22]. Exemplary applications are lifts, distribution grids, microgrids, or automotive applications [7].

There are many storage systems available, and as shown for the selected types and KPIs, every technology shows advantages and drawbacks. On the one hand, depending on the individual use-case requirements, some KPIs can be more important than others, e.g., energy and power density for mobile applications. On the other hand, in some cases of combining different use cases, especially for stationary storage applications, there is a need to fulfill versatile KPIs in the best way possible. Thus, a combination of storage technologies and their KPIs can be a useful tool to enlarge the capability and advantages of the installed system.

2.2. Classification of HESSs
2.2.1. Definition of a HESS

Electrical hybridization of EESs refers to the combination of **two** or **more single storage components** into a system called a HESS. By carefully choosing the components, optimized overall characteristics of energy, power, lifetime, or costs can be achieved to meet the various requirements in complex use-cases. By combining two storage technologies, various single applications as well as multiple applications can be realized at once, and disadvantages of the individual storage types can balance each other out.

On the hardware side, the storage components are electrically connected via cables and power electronics, while on the software side, a so-called EMS is applied to control the power flow between the storage components and optimize the behavior within a system application, e.g., the grid. Depending on the electrical connections, the HESS itself can have the following grid connection options. In case the EESs are combined on a Direct Current (DC) level, the HESS has one grid connection point. If the EESs are connected on Alternating Current (AC) level, it is possible to have either separate connection points for every AC converter or one connection point for all converters. Both aspects, electrical hardware and software, need to be optimized for each HESS and application scenario to enable the best operation modes.

For HESS, two clusters of ESS can typically be distinguished based on ESS technical characteristics [34]:

1. **Primarily ESS cluster**: has to satisfy the requirements of higher peak power demand and has to handle the fast transient fluctuations, e.g., load or Renewable Energy Sources (RES) production. This cluster is marked by fast response time, high power peaks, high efficiency, and high cycle lifetime.
2. **Secondary ESS cluster**: has to comply with the requirement of high storage duration. This cluster is characterized by a low self-discharge rate and high efficiency.

Generally, all storage technologies—electrical, mechanical, electrochemical, thermo-chemical, chemical, and thermal—can be hybridized. Within this study, only the electrical hybridization of RFBs is investigated. Based on the results of two research projects (HyFlow, OMEI) and a comprehensive literature review [7,10–12,22,29–34], recent developments and challenges of HESS based on RFBs are presented. As there are only a few demonstration projects and publications of HESS with RFB, this consideration represents a recent and innovative effort. For the areas of applications and possibilities, literature reviews for different technologies are included.

2.2.2. Evaluation of Key Performance Indicators

The idea of a HESS is to combine different technologies in one system to meet the various requirements in complex use-cases. Therefore, storage technologies with comple-mentary characteristics are hybridized to enable a broader operation and performance range. Complementary characteristics could be opposing as well as similar. For example, a combination of high with low power density is a beneficial opposing characteristic. Life-time is seen as beneficial if combined technologies show similar characteristics, because the lifetime of the combined system depends on the limiting technology. The KPIs regarded

as beneficial if the single batteries show opposing features are energy and power density, reaction time and storage duration. Similar high characteristics are preferred for efficiency, lifetime, shelf life, design flexibility, and safety, whereas similar low characteristics are favored for self-discharge, energy- and power-related costs as well as ecological impact.

The main criterion for hybridization is the beneficial combination of storage duration, power density, and reaction time resulting in five hybrid systems selected for the evaluation. In four hybridization cases, SCs were selected as a fast response and high power component with high lifetime. The respective secondary ESSs, operating as energy components, are LIBs, NaSs, PbAs, and RFBs. The fifth combination, LIB+RFB, is selected as LIBs can perform a similar role to SCs in some application scenarios. The combination is used within the research project OMEI to operate RES and electric charging infrastructure.

The evaluation summary is shown in Table 2. The Harvey balls for the hybrid system are formed out of the single system evaluation from Table 1. Besides those from the previous illustration of results with Harvey balls, the other colors are invented this time as a second evaluation characteristic. The Harvey balls are marked in green if the combination of two storage technologies has a positive influence on the respective KPI, in blue for medium to neutral influence, and red for negative influence. For example, the SC has a filled ball for power density whereas the RFB power density is shown as an empty ball. The result of the combination of both in one hybrid system is a half-filled ball. As described, power density is seen as beneficial if two opposing systems with high and low characteristics are combined in a HESS. This is illustrated with the color green. Another example is the KPI safety for the hybrid system LIB+RFB. This is a combination of a safe system (filled ball) with a system with safety issues (empty ball), also resulting in a half-filled ball for the hybrid evaluation. Nevertheless, the combination leads to potential safety issues in the hybrid system. Thus, the combination has a negative influence for the hybrid system and is marked in red.

Table 2. Evaluation of different hybrid storage combinations based on complementary battery- and application-oriented KPIs.

		SC+LIB	SC+NaS	SC+PbA	SC+RFB	LIB+RFB
Battery oriented	Energy density in Wh/kg	◐	◐	◐	◐	●
	Power density in W/kg	●	◐	◐	◐	◐
	Efficiency in %	●	●	◐	◐	◐
	Self-discharge in %/day	◐	○	◐	◐	●
	Reaction time in *s*	●	◐	●	◐	◐
Application oriented	Cost in EUR/kW	◐	◐	●	◐	◐
	Cost in EUR/kWh	○	◐	◐	◐	◐
	Lifetime in cycles	●	◐	◐	●	●
	Shelf life in years	●	●	◐	●	◐
	Design flexibility	◐	◐	◐	●	◐
	Ecologic impact	◐	●	◐	●	◐
	Safety	◐	●	●	●	◐
	Storage duration	ms-days	ms-days	ms-days	ms-weeks	min-weeks

Hybrid influence: positive influence   no/medium influence   negative influence
Legend: ○ = negative   ◐ = medium   ● = positive
      ○ + ○ = ○   ○ + ◐; ◐ + ◐ = ◐   ◐ + ●; ● + ● = ●

Table 2 shows that a combination with an SC or LIB as a power component has a positive influence in the combination with NaS, PbA, and RFB as they both show high power densities with 3508 and 983 W/kg, respectively. Thus, the combination of SC+LIB has only a neutral influence on the power density as a standalone solution, which is superior

compared with other technologies. While comparing self-discharge between different hybrid configurations, it becomes clear that combinations with RFB and PbA benefit from their low self-discharge rates of 0.13% and 0.23% per day. The combination of SC+RFB has the highest lifetime benefit, as both technologies on their own show high average values of 228,571 cycles for SC and 11,625 cycles for RFB. According to this evaluation methodology based on the given literature data, the best HESS is revealed to be a combination of SC with RFB. This system shows the most filled balls, positive features, as well as green colors, indicating beneficial characteristics due to the hybridization. The combination results in a storage system that shows high lifetime by the widest window of storage duration from minutes to weeks and a medium energy density with complementary power and reaction time elements for a medium cost level. In addition, the positive aspects of design flexibility, safety, and ecological impact are also preserved in the hybrid system. Thus, the following section dealing with coupling architectures of HESSs focuses the combination of SC with RFB.

3. Coupling Architecture Optimization Strategy

3.1. Coupling Architectures of Hybrid Storage Systems

The different ESSs of a HESS must be coupled in such a way that energy exchanges between them are possible. Given a set of ESSs and a required power exchange capability, there are several possible ways of interconnecting the involved ESSs and related power converters. Each one of these coupling architectures offers different features in terms of cost, efficiency, or performance. One of the main decisions is whether to use AC or DC links on the interconnection between devices. DC grids offer several advantages over AC grids: most common energy storage systems are already DC by nature, energy management is much simpler in DC than in AC, DC grids do not present the stability problems that are typical in AC grids, and the power density of a DC grid is higher than of an AC grid. Therefore, DC grids are the best option when interconnecting different energy storage devices. The involved DC/DC converters must face several requirements: (1) they must be bidirectional, (2) they must interconnect ports with a broad range of input or output voltage values, (3) the voltage gain can be low or very large, and (4) sometimes galvanic isolation is required.

The efficiency and cost of a DC/DC converter depends mainly on the required input to output voltage gain. When dealing with common non-isolated DC/DC converters (e.g., buck, boost, buck–boost), the ratio between the power switched by semiconductors and the converted power is equal to the input-to-output voltage gain. Therefore, the higher the input-to-output voltage ratio, the higher the converter cost and the lower its efficiency. On the other hand, isolated DC/DC converters perform input-to-output impedance matching. This way, the converted power is close to the switched power, and high efficiency levels are possible at a reasonable cost. An input-to-output voltage ratio around 4 can be considered the frontier at which the non-isolated DC/DC converter is less competitive than the isolated one.

In this section, a HESS application example is used in order to explain a possible coupling architecture optimization strategy. In this particular case, the HESS must exchange energy with a low-voltage (400 V_{AC}) three-phase industrial grid and contains two ESSs: a 5 kW RFB with a voltage between 40–68 V and a 25 kW SC bank that must be able to store up to 25 kJ of energy. The voltage of the SC bank is not defined and is one of the degrees of freedom of the optimization.

Figure 3 shows the possible three interconnection strategies for the HESS. Option (a) is the most evident and straightforward to propose: each ESS has its own converter. Anyway, considering that the voltage gain is a paramount parameter when selecting a converter and therefore has an important impact on the cost, it could be interesting to explore other options such as (b) and (c) architectures, where the DC/DC converters are in cascade and therefore individual input-to-output voltage ratio can be reduced.
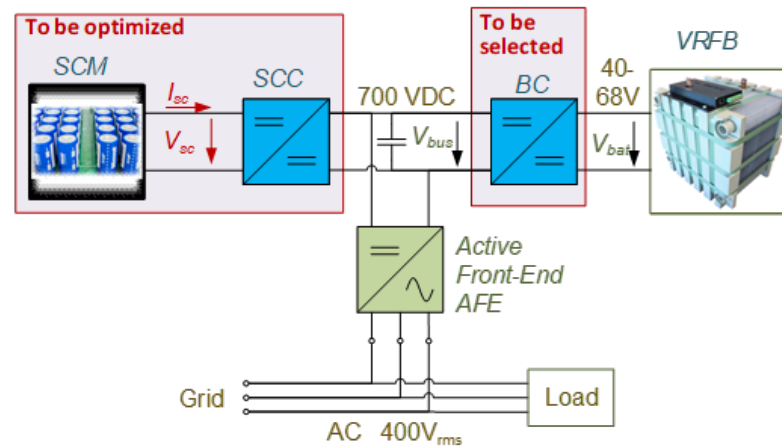
(**a**) Active DC coupling.
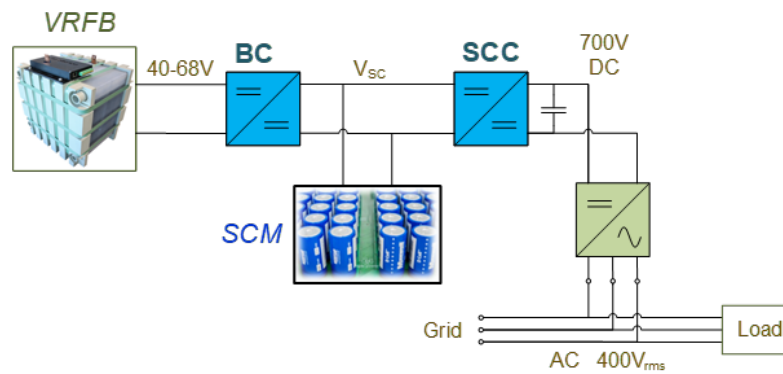
(**b**) Semi-active DC coupling with interconnected SCM.
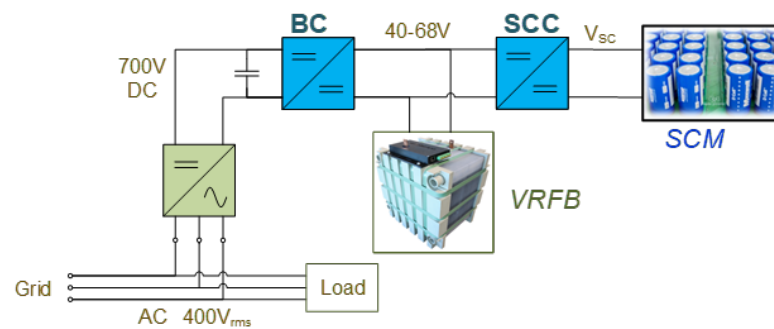
(**c**) Semi-active DC coupling with interconnected VRFB.

Figure 3. Three possible configurations for HESS coupling architecture.

In all possible configurations, the HESS is connected to the grid through a standard Active Front End (AFE) that is linked with a 700 V DC side. SCM is the supercapacitor module, SCC and BC are the supercapacitor and battery converters, and V_{SC} is the voltage at the supercapacitor module.

In order to compare these three architecture proposals, several design parameters have been considered, as seen in Table 3.

In **topology (a)**, the voltage ratio of SCC is to be defined and has no impact on any other parameter. In **topology (b)**, the SCC voltage ratio conditions the BC voltage ratio. The maximum power with low voltage ratio is the power that can be converted by a non-isolated converter cheaper than the isolated full converter option. The minimum power processed with a high voltage ratio denotes the conversion of power with a high conversion

cost. It is important to recall that conversion with low voltage ratio is cheaper than the conversion with a high voltage ratio. The first conclusion can be stated. Considering the total amount of power to be converted, **topology (c)** is not well suited, as it is required to convert 55 kW compared with only 30 kW of the **topology (a)**. Moreover, the minimum power processed with high voltage ratio in **topology (c)** is six times bigger than that of **(a)**. Therefore, we can remove **topology (c)** from the analysis.

Table 3. Comparison of different system architectures.

Design Parameter	Architecture Proposal			
	a	**b**		**c**
Power converted by SCC (kW)	25	30		25
Power converted by BC (kW)	5	5		30
Overall conversion power installed (kW)	30	c35		55
Voltage ratio SCC	TBD	H	L	L
Voltage ratio BC	H	L	H	H
Maximum power processed with low voltage ratio (kW)	25	5	30	25
Minimum power processed with high voltage ratio (kW)	5	30	5	30

Topology (b) offers the degree of freedom of the voltage at the SCM. If a low voltage is chosen, a high voltage ratio is needed at SCC and a low voltage ratio will be enough for the BC. On the other hand, a low SCC voltage ratio leads to a high BC voltage ratio. As there is more power to convert at the SCC, it is interesting to choose a high SC voltage, i.e., the second column of **topology (b)**. Anyway, **(b)** always requires an overall conversion power that is 5kW higher than the **topology (a)**, and does not offer any advantage in terms of voltage ratios that could lead to any cost improvement. Additionally, **topology (a)** is more flexible than **(b)**, as it can handle any modification on the power or voltage values of any of the storage devices without any implications in the conversion chain of the other storage device. Thus, **topology (a)** is selected as the optimum architecture.

3.2. HESS Optimization Strategy

The BC does not require optimization, as there is no degree of freedom but the type of converter. Input–output voltages as well as the power to be converted are already defined. The input-to-output voltage ratio is high, so an isolated DC/DC converter is directly selected. In the case of the SCM and SCC, there are two degrees of freedom to be optimized (see Figure 3a). The nominal (or maximum) voltage of the SCM, V_{SCmax}, is the maximum voltage value at which the SC will be charged. Depending on this value, more or less SCs in series are required, and each SC must be larger or smaller. Therefore, this parameter has an impact on the cost of the SCM. It can also have an impact on the cost of the SCC. On the other hand, for a given amount of discharged energy ΔW, the minimum operating voltage V_{SCmin} depends on the capacitance C of the SCM. The lower the capacitance C, the lower the voltage at which the energy is discharged and therefore, the larger the current. As the cost of the SCC is directly related to the supercapacitor current (I_{SC}), the capacitance of C has a direct impact on the cost of the DC/DC converter. Obviously, the capacitance value also impacts on the cost of the SCM.

Figure 4 depicts the procedure of the optimization of the SCM and SCC. The procedure is based on the analysis of the performance of a large number of different capacitance and voltage values at the SCM.

The input data is a broad range of possible C, V_{SCmax} pairs. Considering the maximum current at the converter and the cost function of the converter, it is possible to compute the cost of the SCC. In the same way, thanks to the knowledge of the capacitance C and the maximum voltage at the SCM, it is possible to compute the number of SC cells in series and the capacitance of each one of them. These last data, combined with the cost per joule and per capacitance of the SC, lead to the cost of the SCM. Finally, both the cost of the

SCM and the SCC are added and the optimum one with the minimum cost is identified. Figure 5a shows the cost per joule of the SC depending of the cell size.

Both SCC and BC share the same high-voltage DC-CCP at 700 V. Figure 5b illustrates the estimated cost per 5 kW of full power isolated (Isol) and not isolated (Non Isol) converter as a function of the low-side current side current. As it can be observed the estimated cost is constant in the case of the isolated technology whereas the non isolated one increases its cost as the low-side current side current increases. One of the advantages of the DC/DC converters is that they can easily be connected in parallel, so it is straightforward to scale power keeping almost the same cost per kilowatt figure. Figure 6 shows the estimated overall cost of the SCM plus SCC pack, considering both not isolated (Figure 6a) and isolated (Figure 6b) converters. As can be observed, the minimum cost of the non isolated case is lower than the isolated converter that is selected. The minimum cost is around EUR 4000 and is achieved with a maximum SC voltage of 650 V. At the minimum cost point the maximum SC and converter current is 58.2 A. The capacitance of the overall module that optimizes the cost is 0.21 F, built with 542 cells of 114 F each.
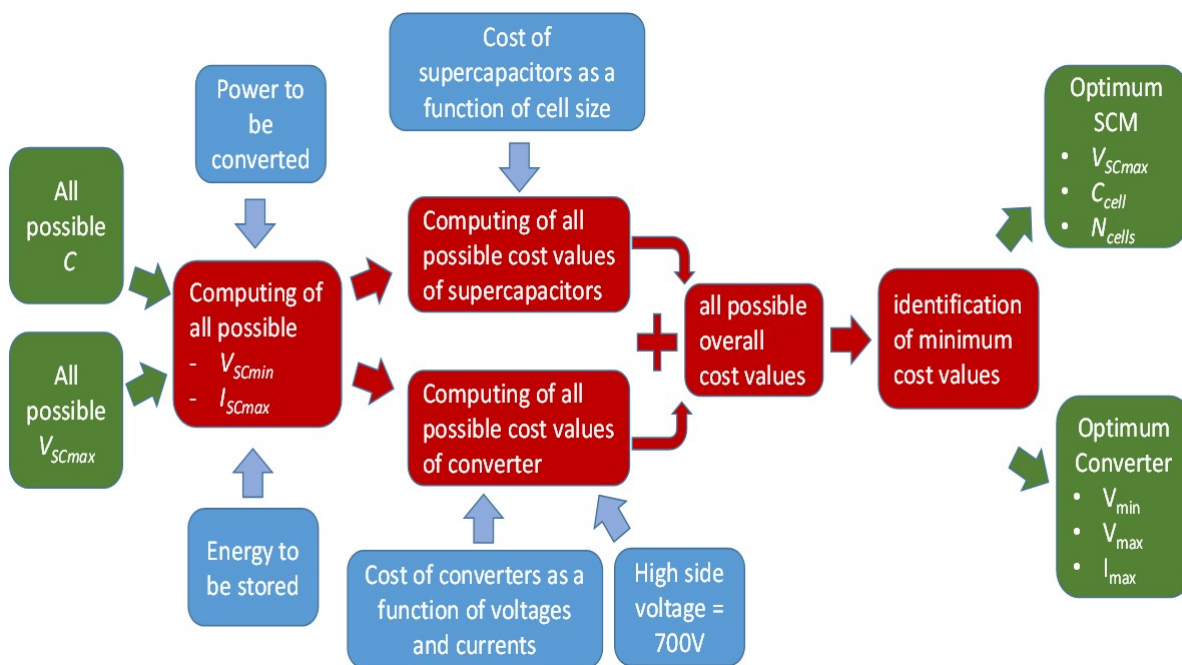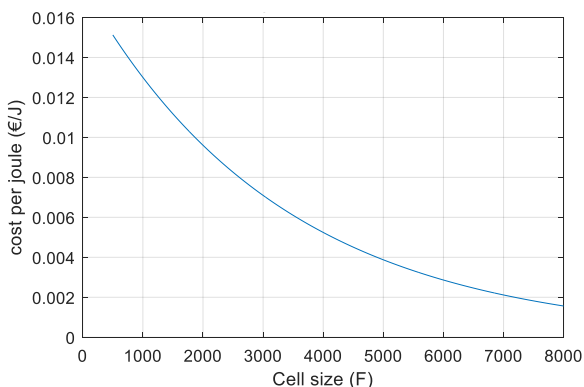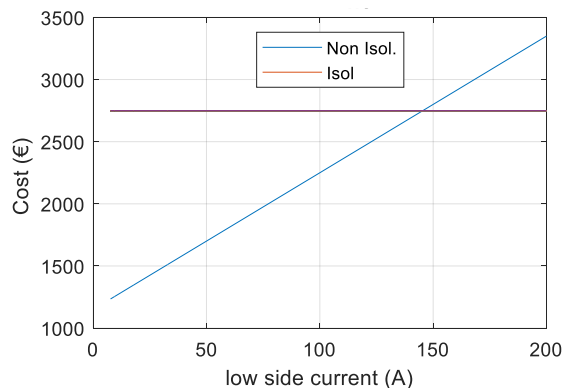

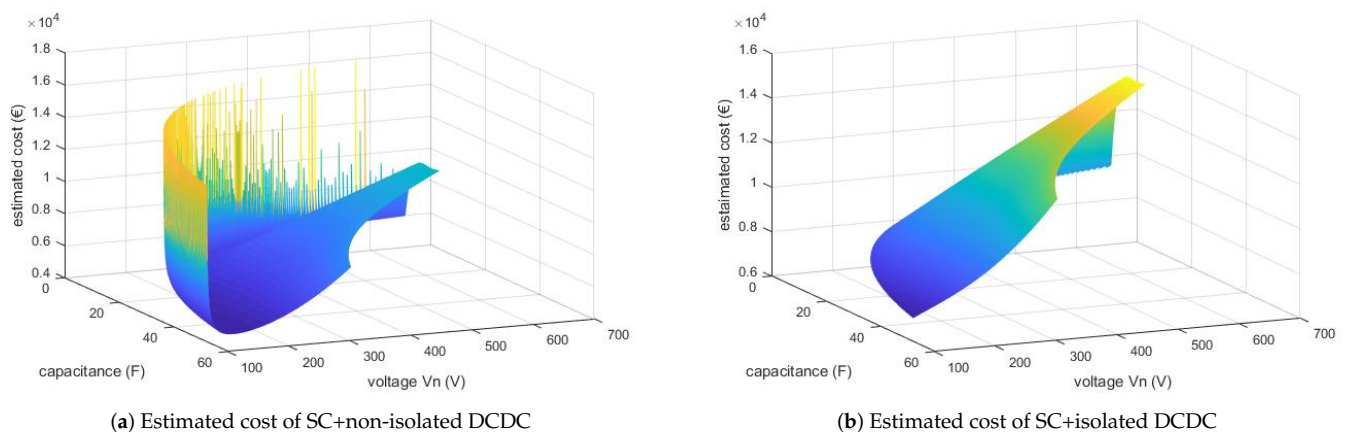**Figure 4.** Flow chart of the optimization procedure.

(**a**) Cost per joule for each cell size

(**b**) Estimated cost of converters @V_{HS} = 700 V/P = 5 kW

Figure 5. Cost of elements: (**a**) cost per joule for each cell size and (**b**) estimated cost of converters as a function of technology and low-voltage side current.

(**a**) Estimated cost of SC+non-isolated DCDC　　　　　　　(**b**) Estimated cost of SC+isolated DCDC

Figure 6. Estimated overall cost considering the SCM and the SCC for (**a**) non-isolated converter and (**b**) isolated converter.

4. Energy Management System (EMS) for HESS

Besides optimal electrical hardware as presented above, HESS need to be optimized in terms of software and management approaches (EMS). Figure 7 illustrates the schematic of a HESS including all power, information, and sensor connections between storage components and the grid. The classification system to choose the best fitting storage technologies for hybridization has been discussed in Section 2. Within this study, RFBs as an energy component (EC) are studied in an hybrid approach using a complementary PC. The optimal electrical connections of two single storage application in one hybrid system has been discussed in Section 3. The EMS acts now as central control unit for the HESS communicating with all storage components, loads, generation, and forecasting units as highlighted in Figure 7. The Battery Management System (BMS) is mostly developed by the battery manufacturers and, thus, is not part of this review. In the following section, the EMS will be deeply studied. Beginning with an outline of the EMS structure and a definition of typical application scenarios, the EMS control techniques are presented based on their control and optimization parameters. The optimization of EMS strategies is then presented with a focus on prediction and currently used control techniques.

4.1. Energy Management Structure for HESS

The structure of a general energy management system can be realized in different ways. The norm ISO 50001, for example, serves a basic structure and can be used as a support for implementation. The standard provides a process to identify necessary framework conditions from collecting all the necessary data, setting strategic and operational energy targets to plan and structure the documentation [35].

The controlling structure for an EMS for HESS is similar to EES systems. The specific parameters and limit values have to be defined for the different application scenarios. Figure 8 shows a method to structure an EMS for HESS. The first step is to define the EMS goals in the specific application scenario. These can be subdivided into system goals and application goals. The applications scenarios are described in Section 4.1.1. The legal framework conditions and operating limits must be taken into account in advance [36]. Adapted to the EMS goals, the requirements, coupling architecture, and dimension can be set on the system components specific to the EC and PC. This results in safety boundaries for the system, for example system limitation values for power, current, and temperatures [37]. In particular, for efficient operation of RFBs, it is important to limit these values. Exceeding these ranges can lead to decreased battery performance, reduced efficiency, and even safety risks such as electrolyte leakage [15]. The control parameters for the application and system specific optimization have to be defined within a permissible operation range. These are explained in Section 4.1.2. Depending on the complexity and number of optimization

parameter, the EMS control technique should be defined. In the first instance, classical and intelligent techniques are differentiated. Section 4.2.2 describes the optimization methods and refers to examples.
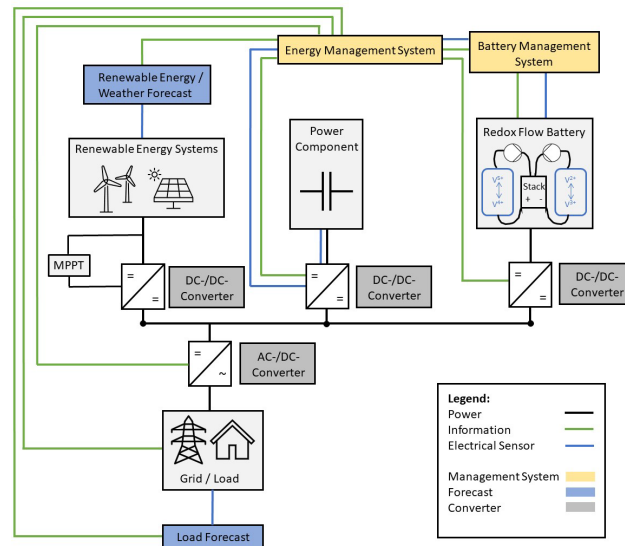

Figure 7. Principle schematic of a HESS including all power, information, and sensor connections between storage components and the grid.
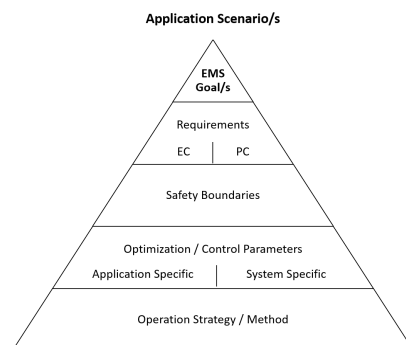

Figure 8. Methods of an energy management structure for HESS.

4.1.1. Application Scenarios

The specific application scenarios serve as input for the EMS design and implementation and especially influence the optimization or control parameters. Applications for EES are widely presented in the literature. To obtain a high amount of data, the investigations of the application fields includes not only RFB but also other stationary storage technologies. This study aims to show which electrical storage applications RFB can cover and how these can be technically and economically optimized specifically through hybridization.

By reviewing 22 publications within this study [1,10,38–57], over 80 different types of stationary application have are first identified. Mobile applications are excluded from this study. As different descriptions where referring to similar applications, a classification system developed in [58] has been applied. Duplications are reduced, and the applications are evaluated to sort them into universal application scenarios. Eleven application scenarios with different purpose, placement, duration, as well as control parameters applicable for a HESS based on RFBs are summarized in Table 4.

Applications with different descriptions but the same technical specifications or goals, e.g., frequency stability and frequency control, have been summarized. Moreover, some for which the control parameters are not clearly described, e.g., capacity support, capacity firming, or electric supply capacity, are formulated with more specific terms relying on already defined system services in the interconnected grid [45]. Some applications, such as

grid flexibility, are too general, and universal control parameters cannot be found, or some are more related to the grid operators business and not yet clearly defined as EES scenarios, e.g.,investment deferral in grids or operational grid management. These applications are omitted from the final summary. Newly developed applications, such as Grid Booster, are also not listed in Table 4 but could be added once demonstration projects have been completed. The remaining 13, now referred to as application scenarios, are classified by their purpose, placement, and control level, as suggested by [58]. Newly added items also classify the duration, control parameters, and required controller rate for the EMS.

The application **purpose** of using a EES is summed up in three categories:

1. *System (S)* describes storage usage for the general stability and maintenance of interconnected grids and the used stability products, e.g., defined in [45,58].
2. *Grid (G)* describes the local grid operation mode maintaining power quality in distribution grids [58].
3. *Manage (M)* sums up all end-user applications aiming at balancing power flows within their system boundary, which must be smaller than a network section [58].

The **physical placement** influences, on the one hand, the used infrastructure and involved stakeholders. On the other hand, the placement includes not only the physical placement but also the spatial distribution of control variables for the management system, e.g., frequency, voltage, and power [58]. Both physical and control placement are often combined, e.g., in home storage. For some applications, the placement is not specifically determined e.g., black start or island grids. Therefore, physical placement is categorized as follows [58]:

1. *Transmission grid (T)*;
2. *Distribution grid (D)*;
3. *Behind the meter at end-user locations (E-U)*.

The **control level** is the summarized decision parameter for a management system to decide which operation mode of the ESS is used at which time and how long it is used. **Power (P)** summarizes all objective functions of EES that are controlled by a power-specific parameter, while **Energy (E)** describes all those controlled by a energy-specific parameter [58]. All scenarios in Table 4 can be applied to single storage systems or HESSs. By using a HESS, it is even possible to combine different application scenarios complementary to the HESS characteristics. For example, the combination of an energy-based (E) and a power-based (P) application scenario is a commonly used approach in hybrid systems.

The **duration** describes the average operation time and can also be described as the time during which the energy storage system has the same control command. The duration of energy storage has been categorized based on the definition of system services in the grid starting with momentary reserve in milliseconds as immediate grid services, followed by primary, secondary, and tertiary reserve in minutes until exchange within one balancing group starts. The latter describes the smallest unit of the energy market model and refers to a virtual energy account to balance any number of energy inputs and outputs [59]. The duration is only fixed for system services, e.g., frequency control [45]. Other application scenarios, e.g., peak shaving or energy time shifting, show only suggestions of applicable time scales and can be seen as a start of the art from the studies literature data base. Similarly to combining different control levels, e.g., power or energy, HESS can enlarge the usable storage duration by adding a short term storage e.g., SC to a mid- to long-term storage e.g., RFB. Thereby, application scenarios as, e.g., momentary reserve and energy time shifting can be combined. Both state-of-the-art research projects, HyFlow and OMEI, built up demonstrators by combining different application scenarios and durations. HyFlow focuses on four different applications scenarios, whereby a combination of high-power and high-energy component is always foreseen [60]. Thus, momentary reserve, peak shaving, and energy time shifting are foreseen for industry grids, weak distribution grids, and UPS [60]. Within OMEI, the HESS is used to balanced fast-charging infrastructure and perform peak shaving as well as energy time shifting of renewable generations and load.

The **control parameter** describes the exact values that are used for the management system. These parameters need to be optimized with the momentary load and generation to satisfy the purpose of the storage usage and are thus application-oriented control parameters. Additionally, the used storage systems also have system-oriented control parameters for each battery used in a HESS, as described in the section above. Both need to be taken into account and prioritized for EMS and optimization techniques. The controller rate or sample rate shows the reaction rate of the EMS and thereby defines the communication and electrical requirements of a HESS. Moreover, this is also the time frame in which the optimal operation mode needs to be calculated and raw data from the application case, e.g., load or generation need to be measured. If the duration of the application is typically low, the controller rate needs to be high, e.g., 20 ms for momentary reserve.

Based on the application scenarios, the following sections describe which optimization routines are applied to identify an optimal power flow within a HESS.

Table 4. Classification of storage application scenarios by their application purpose (S: System; G: Grid; M: Manage), placement (T: Transmission; D: Distribution), control level (P: Power; E: Energy), duration, control parameters, and controller rate. Literature review from [1,10,38–58].

Source	Application	Purpose	Placement	Control	Duration	Control Parameter	Controller Rate
[38,46–50]	Momentary Reserve	S	T	P	t < msec	f_AC [1]	<20 ms
[1,38,43,46,47,49,50,53,54]	Primary Control	S/G	T	P	t < msec	P_AC f_AC [1]	<30 s
[10,38,42]	Secondary Control	S/G	T	P	s < t > 15 min	P_AC f_AC [1]	<5 min
[10,38,42]	Tertiary Control	S/G	T	P	min < t > 60 min	P_AC f_AC [1]	<15 min
[10,38,42]	Black Start	S	-	P	s <t > min	ΔP [3] f_AC [1] U_AC	1–10 s
[1,10,38,42,44,55]	Island Grid [4]	S	-	E	s < t > days	ΔP [3]	1 s–1 min
[1,38,42]	Transmission Support and Stability	S	T	E	t > h	ΔP [3]	1 s–1 min
[10,38,42,49,56,57]	Voltage Support	G /S	T/D	P	15 min < t >h	ΔU [2]	1–15 min
[1,10,38,42,43,46,49,50,52]	Distribution Power Quality	G /S	D	P	s < t > min	ΔP [3]	1 s–1 min
[10,38,43,44,52]	Peak Shaving (all time scales)	M /G	E-U	P	s < t > 15 min	ΔP [3]	30 s–1 min
[38]	Uninterruptible Power Supply	M	E-U	P/E	s < t > h	P f_AC U	<20 ms
[38,46,47,49,50,52,56,57]	Energy Time Shifting	M	E-U	E	15 min < t > days	ΔP [3] t	1–15 min
[1,38,43]	Energy Trading, Arbitrage	M	-	E	15 min < t > h	ΔP [3] EUR/kW EUR/kWh	1–15 min

[1] Allowed frequency range within the German grid 50 Hz +− 0,02 Hz according to DIN EN 50160 [61,62]. [2] Allowed voltage range within the German grid 230 V+−10% according to DIN EN 50160 [61,62]. [3] Residual power ΔP refers to the difference of power demand and supply. [4] Including mini, micro, military, emergency grids or similar.

4.1.2. Control and Optimization Parameters

The application categories in the literature show the potential for HESS. Due to the combination of storage systems, not only technical and economical advantages but also

application extensions and combinations can be achieved. Table 5 shows the advantages and objectives for HESS of the application categories and combinations in the considered literature. The table indicates system and application goals. First and foremost, the storage systems are designed to achieve the application objectives. On the technical side, for example, the parameters of storage capacity demand, power limits, power electronics, and time requirements are used for this purpose.

Table 5. Map of optimization parameters and EMS goals for the hybrid storage application categories (PC: Power Component; EC: Energy Component).

Application	Hybrid Component	Voltage Support PC	Distribution Power Quality PC	Peak Shaving PC	Energy Time Shifting PC/EC
Island grids	EC	Improving transient response, increase efficiency/performance and lifetime of the EC, grid (voltage) quality, supply security [63–65]			Operational limits operation, self sufficiency, economic efficiency, efficiency, reduce energy costs [66,67]
Uninterruptible Power Supply	EC		Utilization of UPS EC, economic efficiency, stability of power system [68]		
Peak Shaving	EC	Minimizing the power fluctuation, self-sufficiency, grid quality, optimizing the capacity ratio of EC, PC [69]	Dimensioning, efficiency, economic efficiency, lifetime, smoothing the current of EC [70]		
Energy time shifting	EC		Dimensioning, efficiency, economic efficiency, lifetime, smoothing the fluctuation of RE [71]	Self-sufficiency, reduce of max. power consumption/generation, utilization of RE, efficiency, dimensioning, lifetime [72]	
Energy Trading/Arbitrage	EC/PC				Economic efficiency (operational costs), efficiency, reduce energy costs [73]

The use of HESSs has the advantage of combining the application goals with the option to optimize the system and the operation process by using a hybrid operation strategy. Optimization targets for the PC and EC are dimensioning, efficiency, lifetime and economic efficiency. These parameters are intended to optimize the HESS systems for the specific application goals. Therefore, control parameters such as capacities, power demand and supply, grid quality values (frequency, voltage), response times, and energy prices play a major role.

Based on this map, the potentials of RFB as EC in the considered applications can also be classified. The analysis of the applications and the KPI from Table 1 show optimization potentials in the operational efficiency, increased lifespan, and economic viability of RFB through hybridization. In particular, the combination with a PC such as a SC and the specific optimization of operation result in technical and economic advantages in implementation. Furthermore, an expanded spectrum of application areas can be defined where a single RFB system is not optimally applied.

Additionally, through the optimization and operation of the HESS, the targets for multiple applications can be achieved. A prerequisite is that the intended purpose takes place at the same placement as shown in Table 4.

4.2. Energy Management Optimization for HESS

The main goal of EMS for HESS is to execute the operation strategy in real time and in an optimal manner. This target is reached by increasing the input variables to the HESS by predicting data that fit the technical HESS requirements and is achieved by selecting a suitable EMS control technique. Figure 9 depicts the real-time architecture of an EMS. This architecture is composed of three steps: (1) prediction, (2) optimization, and (3) HESS component. The prediction model uses historical data such as RE production and weather to forecast important data, e.g., load demand and supply. The optimization model takes as inputs the predicted data, the system parameters and regulations as well as other information tightly linked to the system aims. Once the optimization is carried out, the HESS implements the calculated operation strategy. Finally, an evaluation and improvement process is executed to assess whether the desired changes or objectives have being achieved, or whether there has been progress toward meeting the system goals.
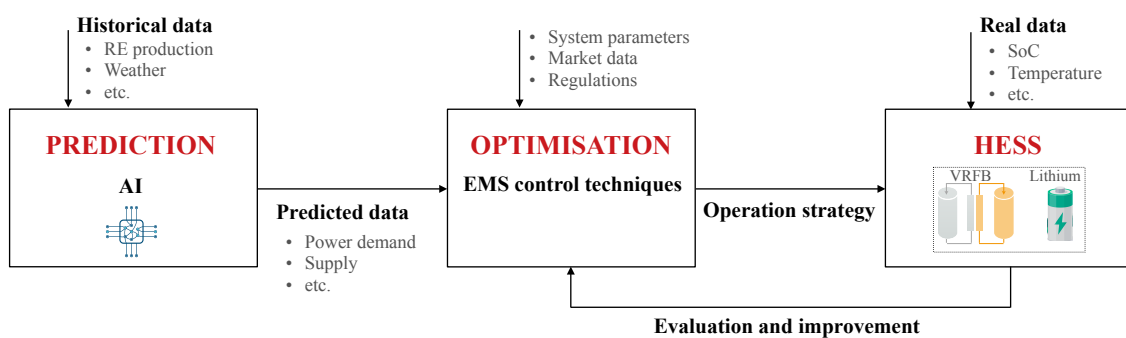

Figure 9. Real-time EMS architecture [74].

4.2.1. Prediction

An optimal EMS not only depends on the current external factors and in the present HESS status but also on prediction of the future system behavior at a particular time based on historical data (see Figure 9). The predicted data, that differ from one application to another, should be identified according to the system specific requirements and goals and should be as faithful as possible, since they will be used to forecast the application status and conditions. RE production, ESS capacity, and weather information are the most widely evaluated types of data in the last few years [75–79].

Many prediction techniques for ESSs are defined in the literature, as highlighted in Table 6. Mixed Integer Linear Programming (MILP) and Neural Network (NN) and its variants Artificial Neural Network (ANN), Recurrent Neural Networks (RNN), and Convolution Neural Networks (CNN) are among the most commonly adopted techniques [77,79,80]. NN is able to achieve accurate results at high speed and is used in many domains, e.g., prediction and optimization. Recently, there is considerable interest in using Reinforcement Learning (RL) in multiple fields, especially in automatic control system, due to its accurate results and high control performance [78,79].

Once built, the performance of any prediction technique should be evaluated. Several evaluation metrics have been standardized in order to give a clear and comprehensive picture of the prediction technique behavior. A set of evaluation metrics are defined in the literature and the well-known metrics are Mean Absolute Percentage Error (MAPE) and Root-Mean-Square Error (RMSE) [75–79]. As the optimization of an EMS is closely related to the quality of the predicted data, minimization of the prediction error is required. This goal can be reached using several methods, including the selection of the best prediction horizon length and the combination of multiple prediction techniques.

Only a small number of studies have addressed the issue of predicting data to optimize an EMS, and nearly all of these studies adopted a single ESS. Further studies should investigate multiple challenges, in particular, regarding prediction data specifically for HESS based on RFB, the identification of the appropriate data to predict and the selection of the best prediction technique.

Table 6. Classification of predicted data.

Predicted Data	Prediction Techniques	Evaluation Metrics
Charging demand [80–82]	CNN, LSTM, RNN	MAPE, MAE, NRMSE
RE production [75–77,79]	CNN, MILP, NN, RNN, ARIMA, GAN, MLP, LSTM	MAPE, RMSE
ESS Capacity [78,79]	MILP, MINLP, NN	RMSE
Charging scheduling and pricing [83,84]	MILP, RL, ANN	N/S
Charging station placement [85,86]	GA, RL, Linear Regression, Decision Trees	N/S

N/S: Not specified.

4.2.2. EMS Control Techniques

The selection of the optimal EMS control technique depends on the pre-defined optimization function (or goal) of the application. Based on the EMS architectural level, optimization functions can be classified into low-level optimization functions and high-level optimization functions [6,7]:

1. Low-level optimization functions control the AC/DC bus **voltage** and the electric **current** flow.
2. High-level optimization functions control many energy management strategies, among which are **power** performance, **SoC** monitoring, ESS **charge/discharge** cycles, and **energy cost** reduction.

The majority of studies, presented in Table 7, focus on high-level optimization functions, especially for power allocation strategy. Furthermore, for HESS based on RFB, power is not the only important variable that needs to be studied, but other parameters such as energy and SoC also have to be considered.

Different control techniques have been proposed in the literature to attain the main objectives of HESS, including system performance optimization, system stability improvement, and computation cost reduction [6,7]. Figure 10 represents in depth classification of EMS control techniques for HESS. These techniques are classified into two groups: classical techniques and intelligent techniques.

1. **Classical control techniques** mainly include filtration-based control, dead beat control, droop control, and sliding mode control. These techniques are the most used in the literature, as demonstrated in Table 7, and are mainly applied for offline implementation independently of the filtration-based control technique.
2. **Intelligent control techniques** are classified into rule-based techniques and optimization-based techniques. Rule-based techniques are among the most widely adopted in previous work due to their simplicity in implementation (see Table 7). However, these techniques are still far from perfect, as they require deep knowledge of the domain and the definition of rules for a complex system is a challenging task. Recently, there has been considerable interest in real-time optimization techniques, with a rapid rise in the use of Deep Learning (DL) and Machine Learning (ML) algorithms, e.g., Neural Network (NN) and Reinforcement Learning (RL). ML techniques deliver accurate results in real time, but on the other hand, they require a lot of training data and suffer from high computational complexity.

More details on these techniques can be found in [7].

As the majority of the current HESS-based applications are implemented online, Table 8 summarizes the advantages and limits of real-time control techniques. Based on Table 8, it is recommended that real-time optimization techniques be adopted for complex systems when accurate results are required.

Table 7. Classification of HESS studies.

| Paper | Energy Storage System | Electric Topologies | Optimization | | General Control Techniques | Used Data |
			Optimization Function	Real Time		
[9]	(H_2/Br_2) RFB, SC	DC coupled	Power	Yes	Mathematical model	Microgrids
[87]	Battery, SC	DC coupled	Power allocation of different ESS	Yes	Classical Real-time optimization	Microgrids/Simulated
[4]	Battery, SC	DC coupled	Reduces measurement inaccuracies	N/S	Classical	N/S
[8]	VRFB, SC	Active topology	Current, SoC	No	Classical Fuzzy logic	EV charging park/Real
[5]	Li-Ion battery, SC	DC coupled	N/S	N/S	Fuzzy logic	Ships
[88]	VRFB, SC	Active topology	Power thresholds	No	Rule-based	Industrial grid—Real/Synthetic EV charging park
[63]	Batteries, SC	DC coupled	Constant voltage to the DC bus	No	Classical	PV, AC- and DC Loads/Simulated
[89]	Battery, SC	DC coupled	N/S	N/S	Global optimization Real-time optimization	Electric vehicle
[90]	Li-Ion battery, SC	DC coupled	Meet power demand Reduce the cost of energy storage device	Yes	Classical Real-time optimization	Ship load
[91]	Battery, SC	DC coupled	Power allocation	Yes	Classical Rule-based	EV application
[64]	Fuel cell, Battery, SC	DC coupled	Provide power for load in time Good tracking performance of HESS current Obtain a stable voltage of the dc bus	Yes	Projection operator adaptive law	N/S
[69]	Battery, SC	DC coupled	Minimizing the power fluctuation Optimizing the capacity ratio of each ESS	Yes	Real-time optimization	N/S
[92]	Battery, SC	N/S	N/S	Yes	Rule-based Global optimization Real-time optimization	Electric vehicle
[93]	battery, SC	DC coupled	Power Charge/Discharge cycle	Yes	Real-time optimization	PV power generation
[67]	Li-Ion battery, SC	AC coupled	Optimize the cycle life of the HESS	Yes	Mathematic model	Microgrids
[72]	Battery, SMES	DC coupled	Control charge/discharge prioritization	No	Classical	Off-grid load profile/Simulated Sea wave energy conversion/Simulated
[68]	Battery, fuel cell,	AC coupled, On grid	Power	N/S	N/S	Grid data/Real
[94]	Battery, SC	Three-level NPC Converter	N/S	N/S	Classical	Electric vehicle
[71]	Battery Superconducting magnetic ESS	One DC/AC converter Two DC/ DC converters	Smoothing the fluctuations of the wind power output	N/S	Device/system-level control strategies	Wind power generation
[95]	Battery, SC	DC coupled	N/S	N/S	Rule-based	Electric vehicle

Table 7. *Cont.*

Paper	Energy Storage System	Electric Topologies	Optimization		General Control Techniques	Used Data
			Optimization Function	Real Time		
[73]	Battery, fuel cell, electrolyzer	DC coupled, On grid AC	Energy costs, power	N/S	Rule-based	Predicted daily data
[66]	Fuel cell, battery, SC	DC coupled, Off grid	Power	Yes	Real-time optimization	Grid data/Real
[65]	Battery, SC	DC coupled	N/S	N/S		Microgrid
[96]	PbA and Li-Ion battery, SC	Three different architectures	Maintain the grid power and voltage	No	Classical	Residential load/Literature data
[97]	battery, SC	DC coupled	Current, voltage	Yes	Real-time optimization	N/S
[98]	Fuel cell, SC	DC converters	Voltage	No	Classical	Electric vehicle/Simulated
[70]	Battery, SMES	DC coupled, On grid	Current	N/S	N/S	Grid data/Real
[99]	Fuel cell, Battery, Electrolyzer	AC bus and DC bus considered	N/S	Yes	Real-time optimization	Residential load

N/S: Not specified

Previous research on the HESS based on RFB can only be considered a first step toward a more profound understanding of the best optimization parameters to be adopted and the optimal EMS control techniques to be used. For complex HESS based on RFB, the power distribution between the different batteries that make up the HESS, as well as the reaction time, represent the most important optimization parameters. On the other hand, the recent HESSs based on RFB are intended for real-time applications, and the appropriate control techniques to achieve this goal are DL algorithms, e.g., NN and RL.
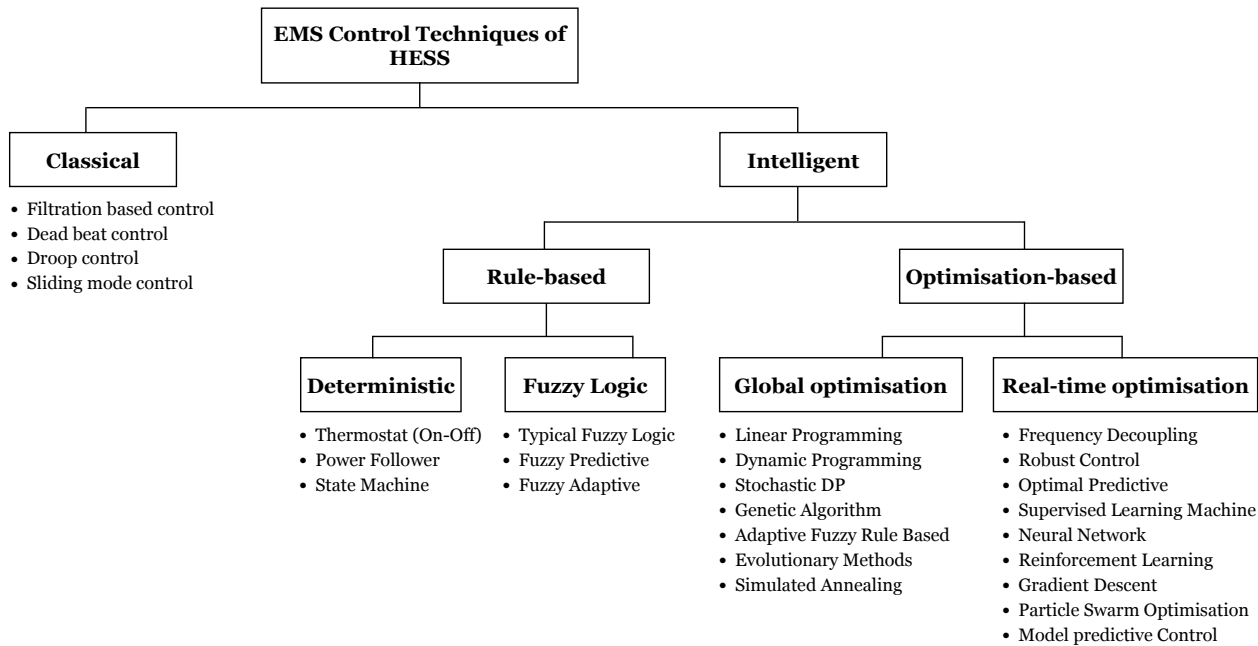

Figure 10. EMS control techniques of HESS [7].

Table 8. A summary of the main real-time EMS control techniques.

	Real-Time EMS Control Techniques	Advantages	Limitations
Classical	Filtration [91]	• Widely adopted for real-time application • Highly computational efficiency • Straightforward	• Complexity of designing filters • Requires an accurate mathematical model • Inefficient in reducing the peak power demand
Rule-based	Fuzzy logic [88,91,92,95]	• Simple implementation • Faster response • Efficient hybrid control strategy • High reliability • Low computational complexity	• Rules are defined based on an expert of the domain • Real-time implementation is the control strategy • Sensitive to changes in system parameters and components
Intelligent / Real-time optimization	MPC [7,92,97]	• Accurate real-time application • Prediction of application future behavior • Avoiding problems • High-scale application control • Easy incorporation of constraints	• Require accurate mathematical model • Sensitive to model parameter variations • High computational complexity
	NN [7,77]	• Accurate real-time application • Low computational complexity • High speed to process results	• Require lots of training data • The prediction accuracy depends on the data sample quality
	RL [85]	• Accurate real-time application • High control performance	• It is data-hungry • It requires a lot of computation
	PSO [69,89]	• Accurate real-time application • Easy implementation • Limited number of parameters	• High computational complexity

5. Related Work

A large number of existing surveys in the broader literature have examined HESS technology. This section outlines the recent reviews on this topic.

In [34], an overview of the different HESS aspects is given. After a brief definition, the author presents the significant advantages and application prospects of HESS. This study shows that HESS is gaining increasing attention in several domains, including smart grid, electric vehicles, and RE park power management. Additionally, it is demonstrated that LIBs play a big part in most of the current HESS applications and they are adopted either as "high energy" or "high power" storage. Then, the different coupling architectures in HESS are investigated, and it turns out that "the two DC/DC converters connected in parallel" is the most commonly used configuration due to its better use of storage capacity. This paper also examines the EMS control techniques and classifies them into rule-based and optimization-based techniques according to power as main control variable. This study briefly points out the main aspects of HESS.

In [7], two fundamental aspects of HESS, namely (1) coupling topologies and (2) EMS control techniques, are investigated. The first part of this work focuses on the architecture, advantages, and limitations of the following coupling topologies: "passive", "semi-active", and "active". The widely used topology in HESS and especially in power systems is "active". The remainder of this study is devoted to an analysis of existing EMS control techniques. The authors identified many techniques and classified them into two groups: classical and intelligent. For each technique, the principle, the features as well as the application domains are specified. Examples of classic techniques are filtration-based control and sliding mode control, and for instances of intelligent techniques, we have robust control, Model Predictive Control (MPC), and hierarchical control. Although this paper mainly presents intelligent control techniques for EMS, research on the technical characteristics of HESS remains limited.

In [6], a survey of SC-based HESSs for standalone DC microgrids is carried out. The paper begins by outlining the different HESS coupling topologies, e.g., passive, semi-active and full active. Furthermore, EMSs are investigated. After identifying the goals and the structure of EMSs, intelligent control techniques are discussed. They are classified into rule-based control techniques and optimization-based techniques. This study explores one type of coupling topology and describes just a few examples of EMS control techniques.

Previous surveys on HESS have mainly investigated the coupling topologies between distinct ESSs and the selection of the suitable EMS control techniques without particularly focusing on a specific type of ESS. Furthermore, RFB have gained increasing interest in the last decade in multiple application domains. Thus, the purpose of this paper is to study the different aspects of HESS based on RFB.

6. Conclusions

HESSs offer high potential to optimize stationary storage applications. The analysis of the KPIs shows the advantages and disadvantages of the different EESs. In many cases, the requirements in the application do not fit perfectly to one storage characteristic of a system. Frequently, the energy and power density limits the operation scenarios. In individual applications, this can usually be compensated by over-dimensioning of the storage system. However, this has negative effects due to the sustainable or economic requirements of the system. Therefore, specific combination of the different storage systems offers a feasible solution. RFB technology profits from combination of SC or LIB in many KPIs (described in Table 2), resulting in high lifetime by the widest window of storage duration, a medium energy density with complementary high power, and fast reaction time for a medium cost level. In this HESS, the RFB acts as an energy component (secondary cluster), while SC or LIB take the role of the power component (primary cluster).

Depending on hybrid components and application scenarios, the coupling architecture of the system has to be optimized. A DC coupled system offers several advantages regarding efficiency and system prices and is selected as an optimized solution for an RFB–SC

combination. A coupling architecture optimization strategy is proposed for the selection of the SC module as well as the converter to optimize efficiency, voltage, and costs.

According to the technical system design, the control strategies for the specific applications offer further optimization potential for HESS. The structure of an EMS is similar to that of an EES, but the possibilities and also the complexity increase. In the first place, the application specific goals have to be defined. Application examples and the control parameters to realize these are summarized in Table 4. In addition, hybridization enables the possibility to add system specific operation goals such as optimizing the dimensioning, efficiency, or the economic rentability. As a supplement, Table 5 shows a map where HESS systems are used for a combined application scenario described in the literature.

Due to the complexity and capabilities of HESS applications, intelligent control techniques such as artificial intelligence are used. As a supplement to real-time operation, prediction data are used to optimize operational efficiency and achievement of the remaining EMS goals.

The use and advantages of HESSs in different combinations and applications are reported in numerous publications. In Table 7, considered publications are listed and itemized according to application specifications. A number of gaps and shortcomings regarding EMS for HESS remain to be addressed:

- The advance of real-time optimization of EMS came at a very high **computational cost**. One solution to address this issue is the use of the **Digital Twin** (DT) concept. DT uses real-world data to create a simulation that predicts system future performance [100]. DT has been recently adopted in many application fields due to several advantages, in particular energy management and operation optimization improvement.
- In the majority of research carried out on HESS, two distinct ESSs are mainly adopted, as illustrated in Table 7, and only three studies have included an RFB [8,9,88]. Further work needs to be conducted on HESS that contain **more than two distinct ESSs** and **at least one RFB**.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating Current
AFE	Active Front End
ANN	Artificial Neural Network

AORFB	Aqueous Organic Redox-Flow Battery
ARIMA	Auto Regressive Integrated Moving Average
BC	Battery Converter
BMS	Battery Management System
CNN	Convolution Neural Networks
D	Distribution Grid
DC	Direct Current
DT	Digital Twin
E	Energy
EC	Energy Component
EES	Electrical Energy Storage
EMS	Energy Management System
ESS	Energy Storage System
E-U	Behind the Meter at End-User Locations
FC	Fuel Cell
GA	Gradient Descent
GAN	Generative Adversarial Network
HESS	Hybrid Energy Storage System
ISC	Supercapacitor Current
Isol	Isolated
G	Grid
KPI	Key Performance Indicator
LIB	Lithium-Ion Battery
LSTM	Long Short Term Memory
M	Manage
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MDPI	Multidisciplinary Digital Publishing Institute
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
MLP	Mixed Linear Programming
MPC	Model Predictive Control
NaS	Sodium–Sulfur Battery
NCM	Lithium–Nickel–Cobalt–Manganese Oxide
NN	Neural Network
Non Isol	Not Isolated
NRMSE	Normalized Root-Mean-Square Error
N/S	Not Specified
OMEI	Open Mobility Electric Infrastructure
P	Power
PbA	Lead–Acid Battery
PC	Power Component
PSO	Particle Swarm Optimization
RE	Renewable Energy
RES	Renewable Energy Sources
RFB	Redox-Flow Battery
RL	Reinforcement Learning
RMSE	Root-Mean-Square Error
RNN	Recurrent Neural Networks
S	System
SC	Supercapacitor
SCC	Supercapacitor Converter
SCM	Supercapacitor Module
SoC	State of Charge
SMES	Superconducting Magnetic Energy Storage
T	Transmission Grid
UPS	Uninterruptible Power Supply
VRFB	Vanadium Redox-Flow Battery
VSC	Voltage at Supercapacitor Module

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