electronics

Review

Optimizing Performance of Hybrid Electrochemical Energy Storage Systems through Effective Control: A Comprehensive Review

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Abstract: The implementation of energy storage system (ESS) technology with an appropriate control system can enhance the resilience and economic performance of power systems. However, none of the storage options available today can perform at their best in every situation. As a matter of fact, an isolated storage solution's energy and power density, lifespan, cost, and response time are its primary performance constraints. Batteries are the essential energy storage component used in electric mobility, industries, and household applications nowadays. In general, the battery energy storage systems (BESS) currently available on the market are based on a homogeneous type of electrochemical battery. However, a hybrid energy storage system (HESS) based on a mixture of various types of electrochemical batteries can potentially provide a better option for high-performance electric cars, heavy-duty electric vehicles, industries, and residential purposes. A hybrid energy storage system combines two or more electrochemical energy storage systems to provide a more reliable and efficient energy storage solution. At the same time, the integration of multiple energy storage systems in an HESS requires advanced control strategies to ensure optimal performance and longevity of the system. This review paper aims to provide a comprehensive overview of the control systems used in HESSs for a wide range of applications. An overview of the various control strategies used in HESSs is offered, including traditional control methods such as proportional–integral–derivative (PID) control, and advanced control methods such as model predictive control (MPC), droop control (DC), sliding mode control (SMC), rule-based control (RBC), fuzzy logic control (FLC), and artificial neural network (ANN) control are discussed. The paper also highlights the recent developments in HESS control systems, including the use of machine learning techniques such as deep reinforcement learning (DRL) and genetic algorithms (GA). The paper provides not only a description and classification of various control approaches but also a comparison between control strategies from the evaluation of performance point of view. The review concludes by summarizing the key findings and future research directions for HESS control systems, which is directly linked to the research on machine learning and the mix of different control type strategies.

Keywords: batteries; hybrid electrochemical energy storage systems; control strategies; energy management system

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1. Introduction

The reckless use of fossil fuels for industry and transport is among the main factors contributing to the increase of environmental pollution and extensive emission of carbon dioxide (CO_2). Growing greenhouse gas emissions have become a major issue that needs international attention, since they fuel global warming [1]. Renewable energy sources (RES) like wind, wave, geothermal, and solar power have quickly become an important source of new electricity production in light of the green energy transition towards carbon neutrality [2]. Renewable energy sources are currently used in various fields including electric mobility, water treatment and water production, and chemical industries [3–5]. According to recent information [6], by the end of 2020, the total installed capacity of solar power had reached 765 GW, while the total installed capacity of wind power had reached 733 GW. The intermittency of RESs power generation, however, poses a danger to the power grid's reliability and safety since problems like wind and solar energy production instability have increasingly emerged as a result of their widespread integration [7]. Energy storage systems (ESS) are becoming essential for the widespread integration of renewable energy sources into power generation, maintaining the security of the electrical grid, and easing the energy system's transition to a more environmentally friendly state because it is a significant resource for flexibility and regulation. Within a variety of DC or AC power sectors, ESSs can offer convenient ways to boost productivity, longevity, and quality [8,9].

Enhancing the reliability and resilience of the electrical grid system, integrating renewable energy sources, and managing energy supply and demand all rely on the implementation of ESSs. Energy storage systems are becoming an integral component of modern electric networks due to their capacity to balance the intermittency of renewable energy sources and provide stable and flexible energy supply [10]. Recent years have seen a major increase in interest in ESSs due to the growing need for sustainable energy alternatives. Energy storage systems play a vital part in tackling the issues related to managing the power flow also in microgrids (MG) by preserving excess energy produced during periods of low demand and releasing it during periods of intense demand, thus boosting the reliability and stability of the grid [11]. In case of microgrids the advantage of ESSs is the capacity to allow the electrical system of MG to incorporate more renewable energy sources [12,13]. There are various types of energy storage systems that are using different operation principles. The various types of ESSs can be classified based on the way a certain kind of energy is utilized for storing. Among the most widely used technologies are mechanical ones, that include flywheels, compressed air, hydro pumped, thermal ones, that include high-temperature storages, latent heat storages [14].

Battery storage systems, or BESSs, are a significant component of ESSs. For example, in a microgrid, BESSs combined with renewable energy sources can be an affordable alternative. By 2030, exclusively in Europe, the Statista Research Department projects that 57 GW of BESSs will be built [15]. Lithium-ion batteries have replaced older technologies in BESSs, particularly for short-term storage. This increased interest in BESSs is being driven by breakthroughs in technology and the declining cost of lithium-ion cells, which appear to be the current dominant existing technology used largely for new installations. Batteries remain the primary expense of BESSs, notwithstanding a decline in cell costs. The energy time-shift, often referred to as self-consumption capacity, of photovoltaic systems is increased by the use of household BESSs. Trends indicate that battery energy storage devices are a common feature of residential solar systems in areas where they are economically feasible. A portion of an evening's electrical needs can be met by discharging a BESS that has been charged with excess photovoltaic energy during the daytime. A larger range of applications, such as frequency regulation, begins after the blackout, and voltage support plus an increase in the self-consumption of RES become possible by the deployment of large-scale BESSs.

In general, battery systems can store energy in the range of 1 to 25 kWh for residential usage and MWh for commercial applications [16]. Both charging and discharging operations cause battery degradation, which shortens the battery's lifespan. The battery degradation process results in varying battery lifetimes, performance degradation, and monetary losses under different operating situations. Therefore, in order to assess battery performance, it is important to assess the health prognostics. There are already many review papers available covering different applications of BESSs. For instance, in [17] the focus is on the use of BESSs for electric propulsion engines in the maritime industry. As more hybrid engine vessels go into service and are ordered, this kind of vessel operation is becoming more and more common, especially in the short-range vessel market.

The hybrid electrochemical energy storage system (HEESS), which combines the advantages of supercapacitors (SC) and diverse chemistry batteries, or only different chemistry batteries, is one of the most promising energy storage technologies. Batteries offer higher energy density and longer cycle life, while supercapacitors are recognized for their high power density and quick charging and discharging times [18,19]. HEESSs, which combine various electrochemical technologies, provide a special combination of benefits that make them perfect for a variety of applications. For instance, HEESSs are becoming quite popular in electric mobility [20]. An HEESS may be able to extend the life of an ESS by reducing the stress on individual energy storage components. By spreading out the charge and discharge cycles among various energy storage techniques, an HESS can reduce the number of cycles that each component experiences and hence lengthen its lifespan. Hybrid energy storage system technology is a rapidly evolving field. The current development status of this technology is promising, with ongoing research and development efforts aimed at improving performance and reliability. These systems are typically developed to address the limitations of individual storage devices and provide a more balanced and efficient energy storage solution.

Researchers first started looking at the possibility of fusing batteries and supercapacitors in the early 2000s, which is when hybrid electrochemical energy storage devices first came into being. Since then, these systems' development has advanced significantly, and they are now being used in a number of industries, such as grid stabilization, renewable energy integration, and transportation [21]. High power and high energy density capabilities are two of the main benefits of hybrid electrochemical ESSs. This makes them perfect for uses like grid stability and electric vehicles, which call for quick charging and discharging. Furthermore, these systems are more efficient than conventional BESSs based only on a homogeneous type of the batteries, which saves running costs and energy waste [22]. Flexibility is another benefit of HEESSs. Through the integration of several battery and supercapacitor types, these systems can be customized to fulfill certain application needs. For instance, a hybrid system with supercapacitors and lithium-ion (Li-ion) batteries can offer a long cycle life and high power density, which makes it perfect for use in electric car applications [23].

Despite the potential benefits of HEESSs, there are several main problems that need to be addressed to fully realize their potential. One of the key challenges is optimizing the integration of different storage technologies to achieve the desired performance and efficiency. This involves developing sophisticated control algorithms and management strategies to ensure seamless operation and coordination among the different components of the system. Another challenge is the cost of HEESSs, which can be higher than traditional single-technology storage solutions. Research is ongoing to reduce costs through advances in materials, manufacturing processes, and system design. Additionally, issues related to safety, reliability, and environmental impact need to be carefully considered to ensure the widespread adoption of HEESSs.

Number of review papers considering HEESSs have been published in recent years. In [24] the authors talked about the significance of employing hybrid energy storage technologies and their growing relevance to the integration of RES. Concept, design, classifications, and a thorough comparison of HEESSs are covered, as well as the latest global trend of HEESSs in RESs and a comparison with key ESS attributes. The same area of application is the focus of [25]. The authors describe interconnection topologies of power electronic devices and provide descriptions of some control strategies.

The main difference in the current review paper compared with previously published ones is not only that RES applications of HESSs are taken into account but also their role in electrical mobility, grid stabilization, and as a source of backup power. The main focus is on the various control systems, their thorough classification, explanation of principles of operation, and also classification of different performance indicators for control systems. With the use of indicators, which are a technique for numerically quantifying the outcomes that the control strategies produce, all these strategies may be assessed, examined, and even compared to one another.

To guarantee maximum performance and endurance, HEESS need advanced control methods [26]. The control strategies for HEESSs, together with their benefits and drawbacks, will be the main topic of this study. Many control strategies—both conventional and intelligent—have been proposed for HEESSs. We will discuss the main types of hybrid electrochemical energy storage systems, including those based on lithium-ion batteries, lead-acid batteries, redox-flow batteries (RFBs) and supercapacitors. We will also explore the challenges associated with controlling these systems, such as balancing the charge and discharge rates of the different components, managing the main characteristics of the system, and optimizing the control algorithms to ensure efficient operation. By examining the latest developments in control techniques for HEESSs, we aim to provide insights into the future of these technologies and their potential to revolutionize the energy storage industry.

The paper begins by description of various electrochemical technologies that are currently used for HESSs discussing the different types of electrochemical battery types used in HESSs and their characteristics (Section 2). The objective is to provide an overview of the current state of recent advancements in battery development, and their classification. The paper then presents an overview of the various control strategies used in hybrid energy storage systems, including traditional control methods such as proportional–integral–derivative (PID) control, as well as advanced control methods such as model predictive control (MPC), fuzzy logic control (FLC), and artificial neural network (ANN) control (Section 3). Then, the methods used to evaluate the performance of control strategies for HEESSs are presented. The importance of accurate performance evaluation in developing effective control strategies is emphasized (Section 4). Discussion of the obtained results takes place in the next part (Section 5), and the application of various control strategies is discussed in the following part (Section 6). In the next part (Section 7), principal information used for the discussion is presented. Then, conclusions are drawn.

Overall, this review paper provides a valuable resource for researchers and engineers working on the design and optimization of HESSs and their control strategies, as well as policymakers interested in promoting the adoption of renewable energy sources.

2. Electrochemical Energy Storages: Secondary Batteries and Supercapacitors

As already mentioned, hybrid electrochemical energy storage systems have gained significant attention in recent years due to their ability to combine the benefits of different electrochemical energy storage technologies. This section provides a review of the different types of electrochemical energy storage, including various types of batteries currently available on the market, or still under the research, and supercapacitors.

Batteries are an essential component of modern life, powering everything from smartphones to electric vehicles. There are three main types of batteries: primary, secondary, and fuel cells. Each type has its own unique characteristics and applications. Primary batteries are single-use batteries that cannot be recharged. They are commonly used in small electronic devices such as remote controls, flashlights, and smoke detectors. Primary batteries have a long shelf life and can hold their charge for years, making them ideal for emergency use. However, they are not cost-effective in the long run and contribute to environmental waste. Secondary batteries, also known as rechargeable batteries, can be recharged multiple times. They are commonly used in larger electronic devices such as laptops, electric vehicles, and solar power systems. Secondary batteries have a higher initial cost than primary batteries but are more cost-effective in the long run. They also produce less environmental waste since they can be reused multiple times. However, they have a shorter shelf life and can lose their charge over time if not used regularly. Fuel cells are a type of battery that uses a chemical reaction to generate electricity. They are commonly used in large-scale applications such as backup power systems, electric vehicles, and space exploration. Fuel cells have a high energy density and can operate continuously for long periods of time. They also produce zero emissions, making them environmentally friendly. However, they have a high initial cost and require a continuous supply of fuel to operate.

Stacks of cells that transform chemical energy into electrical energy make up batteries. Different chemistries based on parallel and series cell connections are used to meet the desired properties of a BESS. Much study and investment are being made in this area at the moment [27]. There is a big variety of batteries used for ESSs, but Figure 1 depicts the primary battery chemistries utilized in BESSs.

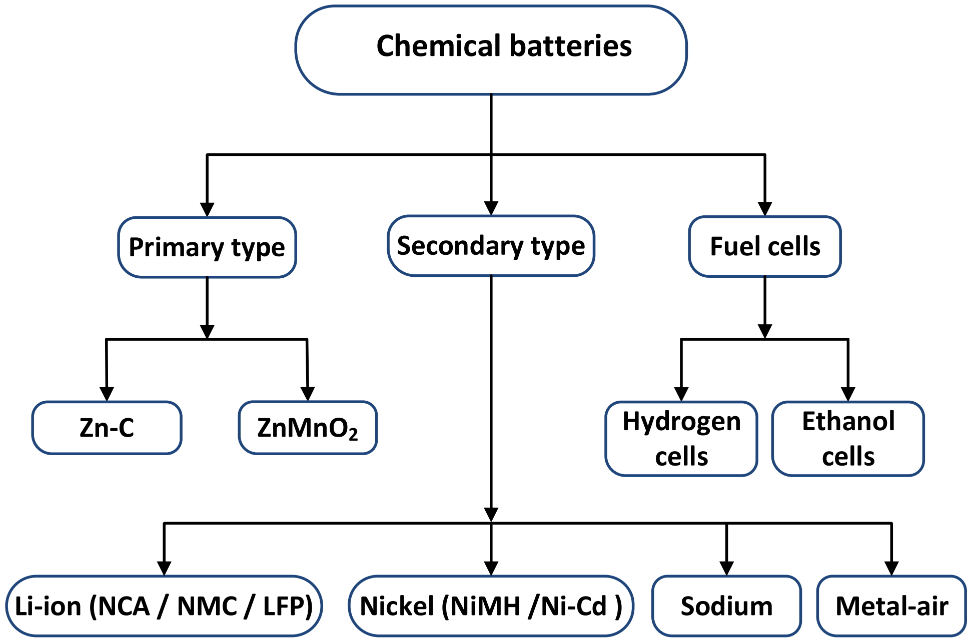

Figure 1. Classification of electrochemical batteries.

2.1. Electrochemistries

Selecting the right chemistry for a given hybrid energy storage application is not an easy choice to make. Every distinct battery chemistry offers certain drawbacks in some situations but is more likely to be beneficial in others. This indicates that choosing a cell involves weighing the benefits and drawbacks of various cell chemistries and shapes.

Although shape and structure can influence ion transportation, the following description only takes into account the chemistry and ignores the additional features provided by the cell packaging. The chemistries' generalities will be the main focus of the assessment. As it was mentioned before primary batteries are typically non rechargeable because of irreversible electrochemical reactions [28]. Therefore, the main focus is on the secondary type of batteries.

2.1.1. Lithium

One of the main types of rechargeable batteries that use lithium as the main component of the anode are lithium batteries [29]. Because these types of batteries recharge more quickly than other commonly used batteries, they are excellent for commercial applications. They are frequently found in electrical gadgets including laptops, cellphones, and electric cars. Because of their high energy density, lithium batteries have the capacity to store large amounts of energy in compact spaces. They additionally feature a lengthy lifespan and may be recharged numerous times. Even though Li-ion batteries have a broad functioning window, to avoid fast degradation it is advised not to attain their charge and discharge levels to the limits [30]. They can be more susceptible to temperature fluctuations and are more costly than other types of battery.

NCA

Nickel and lithium cobalt aluminum oxide is a kind of lithium-ion battery in which the cathode's main constituents are lithium, nickel, cobalt, and aluminum. NCA batteries can provide a lot of power and have a high energy density. They are frequently seen in power tools and electric cars. They can be susceptible to high temperatures and are pricey, though. Because aluminum decreases the impact on the crystalline structure, its presence lessens the volumetric change [31].

Cobalt has favorable structural stability and good electrochemical performance, whereas nickel boasts long-term reversibility. NCA batteries have a high energy density and power output but are expensive and sensitive to high temperatures. Thanks to modern battery management technologies they can guarantee optimal operation when control electronics with a balancing system is included into the BESS containing NCA batteries.

NMC

Lithium nickel manganese cobalt oxide is another type of lithium-ion battery that uses nickel, manganese, cobalt, and lithium as the primary materials for the cathode. NMC batteries have a lower energy density than NCA batteries but are more stable and can provide a longer lifespan [32]. They are commonly used in electric vehicles, power tools, and power systems with integrated renewable energy sources. However, they can be more expensive than other types of lithium batteries.

There are still questions about this chemistry's cost and safety. It is still required to use a battery management system when using a balancing system. In general, nickel manganese cobalt batteries have a longer lifespan and stability.

LFP

LFP is the least expensive cathode material and one of the newest to be used. At higher temperatures, LiFePO4 is more stable than NCA and NMC. In comparison to other chemicals, its nominal voltage is lower. It has been found that temperature has a significant impact on the LFP cells' performance, which is greatly diminished at lower temperatures [33]. One disadvantage of EVs is that their volumetric energy density is lower than that of NMC. Its flat state of charge (SoC) function curve, however, makes it perfect for motor supply, even though it complicates the state of charge reading during cell relaxation.

Compared to other lithium battery types, LFP batteries are less susceptible to temperature fluctuations and have a lower energy density. They are also more stable. They are frequently found in solar power systems, backup power systems, and electric cars. They might, however, weigh more and be bigger than other varieties of lithium batteries.

2.1.2. Nickel Batteries

Metallic nickel and nickel oxide hydroxide are used as electrodes in nickel batteries, a form of rechargeable battery [34]. Under the same electric current circumstances, Li-ion batteries are more energy-efficient than nickel batteries. However, they are preferable at high current rates. Because nickel batteries offer a high energy density, a large amount of energy can be stored in a small amount of space. Power control electronics are far less expensive for BESSs containing nickel batteries since nickel batteries do not require complicated balancing systems because they are typically safer and more resilient against imbalance than lithium batteries [35].

Metal Hydride

The Nickel–Metal Hydride (Ni–MH) battery is one of the most widely used varieties of nickel batteries. Because they do not contain hazardous materials like cadmium, Ni–MH batteries are more environmentally benign and have a better energy density than other types of nickel battery. They are frequently found in high-power applications such as hybrid electric cars, cordless power tools, and others. Ni–MH batteries discharge more slowly than other nickel type batteries [36].

The high energy density of Ni–MH batteries and their ability to store a lot of energy in a short amount of space—is one of its primary benefits. In comparison to Ni–Cd batteries, they also last longer and are less susceptible to the “memory effect”. Ni–MH batteries can also retain their charge for extended periods of time due to their lower self-discharge rate.

Cadmium

The Nickel–Cadmium (Ni-Cd) battery is an additional variety of nickel battery. Because of their fast rate of discharge, Ni–Cd batteries are well-suited for high-power equipment like emergency lighting systems and power tools. However, because they include poisonous cadmium, they are not as environmentally benign as Ni–MH batteries. Furthermore, Ni–Cd batteries are more prone to “memory effect”, which causes the battery to gradually lose its full capacity, and have a shorter lifespan than Ni–MH batteries.

Ni–Cd batteries are a good substitute for lead batteries since they are employed in sealed, maintenance-free cells with a long cycle life and stability in harsh operating conditions [37].

2.1.3. Sodium Batteries

Sodium ions are the charge carrier in sodium batteries, a particular kind of rechargeable battery. These are cutting-edge innovations with the potential to completely transform energy storage, especially in the context of hybrid energy storage systems. The lack of active materials for the battery storage systems is one of its main drawbacks, which is why sodium electrode batteries are intriguing. Because sodium batteries have a high energy density and can store a lot of energy in a little amount of space, this is one of their key advantages [38]. Another advantage is that they do not contain hazardous substances like cadmium or lead, they are also more ecologically friendly and have a longer lifespan than many other types of batteries. Sodium-based batteries have demonstrated potential for several uses. They work very well in HESSs, for example.

In an HESS, high-power output and short-term energy storage can be provided by flywheels or supercapacitors, while long-term energy storage can be provided by sodium batteries. This combination makes it possible to use energy more effectively and may lower the system’s overall cost.

Sodium–Sulfur

Unlike most battery types, sodium–sulfur battery (NaS) technology operates at around 300 °C rather than room temperature. The solid electrodes must melt at a high temperature. Liquid electrodes serve as the basis for the operation; sulfur serves as the anode and sodium as the cathode.

The electrolyte, on the other hand, is made of beta-alumina and is solid. This substance has the ability to conduct sodium ions for the reaction of the battery [39]. The cell of NaS is thermally insulated and hermetically sealed to sustain the high temperature since metallic sodium is sensitive to water. It is anticipated that these batteries will be utilized for uninterruptible power supply, load leveling, and emergency supplies.

2.1.4. Metal–Air Batteries

Metal–Air batteries, also known as Flow batteries, generate electricity through a redox reaction happening in the positive anode between oxygen present in the air and metal. The cells are open to the air to facilitate the reaction [40,41]. The structure is like a fuel cell where the fuel is metal. Compared to the other chemistries, the Metal–Air batteries have more theorical energy density as the oxygen is not stored in the cell.

2.1.5. Chemistry Discussion

After examining the qualitative characteristics of the best-known and most promising chemistries, it is evident that lithium-ion batteries are the best choices for ESSs for cars and general applications. However, solid-state batteries, like sodium anode batteries, should soon replace this chemistry.

It should be mentioned that a control system is always required because, in the majority of cases, battery cell work outside of the safe operation zone might result in hazardous situations that could cause explosions and fires.

Having a control system is crucial when using BESSs, regardless of the chemistry of the batteries. Among the principal causes are the subsequent:

- Safety: The control system continuously monitors the temperature, voltage, and current levels of the battery to prevent overcharging, excessive heat, and other dangerous situations that could cause a fire or explosion.
- Efficiency: The control system optimizes the battery's charging and discharging to ensure that it operates as efficiently as possible. Increased battery life and cheaper maintenance are two benefits of this.
- Performance: In order to meet the demands of the load, the control system ensures that the battery produces the required voltage and power output. It also helps prevent power fluctuations and voltage drops that could damage electronics.
- Monitoring: The control system constantly assesses the health and performance of the battery. Operators are able to detect and resolve issues quickly as a result, preventing downtime and reducing repair expenses.

3. Control Strategies

Within the implementation of an HESS, the control algorithms play a crucial role in ensuring the correct operation of the energy system and the fulfillment of the different performance objectives, managing and coordinating the operation of the various storage elements. Among the diverse tasks that the control strategy can perform in an HESS, it is worth mentioning the following ones [42,43]:

- Optimal energy management: Determine how the energy can be dispatched or distributed among the different storage technologies. Within this scope, it is necessary to consider various features of an HESS, such as the energy and power demand, storage capabilities, characteristics of each ESS technology, and interconnection of all system devices, among others.
- Estimation of key states and indicators: Determine the most important indicators that cannot be directly measured, such as the state of charge (SOC), the state of health (SOH), or the remaining useful life (RUL).
- Safe energy management: Monitor and manage the different variables and indicators of each storage element, ensuring they operate within safe and efficient operational ranges.
- System variables regulation: Ensure the proper control of a signal by means of a defined reference. Most ESS technologies, such as batteries, are sensitive to temperature and voltage variables. Regulating these variables can ensure operation within specified ranges, extending their lifespan and maintaining performance.
- Fault detection and diagnostics: Identify issues within the HESS components or the overall system, allowing for timely maintenance or corrective actions to prevent system failures.
- Grid integration and power quality: Optimize energy flow between the grid and the storage system, contributing to grid stability and supporting power quality.
- Communication and coordination: Ensure effective communication and coordination between different ESS technologies in order to maximize the synergies among various storage elements.

To develop these tasks, there is a wide list of control strategies that can be found in the literature [26]. These strategies differ in properties and performance characteristics such as the model considered, the system linearity, the computational cost, or the robustness, among others. These differences highlight the diversity in control strategies, each with its strengths and weaknesses, making them suitable for different applications and system requirements.

Therefore, the choice of a control strategy depends on the specific characteristics of the system, control objectives, and operational constraints.

There are different control strategies that have been implemented in HESSs. The aim of this section is to discuss them, presenting their characteristics, advantages, limitations, and other important features. The primary objective is to assist the reader in comparing the various strategies and selecting the most suitable one for a particular application or case study.

3.1. Classification of Control Strategies

Generally, classifying the control strategies is not straightforward, being in most cases arbitrary because some controllers may exhibit characteristics of multiple groups, as they often incorporate a combination of techniques to achieve specific control objectives. However, the different control strategies can be classified into four broad groups based on their characteristics and underlying principles [44]:

- Classical controllers: Traditional and widely used algorithms that have been employed in a huge number of applications. These controllers are often characterized by their simplicity, ease of implementation, and effectiveness. Among the existing ones, the proportional–integral–derivative (PID), the root locus control, and the droop control (DC) can be highlighted.
- Model-based controllers: Control systems that utilize mathematical models of the processes or systems they are designed to regulate. These controllers rely on an understanding of the dynamics and behavior of the system to make decisions about how to adjust the control inputs. The sliding mode control (SMC) and the model predictive control (MPC) are example of these control strategies.
- Knowledge-based controllers: Control systems that leverage explicit knowledge, rules, or expertise about a system to make decisions and take control of the actions. These controllers are usually designed based on human knowledge and experience in a particular domain. The rule-based control (RBC) and fuzzy logic control (FLC) are examples of knowledge-based controllers employed in HESSs.
- Learning-based controllers: A class of control systems that utilize machine learning techniques to adapt and improve their performance over time, learning from data, experience, or feedback obtained during operation. The artificial neural network (ANN), deep reinforcement learning (DRL), or genetic algorithms (GA) are examples of recent machine learning techniques developed in HESS control systems.

Each of the strategies described and presented in Figure 2 has its own benefits and drawbacks, and can be used for multiple applications depending on the purpose. Classical controllers can be found in multiple applications across various industries such as process control, motion control, and automotive and power systems, among others. Model-based controllers are utilized in manufacturing, process control, and aerospace industries where a precise understanding of the system dynamics is crucial for effective control. Knowledge-based controllers find applications in areas where human expertise is crucial, such as medical diagnosis or financial analysis. Finally, learning-based controllers find applications where previous control methods may struggle to cope with complex environments, such as robotics or autonomous vehicles. Regarding the benefits and drawbacks of each control strategy topology, Table 1 presents the main advantages and disadvantages of each one of them.

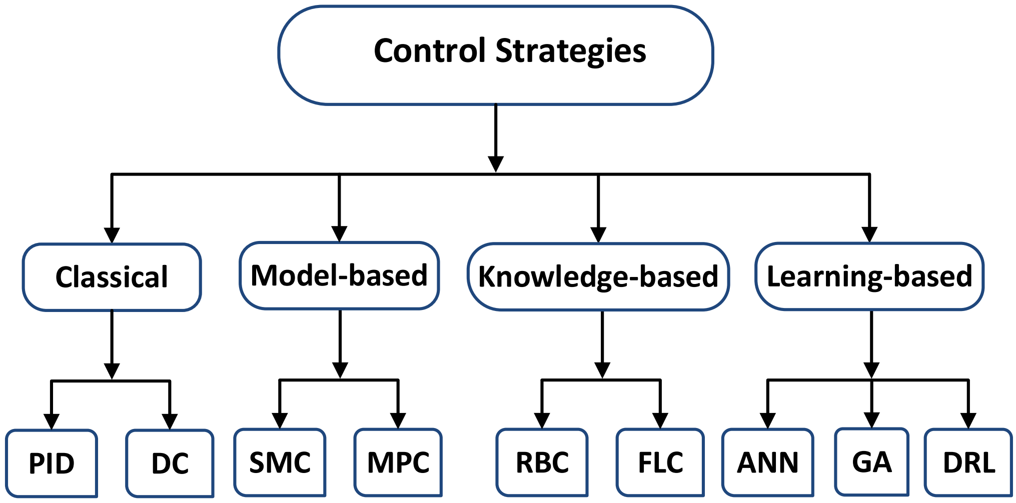

Figure 2. Classification of control strategies with their main techniques employed in HESS control systems.

Table 1. Advantages and disadvantages of the different control strategies [45–47].

Control Strategies	Advantages	Disadvantages
Classical	▪ Simplicity in their design and implementation ▪ Robustness to changes in system behavior ▪ Proven performance ▪ Established methods for parameter tuning	▪ Limited adaptability to complex and nonlinear systems ▪ Performance trade-offs ▪ Manual tuning required with difficulty in handling constraints
Model-based	▪ Precision incorporating detailed understanding of system dynamics ▪ Adaptability to changes in system behavior ▪ Possible optimization of control actions over future time horizon	▪ Model uncertainty can affect the controller's performance ▪ Complexity on develop accurate mathematical models
Knowledge-based	▪ Transparency on the rules and knowledge ▪ Flexibility to be adapted in different scenarios ▪ Intuitiveness	▪ Dependence on humans ▪ Difficulty in knowledge acquisition ▪ No systematic approach to a solution
Learning-based	▪ Adaptability to changes in the system ▪ Generalization of learned knowledge to new situations ▪ Autonomy ▪ Usually, gets to best solutions ▪ Robustness	▪ Data dependence ▪ Training complexity ▪ Computational resources for complex systems and large datasets

3.2. Description of Control Strategies Employed in HESSs

To provide more information about the different control strategies used in HESSs, a brief description of each technique is presented, detailing its operating principle, requirements, and other important features.

- Proportional Integral Derivative (PID)

PID is the most widely used classical controller in engineering and industrial applications, designed to regulate the system's behavior. Thus, it mainly consists of regulating an output measurement, $y(t)$, to track a desired setpoint $SP(t)$. To achieve this operation, the proportional (k_p), integral (k_i), and derivative (k_d) gains are tuned to minimize the error ($e(t)$) between the actual and desired setpoint as can be seen in Figure 3, guaranteeing system stability, and meeting other performance criteria. These criteria include settling time, overshoot, oscillation period, and robustness, among others. Consequently, the tuning process of the PID gains typically involves defining a trade-off problem among these criteria to optimize the controller's performance.

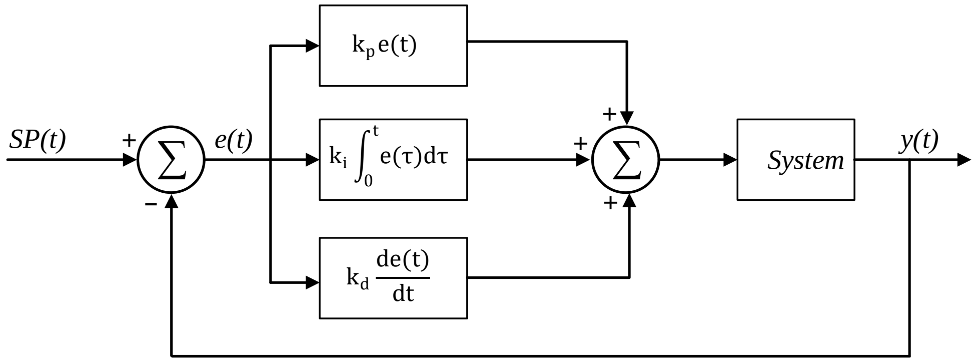

Figure 3. Scheme of a PID controller to track the system output to a desired point.

For simple linear problems, there are many studies and theories that explain and demonstrate how to compute the PID gains to achieve the performance criteria of a specific system [48]. However, for complex systems, the process of adjusting the PID gains is not always straightforward, being necessary to use other tools such as optimization algorithms or recursive methods [49,50].

Concerning their implementation in HESSs, PID controllers offer simplicity, robustness, and adaptability, being possible to be implemented in real time adjusting the gains according to system behavior and changes in operating conditions [51]. However, they may not always provide the optimal control solution for complex HESS configurations with diverse energy storage technologies [52].

- Droop Control (DC)

DC is a method used to coordinate the charging and discharging profiles of multiple energy storage devices. In terms of HESSs, these devices are usually batteries and supercapacitors. The main goal of this technique is to maintain the system stability and balancing the power flow. This technique is usually employed in scenarios where multiple energy sources are connected in parallel, such as microgrids or distributed energy systems. Over the different applications in HESSs, the DC can help maintain system balance, reliability, and resilience in dynamic operating conditions while optimizing the utilization of available energy resources.

The main benefit of DC is the possibility to decentralize control of multiple ESS devices in parallel, allowing for distributed coordination without the need for centralized control. Other advantages of its use include the simple implementation, robustness, and real-time response. On the other hand, it must be noted that DC suffers from limited precision, potential over-compensation, and difficulty in tuning the droop coefficients [53].

DC is usually implemented by means of a proportional control law, relating the power output of the ESS device with deviations in system frequency and/or voltage. Thus, for the case of a frequency DC, it is possible to mathematically express the power output P of an energy storage device i, in response to a frequency deviation Δf:

$$P_i = P_{nom,i} + k_f \cdot \Delta f \tag{1}$$

where P_{nom} is the nominal power output and k_f is the frequency droop coefficient, representing the rate of change of power output with respect to frequency deviation.

On the other hand, for the case of a voltage DC, the equation takes the following form:

$$P_i = P_{nom,i} + k_v \cdot \Delta v \tag{2}$$

where k_v is the voltage droop coefficient used to compensate a change of power output with respect to the voltage deviation Δv.

Concerning their implementation in HESSs, a novel nonlinear dynamic droop controller is used to share power between a supercapacitor and a battery in [54].

- Sliding Mode Control (SMC)

SMC is a model based nonlinear control technique used to drive the system states onto a defined sliding surface, where they must be maintained. This sliding surface is defined in the state space and typically consists of a hyperplane or manifold, as can be observed in Figure 4. In HESSs, the SMC can serve to regulate the operation of the different ESS devices, to ensure the stability, efficiency, and optimal utilization of these resources. Some of these desired operation conditions consist of the state of charge (SOC), power flow distribution and system frequency or voltage [55].

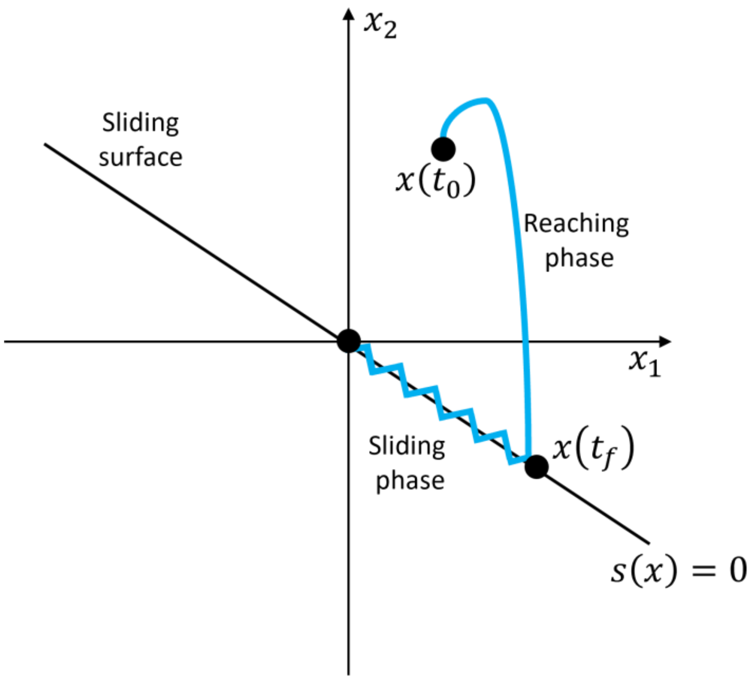

Figure 4. Schematic of the sliding surface of an SMC strategy.

SMC has different advantages, the most important being its robustness against uncertainties or disturbances due to its ability to drive the system states on the predefined sliding surface. Moreover, it can provide a fast response with rapid convergence to the sliding surface. However, SMC suffers from chattering, which is a common phenomenon of this type of technique, consisting of a rapid switching between control modes near the sliding surface [56].

SMC involves the definition of the sliding surface and the design of an appropriate control law that is able to drive the states to this desired surface and maintain them there. On one hand, the sliding surface s is typically defined as a function of the system states x, being possible to defined it as:

$$s(x) = 0 \tag{3}$$

On the other hand, the control law u is typically defined as:

$$u = -F(x) \cdot sgn(s(x)) - k \cdot s(x)\,, \tag{4}$$

where $F(x)$ is a function to shape the convergence behavior, k is the gain used to regulate the sliding motion and achieve the desired performance, and $sgn(s(x))$ is the signum function, which can be compute as follows:

$$sgn(s(x)) = \begin{cases} 1 & s(x) > 0 \\ 0 \quad if & s(x) = 0 \\ -1 & s(x) < 0 \end{cases} \tag{5}$$

Regarding the use of SMC in HESSs, it can be found in applications of hybrid electric vehicles [57] or DC microgrids [58].

- Model Predictive Control (MPC)

MPC is an advanced model-based control strategy that is based on using a dynamic model to predict the future behavior of the system. Thus, the main goal consists of optimizing the control actions over a finite time horizon to satisfy the system requirements. Usually, MPC is defined as an optimization problem where in each sample time, the solver tries to determine the optimal control inputs that satisfy these requirements (minimizing a cost function) taking into account the possible constraints [59]. An example of an MPC diagram can be shown in Figure 5.

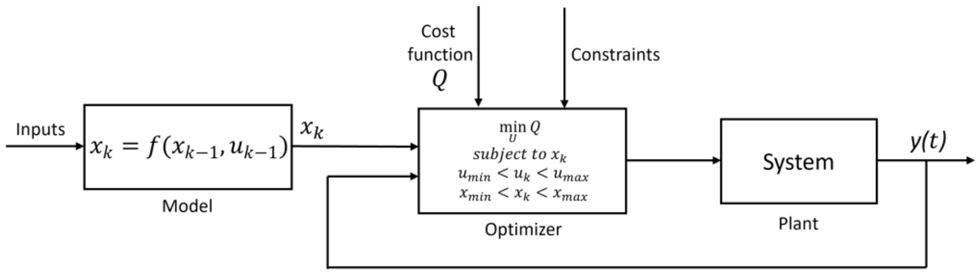

Figure 5. Diagram of the interconnections among the model, optimizer, and system of an MPC controller technique.

Among the main benefits of MPC are its predictive capability, adaptability, and possibility to be used in multivariable control tasks where multiple inputs and outputs are interconnected. However, it requires accurate models capable of properly defining the different phenomena associated to the system, which can be challenging to develop and identify, particularly for nonlinear or time-varying systems. Moreover, it suffers from tuning and computational complexity, which makes it difficult to implement this type of technique in real-time platforms.

As has been mentioned, MPC needs a dynamic model that is usually represented by a set of differential equations:

$$\dot{x} = f(x, u) , \tag{6}$$

where x represents the system states, u is the control inputs, and f is the system dynamic function, which describes how the state evolves based on the current state and control input.

Considering (6), the prediction model can be computed as:

$$x_k = f(x_{k-1}, u_{k-1}) , \tag{7}$$

where x_k is the predicted state at time step k, and x_{k-1} and u_{k-1} are the previous states and control inputs.

Once the model has been defined, it is only necessary to design the optimization problem. For this purpose, it is necessary to define the cost function. In this type of strategy, the cost function quantifies the performance goals and operational objectives. Therefore, it typically includes terms related to minimizing deviations from desired setpoints, minimizing control effort, and satisfying system constraints:

$$Q = \sum_{k=1}^{N-1} L(x_k, u_k) + M(x_N)\ , \tag{8}$$

with Q being the total cost function, N the prediction horizon, L the stage cost penalizing deviations from desired setpoints, and M the terminal cost penalizing the final state of the prediction horizon.

Considering Equations (7) and (8) it is possible to state the optimization problem taking into account the possible system constraints:

$$\begin{gathered} \min_{U} Q \\ \textit{subject to } x_k = f(x_{k-1}, u_{k-1}) \\ u_{min} < u_k < u_{max} \\ x_{min} < x_k < x_{max} \end{gathered} \tag{9}$$

where U is the set of control inputs over the prediction horizon.

By employing MPC in an HESS, operators can achieve optimal energy management, maximize energy efficiency, enhance system stability, and meet operational requirements while considering dynamic changes in energy generation, consumption, and grid conditions [60]. MPC offers a flexible and robust control framework for an HESS, enabling effective integration of renewable energy sources, energy storage devices, and grid interactions. Thus, it is possible to find the MPC in different HESS applications such as light rail vehicles [61] or renewable microgrids and seasonal storage [62].

- Rule-Based Control (RBC)

RBC is a control strategy that is based on the use of predefined rules to compute the system control actions to be developed. Thus, it is a heuristic technique that uses rules as knowledge representation [63]. RBC algorithms use upper and lower set points to control systems within given boundaries of the operating conditions. Usually, the control actions consist of simple switch on/off operations that are imposed by the human knowledge and thresholds that define how to manipulate the information [64].

Among the main advantages of RBC are its transparency, flexibility, and low computational complexity, making it possible for it to operate without the need to solve optimization or complex mathematical problems. On the other hand, it suffers from limited performance and lack of adaptability. Moreover, it directly depends on human knowledge, finding it difficult to deal with complex systems that may arise from conflicting rules that can lead to control ambiguity.

In order to design RBC algorithms, the rules usually come in the form of if/then statements that evaluate the system status. Depending on the answers to these sentences, the different control actions take place. An example of an RB algorithm diagram can be observed in Figure 6.

This technique has been employed in different studies related to HESSs. In [65], it is used to design an energy management system for an experimental battery and supercapacitor HESS used in electric vehicles. A rule-based dual planning strategy of an HESS is developed and analyzed in [66].

- Fuzzy Logic Control (FLC)

FLC is based on the use of fuzzy logic employing linguistic variables, fuzzy sets, and fuzzy rules to develop the system control actions. Different from the RBC, fuzzy logic is understood as a mathematical language where the variables can take values compressed between 0 (false) and 1 (true) [67]. The term fuzzy involves concepts that cannot be expressed as totally true/false, but rather as partially true/false [68]. Therefore, FLC does not operate with discrete values in contrast to classical digital controllers.

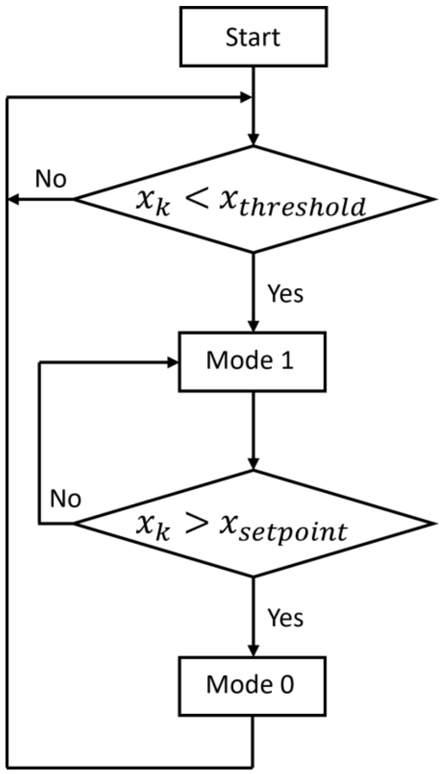

Figure 6. RBC decision scheme principle.

The design of an FLC implies the definition of variables and fuzzy sets to represent the system states and control actions. Based on these definitions, different fuzzy rules are formulated that relate the system inputs with the outputs. To determine the fuzzy output sets, the logic operators and, or, not are usually considered.

The main advantages of this technique are its robustness to uncertainty, its adaptability, and its intuitive design that facilitates understanding, being widely used for commercial and practical applications. As disadvantages must be note its complexity when dealing with large number of fuzzy sets and rules, a design that involves expertise and trial-and-error tuning, and its performance limitation when dealing with complex systems such as nonlinear or time-varying.

FLC has been used in multiple applications concerning HESSs, such as for the management of a grid connected to a PV system [69], for the control of hybrid renewable energy system using real power and wind data [70] or the regulation of the voltage in hybrid electric vehicles [71].

- Artificial Neural Networks (ANN)

ANN are a branch of machine learning techniques based on the use of neuronal organization principles. They mainly consist of the connection of units or nodes (artificial neurons) by means of edges that define the relationships among all nodes. Typically, each node and edge has a weight that is adjusted as learning proceeds and the different outputs are computed by mathematical functions. Usually, the neurons are aggregated into layers, each one of them performing different transformations (functions) of the input signals. These signals pass through the different layers (input, output, and hidden) adjusting the weights through learning algorithms such as backpropagation or reinforcement learning [72]. The typical structure of an ANN is presented in Figure 7.

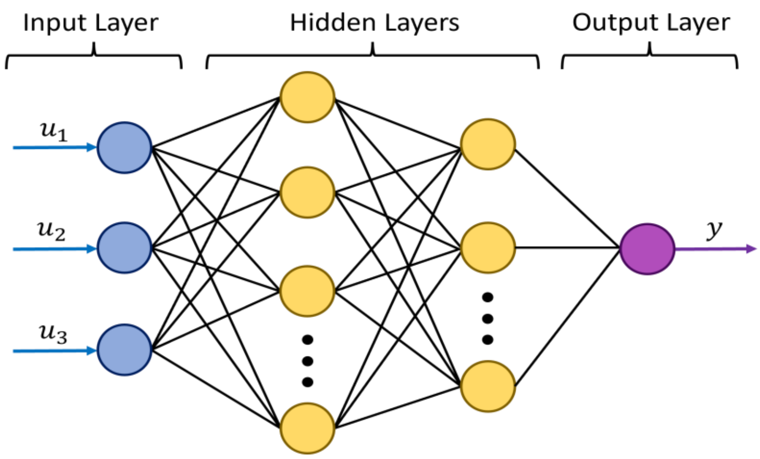

Figure 7. Structure of an ANN with the input, hidden, and output layers.

The main benefits of ANN include the development of complex models capable of adjusting data of nonlinear systems with uncertain relationships, and the adaptability and generalization of neural networks to unseen data. However, they are often black-box models without the possibility of understanding the architectures and extrapolating conclusions or relationships among the different signals. Moreover, they can require complex computational procedures when large amounts of data are used and are susceptible to overfitting.

Among the different applications where ANN are found are the industry fields of robotics, process control, and autonomous devices. Within the scope of HESSs, it is possible to find different studies that present this control strategy. A SOC estimator is developed using an ANN in [73], while a power estimation is developed in [74] for hybrid wind-solar energy systems. In terms of modeling, an ANN is employed in [75] to develop a model of a hybrid electric vehicle.

- Genetic Algorithms (GA)

Genetic algorithms are metaheuristic optimization techniques inspired by the process of natural selection and genetics. These techniques are typically used to search and find high-quality solutions to optimization and search problems using operators such as mutation, crossover, or selection [76].

To design a GA it is necessary to define the candidate control strategies as individuals of a predefined population. Each one of these candidate solutions has a set of properties that can mutate or alter. To perform these changes, the solution candidates are usually represented in binary strings where each bit (or parameter) can represent a control variable or decision. During the optimization procedure, the GA evolves iteratively using a fitness evaluation that quantifies the control objectives (similarly to the cost functions seen in MPC problems). In this algorithm, individuals with higher fitness values are selected for reproduction, while the others are gradually replaced by better solutions over successive generations until the end of the process.

The main advantages of GA are their robustness and adaptability in adjusting the genetic operators, population, and candidates, making it possible to solve non-convex and nonlinear problems. As for the drawbacks, as with other learning-based techniques such as the ANN mentioned, they have a high computational cost, and the structure of the algorithms yields to black-box structures where it is not possible to interpret the results of the resulting control actions.

In terms of applications, GA control finds various domains including robotics, financial engineering, and control system design. Concerning HESSs, GA have been used to develop optimal sizing for a solar photovoltaic and wind turbine generator [77] and to model and design an HESS consisting of photovoltaic panels, a microturbine, and a battery [78].

- Deep Reinforcement Learning (DRL)

DRL is a learning-based control technique that combines reinforcement learning and deep learning, allowing agents to make decisions from unstructured input data [79]. These algorithms operate by training artificial agents to learn optimal control policies. Usually, the agents explore the environment and update the parameters of an ANN through optimization algorithms. The learning process considers two different concepts: the search for new actions (exploration) and leveraging known actions (exploitation). Thus, these strategies can deal with very large input datasets to decide what actions must be performed in order to perform the optimization problem.

The main benefits of the use of DRL controllers are its flexibility and scalability. However, as with previously mentioned techniques, they can lead to overfitting, computational complexity, and lack of interpretability of the results obtained.

DRL has been used for a wide number of applications including robotics, video games, computer vision, education, financial engineering, and healthcare [80]. In the field of HESSs, DRL is used in [81] for balancing lead and hydrogen storage and in [82] for electric vehicles purposes.

4. Performance Evaluation

All the control strategies previously seen usually present high-grade control of the energy, but to gain a better understanding of the reality of their work they need to be studied correctly. All these strategies can be evaluated, reviewed, and even compared using indicators—a tool to quantify in a numeric way the results given by the strategies. The indicators focus on competence to get the best results on the objectives described in all the studies, putting the spotlight on the performance of the system reviewed, making them what is known as performance indicators.

The state of the art for the control of HESSs provides the performance indicators that are most used to analyze the results gained from all the strategies. Some of these indicators can be very specific as a consequence of their objectives but all of them provide information about the results.

4.1. Description of Performance Indicators in HESSs

For a better understanding of all these indicators, this section gives a brief description, an explanation of the objective or object that focuses on evaluation, and a simple explanation of the more common ways to calculate it.

- Energy loss

The energy loss is the energy that is wasted. This loss happens in all the elements that comprise the system (battery, Ultracapacitor, DC-DC).

It is considered an interesting performance indicator as there is a direct relation between lower energy loss and a better performance of the system.

This indicator is calculated for every element considering the models used to explain or simplify them. For the battery and the ultracapacitor this loss is calculated from the resistances in the model while for the DC–DC, it is calculated from the efficiency [82–88].

- RMS current

The RMS current is the root mean square current used to represent the effective value of an AC current. It is usually calculated for batteries.

It is considered an interesting indicator as it is a fair representation of the aging of a battery as its reduction causes a direct increase of the battery's lifetime.

This indicator is calculated with the root square waveform of the battery current, as seen in Equation (10) [82,83,85,87,89–91].

$$I_{RMS} = \sqrt{\frac{1}{T}\int_0^T i^2\, dt} \tag{10}$$

- Cost

The cost is the price or amount of money needed to have the system or power elements working. The type of cost that is usually considered as an indicator is the general cost, which is the addition of all of the costs. However, it can also be considered as only the initial cost, the price necessary to start the use of the engine, or the energy cost. The cost can also be considered in relation to other variables like the annual average cost, which takes into account the time, or the distance-based cost, which takes into account the distance.

It is considered an interesting indicator as a lower cost is usually an objective in control strategies [92–97].

The way it is calculated is by adding all the prices.

- Charge/discharge peak current

The charge/discharge peak current is the maximum flux of energy the battery experiences in its use while being charged or discharged. The variation of current, i.e., the difference between the minimum and the maximum during the battery's use, can also be considered as an indicator, but the peak current is more frequently used.

It is considered an interesting indicator as a lower peak or variation is directly related to a longer battery life.

This indicator is usually calculated by considering the voltage and resistances from the battery model, or is directly measured [83,84,87,98,99].

- State of charge (SOC)

The state of charge, also known as SOC, is the percentage of power that remains in the battery or ultracapacitor. Its opposite, the depth of discharge, which is the percentage of power that has been used in the battery or ultracapacitor, can also be an indicator. Aside from the state of charge in a specific time of the element usage, it is also considered the final SOC, the SOC left when the element finishes an activity, and especially the variation of SOC, the difference between the initial and the final SOC after an activity. As an indicator it is calculated more for the battery.

It is considered an interesting indicator as a lower variation and a greater final SOC are related to a higher lifespan of the battery.

This indicator is calculated with the ampere–hour integration, as seen in Equation (11) or an extended Kalman filter [93,98–103].

$$SOC = \frac{Cr}{Cmax} = \frac{Cr - \eta \int_0^t I\, dt}{Cmax} \tag{11}$$

- Lifespan

The lifespan is the time the battery or ultracapacitor can be used before it stops operating. The end of life is a very similar concept but highlights the moment in time when it stops operating. As an indicator it is calculated more for the battery.

It is considered an interesting indicator as having a longer time of use of the battery is one of the principal objectives in the control strategies.

The way it is calculated is by measuring the time with the simulations [92,96,97,99,104].

- Ah throughput battery

The Ah throughput battery is the energy delivered or stored by the battery.

It is considered an interesting indicator as it is a fair representation of the extension of the battery life as its reduction is connected to a longer battery life.

This indicator is calculated with the derivation in time of the battery current, as seen in Equation (12) [83,101,103,105].

$$A_h = \frac{1}{3600} \int_{t_0}^{t_{end}} |I| dt \tag{12}$$

- Efficiency

The efficiency is the ratio between the energy used and that which is needed for the system. Aside from the general efficiency from the system, other types can also be considered, like the feedback efficiency, which reflects the use of the system during traction conditions, and the storage efficiency, which reflects the use of the system during traction conditions.

It is considered an interesting indicator as a better efficiency indicates better functioning of the system.

This indicator is calculated by dividing the output energy or the energy used and the input energy or the total energy, as seen in Equation (13) [82,98,100,106].

$$\eta = \frac{E_{out}}{E_{in}} \tag{13}$$

- Temperature

The temperature is the amount of heat that is measured from the battery. It is considered an interesting indicator as a lower temperature, especially if the temperature never exceeds the limit indicated by the battery, is directly related to a larger lifespan.

The way it is calculated is by considering the thermal model for the battery to simplify calculations [84,99,105].

- Capacity loss

The capacity loss or fade is the level of charge or energy that is lost and can no longer be used or delivered in a battery.

It is considered an interesting indicator as a larger capacity loss implies a shorter lifespan.

The way it is calculated is usually based on a semi-empirical life model considering the activation energy, the absolute temperature, the Ah throughput, and the battery current rate, as seen in Equation (14) [101,105,107,108].

$$Q_{loss} = B \times e^{\left(\frac{-E_{\alpha}}{RT}\right)} \times A_h^{\rho} \tag{14}$$

- Cycle life

The cycle life, which can also be estimated, is the total number of cycles, which is defined as a charge and a discharge of an element, during its operational lifetime.

It is considered an interesting indicator as a larger cycle life indicates a longer operational lifetime of the element.

The way it is calculated is by measuring it through simulations [89,105,109].

- Energy consumption

Energy consumption is the energy used by the power electric elements.

It is considered an interesting indicator as one of the objectives of the control of the system is the greater use of renewable energies, and bigger energy consumption can replace some of a non-renewable energy.

The way it is calculated is by measuring it from the simulations [94,110].

- Remaining life

The remaining life is the percentage of the life the battery has in comparison with its cycle life or lifespan. Life loss is the complementarity of the remaining life, i.e., how much the battery has already lost.

It is considered an interesting indicator as a longer remaining life implies a longer lifespan.

This indicator is calculated by considering the cycle life and the depth of discharge, as seen in Equation (15) [100,111].

$$Remaining\ life = 1 - \frac{\Sigma \frac{N_{pls}(DOD_{100\%})}{N_{pls}(DOD(t))}}{N_{pls}(DOD_{100\%})} \quad (15)$$

- Total number of charges and discharges

The total number of charges and discharges is the number of times the element is filled and emptied with energy.

It is considered an interesting indicator as the more times the battery is charged, a part of its capacity is lost from the current for the charging, impliying a shorter lifespan.

This indicator is calculated by measuring the number during the simulation [100].

- Battery voltage fluctuation

The battery voltage fluctuation is the difference between the initial and the final voltage during a specific time.

It is considered an interesting indicator as its reduction is directly proportional to the extension of the battery life.

The way it is calculated is by subtracting the difference between the initial voltage and the final one, as seen in Equation (16) [99,112].

$$\Delta V = |V_{out} - V_{in}| \quad (16)$$

- Mileage

The mileage is the distance that the vehicle is capable of achieving with its power elements.

It is considered an interesting indicator as a longer mileage implies a better functioning of the system.

The way it is calculated is by measuring it during the simulations [89].

- Autonomy

Autonomy refers to the time the system is capable of functioning for before it runs out of energy.

It is considered an interesting indicator as a longer autonomy will be considered to be linked to a better performance of the system.

The way it is calculated is by measuring during the simulations [113].

- Fuel consumption

Fuel consumption refers to the fuel used for the system to work properly.

It is considered an interesting indicator as one of the objectives of the control of the system is the greater use of renewable energies.

The way it is calculated is by associating the level of consumption it will need with the energy needed from this method of measuring it through simulations [94].

- Computational time per second

The computational time per second refers to the time needed for the optimization method to achieve its solution.

It is considered an interesting indicator as a lower time of response indicates an easier online implementation.

The way it is calculated is by measuring the time [94].

- Output energy

The output energy is the energy that leaves the element to be used in the system.

It is considered an interesting indicator as longer output energy indicates a greater use of the element that erodes it.

The way it is calculated is with the integrator of the power required of the element [95].

- Peak power impact

The peak power impact is the influence of the maximum power in the element.

It is considered an interesting indicator as a bigger impact will directly affect the performance and life of the element.

The way it is calculated is with the integrator of the power required of the element [95].

- Replacement

The replacement is the times that the battery is changed after stopping being useful. It is considered an interesting indicator as a low battery lifetime will need a bigger number of replacements.

The way it is calculated is by measuring the replacements during simulations [97].

- Energy recovery

Energy recovery is the energy gained to the system from the regenerative braking.

It is considered an interesting indicator as a more efficient capture and usage of this energy indicates a better performance of the system.

The way it is calculated is by measuring the energy [97,114].

4.2. Classification of Performance Indicators

All the previous indicators seem to range across different types of information about the batteries or ultracapacitors. These different objects or objectives, which can be considered areas of information, can become a possible general classification for the performance indicators, offering a clearer picture of the results gained from the control strategies.

For a better understanding of this classifications, below is a brief description of the areas.

- Energy/Capacity: This area includes all the performance indicators that focus on studying the energy of the system or its elements or the capacity of the battery or ultracapacitor, especially the part that is wasted. The energy and capacity indicators are strongly related to the idea of increasing the lifetime of the battery and can also be related to the efficiency.
- Current/Voltage: This area includes all the performance indicators that focus on studying the current and the voltage from the system. Some of the indicators for current and voltage can be related to the information of the lifespan.
- Lifespan: This area includes all the performance indicators that focus on studying what the operational lifetime the battery, or ultracapacitor, can offer while still being completely functional. These types of indicators reveal important information, as it is a direct method to identify the time that the battery is or will be useful.
- State of charge: This area includes all the performance indicators that focus on studying what is known as the state of charge (SOC), which is the energy usable from the battery or ultracapacitor. With the state of charge indicators, some of the information about the level of performance of the system can be obtained. There is also a relation between some of these indicators and the lifetime of the battery.
- Cost: This area includes all the performance indicators that focus on studying the cost of the system, especially the overall cost, but it can also focus on a more specific type of cost depending on the objective.
- Others: This area includes all the performance indicators that are not related to the previous areas and at the same time seem to be focus on more specific information related to very specific objectives.

Considering these categories, all the indicators previously explained have been classified into them, as seen in the Figure 8.

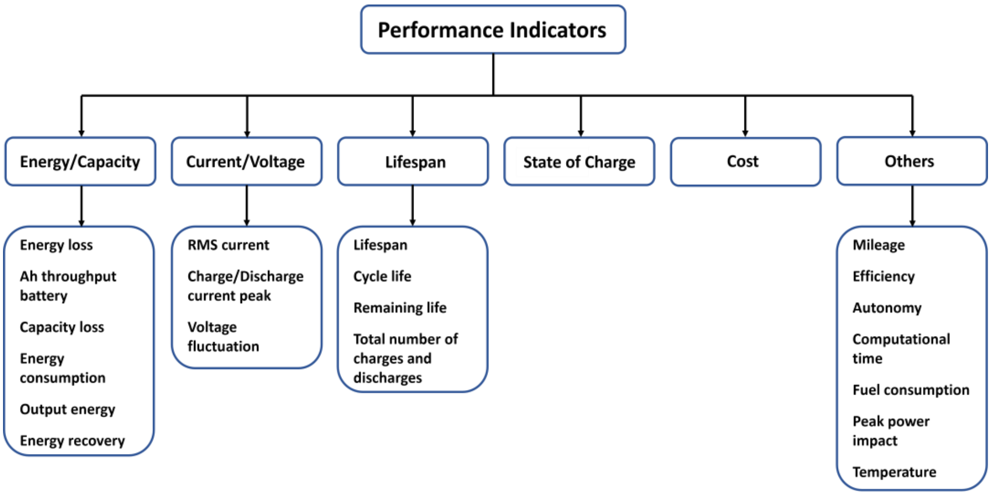

Figure 8. Classification of the different performance indicators.

5. State of the Art of HESSs

The principal information used for the discussion comes from different studies that have proved the way to work with different control strategies with HESSs. To gain a better picture of everything seen, as some of the information has needed to be simplified, below is a summary that scrutinizes every control strategy with the characteristics used for the study, to understand all the possibilities that can manage an EMS. This summary is seen in the Table 2 which considers the control strategy used, the topology considered for the study, some characteristics of the study description on the control strategy, the results, the performance indicators used for the results, and the application.

Table 2. Summary of the different control strategies found in the HESS literature.

Cite	Typology	Control Strategies	Description	Results	Performance Indicators	Application
[82]	Semi-active • Battery • Ultracapacitor	Knowledge-based with optimization Rule based + dynamic programming	EMS rule based, providing an initial set of rules which are afterwards optimized with a DP offline actualizing it with the addition of new rules/conditions.	Better results than rule-based without optimization.	■ Battery current C-rate RMS ■ Energy loss (total, battery, ultracapacitor and DC-DC) ■ Efficiency	■ Plug-in hybrid electric vehicles
[83]	Semi-active • Battery • Supercapacitor	Optimization-based • Adaptive model predictive control (AMPC)	EMS Adaptative model predictive control offering better control with the nonlinear part of the HESS. A quadratic programming (QP) optimization is used to solve de optimization problem in the rolling-horizon.	Better results in general than PI and Model predictive control (MPC).	■ Energy loss (total, battery, ultracapacitor and DC-DC) ■ RMS current ■ Ah throughput of battery ■ Charge/Discharge Peak current	■ Electric vehicles
[100]	Active • Battery (LTO) • Supercapacitor	Knowledge-based with optimization • Fuzzy logic + genetic algorithm	EMS fuzzy logic, based in 2 different layers splitting the process into 2 stages to simply considering 4 different types of working conditions. A multi-objective genetic algorithm is used to optimize the membership functions.	Better results in general than fuzzy logic alone and fixed threshold control strategy.	■ Feedback efficiency ■ Storage efficiency ■ Global average DOD ■ Global average SOC ■ Total number of charges and discharges ■ ESM remaining life ■ ESM life loss ■ Interval life loss	■ High speed rail

Table 2. *Cont.*

Cite	Typology	Control Strategies	Description	Results	Performance Indicators	Application
[98]	Parallel active • Battery (LFP) • Ultracapacitor	Knowledge-based • Adaptative fuzzy logic	EMS fuzzy logic based, providing robust performance with heuristic information. The fuzzy logic is optimized with an off-line optimal parameter tuning and driving pattern recognition.	Slightly better results than other conventional control methods.	■ System efficiency ■ Battery current variation ■ UC SOC difference	■ Hybrid electric vehicles
[101]	Semi-active • Battery • Supercapacitor	Optimization-based • Pontryagin's Minimum Principle (PMP)	EMS Pontryagin's Minimum Principle based, providing an optimal solution calculating Hamiltonians presenting a lower computational time than other optimization-based methods.	Better results than a rule-based strategy or a single battery system.	■ Final battery SOC ■ 10-year capacity loss	■ Electric vehicles
[115]	Semi-active • Battery • Supercapacitor	Knowledge-based and optimization-based • Filtration • λ-control	Comparison between EMS filtration based, with a low frequency (battery) and a high frequency (UC), and an EMS λ-control based with the minimization of a performance criterion considering some constraints.	Optimization based gives better results than filtration.	■ Battery current EMS	■ Electric vehicle
[92]	Semi-active • Battery (LFP) • Battery (LTO)	Knowledge-based with optimization • Fuzzy logic + differential evolution algorithm (DEA)	EMS fuzzy logic based, considering 6 operating modes with its optimization with a heuristic algorithm, a differential evolution algorithm.	Better results than a single battery.	■ Lifespan ■ Annual average cost ■ Distance-based cost	■ Electric vehicle
[84]	Semi-active • Battery (NCA) • Battery (LTO)	Learning-based • Deep Q-Learning	EMS Deep Q Learning based, with a machine learning reinforcement type of method optimizing its reward considering the environment, agents, and actions.	Better results than a single battery and Q-Learning.	■ Current battery ■ Temperature ■ Energy loss	■ Electric vehicle
[93]	• Battery (LFP) • Battery (LTO)	Knowledge-based • Rule based	EMS rule based, considering 6 different operating modes.	Better results than a battery alone.	■ Daily SOC trajectories ■ Cost	■ Electric vehicles ■ Electric Bus
[99]	Semi-active • Battery • Supercapacitor	Knowledge-based • Wavelet + fuzzy logic	EMS wavelet based, with decomposition and reconstruction separating the base and the transient power. A fuzzy logic control is constructed considering the wavelet results.	Better results than battery alone.	■ Battery temperature ■ Battery service life ■ Battery maximum discharge current ■ Battery voltage fluctuation ■ Variation SOC	■ Electric vehicle
[85]	Semi-active • Battery (Nanophosphate Lithium-ion) • Ultracapacitor	Knowledge-based with optimization • Load adaptative rule based + dynamic programming)	EMS Dynamic programming based, determining the optimal control simplifying and breaking down into smaller equations. To get an online optimization, the DP results are used to set a rule based, which is later optimized with a genetic algorithm.	Better results than RB alone.	■ Energy loss (total, battery, ultracapacitor and DC-DC) ■ Max battery current ■ RMS battery current ■ Battery Ah throughput	■ Electric vehicles
[89]	Semi-active • Battery (LTO) • Battery (NCM)	Knowledge-based with optimization • Fuzzy logic + NSGA-II	EMS fuzzy logic based, with 2 different FLC controllers which is optimized with an NSGA-II algorithm optimizing the membership functions proposed by experts.	Better results than fuzzy logic based alone.	■ Mileage ■ Unit distance capacity face rate ■ Cycle life	■ Plug-in hybrid vehicle

Table 2. *Cont.*

Cite	Typology	Control Strategies	Description	Results	Performance Indicators	Application
[107]	Semi-active • Battery (LTO) • Battery (NCM)	Knowledge-based • Fuzzy logic	EMS fuzzy logic based, with all the rules and membership functions composed by experts.	Better results than conventional fuzzy logic.	■ NCM capacity fade ■ LTO capacity fade	■ Plug-in hybrid vehicles
[104]	Semi-active • Battery • Ultracapacitor	Optimization-based and learning-based • Convex optimization • Neuronal network	Comparison between a EMS convex optimization based, an offline method, and a neural network, and a reinforcement learning machine learning method, which is trained with the convex optimization results.	Convex gives better results than Neuronal network.	■ Battery end of life	■ Electric vehicle
[110]	Semi active • Battery (LFP) • Ultracapacitor	Knowledge-based with optimization • Filter based + dynamic programming	An EMS filter based is used to divide the low and high frequency, provided by battery and Ultracapacitor respectively which is optimized by providing the cutoff frequency with dynamic programming.	Better results than filter based alone.	■ Energy consumption	■ Electric vehicle
[105]	Active • Battery (LFP) • Ultracapacitor	Optimization-based • Stochastic dynamic programming	EMS stochastic dynamic programming based, created for online optimization based on an integrated dual-loop optimization with an inner loop based on dynamic programming and an outer loop based on simulated annealing.	Better results than a battery only system.	■ Capacity loss ■ Battery temperature ■ Estimated battery cycle life	■ Plug-in electric vehicle
[86]	Semi-active • Battery (NCR) • Battery (LTO)	Optimization-based • Deterministic dynamic programming (DDP) • Stochastic dynamic programming (SDP)	Comparison between a deterministic dynamic programming, the offline method, and stochastic dynamic programming, the online method.	SDP presents better results than other optimizations based in real time systems.	■ Battery system energy losses	■ Electric vehicle
[113]	Parallel active • Battery • Supercapacitor	Knowledge-based with optimization • Fuzzy logic + particle swarm optimization (PSO)	An EMS fuzzy logic with the membership functions being optimized by particle swarm optimization, a metaheuristic algorithm.	Better results than battery alone system.	■ Autonomy	■ Electric vehicles
[94]	• Battery • Gas engine	Optimization-based • Stochastic model predictive control (MPC) + Pontryagin's Minimum Principle (PMP)	EMS Pontryagin's Minimum Principle based, providing an optimal solution using Hamiltonians that is transformed into an online method with a stochastic model predictive control.	Better results than other optimization-based strategies.	■ Energy consumption ■ Fuel consumption ■ Peak power ■ Total cost ■ Computational time per second	■ Plug-in hybrid electric bus
[95]	Semi-active • Battery (NaNiCl2) • Supercapacitor	Knowledge-based with optimization • Fuzzy logic + genetic algorithm (GA)	EMS fuzzy logic is designed by experts and has its membership functions optimized by a genetic algorithm. Dynamic programming is also considered to compare results.	Better results than a fuzzy logic-based system alone but worse than DP.	■ Output energy from battery ■ Peak power impact on the battery ■ Total energy cost	■ Electric vehicle
[90]	Semi-active • Battery (LFP) • Ultracapacitor	Optimization-based • Pontryagin's minimum principle (PMP)	EMS Pontryagin's Minimum Principle based, providing an optimal solution using Hamiltonians.	Better results than rule-based and some optimization-based systems.	■ Battery RMS current	■ Electric vehicles

Table 2. *Cont.*

Cite	Typology	Control Strategies	Description	Results	Performance Indicators	Application
[96]	Semi-active • Battery (LTO) • Battery (LFP)	Knowledge-based • Filtration-based	An EMS rule-filter based, considering 6 different modes to determine the power split between batteries.	Better results than battery only system.	■ Lifespan ■ Annual average cost ■ Cycle-related cost	■ Electric vehicle
[87]	Semi-active • Battery (Lithium-ion) • Ultracapacitor	Optimization-based with learning-based • Dynamic programming + Random forests	EMS dynamic programming based, connected with a multi-objective Grey Wolf optimizer to acquire the optimal solution to the sizing and objective function while using Random Forests, machine learning trained with the results, to get an online method.	Better results than other random forest systems and similar to dynamic programming system.	■ Energy loss of the battery, the DC/DC and the ultracapacitor and total ■ Root-mean-square current of the battery (RMS) ■ Peak discharge and charge current ■ Ah-throughout of the battery	■ Electric vehicles
[97]	Semi-active • Battery (LFP) • Ultracapacitor	Knowledge-based • Wavelet-based	EMS wavelet based, with decomposition and reconstruction separating the high-frequency, ultracapacitor, and the low frequency, battery.	Better results than a battery alone and a SOP-based system.	■ Battery lifetime ■ Replacement ■ Initial cost ■ Total cost ■ Energy recovery	■ Electric vehicles ■ Electric motorcycles

6. Discussion of Results

The different descriptions and classifications between the control strategies and the indicators provide a breakdown of all the results the different EMS strategies can offer to the HESS. All these strategies seem to present a robust result that is always better than the non-usage of an EMS. The most frequently found control strategies for HESS are knowledge-based and the learning-based. In this section, the focus will be on the comparison between the control strategies whenever possible and the future and challenges that can be faced with the different strategies.

6.1. Comparison between Control Strategies from the Evaluation of Performance

After all the analysis and observations, the existence of an obvious difficulty can be recognized, namely that there is no equality between the studies to make fair comparisons between control strategies. The studies presented may have some similarities between them, but in general they focus on different objectives, and use very different indicators for the results or the characteristics of the study, which differ enough to complicate any kind of comparison. For example, the difference between the use of an electric vehicle or a plug-in hybrid electric vehicle as the object of study can come from the objective, the characteristics, the models or even the simulations. The PHEV will be more likely to try to reduce the usage of fuel or use other models that can present important deviations to be considered. Even when the same performance indicators are used in the studies, which is not common, the results still cannot offer a clear comparison.

After this observation, it was decided that the main comparison that could be made was about the performance indicators used in the different control strategies, as a relation between the two can be made as a way to understand the areas or objectives that the studies using the different types of strategies decide to focus on. Finding a possible correlation between the type of control strategy and the area or objective seen more often in each control or in general, can be a way to understand which performance indicators seem to give better information or if some of the control strategies seem to be used more for some objectives.

The different control strategies seen in the literature are classified into rule-based (rule-based, filtration, fuzzy logic, wavelet), fuzzy logic and optimization (fuzzy logic with genetic algorithms or dynamic programming), optimization-based (MPC, PMP, SDP), optimization and machine learning (DP with random forest, Convex with ANN); and machine learning (DQL) to simplify the results.

After finishing the classification, the number of performance indicators from each type of indicator for each control strategy were counted, which was also done with the total for every category of the indicators. They were counted as each indicator encountered in each reference from the state of the art, considering the category where the control strategy used in that reference had been considered. The indicators that were repeated in different strategies from the same category were both counted. With that information gathered in a table, a graphic for the total and every one of the control strategies was created, as seen in Figure 9.

Figure 9. Relations among the performance indicators and control strategies in the literature concerning the HESS. (**a**) Total control strategies. (**b**) Rule-based control strategies. (**c**) Fuzzy logic and optimization strategies. (**d**) Optimization-based strategies. (**e**) Optimization and machine learning strategies. (**f**) Machine learning strategies.

After the observation of the graphics, the results that can be gathered are that the performance indicators related to the energy of the system or the capacity of the elements of the HESS are the ones that are used more to quantify the results of the different strategies. These type of performance indicator could be considered as more precise to study the results given by the control strategies. In the comparison between the different control strategies, the energy/capacity indicators are the most frequently used of all except the rule-based strategies where the most used are the ones related to the cost, and the rule-based with optimization strategies, where the most used are the lifespan ones.

However, it must be noted which objectives are considered by the studies, as most of them seem to focus on protecting the battery as much as possible, or on decreasing energy losses. Other types of indicator that seem to be considered remarkable are the ones related to current and voltage, and the ones about lifespan, which are also slightly directly related to the same objectives as the energy indicators. One of the impressions given after the analysis is that in some of the cases, the studies use different indicators, and even different type, to quantify similar concepts.

Even if it has been established first that the clear and general comparison between the results from the performance of the control strategies cannot be made, in some of the studies there are similarities and even comparisons between different control strategies which can give a general idea, establishing some general patterns. The first pattern is that the dynamic programming strategy is usually used as a benchmark, as it is a strategy that usually has the best results, but the way it is calculated makes it impossible to use in real time without the support of other types of strategy. The second pattern is that, in general, the strategies known as learning-based or optimization-based seem to have better results than those that are knowledge-based or rule-based. In some of the studies, some of these strategies are compared more directly and show that the indicators get better numbers with learning-based strategies. The third pattern is that, in general, the learning-based strategies need more requirements and time to reach a solution, especially compared with the knowledge-based strategies.

Combining the two later ideas, the general agreement found is that the knowledge-based are usually simpler strategies, which is translated as their being easy to implement. However, at the same time they do not present the best results, and are understood as not giving the best numerical result for the indicators, while the learning-based usually gives better results but can be more complicated to implement. With this statement, it seems to be that the different control strategies can be used for different circumstances or that the characteristics of the HESS can be more determinant to select the EMS.

6.2. Possible Future, Challenges, and Issues in Control Strategies

After an exhaustive review of all the studies, there is a clear drop in the most conventional-based strategies, as they can only offer a very basic control that is contrary to what the HESS usually needs. The search for the best type of EMS has led to the current trend, which is a mix of different strategies, usually between the rule-based and the optimization-based types, as a way to overcome some of the disadvantages by taking advantage of the best parts from the different types, and the study of the machine learning methods, which can also be used a support for the optimization-based type. The possible future of the EMS probably comes from a continuation of this trend, with a major exploration and investigation on the machine learning-type method, investigating the way to achieve better results and the way to implement it more effectively with other methods; and on the combination of different types of methods, exploring the possibility of an increase in the advantages that can be used from all the methods, the achievement of better results or a better merger between the methods, and even an attempt to combine other types of control.

The issues the control strategies can face on their implementation in an HESS depend on the type of control strategy that is been used. As expressed in the previous section, the way they work can display different issues in the way they function, such as the difficulty of online implementation for the optimization-based methods or the possibility of a weak solution for the rule-based methods. However, even if it is characteristic of the type implemented, one of these issues will be faced independently of the method chosen. In a more general way, one of the issues that can exist is that the more information that can be gathered about the system, the better the solution that can be reached, which can be considered a difficulty for some of the applications. Another very frequent issue is that the computational cost for some of the control strategies can be significantly high, complicating the implementation and its usage when a quick result is needed.

One of the general challenges is the way the measurements necessary for the calculations are achieved, as the sensors for some of the information need to be high quality. Related to some of the issues, one of the challenges the EMS can face is the usage of some of them in situations where there is the need to present a reliable solution while dealing with a scarcity of information available about the system.

7. Applications

From the various studies, it is clear that the HESS can offer a better mode to transmit the necessary energy for the system to perform correctly. The different analyses usually agree on the fact that an EMS is the key piece in the upgrade experienced with the change from a single ESS to an HESS. Overall, the combination of an HESS and an EMS, independent of which technique is used, gives a better performance and, specifically, offers a more adaptable storage system for the necessary loads.

This flexibility can only be an improvement to any application that uses a storage system, but specially to the more irregular loads, as it can offer a different or more personalized use of the two different elements that compose the HESS, independently of the type. In that case, the most frequently used application in the different studies is in storage systems for vehicles, both hybrids and pure electrical, as their load profile is usually very irregular while presenting a high use of energy. These kinds of vehicle, to be socially accepted, need to provide a very similar execution to gasoil ones, which is translated to a need for the energy necessary to achieve similar speeds and a high autonomy joined to the irregularity the load always presents, which makes the combination of a HESS and EMS the perfect tool. Although it is more frequently seen in electrical cars and buses, there are also cases for motorcycles and even high-speed trains [97,100].

There are different ways to take advantage of this system with electric vehicles, but the way it is usually done is to program or design the EMS considering some objectives previously identified for the best performance. The principal objective for this is used in electrical cars is to obtain a longer life for the battery or the more energetic battery, usually programming the EMS to not use the battery during the load peaks, protecting it from a high current. With hybrid vehicles, especially plug-in ones, one of the principal objectives is to decrease to the maximum the use of non-renewable energy, in this case fuel, forcing the system to work with more electric energy. Another objective for which the EMS is used is to decrease the possible cost, as the HESS can help to acquire the optimal sizing for the energy needed and the increase of the lifespan can save a lot of money from replacements [87,97].

8. Conclusions

This study of control methods for hybrid electrochemical energy storage technologies outlines the status of research and development, as well as the application of both traditional and cutting-edge approaches. This review paper also contains information about the main components of an HEESS, including a description of various battery chemistries, to aid academics, developers, and application engineers in better understanding specific characteristics, functional principles, and a selection process for different types of control methods for HEESSs.

Various aspects of the operation and key characteristics of control methods for hybrid electrochemical energy storage systems were the subject of review of more than 100 research papers and journal publications that were published between 1995 and 2024. The basic operating principles, classification, applications, and future technologies of control systems for HEESSs are explained. An increasing number of people are using HEESSs to power electric vehicles and provide energy storage at home or on the grid. Additionally, they are essential components of a system that aids in stabilizing the output of renewable energy sources, paving the way for the integration of renewable energy sources in the home and industry.

It is shown that indicators related to the energy of the system and the capacity of HEESS elements are the most used to quantify results. These indicators are considered precise for studying the outcomes of control strategies. Furthermore, the observation points out that the objectives of the studies play a crucial role in determining which performance indicators are prioritized. Many studies focus on protecting the battery and reducing energy losses, leading to the frequent use of indicators related to not only the energy and capacity but also to current, voltage, and lifespan. The interrelation between these indicators and the primary objectives underscores their significance in assessing strategy effectiveness. Additionally, the observation suggests that there is variability in the choice of performance indicators among studies, with some using different indicators to measure similar concepts. This diversity in indicator selection could impact the comparability and generalizability of results across different research efforts. This problem also comes from the differences between the characteristics of the studies conducted.

From what is seen from the EMS, there are two types of control that are more frequently used—optimization-based and rule-based—which present their own challenges and issues. One of the perspectives for the present and future is a mix of these types of strategy to maximize the advantages, and research into new strategies from machine learning. The general issues and challenges that exist for the control strategies are the possible high demand of computational time and the high need of information for a better optimal solution.

It is also shown that the integration of an HEESS and an EMS, regardless of the specific control technique employed, results in improved performance and offers a more adaptable storage solution for varying energy demands. This enhanced flexibility is particularly beneficial for applications with irregular energy loads, allowing for personalized utilization of the different components within the HEESS. The most common application highlighted in the studies is the use of HEESS as a storage system for vehicles, including hybrid and electric cars, due to their irregular load profiles and high energy consumption. These vehicles need to match the performance of traditional gasoline-powered vehicles, necessitating sufficient energy for similar speeds and extended autonomy, making the combination of an HEESS and EMS essential.

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Abbreviations

AMPC	Adaptive Model Predictive Control
ANN	Artificial Neural Network
BESS	Battery Energy Storage System
CO_2	Carbon Dioxide
DC	Droop Control
DOD	Depth of Discharge

DQL	Deep Q-Learning
DRL	Deep Reinforcement Learning
EMS	Energy Management System
ESM	Extended Security Maintenance
ESS	Energy Storage System
FLC	Fuzzy Logic Control
GA	Genetic Algorithms
HESS	Hybrid Energy Storage System
HEESS	Hybrid Electrochemical Energy Storage System
MG	Micro grid
MPC	Model Predictive Control
PID	Proportional–Integral–Derivative
PMP	Pontryagin's Maximum Principle
RBC	Rule Based Control
RES	Renewable Energy Sources
RMS	Root Mean Square
RUL	Remaining Useful Life
SC	Super capacitors
SDP	Stochastic dynamic programming
SMC	Sliding Mode Control
SOC	State of Charge
SOH	State of Health
SOP	State of Power

References

1. Alshehry, A.; Belloumi, M. The Symmetric and Asymmetric Impacts of Energy Consumption and Economic Growth on Environmental Sustainability. *Sustainability* **2024**, *16*, 205. [CrossRef]
2. Balaras, C.A.; Dascalaki, E.G.; Psarra, I.; Cholewa, T. Primary Energy Factors for Electricity Production in Europe. *Energies* **2023**, *16*, 93. [CrossRef]
3. Gevorkov, L.; Kirpichnikova, I. Model of Solar Photovoltaic Water Pumping System for Domestic Application. In Proceedings of the 2021 28th International Workshop on Electric Drives: Improving Reliability of Electric Drives (IWED), Moscow, Russia, 27–29 January 2021; pp. 1–5. [CrossRef]
4. Oladigbolu, J.O.; Mujeeb, A.; Imam, A.A.; Rushdi, A.M. Design, Technical and Economic Optimization of Renewable Energy-Based Electric Vehicle Charging Stations in Africa: The Case of Nigeria. *Energies* **2023**, *16*, 397. [CrossRef]
5. Gevorkov, L.; Domínguez-García, J.L.; Romero, L.T. Review on Solar Photovoltaic-Powered Pumping Systems. *Energies* **2023**, *16*, 94. [CrossRef]
6. IRENA. Available online: https://www.irena.org/publications/2021/Aug/Renewable-energy-statistics-2021/ (accessed on 14 January 2024).
7. Gevorkov, L.; Domínguez-García, J.L.; Filbà Martínez, À. Modern Trends in MultiPort Converters: Isolated, Non-Isolated, and Partially Isolated. In Proceedings of the 2022 IEEE 63rd International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), Riga, Latvia, 10–12 October 2022; pp. 1–6. [CrossRef]
8. Olabi, A.G.; Allam, M.A.; Abdelkareem, M.A.; Deepa, T.D.; Alami, A.H.; Abbas, Q.; Alkhalidi, A.; Sayed, E.T. Redox Flow Batteries: Recent Development in Main Components, Emerging Technologies, Diagnostic Techniques, Large-Scale Applications, and Challenges and Barriers. *Batteries* **2023**, *9*, 409. [CrossRef]
9. Li, Y.; Li, X.; Liu, H.; Wang, Y.; Wang, Y. Recent Advances in Lithium-Sulfur Batteries: Materials and Applications. *Nanomaterials* **2022**, *12*, 230. [CrossRef]
10. Alhijazi, A.A.K.; Almasri, R.A.; Alloush, A.F. A Hybrid Renewable Energy (Solar/Wind/Biomass) and Multi-Use System Principles, Types, and Applications: A Review. *Sustainability* **2023**, *15*, 16803. [CrossRef]
11. Nascimento, R.; Ramos, F.; Pinheiro, A.; Junior, W.D.A.S.; Arcanjo, A.M.C.; Filho, R.F.D.; Mohamed, M.A.; Marinho, M.H.N. Case Study of Backup Application with Energy Storage in Microgrids. *Energies* **2022**, *15*, 9514. [CrossRef]
12. Yang, L.; Cai, Y.; Qiao, Y.; Yan, N.; Ma, S. Research on Optimal Allocation Method of Energy Storage Considering Supply and Demand Flexibility and New Energy Consumption. In Proceedings of the 2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2), Wuhan, China, 30 October–1 November 2020; pp. 4368–4373.
13. Shively, D.; Gardner, J.; Haynes, T.; Ferguson, J. Energy Storage Methods for Renewable Energy Integration and Grid Support. In Proceedings of the 2008 IEEE Energy 2030 Conference, Atlanta, GA, USA, 17–18 November 2008; pp. 1–6.
14. Gevorkov, L.; Domínguez-García, J.L.; Romero, L.T.; Martínez, À.F. Advances on Application of Modern Energy Storage Technologies. In Proceedings of the 2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), Tenerife, Canary Islands, Spain, 19–21 July 2023; pp. 1–6. [CrossRef]

15. Statista. Available online: https://www.statista.com/statistics/1334680/europe-battery-storage-capacity/ (accessed on 14 January 2024).
16. Choi, D.; Shamim, N.; Crawford, A.; Huang, Q.; Vartanian, C.K.; Viswanathan, V.V.; Paiss, M.D.; Alam, M.J.E.; Reed, D.M.; Sprenkle, V.L. Li-ion battery technology for grid application. *J. Power Sources* **2021**, *511*, 230419. [CrossRef]
17. Kolodziejski, M.; Michalska-Pozoga, I. Battery Energy Storage Systems in Ships' Hybrid/Electric Propulsion Systems. *Energies* **2023**, *16*, 1122. [CrossRef]
18. Schubert, C.; Hassen, W.F.; Poisl, B.; Seitz, S.; Schubert, J.; Usabiaga, E.O.; Gaudo, P.M.; Pettinger, K.-H. Hybrid Energy Storage Systems Based on Redox-Flow Batteries: Recent Developments, Challenges, and Future Perspectives. *Batteries* **2023**, *9*, 211. [CrossRef]
19. Zhang, M.; Xu, Q.; Zhang, C.; Nordström, L.; Blaabjerg, F. Decentralized Coordination and Stabilization of Hybrid Energy Storage Systems in DC Microgrids. *IEEE Trans. Smart Grid* **2022**, *13*, 1751–1761. [CrossRef]
20. Porru, M.; Serpi, A.; Damiano, A. Smart energy management of HESS-based electric propulsion systems for urban mobility. In Proceedings of the IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 24–27 October 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 4453–4458.
21. Vosen, S.; Keller, J. Hybrid energy storage systems for stand-alone electric power systems: Optimization of system performance and cost through control strategies. *Int. J. Hydrogen Energy* **1999**, *24*, 1139–1156. [CrossRef]
22. Das, C.K.; Bass, O.; Kothapalli, G.; Mahmoud, T.S.; Habibi, D. Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality. *Renew. Sustain. Energy Rev.* **2018**, *91*, 1205–1230. [CrossRef]
23. Sperling, M.; Kivelä, T. Concept of a Dual Energy Storage System for Sustainable Energy Supply of Automated Guided Vehicles. *Energies* **2022**, *15*, 479. [CrossRef]
24. Atawi, I.E.; Al-Shetwi, A.Q.; Magableh, A.M.; Albalawi, O.H. Recent Advances in Hybrid Energy Storage System Integrated Renewable Power Generation: Configuration, Control, Applications, and Future Directions. *Batteries* **2023**, *9*, 29. [CrossRef]
25. Babu, T.S.; Vasudevan, K.R.; Ramachandaramurthy, V.K.; Sani, S.B.; Chemud, S.; Lajim, R.M. A Comprehensive Review of Hybrid Energy Storage Systems: Converter Topologies, Control Strategies and Future Prospects. *IEEE Access* **2020**, *8*, 148702–148721. [CrossRef]
26. Lin, X.; Zamora, R. Controls of Hybrid Energy Storage Systems in Microgrids: Critical Review, Case Study and Future Trends. *J. Energy Storage* **2022**, *47*, 103884. [CrossRef]
27. Divya, K.C.; Østergaard, J. Battery energy storage technology for power systems—An overview. *Electr. Power Syst. Res.* **2009**, *79*, 511–520. [CrossRef]
28. Dehghani-Sanij, A.R.; Tharumalingam, E.; Dusseault, M.B.; Fraser, R. Study of energy storage systems and environmental challenges of batteries. *Renew. Sustain. Energy Rev.* **2019**, *104*, 192–208. [CrossRef]
29. Goodenough, J. How we made the Li-ion rechargeable battery. *Nat. Electron.* **2018**, *1*, 204. [CrossRef]
30. Peng, J.; Meng, J.; Chen, D.; Liu, H.; Hao, S.; Sui, X.; Du, X. A Review of Lithium-Ion Battery Capacity Estimation Methods for Onboard Battery Management Systems: Recent Progress and Perspectives. *Batteries* **2022**, *8*, 229. [CrossRef]
31. Stan, A.-I.; Świerczyński, M.; Stroe, D.-I.; Teodorescu, R.; Andreasen, S.J. Lithium ion battery chemistries from renewable energy storage to automotive and back-up power applications—An overview. In Proceedings of the 2014 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM), Bran, Romania, 22–24 May 2014; pp. 713–720.
32. Neunzling, J.; Winter, H.; Henriques, D.; Fleckenstein, M.; Markus, T. Online State-of-Health Estimation for NMC Lithium-Ion Batteries Using an Observer Structure. *Batteries* **2023**, *9*, 494. [CrossRef]
33. Mohanty, D.; Chang, M.-J.; Hung, I.-M. The Effect of Different Amounts of Conductive Carbon Material on the Electrochemical Performance of the LiFePO4 Cathode in Li-Ion Batteries. *Batteries* **2023**, *9*, 515. [CrossRef]
34. Wang, L.; Wang, J.; Wang, L.; Zhang, M.; Wang, R.; Zhan, C. A critical review on nickel-based cathodes in rechargeable batteries. *Int. J. Miner. Metall. Mater.* **2022**, *29*, 925–941. [CrossRef]
35. Krishnamoorthy, U.; Gandhi Ayyavu, P.; Panchal, H.; Shanmugam, D.; Balasubramani, S.; Al-rubaie, A.J.; Al-khaykan, A.; Oza, A.D.; Hembrom, S.; Patel, T.; et al. Efficient Battery Models for Performance Studies-Lithium Ion and Nickel Metal Hydride Battery. *Batteries* **2023**, *9*, 52. [CrossRef]
36. Tsais, P.-J.; Chan, L.I. 11—Nickel-based batteries: Materials and chemistry. In *Electricity Transmission, Distribution and Storage Systems*; Melhem, Z., Ed.; Woodhead Publishing Series in Energy; Woodhead Publishing: Southton, UK, 2013; pp. 309–397.
37. Zelinsky, M.A.; Koch, J.M.; Young, K.-H. Performance Comparison of Rechargeable Batteries for Stationary Applications (Ni/MH vs. Ni–Cd and VRLA). *Batteries* **2018**, *4*, 1. [CrossRef]
38. Li, L.; Zheng, Y.; Zhang, S.; Yang, J.; Shao, Z.; Guo, Z. Recent progress on sodium ion batteries: Potential high-performance anodes. *Energy Environ. Sci.* **2018**, *11*, 2310–2340. [CrossRef]
39. Wang, Y.; Zhang, Y.; Cheng, H.; Ni, Z.; Wang, Y.; Xia, G.; Li, X.; Zeng, X. Research Progress toward Room Temperature Sodium Sulfur Batteries: A Review. *Molecules* **2021**, *26*, 1535. [CrossRef] [PubMed]
40. Cheng, F.; Chen, J. Metal–air batteries: From oxygen reduction electrochemistry to cathode catalysts. *Chem. Soc. Rev.* **2012**, *41*, 2172–2192. [CrossRef] [PubMed]
41. Welch, C.; Mohammad, A.K.; Hosmane, N.S.; Zhang, L.; Cho, K.T. Effect of Aluminum Oxide on the Performance of Ionic Liquid-Based Aluminum–Air Battery. *Energies* **2020**, *13*, 2014. [CrossRef]

42. Romaus, C.; Gathmann, K.; Böcker, J. Optimal energy management for a hybrid energy storage system for electric vehicles based on Stochastic Dynamic Programming. In Proceedings of the IEEE Vehicle Power and Propulsion Conference, Lille, France, 1–3 September 2010; pp. 1–6. [CrossRef]
43. Abo-Khalil, A.G.; Sobhy, A.; Abdelkareem, M.A.; Olabi, A.G. Advancements and challenges in hybrid energy storage systems: Components, control strategies, and future directions. *Int. J. Thermofluids* **2023**, *20*, 100477. [CrossRef]
44. Purnama, H.S.; Sutikno, T.; Alavandar, S.; Subrata, A.C. Intelligent Control Strategies for Tuning PID of Speed Control of DC Motor—A Review. In Proceedings of the IEEE Conference on Energy Conversion (CENCON), Yogyakarta, Indonesia, 16–17 October 2019; pp. 24–30. [CrossRef]
45. Franklin, G.; Powell, J.D.; Emami-Naeini, A. *Feedback Control of Dynamic Systems*; Prentice-Hall Inc.: Hoboken, NJ, USA, 1995.
46. Ogata, K. *Modern Control Engineering*; Prentice-Hall Inc.: Hoboken, NJ, USA, 2010.
47. Kuo, B.; Golnaraghi, M. *Automatic Control System*; John Wiley & Sons Inc.: Hoboken, NJ, USA, 2003.
48. Ang, K.H.; Chong, G.; Li, Y. PID control system analysis, design, and technology. *IEEE Trans. Control Syst. Technol.* **2005**, *13*, 559–576. [CrossRef]
49. Wang, L. PID Controller Design for Complex Systems. In *PID Control System Design and Automatic Tuning Using MATLAB/Simulink*; Wiley: New York, NY, USA, 2020; pp. 233–258. [CrossRef]
50. Neto, C.A.; Embiruçu, M. Tuning of PID Controllers: An Optimization-Based Method. *IFAC Proc. Vol.* **2000**, *33*, 367–372. [CrossRef]
51. Abdelwahab, A.M.; Ali, Y.; Ebeed, M.; Abo-Elyousr, F.; Elnozahy, A.; Mohammed, M. Optimization of PID Controller for Hybrid Renewable Energy System Using Adaptive Sine Cosine Algorithm. *Int. J. Renew. Energy Res.* **2020**, *10*, 669–677. [CrossRef]
52. Ye, K.; Li, P. A new adaptive PSO-PID control strategy of hybrid energy storage system for electric vehicles. *Adv. Mech. Eng.* **2020**, *12*, 16878140209585. [CrossRef]
53. Tayab, U.B.; Roslan, M.A.; Hwai, L.J.; Kashif, M. A review of droop control techniques for microgrid. *Renew. Sustain. Energy Rev.* **2017**, *76*, 717–727. [CrossRef]
54. Shabadi, H.; Kamwa, I. A decentralized non-linear dynamic droop control of a hybrid energy storage system blue for primary frequency control in integrated AC-MTDC systems. *Int. J. Electr. Power Energy Syst.* **2022**, *136*, 107630. [CrossRef]
55. Benadli, R.; Bejaoui, M.; Khiari, B.; Sellami, A. Sliding Mode Control of Hybrid Renewable Energy System Operating in Grid Connected and Stand-Alone Mode. *Power Electron. Drives* **2021**, *6*, 145–167. [CrossRef]
56. Clemente, A.; Montiel, M.; Barreras, F.; Lozano, A.; Costa-Castelló, R. Vanadium Redox Flow Battery State of Charge Estimation Using a Concentration Model and a Sliding Mode Observer. *IEEE Access* **2021**, *9*, 72368–72376. [CrossRef]
57. Prasad, P.; Kumar, P.R. Control of Hybrid Energy Storage System for Hybrid Electric Vehicles using Uniform Continuous Higher Order Sliding Mode Control. *Asian J. Converg. Technol.* **2021**, *7*, 202–208. [CrossRef]
58. Aggarwal, S.; Alam, M.; Kumar, J. Sliding Mode Control Scheme for Hybrid Energy Storage Technologies in a DC Microgrid. In Proceedings of the International Mobile and Embedded Technology Conference (MECON), Noida, India, 10–11 March 2022; pp. 486–489. [CrossRef]
59. Fustero, C.; Clemente, A.; Costa-Castelló, R.; Ocampo-Martinez, C. Energy management using predictive control and Neural Networks in microgrid with hybrid storage system. In Proceedings of the IEEE 28th International Conference on Emerging Technologies and Factory Automation (ETFA), Sinaia, Romania, 12–15 September 2023; pp. 1–8. [CrossRef]
60. Tumeran, N.L.; Yusoff, S.H.; Gunawan, T.S.; Hanifah, M.S.A.; Zabidi, S.A.; Pranggono, B.; Yunus, M.S.F.M.; Sapihie, S.N.M.; Halbouni, A.H. Model Predictive Control Based Energy Management System Literature Assessment for RES Integration. *Energies* **2023**, *16*, 3362. [CrossRef]
61. Cheng, L.; Acuna, P.; Aguilera, R.; Jiang, J.; Flecther, J.; Baier, C. Model predictive control for Energy Management of a hybrid energy storage system in Light Rail Vehicles. In Proceedings of the 11th IEEE International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), Cadiz, Spain, 4–6 April 2017; pp. 683–688. [CrossRef]
62. Thaler, B.; Posch, S.; Wimmer, A.; Pirker, G. Hybrid model predictive control of renewable microgrids and seasonal hydrogen storage. *Int. J. Hydrogen Energy* **2023**, *48*, 38125–38142. [CrossRef]
63. Gracia, A.; Crespo, A.; Vérez, D.; Tarragona, J.; Cabeza, L.F. *Control Solutions for TES Applications. Encyclopedia of Energy Storage*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 579–583. [CrossRef]
64. Casini, M. *Building automation systems. Chapter 10 In Woodhead Publishing Series in Civil and Structural Engineering, Construction 4.0*; Woodhead Publishing: Cambridge, UK, 2022; pp. 525–581. [CrossRef]
65. Zhang, Q.; Deng, W.; Zhang, S.; Wu, J. A Rule Based Energy Management System of Experimental Battery/Supercapacitor Hybrid Energy Storage System for Electric Vehicles. *J. Control Sci. Eng.* **2016**, *2016*, 6828269. [CrossRef]
66. Zhuotong, L.; Yi, Z.; Yun, J.; Fang, F. Rule-Based Dual Planning Strategy of Hybrid Battery Energy Storage System. *IFAC Pap. Online* **2022**, *55*, 495–500. [CrossRef]
67. Gerla, G. Fuzzy Logic Programming and Fuzzy Control. *Stud Log.* **2005**, *79*, 231–254. [CrossRef]
68. Zadeh, L.A. Fuzzy Sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
69. Alankrita, A.; Pati, N.; Adhikary, S.K.; Mishra, B.; Appasani, T.S. Fuzzy logic based energy management for grid connected hybrid PV system. *Energy Rep.* **2022**, *8*, 751–758. [CrossRef]

70. Althubaiti, M.; Bernard, M.; Musilek, P. Fuzzy logic controller for hybrid renewable energy system with multiple types of storage. In Proceedings of the IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, Canada, 30 April–3 May 2017; pp. 1–6. [CrossRef]
71. Hussan, U.; Majeed, M.A.; Asghar, F. Fuzzy logic-based voltage regulation of hybrid energy storage system in hybrid electric vehicles. *Electr. Eng.* **2022**, *104*, 485–495. [CrossRef]
72. Bhadeshia, H.K.D.H. Neural networks in material science. *ISIJ Int.* **1999**, *39*, 966–979. [CrossRef]
73. Vidal, C.; Haubmann, M.; Barroso, G.; Shamsabadi, P.M.; Biswas, A.; Chemali, E.; Ahmed, R.; Emadi, A. Hybrid Energy Storage System State-Of-Charge Estimation Using Artificial Neural Network for Micro-Hybrid Applications. In Proceedings of the 2018 IEEE Transportation Electrification Conference and Expo (ITEC), Long Beach, CA, USA, 13–15 June 2018; pp. 1075–1081. [CrossRef]
74. Shafi, I.; Khan, H.; Farooq, M.S.; Diez, I.d.l.T.; Miró, Y.; Galán, J.C.; Ashraf, I. An Artificial Neural Network-Based Approach for Real-Time Hybrid Wind–Solar Resource Assessment and Power Estimation. *Energies* **2023**, *16*, 4171. [CrossRef]
75. Bhatikar, S.; Mahajan, R.; Wipke, K.; Johnson, V. Artificial Neural Network Based Energy Storage System Modeling for Hybrid Electric Vehicles. In Proceedings of the Future Car Congress, Crystal City, VA, USA, 2 April 2000. [CrossRef]
76. Yang, X. Chapter 6—Genetic Algorithms. In *Nature-Inspired Optimization Algorithms*; Academic Press: Cambridge, MA, USA, 2021; pp. 91–100. [CrossRef]
77. Suresh, M.; Meenakumari, R. An improved genetic algorithm-based optimal sizing of solar photovoltaic/wind turbine generator/diesel generator/battery connected hybrid energy systems for standalone applications. *Int. J. Ambient. Energy* **2021**, *42*, 1136–1143. [CrossRef]
78. Ismail, M.S.; Moghavvemi, M.; Mahlia, T.M.I. Genetic algorithm based optimization on modeling and design of hybrid renewable energy systems. *Energy Convers. Manag.* **2014**, *85*, 120–130. [CrossRef]
79. Francois-Lavet, V.; Henderson, P.; Islam, R.; Bellemare, M.G.; Pineau, J. An Introduction to Deep Reinforcement Learning. *Found. Trends Mach. Learn.* **2018**, *11*, 219–354. [CrossRef]
80. Le, N.; Rathour, V.S.; Yamazaki, K.; Luu, K.; Savvides, M. Deep reinforcement learning in computer vision: A comprehensive survey. *Artif. Intell. Rev.* **2022**, *55*, 2733–2819. [CrossRef]
81. Desportes, L.; Fijalkow, I.; Andry, P. Deep Reinforcement Learning for Hybrid Energy Storage Systems: Balancing Lead and Hydrogen Storage. *Energies* **2021**, *14*, 4706. [CrossRef]
82. Li, W.; Cui, H.; Nemeth, T.; Jansen, J.; Unlubavir, C.; Wei, Z.; Zhang, L.; Wang, Z.; Ruan, J.; Dai, H.; et al. Deep reinforcement learning-based energy management of hybrid battery systems in electric vehicles. *J. Energy Storage* **2021**, *36*, 102355. [CrossRef]
83. Wang, L.; Wang, Y.; Liu, C.; Yang, D.; Chen, Z. A Power Distribution Strategy for Hybrid Energy Storage System Using Adaptive Model Predictive Control. *IEEE Trans. Power Electron.* **2020**, *35*, 5897–5906. [CrossRef]
84. Zhuang, W.; Ye, J.; Song, Z.; Yin, G.; Li, G. Comparison of semi-active hybrid battery system configurations for electric taxis application. *Appl. Energy* **2020**, *259*, 114171. [CrossRef]
85. Liu, C.; Wang, Y.; Wang, L.; Chen, Z. Load-adaptive real-time energy management strategy for battery/ultracapacitor hybrid energy storage system using dynamic programming optimization. *J. Power Sources* **2019**, *438*, 227024. [CrossRef]
86. Wegmann, R.; Döge, V.; Becker, J.; Sauer, D.U. Optimized operation of hybrid battery systems for electric vehicles using deterministic and stochastic dynamic programming. *J. Energy Storage* **2017**, *14*, 22–38. [CrossRef]
87. Li, M.; Wang, L.; Wang, Y.; Chen, Z. Sizing Optimization and Energy Management Strategy for Hybrid Energy Storage System Using Multiobjective Optimization and Random Forests. *IEEE Trans. Power Electron.* **2021**, *36*, 11421–11430. [CrossRef]
88. Zhao, C.; Yin, H.; Yang, Z.; Ma, C. Equivalent Series Resistance-Based Energy Loss Analysis of a Battery Semiactive Hybrid Energy Storage System. *IEEE Trans. Energy Convers.* **2015**, *30*, 1081–1091. [CrossRef]
89. Zhou, S.; Chen, Z.; Huang, D.; Lin, T. Model Prediction and Rule Based Energy Management Strategy for a Plug-in Hybrid Electric Vehicle With Hybrid Energy Storage System. *IEEE Trans. Power Electron.* **2021**, *36*, 5926–5940. [CrossRef]
90. Nguyen, B.-H.; German, R.; Trovão, J.P.F.; Bouscayrol, A. Real-Time Energy Management of Battery/Supercapacitor Electric Vehicles Based on an Adaptation of Pontryagin's Minimum Principle. *IEEE Trans. Veh. Technol.* **2019**, *68*, 203–212. [CrossRef]
91. Styvaktakis, E.; Bollen, M.H.J.; Gu, I.Y.H. Automatic classification of power system events using RMS voltage measurements. *IEEE Power Eng. Soc. Summer Meet.* **2002**, *2*, 824–829. [CrossRef]
92. Castaings, A.; Lhomme, W.; Trigui, R.; Bouscayrol, A. Comparison of energy management strategies of a battery/supercapacitors system for electric vehicle under real-time constraints. *Appl. Energy* **2016**, *163*, 190–200. [CrossRef]
93. Zhang, X.; Peng, H.; Wang, H.; Ouyang, M. Hybrid Lithium Iron Phosphate Battery and Lithium Titanate Battery Systems for Electric Buses. *IEEE Trans. Veh. Technol.* **2018**, *67*, 956–965. [CrossRef]
94. Xie, S.; Hu, X.; Xin, Z.; Brighton, J. Pontryagin's Minimum Principle based model predictive control of energy management for a plug-in hybrid electric bus. *Appl. Energy* **2019**, *236*, 893–905. [CrossRef]
95. Yu, H.; Tarsitano, D.; Hu, X.; Cheli, F. Real time energy management strategy for a fast charging electric urban bus powered by hybrid energy storage system. *Energy* **2016**, *112*, 322–331. [CrossRef]
96. Ye, J.; Zhuang, W.; Yin, G. Rule-filter-integrated Control of LFP/LTO Hybrid Energy Storage System for Vehicular Application. In Proceedings of the 2019 IEEE 28th International Symposium on Industrial Electronics (ISIE), Vancouver, BC, Canada, 12–14 June 2019; pp. 1542–1547. [CrossRef]

97. Masih-Tehrani, M.; Ha'Iri Yazdi, M.R.; Esfahanian, V.; Dahmardeh, M.; Nehzati, H. Wavelet-based power management for hybrid energy storage system. *J. Mod. Power Syst. Clean Energy* **2019**, *7*, 779–790. [CrossRef]
98. Yin, H.; Zhou, W.; Li, M.; Ma, C.; Zhao, C. An Adaptive Fuzzy Logic-Based Energy Management Strategy on Battery/Ultracapacitor Hybrid Electric Vehicles. *IEEE Trans. Transp. Electrif.* **2016**, *2*, 300–311. [CrossRef]
99. Hu, J.; Liu, D.; Du, C.; Yan, F.; Lv, C. Intelligent energy management strategy of hybrid energy storage system for electric vehicle based on driving pattern recognition. *Energy* **2020**, *198*, 117298. [CrossRef]
100. Luo, J.; Gao, S.; Wei, X.; Tian, Z. Adaptive energy management strategy for high-speed railway hybrid energy storage system based on double-layer fuzzy logic control. *Int. J. Electr. Power Energy Syst.* **2024**, *156*, 109739. [CrossRef]
101. Zheng, C.; Li, W.; Liang, Q. An Energy Management Strategy of Hybrid Energy Storage Systems for Electric Vehicle Applications. *IEEE Trans. Sustain. Energy* **2018**, *9*, 1880–1888. [CrossRef]
102. Hannan, M.A.; Lipu, M.S.H.; Hussain, A.; Mohamed, A. A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. *Renew. Sustain. Energy Rev.* **2017**, *78*, 834–854. [CrossRef]
103. Dufo-López, R.; Lujano-Rojas, J.M.; Bernal-Agustín, J.L. Comparison of different lead–acid battery lifetime prediction models for use in simulation of stand-alone photovoltaic systems. *Appl. Energy* **2014**, *115*, 242–253. [CrossRef]
104. Yavasoglu, H.A.; Tetik, Y.E.; Ozcan, H.G. Neural network-based energy management of multi-source (battery/UC/FC) powered electric vehicle. *Int. J. Energy Res.* **2020**, *44*, 12416–12429. [CrossRef]
105. Lu, X.; Wang, H. Optimal Sizing and Energy Management for Cost-Effective PEV Hybrid Energy Storage Systems. *IEEE Trans. Ind. Inform.* **2020**, *16*, 3407–3416. [CrossRef]
106. Lee, J.; Kim, J.-M.; Yi, J.; Won, C.-Y. Battery Management System Algorithm for Energy Storage Systems Considering Battery Efficiency. *Electronics* **2021**, *10*, 1859. [CrossRef]
107. Zhou, S.; Chen, Z. Model Prediction and Rule Based Energy Management Strategy for Hybrid Energy Storage System. In Proceedings of the 2019 IEEE 3rd International Electrical and Energy Conference (CIEEC), Beijing, China, 7–9 September 2019; pp. 427–432. [CrossRef]
108. Spotnitz, R. Simulation of capacity fade in lithium-ion batteries. *J. Power Sources* **2003**, *113*, 72–80. [CrossRef]
109. Shen, J.; Dusmez, S.; Khaligh, A. Optimization of Sizing and Battery Cycle Life in Battery/Ultracapacitor Hybrid Energy Storage Systems for Electric Vehicle Applications. *IEEE Trans. Ind. Inform.* **2014**, *10*, 2112–2121. [CrossRef]
110. Huang, J.; Huang, Z.; Wu, Y.; Liao, H.; Liu, Y.; Li, H.; Wen, M.; Peng, J. Optimal Filter-Based Energy Management for Hybrid Energy Storage Systems with Energy Consumption Minimization. In Proceedings of the 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Toronto, ON, Canada, 11–14 October 2020; pp. 1822–1827. [CrossRef]
111. Zhao, B.; Zhang, X.; Chen, J.; Wang, C.; Guo, L. Operation Optimization of Standalone Microgrids Considering Lifetime Characteristics of Battery Energy Storage System. *IEEE Trans. Sustain. Energy* **2013**, *4*, 934–943. [CrossRef]
112. Tantrapon, K.; Jirapong, P.; Thararak, P. Mitigating microgrid voltage fluctuation using battery energy storage system with improved particle swarm optimization. *Energy Rep.* **2020**, *6*, 724–730. [CrossRef]
113. Seixas, L.D.; Tosso, H.G.; Corrêa, F.C.; Eckert, J.J. Particle Swarm Optimization of a Fuzzy Controlled Hybrid Energy Storage System—HESS. In Proceedings of the 2020 IEEE Vehicle Power and Propulsion Conference (VPPC), Gijon, Spain, 18 November–16 December 2020; pp. 1–6. [CrossRef]
114. Wu, T.; Wang, F.; Ye, P. Regenerative Braking Strategy of Dual-Motor EV Considering Energy Recovery and Brake Stability. *World Electr. Veh. J.* **2023**, *14*, 19. [CrossRef]
115. Zhang, S.; Xiong, R.; Cao, J. Battery durability and longevity based power management for plug-in hybrid electric vehicle with hybrid energy storage system. *Appl. Energy* **2016**, *179*, 316–328. [CrossRef]