Intelligent Energy Management Systems for Electric Vehicle Transportation

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Electric Vehicles (EVs) have been gaining interest as a result of their ability to reduce vehicle emissions. Developing an intelligent system to manage EVs charging demands is one of the fundamental aspects of this technology to better adapt for all-purpose transportation utilization. It is necessary for EVs to be connected to the Smart Grid (SG) to communicate with charging stations and other energy resources in order to control charging schedules, while Artificial Intelligent (AI) techniques can be beneficial for improving the system, they can also raise security and privacy threats. Privacy preservation methodologies have been introduced to ensure data security. Federated Learning (FL) and blockchain technology are two emerging strategies to address information protection concerns.

Keywords: electric vehicles ; charging management systems ; smart cities

1. Charging Stations Distribution

Proper placement of CSs can improve station accessibility and, consequently, increase public acceptance of EVs. It can also mitigate the power grid instability issue with the current ever-escalating energy demand [1]. Although EVs charging stations are placed in the transportation network, optimal CS placement approaches should take into account not violating the safe limit of power distribution network parameters (without exceeding a given voltage drop) [2][3]. Survey [4] stated participants' preferences for the distance between charging stations. Accordingly, the favored average distance was estimated to be 0.12 km lower than the placement distance between conventional gas points or, on average, 5 km. According to the report published on July 2021 from Virta.global company, in most countries, a passenger vehicle's average electricity consumption is approximately 0.2 kWh per kilometer [5]. Thus, the coordination between CSs power capacity in the transportation sector and distribution network must be organized [6].

The aforementioned aspects of CSs placement make the formulation and optimization of the solutions a challenging task [7]. Successfully completing this task requires the collection of initial information, including energy distribution network data, transportation network data, road and energy sector limitation metrics, such as the quantity of fast/slow charging plugs installed at stations, the upper safe limit of newly added load to the energy network, etc. [8][9][10]. An optimal CSs distribution method should tactically formulate the distribution problem and efficiently employ functional algorithms. Many studies have been conducted to facilitate easy access to charging points for EV users by identifying the proper siting of charging points utilizing methods, such as genetic algorithm [11], fuzzy neural network [12], linear programming [13][14], and so on. Accordingly, one recently proposed solution tried to optimally combine Chicken Swarm Optimization along with Teaching Learning Based Optimization algorithms to exploit the essential properties of each algorithm in order to increase the introduced solution's efficacy [15]. They framed the problem in a multi-objective model considering various factors, such as EV users' satisfaction and convenience, road traffic, power grid voltage stability, reliability and power loss, economical and cost elements, etc.

While designing an optimal algorithm to distribute CSs, other supplementary social and construction factors, such as investment costs, maintenance and operating expenditures, rural or urban areas placement, population density, etc., should also be considered to be able to prove that the introduced model is effective and also feasible to implement [16]. For instance, to address the need to establish service area CSs on the route of suburbs of cities, the combination of Asymmetric Nash Negotiation and Hybrid Binary Particle Swarm Optimization algorithms can determine regions' EVs charging demands and CSs service range conditions [17].

In [18], a model for charging points spatial pattern investigation was proposed. This literature integrated the Bayesian spacial log-Gaussian Cox technique and intensity surface of charging point positioning prediction to formulate a maximize coverage location model for a two-step optimum charging point deployment. The necessity of developing an intelligent charging point placement is highlighted in [19][20] references, wherein the avoidance of power network grid instability problem is studied. The optimal charging point connections are modeled based on Monte Carlo simulation and multi-objective optimization algorithms, considering traffic and grid capacity, regulations, and costs.

2. Charging Scheduling and Charging Station Selection

Charging batteries embedded in EVs in uncontrolled manners can be detrimental to the battery life [21]. Furthermore, in addition to technological aspects, scheduling the correct time and amount of charging at the nearest available charging point can increase EVs Quality of Experience (QoE) among current, and future users [22]. There are many studies developing methods to estimate EVs driving range relying on details displaying the remaining amount of energy in the battery (state of charging), and external factors affecting the energy consumption, e.g., air conditioning. These studies can be organized into two primary groups of fact-based prediction, and paradigm-based prediction methods [23][24]. Historical energy consumption information captured from an EV characteristic from previous journeys or during a trip is used to estimate the range. History-based prediction models have limited accuracy as they only take into account the last-miles driving energy consumption data and neglect the influence of road and environment conditions and the driving styles on the energy consumption [25]. On the contrary, model-based predictions develop mathematical models to calculate the future energy consumption based on dynamic parameters of the vehicles (route information, speed limits, driving styles, etc.) while driving; hence, this estimated range value may change during the journey [26][27].

Therefore, developing advanced solutions to address charging services scheduling for parked/on-the-move EVs and optimally CS recommendations with the least queuing time will enable sustainable EV adoption by the public.

2.1. Personal Electric Vehicles

An effective CS suggestion model needs information from each individual parties including, EV charging status and location, some of the users' personal data, and also details about CSs [28]. The majority of previous literature tried to solve the issue of finding the closest available CS based on the requester's state of charging and location [29]. The research in [9] explored the time of charging for EVs that are located and parked in CSs, and they proposed optimal CSs with minimum service waiting time in order to increase the QoE. Another reference, [30] performed a decision-making composite model by integrating assessment theory for measurable factors, such as charging duration time, battery monitoring, etc.

Combining different sides (EVs, CSs) properties can also lead to more accurate recommendations. Several techniques have been proposed in applications where EVs users require notifications for the right time of charging, state of battery, nearest charging points, and so on [2][31]. However, they ask for users' personal information from both sides. Prioritizing EVs demands for charging scheduling and refiling is another research topic wherein several mechanisms and algorithms have been designed to improve factors, including energy demand-respond balance [26].

2.2. Electric Taxis

Electric taxis, which are becoming more popular, have different demands than personal EVs. One primary metric for e-taxis is to locate a fast-charging station in the nearest location considering the profit maximization, especially during rush hours [32][33]. Zhang et al. [16] proposed a recommendation strategy to assign e-taxis the best charging location at the best time. For the charging-time modeling, they computed factors such as e-taxi unit time revenue, charging capacity, charging process duration, and time-of-use electricity cost. Charging location modeling, on the contrary, needed the computation of other factors, namely driving duration, queuing time, charging capacity, and charging time. A real-time e-taxis charging point locator model was proposed in [34] based on wide-ranging GPS data processing utilizing e-taxis' history of recharging and real-time GPS directions. This reference aimed to minimize the recharging initialization period considering travel distances, charging cycles, and idleness in stations [35].

2.3. Electric Buses

Another category of EVs, which is e-buses, requires more technological advancements to become adopted widely by many governments. These public vehicles may encounter some prevailing issues, such as longer charging time, uneven and deficient spatial charging facilities distribution, highly dynamic operation factors, and so on. To address large-scale e-bus fleets further promotion, researchers need to investigate regional e-bus lines/stops networks to analyze operational and charging patterns for real-time charging scheduling development [36][37]. Currently, e-buses operating and charging schedules are managed with fixed timetables; however, such offline solutions might not always perform optimally. Dynamic factors, including unpredictable traffic congestion, changing weather/temperature, traffic-light conditions, etc., will affect e-buses performance and will make the optimal strategy creation challenging [38][39][40]. E-bus battery sizing, which is sensitive to its transit service type (duration and roads to take), is another challenging topic since it influences both the range and cost of driving a bus. For instance, findings from a case study in [41] reveal that designated batteries for electric city buses are unnecessarily oversized, considering the regional situations with mild temperatures and short trips.

3. Electric Vehicles Data Security

Although previously reviewed studies have enhanced the functioning of the recommender model, they did not consider the data producers' willingness to expose their personal information to other entities as there are some confidentiality concerns.

3.1. Federated Learning

One of the essential features of FL is privacy. There are some privacy techniques used in FL that can provide meaningful privacy guarantees. *Differential Privacy* is one of the security models, which is also known as k-Anonymity. This method adds noise to the data to hide sensitive information from other entities to make them incapable of restoring the data [42]. Another line of work is *Secure Multi-party Computation (SMC)* which provides a data security framework to ensure complete zero-knowledge among parties except for input/output data. This model involves complicated computation protocols to guarantee high security with the cost of inefficiency [43]. *Homomorphic Encryption* is too adopted in FL to secure users' private data by exchanging training model parameters under an encryption mechanism. In this model, neither data nor the training model itself are not transmitted. Homomorphic Encryption is widely used for training data on the cloud as it provides data-encryption for entities who wish to share information into the cloud environments for data refinement [44][45].

The federate Learning technique is classified into three groups in accordance with the data-division properties [46]. *Horizontal Federated Learning*, which is termed as sample-based FL, is used in cases of datasets where samples are different but they share the same feature space. For instance, two branches of an insurance company may have different users (sample ID space), but the features in the business are similar [47]. In applications where one entity (EV) produces different sample data with the same features (driving duration, GPS, acceleration), the HFL technique can use the data samples in supervised ML methods to predict driving behavior by keeping EV users' data private and safe. Implementing an HFL model is straightforward and does not require a complex algorithmic process. However, HFL is unable to operate properly where there are collaborations of multiple entities (EV, CS, and power grid) from which similar sample data are produced, but each has distinct features. On the other hand, in scenarios where similar data samples share different feature scopes, *Vertical Federated Learning* or feature-based FL is applicable [48]. For instance, an insurance company and a car-rental company datasets may likely include similar users residing in an area; therefore, the two companies' sample ID spaces may have a large intersection, however, their feature spaces differ [49]. As it seems the implementation of VFL models is not as easy as HFL since one extra step is required to perform entity alignment between participants. Therefore, more complex processes with higher computational complexity are included to integrate distinct entities in a ML model considering user data protection. The last category defines a scenario in which datasets are distinguished in both sample ID space and feature space. *Federated Transfer Learning* can be applied to an example of two different companies located in geographically distributed areas with a small intercession among user groups. FTL, which is inspired by the transfer learning model, aims to provide ML approaches in cases where entities suffer from insufficient data samples. For instance, some data are available from a domain (electric bus) that can be used in a prediction model in another EV domain with a limited amount of available data [50].

Optimizing the large-scale communication bandwidth between entities and the aggregator server is necessary among all FL models [51]. Furthermore, FL models are required to provide security for the central server to protect model parameter aggregation [52].

In [53], FL was used to predict EVs network energy demand. They proposed an energy-demand learning-based prediction from the CSs side consideration, in which one central CS provider collects all CSs information and performs the learning process. Their model is based on FL; therefore, no private information was shared. To improve their model performance, the learning model was founded on the CSs grouping algorithm, which could enhance the accuracy of prediction and minimize the communication overhead. Authors in [54] proposed a real-time FL to predict autonomous vehicles steering wheel angle prediction. They included a sliding training window to minimize communication overhead and maximize real-time streaming data rate.

3.2. Blockchain

The initial introduction of Blockchain technology was in 2009 to describe the basis of developing the *Bitcoin* digital currency [55]. This can be another approach to reduce security threats to the private information of data owners [56][57].

Three main consensus protocols have been introduced to facilitate agreement among fully decentralized nodes by considering the validity of transactions. *Proof of Work (PoW)* performs computationally complex operations on each newly added block [58]. Nodes compete with each other to solve these complex operations, which is a cryptographic puzzle, to attach a new block into the blockchain. The purpose of this puzzle is to generate a hash value with several leading zeros that is lower than a target for the hash. The PoW guarantees immutability for the blockchain as to alter a block, all subsequent blocks must be altered, which is computationally infeasible. However, due to enormous computing power, it requires vast energy consumption with low transaction throughput [56]. To address the non-scalability and energy-intensive issues of PoW, *Proof of Stake (PoS)* protocol was presented as a substitute solution. In the PoS consensus algorithm, validators lock up a stake and are randomly selected based on the staking amount of the participating validators to attach a new block into the blockchain network [59]. PoS is considered a cleaner and faster protocol than PoW since it requires lower computation power and higher transaction throughput [60]. The other consensus protocol is called *Delegated Proof of Stake (DPoS)* wherein delegates vote for their favorite validators to generate new blocks in a blockchain network [61]. As each representative has the power to vote proportional to the amount of the stake in the network, this protocol is less likely to become centralized, and it is considered as the democratic version of the PoS protocol. Accordingly, due to the fact that DPoS needs less number of trusted nodes to verify data in each new block of the network chain, it can handle a higher number of transactions with faster confirmation times than PoW and PoS [62][63].

Alternative consensus protocols have been introduced, subject to each application criteria. However, all these protocols should be evaluated based on five key metrics [64][65], depicted in **Figure 1**:

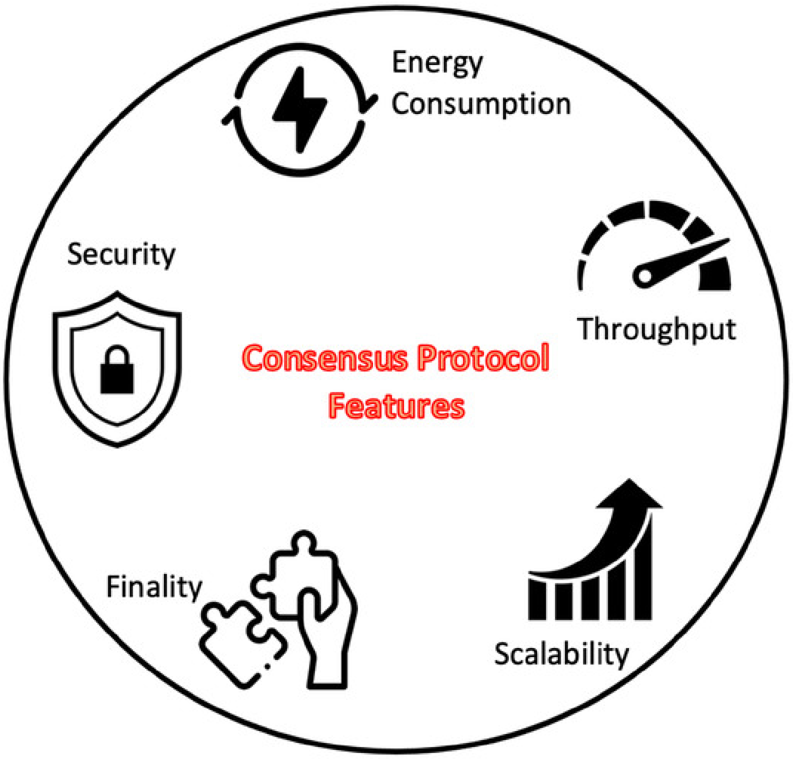

Figure 1. Important properties affecting a consensus protocol performance.

- **Scalability:** Denotes to the capability of a consensus protocol to sustain the overall performance with the addition of nodes, transactions, and data [66].

- **Energy Consumption:** This metric is the key issue of blockchain limited widespread applicability. As an example, PoW consensus protocol has high energy consumption as the block miner selection requires massive computational power [67].

- **Throughput:** Denotes the number of transaction verification and deployment to the blockchain per second (Tps) [68]. For instance, Bitcoin's throughput is approximately 7 Tps [69].

- **Security:** Indicates a consensus protocol resistance to various attacks. For instance, PoW-based models can crash by two major attacks, namely Denial of Service (DoS) and Sybil [70], therefore such a system should present feasible solutions to prevent malicious intrusion.

- **Finality:** Defines the determinism of the blockchain by ensuring that blocks cannot be reversed or changed purposefully once they are added to the chain [71].

In order to automate the execution of an agreement to receive a certain outcome among all participants, *Smart Contracts* are embedded into the blockchain network as simple computer programs to be executed after certain terms and conditions are met [72]. Smart contracts are sets of IF/WHEN-THEN rules written in codes that require an exact sequence of actions to execute predefined agreements. Once a transaction is complete, the blockchain will be updated, and consequently, the transaction will become unalterable [73].

Most of the previous works that utilized blockchain, tried to mitigate data leakage by saving local and global ML models in each active block [60][74]. This technique is believed to perform effectively as a safe information transfer solution [75]. However, it should be noted that participating nodes need to become equipped with high-performance storage devices. Furthermore, with the increment in the number of users (EVs, CSs), the blockchain-based model might encounter an adverse impact on its performance, which results in the model's impracticality for real-time applications, wherein the ML outcomes generations are needed rapidly.

4. Electric Vehicles Energy Trading

Considering the mass penetration of EV industry in the upcoming years, the contribution of the transport sector to greenhouse gas emission, which primarily derives from the extremely burning fossil fuels, will be sharply minimized [76]. However, this amount of power consumption by EVs can lead to another problem by establishing uncontrolled charging demands on the power grids. Neglecting this newly raised issue may cause significant power distribution performance loss, especially during peak hours. Hence, mitigating the EV-development adverse impact on the main grid by proposing solutions implementing power load-balancing techniques is essential [77]. One practical way to support power resources management is to provide a platform allowing energy transfer from EVs to the grids (known as V2G), as well. This concept enables the participation of EV end-users and consumers as prosumers (energy consumer who is also a producer) in a demand-response network communication [78].

EV collaboration with the grid (charging/discharging mechanism) advanced into another stage where not only can EVs provide a two-way energy transferring mechanism with the grid, but they can establish V2X (Vehicle-to-Anything) interactions to exchange energy. Charging trading options are widely attracting researchers' attention, therefore, forming a reliable network with various consumers and prosumers to simply perform energy trading operations is essential [61][79]. The P2P energy trading paradigm allows participants to trade electricity independent of the centralized institutions (e.g., utility companies) [80]. Researchers in [81] proposed an efficient charging data transmission model for V2V communication and charging services. They minimized communication overhead by applying mobile edge computing and utilized a reinforcement learning approach to dynamically select the best data delivery routing path in large-scale vehicular ad hoc networks. A more recently proposed framework in [82] proposed an efficient V2V energy trading mechanism enabling charging price optimization and efficient consumer/prosumer matching. This framework optimized EVs charging scheduling based on the electricity prices prediction and maximized EVs owners' rationality by finding the best match. Other literature [83] proposed an energy trading model for P2P networks in which prosumers are incentivized within a smart grid distributed system. They proved that this single-sided auction-based model can mitigate the overall power demand from the main grid by motivating small providers to participate and maximize their profits.

By Integrating the blockchain technology into the energy-sharing mechanism among connected vehicular networks, literature [84] proposed a blockchain-based machine learning model to maximize the profitability of parked EVs based on a Game-theoretic stochastic bidding process. In [85], an alternative consensus mechanism based on the Hashgraph algorithm was proposed to replace high memory/time-consumption issues of blockchain consensus protocols for computationally constrained EVs. This mechanism uses a gossip synchronization protocol to set up V2V communications in a lightweight and fast way. The study presented in [86] was based on the blockchain and FL to develop a secure energy trading model among energy consumers and prosumers. They also worked on profit maximization by consistent advertisement using clustering and lookup mechanisms.

The author in [87] provided an energy sharing mechanism among EVs founded on the blockchain to allow a reliable and transparent model for a network including various connected agents, such as the power grid, charging point, energy maintenance institutes, etc. They implemented the Practical Byzantine Fault Tolerance (PBFT) agreement schema to lower the system complexity and enable it for real-world environments. The work in [88] presented a secure power trading transaction and communication mechanism among EVs based on the blockchain and smart contract properties. They designed an efficient agreement protocol using Elliptic Curve Cryptography (ECC) and also implemented a two-way power transferring mechanism among EVs and the smart grid to more efficiently manage the energy demand-response balance.

In addition to the previous studies, [89] introduced a blockchain-enabled system with a secure, automated, and transparent energy trading mechanism between EVs using Ethereum smart contracts. This system mainly focuses on increasing the fairness and competitiveness factors by designing a reversed auctioning mechanism between energy consumers/prosumers. They analyzed their security performance over the Ropsten dataset, which is the Ethereum official test network. Last but not least, the research in [90] offered a V2V power exchanging model utilizing the blockchain and fog computing technologies to maximize EVs users' social welfare factor. To enhance their proposed model's operation, they enhanced the PBFT and DPoS consensus protocols and, accordingly, designed the DoPSP agreement protocol with more efficient operation.

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