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Review

Exploring the Synergy of Artificial Intelligence in Energy Storage Systems for Electric Vehicles

Seyed Mahdi Miraftabzadeh , Michela Longo *, Andrea Di Martino , Alessandro Saldarini and Roberto Sebastiano Faranda

Department of Energy, Politecnico di Milano, 20156 Milano, Italy; seyedmahdi.miraftabzadeh@polimi.it (S.M.M.); andrea.dimartino@polimi.it (A.D.M.); alessandro.saldarini@polimi.it (A.S.); roberto.faranda@polimi.it (R.S.F.)
* Correspondence: michela.longo@polimi.it

Abstract: The integration of Artificial Intelligence (AI) in Energy Storage Systems (ESS) for Electric Vehicles (EVs) has emerged as a pivotal solution to address the challenges of energy efficiency, battery degradation, and optimal power management. The capability of such systems to differ from theoretical modeling enhances their applicability across various domains. The vast amount of data available today has enabled AI to be trained and to predict the behavior of complex systems with a high degree of accuracy. As we move towards a more sustainable future, the electrification of vehicles and integrating electric systems for energy storage are becoming increasingly important and need to be addressed. The synergy of AI and ESS enhances the overall efficiency of electric vehicles and plays a crucial role in shaping a sustainable and intelligent energy ecosystem. To the best of the authors' knowledge, AI applications in energy storage systems for the integration of electric vehicles have not been explicitly reviewed. The research investigates the importance of AI advancements in energy storage systems for electric vehicles, specifically focusing on Battery Management Systems (BMS), Power Quality (PQ) issues, predicting battery State-of-Charge (SOC) and State-of-Health (SOH), and exploring the potential for integrating Renewable Energy Sources with EV charging needs and optimizing charging cycles. This study examined all topics to identify the most commonly used methods, which were analyzed based on their characteristics and potential. Future trends were identified by exploring emerging techniques introduced in recent literature contributions published since 2017.

Keywords: artificial intelligence; data management; electric vehicles; energy storage systems; machine learning

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1. Introduction

There is a noticeable upward trend in the interest in applications of Artificial Intelligence (AI) across various research topics, offering undeniable advantages such as higher accuracy of predictive results and reduced computational complexity compared to classical modeling techniques [1]. Implementing these methods has become widespread but has primarily occurred within the last decade. The increasing popularity of Electric Vehicles (EVs) has resulted in a higher demand for energy to power charging operations [2]. This has made it more difficult to accurately estimate driving behavior and charging demand, which calls for a new perspective that can enable fast and dependable responses. AI is revolutionizing Energy Storage Systems (ESSs) by enabling sophisticated optimization algorithms to enhance efficiency and reliability. Intelligent ESSs can optimize energy storage and distribution through AI-powered predictive analytics, leading to more sustainable and cost-effective solutions. A general schematization of the framework based on these assertions is provided in Figure 1. The role of AI can also be explained in the following shape: Its capability to handle big data quickly allows for cross-implementation among different contexts and topics, integrating them as part of the general system and improving related performance. AI algorithms also facilitate real-time monitoring and control of ESSs, ensuring adaptive responses to dynamic energy demands and grid conditions. However, research in this area is relatively recent and ongoing, with a smaller volume of literature compared to other topics.

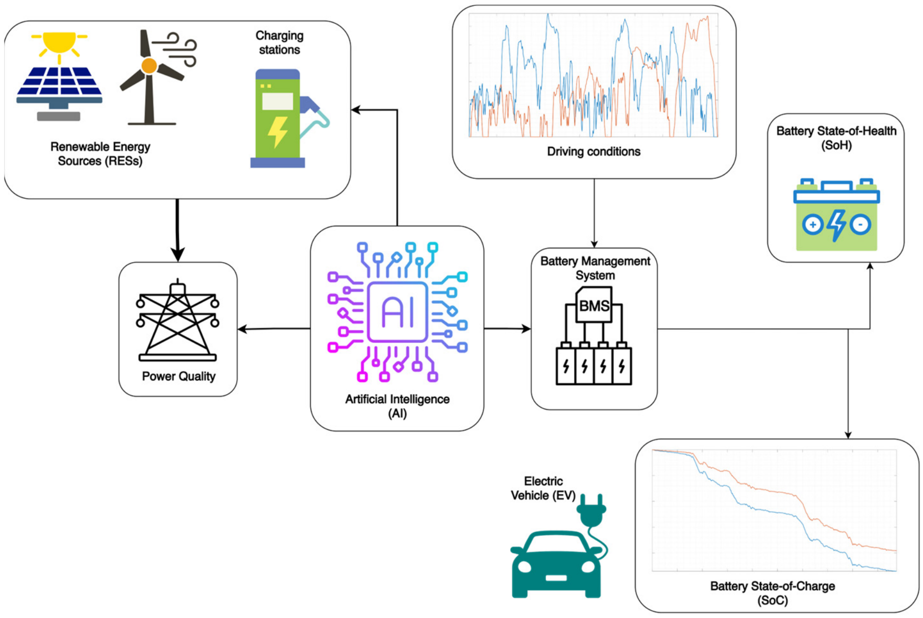


Figure 1. Implementation of AI to ESSs for EVs.

The growth in the usage of EVs and electric mobility is driving the market for numerous ESSs [3]. Therefore, electric and electrochemical devices are employed to fully realize electric motion, given their high efficiency and adaptability to different conditions [4]. Capacitors, supercapacitors, generators, and power converters are remarkable examples in the former category [5,6]. Regarding the latter category, it is essential to establish a relationship with batteries despite the different technologies through which they are produced [7]. In particular:

- Lithium-ion (Li-ion) batteries are the most diffused, given the extended thermal range of operation, load capacity, and reduced mass per cell and internal resistance. However, degradation phenomena are critical, limiting their applicability due to low duration.
- Nickel–Cadmium (Ni-Cd) and Nickel–Metal–Hydride (Ni-MH) batteries are able to reduce dimensions and offer good performance for durability with a high energy density; on the contrary, the reduced thermal operational range limits their application to medical devices.
- Other types of batteries may offer higher energy densities; however, they have different optimal working temperature ranges, which can limit their applications and increase costs.

Additionally, AI advancements can be applied to ESSs [8,9]. In particular, all processes that refer to prediction, communication, and management can benefit from the implementation of AI algorithms that are capable of reducing the processing time of the evaluation process and merging heterogeneous data [10] to set effective strategies aimed at managing the components better and extending the capability of communications in the wake of the Internet of Things (IoT) [11,12].

The need to implement AI for ESSs can be retrieved in the following framework, depending on the following:

- Number of input parameters available;
- Number of output parameters to be determined;
- Complexity of the problem;

- Computational time.

Moreover, AI can handle complex problems without requiring a detailed model, eliminating the need for modelization steps [13]. Several models can be found in the literature regarding ESSs, hereby listed with an increasing level of detail:

- Empirical models (EMs);
- Physical models (PMs);
- Single-Particle Models (SPMs);
- Single-Electrolyte Interface (SEIs);
- Combined.

Starting from macroscale models, EMs are based on indirect relationships between inputs and outputs from experimental observations, especially considering input variables that do not show a proper physical link with the output variables or the process itself. EMs are mainly extrapolated from experiments through "ready-to-use" mathematical relationships [14]. Instead, PMs can describe the working principles of an ESS dealing with physical quantities that can be either directly measured or indirectly estimated [5,15]. PMs are mainly constituted by electro-chemical relationships, thus disclosing a higher level of detail in the model adopted. A further step is the composition of PMs with SPMs and/or SEIs; these can delve into all problems set on a micro-scale referring to damaging mechanisms for cells [11]. In particular, they are able to connect EMs with PMs, but are only used for low values of currents. On the other hand, SEIs are more suitable for describing damaging mechanisms such as lithium plating, cracking, and degradation of cells. Therefore, SEIs provide a physical-based evaluation of the so-called State of Health (SoH).

In the category of "empirical models", there is a further sub-category that needs to be highlighted. This modeling technique arises from the need for more precise knowledge regarding detailed parameters for ESSs, necessitating a simplification of the model. Thus, two distinct approaches emerge. The first approach entails employing passive electrical elements to mimic the behavior of the battery in a simplified manner, known as the Equivalent (or Electric) Circuit Model (ECM) [15]. Here, the physical meaning of the arrangement used for the electric circuit is not linked with the real working principles of the device but instead helps provide the relevant information needed as output. The second approach is derived from the already described approach but exploits the advantages of AI [11,16–18]. Applying Machine Learning (ML) techniques enables the simultaneous achievement of two distinct objectives. First, estimations of the system status need to be provided in a short time period. Second, the trend is to reduce the complexity of the system model, discarding all technical details that are out of the scope of calculations, which would have required significant computational time. In this sense, the implementation of AI is generally valuable in providing an almost real-time response to every query, with some exceptions [19]. The integration of ML is always based on a real dataset that is sufficiently large to allow a reliable training phase for the algorithm.

The significance of hybrid energy storage systems for electric vehicles and efficient energy management strategies are explored in [20,21], focusing on battery ultracapacitor systems and optimal planning and control algorithms for Electric Vehicle Charging Stations. Ref. [22] provides a comprehensive review of lithium-ion batteries, discussing topics such as EV systems, energy management, and future recommendations. Ref. [23] highlights the role of energy storage technology in facilitating the adoption of renewable energy and discusses its integration with artificial intelligence for optimized system control. Additionally, Ref. [24] explores machine learning applications in manufacturing sectors, emphasizing sustainability and environmental impact. Moreover, Ref. [25] emphasizes the importance of optimal planning and control algorithms for Electric Vehicle Charging Stations, focusing on system configurations, energy management, and advanced control issues. It highlights the potential benefits of hybrid designs and portable energy storage systems for enhancing flexibility and profitability in grid-tied EV charging station networks.

To the best of the authors' knowledge, no study has explicitly reviewed AI applications in energy storage systems for the integration of electric vehicles. Therefore, this review aims to investigate the extent to which AI is being integrated into ESSs for EVs, drawing from existing literature contributions and extrapolating potential future trends. This work is motivated by the growing attention AI methods have garnered over the past decade, as they are being applied across diverse topics and fields. However, limitations exist due to the relatively small number of relevant applications considered in this sector, considering its recent relevance and significance. Section 2 introduces the general framework regarding ESSs for EVs, while Section 3 describes the methodology adopted for the literature contributions considered, analyzing each topic in which AI methods are implemented. Section 4 provides a critical discussion on the implemented methods, while Section 5 proposes future trends that are lagging behind the analysis provided and extrapolated.

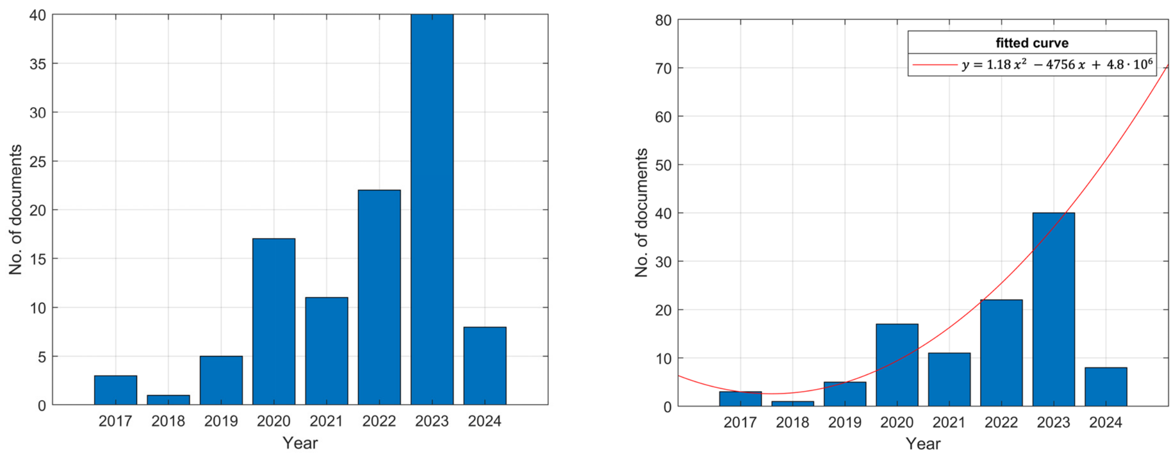
2. Methodology

AI is being implemented in various fields. Its integration into ESSs for EVs has only recently begun to gain significance within the past decade [26]. Contemporary advancements in technology and manufacturing materials dedicated to batteries and technical aspects of managing such systems during their life cycle have favored the implementation of AI in this field [6]. To provide a repeatable analysis, the contributions published in the literature were retrieved through the Scopus database; the search parameters are summarized in Table 1. We examined all relevant contributions published since 2017 regarding the role of AI in ESSs. Contributions published before this threshold were deemed insignificant in terms of quantity and advancements compared to recent publications. Moreover, all resources were evaluated by limiting the language of publication to English and the type of documents considered. Given that this work aims to concentrate on the AI methods applied, our focus primarily lies in journal publications. Figure 2 depicts the trends of published articles over the last six years. Since 2024 is ongoing and the number of publications is very limited, its data are not fully represented in the figure. The trend in the future is expected to grow according to a cubic polynomial trend, meaning that the topic has just gained interest. It can be the overall growth in literature contributions retrieved since 2020, where major policies were approved to boost the public release of economic subsidies to purchase an EV. This trend is also accompanied by a parallel growth in the number of EV charging stations installed and future installations, allowing a broader use of EVs. According to the fitted trend line, the growth in the literature contributions is expected to be stabilized, following a linear path in the following years, even if an exponential trend was observed regarding the use of AI in other topics [27–29]. The database obtained was pre-processed through a bibliometric analysis, thus constituting a first-layer step on the general topic in order to confer systematicity to the analysis. Figure 3 depicts a co-occurrences map based on indexed keywords extrapolated from the original query results. In particular, four clusters can be distinguished regarding the use of AI-learning systems, whose topics are listed as follows:

1. AI methods for Li-ion batteries, in particular for State-of-Charge and State-of-Health estimation;
2. AI methods to control electric power systems, such as battery management systems (BMSs) and battery energy storage systems, and to couple with wind and solar power generation;
3. Blockchain for Internet of Things perspective in realizing smart power grids (V2G) and demand response in cooperation between electric power transmission networks and renewable energy sources;
4. Learning algorithms for performance and information management related to digital storage, energy efficiency, and cost-scheduling.

Table 1. Query for Scopus database.

Title–Abstract–Keywords	Publication Year	Document Types	Language
Artificial intelligence, energy storage systems, electric vehicles	>2016	Excluded conference reviews, conference papers, reviews	Limited to English



(**a**) (**b**)

Figure 2. Number of literature contributions for the use of AI applied to ESSs for EVs: (**a**) absolute numbers per year in the 2017–2024 period and (**b**) trend line for the growth of the topic analyzed.

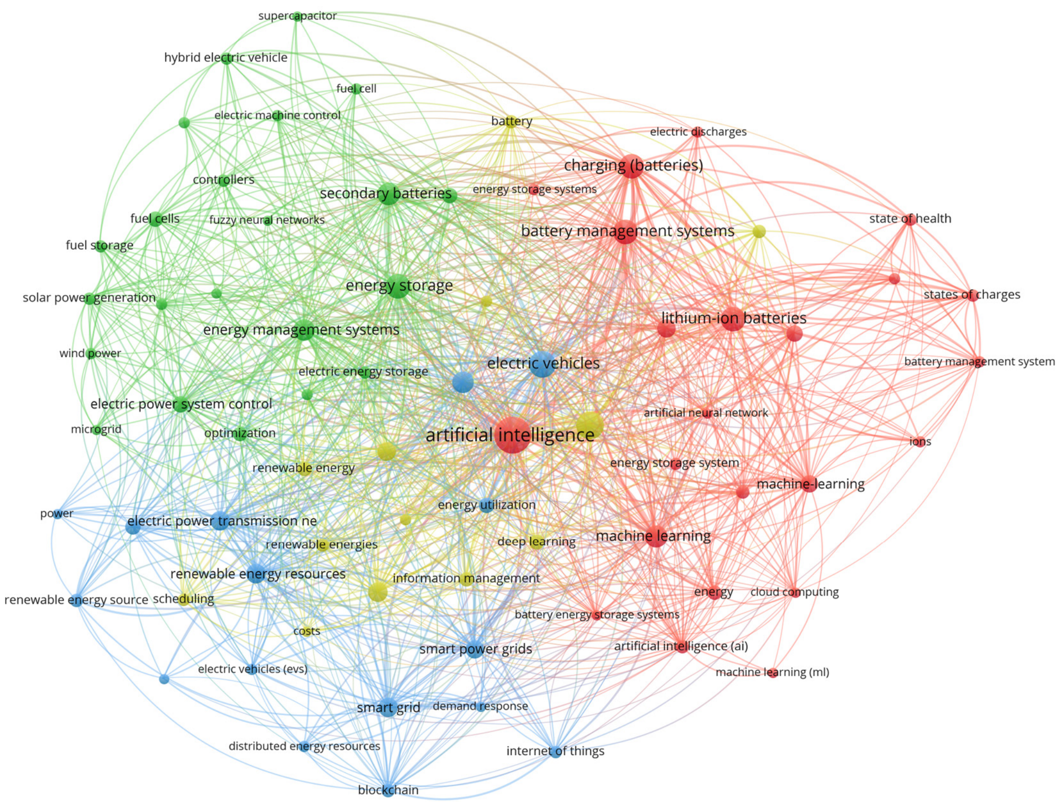


Figure 3. Co-occurrences for the implementation of AI to ESSs for EVs (VOSviewer).

If the analysis is based on a bibliometric point of view like the aforementioned one, the most occurring AI methods identified are very few—Artificial Neural Networks (ANNs) for cluster 1, Fuzzy Neural Networks (FNNs) for cluster 2, blockchain for cluster 3, and Deep

Reinforcement Learning for cluster 4. This leads to considering only a general oversight on the subject, which is acceptable in the presence of many literature contributions. In this case, given the limited number of papers considered (81 items in total), a detailed analysis must be provided to discover the different approaches authors adopt in applying AI to ESSs for EVs.

3. Applications of AI to Energy Storage Systems for EVs

Starting from the actual state of EV diffusion worldwide, the most important topics regarding the relationships between EV operations and ESSs were identified based on the bibliometric inquiry, as reported in Section 2 and depicted in Figure 3. In particular, the topics on which the role of AI is being focused are:

- Battery Management System as the supervisor role in managing battery state parameters during motion and charging;
- Power Quality improvement strictly related to network safety and security;
- Possibility to couple EV charging operations with RESs in order to enhance a fully sustainable charging cycle;
- Optimization of charging and discharging cycle;
- Battery State of Health prediction based on relevant state parameters;
- Estimation of State of Charge (SoC) for the battery based on different operative constraints.

3.1. AI in Battery Management Systems

The use of AI for vehicular subsystems to help manage the energy stored is progressively spreading towards an intensive application [17]. Figure 4 collects the main tasks deployed by BMSs universally. A BMS performs measurements through sensors—in particular, it derives the measurement of battery SoC—and then acts on the system in order to ensure its correct working conditions and safety and realize data communication to transmit relevant information to drivers. Different BMSs can be recognized [30]:

- Passive: The BMS exploits only passive electrical circuit elements to regulate and balance the charge among the cells of a battery.
- Active: The BMS exploits not only passive elements but also elements capable of intervening in the system based on control signals (i.e., amplifiers, transistors).

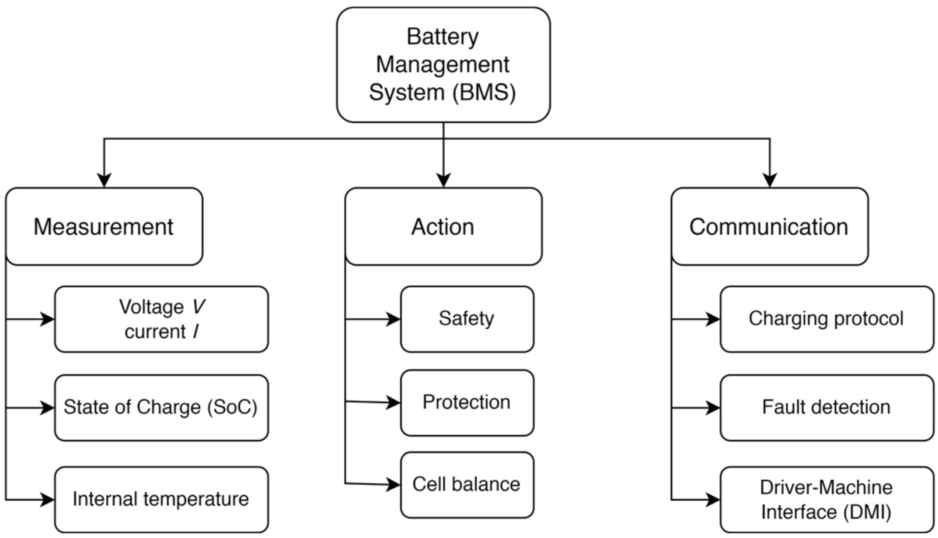


Figure 4. Schematic representation of BMS surveillance and control functions.

ANN is strongly exploited for online and offline evaluation processes, thus assessing the performance of the algorithm chosen in [31]. Positive feedback was observed with the benefit of less energy consumption (−6%), but issues related to the simulation-to-real gap were encountered, thus limiting online application in real time. Moreover, compared to similar contributions developed in this field, the overall energy efficiency evaluated is the highest, reaching 96%, with an average value of 86.1%. In addition, good performance must be reported in terms of the estimated speed and torque, whose errors comprised 0.5–0.6%. Similar results are obtained in [32], where the overall battery performance is improved, with AI cooperating to keep SoC between 63 and 67% and global energy consumption reduced to −6.7%. This testifies that implementing AI carries benefits in the management of ESSs.

The advantages of AI in prediction and quickness in calculations allow for the development of multiple strategies. The Adaptive Neuro Fuzzy Information System (ANFIS) and Model Reference Adaptive System (MRAS) are exploited to improve the performance of BMSs within a controller [33–35]. The MRAS module allows for physical speed sensors to be discarded; thus, traveling speed is estimated through α and β components of motor voltages and currents. ANFIS, which is composed of ANNs combined with fuzzy logic, is structured as follows:

- Two input channels (error and its derivative in time);
- $4 \div 5$ hidden layers;
- One output (i.e., the control signal u).

The addition of fuzzy logic enhances accuracy, especially for SoC estimation, making ANNs universally reliable for results achieved, reducing fatigue, stress, and battery consumption, and improving bus stability. Applications of such a method on BMSs aimed to improve controller performance are translated into higher average efficiency of the module (+7.6%) with a reduction in stress on fuel cells ($-15 \div 30\%$). Fluctuations of overall achievements are related to the different driving cycles considered: either the US Highway Fuel Economy Test (HWFET, also known as Federal Test Procedure FTP-75) or the EU's Worldwide-harmonized Light vehicles Test Procedure (WLTP) [36]. Detaching the evaluation procedure from a physics-based model means neglecting the uncertainty or fluctuations in measured data, on which the model relies to accurately prompt the outcome [37]. Moreover, implementing an ANN-based controller allows for improvement of the robustness of the BMS controller against external disturbances, with related impacts that are contained to within 0.33% [38].

Digital Twin (DT) is an emerging discipline that deals with testbed activities. This technique consists of a digital representation of a real and unique product considering its characteristics, properties, conditions, and behavior, thanks to mathematical models [7]. One of the advantages of adopting DT is the continuous improvement in testing communication protocols to allow for charging or battery swapping sessions, coupling with RESs, and the realization of smart grids in order to assess the overall energy demand based on the correct estimation process of BMSs. In the wake of this, a digital representation of the battery model is exploited in parallel by BMSs to assess the real battery operations—in particular, the estimation of SoC and DoC (Depth of Charge) [3,39]. The application is made possible by implementing hybrid models—i.e., a combination of physics and AI—with a strong constraint regarding the public disclosure of real battery data. This method is designed to increase the accuracy of outcomes since the prediction through ML is accompanied by physics-based models to confer meaningful results [31]. The following technique can also be applied for life cycle predictions and to refine the model through multi-scale dimensions [40]. An interesting application is exposed to some ESSs with energy generated by Electric Multiple Units (EMUs) in railway transportation through AI [41].

3.2. AI in Power Quality

The Power Quality (PQ) issue has emerged in the last decades due to the diffusion of electronic power devices and their interactions with the electricity distribution network [42,43]. As an emerging topic, few contributions to the literature were retrieved. Given their non-linear behavior and the harmonic distortion generated in power grids, the integration of such components must be treated well, especially in the development of smart grids (or microgrids), where the cooperation between EV charging infrastructure, users' loads, RES generation, and ESSs is realized, as Figure 5 depicts [44]. Focusing on PQ is needed to ensure the reliability and safety of the network, stabilize the energy flow, and reduce the detrimental effect of harmonic distortion injected into the grid. The fundamental role of AI here is harmonizing the cooperation between different electric loads—each featured by different generation dynamics and daily load profile—acting on the same distribution grid. PQ issues can be mitigated through passive filtering in the network, but it is necessary to quickly detect the nature of the imbalance-generating downgrades on the power quality transferred [45]. Here, a comparison between the AI approach and Fuzzy Logic Control is performed, with very close final results [45,46]. The potentiality of AI is limited by the training phase, which must be accounted for to increase its accuracy. The need for AI in this field relies mainly on performing optimization processes, data analytics, and asset management, organized into three levels as follows [47]:

- Business;
- Infrastructure;
- Physical.

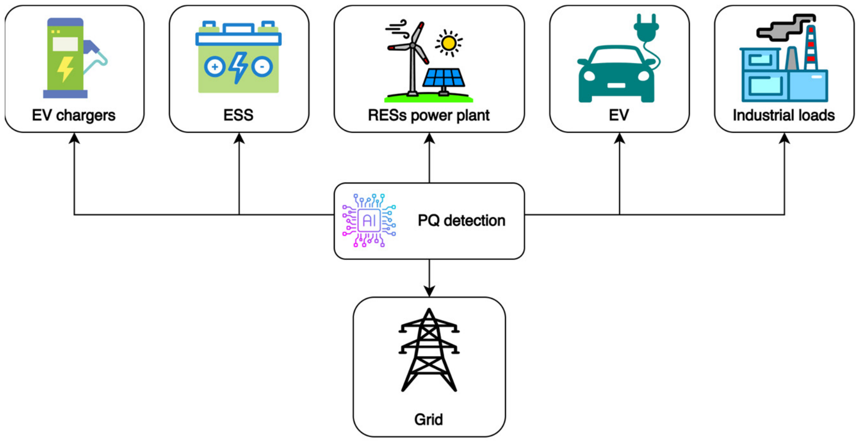


Figure 5. Schematic representation of a smart (or micro) grid and the role of AI in PQ.

With this classification, no link appears to underlie these fields and is related to the main topic of this manuscript. Analyzing the framework in detail makes it possible to discover its hidden rationale. The business level refers mainly to data analytics, which is oriented to offer commercial solutions in a customer–supplier relationship. Moreover, it also involves the presence of all assets capable of generating profits for the company, such as PV power plants, in terms of their presence allowing the company to propose different commercial offers to various customers, i.e., residential or industrial users [48]. Implementing multi-agent deep reinforcement learning as a Markov Decision Process (MDP) has reduced operational costs, increasing income by between +9% and +16% across various case studies, depending on the solar penetration levels. The infrastructure level regards grid management, which involves strategies to improve the operational parameters and exploit the whole grid's potential to respond adequately to the energy demand. Lastly, the physical level pertains to all activities performed on the grid mediated by AI, such as predictive maintenance processes. A different approach can involve the implementation of blockchain protocol to differentiate market management through peer-to-peer trading [49–51]. This last topic is experiencing a significant diffusion when dealing with interconnected systems using IoT since blockchain can keep track of past transactions. The combination of blockchain and AI can generate the Artificial Intelligence of Things (AIoT). Blockchain technology can be leveraged for power management purposes within the smart grid, facilitating more efficient allocation of energy resources to meet demand requirements through collaboration with AI [48]. The comparison between different reinforcement learning (RL) algorithm approaches dealing with building interactions within the grid is evaluated in cooperation with surrogate models and Q-learning [52]. It is a valuable contribution that addresses an essential remark about implementing the AI method that can be easily extended as a general remark for other techniques. The pure RL approach produces a very ineffective behavior in prediction in the presence of a restricted number of episodes to be evaluated. At the same time, the accuracy is strongly improved in cooperation with different AI approaches—such as guidance, short term, and long term with surrogate models with or without rule-based control strategies, and imitation learning—within the same restricted number of evaluated episodes. This resulted in an overall total energy cost reduction of −30%. Another valuable application that cannot be neglected is related to the implementation of AI in a power generation plant to fine-tune an Active Disturbance Rejection Controller (ADRC) to allow for coupling between RESs and EVs [42,46]. The control architecture was tested on several scenarios such as frequency, overvoltage, and power control and allowed to reduce the overshoot and undershoot in the time response if compared to conventional techniques—like PID controllers—and a contemporary reduction in the settling time of about −50%. This is reflected in the general improved stability of the controller.

3.3. Use of AI in RES-EV Coupling

The widespread adoption of EVs requires maximizing Renewable Energy Sources (RESs) to fulfill EV charging energy demands with green energy for sustainable mobility [45,53]. Discussing the reduction in environmental impact in transportation systems appears contradictory without considering the environmental impact of the energy production processes. Especially regarding electric mobility and realizing a system that is fully environmentally sustainable and beneficial for the target of emissions reduction, the coupling between EV charging infrastructure and RES power plants must be considered. This topic is closely connected to the previous one described in Section 3.2 since realizing smart grids is the common field. A careful focus must be set on the different natures of electric loads and flows within the grid; as already mentioned for PQ, EV charging stations are a source of imbalance and harmonic distortion. Coupled with the seasonality and randomness of RES power production, dealing with intermittent power injection poses challenges. However, the realization of smart grids enables the coupling of various loads, and with the assistance of AI techniques, it optimizes energy flows [54], thereby reducing uncertainties. Different methods can be implemented to enact effective grid management, utilizing various approaches [55]. In particular, the implementation of an FLC with respect to a classical ANN-based controller allows for a reduction in the Total Harmonic Distortion index on both grid and load currents below 5%, thus complying with the IEEE-519 standard [56] and being able to reach the maximum possible output power [45]. From this perspective, AI is mainly exploited to optimize energy flows [25,57]. As a general framework, the use of AI in smart grids is needed to harmonize the different loads that can generate demand and, thus, to set up demand response strategies. Moreover, the importance of communications protocol allows for the implementation of AI in smart grids; hence, such algorithms can exploit data availability to provide meaningful results [55]. Also, in this topic, the main task that AI is in charge of is single-objective or multi-objective optimization, depending on the final system to be optimized, whether EMS and smart grids [58,59] or the charging phases of a generic EV [60].

3.4. Optimization of Charging/Discharging Cycles through AI

Numerous researchers have concentrated on AI-based models for EV charging forecasting and scheduling, highlighting their superiority over traditional optimization methods like linear, exponential, and multinomial logit models. However, the focus on EV discharging scheduling, specifically V2G systems, has been limited, as this concept is relatively new and evolving [61]. Therefore, there is a need for a comprehensive review of existing research in EV charging and discharging to identify gaps and propose improvements for future studies. This paper [62] undertakes such a review, categorizing studies into forecasting mechanisms. In addition, a schematization of each charging technique is illustrated in Figure 6. This makes visible the step-by-step changes toward the implementation of AI in charging/discharging optimization cycles:

- In a control-based strategy, the system is set to optimize the charging cycles of a generic EV connected to a charging station; the system realizes only control actions on either the vehicle or charging station side for what concerns charging operations.
- With a smart strategy, the role of AI is to integrate EV charging operations within a V2G management protocol. Here, the system acts as a control strategy for either a vehicle or a charging station based on information flows coming from the power distribution grids, RES production plant, and load demand. The required energy flow is then managed on the infrastructure side.
- In an indirectly controlled strategy, based on the previous step, the role of AI is to determine a dynamic energy price, in addition to the information flow coming from the infrastructure.

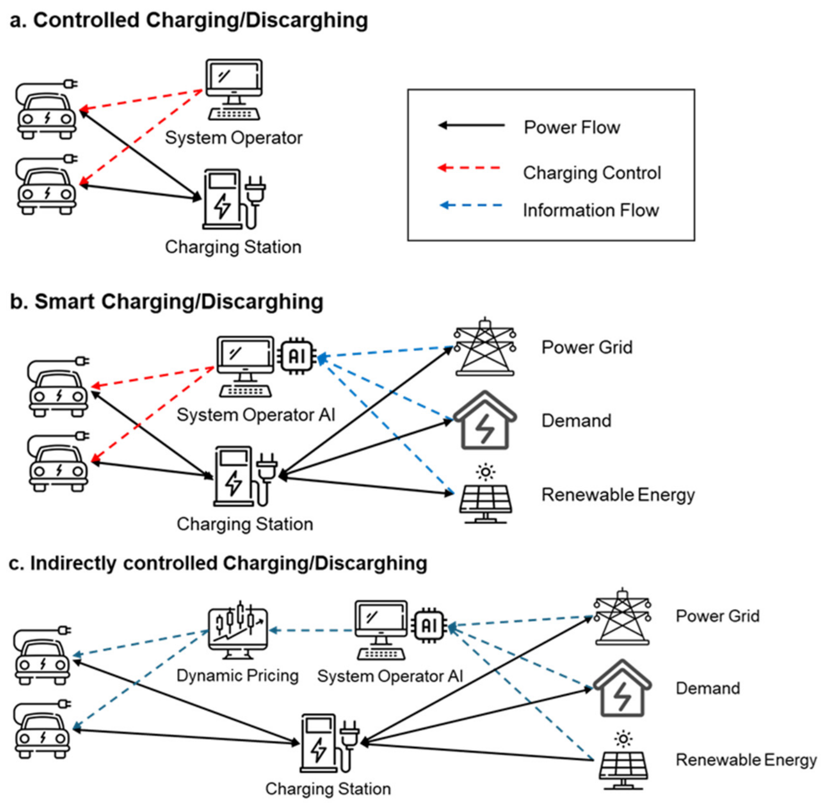


Figure 6. Development phases and corresponding EV charging techniques: (**a**) controlled charging, (**b**) smart charging, (**c**) indirectly controlled charging.

The utilization of V2G services leads to a higher frequency of charging and discharging cycles compared to scenarios without V2G services [63]. Consequently, the potential for battery degradation is more pronounced in the presence of V2G services. Petit et al. conducted an assessment on two types of lithium-ion batteries, Nickel–Cobalt–Aluminum Oxides (NCA) and Lithium Ferro-Phosphate (LFP), revealing varied impacts of V2G on different batteries [64]. Pelletier et al.'s studies highlight that storing batteries at a high SoC expedites calendar aging [65]. Moreover, extensive research underscores that degradation is exacerbated by overcharging and over-discharging, mainly when the battery operates beyond its specified voltage range [66,67]. In [68], a novel ML approach was introduced to forecast future energy consumption. This algorithm exhibited an accuracy of between 93% and 97%. On average, the margin of error of the algorithm in expense predictions was less than 7%. These results suggest significant potential for energy savings, with observed reductions of 37% in energy usage. Ref. [69] employs a Support Vector Machine (SVM) to analyze home charging schedules, leveraging user energy consumption data and SoC information at various intervals. The SVM model achieves nearly 100% accuracy in predicting EV status. While it is acknowledged that battery degradation is an unavoidable process, there are tangible measures to minimize its impact. This includes steering clear of overcharging and over-discharging, advocating for optimal charging/discharging rates, ensuring adherence to the appropriate temperature range, and maintaining the battery at an optimal SoC. Consequently, enhancing the precision of battery degradation estimation and modeling emerges as a critical imperative for the development of robust battery control strategies for both charging and discharging operations.

Numerous utility providers in countries such as India, Sweden, the United Kingdom, Canada, and the United States have widely embraced the Time-of-Use (ToU) electricity tariff strategy. This approach can be implemented to incentivize users to shift their electricity consumption away from peak periods towards off-peak periods. The ToU tariff structure entails distinct pricing for charging during peak, standard, and off-peak hours [70]. The ToU EV charging pricing model was introduced, emphasizing demand price and power-quality considerations [71]. Various EV charging strategies have been specifically modified to align with ToU tariffs with the primary goal of minimizing charging costs. An intelligent approach could be the management of EV charging loads in response to ToU tariffs within a regulated market [72]. This can benefit from using an estimator to predict charging session parameters, such as duration and energy consumption [73]. According to simulation outcomes, the proposed scheduling framework led to a noteworthy 29.42% reduction in average charging costs.

The machine learning approach for energy consumption forecasting achieved an accuracy of between 93% and 97%, with a margin of error in expense predictions of below 7% and observed energy usage reductions of 37%. Meanwhile, the SVM model reported nearly 100% accuracy in predicting EV statuses, particularly in analyzing home charging patterns. Despite differing scopes, both methods significantly enhance efficiency and reduce energy management costs and EV charging schedules.

3.5. Battery Health Prediction Dynamic through AI

Dynamic EV battery health prediction with AI employs advanced algorithms for real-time analysis and modeling of degradation patterns [74]. This approach supports charging optimization, enhancing battery life and overall efficiency. Prognostics in battery health focuses on anticipating future degradation in energy or power, aiming to predict when the performance of the battery will no longer meet satisfactory standards [75]. The constraint is to have a pre-processing phase of the dataset coming from the battery, i.e., adapted to the purposes of the ML process [76]. This operation is oriented to optimize the algorithm aiming to constitute an ML-based battery model, which can be exploited either to benchmark estimation accuracy among different approaches or predict the battery SoH based on available operative data in a straightforward way. The ML modeling process described is illustrated in Figure 7.

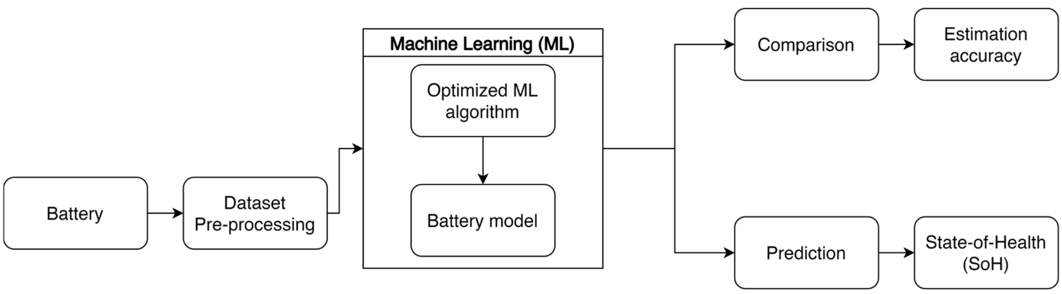


Figure 7. The ML battery modeling schematic.

Recent advancements in communication and AI technologies have spurred the widespread utilization of ML techniques for SoH prediction [77]. ML-based methods, known for their ease of application and independence from detailed degradation mechanisms, have become a focal point in promoting SoH estimation [78]. Gaussian Process Regression (GPR) is the most used, centered on the viability and efficiency of this algorithm for SoH estimation using real-world data [79]. In their study, Afandizadeh et al. presented an ML-based methodology to estimate battery SoH. Emphasizing the importance of precise SoH assessment for predicting battery degradation and optimizing maintenance strategies, the authors conclude that their proposed approach offers accurate and reliable estimates of battery SoH [80,81]. The unique data processing approach integrates Big Data, AI, and IoT technologies, achieving an impressive 99.98% accuracy for the battery model.

A data-driven approach for SoH prediction can be introduced using GPR, selected for its ability to model complex data relationships and capture prediction uncertainty without relying on future load information or DL-based prognostics [82,83]. In [84], the results on the NASA battery dataset show that the proposed method does not exceed 1% error in early SoH predictions.

Artificial Neural Networks (ANNs) avoid traditional mathematical expressions and instead analyze the relationship between input variables (stress factors) and degradation metrics. Leveraging ANNs enables the development of robust degradation models, facilitating on-board estimation of battery SoH [85,86]. This paper [87] introduces an ANN to develop an SoH estimator for lithium-ion battery packs. Impressively, the results demonstrate an extremely low MSE of 1.4×10^{-5}. However, the accuracy of SoH estimation is contingent on a substantial amount of training data. ANNs excel in capturing non-linear relationships, adapting to dynamic environments, and learning autonomously from input data in estimation tasks. However, the complexity, especially in deep architectures, may challenge interpretation. Overfitting is a concern with limited data, and training deep networks demands substantial computational resources. ANNs depend on the quality and quantity of training data, and their black-box nature hinders interpretability.

The results achieved in battery SoH prediction demonstrate significant advancements in accuracy and reliability. For instance, the ML-based methodology achieved an impressive accuracy of 99.98% for battery SoH estimation, surpassing traditional methods. Additionally, the data-driven approach utilizing GPR demonstrated an error rate below 1% in early SoH predictions. These advancements highlight the tangible benefits of advanced AI algorithms for dynamic EV battery health prediction, leading to increased accuracy and reliability compared to conventional methods.

3.6. State-of-Charge Estimation

The SoC estimation process is the topic on which the implementation of AI has been the most focused. Two main branches are studied to evaluate internal temperature and thermal management operated by BMSs [88].

The challenges faced by EVs due to numerous faults in battery packs underscore the importance of assessing the SoC of batteries. The application of AI and ML concepts was introduced to address issues like over-current and over-voltage protection for battery cells. ML algorithms prove valuable in predicting SoC, as they can capture cell dynamics and retain historical data, which is essential for forecasting future charge levels. This delves into various aspects, including different charging methods and energy storage technologies [89]. The exploration of BMS in conjunction with multiple charging methods and energy storage technologies is a focal point in these comprehensive reviews [90,91].

The authors utilized a simple radial-basis ANN to identify the ECM parameters [92]. Inputs were SoC, along with the measured current and voltage, while the output was the Open Circuit Voltage (OCV). A similar approach was adopted where, following the modeling of the battery system with an ANN and a state space model, the SoC was calculated using a dual EKF or another adaptive filter-based estimator [93–95]. Errors were found to be below 1.87%, proving benefits in the online updating function of the NN. A

MISO approach (Multi-Input Single-Output) constituted by a four-input, one-output BPNN can also be adapted for SoC estimation [96,97]. Here, the difference in the estimation error, whether an optimized or a non-optimized BPNN is adopted, can be kept below 4% or 10%, with a sensible difference in the estimation performance. In a more straightforward approach, a two-input, one-output configuration can be chosen, with one hidden layer for the BPNN structure. The inputs are the battery current and terminal voltage, and the SoC is the output variable. Some other approaches can estimate battery SoC directly from an ANN online [98–100].

It is worth noting that the primary drawback of ANNs lies in their need for more neurons to enhance accuracy, limiting their implementation in real-life models. Additionally, each ANN requires training before use, and multiple iterations may be necessary. This renders the trained ANN applicable to only a specific purpose. Furthermore, ANNs lack effectiveness in extrapolation, constraining their ability to calculate the remaining charge time of a battery [101].

Several publications directly calculate SoC using Fuzzy-Logic (FL)-based estimation [102]. SoC and cell capacities can be estimated by comparing cell voltages at the beginning and end of charging, termed the "FL Dissipative Cell Equalization" algorithm. Meanwhile, Sheng and Xiao employed a least-squares support vector machine with fuzzy inference and nonlinear correlation measurement for SoC estimation [103]. FL offers advantages in handling uncertainty, incorporating expert knowledge through rule-based systems, adapting to dynamic environments, and ensuring ease of interpretation. It excels in control systems, especially when precise mathematical models are challenging. However, drawbacks include a potential lack of precision, rule complexity, optimization difficulties, limited scalability for complex problems, and reliance on expert-defined rules over data-driven insights. Evaluating these pros and cons is crucial to assessing the appropriateness of fuzzy logic-based estimation for specific applications.

4. Discussion of AI Methods

The coupling of BMS with AI carries undeniable benefits. When dealing with such techniques, several critical points must be addressed, specifically if applied to battery (or energy) management. The first is related to the availability of a large dataset on which the algorithm can be trained effectively. The number of public datasets is limited, and the majority are not publicly released. In addition, most of them depend on the type of battery tested, as underlined in [30]. For example, the total number of datasets retrieved was 18, where:

- Four datasets could be used for both NCA and LCO;
- Eight with NMC;
- Seven for LFP.

Secondly, after creating the dataset, it is crucial to ensure that the sampled physical parameters align with the algorithm's objectives for training. Thirdly, once the dataset is retrieved, the data within it must be sufficiently reliable, addressing issues related to measurement uncertainty. Lastly, its scope is the most critical factor in determining whether the selected dataset is suitable for the training phase of the algorithm. In other words, the dataset should be modified to evaluate specific relevant aspects, as focusing too heavily on certain parameters could invalidate the entire training phase. It is crucial to give careful attention to the quality of the dataset. Therefore, it is essential to ensure the dataset is accurate and error-free [104]. The most implemented ML technique found throughout the articles analyzed is ANN. In detail, ANN is often developed to evaluate Li-ion battery performance. The accuracy of the evaluation process on battery voltage and SoC was discovered to be more reliable during the discharging phase than charging operations [105]. In addition, the parallel estimation performed in cooperation between ANN and physics-based models such as ECM shows an improvement in accuracy, with a reduced root mean squared error (<1%) and R^2 (~0.96–0.995) [40,106].

Other optimization algorithms are implemented in cooperation with ANN to reach a satisfying optimization convergence. Most of them merge ANN with Particle-Swarm Optimization (PSO) to reach valuable results from an optimization perspective [8,32]. This cooperation is helpful in improving the performance of ANN, especially when the prediction performance of the algorithm is satisfying, in addition to providing optimization parameters or optimization based on historical data. In [8], a comparison between ANN-PSO and Radial-Basis Function (RBFNN) is set, with the latter outperforming the former, with errors below 1%, and the former showing errors in estimation above 4%. One of the applications in BMSs is the time-varying parameter tuning function that can be implemented through AI [107] and Long Short-Term Memory LSTM [108]. In other applications, ANN may reduce the estimation errors compared with offline procedures and methods, limiting the error in accuracy to 0.17–1.55% [109].

Regarding the PQ topics, various ML methods offer potential, though each comes with its limitations. Specifically, Convolutional Neural Networks (CNNs) and Recurrent Neural Network (RNNs) stand out as promising options, each possessing unique characteristics tailored to specific scopes. CNNs are commonly applied in event classification tasks, particularly in object recognition, boasting impressive accuracy rates ranging from 96% to 99% [110–113]. However, it is essential to note that while CNNs excel in recognizing patterns in spatial data, RNNs are better suited for sequential data processing, making them suitable for time-series analysis tasks often encountered in PQ analysis. Therefore, the selection of ML method should be driven by the specific requirements and nature of the PQ dataset being analyzed. Despite that, CNNs do not fit with time-series data, and in order to improve their performance, parallel cooperation with physics-based models such as wavelet or spectrogram RNN instead are capable of dealing with time-series and sequential data for event detection. Generally, the accuracy of RNN lies between 98 and 99% [44]. In addition to CNNs and RNNs, hybrid models combining both architectures, known as Convolutional Recurrent Neural Networks (CRNNs), have emerged as powerful tools in various domains, including PQ analysis. These models leverage the strengths of both CNNs and RNNs, allowing for the extraction of spatial features by the convolutional layers and capturing temporal dependencies through the recurrent layers. CRNNs offer a holistic approach to data analysis, which is particularly beneficial in scenarios where both spatial and temporal information play crucial roles, such as in PQ monitoring and event detection. By integrating CNN and RNN components, hybrid models can achieve superior performance and more nuanced insights compared to using either architecture individually. Thus, exploring the potential of CRNNs in PQ analysis could lead to enhanced accuracy and robustness in detecting and classifying power-quality events.

One of the drawbacks of RNNs is the phenomenon known as the "vanishing gradient", where the gradient signal diminishes exponentially during training, hindering accurate evaluation. Additionally, like many AI methods, RNNs are susceptible to overfitting, resulting in decreased performance as the algorithm struggles to generalize event detection beyond the training data. To address these challenges, Autoencoders (AEs) offer a potential solution by extracting features from sequential datasets or time series [114]. AEs excel in handling lower-dimensionality problems and non-linear models, making them viable alternatives to RNNs. Although AEs may exhibit slightly lower accuracy rates (typically ranging from 96% to 98%), their ability to mitigate overfitting and capture relevant features can lead to more robust and generalized event detection in PQ analysis [115,116].

The Generative Adversarial Network (GAN) is designed to discern whether an event is reliable based on its character or should be discarded. This is achieved through the interplay between a random generator and a discriminator. Such capabilities could prove valuable if implemented for PQ disturbances. In the GAN framework, the algorithm is initially trained to generate input data resembling real-world scenarios, while the discriminator's role is to distinguish between real and generated data through binary classification (0 or 1). However, it is essential to note that while these different methods offer intriguing strengths, each also exhibits weaknesses and limitations in its applicability to the PQ research field.

Therefore, careful consideration is necessary when selecting the most appropriate method for a given PQ analysis.

Another solution involves adopting a pragmatic approach that fosters collaboration among the various methods discussed. The goal is to integrate their specific strengths and mitigate individual weaknesses. By doing so, the overall applicability of the techniques can be enhanced, leading to more robust and effective solutions for PQ issues. A plausible configuration might entail combining CNNs with GANs to discern real events from deceptive yet similar occurrences (e.g., distinguishing potential faults within the network from false alarms). This cooperative arrangement allows for a more comprehensive analysis, leveraging the unique capabilities of each method to improve the accuracy and robustness of event classification in PQ disturbances.

The coupling between RESs and EV charging falls into a broader topic under investigation, which is connected with the realization of smart grids. Here, still valid and as mentioned before for BMSs, the problem is mainly related to global optimization from a management view rather than a proper prediction. Therefore, ANNs are also generally implemented to predict load levels. The optimization is realized by performing PSO on controller parameters in parallel, thus adapting the response of the system based on time-varying coefficients. Realizing smart grids (or micro-grids) stresses the need to deal with demand response, actuating different strategies based on different AI methods adopted. Also, for this case, ANNs are the most used, given their simplicity in implementation [117]. As previously discussed, the collaboration between ANNs and optimization methods yields positive results that enhance algorithm accuracy. However, due to the randomness inherent in human activity, multiple optimization methods can be leveraged in contrast to previous topics. A synergistic approach combining the Mixed Integer Linear Problem (MILP) and Markov Decision Process (MDP) allows AI to address multi-dimensional problems effectively. MILP focuses on optimization scenarios and selecting the best-case solutions among possible scenarios. At the same time, MDP acts as the decision agent, prioritizing choices among a set of alternatives determined by ANN.

Moreover, integrating the Q-learning method enhances the reinforced learning approach, effectively managing high energy consumption costs and reducing dependence on photovoltaic (PV) penetration levels. Additionally, Field-Programmable Gate Arrays (FPGAs) have emerged in pioneering applications for coordinating and controlling loads and RESs. These versatile devices offer promising opportunities for optimizing energy utilization and grid stability in real-time applications. This method can tackle sudden changes in the configuration thanks to its quick responsiveness in calculations. The coupling with several optimization methods contributes to minimizing the results, allowing a benchmark to be settled on which optimization method contributes to reaching the optimal value. In particular, the optimization methods analyzed can reduce -1.7% to -3.77% of the costs considered, with an average of -2% [118].

The topic of health prediction in EV batteries encompasses a different ML technique, such as Gaussian Process Regression (GPR). It offers a data-driven approach that can model complex data relationships and capture prediction uncertainty without relying on future load information. ANNs analyze relationships between input variables and degradation metrics, facilitating robust degradation models for on-board SoH estimation. Also here, from a future perspective, Neural Networks (NN), Relevance Vector Machine (RVM), Autoregressive Model (AM), and SVM could find a relevant opportunity for implementation. These techniques can play a crucial role in estimating the SoH of batteries, aiding in optimizing charging strategies and overall battery efficiency. RVM, AM, and SVM can also contribute to accurate SoH predictions, leveraging real-world data to enhance the reliability of battery health assessments. These ML techniques can collectively empower proactive maintenance strategies and support the longevity of EV batteries by enabling timely interventions based on accurate health predictions.

In the context of SoC estimation, advanced machine learning techniques such as Gated Recurrent Unit (GRU) and RNN and LSTM networks can improve the prediction process. These algorithms can be exploited to accurately predict the SoC of EV batteries and optimize charging and discharging processes while ensuring efficient energy utilization. GRU and LSTM networks excel in handling sequential data, allowing them to capture temporal dependencies and dynamics inherent in battery behavior. Based on historical data and real-time inputs, these models can effectively track changes in battery SoC over time, enabling precise estimations even in dynamic operating conditions. In addition to advanced machine learning techniques, several publications directly employ Fuzzy-Logic (FL)-based estimation for SoC calculation. Fuzzy logic offers a flexible and intuitive approach to SoC estimation, allowing for the incorporation of expert knowledge and linguistic variables to handle uncertainties and imprecisions in battery behavior. This methodology enables accurate SoC estimation even when traditional modeling approaches struggle to capture complex dynamics or where data availability is limited.

Table 2 provides an insightful comparison of various neural network architectures and their respective pros and cons in the context of ESSs for EVs. Feed-forward ANNs, such as multilayer perceptron, are noted for their high accuracy in assessing battery performance, especially when used in conjunction with physics-based models, although they are dependent on large and reliable datasets and may face compatibility issues with specific battery types. CNNs excel in event classification tasks but may have limited compatibility with time series and sequential data. RNNs effectively handle time-series data but are challenged by issues like the vanishing gradient problem and susceptibility to overfitting. DNNs demonstrate the capability to learn complex patterns but may suffer from overfitting with insufficient training data. GANs are praised for their ability to generate realistic data samples and are useful for data augmentation but may encounter training instability and mode collapse. Autoencoders (AEs) are highlighted for their feature extraction and dimensionality reduction abilities, although they may struggle with data semantics and interpretability. GRU and LSTM networks effectively handle sequential data and capture temporal dependencies, but both require careful parameter tuning, and LSTMs can be computationally intensive during training.

Table 2. Summary of AI methods, including advantages and disadvantages, for ESSs related to EV.

Topic	AI Techniques	PROs	CONs
BMS	ANN	High accuracy in evaluating Li-ion battery performance during discharging phases Improved accuracy through parallel estimation with physics-based models (e.g., ECM)	Dependency on the availability of large and reliable datasets Compatibility issues with specific battery types
PQ	CNN	High accuracy in event classification	Limited compatibility with time-series and sequential data Challenges with the vanishing gradient problem
	RNN	Effectively handles time-series and sequential data for event detection	Challenges with the vanishing gradient problem Susceptibility to overfitting
	DNN	Capability to learn complex patterns from data	Prone to overfitting with insufficient training data
	GAN	Capable of generating realistic data samples Useful for data augmentation and synthetic data generation	Training instability Mode collapse
	AE	Extracts useful features from input data Helps with dimensionality reduction and denoising	Reconstruction loss may not fully capture data semantics Limited interpretability

Table 2. *Cont.*

Topic	AI Techniques	PROs	CONs
RES–EV charging	ANN	Simplified implementation for load-level prediction	Dependency on the availability of large and reliable datasets Challenges in handling multi-dimensional problems
SoC	GPR	Models complex data relationships effectively Captures prediction uncertainty without relying on future load information	Computational complexity may be high for large datasets
	NN	Analyzes relationships between input variables and degradation metrics effectively Facilitates robust degradation models	Requires substantial training data for accurate estimation Interpretability may be challenging
	RVM	Offers high-dimensional regression with sparsity and uncertainty estimation Can handle small datasets effectively	Computationally intensive for large datasets Sensitive to parameter tuning
	AM	Suitable for modeling sequential data	May not capture complex non-linear relationships well
	SVM	Effective in high-dimensional spaces Versatile kernel functions for capturing non-linear relationships	Computationally expensive training May suffer from overfitting with noisy data
SoH	GRU	Handles sequential data effectively Captures temporal dependencies in battery behavior	Requires careful tuning of parameters
	LSTM	Long-term memory capability Handles sequential data effectively	Can be computationally intensive during training
	FL	Flexible and intuitive approach	Interpretability may be limited Requires careful tuning of membership functions

Upon initial inspection, there was a bias towards specific topics within the scope of our analysis. Specifically, the implementation of AI is prominently observed in the sectorial applications of SoC and SoH estimation, indicating a significant push in AI utilization in these areas. However, for other topics such as BMS, PQ, RES–EV coupling, and charging/discharging cycles, AI applications are relatively limited in comparison, owing to sustained relevance since 2022. The intersection of BMS and AI sparked initial interest around 2017–2018 and has since evolved significantly over the third time period. Similarly, interest in PQ and RES–EV coupling emerged in literature from around 2020 onwards. Upon closer examination of the bibliographic contributions, it became apparent that a significant portion addressed cross-topic research. For instance, references [38–44] explore the overlap between BMS and PQ, focusing on their combined effects on the grid. This underscores the importance of interdisciplinary collaboration, as the application of AI extends beyond the primary area of interest to adjacent topics. This observation is also valid for references [48–52], which highlight the connection between PQ and RESs due to the latter's significant impact on power-quality management. Undoubtedly, SoC and SoH estimation remain the most prominent research subjects, which is evident not only in the earlier part of the second time period (2012–2016) but also in the broader array of AI techniques employed compared to other topics. As indicated in Table 2, recent topics exhibit a narrower spectrum of AI methods, indicating nascent exploration with deeper applications. ANNs are particularly prevalent, owing to their ease of implementation, except for PQ, which has seen recent interest aligned with various ML methods. This alignment reflects the necessity to address non-homogeneous datasets, as discussed earlier in this section.

5. Future Trends

As future trends and developments, an intriguing dynamic is observed in the implementation of AI within the discussed topics [119]. Given the recent emergence of this field in terms of literature contributions, various AI methods have been implemented in studies conducted over the considered time horizon of 7 years (2017–2024), each with its associated positive and negative implications. The motivations for this phenomenon can be attributed to several factors. Firstly, there is a need for a simple architecture method that allows for application across a broader spectrum of cases. This motivates the initial widespread applications of ANNs, as reflected by the cluster analysis briefly introduced in Section 2, where co-occurrences highlighted the strong association. Secondly, this benefit is evident in the speed of adaptation and training, as ANNs have demonstrated remarkable efficiency in learning from data and adjusting to new information rapidly. Their ability to swiftly process large volumes of data enables them to refine their models and improve performance iteratively, leading to more effective decision-making and problem-solving capabilities. Additionally, the parallel processing capabilities of ANNs contribute to faster training times compared to traditional algorithms, allowing for quicker deployment and integration into practical applications. Lastly, a potential development could involve the cloud-based deployment of such methods, along with all the associated possibilities for further advancements.

BMSs can derive significant benefits from cloud-based applications, offering two main advantages. Firstly, the remote allocation of gathered information involves transmitting data to a remote server in real time, effectively separating the physical hardware from the data collection process. This setup enhances flexibility and scalability while enabling centralized monitoring and analysis. Moreover, a cloud-based architecture facilitates the aggregation of a large volume of data, creating a comprehensive dataset for algorithm re-training and accuracy improvement. Secondly, the potential to implement a battery predictive model mediated through AI in the cloud is promising. By leveraging data gathered from the entire vehicle fleet, this approach enables the development of robust predictive models capable of optimizing battery performance, predicting failures, and enhancing overall efficiency and reliability. This ensures the enhancement of the evaluation process, with estimated benefits in battery management resulting in a decrease in battery wear of approximately 20%. However, this approach also presents several critical aspects that must be highlighted, particularly concerning cybersecurity and the implementation of anti-intrusive protocols. These concerns are essential to address to safeguard sensitive data and ensure the integrity and security of the system against potential cyber threats and unauthorized access [120,121]. Attackers may have an interest in accessing data to:

- Cause unavailability of the systems: By launching denial-of-service (DoS) attacks or exploiting vulnerabilities, attackers can disrupt the availability of systems, rendering them inaccessible to legitimate users.
- Steal personal data: Attackers may attempt to access and exfiltrate sensitive personal information stored within systems, leading to privacy breaches and potential identity theft.
- Interfere with correct functions of systems: Through various means, such as injecting malicious code, tampering with data, or manipulating system configurations, attackers can disrupt the intended operations of systems, leading to errors, malfunctions, or unintended outcomes.

Two possible strategies can limit the danger of cyberattacks and undue access to sensible data [122–124]:

- Blockchain architecture [50,51,55];
- Training AI algorithms able to recognize cyberattacks [125,126].

In this last case, a CNN algorithm was proposed, which outperformed other AI techniques with 98% accuracy.

The latter remarks are still valid for what concerns the coupling between RESs and EV charging [25]. The importance of protection against cyberattacks is a universal concern that permeates all discussed topics. An immediate consequence of the diverse topics discussed here is the necessity for algorithms to identify various aspects and behaviors adeptly, transcending their individual characteristics and capabilities. Collaboration between different methods becomes imperative to enhance resilience against external attacks and bolster the robustness and accuracy of algorithms. For instance, coupling a CNN with GANs and RNNs enables the system to differentiate real events from intrusive attempts while also handling time-series data—a capability lacking in CNNs alone. This cooperative approach can yield numerous benefits, improving the overall potential of systems by enabling multi-stage estimators and enhancing their adaptability to complex scenarios.

Referring to the cluster analysis initially presented in this work, it is important to provide some additional insights to complete the review analysis. The co-occurrence analysis revealed the main topics and the most prevalent methods within the literature. This confirms the findings of the review, particularly highlighting the extensive utilization of ANNs and Fuzzy Logic. However, bibliometric analysis alone may not fully capture the prevalence of ANNs as the most implemented method, especially beyond the specific clusters identified. This comprehensive review explores AI applications in ESSs for EVs, highlighting emerging trends and future directions.

Digital Twin is emerging as a further trend in development. As mentioned in Section 3.1, this discipline can contribute to keeping up to date the dataset on which the estimation process is established [3]. Digital twins can contemporaneously simulate the functionality of focused subsystems, such as batteries, to predict the SoC and SoH while the real system operates. Real-time monitoring of physical parameters of interest enables the algorithm to improve its accuracy performance. The DT approach can predict relevant characteristics of the real system without physical intervention, preserving operational integrity—particularly crucial in operation-based applications like vehicle fleets for transportation. Developed within a digital environment, the collaboration between physical-based and data-driven methods can significantly enhance prediction accuracy and performance.

The integration of DT with AI presents a groundbreaking opportunity to reshape the landscape of ESSs in EVs. Beyond their role in real-time monitoring of battery SoC and SoH, AI-enhanced DTs offer many applications to enhance EV efficiency, reliability, and sustainability. Predictive maintenance emerges as a critical application, where DTs continuously monitor battery performance to identify issues, minimizing downtime and maintenance costs preemptively. Moreover, DTs can dynamically optimize battery usage by leveraging AI techniques like reinforcement learning and adapting charging and discharging strategies to real-time conditions and user preferences. Personalized energy management solutions adjusted to individual driving habits and fleet-wide optimization strategies further underscore the transformative potential of DT–AI integration in maximizing EV performance and longevity. Ultimately, this convergence promises to unlock new frontiers of innovation, sustainability, and resilience in the transportation sector, positioning EVs as integral components of the future energy ecosystem.

6. Conclusions

This paper provides a thorough review of the synergy between AI and Energy Storage Systems for Electric Vehicles. The motivation for exploring such topics derives from the extensive applications of AI methods, which have the capability to estimate output results without the need for a detailed physical modelization. The state of the art on ESSs for EVs is presented, together with the methodology for enquiring about literature contributions. The database was first analyzed preliminarily using a bibliometric approach to provide initial clustering based on co-occurrences. This classification allowed for the selection of the most relevant subjects that the authors considered to be worthy of a noteworthy analysis.

Therefore, each subject was analyzed on a deep insight level in order to discover the AI methods used most and discuss them according to their strengths and weaknesses. An important observation was made regarding the implementation approach, focusing on each aspect that can distinguish the application. During the analysis, it was discovered that ANNs were a popular choice due to their user-friendly setup. ANNs are often combined with Fuzzy Logic and optimization algorithms to enhance their performance and accuracy. However, it was noted that Deep Learning and Reinforcement Learning methods were not widely adopted and were underutilized. Given the recent developments, there is a potential for future improvements in AI techniques. This can be achieved through better cooperation between different methods, allowing for increased operativity and improved accuracy. By merging the advantages of each technique, the limitations that affect performance can be minimized. Cloud-based and DT applications have been found to be the most implemented for these methods, and there is a contemporary synergy between physics-based and data-driven approaches.

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List of Abbreviations

AI	Artificial Intelligence
AIoT	Artificial Internet of Things
AM	Autoregressive Model
ANFIS	Adaptive Neuro-Fuzzy Information System
ANN	Artificial Neural Network
BMS	Battery Management System
BPNN	Back-Propagation Neural Network
CNN	Convolutional Neural Network
DoC	Depth of Charge
DRL	Deep Reinforcement Learning
ECM	Equivalent (Electric) Circuit Model
EM	Empirical model
EMU	Electric Multiple Unit
ESS	Energy Storage System
EV	Electric Vehicle
FL	Fuzzy Logic
FNN	Fuzzy Neural Network
GAN	Generative Adversarial Network
GPR	Gaussian Process Regression
IoT	Internet of Things
LFP	Lithium Ferro-Phosphate
LSTM	Long Short-Term Memory
MDP	Markov Decision Process
MILP	Mixed Integer Linear Problem

MISO	Multi-Input Single-Output
ML	Machine Learning
MRAS	Model Reference Adaptive System
NCA	Nickel–Cobalt–Aluminum Oxides
NN	Neural Network
PM	Physical Model
PQ	Power Quality
PSO	Particle-Swarm Optimization
PV	Photovoltaic
RNN	Recursive Neural Network
RVM	Relevance Vector Machine
SEI	Single Electrolyte Interface
SoC	State of Charge
SoH	State of Health
SPM	Single-Particle Model
SVM	Support Vector Machine
ToU	Time of Use
V2G	Vehicle-2-Grid

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