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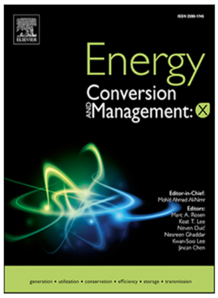

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A Comprehensive Review on AIoT Applications for Intelligent EV Charging/Discharging Ecosystem

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Abstract

As a prompt solution to air pollution, global warming, and fossil fuel shortages, electric vehicle (EV) penetration has been massively increasing. Spontaneously, higher EV utilization increases electricity demand. With the advent of vehicle-to-grid (V2G) technology, EVs play the prosumers' role in the power system. However, this role necessitates an intelligent EV charging ecosystem (IEVC-eco) that coordinates all components effectively, transforming EVs from a potential threat of power system overload into a valuable resource for ancillary services. AI and IoT (AIoT) are robust technologies, and with their contribution, the idea of IEVC-eco will become true. Therefore, in this paper, in addition to the IEVC-eco elements and tool determination, we investigate their AIoT requirements, including communication protocols, standards, and optimization techniques. Additionally, due to the importance of electric vehicle charging station (EVCS) recommendation tools, we endeavor to provide an efficient framework as a versatile gadget that considers all IEVC-eco stakeholders' desires.

Keywords: Smart grid, EV charging/discharging planning, Interoperability, IoT, Privacy

1. Introduction

Planning a decarbonized world as a principal solution to survive the planet's inhabitants has provoked efforts to eliminate fossil fuels from its most reliant customers, i.e., transportation fleets and electricity providers [1]. While vehicle electrification was considered transportation's free-emission solution, renewable energy sources (RES) played the eco-friendly role of electric power producers [2]. However, the role of EVs in the energy sector is twofold. Though EVs affect emissions alleviation positively, they increasingly become the principal customers of the power system according to the anticipation of being roughly half of the new car sales in 2030 [3]. The electrified transportation system burdens several issues on the power system by uncoordinated

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charging, including surges in peak load, overload on transformers and power lines, voltage and frequency disturbances, and the necessity for flexibility services [2, 4].

Figure 1 illustrates the effects of EV penetration on the economy, power system, and environment. In this figure, the beneficial impacts are highlighted in green. It is significant to note that the orange color indicates undesirable outcomes. Transformers and feeders overload results from the high penetration of EVs and uncoordinated charging. Moreover, EV charging occurs during peak hours, making it necessary to upgrade the power system. Voltage and frequency instability and harmonic distortions due to power electronic components of EV chargers are other troubles some EVs pose to the power system [5]. However, V2G technology and EV charging/discharging planning can mitigate undesirable effects [6, 7, 8, 9].

1.1. Background

The current limitations and potential solutions to broadening EV penetration by different aspects, including EV owners, power system operators, and EV manufacturers, are illustrated in Figure 2. The EV owners' main hindrance is the range anxiety that discourages the spread of EV usage. A range of anxiety occurs when an EV cannot reach its destination due to low battery charge and is unable to find a charging station [10]. The development of the number of EVCS and special stand-alone EVCS based on RES and energy storage systems (ESS) is the most effective solution to this obstacle. Charging technology evolutions also mitigate this hindrance by introducing onboard chargers, wireless chargers, and EV charging slot finders. Since more than 30% of EV price is due to its battery cost, retraining battery health is one of the principal concerns of EV manufacturers [11]. Battery thermal management and battery recycling are remedies to this issue [12, 13, 14, 15, 16]. Policymakers also can alleviate EV manufacturers' concerns about EV acceptance in transportation fleets by assigning subsidies for EV purchasing and tax exemptions for EV owners and improving public awareness of EVs' role in protecting the environment [17, 18].

Previously addressed issues like power system instability, degradation of power quality, and increasing peak load are the results of uncoordinated EV charging. It is possible to coordinate EV charging to alleviate EVs' undesirable effects on the grid as storage devices and demand response (DR) programs become more prevalent. Meanwhile, V2G accelerates EV presence amendment in power systems from troublesome to ancillary service providers [19, 20]. By V2G, an individual EV joins the building energy management system's (BEMS) DR programs or a group of parked EVs in the lot, ties into the power system through an aggregator, and trades electricity in a bidirectional power flow [21].

Due to the current relatively low penetration of EVs and lack of proper V2G infrastructure, V2G projects are yet in their initial stages and are currently small-scale [22]. Successful V2G implementation and controlled EV integration into the grid require addressing several major challenges, including the random behavior of EV owners, the lack of interoperable infrastructures, and data security. Additionally, mass adoption of EVs is limited by range anxiety, poor charging facilities, and high battery costs, whereas power system operators are hampered by peak load surges, voltage instability, and complex grid integration.

To overcome such challenges, a paradigm shift toward an AIoT-based structure is required in order to realize optimal bidirectional power and data exchange, optimized charging coordination, and offer safe and harmonious communication between actors. Alongside, policy initiatives such as EV subsidies and dynamic pricing regimes can promote EV penetration and strengthen their role as providers of ancillary services for upcoming power grids [23, 24]. Even though these are huge obstacles, ongoing research has explored some of the facets of EV integration, including infrastructure planning, charging optimization, and secure data exchange, which will be discussed in the following section.

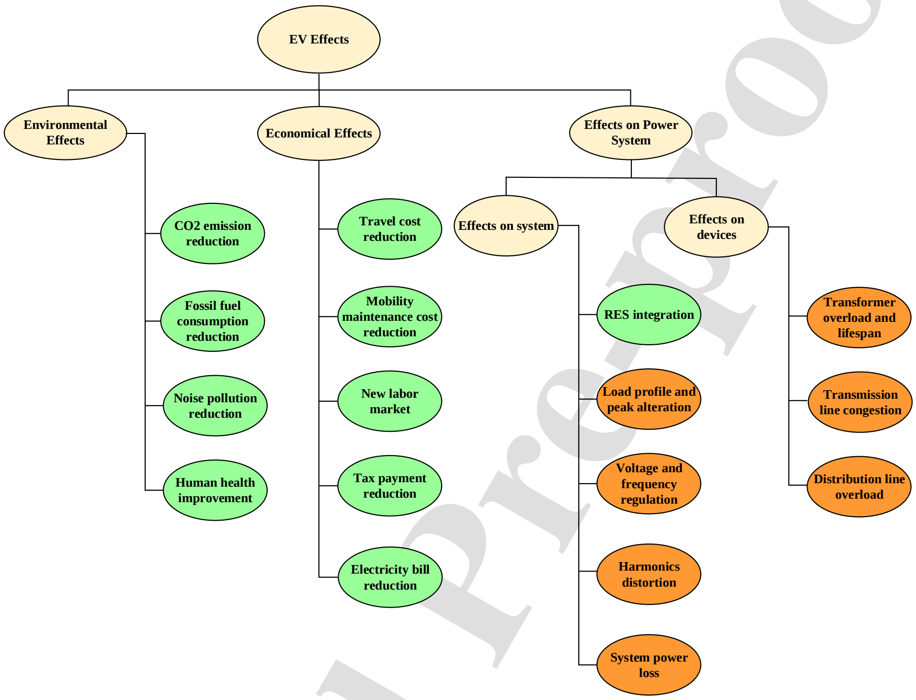

Figure 1: Different aspects of EV utilization

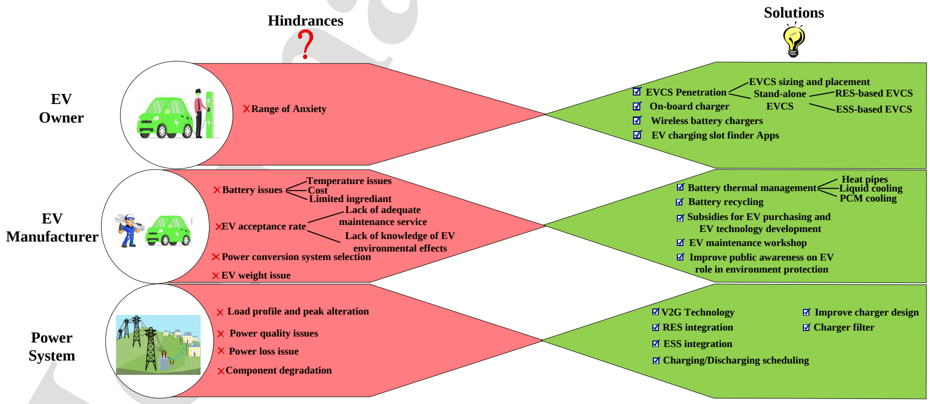

Figure 2: Hindrances of EV owners, Power system, and EV manufacturers and solutions

Table 1: Previous Survey Comparison

Papers	Categories																				
	EVCS							Batteries		AI Application	Communication Infrastructure		EV integration to Microgrid and BEMS	EV Charging/Discharging Scheduling	Contribution on DR	Integration Structure	EV Impact on power system	EV charging modeling	Charging pricing	Technologies	Policies	Standards and Protocols
	Sizing and Placement	Standards	RES Deployment	ESS Deployment	Charging piles	Battery chargers types and control strategies	Wireless battery chargers	Battery technologies	BMS		Technologies	Privacy requirements										
[25, 26, 27, 28, 29, 30, 31]	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x
[32, 33]	x	✓	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[34]	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[35, 36]	x	x	✓	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[37]	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[38, 39]	x	x	✓	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[40]	x	x	✓	x	x	✓	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x
[41]	x	✓	✓	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[20, 42]	x	x	x	x	x	✓	✓	x	x	x	x	x	x	✓	✓	✓	✓	x	x	x	x	x
[43]	x	✓	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[44]	x	x	✓	x	x	✓	✓	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x
[45]	x	x	x	x	x	✓	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x
[46]	x	x	x	x	✓	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[47]	x	✓	✓	✓	✓	✓	✓	✓	x	x	x	x	x	x	x	x	✓	x	x	x	x	x
[12, 13, 14]	x	x	x	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	✓	x	x
[48, 49, 50, 51, 16, 52, 53, 54]	x	x	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[55]	x	x	✓	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[56, 57, 58, 59]	x	✓	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
[60, 61]	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	x	x	x
[62, 63, 64, 65, 66]	x	x	x	x	x	x	x	x	x	✓	x	x	x	✓	x	x	✓	x	x	x	x	x
[67]	x	x	x	x	x	x	x	x	x	x	✓	✓	x	x	x	x	x	x	x	x	x	x
[68, 69]	x	✓	x	x	x	x	x	x	x	x	✓	✓	x	x	x	x	x	x	x	x	x	x
[70, 71]	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	x
[72, 73]	x	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	x	x	x	x
[74]	x	x	✓	✓	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	x
[5]	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	✓	x	✓	x	x	x	x	x
[75, 76]	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	x
[77, 78, 79, 80]	x	x	x	x	x	✓	x	x	x	✓	x	x	x	✓	x	x	✓	x	x	x	x	x
[81]	x	✓	✓	x	x	✓	x	x	x	✓	x	x	x	✓	x	x	✓	x	x	x	x	x
[82, 83, 84, 85]	x	x	x	x	x	✓	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x
[86]	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x	x	✓	x	x	x	x	x
[87]	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x	x
[88, 89, 90, 91]	x	✓	x	x	✓	✓	✓	x	x	x	✓	x	x	x	x	✓	✓	x	x	x	x	x
[92]	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x	x
[93]	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	x	x	x
[6, 7, 8, 9, 19, 94, 95, 96, 97, 98, 99, 100, 101]	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓	✓	x
[102, 103]	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	✓

1.2. Related Work

To address these multi-faceted aforementioned challenges—spanning from EV infrastructure limitations and power grid limitations to optimization and security challenges—scholars have proposed a wide array of strategies for enhancing EV integration with smart grids. Earlier research has highlighted critical areas like charging station placement, battery management, demand-side response, V2G interaction, and secure data exchange. However, most of the existing work is fragmented and usually addresses each technical aspect in isolation without providing an integrated AIoT-driven solution. To enhance the classification of such research, we categorize the existing literature in Table 1 into six general categories. EV infrastructure reviews, integration into power systems, integration into BEMS, penetration factors, battery management systems (BMS), and charging strategies and models are all included in this category. A large and growing body of literature has investigated different technologies and planning of EVCS, batteries, AI applications, and communication as the main EV fleet infrastructures. Researchers considered EVCS sizing and placement, standards, RES deployment, ESS deployment, charging piles, battery charger control strategies, and wireless chargers in the context of improving EVCS components and performance. EVCS penetration directly affects EV acceptability because of the reduction in the EV drivers' anxiety range. Therefore, EVCS placement and sizing are major areas of interest within the field of EV infrastructure. This category of EV-related review literature is in conjunction with the effect of EVs on power systems, and scholars have considered this effect in EVCS planning [25, 26, 27, 28, 29, 30, 31].

Other essential elements of EV infrastructure that scholars consider are EV charger types and topologies. Ref [32] is one of the initial studies that introduced different types of EVCS, sockets, and standards for EV infrastructures. EV on-board charger application investigated in [34] to solve the issue of EVCS shortage number. Recently, Rachid et al. [33] presented a comprehensive review of EV charger topologies and standards. In addition to EV charger types and topologies, Rubino et al. [35] studied the integration of EV chargers to distributed energy resources and ESS. The authors in this paper analyzed worldwide pilot projects on the wireless charging system and mitigation of EV effects on the power system by smart charging. Ali et al. [37] explored ESS applications in the form of single ESS, multi-ESS, and swappable ones as a response to the surge of interest in stand-alone EVCS.

Bhatti et al. proposed a comprehensive review of PV-based EVCS requirements in [38]. The authors in this paper highlighted power converter control strategies for stand-alone and grid-connected PV-based EVCS. In addition to overcoming the shortage of EVCS, RES can help mitigate the adverse effects of EVs on the power grid. As a result, it has been the subject of many comprehensive analyses in this area [39, 40, 41, 36]. The advent of EV DC fast chargers highlighted the role of converters among other EV infrastructures [42]. With the same line of thought, several comprehensive reviews studied power converters' topologies and standards [43, 44, 45, 46].

Wireless EV charging has received considerable scholarly attention in recent years. The design and development of inductively coupled power transfer (ICPT) have been explored in [47, 48, 49, 50, 51, 16, 52, 53, 104] as a crucial technology for EV wireless charging systems implementation. In addition to studying ICPT topologies and designations, Joseph et al. [55] studied its integration with RES, whereas its relevant international standards and existing models have been studied in [56, 57, 58, 59]. Asa et al. [54] reviewed safety concerns of electromagnetic field emissions of wireless EV charging systems as an obstacle to hiring this technology.

In addition to serving as a fuel tank, the battery is an essential part of the EV because it stores electrical energy, enabling V2G technology and the EV's function as a generator in the power system. Some of the works focus on various battery technologies, while the importance of preserving battery lifetime encourages scholars to investigate methods of the battery management system to monitor battery operation [60, 61].

Another area of the literature study focused on EVs is EV charging infrastructure optimization. Optimization algorithms and solutions hired to solve cost functions arranged based on different stakeholders' benefits were classified and analyzed in such efforts [62, 63, 64]. Pandyaswargo examined practical AI-based projects focused on traffic management, EV charging system optimization, and autonomous driving from around the world to recognize challenges in deploying AI in the mobility industry [65]. Abdullah et al. [66] studied reinforcement learning (RL) applications in EV charging and discharging scheduling.

Bi-directional interaction between charging facilities and EVs to plan the EV charging is another aspect that reduces the driver's range of anxiety and mitigates the impact of EV charging on the power system. Therefore, communication infrastructure is another EV fleet infrastructure that has been the subject of literature reviews [67]. As privacy is one of the concerns in data exchange, it is also a vital area of study in EV communication. Elghanem et al. studied radio access technology and its relevant privacy requirements in EV communication [68]. After realizing EV charging environment actors, Unterwegel et al. [69] determined corresponding standards for different EV charging scenarios and the literature privacy gap in utilizing these scenarios. With the same line of thought, Metere et al. [70] studied cryptographic algorithms to provide security in smart charging and V2G. According to the distributed structure of EV charging infrastructures, Zhimomi et al. [71] investigated blockchain applications to provide secure communication in this ecosystem.

Researchers have explored a wide range of features related to the integration of EVs into the power system, including their integration into the microgrid, charging/discharging scheduling, DR contribution, integration structure requirements, and their effects on the power system. Kur et al. [72] investigated the architecture, control, protection, and EMS requirements of microgrids integrated with EVs. Moreover, a survey on EV integration into building energy management systems (BEMS) as a flexible load was accomplished on [73].

Yang et al. [74] examined all the modern power system requirements to join EVs and distributed generators (DG), including control techniques, power flow calculations, risk management, and planning for networks and devices. Islam et al. in [75] and Inci et al. in [76] considered EV integration to power systems by the vehicle-to-everything (V2X) term and classified them into V2H, V2V, V2L, V2G, and V4G. The authors in this paper studied the benefits and hindrances of each technology implementation. Under the category of EV integration to the power system, Anwar et al. [5] analyzed EV scheduling management as a participant in the DR program. For this management, however, other studies discussed different structures and optimization methods [77, 78, 79, 80, 81]. EV impact on the power system from system and equipment points of view has been studied in [82, 83, 84, 85, 86, 87, 88, 89, 90, 91]. Shahriar et al. [92] explored modeling and prediction of EV charging as a basis for EV load prediction using various machine learning algorithms. Limmer [93] examined EV charging pricing mechanisms to control EV load.

EV penetration relies on technologies, policies, and standards. It was discussed by several scholars how EVCS and batteries should be developed in certain countries [6, 7, 8, 94, 95, 96, 97, 98], while others presented roadmaps for improving EV components, including motors, batteries, and body materials, as well as developing standard business models for EV market [9, 19, 99, 100, 101]. EV ecosystem participants' standard and communication protocol prerequisites were discussed in [102]. As a widely used protocol for the smart charging environment, open charge point protocol (OCPP) was examined by Garofalaki et al. [103] for security vulnerabilities.

Yet, A comprehensive review of optimization tools and IoT requirements of IEVC-eco arrangement is not available, according to Table 1.

1.3. Objectives and Contributions

While various studies have explored EV charging infrastructure, optimization techniques, and security concerns, a unified framework integrating AIoT solutions to optimize the IEVC-eco remains largely unexplored. To bridge this gap, this study systematically identifies key actors, their objectives, and their required interactions within the EV charging and discharging ecosystem. Therefore, this study identifies the actors, their objectives, and their required interactions within the EV charging and discharging ecosystem. Here, we consider EVCS as one of the smart city infrastructures and EV to be an active element of the smart grid that enables participation in the DR program with V2G technology. Here, we consider EVCS under smart city infrastructure and EVs as dynamic elements of the smart grid, enabling participation in DR programs through V2G technology. To mitigate the aforementioned problems, we propose in this research an interoperable EV discharging and charging scheduling model utilizing standardized protocols. It also refers to privacy-preserving techniques in ensuring safe data exchange and decision-making processes within the EV ecosystem.

Building upon these identified challenges and objectives, the key contributions of this paper are summarized as follows:

- Determination of IoT requirements for IEVC-eco arrangement.
- Identification of optimization tools more specified on AI application in IEVC-eco.
- Study on the state-of-the-art solutions in optimization of IEVC-eco stakeholders performances.
- Accelerate EV integration to the smart grid with recognition of interoperability requirements in the EV ecosystem and provide a roadmap to accelerate this integration.
- Study on privacy requirements in each level of optimization and communication.
- Arrangement of an interoperable, secure, and distributed framework for EV charging/discharging slot finder as the backbone infrastructure of IEVC-eco, according to our findings.

1.4. Paper Organization

This paper is designed to introduce explicitly and methodically the integration of AIoT solutions into the IEVC-eco. To achieve this, the paper is structured as follows, and each section deals with the most significant problem side and the solutions. Section 2 deals with the structure of IEVC-eco, detailing its most significant components and involved stakeholders for charging and discharging. Section 3 discusses the AIoT necessities and communication protocols, describing the principal technological facilitators necessary for efficient and secure EV-grid interaction. Section 4 explores smart charging optimization methods, presenting various approaches to enhancing scheduling, cost efficiency, and grid stability. Section 5 covers challenges, issues, and future perspectives of EV-smart grid integration, mentioning the key concerns of interoperability, privacy, scalability, and the evolving nature of AI-based EV management. Finally, Section 6 concludes the paper by summarizing the findings and offering potential future research directions

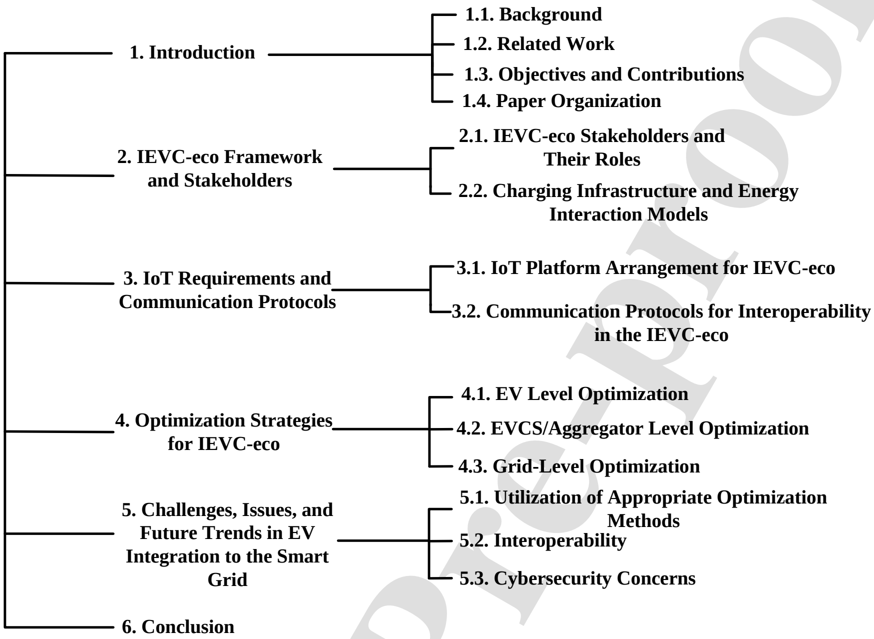

Figure 3: Overall structure and organization of the paper.

for AIoT-enabled EV charging ecosystems. The overall structure and interrelation of the paper's sections are illustrated in Figure 3 to provide a visual overview for readers.

2. IEVC-eco Framework and Stakeholders

To establish a successful IEVC-eco, a clear understanding of the participating entities and supporting technological infrastructure must be achieved. This section clarifies the essential components and entities in the EV ecosystem and also delves into the composition of EV charging infrastructure, including charging technology, power flow approach, and communication protocols. Analysis serves as a foundation for defining AIoT requirements covered in subsequent sections.

2.1. IEVC-eco Stakeholders and Their Roles

Power system operators, EV charging point operators (CPO), electro-mobility service providers (EMSP), electric vehicle owners, original equipment automobile manufacturers (OEM), and E-mobility clearing houses are principal members of the EV fleet, according to Figure 4.

CPO and EMPS provide technical support and management services for EVCSs. Each CPO is responsible for controlling one or more charging points. They are responsible for installing the hardware and software requirements of EV land owners who possess the EVCS. In addition to DC fast chargers installed for large-scale and inter-city EVCS, CPO also installs AC slow chargers for small-scale or stand-alone EVCS inside cities. CPOs integrate EVCS into the power grid with G2V and V2G technologies. Providing back-end and front-end services, CPO enables smart charging. EV users register their charging request amount, locations, and preferred time in the front-end mobile app provided by CPO. Additionally, back-end services that consider power grid limitations and other available energy resources, such as RESs, microgrids, and responsive loads, allow for a flexible power system. Another role of CPO is determining prices for EV owners who utilize its charging infrastructure.

EMSP, also called a mobility operator, collaborates with CPO to offer EV drivers the most suitable charging point. The EMSP applies its brand to front-end and back-end services provided by CPOs and operates the EV business model by issuing bills and invoices for drivers. EMSP facilitates charging payments through the app or RFID cards. CPO and EMSP negotiate with each other through the roaming platform, which is also called the e-mobility clearing house. ERoaming, following the concept of roaming in wireless telecommunication, facilitates exchanging EV users of different CPOs. Therefore, registered EV drivers of each region or country CPOs can use the other region CPOs' infrastructure. With the help of eRoaming, EMSP can coordinate with many CPOs. Recently the main objective of CPOs is scalability to cover more charging points and customers. Aggregated CPOs will motivate EMSP to directly connect to CPOs and weaken the role of eRoaming in the EV ecosystem. OEM includes all EV technology requirements providers, including EV manufacturers, battery producers, maintenance service providers, and even data communication technology providers. The transmission system operator (TSO) is responsible for the uninterruptible electrification of customers by providing a balance between the amount of power consumed on the distribution side and power generated on the power supplier side. The distribution system operator (DSO) is the operator of the power distribution network that is responsible for the establishment, operation, and maintenance of the local public electricity grid.

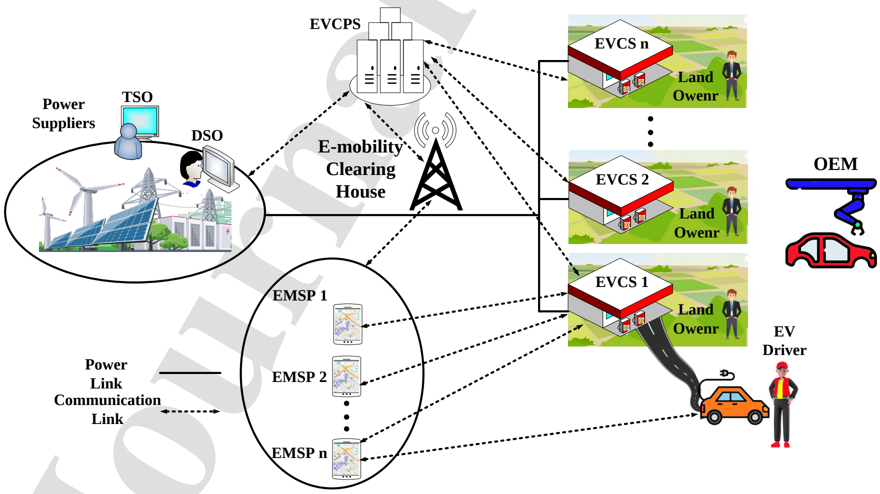

Figure 4: EV ecosystem main components

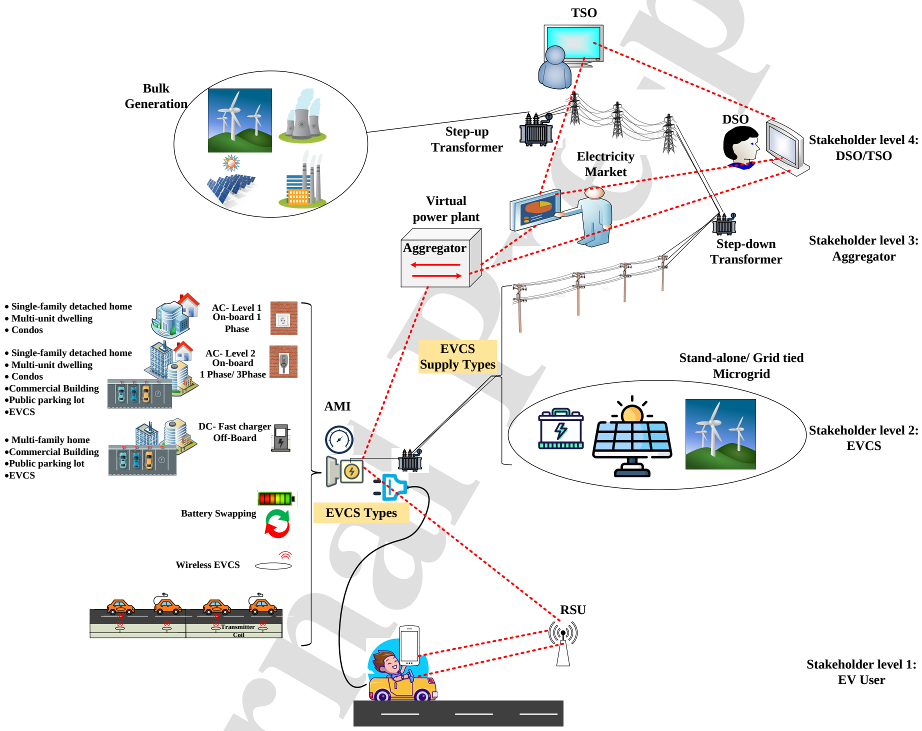

Figure 5: EV fleet infrastructures

Table 2: EV Charging Specifications

Voltage Type	• DC • AC			
Connection Type	Conductive	• Onboard		
	Contactless	Wireless Charging	Electromagnetic Field	• Inductive power transfer • Coupled magnetic resonance • Laser • Microwave • Radiowave
			Electric Field	• Capacitive power transfer
			Mechanical Force	
	Battery Swapping			
Power Flow Direction	Unidirectional	• G2V • V1G		
	Bidirectional	V2X	• V2V • V2B • V2H • V2L • V2G • V4G	
Rate of Delivered Power	SAE J1772	Level 1	Household outlet (AC/120V)	1.4 kW or 1.8 kW
		Level 2	Household outlet or EV charging point (AC/208-240V)	2.5 kW ~ 19.2 kW
		Level 3	Household outlet or EV charging point (AC/208-600V)	Up to 240 kW
	IEC 61851-1	Mod 1	Household outlet (AC/230V) with no safety	
		Mod 2	Household outlet (AC/230V) with in-cable control & protection	• Up to 3.7 kW (residential) • Up to 7.4 kW (industrial)
		Mod 3	EV charging point with control, protection, and communication	3.7 ~ 43 kW
		Mod 4	DC charging	Over 150 kW
Connector Types	AC Connectors (IEC 62196-2)	• Type 1 / SAE J1772 • Type 2 / MENNEKES • Type 3 / SCAME		
	DC Connectors (IEC 62196-3)	• AA / CHAdeMO • BB / Chinese standard (GB/T 20234.3) • CC & DD / Not defined yet • EE / CCS-1 • FF / CCS-2		
	Both AC & DC Connectors	Tesla Connector		

This paper addresses the AI and IoT requirements for EV charging coordination to maximize profitability for stakeholders of EV smart charging systems. Furthermore, the high penetration of EVs and RES has already transformed the conventional unidirectional power grid into a bidirectional smart grid. Therefore, we adopted EV ecosystem components represented in Figure 4 based on our paper objective and modified the components' role according to their equivalent smart grid entities shown in Figure 5.

2.2. *Charging Infrastructure and Energy Interaction Models*

According to Figure 5, there are four levels of stakeholders in EV fleet structures, including EV users, EVCS, aggregators, and TSO/DSO. Each level includes its components and AIoT concerns. The first level of EV stakeholders consists of EV users, whose AIoT requirements are described in Sections 3 and 4. The second level of the EV stakeholders is where the EV charging point (EVCP) is located. Table 2 summarizes EVCP characteristics. EVCP based on the EV charger position is different in the rate of charging and application. EV charger types are onboard, offboard, and wireless.

The onboard chargers facilitate the charging of EVs directly from household outlets. Japan and North American (NA) countries divide the charging rate of onboard chargers based on the society of automotive engineers (SAE) J1772 standard into two levels, including 1.44 kW and 19.2 kW. This rate in European countries is determined according to mod1, mod2, and mod3 of the IEC 61851-1 standard. Because of the low charging rate of onboard chargers and being a burden on EV weight, offboard chargers are introduced with higher charging rates. The offboard chargers are located in charging stations and provide DC voltage for EV batteries and are called fast chargers due to providing charging rates of up to 240 kW according to SAE J1772 and over 150 kW as mentioned in IEC 61851-1. Wireless EV charging is another effort to solve the anxiety rate of drivers, especially in the form of on-road wireless charging. Instead of using a wired connection, electromagnetic fields, electric fields, or mechanical forces transfer electricity to EVs. Among these methods, inductive power transfer, which is a subcategory of the magnetic field, has higher efficiency, and laser and radio waves have lower efficiency [105]. Power transmitters installed under the road charge EVs as they travel on the road. It makes on-road wireless charging a high achievement to neglect EVCS installation and battery production footprints [106].

The power direction in EVCP can be unidirectional or bidirectional. G2V and V1G are technologies that are used in unidirectional power transfer. G2V represents uncoordinated EV charging when there are no interactions between EV and power suppliers about the charging schedule. As a result of this uncoordinated charging, peak demands will arise on the power system. The V1G is an intelligent type of unidirectional charging since scheduling EV charging is based on EV owner and power supplier requirements. One example of a demand-side management scheme is V1G [107]. With the help of optimization algorithms, V1G makes a tradeoff between the preferences of EV drivers and electricity suppliers based on various factors, such as electricity cost and power demand. Residential EVCPs and low-scale EVCSs located in workplaces and commercial buildings are the best locations to implement V1G. This technology shifts EV charging to off-peak hours or during RES power output availability. The bidirectional power transfer of EVs provides an enhanced form of smart charging. In addition to coordination with the grid, EVs can provide ancillary services with reserved energy. This capability of delivering power to the grid appears in different categories, such as V2H, V2B, V2V, V2L, V2G, and V4G, depending on the location of EVCP [108, 109]. By joining DR programs in smart homes and commercial buildings, EVs support V2H and V2B. V2V implies power exchange between EVs in EVCSs and public places. Similar to V2H and V2B, the energy reserved in EV batteries supplies buildings through V2L. However, V2L is characterized by reliability provision in supplying critical loads, such as hospitals, water treatments, communication base stations, and data centers in any contingencies due to the unavailability of a power grid [75]. Large-scale EVCSs support V2G in which EVs deliver power to the power supply, which can be a utility grid or microgrid [110, 111]. Similar to V2H and V2B, the energy reserved in EV batteries supplies buildings through V2L. However, V2L is characterized by reliability provision in supplying critical loads, such as hospitals, water treatment plants, communication base stations, and data centers in any contingencies due to the unavailability of a power grid. V4G is the technology for joining EVs to the grid that provides ancillary services, such as reactive power and harmonic compensation services, during EV charging and discharging [112, 113]. EVs through V4G also can contribute in voltage and frequency regulations [114]. V2H, V2B, V2V, and V2G facilitate participating EV owners in the electricity market. By combining the energy of each EV, aggregators enable

EVs' commitment to the electricity market and provide ancillary grid services [115]. Furthermore, flexibilities coming from RESs will be strengthened with V2G when their excessive power generation can be used for EV charging or preserved in EVs as ESSs and injected into the power system in contingencies and RESs' absence [116].

The other main elements of the EV charging system are the connectors used to connect EVs to EVCP. There are three types of AC connectors, according to part 2 of IEC 62196 [117]. DC connectors include five configurations specified in IEC 62196-3 [118]. AA configuration is mainly used in NA countries and Japan, whereas BB configuration is used exclusively in China due to following the domestic standard GB/T 20234.3.

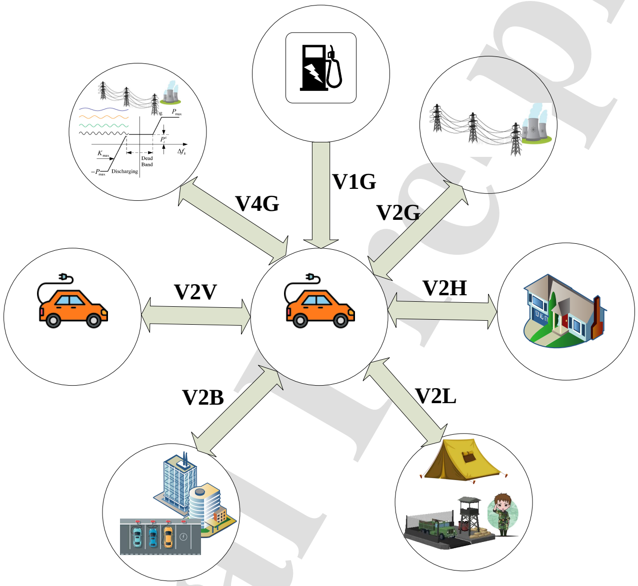

Figure 6: Types of EV integration to the grid

3. IoT Requirements and Communication Protocols

IEVC-eco relies on the IoT, which connects all physical objects across the globe. IoT components and their functions require being taken into consideration while planning the EV charging and discharging timetable. Therefore, in this section, we considered an IoT platform for IEVC-eco in addition to protocols and data exchange requirements.

3.1. IoT Platform Arrangement for IEVC-eco

IoT platforms follow layers and cloud styles [119]. The layer style is composed of three to six layers. The six-layer types include perception, adaptability, network, processing, application, and business. Several services that are deployed as IoT system components define the cloud-style category. We harmonized both styles with EV charging ecosystem requirements and represent the IoT platform according to Figure 7. The following subsection provides a critical overview of each IoT layer, its main constituents, research findings, and field applications.

3.1.1. IoT Layers in the IEVC-eco

The detailed explanation of every IoT layer, its major components, characteristics, and how it is beneficial to the EV charging infrastructure is as follows.

Perception Layer

The perception layer is the foundation of the EV charging infrastructure, where actuators and sensors capture real-time operating and environmental data from EVs, EVCSs, and power system assets. As evident in Figure 6, its principal constituents are:

- Voltage and current sensors for power flow monitoring and energy distribution.
- Global positioning system (GPS) sensors for EV dynamic location and navigation.
- Temperature and humidity sensors for battery and environmental monitoring.
- Smart meters for accurate measurement of consumed energy.

These sensors play a significant role in balancing energy distribution in EVCSs. For instance, Tesla Supercharger stations employ real-time voltage sensors and energy meters to dynamically manage power distribution across several charging units. This enhances charging efficiency, reduces power fluctuations, and avoids overloading [120].

Access Layer

The access layer acts as a middleman, an intermediary between data transfer from sensors to higher-level communication networks, and enables secure local processing. The principal components, as illustrated in Figure 6, are:

- Feeder IEDs for monitoring power distribution.
- Transformer IEDs for voltage regulation and load balancing.
- EVCS IEDs for regulating real-time charging operations.
- BMS modules for SoC computations and battery health monitoring.
- Edge computing nodes are used to reduce latency in data transfer and computation.

To mitigate grid congestion and optimize charging efficiency, edge computing is applied in the access layer to pre-process data before it is transported to cloud services. For example, Pacific Gas & Electric (PG&E) installed smart meters in conjunction with IoT-enabled BMS units that dynamically adjust EV charging rates based on real-time grid demand and electricity market conditions [121]. Local processing guarantees data privacy, minimizes network bottlenecks, and stabilizes the grid.

Network Layer

- The network layer is involved in the seamless communication of data between the EV charging infrastructure. The principal networking technologies employed are as follows in Figure 6:
- Wifi, Bluetooth, and Zigbee for short-range data transfer between EVs and EVCSs.
- Fiber optics for high-speed, low-latency data transfer over long distances.
- Cellular networks (3G, 4G, 5G, 6G) for secure cloud-based communication.
- Roadside Units (RSU) for vehicle-to-infrastructure (V2I) interaction.

The network layer plays a vital role in delivering seamless data exchange among EVs, EVCSs, and the power grid. Wifi technology is mostly applied for communication between EVs and EVCS with short-distance, real-time data sharing. On the other hand, fiber optic networks are applied for high-bandwidth, long-distance communication among EVCSs and utility substations to enable imperceptible signal degradation for long distances. Utilization of 5G connectivity in the EV charging infrastructure is gaining traction since it supports ultra-low latency and high-reliability communication, which is critical to ensure safe, real-time V2G communication. With more 5G infrastructure, grid responsiveness, and V2G coordination should be increased further, reducing communication bottlenecks and making the system more robust [122].

Processing Layer

The processing layer enables data storage, aggregation, and computation-driven decision-making for smart EV charging and discharging. From Figure 7, some of the key processing components are:

- Cloud computing platforms for elastic data storage and AI-driven analytics.
- SCADA systems for supervisory control of EVCS infrastructure and grid interaction.
- Aggregators for synchronizing energy demand and supply optimization.

Cloud analytics here enables proactive energy management and decision-making by the users. Tesla's Charge Stats, for instance, employs cloud computing to provide real-time insights into drivers' EV charging behaviors, energy use, and optimal times to charge their batteries. Based on historic data and predictive analytics, the system maximizes energy savings for EV owners and encourages longest battery life [123].

Application Layer

The application layer provides user interaction and visualization for EV drivers, charging station operators, and grid stakeholders. Figure 7 recognizes key application-level technologies as:

- EVCS finder apps are used to locate and reserve charging stations.
- Energy management control panels to track charging status and pricing in real-time.
- Remote control interfaces for operators to remotely modify EVCS parameters.

The ChargePoint service provides an example of how these features can be integrated. The app enables EV drivers to schedule, filter, and manage their charging sessions and offers integration with smart home energy systems [124]. Such integration simplifies user convenience and stimulates cost-effective energy consumption through smart scheduling.

Business Layer

The business layer manages policy enforcement, stakeholder engagement, and money transactions in the EV charging network. As evident from Figure 6, significant business-layer entities are:

- TSO/DSO to manage energy allocation on the grid.
- EV owners and EVCS operators to coordinate charging demand.
- Billing and payment systems to support automated charging transactions.

A concrete case of business-layer integration is that of the Plug & Charge initiative by the European Union, promoting simplification across networks with ease of access from multiple charging service providers for users using one common account, developing interoperability [125].

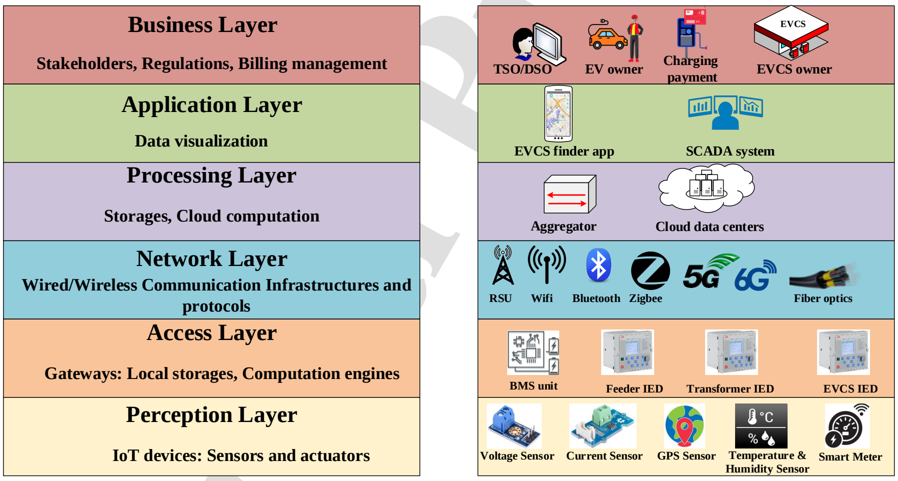

Figure 7: IoT layers in IEVC-eco

3.1.2. Research in IoT for IEVC-eco

Many studies have focused on improving the EV charging infrastructure's intelligence, trustworthiness, and effectiveness using IoT approaches. Such studies tackle the system-level issues in the context of EV deployment, i.e., the cost barriers of EVs and the lack of EVCS, through adopting IoT mechanisms that favor V2X technologies, data-driven scheduling, and economical energy trading.

To contextualize these developments, Figure 8 illustrates the overall IoT-based IEVC-eco architecture and the way in which various layers come together to achieve smart EV charging and discharging. Using this foundation, Table .7 categorizes salient advances in research into functional layers and divides studies by technical topic, which ranges from slot assignment to battery health monitoring to dynamic pricing models.

Substantial work has investigated several elements of the IEVC-eco. Major research directions include:

- BMS implementation
- EV monitoring system
- EV privacy provision in data interaction and charging payment
- EV charging slot finder
- EVCS privacy provision in data interaction and charging payment
- EVCS monitoring system
- EV charging price determination
- EV optimal dispatch

According to Figure 8, the IEVC-eco framework in the lower level contains the BMS unit, which controls battery parameters such as temperature, voltage, current, and other factors. There are mobile apps or websites for EV owners to only monitor the battery status [126, 127, 128] or

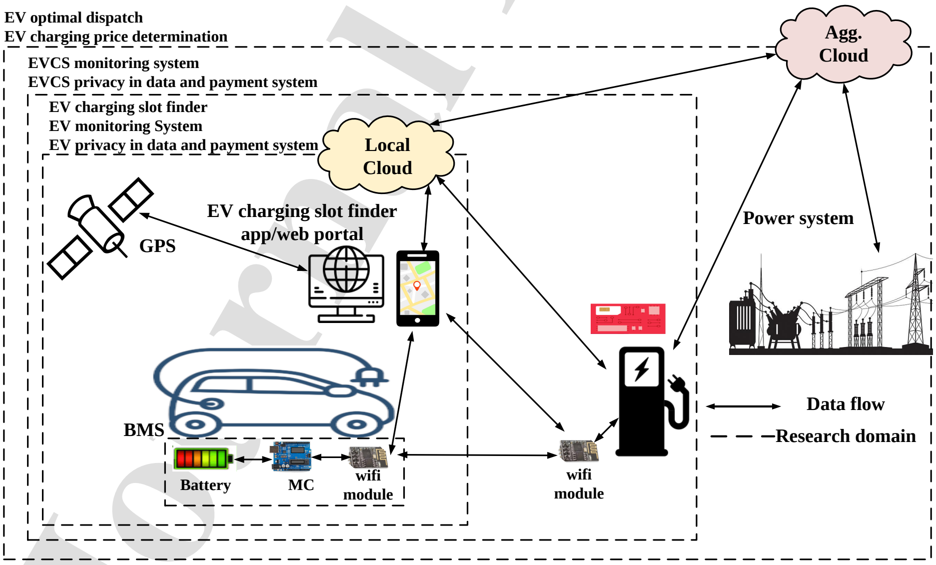

Figure 8: Research area and implementation techniques for IoT applications in IEVC-eco

find or reserve EVCS based on their preferences [129, 130, 131]. Monitoring battery parameters can simplify EV owners' decisions to choose between V2G and G2V [132]. Additionally, it can be used for battery protection in EVCS during the charging process [133]. Another application of monitoring battery data along with V2I and V2V technology is to prevent accidents during driving due to battery failure [134]. Wifi technology, along with IoT protocols such as MQTT [132, 135, 134, 136, 137] or data distribution services (DDS) [138], is widely used in transferring battery parameters to clouds as computing resources located at the edge between EVs and EVCSs, and electricity provider companies [139]. In some EV charging scheduling IoT frameworks, the edge cloud is anticipated between EVs and EVCSs. This edge cloud facilitates the privacy of EV owner data and decreases traffic data in an IEVC-eco. The edge cloud functions are as follows:

- Receive user preference, EV parameters, EVCS availability and specifications, and charging price.
- Deploy data to implement charging/discharging scheduling utilizing optimization methods.
- Save the data in the database.
- Provide EV charging modeling.
- Transfer to EV owners' apps or websites.
- Providing security in data exchange and charging payment.

EVCS and EVs coordinate with the utility grid through the aggregator cloud level. This computation level prepares local scheduling for each EVCS in its domain according to the received energy capacity from the utility grid. To use EVCS services and pay the charging fee, each EV has an exclusive, unique identifier (UID) authenticated by the aggregator-level cloud [140, 141]. The IoT framework facilitates EV charging price determination according to the time of EV charging [142]. The pricing mechanism prevents overload on the EVCS power line supplier [143] and encourages EV charging during the daytime, which results in the load profile peak shaving [144].

Communication efficiency is yet another crucial parameter that has been researched in the case of V2G scheduling. Inala et al. [122] had highlighted the significance of bit error rate and latency of communication among EVs, EVCSs, and utility grids, and the need for strong and reliable communication protocols. To enhance reliability in EVCS systems, others have proposed the use of smart contracts using blockchain technology that compensate EVCS operators automatically for cases where users fail to make advance bookings, consequently reducing idle facilities and improving equity of services [145].

3.1.3. Integration of IoT Layers in IEVC-eco

The above-discussed individual IoT layers do not exist in isolation; instead, they are part of an integrated system that, together, enables the IEVC-eco. Each layer plays a crucial role in providing seamless data transmission and decision-making in the IEVC-eco, from real-time sensor measurements to cloud-based analytics and business operations.

Figure 9 shows the EV charging/discharging slot finder as a typical smart device for IEVC scheduling. The figure highlights how data flows between different IoT layers to facilitate real-time optimization. On the EV side, BMS modules keep tracking and updating SoC, and EV owners use mobile apps or web portals to discover and reserve charging stations. The edge computing layer processes local data to forecast EV load profiles before requests are made to the aggregator level, where EV charging behaviors, price models, waiting times, and charging times are optimized. Grid operators at the TSO/DSO level make decisions on electricity allocation and price strategies based on overall demand.

This convergence highlights the inherent significance of communication and interoperability among different components and parties. Enabling smooth interaction between these layers requires standardized data exchange processes, secure authentication procedures, and an extensible network infrastructure.

3.2. Communication Protocols for Interoperability in IEVC-eco

Figure 10 depicts communication technologies, standards, and types of data exchange in the IEVC-eco. The following communication protocols provide interoperability in this ecosystem over the globe.

3.2.1. OCPP

Open charge alliance (OCA) developed OCPP in 2009 as an open-source protocol to offer interoperability for interactions between electric vehicle supply equipment (EVSE) and the charging management system. EVSEs, which are OCPP clients, transfer data such as the amount of charging power or charging start/stop signals to the OCPP server in the EVCS management system (EVCSMS). This data will be used to schedule EV charging/discharging and maintenance of EVSE. OCPP 2.0 is the latest version published in 2018 to address security for EV owners in the billing process and interaction among EVSE and EV charging management systems [146].

3.2.2. OCPI (Open Charge Point Interface)

This standard assists EV owners in finding EVCS according to their position, charging price, and availability. Therefore, EV owners can use EVSE under different management systems and regulations and expedite the EV Roaming concept in the charging environment [147].

3.2.3. OSCP

OSCP is another protocol developed by OCA to provide interoperability in data exchange between EV aggregator and TSO/DSO. Predicted available power capacity by DSO will transfer with OSCP to EV aggregators [148].

3.2.4. IEC 61850

This standard offers an information model for power system elements and message format to communicate in the smart grid. Part 90-8 of this standard focuses on the EV mobility object model and arranges use cases for communication between EV, EVSE, and EVCSMS [149]. This standard was initially established to support online communication of IEDs in power system substations. IEDs are microprocessor-based devices that provide control, monitoring, and protection in power systems. IEC 61850 defines a set of logical nodes for each IED to represent its functionalities. Each logical node includes data determined by several data objects. IEC 61850-7-420 defines the whole IEVC-eco required data objects [150].

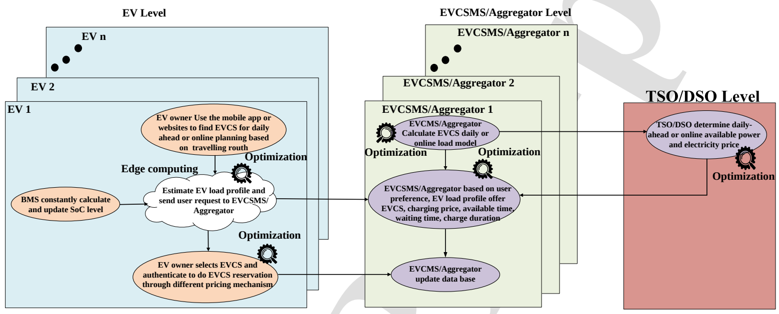

Figure 9: Intelligent EV charging/Discharging scheduling

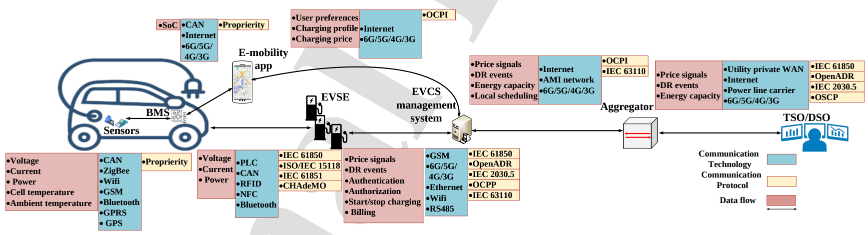

Figure 10: IEVC-eco communication protocols and data exchange requirements

3.2.5. ISO/IEC 15118

EV integration to the smart grid through V2G implementation is supported by the international standard ISO/IEC 15118. This standard determines two types of messages, namely Supply equipment communication controller discovery protocol (SDP) messages and V2G messages. EV and EVCS exchange their Internet protocol (IP) address and port number using the user datagram protocol (UDP) protocol with SDP messages. However, V2G message types transfer over transmission control protocol (TCP) to provide data integrity and authentication via transport layer security (TLS). The prominent feature of this standard is plug& charge. The billing system data exchange is confidential, integrated, and authentic. This feature shortcuts the process of using a credit card, RFID card, or QR code by EV drivers when secure automatic identification of a plugged EV into the EVSE is provided by digital certificates and public key infrastructure.

3.2.6. IEC 2030.5

This communication protocol, widely used in the U.S., designs an application profile to facilitate EV aggregation for participating in DR.

3.2.7. OpenADR

Aggregated EV load or individual EV participation in DR facilitated by OpenADR. DR events exchange between DSO, aggregators, and the EVCSMS.

3.2.8. IEC 63110

This standard development began at the end of 2017 to provide an international interoperable standard replacement for the OCPP protocol. This standard assists the IEVC-eco in three domains: the capacity of transferred energy, the EVCSMS, and EV fleet services. However, the development of this standard is still in progress. This standard supports other interoperable standards, such as IEC 61851 and CHAdeMo as charger standards, IEC 61850 object model and message transfer, and ISO 15118.

4. Optimization Strategies for IEVC-eco

The emphasis of this paper is not on a complete analysis of all computations and optimization methods applicable to the IEVC-eco. Instead, this section is concerned with describing the most prevalent and impactful AI-based optimization techniques that optimize the operation efficiency of IEVC-eco at various levels. Table 3 facilitates this discussion by detailing the specifications, typical applications, advantages, drawbacks, and key examples of each technique in the context of IEVC-eco.

As illustrated in Figure 9, the IEVC-eco is structured on three distinct levels of optimization: the EV level, the EVCSMS/Aggregators level, and the TSO/DSO level. There is a specific approach to each level of optimization tailored to meet particular operating needs and restrictions.

Through the association of some optimization methods with their application in the IEVC-eco in the real world, as meticulously listed in Table 3, this section has aimed at assisting in the identification of proper methods for successful application in reality.

In the next subsections, we discuss the optimization methods of particular interest for each specified level of IEVC-eco, beginning with the EV level.

Table 3: IEV-eco computational techniques requirements

Methods for optimization and computation				Applications in IEVC-eco	Advantages (👍)&Disadvantages (👎)	Examples
AI	Machine Learning	Supervised Learning		• EV load prediction • EV owner behavior prediction • SoC/SoH estimation • RES output power prediction • Charging/discharging price prediction • Weather/Traffic/Event prediction	👍 Using labeled data provides more accurate results than unsupervised learning 👎 Data cleaning is challenging 👎 High computation time of training process 👎 Subjected to over-fitting when trying to increase accuracy	• CNN [151] • XGBoost [152, 153] • ANN [154, 155] • Random Forest [139, 153] • regression [156, 157, 158]
		Unsupervised Learning		• Recommendation System • SoC/SoH estimation • Anomaly Detection	👍 Less effort for data preprocessing compared to supervised learning 👍 Evoke hidden pattern that supervised learning unable to detect 👎 Provided pattern may be impossible to interpret 👎 Non-reliable output since of inaccessible labeled data for evaluation	• LSTM [159, 160] • Transfer learning [156]
		RL	Value-based	• V2G planning in EV, EVCS, and TSO/DSO level • EV aggregator EMS provision	👍 Higher sample efficiency than policy-based methods 👍 More stable learning process than policy-based methods 👍 Better performance in large state space 👎 Subjected to overestimation 👎 Less efficiency in high-dimensional and continuous action spaces	• Q-learning [161] • Hyperopia SARSA [162] • DQN [163] • GNN-Rainbow DQN [164] • DDQN [165] • fitted Q-iteration [166]
			policy-based	• V2G planning in EV, EVCS, and TSO/DSO level • EV aggregator EMS provision	👍 Better convergence performance 👍 Well suited to high-dimensional and continuous action spaces 👍 Learn the stochastic policy 👎 Less sample efficiency 👎 Subjected to converge to a local optimum 👎 Since policy evaluation has high fluctuation in policy and an inefficient model	• [167]

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Methods for optimization and computation				Applications in IEVC-eco	Advantages (👍)&Disadvantages (👎)	Examples
			Actor-critic	• V2G planning in EV, EVCS, and TSO/DSO level • EV aggregator EMS provision	• 👍 Less policy fluctuation compare to policy-based methods • 👍 higher sample efficiency than other RL methods • 👎 Actor and critic interfere with each other's performances. • 👎 High complexity and computation time due to requiring two NN training	• Human-machine DDPG [168] • Safe DRL [169] • DDPG [170, 171]
			Multi-agent	• Online EV charging/discharging pricing • EV smart charging considering whole stakeholders profit • EV charging/discharging scheduling in an interactive environment	👍 Solving multi-objective problems 👍 Considering both self-interests and other agents' interests 👍 Support distributed optimization 👎 High computation cost 👎 Implementation is more challenging compared to single-agent	• [172, 173, 174, 175, 176, 177]
		FederatedLearning		• Facilitate a multi-agent environment of IEVC-eco implementation with privacy and low communication overhead	👍 Provide extendable solution 👍 Efficient training process provision by combination with Muti-agent RL 👍 Privacy provision 👎 Difficulties in hyper-parameters tuning	• [178, 179]
	Game Theory			• Decentralized EV charging/discharging scheduling • EV charging pricing determination	👍 Providing distributed controller 👎 High reliance on the assumption 👎 Difficulties in each decision maker strategies determination 👎 Does not support uncertainties conflicts	• [180, 181, 182]
	Fuzzy Logic			EV charging/discharging scheduling	• 👍 Support uncertainty in the environment • 👎 Require expert knowledge to weight decision-makers variables importance • 👎 Providing more accurate solution costs in highly complex rules	• [138, 122, 183, 184]
Conventional Techniques	MPC			• EVCS scheduling considering uncertainties	👍 Robust in respecting narrow constraints 👎 Inefficient in addressing uncertainty in IEVC-eco 👎 Complexity due to a large number of control parameters 👎 Difficult to provide precise modeling	• [185]

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Methods for optimization and computation			Applications in IEVC-eco	Advantages (👍)&Disadvantages (👎)	Examples
	Dynamic Programming		• Preemptive charging scheduling of EV	👍 Local and optimal solution can be determined 👍 Sample efficient 👎 Single, universal model for dynamic programming is not available 👎 Large memory is required to keep the solution of each subproblem	• [186]
	Statistical Methods	Gaussian	• EV load prediction • EV owner behave prediction	👍 Support large-scale simulation 👎 False results due to producing negative results	
		Weiball	• EV load prediction • EV owner behave prediction • RES output prediction	👍 Provide reasonably accurate and fast prediction with limited information 👎 Not able to keep track of data alteration during the time	• [187]
		KDE	• EV load prediction • EV owner behave prediction	👍 No prior knowledge on data distribution is required 👎 Less efficiency in bounded data	• [163, 188]
		Monte Carlo simulation	• EV load prediction • EV owner behave prediction	👍 Prediction without requiring solving the model analytically 👎 Rely on historical data 👎 Risk of underestimation due to considering the normal distribution of data	• [189, 190]
	Stochastic Methods	Temporal	• EV load prediction • EVCS load prediction	👍 Ideal for one EVCS or one EV load prediction 👎 Ideal for non-interactive EVCS load prediction	• ARIMA [191, 192, 193]
		Spaiotemporal	• EV load prediction • EVCS load prediction	👍 Ideal for the cluster of EVCS load prediction 👎 Complex implementation	• Multi-variate probabilistic model [194]
		Queue	• EVCS load prediction • EVCS congestion prevention	👍 Simplicity in implementation and scalable 👍 Ideal for interactive EVCS load prediction 👎 Requiring deterministic assumptions that are not according to reality	• [161]

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Methods for optimization and computation			Applications in IEVC-eco	Advantages (👍)&Disadvantages (👎)	Examples
	Stochastic Optimization	Robust optimization	• EV charging/discharging scheduling considering uncertainties	👍 Support distributed optimization by multi-stage arrangement of the system 👎 Issue on probability distribution function requirements for uncertain parameters 👎 High computational cost due to complicated formulations	• [195, 188]
		Stochastic programming	• EV charging/discharging scheduling considering uncertainties	👍 Do not require PDF for uncertain parameters compared to the statistical method 👍 Support distributed optimization by the bi-level arrangement of the system 👎 High computational cost due to complicated formulations	• Stochastic random model [196]
	Mixed-integer programming		• EV charging scheduling in EVCS and TSO/DSO level	👍 MILP guarantees optimal solution due to its non-convexity 👍 Supporting by several commercial solvers 👎 Inefficient in addressing uncertainty in IEVC-eco 👎 Subjected to the curse of dimensionality in large-size EV population 👎 Complexity of MINLP due to nonlinearity and risk of non-convexity	• MINLP [197, 198, 199, 200, 201, 202, 191] • MIQP [203, 204]
	Heuristic optimization		• EV charging/discharging scheduling	👍 Guarantees faster and near-optimal solution compared to mixed integer-based methods 👎 Subjected to the curse of dimensionality in large-size EV population 👎 Inefficient in addressing uncertainty in IEVC-eco	• PSO [205, 206, 207, 208] • GA-Intelligent scatter search [209] • DE [135] • ACO [141]
Other Methods	Analytical Methods		• EV energy consumption modeling	👍 Easily integrate to EV slot finder app due to not requiring field tests 👎 High computation cost 👎 Not able to apply conditional factors such as traffic and weather conditions	• [210]

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Methods for optimization and computation		Applications in IEVC-eco	Advantages (👍)&Disadvantages (👎)	Examples
	ADMM	• Providing privacy in EV charging/discharging scheduling • Decentralized EV charging/discharging scheduling	👍 No requirement to precise arrangement of convex objective function 👍 Support high-dimensional problem 👍 Support distributed optimization 👎 Do not guarantee convergence in a finite number of iterations	• [211, 212, 213]
	MCDM	• EV charging slot finder	👍 Scalability 👍 Support uncertainty 👎 Require expert knowledge to weight decision-makers variables importance	• AHP [214] • VIKOR [143] • MOPSO-TOPSIS [102, 215]
	Graph theory	• EV charging slot finder	👍 Support complex environment 👍 Suitable for finding shortest path problems 👎 Subjected to the curse of dimensionality in large-size problems 👎 Require expert knowledge to extract relation between variables	• [216]

4.1. EV Level Optimization

At the EV level, BMS and charging slot finder apps are crucial functionalities that require sophisticated optimization tools. As a crucial task of BMS, SoC estimation contributes significantly to IEVC-eco. Among various tasks handled by BMS, accurate estimation of state of charge (SoC) and state of health (SoH) significantly enhances IEVC-eco.

4.1.1. SoC Estimation

SoC calculation is according to the experimental simulation of battery performance. Therefore, accuracy in battery modeling, historical data, and tracking of battery parameter alteration during EV movement comforts reliable SoC estimation. Battery chemistry and the age of the battery are other critical factors in SoC calculation. The estimated SoC will assist EV load daily load profile estimation. Scholars have considered analytical, statistical, stochastical, and machine learning approaches to address the EV load pattern [217, 218]. Analytical methods try to estimate the EV power consumption model with the assistance of the dynamic parameters of EVs, such as the Virginia Tech comprehensive power-based EV energy consumption model (VT-CPEM) [210]. Using data-sheet-based information for analytical methods eliminates the need to collect experimental data. As a result, EV energy consumption analytical models can easily be incorporated into charging slot finder apps and websites. Statistical approaches simulate EV load by gathering field data and examining experimental relationships of various parameters.

Gaussian as statistical approach and time series-based prediction methods, including conventional methods such as autoregressive integrated moving average (ARIMA) and machine learning based such as long short-term memory (LSTM) and support vector machines (SVM), fitted EV charging profile prediction in EV, EVCS, and aggregator levels [219]. Although statistical methods, such as Gaussian, outperform analytical and machine learning-based methods in the case of computational cost, their predicted model accuracy is low. Due to its non-parametric characteristics, the kernel density estimator (KDE), as another statistical approach, models EV load and EV owner-driving behavior without requiring a prior understanding of data distribution [163, 188]. KDE's main drawback is its low performance across data distribution boundaries. Battery performance modeling in [157] was done by regression tree, which showed less error and training time compared to linear regression, SVM, and narrow neural networks (NN). LSTM NN represented the highest accuracy in the SoC prediction of dynamic EV load compared to Auto ARIMA and random forest [159].

The stochastic approach relies on EV spatial patterns, temporal characteristics, and queue theory in EV load modeling. Aggregated EVCS modeling can be supported by spatiotemporal and queue theory, whereas temporal modeling is suitable for individual EV or EVCS modeling [217].

The EV slot finder program is the other aspect of the IEVC-eco's EV-level capability that needs to be optimized, as was already indicated. EV owners utilize mobile apps for charging/discharging schedules. This recommendation system receives user preferences such as travel plans, daily ahead SoC prediction, or real-time SoC. It requires optimization tools to select available EVCS based on time, distance, and electricity trading price, and calculate EVCS waiting time, which is the summation of the charging process and traveling time to the EVCS to update the user. EV owners will select the offered EV charging/discharging plans. IEVC can be done as a daily ahead or online scheduling. Sarika et al. [139] implemented an EV charging station recommendation system based on a cloud format. EV drivers enter their preferences through the UI of the slot finder app, which has access to the EVCS database in the cloud. The EVCS that meet EV owners' requirements will be selected with the help of the random forest classification method.

4.1.2. SoH Estimation

Accurate estimation of the SoH of EV batteries is important for proper battery management, prognostic maintenance, and maximum lifecycle performance. Unlike SoC, which considers current battery capacity, SoH assesses a battery's long-term degradation and remaining useful life. Aging of the battery is a function of several parameters, i.e., cycle life, temperature cycling, charge-discharge rate, and usage conditions, that combine to complicate SoH estimation.

Among the various methods that have been proposed in the literature to address SoH estimation problems, data-driven and machine learning methods have been particularly dominant due to their high potential to model nonlinear battery aging behavior. Bayoumi et al. offered a comprehensive comparative study that outlined the strengths and weaknesses of various modeling approaches, including direct measurement techniques, physics-based models, and data-driven models. The authors in this paper emphasized that data-driven approaches manage the variability of battery performance under various and shifting operating conditions effectively, outperforming conventional approaches in terms of accuracy and responsiveness [220].

Among the new techniques that have emerged in recent years, ensemble learning models have been highly promising. Naresh et al. presented an ensemble of ensemble models (EEMs) of Random Forests, Gradient Boosting, and AdaBoost with a stacking-based meta-learning approach. This approach could efficiently analyze complex correlations between key battery parameters such as voltage profiles, temperature fluctuations, and charge-discharge cycles. The EEMs were highly accurate (99.9%) with near-error-free predictions [153].

Deep learning methods have also emerged as a key among data-driven approaches, with the long short-term memory (LSTM) networks showing significant benefits. LSTM models are particularly useful in identifying temporal dependencies and complex degradation patterns in large and diversified battery data sets. Additionally, CNN-learned hybrid models integrated with LSTM networks have been shown to possess the capability to automatically extract key degradation features from voltage and current profiles with high accuracy and efficiency in SoH predictions [221]. Safavi et al. validated this hybrid CNN-LSTM model using NASA battery datasets, demonstrating its superiority in automatically discovering valuable features without any human intervention, thus highly enhancing the predictive accuracy and robustness of SoH models [160].

In addition, practical limitations such as imperfect and incomplete measurement periods have been addressed through the creation of weakly supervised learning methodologies. Such procedures use interval labeling techniques and adaptively weighted loss functions to enhance estimation accuracy with real-world application scenarios and thus adequately support scenarios where completely labeled, high-quality data cannot be acquired or are incomplete [222]. Emerging trends in SoH estimation predict a direction towards the integration of traditional electrochemical models with advanced artificial intelligence techniques. Hybrid methodologies that combine physics-informed models with advanced AI techniques will presumably provide even better accuracy, reliability, and explainability in health prediction, hence practically facilitating proactive maintenance policy and prolonging battery life. Zhang et al. demonstrated the efficacy of Gaussian process regression (GPR) models combined with electrochemical impedance spectroscopy (EIS). Their model provided accurate battery capacity fade and remaining useful life (RUL) forecasts, together with identifying significant impedance frequencies that define degradation, thus providing valuable insights for BMS [158]. Due to the complexity and evolving demands of accurate battery health assessment, ongoing advancements in such techniques are of primary importance. Battery management at the vehicle level requires continual advancement, but it also serves as a keystone input into more advanced management and optimization processes at the EVCS/Aggregator level, influencing such tasks as energy management, load profile prediction, and congestion management, as discussed in Section 4.2.

4.1.3. EV slot finder

The EV slot finder applies various factors with different priorities based on stakeholders' insight. Though historical data deployment to determine EV load through machine learning methods will augment EV charging/discharging planning, difficulties in collecting data and poor data quality affect the accuracy of the results. There are methods, such as transfer learning, to overcome the lack of data. Fukushima et al. [156] represented a framework for an EVCS recommendation system at the EV level that worked based on EV SoC prediction. The authors in this paper predicted new types of EVs and deployed transfer learning methods to overcome the lack of recent EV types of trip data. However, the EV slot finder and reservation system requires the following dynamicity of IEVC-eco and online solutions. While EVCS distance, number of charging piles, and EVCS technical characteristics are constant and commonly available through databases located in the cloud, the arrangement of interaction between EV and EVCS, waiting time, charging prices, desired level of SoC, and availability of EVCS are changing dynamically. Hariri et al. [138] implemented a multi-agent system for communication between EV and EVCS and aggregators with the help of the DDS protocol to provide a recommendation system for EV charging/discharging. The authors in this paper carried out the optimization at the EV level, to choose the best EVCS based on user preferences, including EVCS distance, SoC level, and trading power price. A fuzzy logic scheduler was also hired in [184] to provide an EV charging/discharging slot finder while considering user preference similar to [138]. Multi-criteria decision-making (MCDM) optimization is one of the methods of weighting user preferences to assist online EV slot finders. Liu et al. [214] applied an analytic hierarchy process (AHP) to online data such as Charging price, EV arrival time, and desired SoC for EVCS selection. The authors in this paper weighted user expectations based on AHP to find the optimal action between G2V and V2V. VIKOR is another MCDM algorithm type employed in [143] to make online decisions on EVCS selection. Although MCDM algorithms and Fuzzy logic consider dynamic input variables in the EVCS finder app, weighting each criterion requires experts' knowledge and is a complicated task.

4.2. EVCS/Aggregator Level Optimization

EVCSMS or a group of EVCS under the supervision of aggregators based on user preference, SoC level, offer available EVCS, charging price, and waiting time. Several tasks at the EVCS/EVC aggregator's level that require computation and optimization include load profile prediction, energy management, congestion management, and profit maximization.

4.2.1. Load profile prediction

As discussed, EV charging/discharging behavior and EV load in the power system can be modeled based on SoC estimation. EV load prediction at the EVCS level depends on the validity of traffic flow data, EV arrival and departure times, and daily travel patterns. One of the issues in EVCS is the uncertain estimation of EV arrival and departure times. This uncertainty can be handled using Poisson distributions, a method commonly used on historical data

[195]. However, research showed that probability distribution is insufficient to provide accurate forecasting[223]. ARIMA predicted the EVCS load profile based on the expected arrival and departure time and expected daily driving distance of the EV in [224]. The estimated EVCS load was used in day-ahead power system generation scheduling to minimize generation unit production and startup/shutdown costs. Wang et al. [192] used ARIMA in EVCS daily load profile prediction on a university campus. The authors in this paper utilized the predicted load profile to determine the charging price, while the user, through the mobile app, can choose their preference, such as price, departure time, and charging load profile. The economic dispatch of microgrid resources with the presence of EV was done with sequential quadratic programming (SQP) in [204]. The authors in this paper deployed a probability distribution function (PDF) to determine randomness in the initial SoC of the EV fleet. To overcome the inaccuracy of the PDF to catch temporal characteristics of EV charging behavior, Zhang et al. [151] utilized a mixture model. The authors in this paper applied a mixture model distribution to EV traffic flow estimated by a convolutional neural network (CNN) and, considering Markov MMCK queue theory, estimated fast EVCS load. The results showed CNN had a better performance in traffic flow modeling compared to a wide range of other NN methods, including back-propagation neural networks (BPNN), support vector machine (SVM), stacked auto-encoders, time-delayed neural networks (TDNN), growing deep belief network (DBN), and recurrent neural networks (RNN).

4.2.2. Energy and congestion management

Energy and congestion management in EVCSMS is an effort to minimize EV waiting time while maximizing EVCS profit. Energy management at the EV aggregator level was implemented in [168] to reduce the cost of energy purchasing from the grid, power loss, and battery degradation. The daily cost of an EV aggregator was reduced in [190] while regarding the power system's maximum load profile. The authors of this study used the Monte Carlo simulation to test the sensitivity of EVCS smart charging strategy to user choices, including charging rate and waiting time. V2G schedular implemented in EVCS aggregator level with ant colony optimization algorithm (ACO) method optimization [141]. In a multi-microgrid environment, EV is assigned to EVCS to achieve load demand equilibrium, while the EVCS community is graph theory-modeled [216].

4.2.3. Profit maximization

EVCS-maximizing profit is rarely considered in IEVC-eco optimization. EV charging pricing mechanism at the EVCS level is a tool for finding the answer to this issue. While EV charging prices calculated in household and office buildings merged in building EMS and DR programs, scholars rarely settled this issue in public EVCS by DSO price policies such as time of use (ToU) and real-time price (RTP) from a DR point of view. Game theory is one of the popular mechanisms in IEVC-eco pricing determination. Game theory is a mathematically based framework that simulates competing and independent interactions of decision-makers to optimize their performance. Non-cooperative game theory concentrates on the actions players should take independently and logically, while cooperative game theory analyzes players' performance optimization according to the value of their coalition. Differential game theory was hired in [180] to respect both EV and utility grid conflict of interest in DR participation of EV scheduling based on ToU price. Kim et al. [182] to prevent pricing strategies motivation in load profile valley time charging result in another peak load defined dynamic pricing strategies based on game theory. The authors in this paper considered a distributed arrangement for EVs as players to share their dynamic decisions on charging to determine the charging price according to the number of clients on EVCSs. With the same approach utilizing the non-cooperative game theory method, Alsabbagh et al. [181] considered EV owner sensitivity to charging price and charging rate to determine their charging plan, where the charging fee is derived from their behavior at the power distribution level. However, there is the issue of strategy determination for each player in game theory to converge on the best solution, which is complex in the uncertain environment of IEVC-eco. Dang et al. [161] hired Q-learning to deal with the complexity of constraints that considering ToU as the method of pricing charging/discharging in a fast charging station (FCS) will add to the problem of EVCS scheduling. EV charging prices are calculated by two levels of decision-makers, including the government at the upper level and EVCS at the lower level in [208]. An EV charging reservation system to offer the shortest path to EVCS with the help of a deep deterministic policy gradient (DDPG) agent located in the edge cloud was arranged in [171]. Peak shaving for the EVCS load profile was provided using the ToU as a pricing mechanism. Lee et al. [163] modeled the EVCS load pattern using KDE and applied that as one of the EVCS environment states to scheduling V2G with deep Q-network (DQN). The authors in this study considered RTP as a method of EV charging price determination. Maximizing social welfare by government-determined charging prices for satisfying EV owners and obtaining charging prices to boost EVCS profit could find the tradeoff by the bi-level optimization method in this paper. Wang et al. [162] provide an online pricing mechanism to maximize EVCS profit using SARSA. Q-learning, SARSA, DQN, and DDPG are RL-based methods, which we will discuss more in the next section.

4.3. Grid Level Optimization

TSO and DSO play a crucial role in determining daily available power and electricity prices. With the increasing integration of EVs, these operators have significantly impacted the overall load patterns of power systems. The growth in EV penetration introduces higher-order complications, particularly peak load management across various countries, requiring sophisticated methods to examine these effects [225, 194, 189]. Despite these developments, this section addresses how TSOs and DSOs leverage advanced planning and optimization techniques to achieve stability and efficiency. It further details how the evolving demands of EV integration are catered to by innovative charging/discharging planning, privacy and security solutions, and overall grid operations management to align grid operations to these evolving demands.

4.3.1. EV charging/discharging planning

Scholars addressed scheduling EV charging/discharging at different levels of IEVC-eco. This scheduling mainly follows unidirectional power flow for EV charging and bidirectional power flow, including charging and discharging through technologies such as V2G, V2V, and so on. The availability of EV charging schedules facilitates EV participation in the DR. EV charging/discharging coordination has been scheduled with a wide range of centralized and distributed optimization algorithm solutions. From daily ahead to online, EV scheduling can be done considering the time horizon of optimization methods.

The problem formulation of IEVC scheduling includes several constraints, such as the amount of power generation in a specified region by TSO/DSO and EVCS available power, the SoC level of the EV, and EV owner preference. The objective function includes the minimization of costs or the maximization of profits for all stakeholders. The arrangement of bounded conditions and objective functions matches conventional methods such as mixed integer non-linear programming (MINLP) [201, 200, 198, 226]. Many studies have used MINLP optimization techniques to improve EV charging and discharging at the DSO and TSO levels. Although Gorubi, CPLEX, CVX, and GAMS are excellent methods for solving MINLP-based optimization issues, granting a license to use them comes at a price.

In IEVC-eco, there are different levels of stakeholders, and their objectives may overlap. The goals of the utility grid are to reduce system overload and loss, whereas the EVCS and EV owners want to maximize profit and diminish charging costs, respectively. Therefore, distribution and bi-level optimization have received recent attention to be utilized in IEVC-eco.

Meta-heuristic algorithms support solving the multi-objective problem of IEVC. Compared to conventional techniques such as MINLP, the meta-heuristics approach guarantees faster, near-optimal solution achievement. Searching for candidate solutions is the main task of meta-heuristics-based methods, which may result in ineffective policies for a large EV population. Genetic algorithm (GA)-particle swarm optimization (PSO) is a hybrid method that benefits from the effectiveness of GA in discrete space and PSO's performance in the continuous environment to improve convergence speed and solution quality. GA-PSO is used in [207] to size EVCS and RESs to minimize power loss and voltage deviations and transfer EV charging time to the available time of RESs' power output. PSO searching speed was improved in [206] by self-adjusting PSO to schedule EVCS participation in DR.

Optimizing bi-level problems is often simplified using the alternating direction method of multipliers (ADMM) technique based on dual decomposition because it can handle issues of high dimension and support a non-convex objective function. Hu et al. [211] deployed a hierarchically coupled ADMM-based optimization method on EV aggregators to minimize the DR scheduling error. The utility grid in the upper layer determines the DR planning of aggregators in a distributed manner. Each aggregator in the lower layer locally justifies EV charging and discharging, considering battery degradation minimization. To coordinate charging EVs in EVCS located in residential building blocks, an ADMM-based optimization is arranged in [212]. The authors in this paper considered charging EVs at lower electricity prices to decrease electricity bills while giving the highest priority to charging EVs with the lowest SoC. The privacy of EV is maintained by using decentralized ADMM, and the capacity of the transforms that supply EVCS is applied as problem constraints. ADMM convergence speed was improved in [213] with the SQP approach to solving the quadratic objective of cooperative transportation and distribution networks.

4.3.2. Privacy and uncertainty in EV charging/discharging scheduling

One of the significant current discussions in EV charging/discharging coordination is EV privacy consideration, which can be supported by cloud computing that is implemented utilizing bi-level distributed optimization [212, 213]. To maintain EV privacy, EV online participation in DR through G2V is planned by the distributed model predictive control (MPC) method [185].

The smart charging recommendation system, which considers all stakeholders' self-interests, may encounter misuse by users. Alinia et al. [227] deployed group strategy-proofness to avoid EV drivers' false data injection in the on-arrival commitment policy in EVCS to provide maximum social welfare for EV owners. To mitigate the effects of data error in communication between EVCS, substation, and EV, Sah et al. [155] set up a two-layer controller for V2G implementation in an EVCS. The initial layer includes NN, which predicts that the utility grid voltage level will be replaced with false injected data due to communication link failure, and during the real-time charging/discharging scheduling performance. The second layer includes a Fuzzy logic controller that schedules V2G and G2V.

It is ineffective to address uncertainty in IEVC-eco data using traditional approaches that assume accurate knowledge about the uncertainty, such as linear programming, MINLP, meta-heuristic optimization methods, and MPC.

As a branch of machine learning, RL handles model-free optimization. RL is a technique of learning through feedback. RL solves a problem by solving the Markov decision process (MDP) arrangement of the environment, which includes state, action, reward, and a transition function. In RL, an agent is in charge of determining the best course of action in each state by getting input from the environment as a reward for each action. RL consists of two categories: model-based and model-free. The stochastic problem of IEVC matches model-free RL characteristics. In model-free, we do not get access to the accurate environment model. An agent by exploration will make experiences in the environment and exploit what is learned from exploration results.

Model-free RL follows three approaches to solving problems: policy-based, value-based, and actor-critic. In value-based methods, we evaluate each pair of actions and states by the value function and try to find a path to the destination by finding pairs of states and actions with higher values. Therefore, policy in value-based methods is implicitly derived from the value function. Policy-based defines an explicit policy and finds a solution based on the optimum policy. Policy-based methods converge to the optimum solution at a higher speed than value-based methods. However, there is the risk of finding local minima instead of global ones. While Q-learning, SARSA, DQN, and Dual-DQN (DDQN) are value-based approaches, REINFORCE, proximal policy optimization (PPO), and trust region policy optimization (TRPO) are policy-based algorithms. Actor-critic is an effort to utilize the advantages of both value-based and policy-based methods. The actor, who is responsible for selecting actions, is policy-based, and the critic, who evaluates the selected action by the actor, works according to value-based methods. DDPG, soft actor-critic (SAC), asynchronous advantage actor-critic (A3C), and twin delayed deep deterministic policy gradient algorithm (TD3) are examples of actor-critic techniques.

The deep RL (DRL) method by combining NN with RL is another progress in the case of using RL, where deep NN tries to support high-dimensional problems that representative pure RL procedures, such as Q-learning and SARSA, failed to solve. However, by modifying the size of the Q-table, such as the objective and limitation of the problem as a feature function applying to standard states and actions, SARSA could handle the high-dimensional maximizing EVCS profits problem in [162]. However, in some scenarios, objectives and constraints are unknown or fluctuate, such as EV owner preference, which is already referred to as the dynamicity of input variables. RL can also handle the issue of each stakeholder being aggressive in its objectives by modifying the exploration and exploitation processes. To prevent too aggressive EVCS, Wang et al. deployed average profits instead of an ϵ-greedy policy. The authors in this paper represented that their method converged better to the optimal solution compared with other exploration approaches such as Robust simulation-based policy improvement (RSPI), sample-average approximation (SSA), and ϵ-greedy.

DQN, as an enhanced Q-learning method, deploys NN to defeat the complexity of predicting the value function of pairs of states and actions in high-dimensional problems. DQN also improved by utilizing an experience buffer as a container to keep the agent's experience in the exploration environment. This functionality makes DQN robust by offering sample efficiency. DQN in EVCS was hired in [163] to optimize EV charging schedules. Yet, IEVC actions, such as battery charging/discharging, are continuous, while DQN provides discrete action spaces. DDPG is an actor-critic method used in EV charging and discharging environments that provide continuous action space [170, 171]. However, there is a risk of overestimation in deploying DQN-based algorithms, including DDPG, since they consider the max function in their approach to choosing actions. Tao et al. [168] improved the convergence of DDPG in solving the energy management of EV aggregators by injecting expert knowledge through rule-based frequency and voltage constraints, improving exploration, and shaping rewards.

5. Challenges, Issues, and Future Trends in EV-Smart Grid Integration

Smartening the EV charging ecosystem confronts several challenges and issues, including interoperability, cybersecurity concerns, and the utilization of appropriate optimization methods.

5.1. Utilization of Appropriate Optimization Methods

AI optimization is a dynamic and rapidly developing set of methods that are increasingly at the heart of the efficiency, intelligence, and responsiveness of EV charging/discharging systems. Such systems, which are central to the transition to decarbonized transport and low-carbon energy grids, need to be underpinned by robust and scalable optimization technologies that can cope with high-dimensional, stochastic, and multi-agent domains in real time. Although the initial work was mostly model-free reinforcement learning due to its flexibility and ability to make decisions, the scope has expanded manifold since then. Methods such as large language models (LLMs), transformer networks, and Informer models are being studied increasingly based on their scalability, long-sequence modeling capability, and use towards distributed and temporal settings.

This section continues in the same vein by considering both the evolving landscape of optimization in the IEVC-eco and the overall evolution of AI optimization methods and proposing directions for their integration. This three-layered examination presents an integrated view of how AI optimization shapes the future of smart, secure, and sustainable IEVC-eco.

5.1.1. Current development directions in IEVC-eco

Among different optimization methods, model-free RL effectively supports the stochastic and multistage decision-making process of EV charging/discharging planning. However, there are some issues and challenges related to deploying RL that we will address here, including complex implementation, high computational costs, and privacy.

IEVC-eco includes several stakeholders who follow their interests and constraints. Therefore, some crucial duties need extra care to ensure their safe performance while adhering to their limitations. As an illustration, the appropriate level of EV charging is necessary to apply in our policy to maintain. Several methods, including reward shaping and constraint MDP, will satisfy constraints. The evaluation of agent performance in RL involves receiving feedback from the environment through reward. Hence, constraints' effects will be incorporated as a penalty when forming reward signals. However, it requires prior knowledge to arrange rewards with coefficients that guide the agent's policy to explore the safe area. Weighting the combination of different objectives is another approach to respect the multi-objective characteristics of IEVC. Multi-objective DRL using several reward signals and value functions is another solution. Providing a constrained MDP and solving it through safe DRL is a solution that has one objective while respecting the restrictions of the problem and other aspects.

Considering IEVC as a multi-objective problem and applying solutions such as finite MDP and reward shaping, it still suffers from high computation costs. Deploying a centralized approach in the IEVC arrangement suffers from a lack of scalability. Multi-agent is another RL-based approach that provides optimization solutions under the distributed methods category. In a cooperative multi-agent system, all agents have the same objectives, while in a non-cooperative system, each agent endeavors to maximize their goals.

Moghaddam et al. [175] hired a cooperative multi-agent RL algorithm for EV charging schedules. The authors in this paper considered two agents, including the utility grid and EVCS, with the objectives of shifting EV load to off-peak hours and maximizing profit, respectively. In this study, the utility grid controls load by providing the charging price through online monitoring of the network and applying it as a reward for EVCS actions. To establish charging/discharging costs, Zou et al. [172] proposed a double auction system for prosumer communities. The authors in this paper considered maximizing social welfare for EV owners and prosumer communities while satisfying the desired EV charging level of auction losers. To decide on compensating for the power shortage of the prosumer communities by purchasing power from the grid, the multi-agent RL could tackle the stochastic behavior of RES and EV owners' decisions. Although this study tackled the selfish behavior of each agent by considering double action and introducing global agents to justify the greedy behavior of the agents, their coordination is still ambiguous, especially in the case of time. As a solution to time synchronization in [173], a distributed RL-based multi-agent system for electric taxi charging scheduling, a time agent, a synchronize utility agent, an EV agent, an EVCS agent, and an agent for traffic data provision with the precision of one second.

Dong et al. [177] trained EV agents in a centralized multi-agent-based architecture, but EVs independently chose to participate in V2G to maintain the privacy of EV drivers. However, independent EV agents may behave selfishly, which could be defeated by defining a global reward to justify the desires of each EV agent. With the same line of thought, Zhang et al. [176] offered an EV charging recommendation system based on multi-agent RL with centralized training and distributed execution. The authors in this paper considered multiple objectives, including minimizing waiting time, charging costs, and failure to accept system suggestions by EV owners. While Dong et al. [177] considered EVs and the utility grid to be agents of this multi-agent structure, the recommendation system prepared by Zhang et al. [176] included EVs and EVCS as agents. However, planning EVs and arranging intelligent charging requires the cooperation of EVs, EVCSs, and the utility grid. Federated learning is a new approach to distributed machine learning by facilitating learning in edge devices and minimizing the amount of shared data in a collaborative environment while offering privacy to all participants. The EVCS privacy in load prediction by the aggregator was provided by federated learning in [178], while EVCS just shared their trained model.

Distributed, privacy, generalization, and fair training are the main characteristics of federated learning that can be used in conjunction with multi-agent reinforcement learning. FedAvg is one of the popular federated learning-based methods that uses the average weighted of all agent parameters to train a model for each agent. This approach will increase the fluctuation in agent performance because of its inaccuracy. There is another approach called FedFormer to tune the agent's performance through sharing encoders network.

Although Federated learning is a robust method to support the distributed environment of IEVC-eco, it suffers from complexity in local and global parameter determination. Additionally, Wang et al. [179] proved that hiring federated learning cannot guarantee the privacy of interactions among EV, EVCS, and the utility grid individually and endanger the system by spoofing and man-in-the-middle attacks during the agents' interactions. Therefore, additional arrangements, such as validation agents by authentication is unavoidable.

5.1.2. Broader Advances in AI Optimization and Their Integration into IEVC-eco

Recent advances in AI optimization extend much beyond problem-specific solutions and now encompass a variety of architectures, algorithms, and frameworks that are capable of solving complex optimization problems in real-time, distributed, and privacy-constrained environments. Broader advances have the potential to reconstruct existing optimization challenges in the IEVC-eco with more powerful, generalizable, and scalable instruments. To position the emerging figure of optimization technologies, the present subsection refers to several pivotal developments in AI that hold direct or near-future relevance for the global IEVC-eco.

The following developments illustrate major trends defining the shape of future intelligent optimization systems:

- Transformer-Based and Time-Series Optimization Models: Transformer models have emerged as the superior model in AI due to their capacity to represent long-range dependencies and process in parallel efficiently. Originally developed for natural language processing, transformers have subsequently been used for optimization and decision-making in the high-dimensional time domain. Informer and FedFormer, for instance, were competitive in long-sequence time series prediction and federated learning scenarios. Due to their ability to handle asynchronous, distributed input, they become better suited for load forecasting, energy demand forecasting, and real-time adaptive scheduling on EV charging networks.

- LLMs for Optimization-Aware Reasoning: LLMs, traditionally used in generative applications, are now being fine-tuned for symbolic reasoning, logic programming, and meta-optimization [228]. In EV infrastructures, LLMs can be used to help with code generation for algorithmic decision-making, policy synthesis, and multi-agent system coordination. With their natural generalization ability and scalability, they hold promise in multi-modal data interpretation, strategic recommendation, and control synthesis, particularly when used with lightweight agent-side models or in a hierarchical planning framework.

- Federated and Privacy-Preserving Optimization: With privacy emerging as the key concern in collaborative optimization, federated learning has gained popularity across fields. FedAvg was the de facto standard, but newer approaches such as FedFormer and secure aggregation with homomorphic encryption are changing the manner in which models can be trained among distributed agents with minimal data exposure. These frameworks not only improve learning precision in non-independent and identically distributed (IID) data environments but also address scalability and robustness challenges through the implementation of asynchronous training, hierarchical aggregation, and compression-aware protocols [229].

- Secure and Ethical AI for Decision Optimization: AI optimization techniques are increasingly inclusive of security-aware and ethically constrained learning objectives. These include differential privacy, adversarial robustness testing, and fairness-aware optimization techniques, which are of considerable significance in IEVC-eco, where real-time control intersects with consumer rights, safety-critical decision-making, and infrastructure integrity [230].

The comparative summary of existing and future AI optimization techniques relevant to the IEVC-eco is shown in Table 4.

Table 4: Integration of Advanced AI Techniques into IEVC-eco

Challenge	Existing Solution	Emerging AI Approaches	Impact on IEVC-eco
Demand Forecasting	Time-series models, RL-based predictors	Informer, FedFormer, Transformer-based Forecasting	Improves long-range load prediction accuracy
Real-Time Control	Model-free RL, rule-based controllers	Real-time DRL, Transformer-enhanced Scheduling	Enhances adaptability and decision latency
Privacy and Data Sharing	FedAvg, centralized logging	Federated Learning, Homomorphic Encryption	Preserves privacy, supports collaboration
System Coordination	Multi-agent RL, double auctions	LLM-assisted Coordination, Secure Multi-agent Systems	Optimizes stakeholder objectives safely
Ethical & Secure Operation	Manual review, fixed pricing policies	Fairness-aware Optimization, Differential Privacy	Increases trust, equity, and compliance

5.2. Interoperability

As discussed in Section 2, IEVC-eco includes several stakeholders. Each of them utilizes heterogeneous elements, technologies, and applications. This diversity isolates IEVC-eco elements from each other in a vertical arrangement. In this manner, data is generated and consumed in each domain separately. However, IEVC-eco requires whole entities to communicate in an open system supporting interoperability. IEVC-eco components can communicate with and deliver services to one another thanks to this feature. The information model and communication technologies should be designed with the aim of achieving interoperability, which is defined as an understandable language for all system elements.

There are different aspects to providing interoperability in IEVC-eco, including seamless charging connectors, interoperable communication among stakeholders, a publicly accessible charging payment system, and unified standardization. Table 2 represents the different types of available charging connectors. The Types 1 and 2 charging interfaces are not exclusive to plugs. The combined charging system (CSS) is a significant effort to provide the infrastructure that supports both AC and DC fast charging systems. Since shortening the time of charging EVs and lighter vehicles due to using off-board chargers, fast charging-based EVCS is spreading drastically around the world. However, the lack of a unique standard for fast EV chargers increases the complexity of EVCS functions and expenses, causing EV drivers' range anxiety to rise.

Interoperability in communication has two aspects: the information model and the message format. IEC 61850 is a standard that supports interoperability in both directions. IEC 61850 enables seamless integration of EVs, EVCS, and EV aggregators into power systems. Using IEC 61850 logical nodes for EV and EVCS, V2G and G2V are implemented in an Ethernet-based parking lot communication network [231]. While fast response-required actions in [232], such as start and stop charging, are mapped onto the GOOSE protocol of IEC 61850, MMS-based messages carry charging requests. In this study, the ideal method for sending measurement data, such as the SoC level, is via SV messages. Aggregated EVs provided ancillary services such as load restoration, while GOOSE messages supported the real-time interaction requirement of this arrangement [233]. IEC 61850 also facilitates a common language between EVs, PVs, and smart meters to participate in building EMS [234]. There are cybersecurity concerns about employing the GOOSE message, even with IEC 62351 deployment as a secured extension of the IEC 61850 standard. Yet, secure DDS as an IoT protocol is already used to provide security features in IEC 61850-based message interactions in the smart grid. This arrangement also facilitates using the existing internet infrastructure safely and reduces the cost of a dedicated communication infrastructure [235].

Any EVCS operating under the CPO's control may take a variety of proprietary payment methods, including applications and access cards. As discussed in Section 2, ISO 15118 facilitates open payment through the plug-and-play feature and its security requirements. There is enough room for further progress in the open payment system to arrange interoperability for the customer side. Interoperability is viable by e-roaming between charging networks to release any membership or account requiring charging payment. The recent version of ISO 15118, published in April 2022, was a sign of progress in this area by clarifying several plug-and-play installation processes in EVs. This recent version also covers the security concerns gap of the previous version in communication between EV and EVCS by mandating TLS and cryptography algorithms [125].

Despite the efforts indicated above to ensure interoperability provision for IEVC-eco, unified standardization is still an open issue. Deployed standards vary from country to country and even in provinces and states within a country. Although standard implantation is inclusive on a global scale, there is a lack of consistency in its implementation due to various interpretations.

5.3. Cybersecurity Concerns

Although IoT provides connectivity to implement IEVC-eco, it also endangers entities in this environment with security and privacy concerns. This concern can be categorized into three levels: EVs, EVCSs, and communication infrastructures.

5.3.1. EV cybersecurity concerns and solutions

BMS and EV charging slot finder apps or websites are targets of EV-level hackers. The EV battery's efficiency and long life depend on BMS performance.

The BMS estimates and controls the humidity, temperature, and battery SoC levels. In the data exchange between BMS and EVCS to estimate the SoC, there is a risk of attack and manipulation of battery parameters, such as voltage and current [236]. Consequently, battery degradation or failure will result from charging batteries beyond predefined boundaries [237]. EV information, including location, charging/discharging profile, identity, and payment, will be shared with EVCS, and there is a risk of tampering with and spoofing the data. The other security issue related to EV interactions is the vulnerability of charging slot reservation apps and websites to denial-of-service (DOS) or distributed denial-of-service (DDOS) attacks and making redundant reservations. Attackers disrupt the optimization process of EV charging scheduling by using phishing attacks against charging slot finder apps or websites. The wrong DR incentives are injected into apps to encourage EV charging during peak hours and impose instability on the power system [238]. There is also the risk of sniffing the ID of EVs and impersonating them for charge billing. Additionally, this scenario can happen in communication between EVCS and aggregators. Authentication, anomaly detection, blocking IP, cryptography, tamper-proof hardware, and intrusion detection are solutions for BMS cybersecurity attacks.

Various machine learning techniques are put into practice for anomaly detection and intrusion detection as prominent solutions for BMS cybersecurity attacks. Rahman et al. [239] deployed NN to predict SoC level, and the cyberattack on BMS is detectable by comparing it with the measured one. By injecting malware into the CAN bus, mobile apps can conduct cyberattacks. This data intrusion was detected by DNN in [240]. A study in [241] showed a phishing attack on the EV slot finder app to take the departure time data of EVs to EVCS, and data intrusion in communication between DSO and aggregators made the demand and consumption of the power grid unbalanced. This instability resulted in EVs charging lower than the desired SoC level and grid congestion.

The use of blockchain to provide security in networking, access control, and data transmission has recently attracted considerable interest. Blockchain can accommodate the essential characteristics of IEVC-eco, such as distributed, shared databases and peer-to-peer communication. Interactions in IEVC-eco will be immutable by logging time, data, and the history of participant blocks through authentication handled by cryptography. Smart contracts enhanced the authentication techniques concept, where predefined codes in the blockchain automatically run agreements and asset transfers without requiring a trusted intermediary. BMS firmware is protected from cyberattacks by the cryptographic hash and smart contract in [242]. Authentication augmentation by utilizing blockchain alleviates man-in-the-middle and DoS cyberattacks at each level of security concerns in IEVC-eco.

Table 5: IEVC-eco cyber attack types and solutions

Attack level in IEVC-eco		Type of attack	Attack target	Solutions
EV [243, 244]	BMS	• DoS • DDoS • Spoofing • Man-in-the-middle • Tampering	• Battery degradation • Battery failure • Safety hazards	• Authentication • Anomaly detection [239] • Blocking IP • Tamper-proof hardware • Intrusion detection [239] • Blockchain [242]
	Charging slot finder apps/Websites	• DoS • DDoS • Spoofing • Phishing attack • Man-in-the-middle • Tampering	• Identity theft • Payment fraud • Using EV as an entry point for spreading malware to IEVC-eco • Power grid instability	• Authentication • Blocking IP • Firewall • Reputation-based schemes
EVCS [243, 245]		• DoS • Man-in-the-middle • Spoofing • Energy repudiation • Information Leaking	• Prank • Electricity theft • Identity theft • Payment fraud • Intentional Overcharging/discharging battery • Using EVCS as an entry point for spreading malware to IEVC-eco • Power grid instability	• Anomaly detection [246] • Authentication • Firewall • Intrusion detection [246, 247, 248] • Reputation-based schemes
Communication medium and protocols		• DoS • Man-in-the-middle • Eavesdropping • Side Channels • Jamming	• Prank • Users' private information theft • Identity theft • Payment fraud • Intentional Overcharging/discharging battery • Using EVCS as an entry point for spreading malware to IEVC-eco • Power grid instability	• Authentication • Encryption • Intrusion detection [240]

5.3.2. EVCS cybersecurity concerns and solutions

The functionality of EVCS as a bridge for supplying EVs with power highlights the threat of EVCS's cybersecurity attacks since they affect both EVs and the power grid. Throughout the charging schedule, EVCSs collect personal data from EV owners, such as charging profiles and payment information. Another duty of EVCS is to control and monitor the charging process for EVs using data on energy usage and charging status.

Cyberattacks on EVCS can take different forms, such as DoS, man-in-the-middle, sniffing, and information leakage. EVCS becomes inaccessible for EV owners due to DoS attacks that manipulate the charging process and overload the network with traffic. Another attack that allows

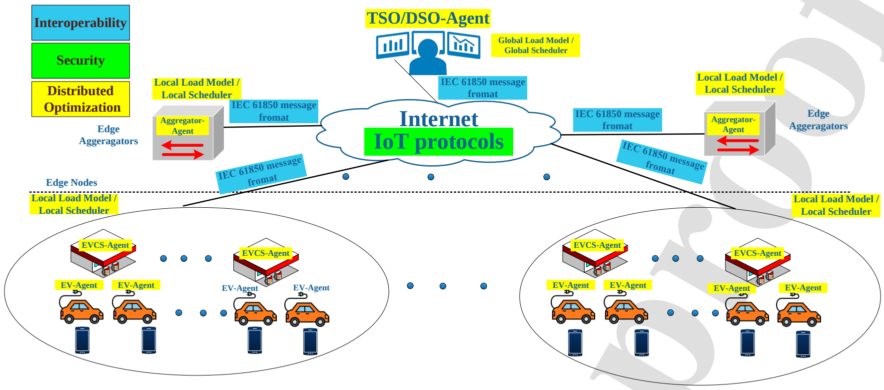

Figure 11: An overview of optimized EV charging slot finder considering whole stakeholders' requirements

for the sniffing of EV owners' personal information and payment details is a man-in-the-middle attack. The entire IEVC-eco is attacked by using EVCS as a point of entry.

As EVCS transfer power, rated up to 350 kW, cybersecurity attackers become more concerned about intruding on EV and EVCS interactions. As a result, the power systems would be burdened with voltage instability [249]. The hidden Markov decision process was hired in [246] to detect intrusions and anomalies in the interaction between EV and fast EVCS. The decision tree technique and filtered classifier are used in [247] to identify malicious traffic and prevent DDoS attacks on EVCS. However, to offer EVCS infrastructure security against spreading covert cyberattacks to the system hardware, a proactive mechanism for intrusion detection in the physical layer is needed in addition to the network layer. This idea is followed in [248] for EVCS cybersecurity implementation using LSTM to detect DDoS attacks, considering their effect on the electrical parameters of EVCS infrastructure.

5.3.3. Communication medium and protocols, cybersecurity concerns and solutions

The communication vulnerability of IEVC-eco can be divided into in-vehicle communication and outside-vehicle communication. In-vehicle communication includes wired and wireless communication. Cyberattacks threaten the CAN protocol, which is commonly used in vehicles to communicate. CAN communications provide confidentiality and authentication through encryption [250]. Based on a modified SVM in [251], anomalies were detected in CAN data.

Wifi and Bluetooth communication technologies utilized in the mobile app to control the charging process of EVs in the smart home, or EVCS, are vulnerable to man-in-the-middle attacks. Such attacks by manipulating charging justifications, such as the current level, resulted in physical damage to smart homes, EVCS, or EVs [252]. Navigation and dynamic SoC estimation in IEVC-eco are estimated with GPS data. Therefore, any GPS false data due to GPS spoofing or jamming inserted in charging and discharging scheduling optimization algorithms affects the system's operation [253]. Roadside units (RSU), as communication infrastructure facilitating interactions between EVs and higher levels of IEVC-eco, are subject to eavesdropping.

- Lack of real-time test by cyber-physical hardware-in-the-loop

- The necessity of utilizing commonly used standard protocols such as IEC 61850, distributed network protocol (DNP3), Modbus, and time synchronization information such as pulse per second (PPS), precision time protocol (PTP), simple network time protocol (SNTP), and IEEE 1588 in cyberattack scenarios.

- Lack of specific standards to address BMS requirements, especially cybersecurity concerns [254, 255].

- Due to the complexity and distributed nature of IEVC-eco, the security of each party's provision by means of intrusion detection and firewall implementation is not viable. There is a requirement for coordination among all stakeholders, considering their authorities, operations, and roles in security provision [256].

- There is an abundance of studies on different types of cyberattacks on EV, EVCS, and power systems; however, studies on how to deal with and restore the system after attacks are limited [257].

According to the interoperability, security, and optimization requirements of IEVC-eco, we arranged the EV slot finder shown in Figure 11, considering all stakeholders in this environment. Each agent represents stakeholders, including EV owners, EVCS, EV aggregators, and the TSO/DSO. Multi-agent reinforcement learning, with the assistance of federated learning, arranges cloud-edge-based distributed optimization. Each agent has its optimization performance at the edge level; the local agent provides each agent's scheduling, while aggregators at the edge computing level coordinate EV and EVCS performances. TSO/DSO, as a global agent, schedules charging/discharging at the aggregator level. The presented framework benefits from federated learning to decrease the bandwidth requirements for data exchange. The other advantage of our proposal is using IEC 61850 for the data model and message format to provide interoperability. The IoT protocol deployed here should support distributed environments, such as DDS or extensible messaging and presence protocol (XMPP), which is beneficial for the system by avoiding the construction of new infrastructure for communication. As was previously mentioned, federated learning is still open to malicious attacks, but adopting IoT protocols that support security defeats this hindrance.

5.4. Empirical Validation and Practical Application of IEVC-eco

It is essential to acknowledge that while the IEVC-eco framework has been conceptually developed in this work, the proposed IEVC-eco framework itself is theoretically conceived without any supporting simulations or case studies applied to demonstrate the practical viability of the synergistic AIoT approach in the first place. Nevertheless, the literature available, summarized in Table .7, provides overwhelming implicit evidence for feasibility in practice. Experiments referenced in Tables .7 and 3 explicitly demonstrate the successful deployment of the same AI and IoT technologies for EV load forecasting, charging schedules, grid optimization, and anomaly detection, with real-world efficacy and practicability. Rigorous simulation and case study verification will be conducted as future work using well-established simulation environments (e.g., MATLAB/Simulink, Python) and publicly available realistic datasets (EV charging patterns, grid demand profiles, renewable energy generation). This direct empirical examination will lead to the development of operational confidence in the IEVC-eco system and the direct identification of feasibility issues.

6. Conclusion

This research explores AIoT applications in the IEVC-eco with respect to how AI optimization techniques and IoT infrastructures can together contribute to the complexity of the ecosystem. Through a comprehensive literature review, we discovered that while there has been remarkable advancement in meeting IoT needs—e.g., communication protocols, data guidance, and compatibility—the bulk of the solutions that have been proposed so far are very conceptual or simulation-based, with minimal actual implementation. Our investigation highlighted the benefits of AI-driven methodologies, particularly reinforcement learning, in addressing uncertainty and interactions among IEVC-eco stakeholders like EV users, EVCS operators, aggregators, and grid operators. Machine learning models outperformed conventional statistical methods in forecasting EV load profiles, and multi-agent reinforcement learning was particularly effective in addressing distributed scheduling problems in a privacy-preserving manner with federated learning mechanisms.

To address the gaps in current research, we proposed an overall framework for EV slot scheduling that makes it compatible with standardized communication protocols like IEC 61850 and supports secure distributed decision-making using federated multi-agent reinforcement learning. This framework is designed to address the basic challenges of scalability, privacy, and uncertainty and to accommodate the operational needs of all participants. Real-world deployment, however, remains a persistent challenge. Future research must focus on the empirical simulation and real testbed validation of such frameworks, on hybrid AI approaches to adaptive scheduling, and on edge computing architectures that can support decentralized optimization in real-time. Moreover, cybersecurity, user behavior modeling, and large-scale interoperability barriers have to be overcome to enable a secure and intelligent EV charging infrastructure. Ultimately, the application of AI and IoT technologies holds significant potential to make EV integration an innovative, efficient, and sustainable extension of the smart grid.

7. Data availability

No data was used for the research described in the article.

8. Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix .1. Nomenclatures

Table .6: Acronyms.

Abbreviation	Description
A3C	Asynchronous advantage actor-critic
ACO	Ant colony optimization algorithm
AHP	Analytic hierarchy process
AI and IoT	AIoT
ARIMA	Autoregressive integrated moving average

Abbreviation	Description
BESS	Battery energy storage systems
BEMS	Building energy management system
BMS	Battery management systems
BPNN	Back-propagation neural networks
CNN	Convolutional neural network
CPO	Charging point operators
CSS	Combined charging system
DBN	Deep belief network
DDQN	Dual deep Q-learning
DDPG	Deep deterministic policy gradient
DDS	Data distribution services
DER	Distributed energy resources
DG	Diesel generator
DNN	Deep neural network
DNP3	Distributed network protocol
DDoS	Distributed denial-of-service
DoS	Denial-of-service
DPG	Deterministic policy gradient
DQN	Deep Q-network
DR	Demand response
DRL	Deep reinforcement learning
DSO	Distribution system operator
EEM	Ensemble of ensemble models
EIS	Electrochemical impedance spectroscopy
EMS	Energy management system
EMSP	Electromobility service providers
ESS	Energy storage systems
EVs	Electric vehicles
EVCP	EV charging point
EVCS	Electric vehicle charging station
EVCSMS	EVCS management system
EVSE	Electric vehicle supply equipment
FCS	Fast charging station
GA	genetic algorithm
GPR	Gaussian process regression
GPS	Global positioning system
GRU	Gated recurrent unit
ICPT	Inductively coupled power transfer
IEVC	Intelligent EV charging/discharging
IEVC-eco	Intelligent EV charging/discharging ecosystem
IID	Independent and identically distributed
IP	Internet protocol
KDE	Kernel density estimator
LLM	Large language model
LSTM	Long short-term memory neural networks
MCDM	Multi-criteria decision-making

Abbreviation	Description
MDP	Markov decision process
MINLP	Mixed-integer nonlinear programming
MPC	Model predictive control
NA	North American
NN	Neural networks
OEM	Original equipment automobile manufacturers
OCA	Open charge alliance
OCPI	Open charge point interface
OCPP	Open charge point protocol
PCC	Point of common coupling
PDF	Probability distribution function
PPO	Proximal policy optimization
PSO	Particle swarm optimization
PPS	Pulse per second
PTP	Precision time protocol
PVs	Photovoltaics
RES	Renewable energy sources
RL	Reinforcement learning
RNN	Recurrent neural networks
RSPI	Robust simulation-based policy improvement
RSU	Roadside Units
RTP	Real-time price
RUL	Remaining useful life
SAC	Soft-actor critic
SAE	Society of automotive engineering
SDP	Supply equipment communication controller discovery protocol
SNTP	Simple network time protocol
SoC	State of charge
SoH	State of health
SQP	Sequential quadratic programming
SSA	Sample-average approximation
SVM	Support vector machines
TCP	Transmission control protocol
TD3	Twin delayed deep deterministic policy gradient algorithm
TDNN	Time-delayed neural networks
TL	Transfer learning
TLS	Transport layer security
ToU	Time of use
TRPO	Trust region policy optimization
TSO	Transmission system operator
UDP	User datagram protocol
UID	Unique identifier
V2G	Vehicle-to-grid
V2X	Vehicle-to-everything
VTCPEM	Virginia Tech comprehensive power-based EV energy consumption model

XMPP	eXtensible messaging and presence protocol

Appendix .2. Classification of studies on IoT arrangement for IEVC-eco

Table .7: Classification of studies on IoT arrangement for IEVC-eco

Ref	Application	Objective	EV Type	EVCS Type	AI/IoT	IoT Model Specification							
						Framework	Implementation						
							Mobile app	routing system	Connectivity and implementation environment			Computing environment	
									EV	EVCS	Power system	EV	Aggregator
[212] 2015	EV optimal dispatch	EV privacy	N.S.	Residential building parking	AIoT	Yes	N.A.*	N.A.	CAN	wired wireless	N.S.**	N.S.	N.S.
[138] 2018	EV charging slot finder	User preference satisfication	N.S.	N.S.	AIoT	Yes	N.S.	Google map	HTTP DDS protocol Laptop	HTTP DDS protocol Laptop	Smart Grid Testbed	N.S.	N.S.
[258] 2018	EV charging slot finder	Mobile app	N.S.	N.S.	IoT	Yes	N.S.	Google map	HTTP websockets	ESP8266 wifi GSM	N.S.	N.S.	N.A.
[144] 2018	Load balance	EV charging price determination	N.S.	RES-based	IoT	Yes	N.A.	N.A.	GSM MATLAB	GSM MATLAB	N.A.	N.A.	N.A.
[132] 2018	BMS	G2V/V2G	N.S.	N.S.	IoT	Yes	Firebase cloud mobile app	ESP8266 wifi MQTT Protocol	N.A.	N.A.	N.A.	Adafruit IO	N.A.
[259] 2018	EVCS monitoring system	V2G	N.S.	RES-based	IoT	Yes	N.S.	N.A.	MATLAB Simulink Battery	MATLAB Simulink	N.S.	N.A.	N.S.
[259] 2018	Smart residential EVCS	V2G based on ToU	N.S.	RES-based	IoT	Yes	N.A.	N.A.	Battery MATLAB Simulink	MATLAB Simulink	N.S.	N.S.	N.S.
[129] 2019	EV charging slot finder	User preference satisfication	N.S.	N.S.	IoT	Yes	Website HTML	GPS	HW using Li-ion battery CAN Bus	N.A.	N.A.	WAMP	N.A.
[127] 2019	online monitoring app	EV monitoring system	N.S.	N.S.	IoT	N.S.	N.A.	N.A.	Raspberry Pi cellular network	N.A.	N.A	Cloud	N.A.
[197] 2019	EV charging slot finder	EV privacy	N.S.	parking lot supply by MG	AIoT	Yes	N.S.	GPS	Wifi	Wifi	N.S.	N.S.	N.S.
[145] 2019	EV optimal dispatch	EV charging price determination	N.S.	Fast charging	IoT	IoT and Blockchain framework	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
[260] 2019	EVCS security	EV authentication app	N.S.	N.S.	IoT	IoT and Blockchain framework	Xamarin	N.A.	ESP8266 wifi module	wifi Ethernet	N.A.	Amazon web service	N.A.
[261] 2020	EV charging slot finder	EV privacy	N.S.	N.S.	AIoT	Yes	PHP programming language	Google map	LTC 4150, ESP 8266 wifi module and Arduino	Fast EVCS AC level II	N.A.	cloud SQL	N.A.
[130] 2020	EV charging slot finder	User preference satisfication	N.S.	N.S.	IoT	Yes	thinkspeak app	Google map	ESP8266 wifi module	N.A.	N.A.	thinkspeak Cloud	N.A.
[135] 2020	EV optimal dispatch	power grid balance	N.S.	N.S.	AIoT	Yes	N.A.	N.A.	N.S.	N.S.	ZigBee MQTT protocol	N.A	N.A.

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Table .7: (continued from previous page)

Ref	Application	Objective	EV Type	EVCS Type	AI/IoT	IoT Model Specification							
						Framework	Implementation						
							Mobile app	routing system	Connectivity and implementation environment			Computing environment	
									EV	EVCS	Power system	EV	Aggregator
[262] 2020	BMS	V2G scheduling	N.S	N.S	AIoT	Yes	Android mobile App	N.A.	ESP8266 wifi	balanced charging plate board	B6 AC Li-po battery charger TCP/IP over wifi	Raspberry Pi TCP/IP over wifi	Cloud HTTP
[128] 2020	BMS	Smart OBC	N.S.	N.S.	IoT	Yes	Android studio	Google map	ESP8266 wifi	N.S.	N.A.	N.S	N.S.
[140] 2020	EV charging slot finder	EV privacy	N.S.	N.S.	IoT	Yes	N.A.	GPS	N.S.	N.S.	N.S.	N.S.	N.S.
[263] 2020	WPT	Transferring data between onborad charger and transmitter	N.S.	Wireless charging	IoT	Yes	N.A.	N.A.	ESP8266 wifi	ESP8266 wifi	N.A.	ThingSpeak cloud	N.A.
[264] 2020	BMS	battery charging and swapping decision	N.S.	Swapping	IoT	IoT and Blockchain framework	web app	N.A.	Raspberry pi Python libraries Web3.py and PyOTA	N.S.	N.A.	N.S.	N.S.
[134] 2021	EV charging slot finder	V2V V2I	N.S.	N.S.	IoT	Yes	thinkspeak app	GPS	MATLAB HTTP MQTT protocol	N.A.	N.A.	thinkspeak Cloud	N.A.
[136] 2021	EV charging slot finder	User preference satisfication	N.S.	N.S.	IoT	Yes	Firebase cloud mobile app	ESP8266 wifi MQTT Protocol	N.A.	N.A.		Adafruit IO	N.A.
[142] 2021	Dynamic pricing for V2G	EV privacy	N.S.	N.S.	N.S	Yes	N.A.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
[122] 2021	Reliable network for V2G	V2G scheduling	N.S.	N.S.	AIoT	Yes	N.S.	N.A.	wifi	wifi, Optical fiber	Optical fiber	MATLAB	MATLAB
[154] 2022	BMS	SoC prediction	N.S.	N.S.	AIoT	Yes	Firebase cloud mobile app	N.A.	ESP8266 wifi module	N.A.	N.A.	Firebase Cloud	N.A.
[133] 2022	BMS	SoH monitoring	N.S.	RES-based	IoT	Yes	Bylnk mobile app	N.A.	ESP8266 wifi module	N.A.	N.A.	N.S.	N.A.
[126] 2022	BMS and EVCS monitoring	online EV monitoirng during G2V/V2G	N.S.	N.S.	IoT	Yes	thinkspeak app	N.A.	Thinkspeak Cloud MATLAB	Thinkspeak CAN bus MATLAB	N.A.	Cloud MATLAB	N.A.
[139] 2022	EV charging slot finder	User preference satisfication	N.S.	N.S.	AIoT	Yes	streamlit API	bikemap.net route planner	N.S.	N.S.	N.A.	streamlit cloud	N.A.
[131] 2022	BMS and EVCS monitoring	User preference satisfication	N.S	N.S.	IoT	Yes	N.S.	N.S.	N.S	N.S.	N.A.	N.S.	N.A.

Table .7: (continued from previous page)

Ref	Application	Objective	EV Type	EVCS Type	AI/IoT	IoT Model Specification							
						Framework	Implementation						
							Mobile app	routing system	Connectivity and implementation environment			Computing environment	
									EV	EVCS	Power system	EV	Aggregator
[141] 2022	EV optimal dsipatch	V2G scheduling EV privacy	PHEV	N.S.	AIoT	Yes	N.S.	N.S.	ISCP-PV wifi	HW using Li-ion battery Wired/Wireless	N.S.	N.S.	N.S.
[143] 2023	Minimize EV waiting time	Focus on EV-EVCS interactions	N.S.	N.S.	AIoT	N.S.	N.S.	N.S.	LPWAN Minicast protocol Cooja simulator	LPWAN Minicast protocol Cooja simulator	N.A.	Distributed Framework	N.A.
[137] 2023	BMS	charging/ discharging monitoring	N.S.	N.A.	IoT	Yes	Angular technol-ogy	N.A.	Toyota Prius battery MQTT protocol	N.S.	N.A.	N.S.	N.A.

* N.A.: Not applicable, ** N.S.: Not specified

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A Comprehensive Review on AIoT Applications for Intelligent EV Charging/Discharging Ecosystem

Highlights

- This paper presents an AIoT-driven EV charging ecosystem optimizing stakeholder benefits.
- A novel V2G framework integrates renewable energy sources into EV charging infrastructure.
- AI-based optimization techniques enhance EV charging scheduling and grid stability.
- Privacy and interoperability challenges are addressed through secure, scalable solutions.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: