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Non-Cooperative and Cooperative Urban Intelligent Systems: Joint Logistic and Charging Incentive Mechanisms

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***Abstract*—Autonomous vehicles (AVs) have become an emerging crucial component of the intelligent transportation system (ITS) in modern smart cities. In particular, coordinated operations of AVs can potentially enhance the quality of public services, e.g. logistic and AV charging services. However, the joint logistic and AV charging scenario involves the sophisticated interactions between a large number of complicated agents, dynamic logistic, and electricity prices in real-world systems. Since AVs are individuals owned by different parties, the design of attractive incentive to motivate them to provide multiple public services becomes a fundamental issue. In this paper, we develop an urban intelligent system (UIS) by exploiting the efficient incentive mechanisms, e.g. non-cooperative and cooperative game theoretic approaches, to motivate the AVs to provide logistic and charging services in UIS. For the non-cooperative game approach, we formulate the interaction between the selfish AVs and the aggregator as a Stackelberg game. Meanwhile, the aggregator, known as the leader in the game, aims to decide the logistic and electricity trading prices, and then the AVs, executed as the followers, determine their service schedules. Furthermore, considering that all the players are willing to cooperate, we develop a cooperative potential game for the selfless AVs to maximize the social welfare of the UIS. These case studies demonstrate the effectiveness and practicability of proposed incentive mechanisms that can motivate EVs to provide high quality logistic and charging services by maximizing their utilities. Also, both the proposed schemes provide significant system revenues than that of conventional system optimization-based approaches.**

***Index Terms*—Autonomous vehicles, frequency regulation, game theory, intelligent transportation systems, logistic service, vehicle-to-grid.**

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I. INTRODUCTION

WITH the development of advanced technologies, the notion of smart city has emerged as a promising paradigm to enhance the quality of life in urban areas. By incorporating various innovative information and communication technologies (ICTs), smart cities aim to improve the quality of many urban operations and services by exploiting various advanced technologies. This objective can be achieved under the effective deployment of urban Internet-of-Things (IoT) [1], [2] that are capable of upgrading traditional and existing public services, e.g. transportation systems. Indeed, Intelligent Transportation Systems (ITSs), as one of the essential components in a smart city, are able to function the city transportation system productively such that the conventional vehicular transportation within cities can be improved. In general, the upgrade of traditional transportation systems to ITSs requires the application of autonomous vehicles (AVs) [3]. Considering the use of vehicular technologies, ITS can leverage abundant vehicular information to remotely broadcast and determine the routing instructions to achieve the desired ITS objectives [4]. Thus, the deployment of AVs contributes not only to more efficient and safer transportation circumstances, but also to enhancing core urban services, e.g. logistic services.

Logistic services in ITS aim to handle mainly parcel delivery operations in urban areas, which refer to the distribution of goods to the final destination in the supply chain management [5]. The increasing demand for fast and punctual parcel delivery operations advocates the adoption of more energy-efficient and environmental friendly city logistic services. In fact, the utilization of AVs can effectively fulfill these requirements. Since AVs are generally equipped with a large storage occupancy and are capable of adopting dynamic and cost-effective routing [6], the supply chains, such as the parcel delivery process, can be further optimized by AVs. For instance, it has been demonstrated in [7] that the planning and scheduling of industrial processes can be optimized in couriers and express services through the utilization of AVs.

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Hence, by implementing efficient AV coordination approaches, the quality of city logistic services can be notably enhanced. In fact, recent research studies have also demonstrated the effectiveness of AV-supported logistics services in ITS, see [7]–[11] for more examples.

On the other hand, it is envisioned that future sustainable smart cities will incorporate remarkable renewable generations into the city power grid [12]. However, the intermittency and uncertainty characteristics of renewable generations result in inevitable random and uncorrelated power fluctuations in the grid, which further jeopardize the stability of the city power grid. To tackle this problem, one possible solution is to utilize the installed batteries of the large numbers electric vehicles (EVs) to mitigate the fluctuation of renewable generations. Since most AVs are made in the form of EVs [13], they can greatly contribute to the regulation of grid stability through efficient energy management, such as dynamic wireless charging approaches. The promising application of dynamic wireless charging facilities enable AVs to charge while they are in motion over the dynamic charging facilities. Since AVs are typically powered by electricity and they use batteries to store power for propulsion in smart cities, they can actively participate in vehicle-to-grid (V2G) systems, cf. [14], [15], in order to provide power system services, such as power grid frequency regulation [16]. However, they are developed based on the grid optimization and optimistically assume that the system operator assigns fixed schedules to the AVs. In practice, AVs are owned by different customers who are generally more concerned about their utilities rather than the overall system operations. Hence, it is still a pressing issue of how to motivate AVs to participate in the both transportation and city power grid systems and provide joint urban logistic and charging services.

To address the aforementioned issues, efficient incentive mechanism, i.e., game theory, can provide an effective framework for analyzing the relationship between the individual utility and the system goals. For game theoretic approaches, each decision-maker develops a unique plan that optimizes its own utility rather than following the instructions from a centralized controller. Since each AV can select the best strategy to maximize its utility, game theoretic approaches naturally ensure the satisfaction of AV utilities in the system that motivate the participation of AVs in providing joint logistic and charging services. In fact, most of existing studies have investigated the AV scheduling problem with the provision of a single public service through various game theoretic methods, e.g. logistic services [17], [18] and charging services [19], [20]. However, there are still some research gaps in these works. For example, the studies in [17], [19] proposed explicit pricing models that forego some benefits offered by associated companies in order to directly motivate AVs to provide logistic or charging service. Therefore, it inspires us to develop an implicit smart pricing model that can determine the logistic and charging prices based on the real-time information signals from the transportation and power grid systems. In this way, the related companies may provide logistic and charging services without having to pay the AVs directly, which lowers their expenses. Furthermore, the neglect of multiple public services provisioning sacrifices the potential benefit of the UIS operations under the limited number of participated AVs. Even worse, applying the existing results, e.g. [17]–[20], to practical systems would result in low operational efficiency in completing various tasks due to the increasing demands of multiple public tasks offered in urban areas. Hence, this encourages us to develop a smart pricing scheme to motivate AVs to implicitly provide multiple public services, e.g. logistic and charging services.

In this paper, we develop both the non-cooperative and cooperative game theoretic approaches for an urban intelligent system (UIS) by exploiting AVs. The two formulated games jointly provide AV logistic and charging services in urban areas. In particular, we focus on the determination of the best strategy for the joint services in a cost-effective manner. Meanwhile, logistic and electricity pricing models are developed to motivate AVs to provide joint services implicitly. The main contributions of this work are summarized as follows:

- Different from the existing approaches, e.g. [7]–[11], [21]–[23], that unilaterally consider the application of either logistic or charging service, we design a generic UIS framework to jointly provide city logistic and charging services using AVs, which also guarantees effective path planning operations that can reduce the service time of joint schemes and the power consumption of the AVs.
- Unlike the existing studies [17]–[20] that have only designed unique incentive pricing models for providing single public service, we devise a general pricing model creating certain incentives to accommodate AVs to provide both the logistic and charging services implicitly. In addition, we study both non-cooperative and cooperative game theoretical approaches to motivate multiple types of AVs to jointly provide these services by reacting to the decision prices for the joint service. Through efficient cooperation, we can obtain the optimal social welfare of the aggregator and the participated AVs in a distributed manner.
- We analyze the existence and uniqueness of Nash equilibrium of these games and present that both AV logistic and charging services can achieve the near-optimal performance. Then, we assess the performance evaluation of the proposed UIS framework through a comprehensive series of case studies, which confirm its cost-effectiveness.

The rest of this paper is organized as follows. In Section II, we examine closely the related studies and highlight the technical challenges involved in this work. For Section III, we develop the system architecture, including transportation networks, AVs, and system operations. In Section IV, we formulate the proposed incentive mechanisms with well-defined constraints and utility functions. Then, Section V introduces the formulation of a non-cooperative approach with the devised algorithm, while Section VI illustrates the formulation of a cooperative approach and its related algorithm. Section VII details the case studies that evaluate the proposed incentive approaches and Section VIII concludes this work.

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II. Related Work

With the gradual adoption in smart cities, AVs, known as to possess a crucial role in ITS, are expected to contribute to city logistic services. It is expected that AVs can provide high-quality city logistics services under the coordination of ITS control centers. There are several pieces of existing research work on studying the benefit of parcel delivery services provided by AVs, such as [7]–[9], [11]. For instance, a dynamic EV routing model was designed in [8] for goods delivery in logistics industry, which considered a time-varying traffic condition and the EV charging patterns. Moreover, in large-scale urban areas, [9] devised an efficient algorithm to manage the AVs to deliver parcels in a safe and efficient manner. Considering the rapid increase on logistics demands, a system was developed for planning and control the delivery service in [7]. This approach further optimizes the efficiency of dispatching process and improve the service quality with less required numbers of vehicles. Lastly, a pricing mechanism was developed in [11] to encourage market competition by accommodating multiple AV operators. However, none of these studies on AV logistics jointly consider practical AV charging behaviors. In fact, the dynamic energy consumption caused by the motions of AVs can greatly affect the task completion of AVs, especially to accommodate massive long-distance parcel delivery tasks.

Considering the development of future sustainable smart cities, dynamic wireless charging operations pose a significant impact on the city power grid. Specifically, since power tracks (PTs), i.e., the power supply units, are deployed beneath the traffic roadways for energy transfer operations, AVs can be controlled to charge while in motion under multiple route plans [24]. Meanwhile, through the reliable wireless power transfer techniques [25], the security and privacy among the AV fleet during the charging/discharging process can be further ensured. Hence, such techniques can indeed facilitate the effectiveness of the AV resource management, e.g. [26]. Inspired by this emerging application, recent studies have focused on designing dynamic wireless charging protocols for EVs [21]–[23]. In addition, considering the interaction between AVs and the power grid, EVs can significantly influence the grid's demand-side management through dynamic wireless charging. For instance, [27] explored the potential benefit of EV dynamic wireless charging systems for the demand-side management. Moreover, the provision of V2G regulation services can further assist the stabilization of power grid, which has been demonstrated in [28]–[30]. Even though an EV dynamic wireless charging system proposed in [31] accounted the dynamic V2G scheduling scheme with the provision of V2G regulation services, the time-varying EV driving patterns were not addressed by existing results. In this work, we address both the logistic and charging problem of AVs by means of an UIS framework, since the AV driving patterns are related to the schedules of logistic services in the city area.

In addition to the aforementioned studies, an AV logistic system was proposed in [15] for cooperative charging and routing behaviors of AVs in the city area. Additionally, an optimization problem for offering AV logistic services was developed in [32] based on the schedules for request allocation, vehicle routing, and battery charging, which was solved by the devised two-stage scheduling method. Furthermore, a pricing scheme in [33] was established as a core-selecting mechanism to maximize the customer's utility and prevent shill-bidding, which is designed based on the Vickrey-Clarke-Groves mechanism. Yet, these approaches are designed from the perspective of system optimization and optimistically assume that AVs follow the fixed schedules dispatched by the system operator. In order to investigate the relationship between the behaviours of the system goal and AVs, several existing studies have studied the AV scheduling problem with the provision of a single public service through various game theoretic methods, e.g. [17]–[20]. For the provisioning of logistic services, [17] proposed two incentive game models to maximize the platform's profits while [18] designed a dynamic Bayesian game approach to minimize the AV delivery cost. However, these aforementioned studies do not consider the detailed charging scheme for battery-driven AVs, even if their mobility patterns are considered in the city area. To consider the AV charging schemes, [19] and [20] proposed both the non-cooperative and cooperative game approaches for the provisioning of charging services, which included demand and renewable generation uncertainties, respectively. However, the authors in [19], [20] do not consider the mobility operation of EVs under the ITS, e.g. the neglect of allocation scheme for matching EVs to EV aggregators in the city area, which indeed affects the charging behaviors of EVs. In practice, an improper allocation plan may easily lead to unnecessary waiting time for EVs to charge at available EV aggregators due to the limited number of EV aggregators. As a result, it is crucial for the system to coordinate EV charging schedules by properly assigning EVs to EV aggregators. In this paper, we propose the use of non-cooperative and cooperative game theoretic approaches to motivate the participation of AVs in providing both logistic and charging services implicitly in smart cities, which consider the design of smart pricing models.

III. System Design

A. Road Network

To accurately depict the physical distance and linking from one location to another within a given area, the road network can be described based on graph theory [34]. The road network is described as a directed graph $G(\mathcal{V}, \mathcal{E})$, where the set of nodes $\mathcal{V}$ represents the junction locations of the road segments, which are connected by the edges in the set $\mathcal{E}$. For each road segment $(i, j) \in \mathcal{E}$ at time t, we further define $d_{ij}^n(t)$ as the travel distance of AV n from location i to location j. Due to potential asymmetries between distinct route plans, it should be noted that $d_{ij}^n(t)$ may not always equal $d_{ji}^n(t)$. Besides, we consider the PTs are embedded over the certain number of the road paths of the city traffic network.

B. Autonomous Vehicles and AV Aggregator

Both public and private AVs are taken into account in our design. The set of participating AVs is denoted as $\mathcal{N}$. By

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traveling between any two locations (i, j), where $i, j \in \mathcal{V}$, the AVs successfully achieve their assigned parcel delivery objectives. It should be noted that the AVs can transport packages for a predetermined time period. Each service request is then given to the n-th AV and they must complete before the service deadline. In addition, the number of logistic service requests during the participation period are predetermined before the execution.

In a city area, we consider multiple AV aggregators represented by different entities managing the fleet of specific AVs individually. Each aggregator can be regarded as a subordinate component of multiple aggregators that are connected to the system operator. The size of an aggregator is determined by the size of its subordinate AV fleets, geographical factors, communication radius, etc. The operation of an aggregator in the proposed UIS refers to the coordination in [29], which elaborates a multi-level vehicle-to-grid system structure with the utility grid operator, the aggregators, and the EVs.

C. System Operations

Fig. 1 provides an overview of the UIS system architecture. The multi-level structure considers two different types of interaction incentive mechanisms, namely, the system-aggregator incentive game and the aggregator-AV incentive game. Each mechanism operates between a node and its immediate subordinate nodes. In this paper, the focus is the design of the aggregator-AV game, which governs how an aggregator of AVs interacts with its attached AVs to satisfy the logistic and charging requests in an arbitrary region of urban areas. The specific design of this incentive game is shown in Fig. 2. Meanwhile, both traffic and energy information are considered in the UIS operator so as to provide joint logistic and charging service. In practice, different types of AVs are belonged by their contracted parties and they have their own preferences to select either of the incentive mechanisms due to the individual goals of these parties. However, the unilateral consideration of a non-cooperative game for AVs can incur more losses for the utilities of both AVs and the aggregator due to the competition among the AVs and the selfishness of the AVs and the aggregator. Therefore, we propose incentive mechanisms for both non-cooperative and cooperative aggregator-AV systems, which can simultaneously execute in the system to achieve the overall functionality of UIS. Additionally, different from the optimization-based approaches that provide single public service [7]–[11], [21]–[23], we consider the provision of multiple public services simultaneously to further improve the efficiency of system operations under the limited number of AVs, especially for joint logistic and charging services.

By scheduling the participated AVs, the proposed UIS seeks to provide both logistical and charging services in smart cities. As shown in Fig. 2, two basic functions are included in the smart agent. First of all, each agent, i.e. agent $k \in \mathcal{N}$ in Fig. 2, can compute both the logistic and charging/discharging schedules for each AV via the computing unit. Then, through the distributed computation among these agents, the optimal AV schedules for the game can be determined. After that, each agent shall exchange the information by communicating with

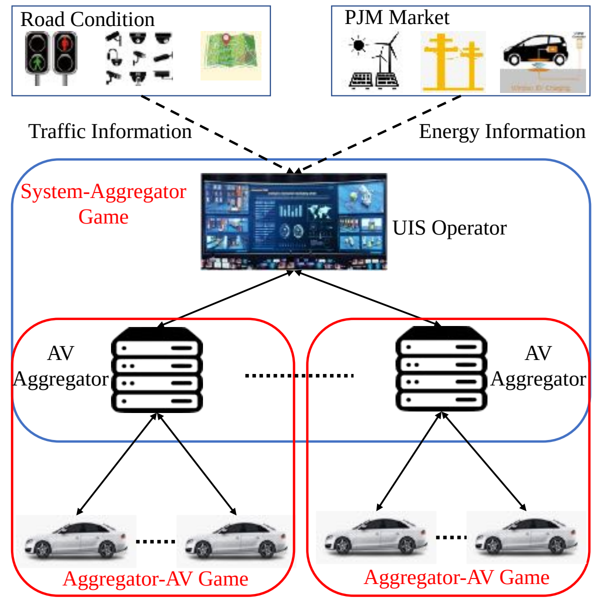

Fig. 1. Architecture of the proposed urban intelligent system (UIS).

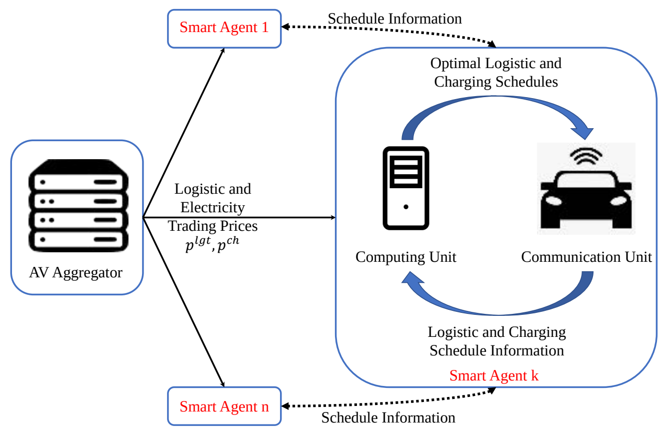

Fig. 2. Agent-based information flow in the proposed UIS.

the aggregator or other smart agents. In this direction, one smart agent can share the scheduling information with other smart agents and receive pricing signals from the aggregator. Besides, in contrast to the cooperative approach that all the players are willing to cooperate to maximize the social welfare of the entire system, we further study the case where all the players in the non-cooperative system, aim to maximize their own utilities in a selfish way. The related steps of the games indeed follow the concept of game theory shown in [35]. Last but not least, in practice, there may exist some groups select to participate the non-cooperative games due to the their own preferences rather than participating the cooperative game to further improve the social welfare of the entire system. In this case, we need to consider the coexistence of these two games in UIS in order to assessing its practicability for dynamic and complex urban environment.

IV. System Model

As illustrated in Section III, the goal of UIS is to address the open problem of joint parcel delivery and charging for all the participating AVs in urban areas. This section mainly describes

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TABLE I
NOMENCLATURE FOR AV LOGISTIC SERVICES.

$\mathcal{V}$	Index set of nodes
$\mathcal{E}$	Index set of road paths
$\mathcal{N}$	Index set of AVs
x_{ij}^n	Binary variable of whether AV n traverses road (i,j)
L_n^{src}	Departure point of AV n
L_n^{dst}	Destination point of AV n
$L_{n,q}^{\text{dst}}$	Deliver location of AV n at request q
$\mathcal{Q}$	Total logistic request set of all AVs
$\mathcal{Q}_n$	Logistic request set of AV n
d_j^n	Staying duration of AV n at node j
$D_{n,q}$	Service duration of AV n at request q
$T_n^\star$	Service deadline of AV n
$\overline{T_{n,q}}$	Maximum required service time for AV n at request q
$\underline{T_{n,q}}$	Minimum required service time for AV n at request q
τ_j^n	Time of arrival of AV n at node j
T_{ij}^n	Travel time of AV n on road (i,j)
α^n	Unit routing cost of AV n
β^n	Unit transportation service cost of AV n

our game formulations to the aforementioned problem in depth. Table I provides a clear explanation of all relevant parameters.

A. Operational Constraints

Let x_{ij}^n be a binary variable that indicates whether AV $n \in \mathcal{N}$ traverses over the road segment (i,j) as follows:

$$x_{ij}^n = \begin{cases} 1 & \text{if AV } n \text{ traverses road segment } (i,j) \in \mathcal{E}, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

In practice, AVs can make numerous visits and stop at the same node in the course of different trips. Yet, to simplify the formulation of our problem, each AV $n \in \mathcal{N}$ is supposed to visit each node of the transportation network only once under each service request q. Then, we designate $\tau_j^n \geq 0$ as the time when AV n reaches node j. In addition, the time duration of AV n staying at node j is specified as $d_j^n \geq 0$.

Besides, AV routing and parcel delivery are the two key operations covered by the proposed UIS. To ensure real-world applicability, all AV operations must be carried out by satisfying a set of specified constraints.

1) Route Constraints: The n-th AV in UIS will arrive at its destination after being assigned a request for a specific operation, such as parcel delivery. This suggests that in order to reach the final location, the AV needs to traverse across at least one road segment, which can be accomplished by

$$\sum_{i \in \mathcal{V}} x_{ij}^n \geq 1, \ \forall n \in \mathcal{N}, \ j \in \{L_{n,q}^{\text{dst}} | q \in \mathcal{Q}_n\}, \tag{2}$$

where $\mathcal{Q}_n$ is the index set of logistic service requests of AV n and it is related to the number of parcels delivered during the entire service period.

The AV network flow model is modeled based on the city's road network. The incoming and outgoing flows are denoted by $\sum_{i \in \mathcal{V}} x_{ij}^k$ and $\sum_{i \in \mathcal{V}} x_{ji}^k$, respectively. For AVs, the connectivity of the consecutive road segments can be ensured by

$$\sum_{i \in \mathcal{V}} x_{ij}^n - \sum_{i \in \mathcal{V}} x_{ji}^n = \begin{cases} 1 & \forall n \in \mathcal{N}, j = L_n^{\text{dst}}, L_n^{\text{src}} \neq L_n^{\text{dst}}, \\ -1 & \forall n \in \mathcal{N}, j = L_n^{\text{src}}, L_n^{\text{src}} \neq L_n^{\text{dst}}, \\ 0 & \text{otherwise,} \end{cases} \tag{3}$$

where the departure and destination points of the associated routes are denoted by L_n^{src} and L_n^{dst}, respectively. When AV n approaches node j, the first two cases in (3) guarantee that there would be an incoming and an outgoing flow between the departure and destination locations, respectively. Let us consider all road interactions, excluding those involving the departure and destination points, as an example. An incoming flow would result in an outgoing flow if AV n reaches node j. Otherwise, there would be an equal number of incoming and leaving AV flows. As a result, (3) ensures the connectivity of vehicular routes.

In practice, some routes may be restricted to certain types of cars. Private AVs, for instance, are not permitted to drive on the road segments that are only available for authorized vehicles, i.e., autonomous public buses utilized in [36]. We can implement additional restrictions to take into account such possibilities. First of all, we define $(\mathcal{V}', \mathcal{E}')$, where the set of nodes $\mathcal{V}' \subset \mathcal{V}$ signifies road intersection points connected by the set of edges $\mathcal{E}' \subset \mathcal{E}$ in the restricted zone. Assume that AV n is restricted for accessing to road (i,j). The related constraint can be expressed as $x_{ij}^n = 0, \ \forall i \in \mathcal{V}', j \in \mathcal{E}'$. This constraint indicates that AV n is not permitted to move between node i and node j because they are within a restricted area.

2) Logistic Service Constraints: The quality of the logistic services is mainly measured by the delivery time spent of AV n. The minimum time duration to stay is indicated when AV n loads or unloads parcels at node j by

$$d_j^n \geq D_{n,q}, \ \forall j \in \{L_{n,q}^{\text{dst}} | q \in \mathcal{Q}_n\}, \ \forall n \in \mathcal{N}, \tag{4}$$

where $D_{n,q}$ is the service time for loading or unloading parcels for the n-th AV.

Additionally, keep in mind that τ_j^n denotes the time where AV n reaches node j. The duration of AV n traversing the relevant road segments must also be taken into account for accuracy of estimation. When the AV moves through $(i,j) \in \mathcal{E}$, τ_j^n should be no less than the sum of the trip time and the time for loading the packages, as determined by

$$\tau_j^n \geq \tau_i^n + d_i^n + T_{ij}^n, \ \forall x_{ij}^n = 1, n \in \mathcal{N}, i,j \in \mathcal{V}, \tag{5}$$

where T_{ij}^n represents the n-th AV's travel time from node i to node j. Then, its parcels will be delivered to the destination point by following

$$\underline{T_{n,q}} \leq \tau_j^n \leq \overline{T_{n,q}}, \ \forall n \in \mathcal{N}, j \in \mathcal{V}, \tag{6}$$

where $\underline{T_{n,q}}$ and $\overline{T_{n,q}}$ are the expected minimum and maximum times at request q. Finally, the service deadline of the system operations is the time required to complete the service, which follows where the expected minimum and maximum times at request q are denoted as $\underline{T_{n,q}}$ and $\overline{T_{n,q}}$, respectively. The

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TABLE II
NOMENCLATURE FOR AV CHARGING SERVICES.

$y_{n,t}$	Time-varying route plan of AV n at time t
$\mathcal{T}$	Index set of timeslot
$P_{n,t}$	Active power of AV n at time t
P_n^{dch}	Maximum discharging power of AV n
P_n^{ch}	Maximum charging power of AV n
$\text{SOC}_{n,t}$	State-of-charge of AV n at time t
Δt	Length of a time slot
Cap_n	Installed battery capacity of AV n
η^{ch}	Charging efficiency
η^{dch}	Discharging efficiency
$d_{ij,t}^n$	Travel distance of AV n for path (i,j) at time t
$v_{ij,t}^n$	Travel velocity of AV n for path (i,j) at time t
$\theta_{ij,t}^n$	Delay parameter for path (i,j) at time t
λ^n	Unit energy consumption of AV n
SOC_n^0	Initial state-of-charge of AV n
$\text{SOC}_n^\star$	Charging requirements of AV n
$\overline{\text{SOC}}_n$	Upper bound of state-of-charge for AV n
$\underline{\text{SOC}}_n$	Lower bound of state-of-charge for AV n

completion time for the service is related to the service deadline for system operations, as described by

$$\tau_{L_n^{\text{dst}}}^n \le T_n^\star,\ \forall n \in \mathcal{N}, j \in \mathcal{V}. \tag{7}$$

Due to the existence of restricted roads, the visiting time of AV n, τ_i^n where $i \in \mathcal{V}'$, is set to zero. Accordingly, AV n is unable to visit node i based on (5). The operational limit of τ_j^n can be included for the case when AV n is only permitted to move at node j in a specific time period.

3) Linear Transformation: It is clear from the problem as previously formulated that the objective function and the majority of constraints are affine. As a result, the optimization problem can be handled with relative ease. However, constraint (5) is modeled under the case $x_{ij}^n = 1$. This constraint cannot be directly modeled without prior information on x_{ij}^n. To address this issue, we attempt to transform (5) into its equivalent linear form. Prior to that, the following two cases are taken into account:

- Case 1: If $x_{ij}^n = 0$, starting from node i through $(i,j) \in \mathcal{E}$, AV n won't visit node j. Since τ_j^n is constrained within a feasible region, there is no relationship between τ_i^n and τ_j^n. Similar to this, C_i^n and C_j^n have no direct relation.
- Case 2: If $x_{ij}^n = 1$, τ_j^n must be greater or equal to the right hand side of constraint (5).

Then, constraint (5) is transformed into the equivalent linear form by using the big-M reformulation [11], [14], [15], [37] as

$$\tau_j^n \ge \tau_i^n + d_i^n + T_{ij}^n - M(1 - x_{ij}^n),\ \forall n \in \mathcal{N}, i,j \in \mathcal{V}, \tag{8}$$

where M is a sufficiently large number to guarantee the feasibility of this constraint.

4) Dynamic Wireless Charging/Discharging: In this part, we aim to tackle the AV dynamic wireless scheduling that AVs are willing to participate. Within the total time period $\mathcal{T}$, the AVs perform dynamic wireless charging/discharging while providing the logistic services in the city area. Moreover, the stability condition of the city smart grid system should also be fulfilled since the provision of ancillary services in the urban area is considered. Here, we further extend the mathematical model in [31]. The operation bounds for charging and discharging powers of AV n follow

$$P_n^{\text{dch}} \le P_{n,t} y_{n,t} \le P_n^{\text{ch}},\ \forall n \in \mathcal{N}, t \in \mathcal{T}, \tag{9}$$

where $P_n^{\text{dch}} \le 0$ and $P_n^{\text{ch}} \ge 0$ are the discharging and charging power of AV n, respectively. Symbol $y_{n,t}$ presents the binary parameter to indicate whether AV n is traveling over the PTs or not. For instance, if AVs do not participate the dynamic wireless scheduling, $y_{n,t} = 0, \forall t \in \mathcal{T}$, holds for the entire time period, which further reflects that such AVs are known as the group that solely considers traveling on roads without wireless charging or discharging.

The charging and discharging activity of AV n is then carried out while it is connected with the PTs and operates dynamic scheduling operation at each time slot. As a result, it is possible to determine the state-of-charge (SOC) of each participating AV $n \in \mathcal{N}$ at time t by

$$\text{SOC}_{n,t+\Delta t} = \text{SOC}_{n,t} + \frac{\Delta t}{\text{Cap}_n} \eta(P_{n,t}) P_{n,t},\ t \in \mathcal{T}, \tag{10}$$

where $\text{Cap}_n > 0$ represents the installed battery capacity of AV n, and $\eta(\cdot)$ denotes the energy efficiency of the charging/discharging power of each AV, which is calculated by

$$\eta(P_{n,t}) = \begin{cases} \eta^{\text{ch}} & P_{n,t} \ge 0, \\ 1/\eta^{\text{dch}} & P_{n,t} < 0, \end{cases} \tag{11}$$

where $\eta^{\text{ch}}, \eta^{\text{dch}} \in (0,1]$ represents the charging and discharging efficiencies of each participated AV n, respectively.

Recall that the travel distance of AV n from point i to point j at time t is defined as $d_{ij,t}^n$. The time-varying energy consumption of the battery level of AV n at time t can then be described as

$$\text{SOC}_{n,t+\Delta t} = \text{SOC}_{n,t} - \frac{\lambda^n}{\text{Cap}_n} d_{ij,t}^n, \tag{12}$$

where $\lambda^n \ge 0$ denotes the unit energy consumption factor of AV n.

The travel speed across the road segment $(i,j) \in \mathcal{E}$ at time t is indicated as $v_{ij,t}^n$ for AV n. The actual routing plans for the AV may be influenced due to the immediate changes of city traffic conditions, which further affects the travel speed of AV n. Therefore, according to [31], we introduce a delay parameter $\theta_{ij,t}$ to present the instantaneous traffic condition, e.g. the sudden traffic congestion. Since this parameter is relevant to the vehicle travel speed, we can have

$$d_{ij,t}^n = \left(v_{ij,t}^n - \theta_{ij,t}\right) \Delta t,\ \forall n \in \mathcal{N}, (i,j) \in \mathcal{E}. \tag{13}$$

Through the connections of wireless PTs, it also meets the energy demand of charging/discharging scheduling in addition to completing the routing plans for each AV n. Each AV n's required SOC level corresponds to the energy requirement. Let $\text{SOC}_{n,\text{ini}}$ and $\text{SOC}_{n,\text{req}}$ represent the starting SOC of the AV n at the source location and the required SOC level of the AV n, respectively. Before arriving at the final destination, the charging requirement must be satisfied as indicated by

$$\text{SOC}_{n,|\mathcal{T}|} \ge \text{SOC}_n^0 + \text{SOC}_n^\star,\ \forall n \in \mathcal{N}, \tag{14}$$

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TABLE III
NOMENCLATURE FOR PROPOSED MODEL.

U_n^{lgt}	Utility function for AV n in logistic services
U_n^{ch}	Utility function for AV n in charging services
U_n	Total utility function for AV n
α_{ij}^n	Unit fuel consumption cost for AV n
$R_{n,q}^{\text{lgt}}$	Base revenue for AV n at logistic request q
$p_{n,q}^{\text{lgt}}$	Trading price for logistic service of AV n
$p_{n,t}^{\text{ch}}$	Trading price for charging service of AV n at time t
$\text{SOC}_n^{\text{base}}$	Base satisfaction level related to the SOC of AV n
γ_n	Sensitivity index for AV satisfaction
U_A^{lgt}	Utility function for the aggregator in logistic services
U_A^{ch}	Utility function for the aggregator in charging services
U_A	Total utility function for the aggregator
$c_{n,q}$	Operation cost for managing AV n at request q
p^{reward}	Reward index for providing logistic service
R^{reg}	Reward for providing daytime regulation service
p_t^{tot}	Trading price with the city power grid at time t
E_t^{tot}	Trading energy with the grid operator at time t
P_t^{tot}	Total active power of the city area at time t
P_t^{reg}	Regulation signals at time t
p^{lgt}	Reference price for logistic service
p^{ch}	Reference price for charging service
$\overline{p}$	Upper bound of reference price
$\underline{p}$	Lower bound of reference price
P_t^{load}	Base load of the aggregator at time t
δ	Ratio of selling to buying electricity price

where $\text{SOC}_n^{\star}$ is the charging requirement of AV n.

Additionally, over-charging and deep-discharging circumstances should be avoided during the charging/discharging process. Consequently, at time t, the operational limits of SOC should be

$$\underline{\text{SOC}_n} \leq \text{SOC}_{n,t} \leq \overline{\text{SOC}_n},\ \forall n \in \mathcal{N}, \tag{15}$$

where $\underline{\text{SOC}}_n$ and $\overline{\text{SOC}_n}$ denote the lower and upper SOC limits of AV n, respectively.

Without loss of generality, the following assumptions are adopted before the problem formulation:

1) During the participation time, each AV reports its travel schedules with individual charging requirement.
2) The regulation services are zero-energy services due to the zero expectation of the required energy requirement for a sufficiently long period.

For the first assumption, it is assumunly adopted in the related studies, e.g. [28] and [29]. On the other hand, given that requests for regulation services result from grid power forecast errors, the second assumption is also reasonable [38].

B. Autonomous Vehicle Model

1) AV Logistic Service: For each AV n, the utility function of providing logistic service is defined as

$$U_n^{\text{lgt}} = -\sum_{t\in\mathcal{T}}\sum_{(i,j)\in\mathcal{E}} \alpha_{ij}^n d_{ij,t} x_{ij}^n + \sum_{q\in\mathcal{Q}_n}\Big(R_{n,q}^{\text{lgt}} - p_{n,q}^{\text{lgt}}(\tau_{n,L_{n,q}^{dst}} - \underline{T_{n,q}})^2\Big), \tag{16}$$

where α_{ij}^n denotes the unit fuel consumption cost for AV n and $R_{n,q}^{\text{lgt}}$ is the base revenue for providing logistic service for AV n at request q. In addition, $p_{n,q}^{\text{lgt}}$ denotes the individual trading price for logistic service of AV n by the service time of all the AVs $\tau_j^{\mathcal{N}} = \{\tau_j^1, \tau_j^2, ..., \tau_j^N\}$. This concave utility function reflects the cost for AV traveling and the revenue for trading price for logistic service. Meanwhile, the larger difference of the third term indicates a higher cost on providing the AV logistic service.

2) AV Charging Service: Besides logistic services provided by the AVs, the dynamic wireless charging/discharging behaviors of AVs in a smart city is also considered in this paper. When the AVs travel over the road segments installed with PTs, the AVs can follow their preferences on participated dynamic wireless scheduling. For the participated AVs in dynamic wireless scheduling, the related utility function for the AVs is shown as

$$U_n^{\text{ch}} = -\sum_{t\in\mathcal{T}} p_{n,t}^{\text{ch}} P_{n,t}\Delta t + \gamma_n \ln\left(\text{SOC}_n^{\text{base}} + \text{SOC}_{n,|\mathcal{T}|}\right), \tag{17}$$

where $p_{n,t}^{\text{ch}}$ denotes the individual trading price for charging service of AV n by the charging/discharging powers of all AVs $P_{\mathcal{N},t} = \{P_{1,t}, P_{2,t}, ..., P_{N,t}\}$. The first term in (17) reflects the cost of buying electrical energy and the revenue of selling electrical energy while the second term shows the satisfaction of participating in dynamic wireless charging/discharging. For the second term, by following [20], $\text{SOC}_n^{\text{base}}$ can be denoted the base satisfaction level related to the SOC of AV n. Note that the function $\ln(\cdot)$ is monotonically increasing and strictly concave with respect to $\text{SOC}_{n,|\mathcal{T}|}$, which is the SOC level at the end of the time period. Besides, γ_n is the sensitivity index for AV satisfaction and it maps the trade-off between the satisfaction level and economical benefit of each AV. Specifically, this index maps the satisfaction of AV scheduling, which relates to its economical benefit. In this way, the different AV objectives can be denoted by a uniform utility function.

By considering both AV logistic and charging services, the overall utility function for AV model can be described as

$$U_n = U_n^{\text{lgt}} + U_n^{\text{ch}},\ \forall n \in \mathcal{N}. \tag{18}$$

C. Aggregator Model

1) Aggregator Logistic Service: Considering the provision of logistic service on the aggregator, one of its utility includes three parts, namely, the operational cost to coordinate AVs to provide city logistic services and the reward from trading with AVs. Hence, such a utility function of the aggregator can be described as

$$U_A^{\text{lgt}} = -\sum_{n\in\mathcal{N}}\sum_{q\in\mathcal{Q}} c_{n,q} + R_{\mathcal{N}}, \tag{19}$$

where $c_{n,q}$ denotes the operation cost for managing AV n at request q. $R_{\mathcal{N}}$ is defined as the reward function related to the AV trading price on providing the logistic service at each request $q \in \mathcal{Q}$. This reward function can be denoted by

$$R_{\mathcal{N}} = \frac{p^{\text{reward}}}{\sum_{n\in\mathcal{N}}\sum_{q\in\mathcal{Q}_n}\tau_{n,L_{n,q}^{\text{dst}}}}, \tag{20}$$

where p^{reward} is the reward index for providing logistic service in the city. The function $R_{\mathcal{N}}$ indicates the reward received at the aggregator when providing the logistic services by means of the fleet of AVs, which is associated with the service complete time of each logistic request q, $\tau_{n,L^{\text{dst}}_{n,q}}$.

2) Aggregator Charging Service: On the other hand, for the charging service provided by the aggregator, the related utility function comprises three main components, including the cost/revenue from trading with the participated AVs, the cost/revenue from buying/selling energy from/to the city smart grid system, and the revenue on providing the V2G regulation service. Hence, we describe this utility function of the aggregator as

$$\begin{aligned} U_A^{\text{ch}} = &- \sum_{t\in\mathcal{T}} p_t^{\text{tot}} E_t^{\text{tot}} + \sum_{n\in\mathcal{N},t\in\mathcal{T}} p_{n,t}^{\text{ch}} P_{n,t}\Delta t \\ &- \Big(R^{\text{reg}} - \xi \sum_{t\in\mathcal{T}} (P_t^{\text{tot}})^2\Big), \end{aligned} \tag{21}$$

where p_t^{tot} denotes the trading price with the city power grid and $E_t^{\text{tot}} = \sum_{n\in\mathcal{N}} P_{n,t}\Delta t$ is the trading energy with the grid operator. Moreover, $\xi \in (0, 1]$ is the penalty factor to assess the performance of the regulation services in consideration of the battery degradation issue, while R^{reg} is the base reward for providing these services in the city area. The first term presents the cost/revenue from buying/selling energy from/to the system operator, while the second term indicates the revenue from trading with the participated AVs. Then, the total active power profile of the city smart grid, $P_{\mathcal{T}}^{\text{tot}}$, is calculated by

$$\sum_{t\in\mathcal{T}} P_t^{\text{tot}} = \sum_{t\in\mathcal{T}} \Big(P_t^{\text{reg}} + \sum_{n\in\mathcal{N}} P_{n,t}\Big), \tag{22}$$

where $P_{n,t}$ and P_t^{reg} denote the power profile of AV n and the regulation signals from the energy market at time t, respectively.

By considering both AV logistic and charging services, the overall utility function for the aggregator in the system is given by

$$U_A = U_A^{\text{lgt}} + U_A^{\text{ch}}. \tag{23}$$

Besides, the aggregator aims to maximize its own utility function by choosing the appropriate fixed prices $p^{\text{lgt}}, p^{\text{ch}}$ for providing logistic and charging services, respectively. The operating conditions is defined as

$$\underline{p} \le [p^{\text{lgt}}, p^{\text{ch}}] \le \overline{p}, \tag{24}$$

where $\underline{p}$ and $\overline{p}$ are the lower and upper bounds of the reference price, respectively.

3) AV Trading Price Model: The AV trading price model includes two main parts, namely, logistic and charging trading prices. The trading price for AV logistic service is defined as

$$p_{n,q}^{\text{lgt}} = p^{\text{lgt}} \left(\frac{\tau_{n,L^{\text{dst}}_{n,q}}}{\overline{T}_{n,q}}\right). \tag{25}$$

The proposed trading pricing model for the AV logistic services in (25) is the charging variable price indicator, which denotes the service quality in the AV logistic system. Specifically, it is represented by the ratio of the delivery completion time of each request $q \in \mathcal{Q}_n$ to the maximum allowable service deadline for each AV. This pricing model can drive the AVs to complete delivery service sooner such that they pay the relatively low service fee at each logistic request. Thus, the AVs can be motivated to provide efficient and quick logistic services in a smart city.

Besides the AV logistic trading price model, the AV electricity price model upon the same time period is further implemented. The trading price model for AV charging service is denoted as

$$\begin{aligned} p_{n,t}^{\text{ch}} &= p^{\text{ch}} \zeta(P_{n,t}) \Big(P_t^{\text{load}} + P_t^{\text{reg}} + \sum_{k\in\mathcal{N}} P_{k,t}\Big) \\ &= p^{\text{ch}} \zeta(P_{n,t}) \Big(P_t^{\text{load}} + P_t^{\text{reg}} + P_{n,t} \\ &\quad + \sum_{k\in\mathcal{N}\setminus\{n\}} P_{k,t}\Big), \end{aligned} \tag{26}$$

where $P_t^{\text{load}} \ge 0$ denotes the base load of the aggregator at time t. In addition, this model represents the equivalent total load when the V2G technique is implemented. To differentiate the buying/selling price, we define $\zeta(P_{n,t})$ as follows:

$$\zeta(P_{n,t}) = \begin{cases} 1 & \text{if } P_{n,t} \ge 0, \\ \delta & \text{if } P_{n,t} < 0, \end{cases} \tag{27}$$

where δ is the ratio of the selling price to the buying price on AV charging service.

This proposed AV electricity price model takes the equivalent load P_t^{load} as a price indicator, which follows [20]. Based on (26), it can motivate AVs to provide the regulation services during the participation period. When $P_t^{\text{reg}} > 0$, AVs are motivated to perform discharging mechanisms when the smart grid requires the regulation up operation. The reason is that higher selling price gives incentives for AVs to sell electricity back to the smart grid. Similarly, when $P_t^{\text{reg}} < 0$, AVs are motivated to charge more since the buying prices becomes lower. Thus, without any control from the system, AVs can autonomously provide the V2G regulation services to stabilize the grid by reacting to the trading prices.

V. Non-Cooperative Incentive Game Approach

In this section, we investigate the incentive mechanism for the non-cooperative system, in which all the players in the system, such as AVs and the aggregator, are selfish, and the objectives are both to maximize their individual utilities. Here, we formulate the interaction between the aggregator and as a Stackelberg game [39] over the participation time period $\mathcal{T}$. Moreover, we prove the existence and uniqueness of the Nash equilibrium of this game shown in the following.

A. Nash Equilibrium for AV Problems

For the formulated AV problems, given the strategies and trading prices of other AVs, the aim is to determine the logistic and charging service schedule that maximize its own utility function, which is denoted as

$$\begin{aligned} \mathbf{P1}: \quad & \text{maximize} \quad U_n & \text{(28a)} \\ & \text{subject to} \quad [x^n_{L_n^{\text{src}} L_n^{\text{dst}}}, \tau^n_{L_n^{\text{dst}}}, P_{n,\mathcal{T}}] \in \mathcal{Z}_n, & \text{(28b)} \end{aligned}$$

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where $x^n_{L_n^{\rm src}L_n^{\rm dst}}$ refers to the binary variable defined in (1) over the routing plan $(L_n^{\rm src}, L_n^{\rm dst})$ and $\tau^n_{L_n^{\rm dst}}$ is the time when AV n arrives at node $L_n^{\rm dst}$. The feasible strategy set of AV n for the non-cooperative game is defined as $\mathcal{Z}_n$, which includes all the feasible sequence of AV traverse trajectory $x^n_{L_n^{\rm src}L_n^{\rm dst}}$, node arrival time $\tau^n_{L_n^{\rm dst}}$, and charging/discharging powers $P_{n,\mathcal{T}}$. Then, the strategy set for this game can also be shown as

$$\mathcal{Z}_n = \{x^n_{L_n^{\rm src}L_n^{\rm dst}}, \tau^n_{L_n^{\rm dst}}, P_{n,\mathcal{T}} \text{ subject to } (2)-(7), (9), (10), (12), (14), \text{and } (15)\}. \tag{29}$$

The game $\mathcal{W}(\mathcal{Z}, \mathcal{F})$ is the set of coupled optimization problem **P1** of all the AVs. It includes the strategy set $\mathcal{Z} \triangleq \prod_{n=1}^N \mathcal{Z}_n$ and the related payoff function that is denoted as $\mathcal{F}(\mathcal{N}) = \sum_{n\in\mathcal{N}}(U_n)$, which is also defined as the Nash equilibrium problem with the set of feasible solution [40]. Basically, a Nash equilibrium solution is a feasible value of $\mathcal{Z}_n^*$ under the condition that no AV may unilaterally deviate and obtain more benefit if the other AVs' strategies do not change. In the meantime, the best response of AV n refers to the strategy of AV n at the Nash equilibrium.

B. Pricing Game for Aggregator

Since the best responses of all the AVs on the joint services are obtained via the previous process, the aggregator thereby minimizes its utility by selecting the proper trading reference prices $p^{\rm lgt}$ and $p^{\rm ch}$. Then, we can formulate the pricing game optimization problem as

$$\mathbf{P2}: \quad \text{maximize} \quad U_A \tag{30a}$$
$$\text{subject to} \quad (25). \tag{30b}$$

C. Existence and Uniqueness of Nash Equilibrium

In this part, we utilize the variational inequality theory to demonstrate the existence and distinctiveness of the Nash equilibrium for the proposed non-cooperative game. The existence and uniqueness of the Nash equilibrium may not be guaranteed due to the intricacy of the formulated game. Hence, we impose the following assumptions:

Assumption 1: $\delta = 1$ in **P1**.

Assumption 2: $\eta^{\rm ch}, \eta^{\rm dch} \geq 0.95$ in (11).

These two assumptions are based on the provision of AV charging services in practical systems. Assumption 1 means that the electricity purchasing price from the aggregator to AVs is equal to the selling price from AVs to the aggregator. For the non-profit local trading center that ensures the satisfaction of the optimal social welfare of energy buyers and sellers, it is essential that the electricity purchasing price is set as the same value as the selling price. In addition, the effect is further discussed if these prices are not equal. For the logistic scheme, if the logistic purchasing price is higher than the selling price, the AVs prefer to execute fewer service requests. When the logistic purchasing price is less than the selling price, more economical profits can be earned from the participated AVs. Besides, AVs can always earn profits through energy arbitrage in the V2G system if the selling electricity price is higher than the buying price, which not a ideal circumstance in the energy market. On the other hand, AVs will lose their incentives to sell any reserved electricity back to the power grid if the selling electricity price is lower than the buying price. In this case, they fail to provide the regulation services. Therefore, according to the validation in [20], it is feasible to assume that the buying price equals the selling price. Besides, Assumption 2 refers to the energy efficiency of Lithium-ion battery that achieves over 95%, which follows [41].

Then, some lemmas based on the variational inequality theory are utilized to facilitate the proof in the game theory shown in the followings:

Lemma 1: Given the formulated game in **P1**, for each AV n, we have:

1) The strategy set of $\mathcal{Z}_n$ is convex and close.
2) The utility function is convex and differentiable in any variables of the set $\mathcal{Z}_n$.

Then, we transform the game $\mathcal{W}(\mathcal{Z}, \mathcal{F})$ to $\mathbf{VI}(\mathcal{Z}, \mathbf{f})$, where $\mathbf{f} = (\bigtriangledown U_n)_{n=1}^N$ and $\bigtriangledown(\cdot)$ denotes the gradient operator in calculus. Suppose that the set $\mathcal{Z}$ is compact (closed and bounded) and convex, and the function $\mathbf{f}$ is continuous. The set of solutions is then nonempty and compact. Therefore, given $\mathbf{VI}(\mathcal{Z}, \mathbf{f})$ admits a singular solution if $\mathbf{f}$ is strongly monotone on $\mathcal{Z}$. The existence and uniqueness of the Nash equilibrium are demonstrated by the subsequent theorem.

Theorem 1: For any combination $[p^{\rm lgt}, p^{\rm ch}]$ chosen by the aggregator, the existence of a Nash equilibrium of the formulated game $\mathcal{W}(\mathcal{Z}, \mathcal{F})$ is guaranteed.

Proof: The strategy set of the game is defined by the set of constraints (2)−(7), (9), (10), (12), (14), and (15). By the definitions in [42], the feasible set defined by (2) and (3) is convex. Then, it is also clear that the feasible solution set spanned by (4), (6), (7), (9), (10), and (12) is clearly convex. Through linear transformation, constraint (5) can be converted to (8), which is also convex. As for (14), and (15), they are proved to be convex by following the proof of Lemma 2 in [28]. Therefore, the feasible region defined by the strategy set of the game, known as the intersection of the above convex sets, is convex.

Besides, the utility function includes two parts, namely, $U_n^{\rm lgt}$ and $U_n^{\rm ch}$, respectively. For function $U_n^{\rm lgt}$, by taking the second derivative of $U_n^{\rm lgt}$ with respect to $\tau^n_{L_n^{\rm dst}}$, it can be proven that the utility function $U_n^{\rm lgt}$ is convex. Similarly, by taking the second derivative of $U_n^{\rm ch}$ with respect to $P_{n,\mathcal{T}}$, one can verify that $U_n^{\rm ch}$ is convex. Therefore, the positive sum of these two convex functions is convex, which further indicates that the utility function (18) is convex. Considering Lemma 1, we can conclude that there exist at least one solution for the game. ■

Theorem 2: For any trading price combination $[p^{\rm lgt}, p^{\rm ch}]$ given by the aggregator, the uniqueness of a Nash equilibrium of the formulated game $\mathcal{W}(\mathcal{Z}, \mathcal{F})$ is guaranteed.

Proof: The utility function U_n includes two parts, namely, $U_n^{\rm lgt}$ and $U_n^{\rm ch}$. The Hessian matrix is obtained by taking the second derivative of the convex utility function (18). The idea of mathematical induction makes it simple to demonstrate that all of the leading principal minors in the Hessian matrix are negative. The Hessian matrix is hence negative definite. Therefore, the Hessian matrix is negative definite. Then, based on the theory in [42], this function is monotone on $\mathcal{Z}$. Given $\mathcal{W}(\mathcal{Z},\mathcal{F})$, if $\mathcal{F}$ is strongly monotone on $\mathcal{Z}$, $\mathcal{W}(\mathcal{Z},\mathcal{F})$ then ensures a unique solution. Since $\mathcal{W}(\mathcal{Z},\mathcal{F})$ is equivalent to $\mathbf{VI}(\mathcal{Z},\mathbf{f})$, the uniqueness of the Nash equilibrium for the game $\mathcal{W}(\mathcal{Z},\mathcal{F})$ is also ensured. In conclusion, the uniqueness of the Nash equilibrium for the game $\mathcal{W}(\mathcal{Z},\mathcal{F})$ is guaranteed. ■

Accordingly, by solving the strongly monotone utility function, the uniqueness of the Nash equilibrium for the game $\mathcal{W}(\mathcal{Z},\mathcal{F})$ can be presented. The equilibrium of the Stackelberg game is then demonstrated when the aggregator sets the optimal prices based on the best responses of AVs.

D. Algorithm for Non-Cooperative Strategy

Based on the existence and uniqueness of Nash equilibrium, we devise an algorithm to effectively find the solution of the Nash equilibrium problem for AVs and the aggregator.

Algorithm 1 presents the devised non-cooperative best response-based AV algorithm. Initially, it requires the selection of feasible starting points $\mathcal{Z}_n^0$. Then, each AV addresses its own problem by solving **P1** with the parameters of the logistic and charging services in a distributed manner. By solving **P1** in each iteration, we utilize the branch-and-bound approximation to compute the optimal solutions. Note that if there exists a unique Nash equilibrium, the branch-and-bound approximation [43] is guaranteed to converge to the Nash equilibrium. Here, the iteration number is set as m, which M is capped at the maximal allowable iteration number. Moreover, the convergence tolerance, which is defined as ϵ, follows the rule $|\mathcal{Z}_n^m - \mathcal{Z}_n^{m-1}| \leq \epsilon_f$. Furthermore, the computation complexity of this algorithm depends on the number of time slots $|\mathcal{T}|$ and number of nodes $|\mathcal{V}|$. The time complexity of Algorithm 1 is $\mathcal{O}(|\mathcal{V}|^2 + |\mathcal{T}|^{3.5})$ in each iteration, which only depends on the number of nodes in the traffic network and the number of timeslots $|\mathcal{T}|$ since this problem is solved in a distributed manner. Last but not least, since this problem is solved with the three variables $x^n_{L_n^{\text{src}}L_n^{\text{dst}}}$, $\tau^n_{L_n^{\text{dst}}}$, and $P_{n,\mathcal{T}}$ in each iteration, the information privacy of each user can be preserved since the data is related to the AV mobility patterns. The related data includes the service time of each AV, the routing plan of each AV, and the SOC of the AV's battery. During this process, this user privacy information do not need to be reported in advance to the AV aggregator.

Algorithm 1 Non-Cooperative Best Response-Based AV Algorithm

1: Select any feasible starting points $\mathcal{Z}_n^0$ for AV n and initialize the iteration index m.
2: **for** m = 1: M **do**
3:   Compute the optimal solutions $\mathcal{Z}_n^m$ based on **P1**.
4:   **if** the stopping criterion is met **then**
5:     Return the optimal solutions as $\mathcal{Z}_n^*$.
6:   **else**
7:     Set $m \leftarrow m$ + 1
8:     Return to Step 3 for next iteration.
9:   **end if**
10: **end for**

VI. Cooperative Incentive Game Approach

Considering the competition among AVs and the selfishness of AVs and the aggregator, the non-cooperative approach incurs more losses for the utilities of both the AVs and the aggregator. In this section, we study a cooperative approach in the system, in which all the players prefer to cooperate in order to maximize the system social welfare. Hence, a potential game method is developed in a distributed manner.

A. Problem Formulations

For a cooperative system, the social welfare maximization problem for the system is formulated as the sum of the utility of the aggregator and the utilities of all the AVs. Then, the utility function for the cooperative game of the system is described as

$$\begin{aligned}\Psi =& \sum_{n\in\mathcal{N}} U_n + U_A \\ =& -\sum_{n\in\mathcal{N}}\Bigg(\sum_{t\in\mathcal{T}}\sum_{(i,j)\in\mathcal{E}}\alpha_{ij}^n d_{ij,t} x_{ij}^n + \sum_{q\in\mathcal{Q}_n}\Big(R_{n,q}^{\text{lgt}} \\ & - p_{n,q}^{\text{lgt}}(\tau_{n,L_{n,q}^{dst}} - \underline{T_{n,q}})^2\Big) + \gamma_n \ln\Big(\text{SOC}_n^{\text{base}} \\ & + \text{SOC}_{n,|\mathcal{T}|}\Big)\Bigg) - \sum_{n\in\mathcal{N}}\sum_{q\in\mathcal{Q}} c_{n,q} + R_{\mathcal{N}} \\ & - \sum_{t\in\mathcal{T}} p_t^{\text{tot}} E_t^{\text{tot}} - \Bigg(R^{\text{reg}} - \xi\sum_{t\in\mathcal{T}}\Big(P_t^{\text{tot}}\Big)^2\Bigg). \end{aligned} \quad (31)$$

By (31), we can thus formulate the social welfare maximization problem as

$$\begin{aligned}\mathbf{P3}: \quad & \text{maximize} \quad \Psi & (32a)\\ & \text{subject to} \quad (2)-(7), (9), (10), (12), (14), \text{and } (15). & (32b)\end{aligned}$$

Here, we define the feasible strategy set of **P3** as $\mathcal{H}_n = \{x^n_{L_n^{\text{src}}L_n^{\text{dst}}}, \tau^n_{L_n^{\text{dst}}}, P_{n,\mathcal{T}}$ satisfying all the constraints$\}$. According to game theory, a potential game refers to the reflection of a single global function whether there are any incentives of all the players to alter their strategies or not. Based on this concept, we denote Ψ as the potential function. When AV n changes from the strategy action $\mathcal{H}_n^1$ to $\mathcal{H}_n^2$, the difference in the potential function Ψ equals the difference of the utility function of this player. For this game, the optimal action of the potential function refers to the Nash equilibrium and such action further indicates that the optimal social welfare can be achieved. Thus, in a cooperative system, the utility function of AV is described as

$$\begin{aligned}\Phi_n =& -\sum_{t\in\mathcal{T}}\sum_{(i,j)\in\mathcal{E}}\alpha_{ij}^n d_{ij,t} x_{ij}^n + \sum_{q\in\mathcal{Q}_n}(R_{n,q}^{\text{lgt}} \\ & - p_{n,q}^{\text{lgt}}(\tau_{n,L_{n,q}^{dst}} - \underline{T_{n,q}})^2) + \gamma_n \ln(\text{SOC}_n^{\text{base}} \\ & + \text{SOC}_{n,|\mathcal{T}|}) - \sum_{q\in\mathcal{Q}} c_{n,q} + \frac{p^{\text{reward}}}{\sum_{q\in\mathcal{Q}_n}\tau_{n,L_{n,q}^{dst}}} \\ & - \sum_{t\in\mathcal{T}} p_t^{\text{tot}} E_t^{\text{tot}} - \Bigg(R^{\text{reg}} - \xi\sum_{t\in\mathcal{T}}\Big(\overline{P}_t^{\text{tot}}\Big)^2\Bigg), \end{aligned} \quad (33)$$

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where the first four terms are related to the cost and revenue of providing the AV logistic services, while the other terms correspond to the cost and revenue of providing regulation services for UIS. In addition, the trading price for AV logistic services is denoted as $p^{\text{lgt}}_{n,q}$, which refers to (25). Besides, according to the price model formulated in [20], the electricity trading price between the system and the aggregator can be set as $\overline{P}^{\text{tot}}_t$. Therefore, it can be denoted as

$$\overline{P}^{\text{tot}}_t = p_{\text{G}}\zeta(P_{\text{G},t})\Big(\overline{P}^{\text{load}}_t + P^{\text{reg}}_t + \sum_{k\in\mathcal{N}} P_{k,t}\Big), \tag{34}$$

where p_{G} denotes the fixed price set by the energy market and $\overline{P}^{\text{load}}_t$ denotes the base load of the smart grid at time t, which is related to the load demand without the incorporation of V2G. In addition, $\zeta(P_{\text{G},t})$, which is defined as the buying/selling prices function, is calculated in the similar way shown in (27). Note that in (34), it can be proved that the sum of charging costs from all the AVs is no less than the total cost that the aggregator pays to the grid such that the AV aggregator can always earn profits.

Based on the structure of a potential game, the utility function in (33) combines costs and revenues from both AVs and the aggregator. Note that the actual AV utility function refers to the sum of the first, the second, and the fifth terms. The rest of the terms are used to facilitate achieving optimal system social welfare. Hence, in a cooperative system, (33) can be viewed as a reinforced AV utility function.

The cooperative game is formulated as $\mathcal{J}(\mathcal{H},\mathcal{K})$, which comprises the strategy set $\mathcal{H} \triangleq \prod_{n=1}^{N}\mathcal{H}_n$ and the payoff function $\mathcal{K} = \sum_{n\in\mathcal{N}}\Phi_n$. Given the utility function, Φ_n is an exact potential game since the following constraint holds:

$$\begin{aligned}\Psi(\mathcal{H}^1_n,\mathcal{H}_{-n}) &- \Psi(\mathcal{H}^2_n,\mathcal{H}_{-n})\\ &= \Phi_n(\mathcal{H}^1_n,\mathcal{H}_{-n}) - \Phi_n(\mathcal{H}^2_n,\mathcal{H}_{-n}),\end{aligned} \tag{35}$$

where $\mathcal{H}_{-n}$ denotes the strategy set of other AVs except for AV n. The social welfare function in the cooperative system can, in a single potential function, capture the incentive of AVs to alter their strategies. Then, the solution of the formulated problem can be obtained by collectively solving the following problem, shown as:

$$\textbf{P4}: \quad \text{maximize} \quad \Phi_n \tag{36a}$$

$$\text{subject to} \quad [x^n_{L_n^{\text{src}}L_n^{\text{dst}}}, \tau^n_{L_n^{\text{dst}}}, P_{n,\mathcal{T}}] \in \mathcal{H}_n. \tag{36b}$$

B. Existence and Uniqueness of Nash Equilibrium

The existence and uniqueness of the Nash equilibrium for the proposed cooperative game are presented in this section. Based on the assumptions mentioned in the previous section, the theorem and proof for the cooperative system are provided in the following.

Theorem 3: Based on Assumptions 1 and 2, the existence and uniqueness of the Nash equilibrium of the game $\mathcal{J}(\mathcal{H},\mathcal{K})$ are guaranteed.

Proof: For the potential game $\mathcal{J}(\mathcal{H},\mathcal{K})$, the potential function, known as the social welfare function of the system, is defined in (31). There should be at least one Nash equilibrium in the potential game based on its properties. By exploring the property of **P3**, the uniqueness of the Nash equilibrium is guaranteed. Besides, for (31), by taking the second derivative of this function with respect to the variables, this function is shown to be strictly concave. In addition, given that Assumptions 1 and 2 hold, the feasible set $\mathcal{H}$ is convex, which follows the proof of Theorem 1. Hence, the optimal unique solution for **P3** is obtained. Since **P3** and $\mathcal{J}(\mathcal{H},\mathcal{K})$ both share the exact same solution. Thus, it is ensured that $\mathcal{J}(\mathcal{H},\mathcal{K})$ admits the uniqueness of the Nash equilibrium. ■

C. Algorithm for Cooperative Strategy

The objective of the potential game is to determine how the achieved utility is fairly distributed among the participated AVs. The main purpose is to determine the stability of the coalition and establish how different disjoint coalitions of AVs can achieve the objective and how the achieved utility is fairly distributed among the members of each coalition. Hence, we devise a related algorithm for the cooperative game approach to present the entire process. Based on the existence and uniqueness of Nash equilibrium, the related algorithm is devised for AVs and the aggregator to find the Nash equilibrium in an effective manner.

Algorithm 2 presents the devised cooperative best response-based AV algorithm. Initially, it requires the selection of feasible starting points in the set $\mathcal{H}^0_n \in \mathcal{H}_{\mathcal{N}}$. Then, each AV fairly addresses its own problem by solving **P4** with the parameters of logistic and charging services in each iteration. Based on the utilization of the branch-and-bound approximation on solving **P4** in each iteration, the existence and uniqueness of the Nash equilibrium point are ensured. After that, the stopping criterion of this algorithm is checked. If the solutions satisfy the stopping criterion, the solutions are updated as the final optimal solutions. Last but not least, the time complexity of Algorithm 2 is $\mathcal{O}(|\mathcal{V}|^2+|\mathcal{T}|^{3.5})$ in each iteration, which is only depends on the number of nodes in the traffic network and the number of timeslots $|\mathcal{T}|$ since this problem is solved in a distributed manner. For the security and privacy concerns of this devised algorithm, the privacy information of each user can indeed be preserved and they do not required to be reported in advance to the AV aggregator.

Algorithm 2 Cooperative Best Response-Based AV Algorithm

```
1:  Select any feasible starting points H^0_N for AV n and
    initialize the iteration index m.
2:  for m = 1: M do
3:     Compute the optimal solutions H^m_N based on P4.
4:     Broadcast the solutions to other AVs.
5:     Set m ← m + 1
6:     if the stopping criterion is met then
7:        Update the optimal solutions as H^*_N.
8:     else
9:        Return to Step 3 for another iteration.
10:    end if
11: end for
```

VII. Case Studies

In this section, we evaluate the effectiveness of the proposed game theoretic methods. After describing our setup for the experiment, we evaluate the proposed approaches' quality of logistic and regulation services within real-world traffic networks. Then, we study the effects of various AV fleet sizes on our evaluation metrics. After that, we examine the convergence of the two game theoretic approaches. Finally, we investigate the social welfare of the entire system.

A. Simulation Setup

We evaluate the performance of the proposed UIS in real-world transportation systems. In particular, we conduct the simulations in Garden City, Alabama, where the related traffic map is gained from a public source[1]. This urban area comprises a total of 106 nodes and 268 edges with different lengths of road segments. Based on the OpenStreepMap data [44], we construct a road network of the area. In particular, all the primary, secondary, tertiary, and residential roads/paths are extracted to construct a graph as depicted in Fig. 3. The maximum and minimum edge lengths are 939.51 meters and 4.25 meters, respectively. In addition, we set the system operational period from 9:00 a.m. to 3:00 p.m. to capture the daily AV mobility patterns, which can be divided into $|\mathcal{T}|= 180$ slots with $\Delta t = 2$ minutes.

Our parameter settings for the AV logistic and regulation services are presented below. We first set the deadline for approaching the final destination of the parcel service equal to the system operational period. Then, the service time for loading and unloading parcels follows U[5, 30] minutes and each service request deadline varies between 60 to 180 minutes, where U[·] is the uniform distribution operator. Based on [45], we set the β^n and transport costs α_{ij}^n to $83.68 per hour and $1.73 per mile, respectively. The final destination of the parcel delivery of every service request is randomly chosen and it is different from the departures. Meanwhile, the priority of requests is linked with the related deadlines. Each AV executes multiple travel schedules due to various service requests and we set the rest time between two consecutive service plans to 2 minutes. Besides, the operation cost for managing AV $c_{n,q}$ is set to $20.79 [46]. On the other hand, for the regulation services, we exploit the regulation signal data on September 1, 2017 [47], which considers a random forecast error $e(t) \sim N(0, 0.3)$ during the investigated time period. By following the PJM market standard [48], the base regulation reward is set to $40 per MWh and the regulation capacity of the Garden City is set to 300 kW.

The settings for AVs are presented in the following. There are two types of electric AV groups with $|\mathcal{N}|= 50$, e.g. BMW i3 with 42 kWh [49] and Tesla Model X with 100 kWh [50]. We assume that each AV travels with a fixed velocity of 40 kilometers per hour. In the meantime, the unit energy consumption λ^n of each AV is set to 1.112 kWh per kilometers. In this work, we assume that these two groups of AVs solely participate in dynamic wireless charging/discharging so as to investigate the ideal system performance. The dynamic wireless charging systems follow the charging standard SAE J2954 with the WPT Power Class 1 and 2 [51]. Then, the discharging and charging power limits are set to -7 kW and 7 kW, respectively. Moreover, the efficiency for charging/discharging is set to 0.9. Besides, we model the SOC settings of AVs based on the uniform distribution, which can be denoted as U[·] [28]. Specifically, we set the initial SOC of AV n as U[30%, 40%], while the charging requirement is set to follow U[0%, 20%]. The charging/discharging mechanism's safety condition is taken into account when the minimum and maximum SOCs are U[10%, 20%] and U[90%, 99%], respectively. Last but not least, the charge price is set to $0.59 per kWh, which is in line with Manhattan's current price, and the average grid electricity price p_{G} is set to 0.01.

[1]https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/CUWWYJ

B. Performance Metrics

We consider the variance of the selected urban area's total active power profile P^{tot} to be one crucial performance metric, which is calculated by

$$\mathrm{Var}(P^{\mathrm{tot}}_{\mathcal{T}}) = \frac{1}{|\mathcal{T}|}\sum_{t\in\mathcal{T}}\left((P^{\mathrm{tot}}_t - \frac{1}{|\mathcal{T}|}(\sum_{t\in\mathcal{T}}(P^{\mathrm{tot}}_t)\right)^2. \tag{37}$$

A lower variance value indicates improved daytime V2G regulation service, which also demonstrates flatness of the active power profiles of the city smart grid.

C. Scenarios for Comparison

We consider four different typical scenarios to evaluate the effectiveness of the proposed system model in the following:

1) S1: Proposed non-cooperative approach.
2) S2: Proposed cooperative approach.
3) S3: System optimization approach in providing logistic services [37].
4) S4: System optimization approach in providing regulation services [31].

The non-cooperative approach formulated in Section V is denoted by S1. In S1, we consecutively execute $|\mathcal{T}|$ time slots through the non-cooperative best response-based algorithm and then obtain the average value as the final solutions. S2 presents the proposed cooperative game theoretic approach formulated in Section VI. We also obtain the average values by consecutively running $|\mathcal{T}|$ time slots through the cooperative best response-based algorithm. Note that S1 and S2 consider both the provision of logistic and regulation services in the city area. Other than the previous two scenarios, S3 solely considers the provision of logistics services in the city area. Specifically, it solves the joint routing and charging problem by means of mixed-integer linear programming in a distributed manner. Furthermore, S4 unilaterally considers regulation services provided by AVs. For this framework, we deploy the optimal dynamic V2G wireless charging/discharging framework with the implementation of Dijkstra's algorithm [52]. The utilization of Dijkstra's algorithm aims to investigate the shortest distance of every AV routing plan.

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(a) (b)

Fig. 3. The downtown map and road network of Garden City. (a) Garden City downtown map. (b) Garden City downtown road network.

D. Effectiveness of Proposed Mechanisms in Logistic Services

In this part, we mainly study the practicality of the proposed games on the real-world traffic network of Garden City. The directed graph is obtained through the related dataset reflected in Fig 3b. Then, we simulate the above four scenarios to measure the efficacy of the AV logistic service.

Based on the settings in Section VII-A, we first study the AV utility and average computation time of the two proposed games in comparison to the other two baseline approaches. Table IV shows that both S1 and S2 obtain higher AV utility, which efficiently motivates the AVs to participate in providing AV logistic services. Since S3 only provides AV logistic services in the city, the AV utility is lower than that of the other three techniques. Therefore, it is apparent that both S1 and S2 can achieve the provisioning of AV logistic and regulation services through effective motivations. The reason is that the proposed path planning scheme can achieve a lower joint service time and the power consumption of the AVs shown in Table IV such that both S1 and S2 can contribute to relatively higher AV utilities. Besides, we can observe that the computation times of S1 and S2 are relatively high when compared with S3 and S4. The reason is that both S1 and S2 consider the joint provision of AV logistic and charging services, which further increases the computational complexity of the problems with more operational constraints.

Next, we investigate the benefits of multiple logistic requests. Specifically, during the operational time period, we evaluate four cases with 1, 2, 3, and 4 logistic service requests, respectively. According to Tables V, it indicates lower AV utility in S1 with the increased number of service requests since AV needs to pay more for providing the logistic services. Then, for S2, the AV utility becomes higher when increasing the number of service requests. This result also indicates that the more requests arranged by the system, the better contribution on the provision of both logistic and regulation services in the city can be obtained. Regarding average computation time, we can observe that the values of S1 and S2 are close to those of S3 and S4. This is due to the fact that the solution space does not change as a result of an increase in service requests, which do not affect the number of problems created. Therefore, these results show the effectiveness of the proposed games in providing AV logistic services.

TABLE IV
COMPARISON OF DIFFERENT SCENARIOS IN LOGISTIC SERVICES.

Scenarios	S1	S2	S3	S4
Average AV Utility (US$)	487.81	522.52	106.82	448.82
Mean computation time (min)	28.80	24.58	4.88	9.44

TABLE V
PROPOSED GAMES IN DIFFERENT NUMBER OF LOGISTIC REQUESTS WITH 50 AVS.

Number of logistic requests	1	2	3	4
S1:				
Average AV Utility (US$)	487.81	478.52	469.25	456.90
Mean computation time (min)	11.40	14.65	13.90	15.32
S2:				
Average AV Utility (US$)	522.52	547.85	573.03	598.55
Mean computation time (min)	28.80	24.67	24.88	22.13

E. Effectiveness of Proposed Mechanisms in Regulation Services

The effectiveness of the proposed game theoretical approaches is evaluated based on the quality of the daytime V2G regulation service provided in the city. It is reflected by the variance of the total active power profile of the city smart grid. We assume that the PTs are installed over all the road segments in the city. The result is shown in Fig. 4. In this figure, we can observe that both S1 and S2 can effectively smooth out the active power fluctuations during the complete time period. S2 achieves a better performance than S1 because S1 incurs more losses for the utilities of both the AVs and the aggregator. For S3, since it only considers the logistic service providing, the neglect of AV charging services cannot influence the active

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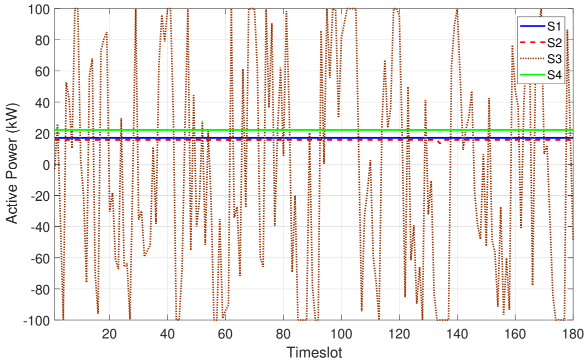

Fig. 4. Comparison of different scenarios in regulation services.

TABLE VI
PERFORMANCE OF REGULATION SERVICES UNDER DIFFERENT SCENARIOS.

Scenarios	S1	S2
$\mathrm{Var}(P^{\mathrm{tot}}(\mathcal{T}))$ (k^2W^2)	3.50×10^{-2}	8.90×10^{-3}
$\mathrm{Var}(f^{\mathrm{tot}}(\mathcal{T}))$ (Hz)	6.92×10^{-8}	2.18×10^{-8}
Scenarios	S3	S4
$\mathrm{Var}(P^{\mathrm{tot}}(\mathcal{T}))$ (k^2W^2)	8.20×10^{-3}	4.93×10^{3}
$\mathrm{Var}(f^{\mathrm{tot}}(\mathcal{T}))$ (Hz)	1.07×10^{2}	5.34×10^{-14}

power profile of the city power grid. Besides, S4 can achieve a better performance in flattening the power fluctuations, since the objective of this approach mainly focuses on the quality of the provision of AV charging services. Additionally, Table VI presents a similar result, demonstrating that S1 and S2 both have relatively low variance values, resulting in greater performance in providing the daytime V2G regulatory service.

Furthermore, we investigate the impact of different scenarios on the grid frequency. We denote f^{tot} as the grid frequency of the city area. Table VI presents the effects of the grid frequency under various approaches. Note that the grid operates at a standard frequency of 50 Hz and the stable region of this system is within the $[49.5, 50.5]$ Hz range, which presents a tolerance bound at 1% based on its operational requirements. Table VI shows that S1, S2, and S4 can all satisfy the stability requirements of the city power grid, while S3 cannot keep the grid stable due to large volatility in frequency deviations. Thus, our proposed non-cooperative and cooperative games can both ensure the grid stability in UIS.

F. Sensitivity Analysis Under Irresponsive AVs

From the previous discussion, all of the AVs are assumed to be responsive to maximize their own utilities in the game. However, in practice, there may exist irresponsive AVs that do not desire to alter their individual strategies so as to maximize their own utilities. For example, for the non-cooperative game, several AVs may perform deterministic delivery and charging strategies rather than operating in response to time-varying prices. In this case, these AVs can be regarded as "noisy players" in the game who may worsen the performance of both logistic and regulation services. In this part, we investigate the sensitivity analysis taking into account irresponsive AVs in the non-cooperative game, which is reflected by the service

TABLE VII
SENSITIVITY ANALYSIS UNDER IRRESPONSIVE AVS IN NON-COOPERATIVE GAME.

Proportion of irresponsive AVs	20%	40%	60%
$\mathrm{Var}(P^{\mathrm{tot}}(\mathcal{T}))$ (k^2W^2)	9.17	56.12	615.03
Mean unit cost per AV (US$)	460	474	493
Proportion of irresponsive AVs	80%	100%	
$\mathrm{Var}(P^{\mathrm{tot}}(\mathcal{T}))$ (k^2W^2)	1.82×10^{3}	5.16×10^{3}	
Mean unit cost per AV (US$)	512	532	

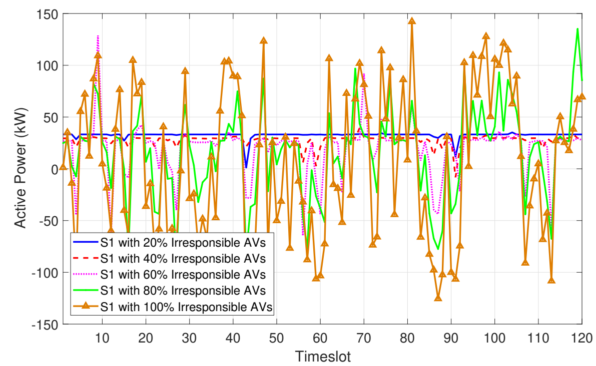

Fig. 5. Performance of regulation services under different proportion of irresponsive AVs in non-cooperative game.

quality with different portion of irresponsive AVs. Here, we assume that all the irresponsive AVs perform constant charging powers and operate in a fixed delivery time. Specifically, for the delivery time, we set $t^n_{L_n^{\mathrm{dst}}} = \overline{T_{n,q}}$, while we set $P_n(t)$ to a fixed value of AV n based on its charging requirement during the total time period. The result of the profile of active power is shown in Fig. 5. It is obvious that S1 with less irresponsible AVs can achieve the most flatten active power profile while S1 with full irresponsible AVs performs the worst. In addition, the variance of each profile in Fig. 5 is presented in Table VIII. This result also indicates that the variance is the smallest when 20% AVs in the system are irresponsive, which further indicates that S1 achieves better quality in providing regulation services in this situation. Furthermore, the effectiveness of Algorithm 1 is indeed reflected. Specifically, during the iterative process, the behaviors of irresponsive AVs can be detected by other responsive AVs and then they can manipulate their own strategies accordingly. In addition, when the proportion of irresponsive AVs increases, the variance raises such that the quality of regulation services is in turn deteriorated. Besides, considering the unit cost per AV in logistic and charging operations, the increasing trend also indicates the reducing quality of joint service when the number of irresponsive AVs increases.

G. Impact of Different Fleet Size

We further study the impact of different fleet size on the performance of the proposed approaches, which is associated with the scalability of the proposed games. In this part, we evaluate the system performance of five cases with 10, 20, 30, 50, and 100 AVs, respectively. Meanwhile, we utilize three different performance metrics being tested, shown in Fig. 6 and Table IX. According to our results in Fig. 6, the variance of

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TABLE VIII
PROPOSED GAMES IN MULTI-AGGREGATORS-BASED SYSTEM WITH 50 AVS.

Number of AV aggregators	1	2
Number of AVs per aggregator	50	25
Total Aggregator Utility (S1) (US$)	2.43×10^4	2.36×10^4
Total Aggregator Utility (S2) (US$)	2.61×10^4	2.60×10^4
Total Regulation reward (S1) (US$)	-3.48×10^4	-6.75×10^4
Total Regulation reward (S2) (US$)	-2.98×10^4	-5.75×10^4
Number of AV aggregators	5	
Number of AVs per aggregator	10	
Total Aggregator Utility (S1) (US$)	2.11×10^4	
Total Aggregator Utility (S2) (US$)	2.55×10^4	
Total Regulation reward (S1) (US$)	-1.33×10^6	
Total Regulation reward (S2) (US$)	-9.63×10^5	

TABLE IX
IMPACT OF DIFFERENT FLEET SIZE OF AVS.

Number of AVs	10	20	30
Average AV Utility (S1) (US$)	422.06	465.58	477.04
Average AV Utility (S2) (US$)	509.65	518.15	521.23
Mean Computation time (S1) (min)	23.68	24.01	24.05
Mean Computation time (S2) (min)	24.47	19.94	22.10
Number of AVs	50	100	
Average AV Utility (S1) (US$)	487.81	489.57	
Average AV Utility (S2) (US$)	522.52	537.65	
Mean Computation time (S1) (min)	28.80	26.15	
Mean Computation time (S2) (min)	24.58	23.15	

the active power profile of the city power grid decreases with the increasing number of AVs, indicating better performance in providing the V2G regulation service in the city. Moreover, based on Table IX, fleet size expansion improves the system's revenue. This illustrates that more participating AVs results in a better solution.

We also study the performance of the multi-aggreagtor-based system. Based on the previous settings, we consider the city region with 1, 2, and 5 AV aggregators, respectively. The scale of these aggregators are determined by the participated AV fleet size in evenly separated geographical region of the urban area. In this part, we assess the total AV aggregator utilities in S1 (23) and S2 (31) and the total regulation reward in (21). According to our results in Table VIII, with the increase of the number of AV aggregators in the city, higher regulation reward can be achieved. Hence, more AV aggregators in the urban area can further help improve the performance in providing the V2G regulation service. In addition, the total aggregator utilities for both S1 and S2 are relatively high. It shows that the utilities of both the aggregators and the AVs are balanced.

Furthermore, we investigate the distributed method's computing complexity in each of these five scenarios. By emphasizing the computation time, we can observe that as shown in Table IX, the computational complexity of the proposed games increases on a relatively small scale in proportion to the number of AVs, since there are more operational constraints on the optimization problem as there are more AVs presented in the system. Therefore, it confirms the efficiency and scalability of the proposed games. This indicates that even though the computation time increases, the sophisticated problem, e.g. with 100 AVs, can still be solved in an efficient manner.

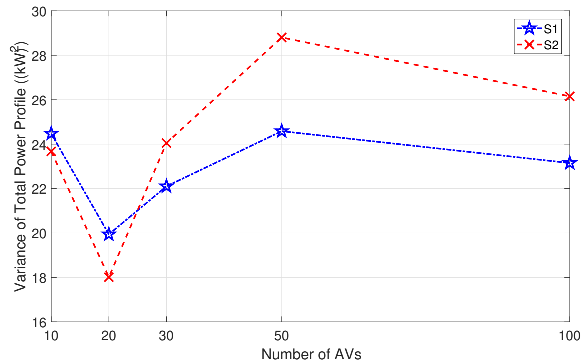

Fig. 6. Variance profiles under different fleet size of AVs.

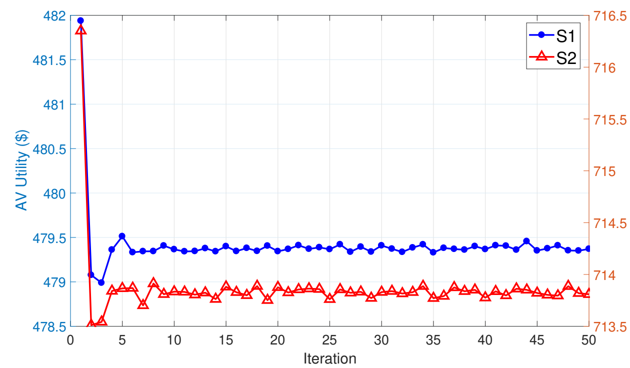

Fig. 7. Effect of proposed game theoretical approaches on convergence.

H. Convergence Analysis

To validate the exactness and uniqueness of the Nash equilibria of the proposed game, we assess the convergence of the Nash equilibrium for both the non-cooperative and cooperative approaches, shown in Algorithms 1 and 2. In this part, we assess the case with 50 participating AVs. Besides, the corresponding tolerance is set to 10^{-5}. The result is shown in Fig. 7. One may observe that convergence of the objective value through S1 occurs after approximately 6 iterations, which is shown in blue color. Meanwhile, the tolerance threshold is activated in Algorithm 1. Similarly, the objective value through S2, shown in red color, converges after 9 iterations. These results validate the exactness and uniqueness of the Nash equilibria of the proposed games of the devised algorithms.

VIII. CONCLUSION

In this paper, we adopted the incentive mechanisms for enabling an UIS, which consisted of a non-cooperative and cooperative game strategy for tackling the provision of AV logistic and charging services. First of all, a system architecture for the UIS was developed. Then, considering the interaction between the aggregator and AVs in the smart city, we formulated a non-cooperative game approach based on a Stackelberg game, where the aggregator determines the logistic and electricity trading prices as a leader while the AVs decide their strategies as followers. In the meantime, we proposed a cooperative approach for the aggregator and AVs by following a potential game so as to pursue the optimal social welfare of the UIS. Besides, the existence and uniqueness of the Nash equilibria for both non-cooperative and cooperative games were validated, since the related algorithms were devised to obtain the solution of the Nash equilibria. Case studies validated the efficient performance of the proposed non-cooperative and cooperative approaches in UIS by providing both AV logistic and charging services in different cases. In addition, the AV utilities could be maximized via the non-cooperative strategy while the social welfare of AVs and the aggregator could be further improved through the cooperative approach. For our future work, we will extend the system model to a stochastic game that considers the uncertainties introduced by heterogeneous service requests. In addition, we will consider to develop a multi-aggregator-based incentive game to balance various aggregators' utilities.

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