# Urban Internet of Electric Vehicle Parking System for Vehicle-to-Grid Scheduling: Formulation and Distributed Algorithm

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***Abstract*—The application of Internet of electric vehicles has greatly enhanced the efficiency of the urban intelligent transportation system. The coordination of Internet of electric vehicles is crucial for improving the quality of public services in smart cities, such as vehicle-to-grid regulation and edge computing service. However, existing studies have unilaterally considered the application of one of these two services, which neglects the potential benefits of their combined optimization. In this article, we propose an urban Internet of electric vehicle parking system for vehicle-to-grid scheduling. Specifically, we solve the problems of Internet of electric vehicles allocation and scheduling with joint vehicle-to-grid regulation service and edge computing service. First of all, we formulate the joint problem as a mixed-integer quadratic programming problem. Then, through the alternating direction method of multipliers method, we decouple the main problem into sub-problems for Internet of electric vehicles. Then, we devise a distributed algorithm to solve each sub-problem. The simulation results show that our proposed model is effective in Internet of electric vehicles' allocation and vehicle-to-grid scheduling for the joint regulation and edge computing service. Furthermore, the power fluctuations of the city power grid can be well flattened by providing the vehicle-to-grid regulation service through effective communication network protocols.**

***Index Terms*—ADMM, distributed algorithm, edge computing, IoEV, V2G scheduling.**

## List of Acronyms

| | |
|---|---|
| ADMM | Alternating Direction Method of Multipliers. |
| CPU | Central Processing Unit. |
| EVs | Electric Vehicle. |
| HIL | Hardware-In-the-Loop. |
| ICTs | Information and Communication Technologies. |
| IoEV | Internet of Electric Vehicle. |
| IoEVA | Internet of Electric Vehicle Aggregator. |
| IoT | Internet of Things. |
| IoVs | Internet of Vehicles. |
| ITS | Intelligent Transportation System. |
| MIQP | Mixed-Integer Quadratic Programming. |
| PJM | Pennsylvania-new Jersey-Maryland interconnection. |
| ROE | Ratio Of the Energy requirement. |
| SAGINs | Space-Air-Ground Integrated Networks. |
| SOC | State Of Charge. |
| VANETs | Vehicular Ad-hoc NETworks. |
| V2G | Vehicle-to-Grid. |
| V2V | Vehicle-to-Vehicle. |

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## I. Introduction

OWING to the development of advanced technologies, the smart city era has emerged to enhance the quality of life in urban areas. Through incorporating various innovative Information and Communication Technologies (ICTs), the quality of many urban operations and services can be improved under the effective deployment of urban Internet of Things (IoT) [1]. Referring to the smart system with interrelated and Internet-connected objects exchanging information, the utilization of IoT over a wireless network can upgrade traditional public services, e.g., vehicle coordination in Intelligent Transportation System (ITS). By facilitating communication technologies in ITS, wireless communication among intelligent vehicles can ultimately be established, such as Internet of Vehicles (IoVs) [2], [3], [4]. Through reliable and efficient Vehicle-to-Vehicle (V2V) wireless communications, the application of IoVs with the Vehicular Ad-hoc NETworks (VANETs) contributes to the efficient and intelligent prospect for the future development of ITS [5].

Additionally, the utilization of IoVs can facilitate both the vehicle-to-roadside base station and inter-vehicle communications through VANETs [6], requiring occasional connectivity to share positioning information. Several existing studies have investigated the application of IoVs in smart cities [7], [8], [9], [10], [11]. In [7], the performance of heterogeneous IoV applications was assessed based on the V2V network resource management. An optimization framework was developed in [8] for maximizing total utility, which considers the transmit power of IoVs and their trajectories. In addition, [9] investigated the IoVs' security in multi-beam satellite-enabled vehicle communications so as to improve the quality of service for each user. Furthermore, in [11], relying on the IoV, a federated edge learning framework is proposed to support autonomous driving in the vehicular platoon. These studies demonstrate the advanced applications relying on IoV, which facilitates the operations of smart cities.

In smart cities, the application and impact of IoVs in providing public services have already been investigated, such as vehicle routing [12], [13], [14] and electricity trading [15], [16], [17], [18]. In [12], the routing algorithms in the IoVs were reviewed. [13] proposed a routing algorithm to study the effect of vehicle position and potential association features to get a more accurate vehicle prediction trajectory. Moreover, in [14], a network representation learning model named DynWalks is proposed to achieve more accurate vehicle trajectory clustering in real-world scenarios. On the other hand, as it has been analyzed in [15], it is feasible for EVs to access the IoV. Hence, these vehicles, defined as Internet of Electric Vehicles (IoEVs) [16], can greatly contribute to the sustainability of future smart cities through efficient electricity trading approaches. In [17], a V2V electricity trading scheme was proposed based on the Bayesian pricing game. Furthermore, in order to maximize social welfare, an energy trading architecture based on fog computing was proposed in [18]. However, the aforementioned studies unilaterally consider the application of vehicle routing or electricity trading by means of IoEVs. By combing at least two or more various operation modes in ITS, e.g. IoEV routing, and scheduling, the application of multi-mode transportation operations can bring substantial benefits to improving social welfare in smart cities.

Considering the multi-mode transportation applications in smart cities, there are some existing works on designing the system frameworks of IoEVs to provide joint public services [19], [20]. For example, [19] proposed a novel problem for IoEV-assisted multi-drone routing and scheduling on path planning. Considering the utilization of IoEVs in the transportation network, a joint routing and charging scheduling optimization problem was formulated in [20] to optimize the system performance. The utilization of IoEVs can indeed affect the stability of the city power grid through the availability of Vehicle-to-Grid (V2G) technology. V2G technology, as an emerging technique, can utilize the batteries of IoEVs to bring power back to the power grid. Hence, the IoEV batteries can be regarded collectively as distributed energy storages to follow power control signals to provide different ancillary services [21], such as frequency regulation service.[1] The objective is to maintain the grid frequency at its nominal value. Through the provisioning of this service, a hierarchical system model was developed in [22] to jointly provide voltage and frequency regulation services by means of EVs. In addition, [23] proposed a novel framework for joint optimal allocation and scheduling for EVs in providing the V2G frequency regulation service. However, these approaches assumed perfect communication during the entire operation period. In practice, the schedules of EV operations can be substantially affected by the availability of the city communication network. The performance of IoEV multi-modal operations in smart cities is influenced by a number of desirable properties, such as decentralization, security, transparency, immutability, and automation [24]. In this case, Space-Air-Ground Integrated Networks (SAGINs), known as a crucial role in the city communication network, are capable of providing cost-effective, large-scale, and flexible wireless coverage and communication services for IoEVs, i.e. [25]. What is more, the feasibility of IoEVs under the Internet service and energy management strategy was demonstrated in [26] through Hardware-In-the-Loop (HIL) simulations. Since the aforementioned works only solve the optimal V2G scheduling problem with IoEVs, they fail to consider the coupling effect of the IoV services in IoEV scheduling schemes.

To bridge the research gaps related to the current systems, in this work, we propose an urban IoEV parking system for V2G scheduling. Specifically, a system framework for the provision of joint Internet and V2G services through IoEVs in a city is developed. Note that, the V2G scheduling is a Mixed-Integer Quadratic Programming (MIQP) problem, which is a Non-deterministic Polynomial-time (NP)-hard problem [27]. And the communication and computing resource allocation in this system framework makes it more complex. To support more IoEVs in smart cities, the scalability of the proposed system should also be considered. Motivated by these problems in the current IoEV systems, the major efforts of this research work are shown as follows:

1) We develop a framework to account for IoEV joint edge computing and V2G services in a smart city. This model is more general and practical than the existing studies since it has been developed under real-world constraints.
2) We formulate a joint problem to consider both network access control and V2G scheduling, which is based on the city communication network functions and energy demand.
3) We devise a distributed algorithm to decompose the formulated problem into the sub-problem of each IoEV through the utilization of the Alternating Direction Method of Multipliers (ADMM). This helps to improve the scalability of the proposed system.

The rest of this article is organized as follows. Section II presents and illustrates our proposed system model. In Section III, we formulate a joint problem for providing edge computing and V2G services in a city by means of IoEVs. In Section IV, we devise a distributed algorithm to solve the optimization problem effectively. The performance evaluation of the system model is covered in Section V. Finally, we conclude this work in Section VI.

## II. System Model

### A. Road Network

The road network is associated with the city traffic network, which can be used to identify the distance from one point to

[1] The frequency regulation services belong to secondary frequency regulation services, which aims to balance the grid supply and demand from seconds to minutes.

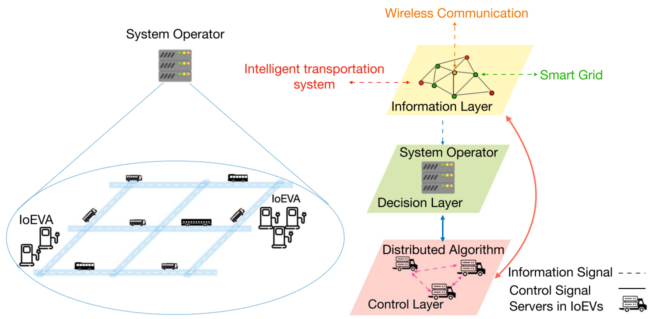



Fig. 1. Proposed system model.

another point. For ease of representation, the road network can be modelled by a complete directed graph $G(\mathcal{S}, \mathcal{E})$, where $\mathcal{S}$ denotes the set of all points of IoEVs and Internet of Electric Vehicle Aggregators (IoEVAs), and $\mathcal{E}$ represents the road edges connecting the points inside the city. The road system is constructed based on the specific route from point $s$ to point $v$ with the relevant distance for each $(s, v)$ pair. Meanwhile, $d_{s,v}$ defines the distance travelling from point $s$ to point $v$. Note that the travel distance $d_{s,v}$ is not equal to the travel distance $d_{v,s}$ due to the different travelling plans. Furthermore, we deploy Dijkstra's algorithm [28] to obtain the shortest path travelling from point $s$ to point $v$.

### B. IoEV Aggregators and IoEVs

Inside a city, we denote $\mathcal{K}$ as the set of parking garages, which is also the set of IoEVAs. We first denote $A_k$ as the available parking capacity for IoEVA $k$. The basic principle for IoEVA $k$ is to assign a fleet of IoEVs to park and to provide charging/discharging services. The operational time period of IoEV aggregators is denoted as $\mathcal{T}$, which can be divided into a set $\mathcal{T} = \{1, \ldots, |\mathcal{T}|\}$ of $|\mathcal{T}|$ time slots.

We define the set of participated IoEVs $\mathcal{N}$, and it can travel from the starting point $i \in \mathcal{F}$ to the assigned IoEVA $k \in \mathcal{K}$. In this work, we focus on one type of participating IoEVs in the city area, e.g. V2G-capable public electric buses. The reason is that these buses in a city are operated under their own pre-determined schedules, such as the actual school bus schedules in [29]. Hence, the availability of a bus to participate in charging/discharging services can be assumed to be known in advance. This assumption has been widely adopted in V2G scheduling schemes, e.g. [22], [23], [30], [31], [32]. After IoEV $n$ completes its task, it will receive the parking assignment from the assigned IoEVA, and then perform V2G scheduling when it parks. Each IoEV $n$ is expected to stay for a pre-defined time duration $D_n$ after it is plugged in at the IoEVA $k$.

### C. System Operation

The system architecture is proposed as shown in Fig. 1, which refers to the urban IoEV parking system. This three-layer system architecture consists of three major parts, namely, the information layer, the decision layer, and the control layer. The operation of each layer is illustrated in the following:

- *Information layer:* The system operator aims to gather information from the three smart systems, such as wireless communication, smart grid, and intelligent transportation system. Specifically, the smart grid is capable of collecting the power flow information from the local region and/or the regulation signals from the Pennsylvania-New Jersey-Maryland Interconnection (PJM) market, while the intelligent transportation system can gather the traffic information of time-varying road networks. By means of the wireless communication network, both smart grid and intelligent transportation systems can guarantee reliable and robust information transmission and decision-making processes. The information is gathered and delivered to these systems so as to coordinate the relevant Internet services in smart cities at the time period $\mathcal{T}$.
- *Decision layer:* When the system operator receives the information from the above smart systems, it performs to decide the allocation of IoEVs and the related V2G scheduling scheme. More specifically, the designed allocation scheme would keep the aggregator power demand of IoEV balanced in the smart grid. In the meantime, the proposed V2G scheduling scheme can both satisfy the conditions of IoEVs and ensure the quality of the V2G regulation service. Finally, these decisions are sent to the control layer.
- *Control layer:* The decision strategies are sent to the participated IoEVs from the decision layer in the system. These decision strategies include the determination of the allocation scheme and the V2G scheduling scheme for IoEVs. The control layer delivers the information on these decisions through the VANETs, which are provided by the IoEV-assistant wireless communication system. Considering the control signals being broadcasted, the participated IoEVs send back their commitments afterwards. The bi-directional process guarantees reliable and robust information transmission.

Different from the conventional EV system in [23], we further consider the edge computing scenes between the IoEVs and the system operator. Specifically, the process of computing resources in wireless communication is utilized to facilitate IoEV operations. When the participating IoEVs park at the IoEVAs, the computing resources are free. In this case, each IoEVs can be regarded as an edge server with enough power and computing capacities. These edge servers are capable of providing related edge services to vehicular applications based on the computational resources and caching space requirements of each individual server, e.g. autonomous driving. Each individual IoEV can be regarded as an edge node to share the responsibility for the system operator through the distributed algorithms. Meanwhile, the task is offloaded to this edge node directly. After the execution of the computing task, the destination of the edge node returns the outcome to the upper layer of the system.

## III. Problem Formulation

This section presents the problem formulation related to our proposed social cost model, which consists of the charging cost of the IoEVs, the parking cost of the IoEVs, the reward for providing V2G regulation service, and the reward for providing edge computing service for the IoEV. The operational constraints and control objectives of the proposed social cost model are included as follows.

### A. Operation Constraints

*1) Parking Constraints:* To jointly consider the IoEV allocation and V2G scheduling scheme, we can divide the operational constraints into two main parts, including vehicle parking and charging/discharging constraints. For the parking scheme, we introduce a binary variable $x_{n,k,t}$ to facilitate the parking allocation problem for IoEV $n$ in the city, which can be expressed as:

$$x_{n,k,t} = \begin{cases} 1 & \text{if IoEV } n \text{ is assigned to IoEVA } k \\ & \text{at time } t, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

For the simplicity of formulation, we further define another binary variable $y_{n,k}$ as:

$$y_{n,k} = \begin{cases} 1 & \text{if IoEV } n \text{ is assigned to IoEVA } k, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

To coordinate the parking schedule of all IoEVs to each IoEVA, each IoEV $n$ should be static during the period $t \in [t_{n,\text{in}}, t_{n,\text{out}}]$, where $t_{n,\text{in}}$ and $t_{n,\text{out}}$ are the arrival time and departure time of IoEV $n$, respectively. Let $D_n$ be the parking duration of IoEV $n$, and we can express the time relationship as:

$$t_{n,\text{out}} = D_n + t_{n,\text{in}}, \quad \forall n \in \mathcal{N}. \quad (3)$$

For the parking assignment of IoEVs, each IoEV $n$ is only assigned to one IoEVA $k$ during the parking period, which is denoted as:

$$\sum_{k\in\mathcal{K}} y_{n,k} = 1, \quad \forall n \in \mathcal{N}. \quad (4)$$

During the parking period, each IoEV $n$ is allowed to stay for an adequate time duration in order to prepare for the upcoming trip. Hence, the parking duration can be further denoted as:

$$D_n y_{n,k} \le \sum_{t\in\mathcal{T}} x_{n,k,t} \le M y_{n,k}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \quad (5)$$

where $M$ is a sufficiently large positive number.

When IoEV $n$ is assigned to be parked at IoEVA $k$ at Time $t \in [t_{n,\text{in}}, t_{n,\text{out}}]$, we do not decide the additional parking assignment for IoEV $n$. The reason is that each IoEV $n$ is assigned to only one IoEVA $k$ before $t_{n,\text{in}}$ and after $t_{n,\text{out}}$, which follows:

$$\sum_{t=1}^{t_{n,\text{in}}-1} x_{n,k,t} = 0, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \quad (6)$$

$$\sum_{t=t_{n,\text{out}}}^{|\mathcal{T}|} x_{n,k,t} = 0, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}. \quad (7)$$

Since the capacity of each IoEVA is limited, we assume that the available parking spaces of each IoEVA are bounded by the maximum available capacity, $A_k$, which follows:

$$\sum_{n\in\mathcal{N}} x_{n,k,t} \le A_k, \quad \forall k \in \mathcal{K}, t \in \mathcal{T}. \quad (8)$$

Besides, the total distance traveling from the location $i$ to IoEVA $k$ and IoEVA $k$ to the location $j$ should not exceed the maximum allowable distance $d_n^{\max}$, which is expressed as:

$$(d_{n,ik} + d_{n,kj}) y_{n,k} \le d_n^{\max}, \ \forall n \in \mathcal{N}, k \in \mathcal{K}, i, j \in \mathcal{F}, \quad (9)$$

where location $i$ and $j$ are the starting and ending points of IoEV $n$, respectively.

*2) Charging/Discharging Constraints:* When IoEV $n$ is parked at IoEVA $k$, IoEVA can manage each participating IoEV to perform a V2G scheduling scheme when receiving the regulation signals from the grid operator. By considering the total participation time period $\mathcal{T}$, we can formulate the V2G scheduling problem for the city area with the participation of frequency regulation service. Here, we assume that the arrival and departure times are similar to the plug-in and plug-out times for IoEVs. We first define the set of constraints for charging/discharging constraints. The charging/discharging power of each IoEV $n$ at Time $t$ is defined as:

$$P_n^{\text{dch}} \le P_{n,t} \le P_n^{\text{ch}}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \quad (10)$$

where $P_n^{\text{dch}}$ and $P_n^{\text{ch}}$ refer to the discharging and charging power limits of IoEV $n$, respectively. Let $U_n$ be the installed battery capacity of IoEV $n$. Then, the State Of Charge (SOC) condition of each IoEV $n$ at time $t$ is denoted as $\Upsilon_n(t)$, and it can be calculated as:

$$\Upsilon_{n,t+\Delta t} = \Upsilon_{n,t} + \frac{\Delta t}{U_n} \eta(P_{n,t}) P_{n,t}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \quad (11)$$

where $\eta(\cdot)$ denotes the energy conversion efficiency of IoEV $n$. Meanwhile, we define the charging/discharging efficiency of IoEV $n$ as:

$$\eta(P_{n,t}) = \begin{cases} \eta^{\text{ch}} & \text{if } P_{n,t} \ge 0, \forall n \in \mathcal{N}, t \in \mathcal{T}, \\ \frac{1}{\eta^{\text{dch}}} & \text{if } P_{n,t} < 0, \forall n \in \mathcal{N}, t \in \mathcal{T}, \end{cases} \quad (12)$$

where $\eta^{\text{dch}}$ and $\eta^{\text{ch}}$ denote discharging and charging efficiencies, respectively.

By performing V2G scheduling, each IoEV shall ensure its own charging requirement before the plug-out time. This can be expressed as:

$$\sum_{t=t_{n,\text{in}}}^{t_{n,\text{out}}} \eta(P_{n,t}) P_{n,t} \ge E_n^{\text{req}}, \quad \forall n \in \mathcal{N}, \quad (13)$$

where $E_n^{\text{req}}$ denotes the minimum energy level required to be fulfilled for IoEV $n$ when plugged out. Specifically, this is directly associated with the SOC requirement for IoEV $n$.

Making use of the charging/discharging mechanism, we should protect the battery so as to prolong the battery life. Hence, we need to avoid the over-charging/discharging scenarios. Thus, we have:

$$\Upsilon_n^{\min} \le \Upsilon_{n,t} \le \Upsilon_n^{\max}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \quad (14)$$

where $\Upsilon_n^{\min}$ and $\Upsilon_n^{\max}$ are the lower and upper bound of SOC of IoEV $n$ at time $t$.

*3) Vehicular Communication and Computation Constraints:* In this part, we assume that the IoEVs are connected with the system operator. The connectivity of the communication links between IoEVs and the system operator shall affect the quality of both V2G regulation and edge computing services provided in the city area. Hence, to model it, we follow the communication and computation model that is proposed in [33] to calculate the power consumption of communication and computation. Let the effective switched capacitance of the onboard Central Processing Unit (CPU) be $\beta$, the clock frequency of the onboard CPU be $f^{\text{cpu}}$, and the number of the CPU clock cycles required to process per-bit input data is $W$. The power consumption $P^{\text{cpu}}_{n,t}$ at time $t$ of IoEV $n$ is calculated as:

$$P^{\text{cpu}}_{n,t} = \iota_{n,t}\beta W \left(f^{\text{cpu}}\right)^2, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \tag{15}$$

where $\iota_{n,t}$ denotes the volume of data that is processed by IoEV $n$ at time $t$. Since this flow of the data is correlated to the computing resources, we use a weighting factor ($\varsigma$) to reflect the data that has to be transmitted, $G_{n,t}$, and it is calculated as:

$$G_{n,t} = \varsigma\iota_{n,t}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \tag{16}$$

The achievable data rate for transmitting these data, denoted as $\varkappa_{n,k,t}$, is expressed as:

$$\varkappa_{n,k,t} = \omega \log_2\left(1 + \frac{p^{\text{com}}_{n,k,t}}{N_0 d^{\pi}}\right) \approx 1.44\omega \cdot \frac{p^{\text{com}}_{n,k,t}}{N_0 d^{\pi}_k}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \forall k \in \mathcal{K}, \tag{17}$$

where $\omega$ is the available bandwidth and $d_k$ is the distance between the IoEVA $k$ and the system operator. Moreover, $\pi$ is the path loss exponent, and $N_0$ is the environment noise power. $p^{\text{com}}_{n,k,t}$ is the IoEV communication power. Thus, the communication energy consumption of IoEV $n$ at time $t$, $P^{com}_{n,k,t}$, can be calculated as:

$$P^{\text{com}}_{n,k,t} = p^{\text{com}}_{n,k,t}\Delta t = \frac{\varsigma\iota_{n,t}N_0 d^{\pi}_k}{1.44\omega}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \forall k \in \mathcal{K}. \tag{18}$$

### *B. Control Objective*

The proposed framework is formulated to consider all the social costs and reward IoEVs. Our goal is to minimize the total social cost, denoted as $C^{\text{tot}}$. Consider that IoEVs are able to provide frequency regulation service for smart grid and edge computing service for vehicular communication when they are parked inside IoEVA. In addition, when IoEVs are parked in the IoEVA, the parking cost and the charging cost are needed to be considered. Thus, the total social cost is formulated as:

$$C^{\text{tot}} = C^{\text{park}} + C^{\text{ch}} - R^{\text{reg}} - R^{\text{ecs}}, \tag{19}$$

where $C^{\text{park}}$ and $C^{\text{ch}}$ denote the total parking and charging costs, respectively. Moreover, $R^{\text{ecs}}$ and $R^{\text{reg}}$ are the rewards for providing edge computing and regulation services. All these four costs and rewards are measured in local currency units. Specifically, the parking cost of the IoEVs can be further calculated by

$$C^{\text{park}} = \sum_{n\in\mathcal{N}, t\in\mathcal{T}, k\in\mathcal{K}} \alpha_k x_{n,k,t}, \tag{20}$$

where $\alpha_k$ indicates the parking cost when IoEVs are parked at IoEVA $k$.

Then, for the V2G scheduling scheme, we consider the scheduling framework for IoEVs in the city. In the city power grid, the power imbalance between the generations and loads occurs all the time. For such power imbalance, the purpose of our work is to develop a vehicle scheduling framework with the V2G regulation service so as to alleviate the power fluctuations of the city power grid and then stabilize the city power grid. Thus, the total active power profile of the city power grid at time $t$, can be denoted as:

$$P^{\text{tot}}_t = P^{\text{reg}}_t + P^{\text{A}}_t, \quad t \in \mathcal{T}, \tag{21}$$

where $P^{\text{reg}}_t$ denotes the regulation signals of the city power grid. In addition, $P^{\text{A}}_t$ is the aggregated active power of all IoEV $n$ in the city, which can also be calculated as:

$$P^{\text{A}}_t = \sum_{n\in\mathcal{N}} P_{n,t}, \quad t \in \mathcal{T}. \tag{22}$$

We assume that $\gamma_k$ is the charging/discharging price of IoEVA $k$. Thus, the charging cost of IoEV $n$ can be calculated as:

$$c^{\text{ch}}_{n,t} \geq \gamma_k P_{n,t} x_{n,k,t}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, k \in \mathcal{K}. \tag{23}$$

Then, the total charging cost of the system can be expressed as:

$$C^{\text{ch}} = \sum_{n\in\mathcal{N}, t\in\mathcal{T}} c^{\text{ch}}_{n,t}. \tag{24}$$

Additionally, the reward for providing frequency regulation service is covered when performing V2G scheduling schemes of the participating IoEVs. This reward is directly associated with the quality of the V2G regulation service. Therefore, the reward function is formulated as:

$$R^{\text{reg}} = \Psi - \xi \sum_{t\in\mathcal{T}} \left(P^{\text{tot}}_t\right)^2, \tag{25}$$

where $\Psi$ is the base reward for providing such service in the city. $\xi$ is the penalty factor for the performance of the regulation service, which is related to the battery degradation conditions of IoEVs.

Furthermore, the reward of the IoEVs also covers the reward for providing edge computing services. The edge computing service is that the IoEVs in the IoEVA can function as the edge server, which provides computing service to the IoT devices that are connected to the IoEV. We assume that each IoEV can provide $\iota_{n,t}$ computing resources at the IoEVA. The reward of IoEV $n$ can be calculated as:

$$r^{\text{ecs}}_{n,t} = \varrho\iota_{n,t}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \tag{26}$$

where $\varrho$ is the reward for each unit of computing resources. The operation cost for providing edge computing service is denoted as:

$$c^{\text{ecs}}_{n,t} = \gamma_k \sum_{\forall k\in K} \left(P^{\text{com}}_{n,k,t} + P^{\text{cpu}}_{n,t}\right) \times x_{n,k,t}, \quad \forall n \in \mathcal{N}, t \in \mathcal{T}, \tag{27}$$

After that, the total reward for IoEVs can be calculated as:

$$R^{\text{ecs}} = \sum_{n\in\mathcal{N}, t\in\mathcal{T}} \left(r^{\text{ecs}}_{n,t} - c^{\text{ecs}}_{n,t}\right). \tag{28}$$

To sum up, the general form of this optimization problem can be formulated as:

$$\begin{aligned} &\min \quad \varpi^{\text{ch}}\left(C^{\text{park}} + C^{\text{ch}} - R^{\text{reg}}\right) - \varpi^{\text{ecs}} R^{\text{ecs}}, \\ &\text{s.t.} \quad (1) - (13), (16) - (28), \end{aligned} \tag{29}$$

where $\varpi^{\text{ch}}$ and $\varpi^{\text{ecs}}$ are the weighting coefficient of the IoEV charging and computing services, respectively. By adjusting these weighting factors, we can further investigate the effect of these services on the social cost of the entire system. The proposed joint problem in (29) is formulated as aMIQP. According to [27], this problem is an NP-hard problem, and we can solve this problem efficiently by devising a distributed algorithm in a scalable manner.

## IV. ADMM-Based Distributed Algorithm

Since the problem formulated in (29) is indeed a MIQP problem, the computation time grows rapidly when increasing the number of IoEVs. For the purpose of scalability, a distributed approach should be utilized to solve this problem. However, due to the constraint (8), the problem in (29) is hard to split. To decouple the problem in (29), the Lagrangian dual decomposition method [34] could be utilized to relax the problem and devise a suitable algorithm. Due to the poor convergence performance of that method, we consider the use of ADMM to decompose the problem into sub-problems that can be solved by each IoEV in this study. The key idea of the ADMM approach is to introduce a set of vectors that satisfy the constraints that cannot be separated. In this case, the original problem is divided into two optimization problems. One problem is spreadable and can be solved by each IoEV. The other one guarantees that all the constraints will be satisfied, and the final result will converge to the optimal solution. The detailed derivation of the ADMM-based approach is as follows.

### A. Derivation of ADMM Approach

Based on the problem formulated in (29), we first re-organize the objective function as:

$$\begin{aligned} C^{\text{tot}} = \sum_{n\in\mathcal{N}} \Bigg[ &\varpi^{\text{ecs}} \Bigg( \sum_{t\in\mathcal{T},k\in\mathcal{K}} \alpha_k x_{n,k,t} + \sum_{t\in\mathcal{T},k\in\mathcal{K}} c^{\text{ch}}_{n,t} \\ &- \Psi/|\mathcal{N}| - \sum_{t\in\mathcal{T}} \left(P^{\text{reg}}_t/|\mathcal{N}| + P^{\text{A}}_t\right)^2 \Bigg) \\ &- \sum_{t\in\mathcal{T},k\in\mathcal{K}} \varpi^{\text{ecs}} \left(r^{\text{ecs}}_{n,k,t} - c^{\text{ecs}}_{n,k,t}\right) x_{n,k,t} \Bigg]. \end{aligned} \tag{30}$$

Since the constraint (8) cannot be split in the original problem, we thereby introduce a set of vector $z_n$ and a global objective function $g(z_n)$ to re-define the original problem:

$$\begin{aligned} &\min \quad \sum_{n\in\mathcal{N}} f_n(x_n) + g(z), \\ &\text{s.t.} \quad x_n = z_n, \end{aligned} \tag{31}$$

where:

$$g(z) = \begin{cases} 0 & \text{if z satisfies (8),} \\ \infty & \text{otherwise.} \end{cases} \tag{32}$$

Note that, the original problem in (29) is formulated as a MIQP. According to [35], it follows that the point-wise supremum of convex functions of $(x, z)$ is convex since the quadratic function is convex. The choice of cost functions and parameter selection is based on the physical characteristics of power loads and IoEV settings. Thus, the original problem in (29) is convex and feasible. The ADMM algorithm approaches the solution of the original problem in (29) as long as the problem is feasible and convex [36]. In this condition, we adopt two assumptions throughout the article:

*Assumption 1:* $g(\cdot)$ is increasing and differentiable, and $g(z)'' \geq \varphi$, for all $z$.

*Assumption 2:* $f(\cdot)$ is increasing and differentiable, and $f_n(x)'' \geq \phi$, for all $x$.

These two assumptions are widely adopted in the power system [37], [38], [39]. They establish sufficient conditions for the convergence of the ADMM algorithm.

With $f(x) = \sum_{n\in\mathcal{N}} f_n(x_n)$, the corresponding augmented Lagrangian function of (30) is:

$$L_\rho(x, z, y) = f(x) + y^T(x - z) + \frac{\rho}{2}\|x - z\|_2^2, \tag{33}$$

where $\rho$ is the penalty parameter of the augmented term and $y = [y_0, y_1, \ldots, y_{\mathcal{N}}]^T$ is a vector of the Lagrangian variables. To solve problem (30), we minimize over the primal variables $x$, $z$ and maximize over the Lagrangian variables $y$ as explained in [27]. And, the ADMM algorithm solves the problem using an iterative process. The problem above is separable, and we can formulate IoEV $n$ subproblems for each $x_n$ update:

$$x_n^{k+1} = \arg\min_{x_n} \left( f_n(x_n) + \frac{\rho}{2}\|x_n - z_n^k + y_n^k\|_2^2 \right) \tag{34a}$$

$$z^{k+1} = \arg\min_{z} \; g(z) + \left( \frac{\rho}{2} \sum_{n=1}^{\mathcal{N}} \|z_n - x_n^{k+1} - y_n^k\|_2^2 \right) \tag{34b}$$

$$y_n^{k+1} = y_n^k + x_n^{k+1} - z_n^{k+1}. \tag{34c}$$

### B. Convergence Analysis

*Convergence Criteria*: As defined in [27], the necessary and sufficient optimality conditions for the ADMM problem are primal feasibility. The primary residual at the $k+1$-th iteration can be obtained as:

$$r^k = x^{k+1} - z^{k+1}. \tag{35}$$

And, the dual residual is:

$$s^k = -\rho\left(z^{k+1} - z^k\right). \tag{36}$$

When these two residuals converge to zero as ADMM proceeds, the optimality conditions for the ADMM problem can be achieved.

*Stopping Criteria*: The stopping criterion is that the primal and dual residuals must be small enough. In this context, we assume:

$$\|r^k\|_2 \leq \varepsilon^{\text{pri}}, \tag{37}$$

$$\|s^k\|_2 \leq \varepsilon^{\text{dual}}, \tag{38}$$

is the stopping criteria, where $\varepsilon^{\text{pri}} > 0$ and $\varepsilon^{\text{dual}} > 0$.

*Penalty Parameter:* In this work, we follow the guidelines in [27], and choose to use a variable step size in order to improve convergence speed:

$$\rho^{k+1} = \begin{cases} \tau^{\text{incr}}\rho^k & \text{if } \|r^k\|_2 > \mu\|s^k\|_2, \\ \rho^k/\tau^{\text{decr}} & \text{if } \|s^k\|_2 > \mu\|r^k\|_2, \\ \rho^k & \text{otherwise.} \end{cases} \tag{39}$$

*Theorem 1:* By applying the ADMM approach in (34), the system converges to the optimal value $C^*$ as the iteration step $k \to \infty$.

*Proof:* According to [35], it follows that the point-wise supremum of convex functions of $(x, z)$ is convex since the quadratic function is convex. Hence, $f(\cdot)$ and $g(\cdot)$ in (31) are convex. Then, we can know that $f(\cdot)$ and $g(\cdot)$ are also close and proper based on the Assumptions 1 and 2. Therefore, we have the strong duality holds for the original optimization problem in (33). According to [39], the optimal solution, denoted by $(x^*, z^*, y^*)$, is the saddle point for the Lagrangian $L_0(x, z, y)$ in (34). Since $(x^*, z^*, y^*)$ is the saddle point for $L_0$, we have:

$$L_0\left(x^*, z^*, y^*\right) \leq L_0\left(x^{k+1}, z^{k+1}, y^*\right). \tag{40}$$

Here, the $L_0(x^*, z^*, y^*)$ is $C^*$. We assume that $C^{k+1} = f(x^{k+1}) + g(z^{k+1})$, by substituting it into (40), we have:

$$C^* \leq C^{k+1} + y^{*\mathrm{T}} r^{k+1}. \tag{41}$$

We can easily imply that $r^k \to 0$ as $k \to \infty$ according to [39]. Then, the right-hand side in (41) goes to zero as $k \to \infty$, since $r^{k+1}$ goes to zero. Therefore, we have proved that $\lim_{k\to\infty} C^k = C^*$.

### C. Complexity Analysis

In this study, the complexity of the ADMM approach in Algorithm 1 is $O(1/\varepsilon^2)$. Moreover, we use the interior-point method to solve the original MIQP problem (29), and the complexity is $O(\nu^{3.5}\log(1/\varepsilon))$. Here $\nu$ is the number of variables, which is determined by the variable $(x_{n,k,t}, y_{n,k}, P_{n,t})$, and thus $\nu = |\mathcal{N}||\mathcal{K}||\mathcal{T}| + |\mathcal{N}||\mathcal{K}| + |\mathcal{N}||\mathcal{T}|$.

### D. Interpretations of the ADMM Approach

The ADMM approach decomposes the formulated problem into the sub-problem of each IoEV. To implement this ADMM approach, the IoEV parking system proposed in Section II.C is adopted. All the required information for the optimization is delivered through the information layer and gathered at the system operator, which is a single centralized location e.g. the center of the city. Then, the system operator would broadcast this information and an incentive signal to all the IoEVs.

When an IoEV receives this information, it would formulate its own subproblem of optimizing the social cost through local parameters, e.g. the SOC of the IoEV, the routing plan of the IoEV, and the location of the IoEV, etc. All the IoEVs would calculate their own optimization problem in (34a). The results would be sent back to the system operator.

**Algorithm 1:** ADMM Approach.

**Input:** The initial strategy state $x^0$, $z^0$, $y^0$, the initial step size $\rho^0$, the feasibility tolerances $\varepsilon^{\text{pri}}$ and $\varepsilon^{\text{dual}}$;
**Output:** The IoEV allocation and V2G scheduling;
**while** $\|r^k\|_2 \geq \varepsilon^{\text{pri}}$ or $\|s^k\|_2 \geq \varepsilon^{\text{dual}}$ **do**
  **for** each IoEV $n \in N$ **do**
    Pull the global consensus values $z^*$ and the dual variable $y^*$ from the system operator;
    Solve the subproblem (34a) for IoEV $n$ so as to get the optimal values $x_n^*$;
  **end for**
  Push these results to the system operator;
  Determine the consensus problem (34b) in the system operator so as to get the global consensus values $z^*$;
  Calculate the dual variable $y^*$ by (34c);
  Update the $r^k$ and $s^k$ according to (35) and (36) respectively;
  **if** $\|r^k\|_2 > \mu\|s^k\|_2$ **then**
    $\rho^{k+1} = \tau^{\text{incr}}\rho^k$;
  **else if** $\|s^k\|_2 > \mu\|r^k\|_2$ **then**
    $\rho^{k+1} = \rho^k/\tau^{\text{decr}}$;
  **end if**
  $k = k + 1$;
**end while**

After receiving all the results, the system operator would re-organize the allocation problem of the IoEVs through sub-problem (34b) to avoid congestion at the IoEVAs. This global optimization solution would be stored in the system operator and passed to IoEVs iteratively after each update. This consensus constraint also ensures that all local solutions will converge to the global solution. The process can be considered as an iterative majority voting rule. Every IoEVs votes to maximize its own profit or minimize its own cost. And, the system operator is to balance the individual benefit and select the majority direction. The voting result would be sent back to the participants, and they would revise their proposal according to the broadcast message to optimize their interest. This voting process will perform iteratively until all IoEV consent on the allocation and V2G scheduling.

In this case, (34c) can be recognized as the shadow social cost. It indicates the potential cost of waiting for the charging position in the IoEVA and or the traffic jam on the route. With increased shadow social costs, the IoEVs are less likely to go the same IoEVA. Algorithm 1 shows the pseudo-code of the ADMM approach.

## V. Performance Evaluation

In this section, we assess the performance of the proposed urban IoEV parking system. First of all, we introduce the simulation setup. Then, the scenarios for comparison are presented,


Fig. 2. Google map of: (a) Manhattan in New York City, (b) Central in Hong Kong, (c) City of London.

as well as the performance metrics for the simulation. Finally, we show the simulation results and discuss each case in detail.

### A. Simulation Setup

In the simulation, we evaluate the performance of the proposed parking system in Manhattan of New York City shown in Fig. 2(a). Making use of the practical bus schedule in the Manhattan area, we consider the total operational period is from 8:00 a.m. to 3:00 p.m., with seven hours being divided into $\mathcal{T} = 210$ slots. Each time slot has a time duration of $\Delta t = 2$ minutes. Here we focus on using the electric school bus model for the participated IoEVs in simulation due to its predictable driving patterns and relatively large installed battery storage. In practice, various types of IoEVs can be utilized in the proposed urban IoEV parking system. The area of Manhattan is gained with the rough scales of 4 km $\times$ 4 km in the Google map shown in Fig. 2(a). In this captured area, we assume that the total number of IoEVAs is eight, which are shown in green points. We assume that the capacity of the IoEVAs is available, which is 10 of each. The parking cost of IoEVAs $\alpha_k$ in Manhattan is set to \$5 per hour following the actual Manhattan parking cost. For the V2G scheduling of IoEVs during this period, we use the regulation signal data on 1 September 2017 [40]. In addition, we set the base regulation reward to \$40 per MWh following the PJM market standard. The regulation capacity of the Manhattan area is assumed to be 1440 kW.

The settings for IoEVs are shown in the following. Considering IoEVs traveling in the urban area, the unit energy consumption $\beta_i$ of each IoEV is set to 20 kWh per 100 kilometers. Each IoEV is installed with 80 kWh battery capacity [41]. By following the standard in [42], we assume that the fast discharging and charging limits are $-70$ kW and 70 kW, respectively, and the charging/discharging efficiency is set to 0.9. For SOC settings of IoEVs, we model them based on the uniform distribution [23]. More specifically, the startup SOC of each IoEV follows $U[0.4, 0.5]$, and the SOC level requirement after the scheduling services follows $U[0.6, 0.9]$. When IoEVs perform the charging/discharging mechanism, their SOCs should satisfy the conditions of the upper limit following $U[0.9, 0.99]$ and the lower limit following $U[0.2, 0.3]$. When IoEVs are participating charging mechanism, the related charging price is set to \$0.59 per kWh by following [23]. In the edge computing services, we follow the same model proposed in [33]. To provide the computing services, the effective switched capacitance of the onboard CPU ($\beta$) is set to $10^{-28}$, and the number of the CPU clock cycles required to process per-bit input data ($W$) is set to 1550.7, and the clock frequency of the onboard CPU $f^{cpu}$ is set to 800 MHz. The computation demand is fixed at $p^{com}_{n,k,t} = 1 \times 10^8$ bits/s. Considering the communication cost for providing the edge computing service, the available bandwidth ($\omega$) is set to 10 MHz, the path loss exponent ($\pi$) is set to 3 and the environment noise power is set to -50 dBm. The weighting factor ($\varsigma$) to reflect that the data has to be transmitted is set to 0.1 and the reward for edge computing service ($\varrho$) is set to $\$0.83 \times 10^{-16}$ per bit. We consider 36 IoEVs to participate in this urban IoEV parking system as the *default setting*.

Finally, for the centralized optimization, the stopping criteria is set with the tolerance $\epsilon = 10^{-5}$. For the ADMM algorithm, the step size ($\rho$) is set to 0.1 at the beginning. The stopping criteria is set with the primal feasibility threshold $\varepsilon^{pri} = 10$, and the dual feasibility threshold $\varepsilon^{dual} = 10$. The variable step size is selected according to (41), where $\mu = 10$ and $\tau^{incr} = 2$.

### B. Scenarios for Comparison

This simulation mainly focuses on the urban IoEV parking system in Manhattan of New York City which is shown in Fig. 2. We conduct different scenarios by measuring the efficacy of our proposed two algorithms, the centralized IoEV parking algorithm (S0) is presented in (29) and the decentralized ADMM algorithm (S1) is presented in (37). Moreover, in order to assess the relationship between the V2G scheduling and edge computing schemes, we conduct the scenario that does not provide the edge computing service (S2), the scenario that does not provide V2G regulation service (S3), and the scenario that does not provide both of the edge computing service and the V2G regulation service (S4). All of these three above scenarios are evaluated under the same settings via the centralized IoEV parking algorithm so as to achieve the global optimal results.

Without loss of generality, we also evaluate our proposed algorithms under different network sizes. The parking system of the Central in Hong Kong and the City of London is considered. The area of Central in Hong Kong contains the rough scales of 1.5 km $\times$ 1.5 km in the Google map shown in Fig. 2(b), and the area of the City of London includes the rough scales of 3 km $\times$ 3 km in the Google map shown in Fig. 2(b). In the scenario of the Central in Hong Kong (S5) and the scenario of the City of London (S6), they follow the same parameter setting as that of the default setting in Manhattan.

### C. Performance Metrics

On one hand, to evaluate the effectiveness of the proposed urban parking system, we are interested in three performance metrics. We first consider the variance of the total power profile $P_{\mathcal{T}}^{total}$. The variance function is expressed as:

$$\mathrm{Var}\left(P_{\mathcal{T}}^{\mathrm{tot}}\right) = \frac{1}{|\mathcal{T}|}\sum_{t\in\mathcal{T}}\left(P_t^{\mathrm{tot}}\right)^2 - \frac{1}{|\mathcal{T}^2|}\left(\sum_{t\in\mathcal{T}}P_t^{\mathrm{tot}}\right)^2. \quad (42)$$

A smaller variance value indicates better performance in providing the V2G regulation service. It also presents that the active power fluctuations of the city power grid can be better flattened. Then, to evaluate the profit and the power consumption of providing edge computing service, we also evaluate the reward for edge computing service and the IoEV power consumption. The IoEV power consumption represents the power consumption of the computing service and the communication service.

On the other hand, in order to evaluate the efficiency and the effectiveness of our proposed ADMM algorithm, there are five performance metrics for comparing the result of S0 and S1. Besides the power profile $P_{\mathcal{T}}^{\mathrm{A}}$ and the reward for the edge computing service mentioned above. We also assess the CPU time, parking cost, charging cost, and the V2G regulation service reward. The CPU time represents the efficiency and scalability of the ADMM approach. Lower CPU time reflects more IoEVs that can be served in our urban IoEV parking system. Additionally, the remaining four metrics reflect the effectiveness of the ADMM approach.

Finally, we also assess the satisfaction of the fleet on charging. According to [43], we define the Ratio of the Energy requirement (ROE) as the ratio of the energy requirement, which is calculated by

$$\mathrm{ROE} = \begin{cases} 1, & E_n^c \geq E_n^{\mathrm{req}} \\ \frac{E_n^c}{E_n^{\mathrm{req}}}, & E_n^c \leq E_n^{\mathrm{req}}. \end{cases} \quad (43)$$

where $E_n^c$ denotes the actual charged energy from IoEVs and $E_n^{\mathrm{req}}$ is the required energy of IoEVs. When ROE $= 1$, it holds that the charging requirement of each IoEVs $n \in N$ is satisfied.

### D. Simulation Results

*1) Smoothing Quality of Proposed System:* We first evaluate the performance of our proposed urban parking system under different scenarios with a centralized approach. In Fig. 3, we assess the performance of the regulation service between different scenarios with the centralized algorithm. It can be clearly observed that, in S0 and S2, where the V2G regulation service is provided, the active power fluctuations of the city power grid can be alleviated. It presents the effectiveness of the proposed urban IoEV parking system in providing the V2G regulation service. Since the S3 and S4 do not provide the regulation service, they perform relatively worse in flattening the active power fluctuations. The variance of the total power profile of various scenarios in kW$^2$ can be shown in Table I, which indicates a similar result related to Fig. 4.

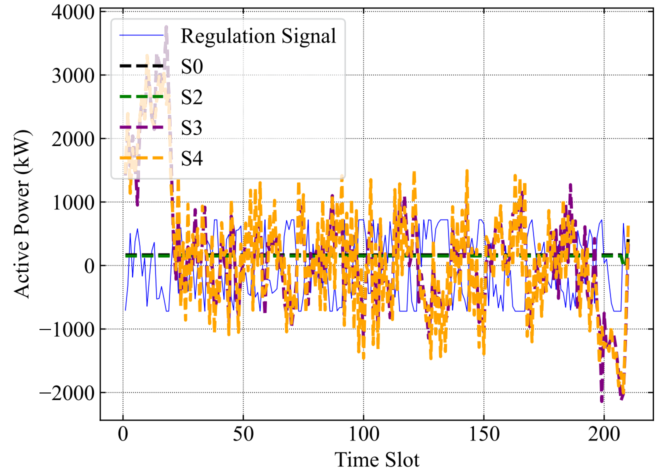



Fig. 3. Comparison of different scenarios in joint allocation and V2G scheduling.

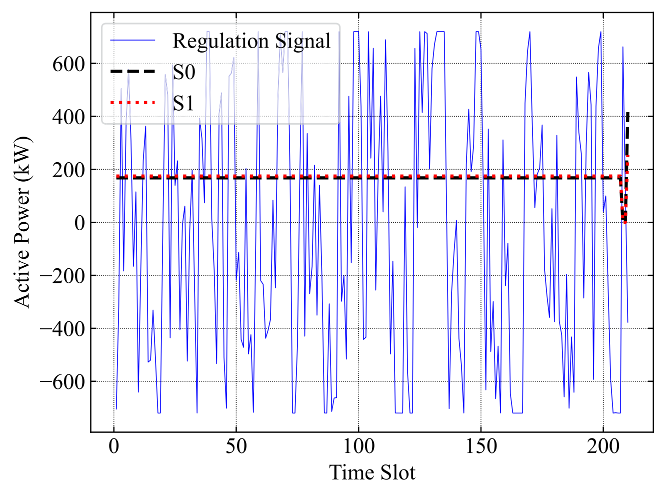



Fig. 4. Comparison of centralized approach and ADMM approach in terms of V2G scheduling.

*2) Effectiveness of ADMM Approach:* Here, we evaluate the effectiveness of the devised distributed algorithm is evaluated based on the performance of providing the regulation service. Indeed, the quality of the service is reflected by the total power profile in the city power grid. We first evaluate the performance between our devised centralized algorithm (S0) and distributed algorithm (S1). In Fig. 4, our proposed centralized algorithm is shown by the black dashed line while the results of the ADMM approach are shown by the red dotted line. Apparently, the profile of S1 is close to the profile of S0, which indicates that

TABLE I
COMPARISON OF DIFFERENT SCENARIOS IN POWER

| Scenario | S0 | S1 | S2 | S3 | S4 |
|---|---|---|---|---|---|
| Variance ($P_T^{total}$) | $5.6 \times 10^3$ | $7.2 \times 10^3$ | $4.0 \times 10^3$ | $9.4 \times 10^6$ | $1.1 \times 10^7$ |
| Average SOC after charging | 77.67 | 79.92 | 75.17 | 76.54 | 75.92 |
| Standard Deviation of SOC after charging | 5.41 | 12.96 | 4.53 | 2.95 | 1.52 |
| ROE | 1 | 1 | 1 | 1 | 1 |

TABLE II
INVESTIGATION OF SOCIAL COST AND REWARD

| Scenario | Charging Cost ($USD) | Total Cost ($USD) | V2G Reward ($USD) | ECS Reward ($USD) | Total Reward ($USD) |
|---|---|---|---|---|---|
| S0 | 646.5 | 1882.5 | 195.8 | 207.0 | 402.8 |
| S1 | 749.0 | 1985.0 | 195.8 | 151.6 | 347.4 |
| S2 | 547.2 | 1783.2 | 195.8 | 0 | 195.8 |
| S3 | 580.9 | 1816.9 | 0 | 207.0 | 207.0 |
| S4 | 512.7 | 1748.7 | 0 | 0 | 0 |

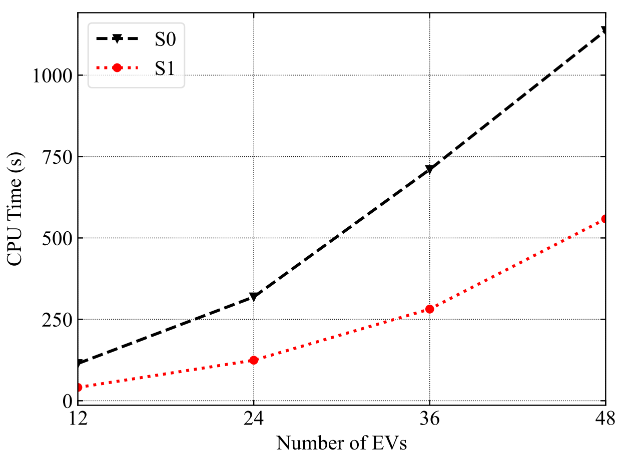



Fig. 5. Comparison of centralized approach and ADMM approach in terms of CPU time.

the distributed algorithm obtains a near-optimal solution for the urban IoEV parking system.

*3) Efficiency of ADMM Approach:* In this part, we evaluate the efficiency of the ADMM approach. The efficiency of the devised ADMM algorithm is evaluated based on CPU time. In practice, one major issue to prevent the optimization algorithm to be implemented is the scalability issue. Indeed, the scalability of the algorithm is reflected by the CPU time for computing. We first evaluate the CPU time between our devised ADMM algorithm and the centralized algorithm (central). In Fig. 5, we can see that our proposed ADMM approach, shown as the red dotted line, outperforms the centralized algorithm. The centralized algorithm consumes about 6$\times$ CPU time under the same settings to find the optimal result. It indeed presents the efficiency of the ADMM approach.

*4) Investigation of Social Cost and Reward:* We further investigate the social cost and reward via the devised distributed algorithm in comparison to the centralized method. The result is shown in Table II. Note that, all these costs and rewards are measured in US dollars. In addition, the V2G reward is only considered during the time period that the V2G regulation service is provided. First of all, compared with S2, S3, and S4, both S0 and S1 achieve the highest total reward, which is calculated by the summation of V2G and edge computing service (ECS) rewards, even if the provision of the joint service requires a relatively high total cost. Besides, for S1, since the retained profits of providing edge computing service become lower, it intuitively reflects that several IoEVs are assigned to the IoEVAs located farther away, which leads to higher power consumption. This process also results in higher charging costs and energy consumption of IoEVs that are reflected in Fig. 3. Additionally, the utilization of the spare computing resource at each IoEV provides additional profit without jeopardizing the performance of the V2G system. Furthermore, considering the charging cost of S3 and S4, this difference indicates the additional power consumption in providing the edge computing service.

*5) Quality of EV Charging:* Besides, we further study the quality of IoEV dynamic charging of the proposed system model. From Table I, we can observe that all these scenarios have ROE $= 1$ on average, which means that they can fulfil the IoEVs' charging requirements so as to indicate the satisfaction of IoEV customers. Then, we also investigate the SOC of the IoEVs after charging behaviours. Naturally, in S4, it achieves the lowest mean and standard deviation of the SOC because it only focuses on finding the IoEVAs with the lowest cost. Then, the mean and the deviation of the SOCs for S0, S2, and S3 are all a bit higher than that in S4. This is due to the provisioning of the V2G scheduling service and the IoV service. Finally, compared with the centralized approach in S0, S1 achieves higher average SOC and standard deviation of the SOC since it generates the sub-optimal solution.

*6) Impact of Fleet Size:* In this part, we assess the impact of the fleet size under different scenarios. We first compare the performance of providing the V2G regulation service between different numbers of IoEVs. It is apparent that our proposed urban IoEV system can still flatten the active power fluctuations of the smart grid under different numbers of participating IoEVs. Moreover, the positive power level of the curves presents the requirements for fulfilling SOCs of all participating IoEVs. As the number of participating IoEVs increases, a higher power level can be achieved.

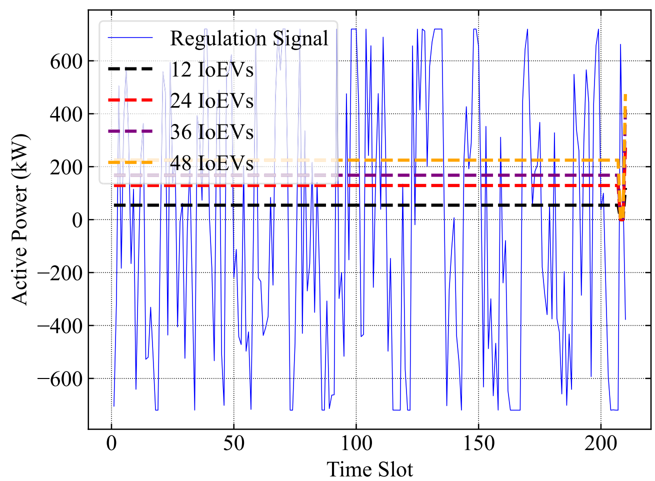



Fig. 6. Comparison of different numbers of IoEVs in V2G scheduling.

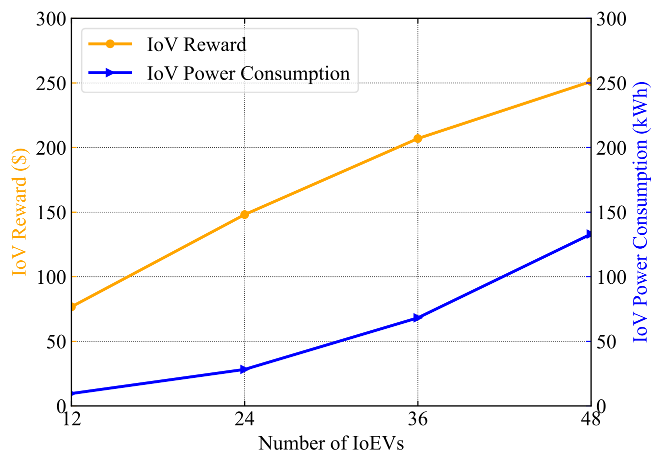



Fig. 7. Comparison of different numbers of IoEVs in edge computing service.

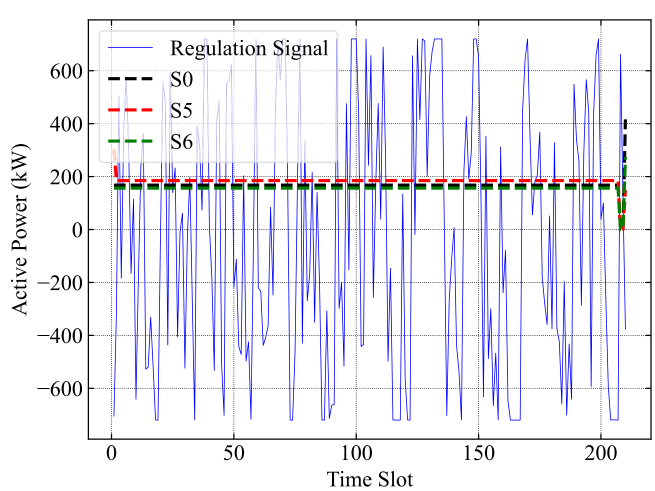
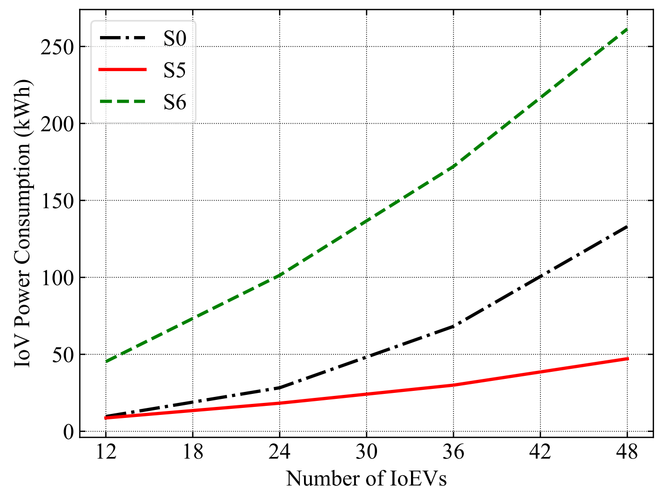
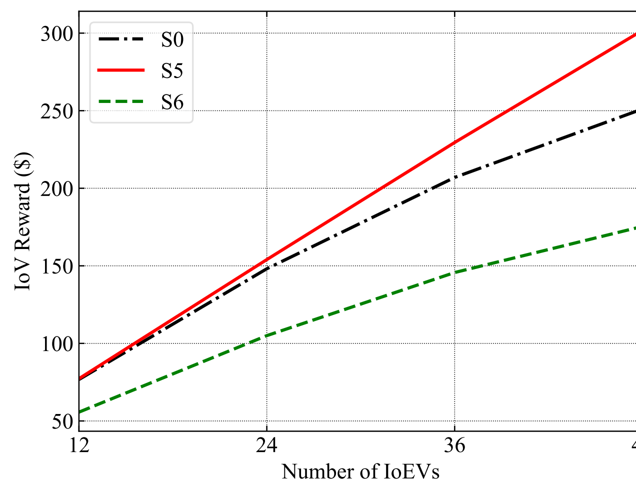



Fig. 8. Impact on the network size in V2G scheduling.

Besides, in Fig. 7, we evaluate the impact of the number of IoEVs in providing the edge computing service. Here, the metrics of interest are the reward for edge computing service, shown by the orange line, and the power consumption for providing the edge computing service, shown by the blue line. The power consumption of the edge computing service reflects both the communication cost and the computing cost for the IoEV system, which can be calculated from (18) and (15), respectively. As it is shown in (18), the power consumption for the wireless communication is related to the exact location of the IoEVAs. When the number of participating IoEVs increases, remote IoEVAs have to be occupied due to the limited capacity of each IoEVA. Thus, the slope of the IoEV cost profile changes accordingly. Moreover, the value of such reward represents the retained profit of providing computing resources to the IoEV system, which can be calculated from (28). As it can be seen from (26), the income of the computing resources provided by each IoEVs is similar. Thus, the reward for edge computing service is linearly dependent on the power consumption by providing the edge computing service.




(a)




(b)

Fig. 9. Impact on the network size in: (a) IoEV power consumption, (b) Reward for edge computing service.

*7) Tractability for Different Network Scales:* In this part, we assess the impact of the network size under different scenarios. Fig. 8 shows the performance of providing the V2G regulation service under different scenarios. The number of participating IoEVs is thirty-six. It shows that our urban IoEV parking system can flatten the active power fluctuations under all these scenarios. Thus, the high quality of the V2G regulation service provided in these areas is guaranteed.

Then, we focus on the cost of the edge computing service in different scenarios, which is shown in Fig. 9(a). Similar to Fig. 7, as the number of IoEVs increases, more IoEVAs are utilized to allocate the IoEVs, which contributes to the dramatic increase in IoEV power consumption. This process has been further intensified with the larger scale of the network size. The IoEV power consumption in S6 is more than 5× of that in S5. This phenomenon further decreases the reward for edge computing services that are shown in Fig. 9(b).

## VI. Conclusion

In this article, we proposed an urban IoEV parking system for IoEVs in a city. This urban IoEV parking system refers to utilizing the idle resources in IoEVs, so as to provide additional computing resources for edge computing and improve the efficiency of regulation service in the smart grid system. In the proposed urban IoEV parking system, we jointly considered the problem in IoEV allocation and V2G scheduling in a city. A MIQP problem that minimizes the total social cost was formulated. We found that the optimal social welfare of the system can be achieved through the proposed system. In order to solve it effectively, we formulated the subproblem for each IoEV by decomposing the original main problem through the ADMM method. The simulation results showed that our proposed model is effective in IoEV allocation and V2G scheduling. Specifically, the smoothing quality of both city power and grid frequency profiles can be achieved by relying on our proposed system framework. Moreover, this system can further facilitate the emergency IoEV service with additional spare computing resources. More rewards and a stable power profile can be obtained with the increase in the IoEV fleet size. Last but not least, the effectiveness of our proposed model in different network scales is guaranteed by means of the distributed algorithm. For future work, since this work does not consider real-time traffic conditions, we will extend this system to a more general system with the implementation of deep learning approaches.

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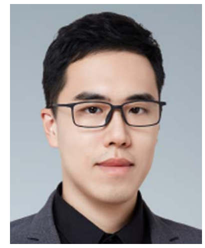

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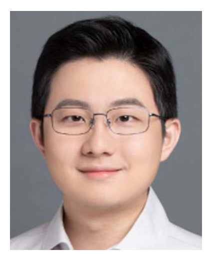

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