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Smart Electric Vehicle Charging in the Era of Internet of Vehicles, Emerging Trends, and Open Issues

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Abstract: The Internet of Vehicles (IoV), where people, fleets of electric vehicles (EVs), utility, power grids, distributed renewable energy, and communications and computing infrastructures are connected, has emerged as the next big leap in smart grids and city sectors for a sustainable society. Meanwhile, decentralized and complex grid edge faces many challenges for planning, operation, and management of power systems. Therefore, providing a reliable communications infrastructure is vital. The fourth industrial revolution, that is, a cyber-physical system in conjunction with the Internet of Things (IoT) and coexistence of edge (fog) and cloud computing brings new ways of dealing with such challenges and helps maximize the benefits of power grids. From this perspective, as a use case of IoV, we present a cloud-based EV charging framework to tackle issues of high demand in charging stations during peak hours. A price incentive scheme and another scheme, electricity supply expansion, are presented and compared with the baseline. The results demonstrate that the proposed hierarchical models improve the system performance and the quality of service (QoS) for EV customers. The proposed methods can efficiently assist system operators in managing the system design and grid stability. Further, to shed light on emerging technologies for smart and connected EVs, we elaborate on seven major trends: decentralized energy trading based on blockchain and distributed ledger technology, behavioral science and behavioral economics, artificial and computational intelligence and its applications, digital twins of IoV, software-defined IoVs, and intelligent EV charging with information-centric networking, and parking lot microgrids and EV-based virtual storage. We have also discussed some of the potential research issues in IoV to further study IoV. The integration of communications, modern power system management, EV control management, and computing technologies for IoV are crucial for grid stability and large-scale EV charging networks.

Keywords: blockchain; cloud computing; distributed renewable energy; electric vehicles; edge computing; Internet of Vehicles; machine learning; smart grids; transactive energy

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1. Introduction

According to the International Energy Agency 2017 report [1], the electric car market has experienced significant growth over the years, with an electric car stock ranging between 9 and 20 million by 2020 and between 40 and 70 million by 2025. The EV30@30 campaign has set a collective goal of a 30% EV market share by 2030 [1]. Smart vehicles have become a larger and integral part of the Internet of Things (IoT) infrastructure. For example, it was projected that the number of cars worldwide is set to double by 2040 [2]. As cities grow, such connected and smart vehicles will be massively deployed on the roads. That relies on massive information exchange computing and communication infrastructures. These trends represent important steps of Vehicular Ad Hoc Networks (VANETs) towards the realization of the Internet of Vehicle (IoV). IoVs will offer communications, storage, intelligence, and learning capabilities to predict the customers' intentions [3].

The future IoV ecosystem is expected to provide new roles for the power grid. As illustrated in Figure 1, the IoV vision is to connect people, fleets of electric vehicles, utilities, power grids (centralized generation, distributed renewable energy generation, distributed storage), peer-to-peer (P2P) transactions, heterogeneous communication networks (e.g., IEEE 802.11p, IEEE 802.11n/ac, 3G/4G LTE/5G), and computing infrastructures in the loop for a sustainable society. As the world enters the era of IoV, where Vehicle-to-Grid (V2G), Vehicle-to-Roadside (V2R), Vehicle-to-Vehicle (V2V), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Infrastructure (V2I) communications are the building blocks of the IoV ecosystem, a cloud computing (both centralized and distributed) platform is essential not only for mitigating management complexity but also for computing and storing big data and supplying resources to P2P direct energy trading between consumers and producers for economies of scale (refer to Section 5 for direct energy trading).

To put things into perspective, note that conventional Vehicular Ad Hoc Networks (VANETs) simply enable sharing messages among vehicles. Going beyond this, IoV as an integral part of the Internet of Things (IoT) enables a range of new capabilities and services far beyond today's VANET offerings. IoV considers each vehicle an IoT smart object that enables vehicles not only to gather data based on its sensing capabilities and disseminate messages between peers but also allows vehicles to process and compute such information (e.g., roadside information, obstacles, hazardous location notification, congestion, or location information). The large-scale deployment of EVs, including commercial trucking (e.g., FedEx, Frito-Lay, Duane Reade have incorporated EVs into their commercial fleets) in IoV will bring many advantages, especially for smart grids and smart cities, and will reduce greenhouse gas emissions by an estimated 48 million metric tons per year by 2030 [4]. Further, IoV is expected to improve traffic efficiency and management and enhance traffic safety via learning capabilities. In addition, IoV helps accelerate the emerging transportation-as-a-service business model (e.g., served by on-demand autonomous EVs) and also improves social equity by creating innovative business models; specifically, low-income households could participate in P2P energy trading virtual marketplaces and benefit from the value created by IoV technologies.

Due to the growing number of EVs on the road, there are also growing numbers of charging/discharging stations (e.g., more than 8000 charging stations, including standard and Telsa superchargers in Norway). However, large-scale EV charging in the IoV ecosystem poses many challenges. For example, the uncoordinated charging demands of EVs increase the load during peak hours, which in turn has a negative impact on the stability of power grids due to its sizable rating. Typically, an EV draws approximately 7 kW power from the grid even with level-2 charging, which is significantly higher than the peak demand of most of the residential households [5]. Moreover, EV owners tend to charge their EVs after returning from work, which is also the time of peak demand in the grids, thereby coinciding with the power drawn from EV and household peaks. This scenario leads to a significant increase in system peak demand and threatens the stability of the power grid. In addition, the charging management in a network of charging stations (CSs) requires massive data exchange and processing. It should be noted that charging management for EVs is important to achieve efficient energy management and the stability of the power grid. Studies showed that there are major challenges include: selecting a charging station to design a reasonable charging plan and constructing an efficient communication framework between EVs and the power grid [6]. Therefore, cloud-based charging management is gaining attention. The scalability, flexibility, security, and on-demand performance of cloud computing provide an efficient platform for EV charging [7]. Existing studies (e.g., [8] and references therein) deal with the cloud-based charging and discharging management in public CSs for demand response. However, they do not deal with two levels of cloud-based charging management of large-scale EVs nor do they consider different service requirements of multi-class EVs and scenarios of multi-class CSs. As a representative IoV use case, we investigate cloud-based charging management of EVs in IoV to reduce computational and communication complexity while yielding better profit, thus maintaining the differentiated quality of service (QoS). From a charging management viewpoint, we have proposed a cloud-based EV charging system that contains cloud server planning, capacity planning for charging stations, and price-incentive mechanisms. From an architectural perspective, we have introduced a network architecture of a two-level of cloud computing-based EV charging system. While distributed renewables will be beneficial in the IoV ecosystem to meet the surplus demand of EVs, it also creates stability and availability issues in power systems, which are discussed in greater detail later.

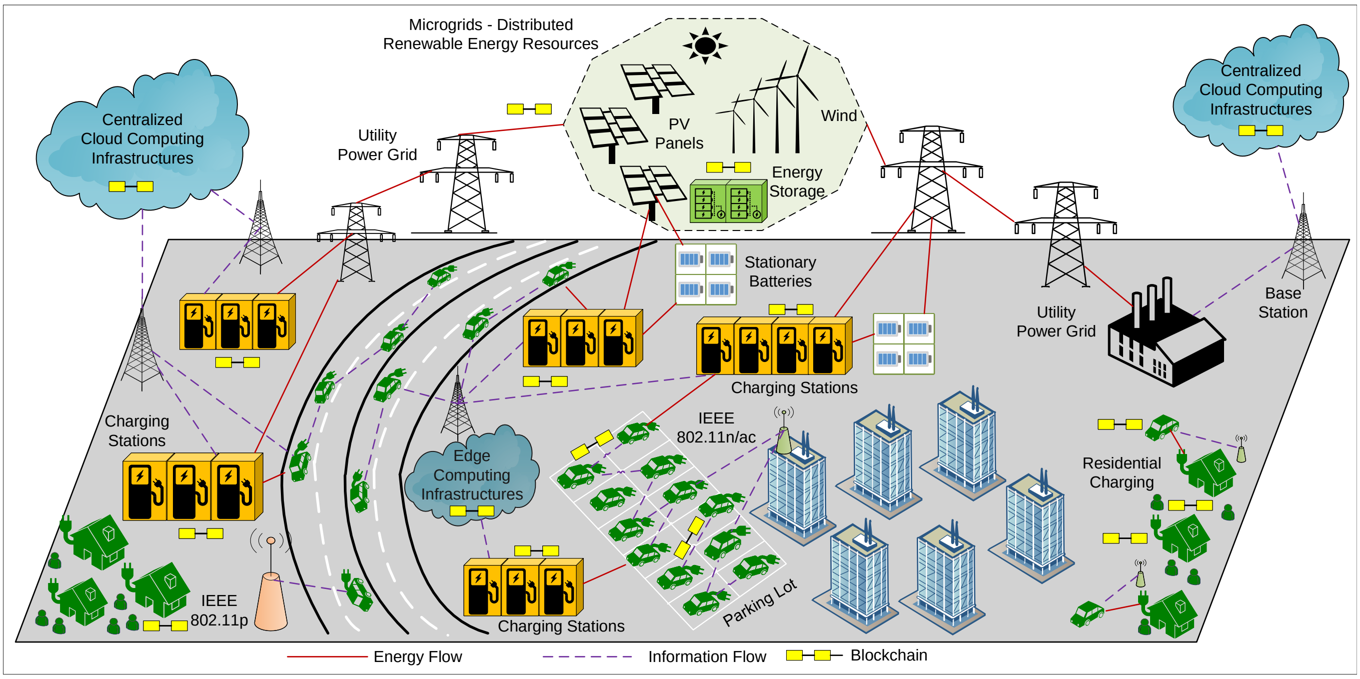

Figure 1. The Internet of Vehicles (IoV) vision: People, fleets of electric vehicles, utilities, power grids (centralized generation, distributed renewable energy generation, distributed storage), peer-to-peer (P2P) transactions as well as control, communications, and computing infrastructures are in the loop for a sustainable society.

To fully realize the potential of the emerging IoV, many enabling technologies playing crucial roles in its implementation have been growing fast. In this paper, we present seven major emerging trends. That includes decentralized energy trading based on blockchain and distributed ledger technology, behavioral science and behavioral economics, artificial and computational intelligence and its applications, digital twins of IoVs, software-defined IoVs, and intelligent electric vehicle charging with information-centric networking, and parking lot microgrids and EV-based virtual storage. These trends represent beyond the conventional power and communications fields and will demand collaborative and sustained interdisciplinary measures. Further, to provide a broader technological perspective, we have discussed other emerging trends, including digital twins of the IoV, software-defined IoVs, and intelligent electric vehicle charging with information-centric networking. We have also discussed multiple research issues in IoV, including grid congestion, IoV charging mechanism, design issues, security and privacy, high mobility of vehicles, QoS and QoE, and multi-dimensional randomness and heterogeneity. The grid instability has a significant impact on the service provided to customers, the reputation of the system operators, existing infrastructure, and charging operations in a network of charging stations. An unstable grid might also cause voltage collapse. Towards this end, the key contributions of this paper are summarized as follows.

- We have discussed an overview of IoV to provide the next step of EV research.
- We have envisioned the Internet of Vehicles (IoV) in a broader context, where people, fleets of electric vehicles, utilities, power grids (centralized generation, distributed renewable energy generation, distributed storage), peer-to-peer (P2P) transactions as well as control, communications, and computing infrastructures are in the loop for a sustainable society.
- Two-tier cloud computing-based EV charging management in IoV is developed and evaluated.
- Major enabling technologies in IoV are thoroughly discussed.
- Multiple issues in IoV are thoroughly discussed that open up future research directions.

The remainder of the paper is structured as follows. Section 3 describes a two-tier cloud computing-based EV charging management in IoV, including network architecture and operations. Section 4 presents the performance evaluation of cloud-based EV charging in IoV. Emerging trends in IoV are detailed in Section 5. Open research issues are discussed in Section 6. Finally, Section 7 concludes the paper.

2. Related Work

Several studies can be found in EV charging. However, there have been a few studies on IoV-based charging management in recent years. For example, the CS placement optimization problem integrated with the IoV-based framework was proposed in [9]. In [10], the authors proposed the IoV-based energy trading system with fog computing to reduce the peak load from EVs. An online double auction method for EVs was proposed in [11] to address the issues of demand response. To protect customers' privacy and reduce the power cost, a cloud-based scheduling method for EV charge and discharge management was proposed in [12]. A blockchain-enabled energy trading with the Stackelberg game model between V2V was studied in [13] to perform the optimization for the roles of the system operator, power buyers, and validator nodes. Demand response has been used as a method to shift the peak load. Therefore, some studies explored the demand response-based mechanism in IoV. For example, motivating more customers to get involved in the demand response method, a contract theory-based incentive mechanism is proposed in [14] for EVs.

Centralized and decentralized scheduling has been studied for EVs. For example, a cloud-based scheduling for EVs and fleets of shared-use electric vehicles [8,15] and utilizing big data technology to analyze the decentralized scheduling of EVs with mobile edge computing (MEC) [16] have been studied. Similarly, MEC-enabled charging and discharging scheduling were presented to optimize EVs' performance (waiting time) in charging stations [17]. Further, MEC-based charging/discharging scheduling for mobile EVs was proposed in [18]. Cloudlet-based charging station recommendation for EVs was proposed with federated learning [19]. Based on software-defined networking, a hierarchical architecture for wireless vehicular networks was studied in [20].

3. Two-Tier Cloud Computing-Based EV Charging Management in IoV

3.1. Network Architecture

Existing power network architectures mainly focus on grid protection or power distribution and thus cannot account for the large-scale communication demands and IT services (e.g., forecasting and scheduling of charging loads according to various power grid conditions, coordination of multiple charging stations, searchability for charging stations and available charging outlets, reservation of charging stations, exchange of real-time roadside information between EVs, software upgradability, payment and consumption cost, optimizing operations using analytics services, among others) of EVs in the IoV era. To mitigate these shortcomings, we aim to integrate cloud computing (i.e., coexistent centralized cloud and decentralized edge computing) and power grid infrastructures as a multi-purpose asset. As shown in Figure 2, our proposed architecture consists of multiple layers: (a) cloud computing, (b) edge (fog) computing [21], and (c) V2G and V2I communications. With V2I communications on highways and parking lots, it is necessary for EVs to communicate with charging stations and system operators (e.g., Pacific Gas and Electric Company, San Francisco, CA, USA). Note that from a safety perspective, a low-latency and high-reliability V2I solution, in the long run, is significantly more important than V2V communications [22]. Edge (fog) computing exploits wireless one-hop communication and the store-and-forward principle provides EVs with low-latency, high-bandwidth, real-time information about the current charging performance, high availability, improved network reliability, fast response, and backhaul traffic reduction. Further, edge computing infrastructures are decentralized and serve as local storage of the remote centralized cloud, while periodically synchronizing with it, and offer various innovative edge applications and services [21].

The future IoV may rely on emerging cellular V2X (C-V2X) communications, which consists of V2V, V2I, and vehicle-to-pedestrian (V2P) direct communications, and vehicle-to-network (V2N) wide-area communications to serve next-generation smart EVs [23–25]. There is an enormous benefit from the applications and services of V2X of the intelligent transportation system. C-V2X is expected to bring added value to advanced driver assistance services such as traffic signal timing/priority, collision avoidance safety systems, real-time traffic/routing service, efficient road traffic management, cloud services, safety alerts to pedestrians and bicyclists, and lower pollution, accidents, and driving times. The salient features, e.g., channel coding, synchronization, transmission scheme, resource multiplexing across vehicles, resource selection or dynamic scheduling, spectrum band, a standard roadmap towards 5G, retransmission repeat request, transmission range, use cases, roadmap, and differences of C-V2X communications compared to DSRC are summarized in Table 1.

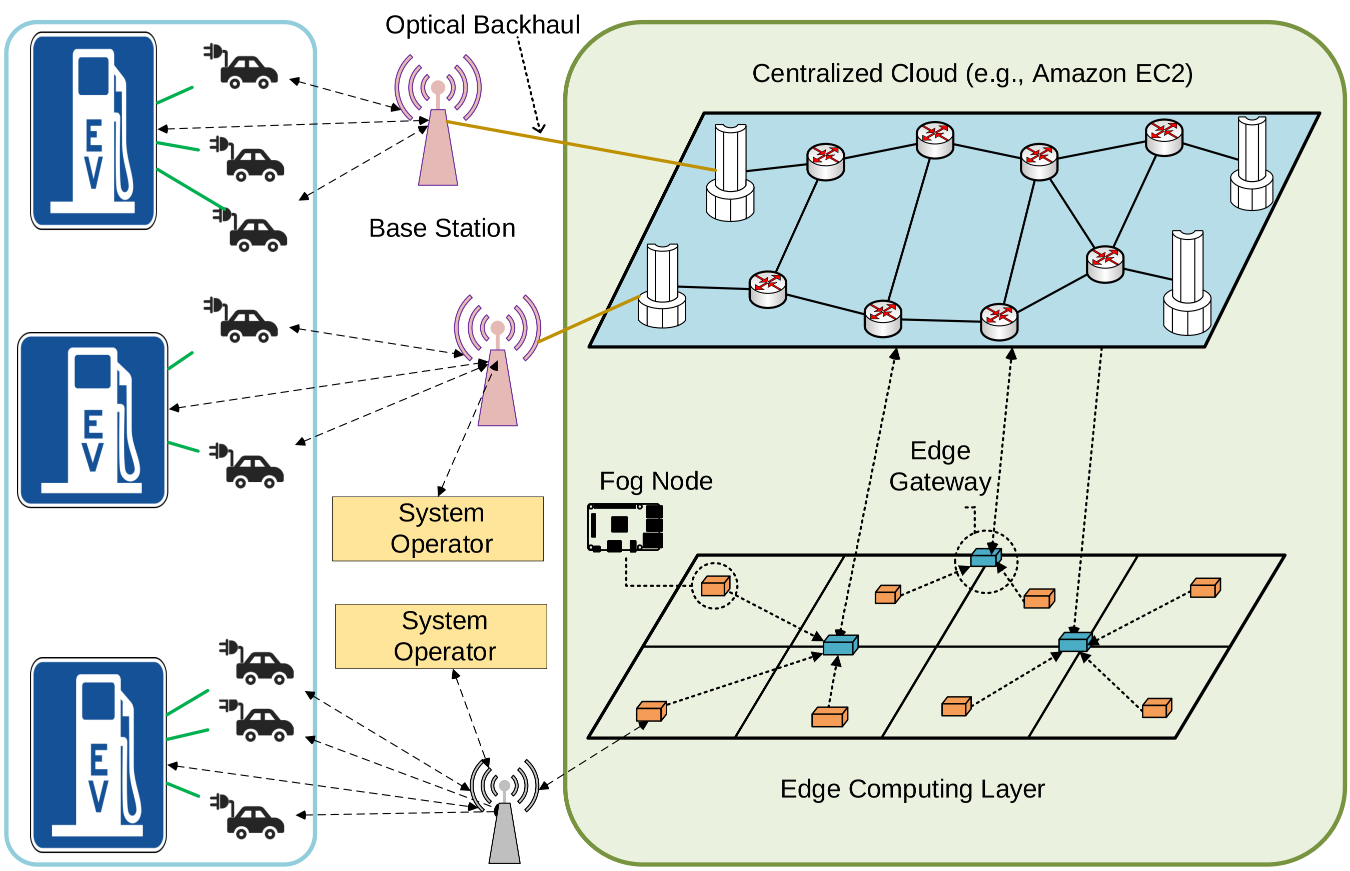

Figure 2. Network architecture of two-tier cloud computing-based EV charging management system in IoV.

Table 1. Comparison of emerging cellular V2X (C-V2X) communications and conventional dedicated short-range communications (DSRC).

Parameters	**C-V2X (or LTE V2X)**	**DSRC**
Channel coding	Turbo codes (for data channel) and tail-biting convolutional code (TBCC) (for control channel)	Convolution codes
Synchronization	Synchronous	Asynchronous
Transmission scheme	Single-carrier frequency division multiplexing (SC-FDM), which allows more transmit power than OFDM	Orthogonal frequency division multiplexing (OFDM)
Resource multiplexing across vehicles	Frequency-division multiplexing (FDM) and time-division multiplexing (TDM)	TDM
Resource selection	Semi-persistent scheduling or dynamic scheduling	Carrier sense multiple access with collision avoidance (CSMA-CA)
Spectrum band	5.9 GHz	North America: 5850–5925 MHz; Europe: 5795–5815 MHz, 5855/5875–5905/5925 MHz; Japan: 755.5–764.5 MHz, 5770–5850 MHz
Standard	3GPP—Release 14 and roadmap towards 5G	IEEE 802.11p
Retransmission	Hybrid Automatic Repeat Request (HARQ)	No HARQ
Transmission range	Up to 225 m	Over 450 m via direct mode and more than that via cellular
Use cases	A wide range of use cases (e.g., road safety services, traffic flow optimization, enhanced positioning, control loss warning, emergency stop, curve speed warning, vehicle platooning, remote driving, extended sensor, and state map sharing a dynamic ride sharing, collective perception of the environment, high-definition content delivery)	Limited use cases (e.g., vehicular safety applications, V2V communications, toll collection)
Roadmap	Leverages and enhances existing LTE networks with roadmap toward 5G-based V2X	Not many new activities in IEEE 802.11 standards for next-generation DSRC technology. Cellular D2D may obsolete IEEE 802.11p, but hybrid and complementary solutions are possible.

3.2. Operations

We developed a hierarchical charging management system, where two classes of EVs communicate with two different clouds depending on their QoS requirements. The involved actors and their functionalities in the system are as follows.

Electric Vehicles and Charging Stations: Based on the different charging requirements and geographical distribution, we divide EVs into two categories: EVs at a highway exit and EVs in a parking lot. Further, each EV is equipped with a Li-ion battery that enables them to store energy, whereby different QoS requirements of EVs are taken into account. EVs in both highway or parking lot scenarios communicate with the edge or remote cloud to send their information (e.g., spatial location, charging demand) to and receive messages from the cloud (e.g., price, discount, charging capacity of nearby CSs, charging schedule). Multi-class CSs (DC fast charge and Level 2) are considered. CSs in highway exits are placed where the traffic flow is heavy and each charging station supports multiple EVs charging simultaneously. CSs in parking lots are randomly placed in a city, whereby their locations, capacity, availability are communicated to all EVs via the clouds. Note that the class of charging station affects the performance of our proposed solution, as investigated in more detail in Section 4.

System Operator (SO): The SO purchases energy from utilities and provides charging services to EVs in CSs. Furthermore, the SO as the operator (e.g., Pacific Gas and Electric) distributes energy to its sub-networks and allocates energy to CSs. It is responsible for providing secure system operation and tracking the power schedule. Furthermore, the SO interacts with the cloud control center (CCC) via an LTE network to provide power supply and pricing information. It also receives capacity planning and price information from the CCC and reaches an agreement on the capacity and discount price (see Figure 3). The SO aims at maximizing profit in one of two ways: It either encourages EVs to delay charging by offering an incentive, or the SO purchases additional electricity from the utility when the charging demand exceeds supply.

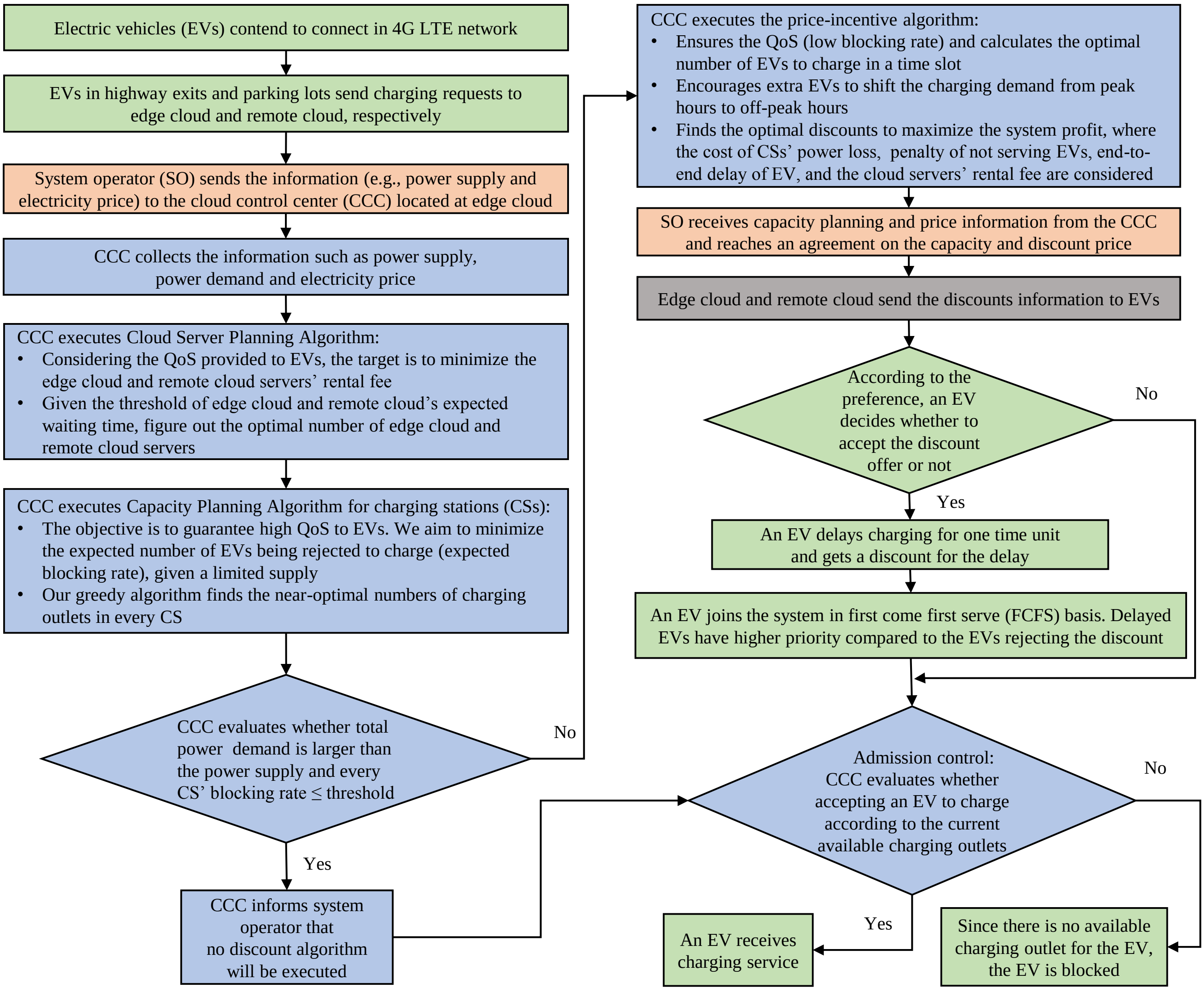

Figure 3. Proposed approach for cloud-based EV charging in IoV: Functionality and interactions among entities.

Computing and Control: The remote cloud (e.g., Amazon EC2) with large-scale computing infrastructures provides computing, storage, caching, and networking services to EVs. Alternatively, the edge cloud offers cloud computing services (computing, storage, caching, networking) and provides mobile broadband experiences to EVs [21]. The CCC is a functional component that runs in the cloud and provides the following three functions: executing server planning, capacity planning, and running price-incentive algorithms at the edge cloud (see Figure 3). The goal of cloud server planning is to reduce the rental fee of a server for given QoS requirements, whereas the goal of capacity planning is to minimize the blocking probability for a given power supply. The CCC incentivizes EVs to shift their charging schedule to the slack period by proposing a discount. In addition, the CCC performs admission control, where it checks all requests and decides whether or not to admit a given EV for charging in the current timeslot taking the current capacity and available charging outlets into account.

For illustration, Figure 3 depicts all aforementioned operations of the system in a comprehensive functional diagram. Specifically, in the optimal cloud server planning, we model the CCC to be $M/M/c$ queuing system. The objective function in cloud sever planning is to reduce the total cost of both remote and local cloud servers. The average waiting time in the cloud servers is considered in the constraints. In the capacity planning of charging stations, we model each station to be $M/M/c/c$ queue. The optimization problem is formulated to minimize the expected blocking rate, given the limited supply.

In the price-incentive (PIM) method, the objective function aims at maximizing all the profits in the whole charging network. In the optimization formulation, it is guaranteed that the sum of EVs accepting to delay charging from one preceding time slot and EVs rejecting to delay charging is smaller or equal to the optimal arrival rate. On the other hand, in the capacity expansion (CEM) method, the penalty for SO purchasing extra power is taken into account in the profit formulation.

4. Performance Evaluation of Cloud-Based EV Charging in IoV

This section discusses results and findings of cloud-based EV charging obtained from an analytical evaluation of the considered scenarios. We compare and analyze our two proposed methods (PIM and CEM) with a baseline scheme of uncontrolled EVs. More specifically, PIM shifts high demands from on-peak to off-peak hours by offering a discount to EVs, while CEM is used by the SO to purchase sufficient electricity from the grid to satisfy the given EV's demands. The performance metrics of interest include cloud server allocation, demand response (charging demand and outlet allocation), weighted blocking probability, and discount. The weighted blocking probability is defined as the average percentage of unserved EVs.

The proposed schemes are evaluated via an $M/M/c$ queuing model [26]. We assume a 20 MHz bandwidth, average EV transmission rate of 5 Mbps. A total of 186 2022 Nissan Leaf S electric cars with a 40 kWh Li-ion battery and 187 Jaguar electric cars with an 85 kWh Li-ion battery were adopted in the evaluation. A total of 188 EVs arrive at the charging stations with an hourly arrival time distribution [26]. Further, we consider an Amazon EC2 California as a remote cloud, similarly to [21]. The system parameters are listed in Table 2. Matlab was used to simulate the proposed models and obtain the results. In the implementation process, the dynamics, for example, hourly charging outlets allocation, hourly charging demands, hourly offered discount, hourly served EV, were considered and implemented.

Table 2. Parameters and their values.

Parameters	Value
Transmission bandwidth	20 MHz
Transmission rate	5 Mbps
Charging levels (kW)	150, 100, 50, 19.2
Electricity supply	350 MW
Service rate of edge cloud servers	2400 EVs/h
Service rate of remote cloud servers	600 EVs/h
Battery size for 2020 Nissan Leaf EVs	40 kWh
Battery size for Jaguar	85 kWh
Charging levels for 2020 Nissan Leaf EVs	50 kW, 19.2 kW
Charging levels for Jaguar	150 KW, 100 kW
Number of charging stations at highway exits	20
Number of charging stations at parking lots	20

Table 2. *Cont.*

Parameters	Value
EV arrival rate at highway exits (hourly)	4, 2, 3.2, 3, 2.5, 1, 2, 3.5, 2.8, 2.5, 3, 1.8, 2.8, 3.6, 2, 1.2, 2.7, 2.8, 2, 3, 5 (thousand)
EV arrival rate at parking lots (hourly)	3.2, 2.5, 2.2, 5, 3.3, 2.5, 1.7, 1.6, 3, 2, 3, 2.8, 2.9, 3, 3, 2.8, 2.5, 1.9, 3, 1.8
Number of charging stations at highway exits with 150, 100, 50, and 19.2 kW charging level, respectively	4, 4, 6, 6
Number of charging stations at parking lots with 150, 100, 50, and 19.2 kW charging level, respectively	4, 4, 6, 6

Figure 4 depicts the allocation of a number of edge cloud servers and remote cloud servers. The number of cloud servers depends on the EV traffic. The service rate of the edge and remote cloud servers are listed in Table 2. Since there is no traffic at the parking lots at off-peak hours [1–5,11–13,20–24], the number of remote cloud servers is zero. At peak hours 8, 9, and 16, more remote cloud servers are allocated to satisfy the average waiting time threshold. Compared to the remote cloud, fewer servers are allocated to the edge cloud because of its faster processing ability and more even hourly arrival time distribution. At off-peak hours [1,7,11,15,18,24], the statistics of the three cases in Figures 5–7 are the same due to sufficient supply. Figure 5 depicts the hourly charging demand. The charging demand in baseline and CEM are the same since the number of EVs arriving at the charging stations is the same, which is listed in Table 2. We observe that if supply is insufficient to ensure that the blocking probability remains within the threshold, the load at peak hours 8, 9, and 16 is shifted to off-peak hours with PIM. A certain percentage of EVs accept the proposed discount to delay charging based on the model in [26]. With CEM, the SO purchases more electricity to alleviate the peak load at hours 8, 9, and 16. As a result, Figure 6 shows that CEM's number of charging outlets in all charging levels at these peak hours is greater than in the other two cases.

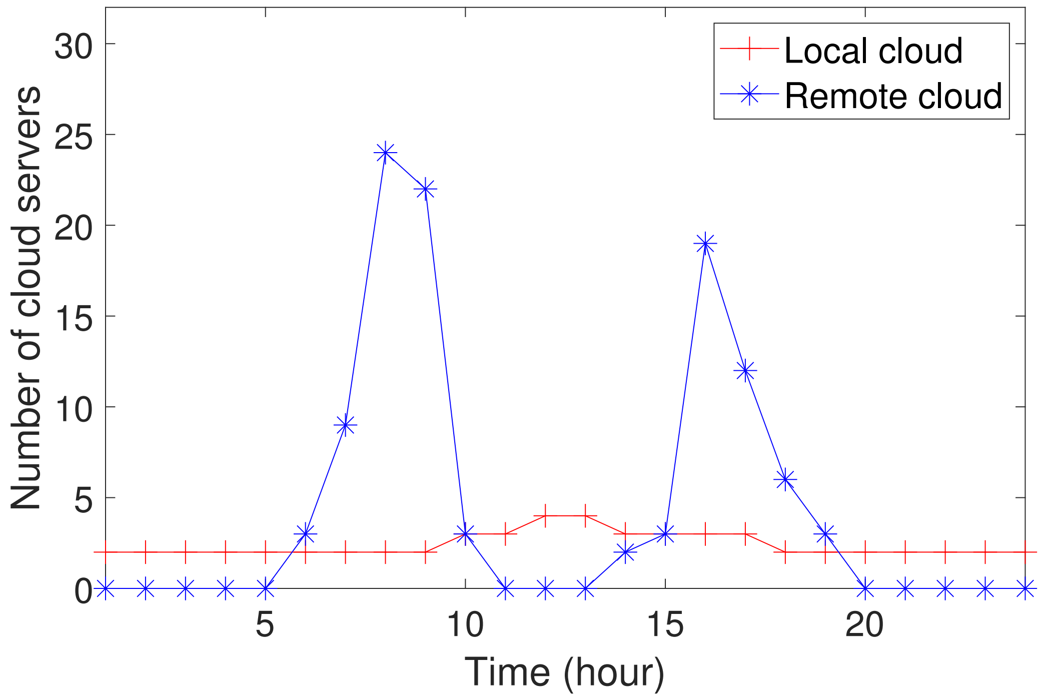

Figure 4. Allocation of both cloud servers.

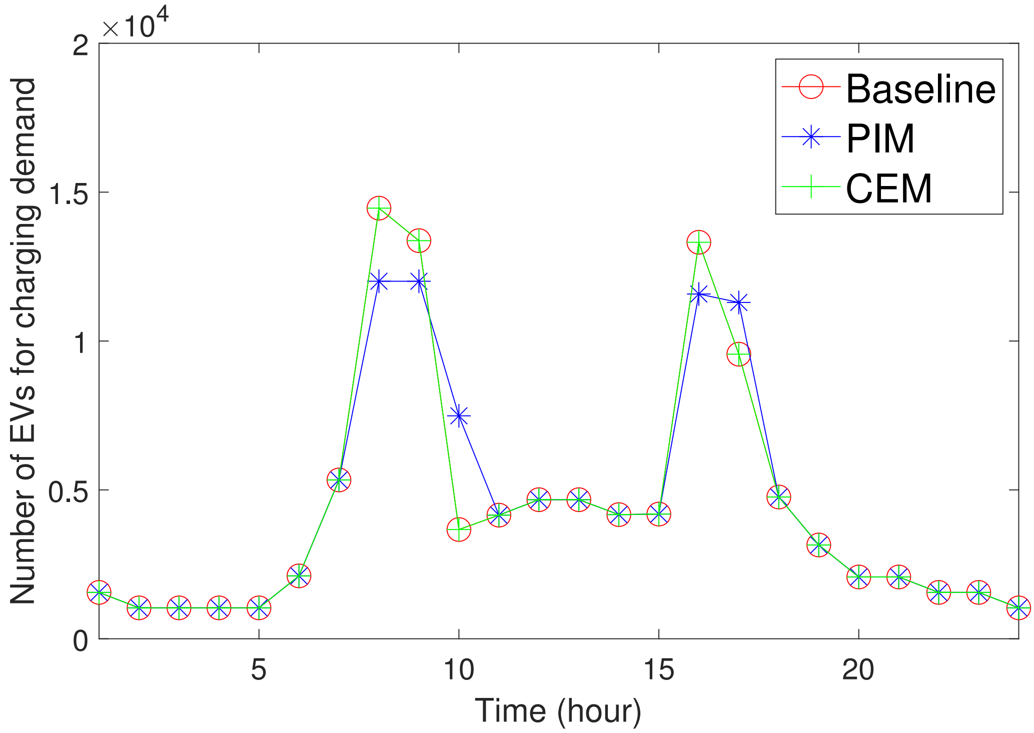

Figure 5. Comparison of charging demand.

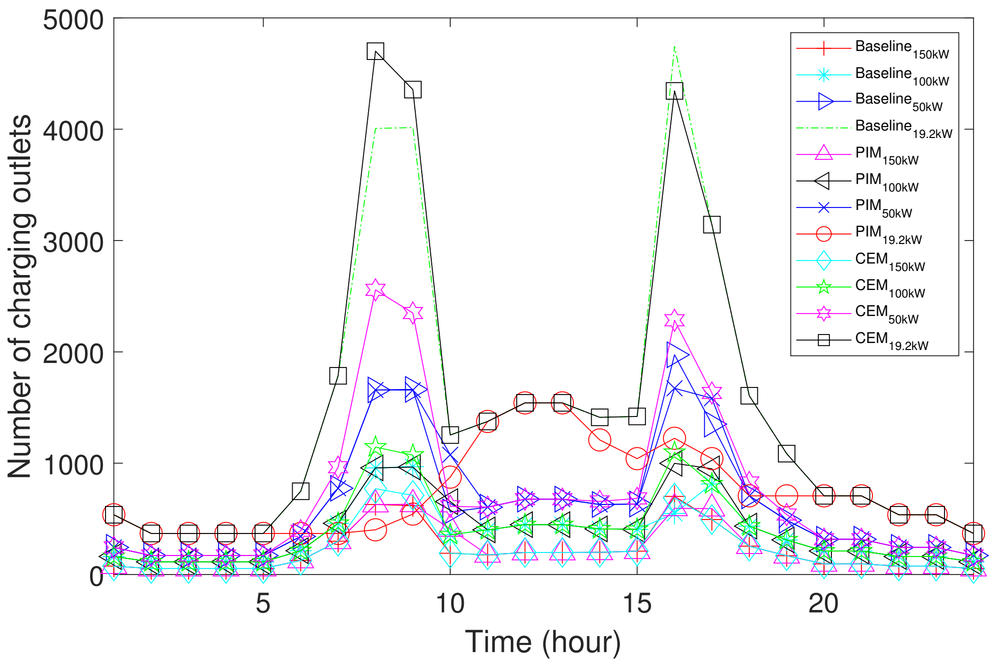

Figure 6. Allocation of charging outlets.

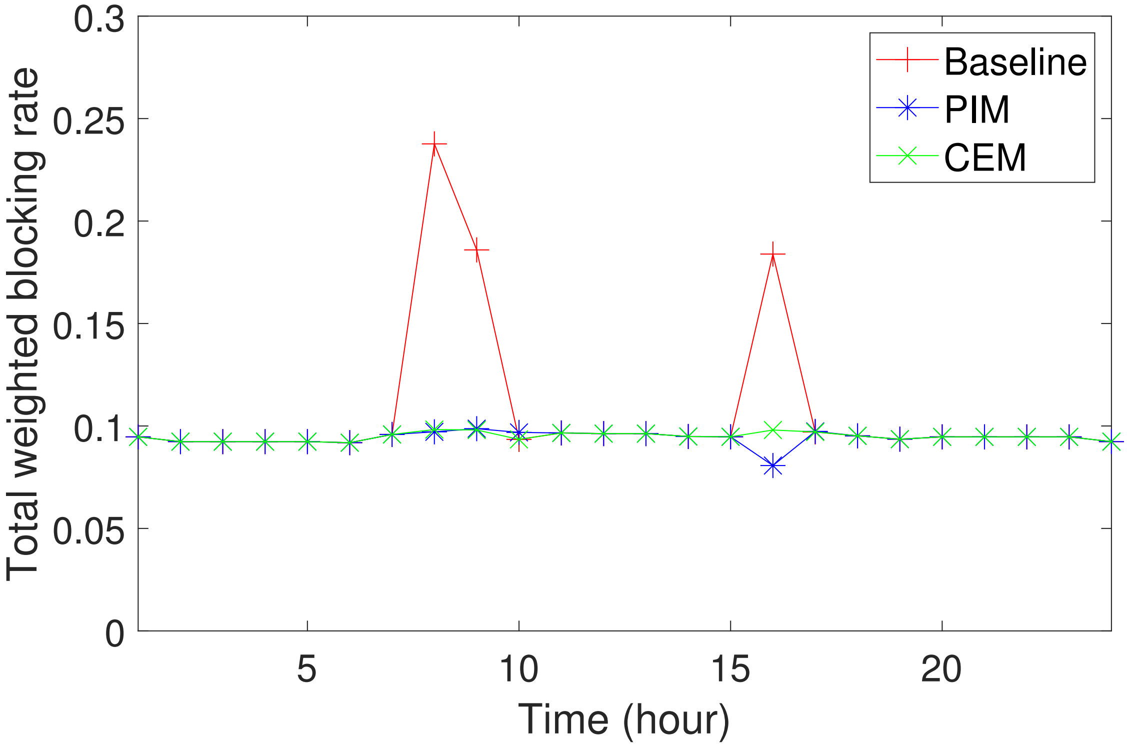

Figure 7. Comparison of weighted blocking rate.

Figure 7 shows the total weighted blocking rate in a network of CSs. Due to the insufficient supply during peak hours 8, 9, and 16 in the baseline scheme, more than 15% of the EVs have to be rejected in the charging system. Consistent with the results in Figure 5, the weighted blocking rate in the baseline scheme at peak hour 8, 9, and 16 are higher than 0.15, while it is within the threshold value (0.1) with both PIM and CEM. Figure 8 depicts the discount in PIM. At peak hours 8, 9, and 16, the charging demand is high. Thus, the discount is offered both at the CS in highway and parking lots. The amount of discount depends on the demand condition of each CS. Higher demand leads to higher discounts to encourage more EVs to delay charging. Even though the EVs at the highway should be offered a higher discount to delay charging, the discount for parking lots is higher in every charging level compared to the highway scenario. This is because the charging demand in parking lots during peak hours is much higher than the case in highways, according to the arrival time distribution [26]. In other words, a higher discount in parking lots is needed to decrease a larger amount of charging demand compared to the highway case.

Overall, from our obtained results, we observe that PIM and CEM outperform the baseline scheme, whereby CEM requires simpler communication procedures than PIM, though it weakens grid stability. Conversely, PIM is able to mitigate the negative impact on the grid while maintaining high system performance and QoS assurance.

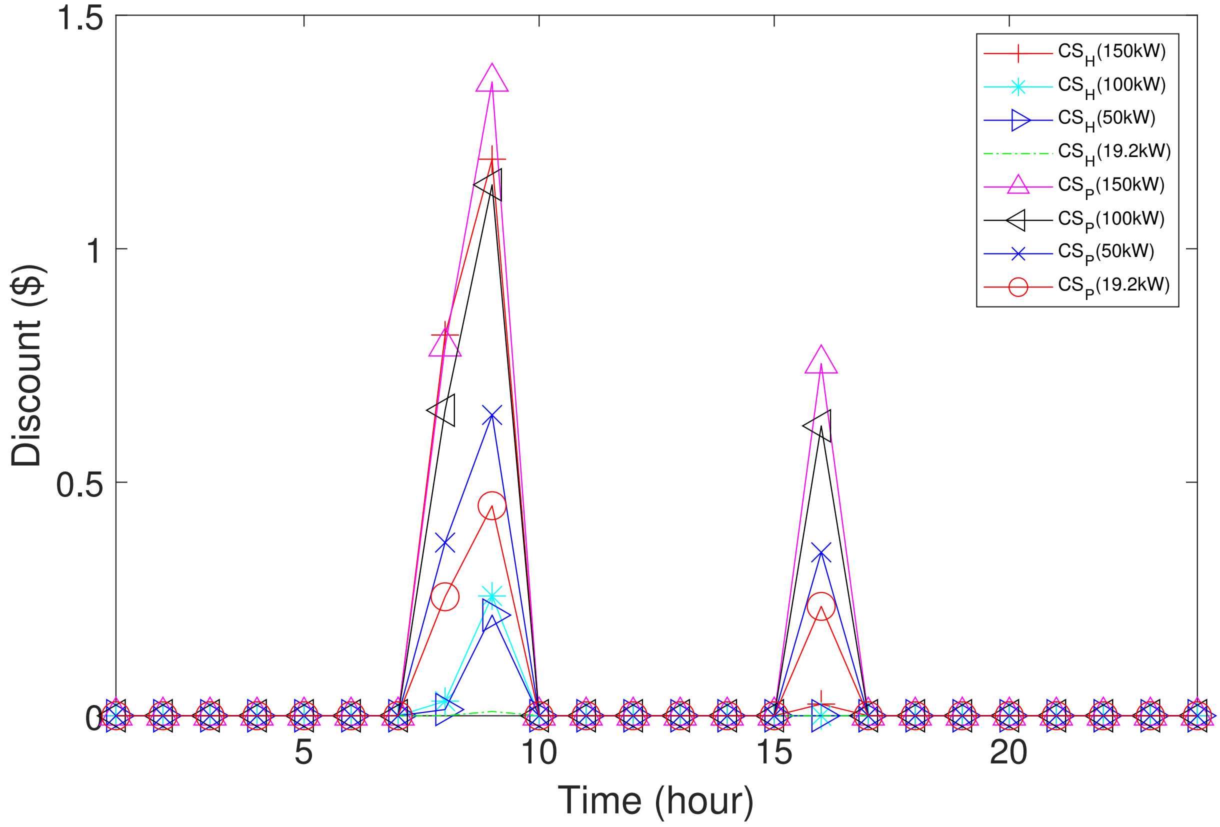

Figure 8. Average offered discount in CSs in the case of PIM.

5. Emerging Trends in IoV

This section discusses the following major emerging trends in IoV:

1. Decentralized Energy Trading Based on Blockchain and Distributed Ledger Technology: The blockchain is a distributed ledger that is visible throughout the network. Each time a transaction occurs, it is updated to the ledger after verification without the need for a third-party intermediary. Blockchain is a new technology that mixes P2P networks with a distributed consensus process that uses cryptography, mathematics, and economic models. Bitcoin, for example, is one of the most widely used decentralized cryptocurrencies [27].
Blockchain is the latest general-purpose technology (GPT), which is still in its infancy. It has not been adopted widely in transactive energy and digitization of electron exchanges. However, the concept of a local energy market is emerging these days, whereby prosumers (energy producers and consumers) work in unison to equilibrate demand-supply by the use of two-party contracts giving rise to neighbor-to-neighbor transactions [27,28]. Blockchain technology is popularized as an economic overlay in the interlinked world, i.e., IoT [28,29]. Energy is one of the newest sectors to embrace blockchain-based technologies. Application of such technologies permits tracking energy usage for a decentralization of energy transactions and supply systems. Blockchain-based peer-to-peer energy trade offers a lot of promise and is causing sectors to take notice. For example, Siemens collaborated with LO3 Energy to test blockchain-enabled energy microgrids on Brooklyn Microgrid (community microgrids in Brooklyn, NY), which has been evolving its business model for energy trading over the last few years. This model may depict the energy trade of the future.
Similarly, Distributed Ledger Technology (DLT) also provides cryptocurrency exchanges, which can be ideal for secure payment mechanisms and can improve vehicle cooperation. Not only this, DLT is transparent as all nodes can access the ledger.

DLT is private as it provides a pseudonymous address to each user. This provides a pathway to automatic data/resource exchange platform [30]. For IoV applications, DLT has been proposed for access control [31,32] and also to eliminate common attacks or forged messages using validation techniques [33,34].

The blockchain is part of a larger computing infrastructure that should also include storage, communications, file services, and other functions. Blockchain in general and particularly in the energy sector poses multi-dimensional challenges, thus moving assets to the blockchain is still in the early stage rather than a viable mainstream approach. Technical issues include scalability, network bandwidth and size, cybersecurity, handling of private-sensitive data (e.g., consumption, locations, transactions), interoperability among blockchain systems, and storage requirements. Further, investigating the communications between the blockchain ledger and control systems at different granularities (i.e., local, system, and system of systems levels) [35] is also challenging. It is essential to develop an open source testbed for blockchain-based transactive energy to fully understand its potential benefits and pitfalls under real-world scenarios. From a business viewpoint, blockchain lacks best practices, business models, and legal settlements. Currently, Bitcoin is dominating the market. However, for healthy competition, multi-currency systems should be developed. A fundamental hurdle of blockchain is the huge amount of energy consumption per transaction with approximately 300 kWh of electricity being needed for each Bitcoin transaction. Moreover, a single Bitcoin transaction has an electrical energy footprint of 2186.75 kWh, which is approximately equal to the power consumption of an average U.S. household over 74.95 days [36]. For illustration, Figure 9 depicts how Bitcoin and Ethereum combined would rank among the energy consumption of entire countries. Similarly, Figure 10 shows Bitcoin's energy consumption relative to some of the world's biggest energy consuming nations.

We also note that blockchains are not suitable for handling massive computations and running consensus algorithms in EVs since they have limited computational power and storage capabilities. To address these high computation and high bandwidth issues, mobile-edge computing empowered fiber-wireless (FiWi) broadband networks, which offer distributed cloud computing capabilities (computing, storage, network, caching) at the edge of networks and combine the reliability and high capacity of optical fiber backhaul (e.g., 10 Gbit/s Ethernet Passive Optical Network (EPON)) with the cost-savings and ubiquity of wireless front-end networks (e.g., WiFi, 4G LTE, 5G) [21,37], may be one of the potential candidates. Concerning standardization issues, ISO has recently established a new technical committee (ISO/TC 307) for blockchain and distributed ledger technologies. Very recently, the Blockchain Interoperability Alliance announced its aim to promote interconnectivity between blockchain networks and develop common industry standard protocols and architectures.

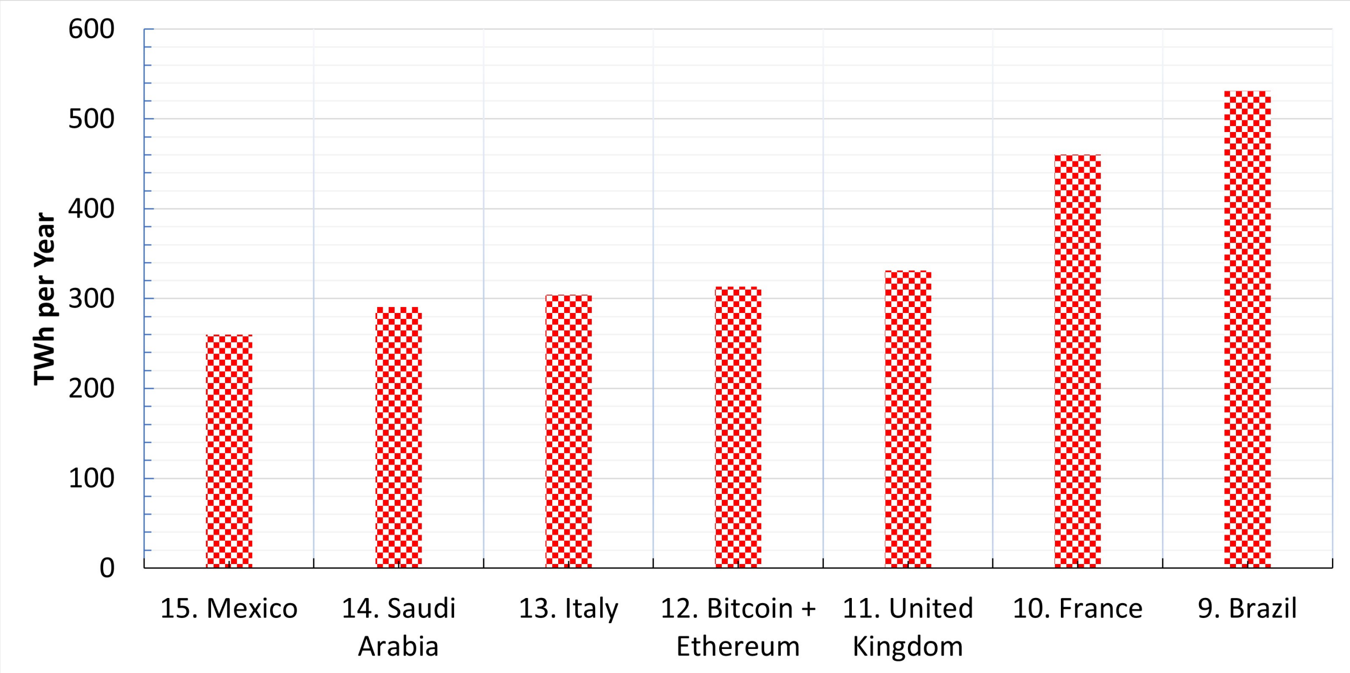

Figure 9. Energy consumption by country including Bitcoin and Ethereum (energy consumption of each country according to International Energy Agency and Bitcoin energy index is adopted from https://digiconomist.net, accessed on 1 January 2022).

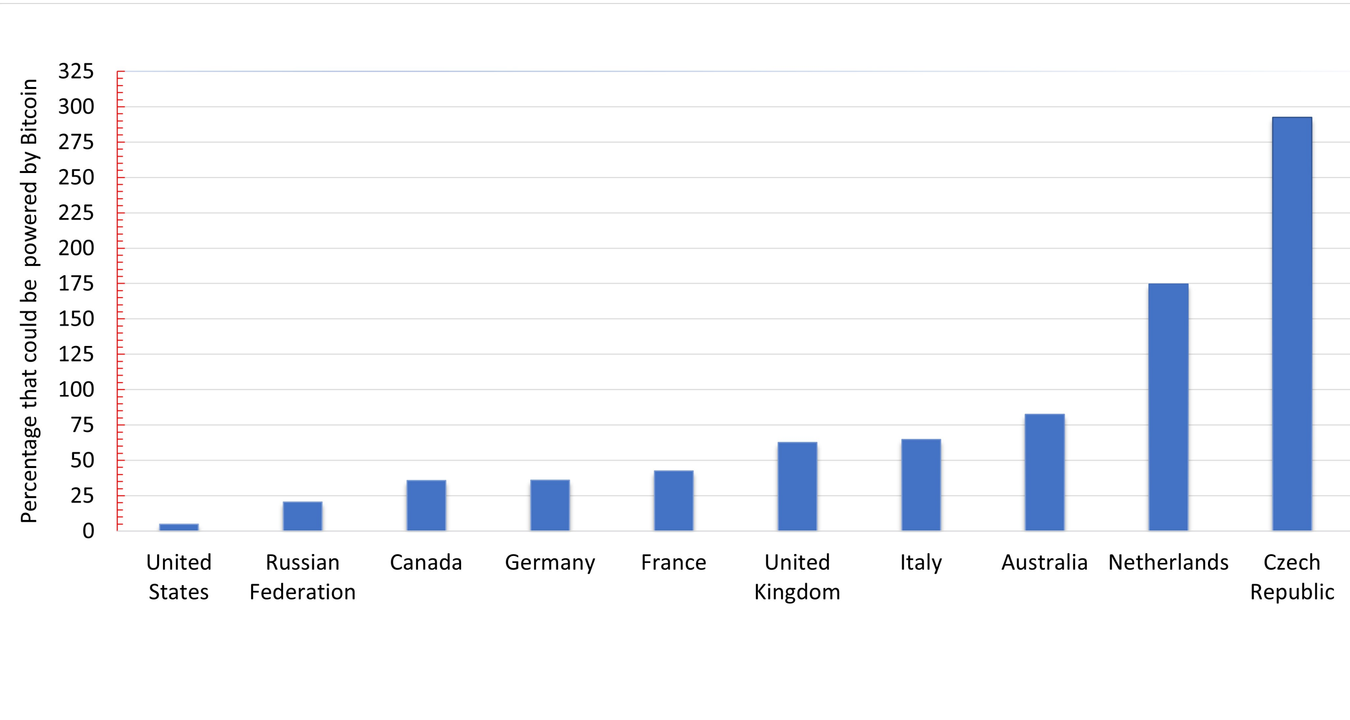

Figure 10. Bitcoin energy consumption relative to many countries (energy consumption of each country according to International Energy Agency and Bitcoin energy index, adopted from https://digiconomist.net, accessed on 1 January 2022).

2. Behavioral Science and Behavioral Economics: Going forward, we explore the potential of behavioral economics, a *Nobel-Prize-winning theory*, as a decision-making framework that helps understand how uncertainty impacts energy trading. Behavioral

economics, which incorporates insights from psychology, judgment, decision-making, and economics to make better predictions about economic behavior [38], has only recently started to be applied in the energy sector. The widespread and successful adoption of EVs and energy efficiency in IoV depends not only on the efficient control and communications systems and charging infrastructures but also largely on the human interaction with energy systems, i.e., behavioral science and human psychology. Nudge theory ("a nudge is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" [38]; Richard H. Thaler, the father of "nudge theory", was awarded the Nobel prize in 2017 for his contributions to behavioral economics)—a bridge between the economic and psychological (e.g., adaptation, loss-aversion, reflection, mental accounting) analyses of individual decision-making, explains about encouraging people to make better choices for themselves and society [38]. Nudging holds a powerful promise rather than economic incentives and can be applied in IoV to nudge prosumers and overcome cognitive barriers. Such barriers may include social norms, status quo bias, habit, peer influence, bounded rationality, unawareness of relevant information sources, risk aversion, extremeness aversion, endowment effect, choice overload, and heuristics, just to name a few. It is noteworthy that nudge-based mechanisms that include changes to the physical environment, simplification and framing of information, use of descriptive social norms, and changes to the default option, have been widely applied in the context of financial services. However, nudging and the impact of behavioral insights have not yet been widely studied as a means of changing customers' behavior in the energy sector [39]. Human behavior within and between individuals varies depending on multiple factors, including context, social norms and values, public appeals, incentives, rewards, and time. It is interesting to investigate how prosumers make decisions and act on them in a particular context by considering a design of dynamic pricing algorithm, routing of EVs, delay tolerance in charging models, energy efficiency and time-varying discount models, dynamic ride-sharing options, and energy trading models for the local energy market. This may be accomplished by analyzing big data of actual behavior, designing systematic predictive models, and estimating predictive accuracy with the help of artificial intelligence and deep learning.

3. Artificial and Computational Intelligence and its Applications: Given the emergence of AI in other sectors such as wireless communications, artificial and computational intelligence should lie at the heart of IoV and therefore highlight promising AI applications in IoV. AI and machine learning techniques can be used to analyze large amounts of data and predict the operations and build the models for knowledge of how power distribution, transmission, and generation systems work and how to allocate energy resources efficiently. Additionally, machine learning can be used to study the behavior of players in energy markets, energy pricing patterns, and fast recovery from storms, cyber-attacks, solar flares, and other disruptions [40]. Furthermore, computational intelligence techniques such as evolutionary algorithms [41] have shown great potential due to their capability of dealing with multiobjective optimization problems in smart grids with relatively low demand for computational resources. A similar approach can be applied in IoV to address multiobjective optimization issues in energy trading, mobility and routing, and demand-response under uncertain conditions of distributed renewable energy resources. It should be noted that EV routing problems in the network of charging stations is a logistics issue and mostly takes the distance between charging stations and the energy-constrained shortest path. Machine learning-based distributed routing algorithms help resolve this issue, where different types of constraints such as uneven demand at the charging station, availability of charging stations, cost of routes, and capacity constraints should be considered. The algorithm should ensure that EV chargers receive a proportionally fair (axiomatically justified fairness) share of the available capacity of the network of charging stations.

4. Digital Twins of Internet of Vehicles:
A Digital Twin (DT) is a probabilistic, multiphysics, multiscale simulation of a system that incorporates the best available physical models, sensor updates, and fleet history. The DT incorporates sensor data from the vehicle's onboard integrated vehicle health management (IVHM) system, maintenance history, and all accessible historical and fleet data gathered by data mining and text [42]. The twinning process is permitted by the non-stop interaction, communication, and synchronization between the DT, its physical counterpart, and the surrounding environment [43]. Recently, there have been some studies on DT and autonomous vehicles. For example, the role of DTs in connected and automated vehicles is discussed in [44]. Further, Reference [45] discusses a framework for vehicular digital twins, which includes data collection, data processing, and analytics phases.
The development of a vehicle is a multi-year process taking anywhere from five to six years [46]. Product design has a huge impact on sustainable design as a small drawback during the design development stage can hamper vehicle development. In such a scenario, a digital twin can help cover all phases of development from design, production to maintenance [47]. However, implementing DT for IoV also has its challenges. DT has a high cost of implementation as it is based on the development of high-fidelity simulation models. This needs a huge amount of data and is expensive in terms of time. Implementation of DT for IoV should always lead with a cost-benefit analysis [48]. While considering DT implementation as a challenge for the IoV, it should also be considered that DT is self-evolving [49]. DT can be developed at the same pace as its physical counterpart creating a closed-loop development ecosystem where models are created and optimized with its physical counterpart, thus maturing the models [43]. This helps achieve high-fidelity data to design DT models for IoV.
5. Software-Defined Internet of Vehicles: To expand the capabilities (e.g., cooperative data dissemination, security, routing) of vehicular networks and improve the efficiency of IoV and simplicity of their management, there have been studies on bringing Software Defined Networking (SDN) concepts to vehicular networks [50–54]. SDN can be implemented from the edge networks to the vehicles by implementing base stations having SDN capabilities in the vehicles. This helps tackle the existing issues such as scalability of the network, security of the IoV networks, and quality of experience (QoE) of vehicles in the IoV environment. For these issues, Reference [55] presents a new policy-driven framework considering the security and efficiency of IoV networks.
6. Intelligent Electric Vehicle Charging with Information-Centric Networking (ICN): ICN is an emerging and promising network architecture that has a focus on content delivery as opposed to the pairwise communication between end-hosts. ICN has innate support of location-independent content/information distribution through the means of in-network caching and multicast, as well as mobile computing [56]. Reference [56] proposes ICN for charging intelligent electric vehicles to counter against the ineffectiveness resulting from a host-centric model. ICN can help boost the quality and security in in-charging vehicles and reduce the security as well as communication complexity [56]. The architecture of ICN presented in [56] defines entities and interactions among different actors such as distribution system operators, energy providers, EV, e-mobility service providers, charging stations, charging stations operator, and governing entities.
7. Parking Lot Microgrids and EV-Based Virtual Storage: Another recent trend in IoV is the concept of parking lot microgrids. Reference [57] proposes a new structure for a parking lot microgrid with the introduction of day-ahead peak-shaving and valley-filling. The parking lots are designed to have smart charging stations where the EV charging is performed based on the owner's/grid requirement and flexibility. The parking lot microgrids can have heat ventilation, air conditioning, lighting, and energy sources such as rooftop solar and generators. EV are flexible components with potential where data-driven approaches can be employed to optimize the per-

formance of parking lot microgrids. With the application of optimization and linear techniques, References [57,58] presents that the parking lot microgrid can provide flexibility as well as profit.

Moreover, EVs are presented as a bidirectional electrical load where the realization of V2G is also a possibility. EVs can help support the distribution networks by acting as virtual storage. Reference [59] proposes an approach where EVs are presented as energy storage devices. The aggregation and control methodology for the grid is presented in the literature as consideration of individual EVs have numerous challenges, including computational efficiency. Reference [59] presents that the required flexibility for such an approach can only be realized if the EV's requirements are prioritized while designing a storage system based on EVs.

6. Open Research Issues in IoV

IoV is a dynamic and complex system and IoV applications pose multiple technical issues that hinder the successful implementation of IoV. This following list can by no measure be complete. Instead, we focus on seven important aspects among others and briefly discuss them.

1. Grid Congestion: Power grids face many issues due to massive deployments of EVs in IoV. First, due to sizeable ratings of EVs, their high penetration creates voltage and/or thermal limit violations, hereafter called grid congestion, in most existing power grids. The massive deployment of EVs also impacts the stability and reliability of the bulk power system. Since the sustained operation of massive EV deployments reveals new intra/inter-regional transmission constraints and adds to system peak, existing levels of system reliability based on interruptions/duration matrices (e.g., system average interruption frequency index (SAIFI), expected energy not served (EENS)) will no longer guarantee the targeted reliability level set forth by regulatory councils (e.g., North American Electric Reliability Corporation, Atlanta, GA, USA). Further, rapid/random fluctuations of substantial power resulting from EV charging/discharging threaten power balancing. Such large variations in power not only jeopardize the stability of the power system but also require increased spinning reserves to compensate for power fluctuations. The mobile nature of EVs not only adds uncertainty and complexity to the grid operations but also introduces a weak link for cyber-attacks to the overall electrical systems [5]. Moreover, designing a proper aggregation framework and strategies for trading small amounts of flexibility to different grid services is challenging in IoV.
2. Impact on Power Grid: The grid instability has a significant impact on the service provided to customers, the reputation of the system operators, existing infrastructure, and charging operations in a network of charging stations. An unstable grid might also cause voltage collapse. Electric vehicles can cause an instantaneous increase in load, which can lead to power system instability [60]. The effect of EV charging load and voltage stability is presented by [61,62]. Reference [63] presents an investigation on the effect of EV charging load on voltage deviation at the node. Increased EV charging load can affect peak load demand, power quality, and transformer performance [60]. Peak load demand can be increased due to EV charging load, which has an adverse effect on the margin [64,65]. Power quality is the ability of a power system to supply a steady and disturbance-free power output within allowed voltage and frequency deviations [66]. As PV charging load is non-linear in nature it can present a threat to the quality of power and introduce frequency deviations [67] and voltage sag [68]. Increased EV charging load can also increase the burden on the distribution transformer, which can decrease the transformer's life cycle [69].
3. IoV Charging Mechanism: The sizeable rating of IoVs provided by electrical energy storage and V2G capabilities create a number of opportunities (e.g., operational framework, control strategies) in the IoV era. Currently, the majority of electrical grids implement centralized control frameworks, where a handful of large power

plants are dispatched for ensuring balancing. The deployment of EVs in IoV will entail millions of small DERs spread across the whole network, calling for distributed control frameworks. A hierarchical control framework, which is capable of enabling EVs to participate in multiple-grid services can be one of the solutions for distributed control. For instance, hourly resolution control can be deployed for grid decongestion, whereas fraction-of-second resolution control is desired to exploit EVs for frequency regulation and hence stability. A combination of centralized–decentralized aggregation strategies is desirable for aggregation of flexibilities from spatially distributed EVs and their operational integration to utility decision-making frameworks. Since future power grids will exhibit tight integration of power, communication, and control, multi-disciplinary modeling and simulation are desired to quantify the impact and grid support capabilities of massive IoV deployment.

For improved congestion management, reliability, security, and resiliency, IoVs should incorporate local intelligence and decision-making capabilities such as front-end-controllers, which integrate local intelligence (e.g., voltage or frequency-based adaptive control based on measurement at the grid point of common coupling) to use EVs' flexibilities for grid congestion. They also can act as a communication interface with upstream resources for improving grid reliability and stability. In addition, the front-end controller may incorporate well-defined cyber-physical security algorithms for EVs, thereby improving grid resiliency against cyber-physical threats.

4. Other Design Issues: There are important design issues, including pricing strategies [70] and transparent energy trading models for energy transactions. In an open energy market, where multiple stakeholders (e.g., utilities, EVs) with multiple objectives coexist, price competition is different from an oligopoly market [41]. It is important to note that today's payment solutions are ill-suited to handle massive amounts of micro-transactions due to limited capacity and high transaction costs. That makes high demands of micro-transactions impractical. However, a single-fee micro-payment protocol, which accumulates multiple smaller transactions into one larger transaction might be helpful [71]. However, this requires further investigation. Finally, the traditional centralized energy market, consisting of large numbers of EVs spread across a wide area network, cannot guarantee energy availability in real-time for balancing demand and supply.
5. Security and Privacy: Extensive use of communication protocols during V2G, V2R, V2V, V2P, V2I, vehicle-to-sensor (V2S) interaction makes IoV based devices vulnerable to security attacks [72,73]. For example, the types of attacks may be summarised as eavesdropping, jamming, spyware, denial of service (DoS), GPS spoofing, network jamming, illusion attacks, location tracking, etc. [72–76]. In Europe, IoV must satisfy the General Data Protection Regulation (GDPR) (General Data Protection Regulation: https://gdpr-info.eu/, accessed on 10 January 2022).

   The wired sensors communications are vulnerable to malware. In the case of wired sensor networks, the attackers can take control over the CAN bus and perform attacks such as DoS attack [74,75]. Moreover, using the wireless sensor networks attackers can perform the intra-vehicle network attack [76,77]. Other security issues of V2V communications include selfish attack where an EV might refuse to connect and cooperate with another vehicle, modification attack where an attacker may act as a man-in-the-middle and alter messages, Sybil attack where a malicious node poses as multiple identities, false data injection attack where a malicious node sends incorrect information to communicating vehicles, and eavesdropping attack by an unauthorized node to eavesdrop to exploit sensitive data [72]. V2I communications are also vulnerable to privacy attacks based on the geographical location of the vehicle that is being transmitted [72].
6. High Mobility of Vehicles: Another consideration with the IoV is communication issues that arise because of the high mobility of vehicles. The increasing penetration of IoV requires fast and frequent communication between different participating

entities. It has a very strict hand-off and latency requirement [78,79]. The mobility considerations have to address fog and cloud computing technology integration, balance the signaling load on C/U-plane, and also integrate multiple advanced computing technologies addressed in the previous sections of this paper [21,78].

7. QoS and QoE: Due to the complex data content as well as high response requirement from the users, there are stringent service requirements between various networks such as terrestrial networks, aerial networks, and satellite networks. Hence, consideration of an advanced content caching strategy and resource utilization is essential for IoV [80,81]. Further, in-vehicle communication requires stringent QoS for simultaneous real-time traffic. Time-Sensitive Networking (TSN) (IEEE 802.1Q) (Time-Sensitive Networking (TSN) Task Group: https://1.ieee802.org/tsn/, accessed on 10 January 2022) is one of the most promising candidates for deployment in vehicles [82,83]. Since QoS and QoE are vital for the IoV, we may need to wait for 6G to meet all requirements (e.g., ultra-low latency to avoid collisions between vehicles that are controlled remotely, zero tolerance for packet loss, guarantee, and assurance of services). For example, Network 2030 [84] defined time-engineered communications services (e.g., autonomous traffic communication) and criteria. Among them, on-time service guarantees are served by accurate time with the smallest resolution of measurable time (in the order of 1 ms) [84]. To harmonize the operation of massively connected vehicles, the on-time delivery of information is mandatory.
8. Multi-dimensional Randomness and Heterogeneity: The network traffic data has the characteristics of large data scale, multi-network, and multi-source, complex heterogeneity, diverse collection methods (e.g., flow and batch), high dimensionality and complex structure [85]. The development of IoV signifies an increased number of vehicles connected to the Internet through cloud computing. It also means the connected vehicles transmit the monitored data, and there is a possibility of interception of data. Hence, the IoV needs a heterogeneous system capable of confidentiality, key revocation, integrity, authentication, and non-repudiation as the high-level security features [86].
9. Adoption of Smart Charging Stations: Smart charging stations can be adopted to charge and discharge the EVs; however, numerous challenges need to be considered during this adaptation. Some challenges associated with EVs are as follows [87]:
    - Integration of EVs and smart grids,
    - Concerns related to a driving range,
    - Effect of auxiliary loads,
    - Hesitancy to participate in the V2G networks,
    - EV performance mismatch between the lab and the real world,
    - Inadequate government regulation,
    - Underdeveloped charging infrastructure,
    - EV maintenance and expensive batteries.

    EVs can be integrated with the smart grid for those solving problems. However, there are additional concerns with V2G technology. Issues to be considered are system overload, the high initial cost to develop infrastructure, load mismatch, and unmanaged recharging of EV batteries [87]. The literature presents significant approaches towards V2G integration and smart charging [88–90]. Reference [88] presents a flexible V2G coordination scheme. These schemes relate mostly to commercial/ office buildings that already have EV charging infrastructure. The approach suggests connecting EVs to the grid during off-hours as well as utilizing EVs to provide V2B services including load distributions and demand responses. Smart EV charging can be improved by utilizing distributed energy resources and battery energy storage systems. Similarly, Reference [89] also presents research on fast-charging stations considering QoS. It should be noted that the fast charging infrastructure can exert strain on existing power grids and, hence, charging stations integrated with energy storage devices are used. Three scenarios ranging from normal conditions to optimal situations are presented. The results show overall improvements leading to profitability, as well as efficiency, satisfying both the power grid as well as drivers.

7. Conclusions and Outlook

We introduced a unified vision of the IoV, in which cloud-based EV charging management is presented as a use case of IoV by incorporating the diverse service requirements of customers and two-tier cloud (edge and remote cloud) computing infrastructure. Considering EV arrival distribution, diverse communication requirements, different charging demands at CSs, and limited supply, we proposed a hierarchical model, which included cloud server planning, CS capacity planning, PIM, and CEM methods of charging management. The proposed architecture has several benefits. Notably, due to the proximity of edge computing infrastructures to EVs, real-time IoV services can be supported. Further, the coexistence of edge and cloud computing helps reduce computing and communications complexity in a low-cost and scalable manner. Our results reveal the merits and efficiency of the proposed models. With regard to uncontrolled customers, the system profit in our system is increased by 10.2% and the QoS (low blocking rate and short waiting time in the cloud servers) is guaranteed to EVs. In the proposed model, we did not consider the scenarios of EV routing during peak hours. In the future study, EV routing strategies in a network could be applied to resolve the uneven charging demands at CSs. Further, in the proposed models, the optimization problem formulations belong to non-deterministic polynomial-time (NP)-hard problems. Therefore, approximate algorithms were developed to achieve more efficient results.

The social and environmental impacts of this paper are involved in providing grid stability during peak system demand, supporting efficient communication among EVs, CSs, and cloud control centers, and helping to improve system performance to increase profit for the system operator and satisfy customers' QoS and charging requirements. One of the directions for future research would be implementing energy storage units in the charging stations to further stabilize the grid. Further, studies reveal that integrating human behavior models has become crucial in DMS [91,92]. The role of behavioral economics that we have highlighted in this paper will be instrumental in the overall operation of IoV in the future. Being a multidisciplinary and integrative research area, IoV must address both technological and social dimensions from architectures to innovations in user behavior to realize its full potential and support societal benefits. Looking beyond the short-term, bringing principles of behavioral economics to both energy and transportation sectors in conjunction with edge computing and AI represent an exciting new research area without any doubt, though there are uncertainties about which experimental and theoretical studies should be performed in large-scale scenarios to study the impact of both short- and long-run behavioral changes. Moreover, the integration of communications, modern control, and computing technologies for IoV is of vital importance and yet one of the most complicated issues. Blockchain-based energy trading, behavioral economics for the energy sector, and power system complexity are thoroughly discussed in the context of IoV, which may open up new exciting research directions. Towards this end, we argued that one of the most innovative and exciting avenues in IoV is the development of blockchain-based decentralized energy trading, which is synergistically empowered by AI, the nudge theory, and edge computing. Finally, we have elaborated on multiple open research issues in IoV.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CCC	Cloud Control Center
CS	Charging Station
CEM	Capacity Expansion Method
DoS	Denial of Service
DLT	Distributed Ledger Technology
DT	Digital Twin
EV	Electric Vehicles
EPON	Ethernet Passive Optical Network
EENS	Expected Energy Not Served
ICN	Information-Centric Networking
IoV	Internet of Vehicles
IVHM	Integrated Vehicle Health Management
P2P	Peer-to-Peer
PIM	Price-incentive Method
QoS	Quality of Service
QoE	Quality of Experience
SAIFI	System Average Interruption Frequency Index
SDN	Software Defined Networking
SO	System Operator
TSN	Time-Sensitive Networking
V2G	Vehicle-to-Grid
VANET	Vehicular Ad Hoc Networks
V2R	Vehicle-to-Roadside
V2P	Vehicle-to-Pedestrian
V2I	Vehicle-to-Infrastructure

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