Charging Pricing for Autonomous Mobility-on-demand Fleets Based on Game Theory

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***Abstract*—Considering the enormous potential application of autonomous mobility-on-demand (AMoD) systems in future urban transportation, the charging behavior of AMoD fleets, as a key link connecting the power system and the transportation system, needs to be guided by a reasonable charging demand management method. This paper uses game theory to investigate charging pricing methods for the AMoD fleets. Firstly, an AMoD fleet scheduling model with appropriate scale and mathematical complexity is established to describe the spatio-temporal action patterns of the AMoD fleet. Subsequently, using Stackelberg game and Nash bargaining, two game frameworks, i. e., non-cooperative and cooperative, are designed for the charging station operator (CSO) and the AMoD fleet. Then, the interaction trends between the two entities and the mechanism of charging price formation are discussed, along with an analysis of the game implications for breaking the non-cooperative dilemma and moving towards cooperation. Finally, numerical experiments based on real-world city-scale data are provided to validate the designed game frameworks. The results show that the spatio-temporal distribution of charging prices can be captured and utilized by the AMoD fleet. The CSO can then use this action pattern to determine charging prices to optimize the profit. Based on this, negotiated bargaining improves the overall benefits for stakeholders in urban transportation.**

***Index Terms*—Charging pricing, autonomous mobility-on-demand, Stackelberg game, Nash bargaining.**

NOMENCLATURE

A. Parameters

$\alpha_{f,t}$	Electricity price at which charging station f connects to distribution system in time slot t
λ^{dist}	Cost per unit distance of vehicles
Δt	Length of a time slot
$\Delta\pi_{f,t}$	Difference between adjacent two price levels for charging station f and time slot t
c^0	Initial state of charge (SOC) of each vehicle
$C_f^{\max}$	The maximum charging capacity of charging station f
d_i	Distance of edge i in augmented network
$i_{\text{ori, loc}}, i_{\text{des, loc}}$	Corresponding locations of original node and destination node of edge i in augmented network
$i_{\text{ori, time}}, i_{\text{des, time}}$	Corresponding time of original node and destination node of edge i in augmented network
$i_{\text{ori, soc}}, i_{\text{des, soc}}$	Corresponding SOCs of original node and destination node of edge i in augmented network
$n_{\text{loc}}, n_{\text{time}}, n_{\text{soc}}$	Location, time, and SOC of node n in augmented network
$o_{\text{ori, des}, t}$	Number of passenger orders requesting movement from origin to destination during time slot t
P^{cha}	Charging power for each vehicle or each charging pile
r^{in}	Income per unit distance of serving passenger orders
s_n	Flow injected from outside of network to node n
$t^{\max}$	Last time slot within scheduling range
t^{price}	Number of time slots to keep charging price unchanged
V_g	Number of vehicles initially parked at location g

B. Sets

$\mathcal{F}$	Set of charging stations
$\mathcal{G}$	Set of spatial locations in traffic network
$\mathcal{N}$	Set of nodes in augmented network

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$\mathcal{T}$	Set of time slots
$\mathcal{T}^{\text{price}}$	Set of time slots in $\mathcal{T}$ where pricing decisions need to be made
$\mathcal{I}^{\text{ser}}, \mathcal{I}^{\text{re}}, \mathcal{I}^{\text{cha}}, \mathcal{I}^{\text{stop}}$	Sets of service edges, rebalancing edges, charging edges, and stopping edges in augmented network

C. Variables

$\theta_{f,t}$	Integer variable representing level of charging price at charging station f during time slot t
$\pi_{f,t}^{\text{CSO}}$	Numerical value of charging price at charging station f during time slot t
e_n	External outflow from node n to outside of network
$p_{f,t}^{\text{EV}}$	Charging power at charging station f during time slot t
$x_{\text{ori, des}, t}^{\text{drop}}$	Abandoned flow in passenger demand from origin location to destination during time slot t
x_i^{cha}	Flow on charging edge i
x_i^{re}	Flow on rebalancing edge i
x_i^{ser}	Flow on service edge i
x_i^{stop}	Flow on stopping edge i

1. Introduction

The operational practices of companies such as Uber, Lyft, and Didi in the real world have proven that, compared with private cars and traditional taxis, shared mobility systems can more effectively meet urban transportation demands and significantly improve the utilization of vehicles, roads, and parking facilities [1]. Building on shared mobility, technological breakthroughs in areas such as Internet of Vehicles and autonomous driving further provide powerful momentum for the transformation of transportation modes, giving rise to the concept of autonomous mobility-on-demand (AMoD) [2]. The AMoD system is considered as a highly transformative and promising solution to efficient transportation. Evaluation results from existing research show that in the same conditions of transportation demands and environment, one AMoD vehicle can replace seven private cars [3]. From the perspective of urban transportation, deploying AMoD systems based on electric vehicles (EVs) will significantly reduce the demand for public parking and decrease environmental pollution and carbon emissions. Currently, the AMoD mode has received extensive attention from various companies such as RideOS [4] and Zoox [5] in the United States, EasyMile [6] in France, and more. It can be imagined that AMoD may become a major transportation mode in future cities. Privately owned cars and traditional taxis rely on decentralized decision-making by drivers, while the AMoD fleet, with the information aggregation and centralized dispatching of the platform, can more effectively coordinate their routing and charging schedules driven by profit [1]. As a result, the randomness in the operational patterns of fleets is greatly reduced, demonstrating stronger rationality in decision-making.

The characteristics of an AMoD fleet that is centrally dispatched by a platform are well recognized by researchers in the field. Many studies have explored control methods for optimizing the operation of AMoD fleets, with a focus on coordinating passenger pickups, navigation to destinations, the movement of empty vehicles (in preparation for future actions), and their relationships [7]. Vehicle routing problem (VRP) in the field of operations is a classic framework for planning vehicle routes, making it suitable for the vehicle-centric AMoD dispatching model [8]. In such methods, vehicle routing is typically represented by binary variables, with a value of 1 when the vehicle travels a road in the network [9]. For large-scale fleets at the city level, the scale of VRP, which is an NP-hard problem, poses significant challenges to exact optimization. Therefore, the focus in the field of operations is mainly on the development of heuristic rules and algorithms. Considering the scale of the problem, network flow models have been proposed as an approximation method. In these methods, both the fleet and customer orders are modeled as flows in the network, which are continuous variables that need to satisfy the constraints such as consistency and flow conservation [10]. The network flow model replaces "vehicles" with "flows" and continuous variables instead of discrete variables. While it may be challenging to precisely obtain the route of each vehicle directly from network flows, it significantly reduces the scale of the problem, thus providing a foundation for city-level fleet scheduling [1]. A substantial amount of related work has been developed based on the network flow model such as congestion-aware AMoD system scheduling [11], intermodal transportation systems with AMoD [12], and model predictive control for AMoD systems [13], [14]. Despite different topics, the fundamental paradigm of these studies is to establish an extended traffic network, representing various types of vehicle behaviors with "flows" in the network, and then solving the corresponding optimization or control problems. In addition to optimization and control methods, there have also been the studies that use reinforcement learning to schedule AMoD fleets [15], [16]. The above studies have made important contributions to optimizing the operation of AMoD systems, but they overlook charging decisions and give little consideration to the interaction between the AMoD fleet and the charging station operator (CSO). The rational behavior exhibited by centrally managed large-scale fleets will have a significant impact on the operation of charging stations, enabling AMoD fleet managers to enter into a game with CSOs. Such commercial interactions between large entities are almost impossible in the current scenario, where the dominant players in the transportation system are fragmented and uncoordinated EVs.

Due to the vast potential of AMoD systems in future urban transportation, the charging schedule for electric AMoD vehicles will be a crucial link connecting the power system and the transportation system [17]. Currently, some studies related to AMoD explicitly involve the interdependency between the transportation and power sectors, highlighting the crucial role of charging behavior in connecting these two systems. For instance, building upon the framework of

AMoD system dispatch, several studies are dedicated to coordinating the optimization between the AMoD system and the power system [17], [18]. Some studies further consider additional objectives such as integrating renewable energy sources and reducing carbon emissions [19]. However, the focus of such studies remains on scheduling models and algorithms, which often consider the local marginal prices at power system nodes as model parameters or assume a centralized entity to coordinate the optimization between the AMoD system and power system. Such methods overlook the significant role of CSOs as independent entities and disregard the fundamental role of charging service prices as perceivable information for the AMoD fleet. To the best of the authors' knowledge, very few studies explicitly recognize the independent entity status of charging stations. Among them, some studies consider charging station planning for AMoD fleets [20], [21], while others deal with the competition among multiple CSOs in the face of AMoD fleets [3]. However, the focus of this paper differs from these studies, as both charging station planning and competition among charging stations fall beyond the scope of this paper.

Real-world experience illustrates that the power system does not attempt direct coordination with vehicles in the transportation system. It is the CSOs who actively engage in demand-side response and participate in bidding within the electricity market [22]. CSOs must initially consider the mutual impact between themselves and the entities within the transportation system, which forms the foundation for aggregating resources and interacts with the power system. Therefore, the interaction between the CSO and the AMoD fleet, often overlooked in existing studies, deserves emphasis and attention. Moreover, the emphasized interaction in this paper does not solely refer to the physical interaction between charging stations and AMoD vehicles; rather, it focuses on the interaction between CSO and AMoD fleet manager as decision-makers. The charging price, a crucial variable impacting the interests of both decision-makers, inevitably becomes the core of their interaction. Thus, this paper focuses on the patterns of conflict or cooperation that emerge between these two major decision-makers surrounding the charging price. Both the AMoD fleet and the CSO are not only backgrounds or boundaries for each other, but rational entities. Starting from this perspective, this paper aims to present distinct findings and insights compared with existing studies.

1) In contrast to studies focused on enhancing AMoD system performance through advanced dispatch control [7]-[16], this paper does not confine itself to traffic characteristics. Instead, it considers the charging behavior and energy characteristics of the AMoD fleet. Moreover, this paper thoroughly investigates the interaction between the AMoD fleet and the CSO.

2) In contrast to studies that collaboratively optimize the AMoD system and the power system [17]-[19], this paper explicitly delineates the independent decision-making status of the CSO. The interaction with the AMoD fleet and its impact come from the charging price signals provided by the CSO, aligning more closely with realistic operational situations.

3) In contrast to existing studies on charging pricing from the perspective of CSOs [22]-[26], this paper considers the price-based interaction between the CSO and the AMoD fleet as a novel object of investigation. On the one hand, the rational spatio-temporal action patterns of the AMoD fleet cannot be adequately described by traditional traffic assignment models. On the other hand, the rationality exhibited by the centrally managed large-scale fleet qualifies it for equal interaction (e.g., negotiation) with the CSO, thereby expanding the mechanisms behind the charging pricing.

In summary, the interaction between the CSO and the AMoD fleet, as two major commercial entities in future urban transportation, will play a pivotal role. Their interaction will form the foundation for future interactions between the power and transportation systems, accompanied by a distinctly different business model from existing charging stations. Currently, the potential and effects of the interaction framework have not been fully discussed. Game theory, as a theory analyzing optimal decisions and strategic interactions among multiple players, has been widely applied in fields involving multi-player decision-making such as charging pricing [25]-[27]. Therefore, in discussing the interaction between the CSO and the AMoD fleet, game theory naturally becomes a powerful tool.

From the perspective of game theory, this paper designs cooperative and non-cooperative game frameworks for the CSO and the AMoD fleet and compares their implications and characteristics. The main contributions of this paper are summarized as follows.

1) An AMoD fleet scheduling model with appropriate scale and mathematical complexity is established to describe the spatio-temporal action patterns of the fleet, laying the foundation for the interaction between charging stations and the AMoD platform.

2) The non-cooperative pricing strategies of CSOs facing the AMoD fleet are analyzed using Stackelberg game framework, capturing the fundamental interaction trends between the two entities. A solution method for the sub-game perfect Nash equilibrium is given based on the characteristics of the problem.

3) The possible cooperative interaction mode between the CSO and the AMoD fleet is discussed based on Nash bargaining, taking non-cooperation as a baseline. The mechanism of charging price formation is expanded. From the inherent meaning of the game problem itself, the rationality of breaking the non-cooperative dilemma to achieve cooperation and the natural resistance of participants to betrayal are clarified.

4) The implications and properties of the two frameworks using Stackelberg game and Nash bargaining are compared, and numerical experiments based on real-world city-scale data are provided to verify these results.

The remainder of this paper is organized as follows. Section II introduces the decision modeling for the AMoD fleet and the CSO. Section III presents two game frameworks designed for charging pricing, i.e., non-cooperative and cooperative. Numerical experiments based on real data from Chengdu, China are conducted in Section IV, and Section V concludes this paper.

II. Decision Modeling for AMoD Fleet and CSO

A. AMoD Fleet Scheduling

1) Augmented Time−Space−Energy Network

Inspired by [17], [28], this paper presents a scheduling model for the AMoD fleet based on multi-commodity flow problem in an augmented time−space−energy network. From network flow perspective, the decision of a certain number of homogeneous vehicles to move from one location to another is described as a flow behavior in the dimensions of time, space, and energy. The vehicle flow in the model is relaxed as continuous variables, referred to as "fluidic relaxation" [29]. Although the approximate nature of the network flow model may not be suitable for developing real-time controllers for AMoD systems, it is sufficient for evaluating the spatio-temporal action patterns of the AMoD fleet when interacting with charging stations [18].

The construction of an augmented network relies on the discretization of time and energy (or state of charge (SOC)). Nodes and edges in the network will contain information about time, location, and energy, enabling stronger decision modeling capabilities. Figure 1, which uses a four-node traffic network as an example, consists of three regular nodes and one charging station node. In the corresponding augmented network, the traffic network is expanded along the time and SOC dimensions, and each augmented node is a triplet of location, time, and SOC. Therefore, the edges between nodes can simultaneously represent movement in space, progression in time, and changes in SOC.

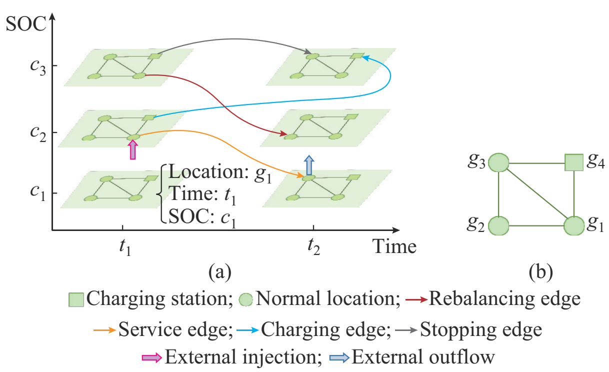

Fig. 1. Schematic diagram of an augmented time−space−energy network. (a) Augmented time−space−energy network. (b) Traffic network topology.

There are four types of edges in the augmented network.

1) Service edge: a service edge indicates a certain number of vehicles carrying passengers, completing the process of transporting passengers from the original location to the destination. Hence, it involves a change in location, a passage of time, and a decrease in SOC.

2) Charging edge: a charging edge represents a certain number of vehicles going through the process of charging at a charging station. Thus, the starting and ending locations of a charging edge are the same, and only a passage of time and an increase in SOC occur.

3) Rebalancing edge: a rebalancing edge represents a certain number of vehicles without passengers transferring from one location to another, expressing a change in location, a passage of time, and a decrease in SOC.

4) Stopping edge: a stopping edge signifies a certain number of vehicles staying in place, waiting for the next action. Thus, there are no changes in location or SOC, only the passage of time.

In addition to the flow within the network, to ensure formal flow conservation, the external injection and outflow of each node need to be defined.

1) External injection: external injection only occurs at nodes in the initial time slot of the augmented time−space−energy network. It essentially specifies the initial location and SOC of each vehicle. Since flow cannot be generated out of nowhere, the corresponding amount of flow needs to come into the network from these nodes.

2) External outflow: external outflow only occurs at nodes in the final time slot of the augmented time−space−energy network. It describes the location and SOC of each vehicle at the end of the schedule. Since nodes are not allowed to store flow, flow will go out of the network from these nodes.

2) Mathematical Model

The AMoD fleet scheduling model based on network flow is established in an augmented time−space−energy network. The symbols related to the augmented network include n_{loc}, n_{time}, n_{soc}, d_i, $i_{\text{ori,loc}}$, $i_{\text{ori,time}}$, $i_{\text{ori,soc}}$, $i_{\text{des,loc}}$, $i_{\text{des,time}}$, and $i_{\text{des,soc}}$. It should be noted that time and SOC are both discretely segmented. The sets used in the model include $\mathcal{N}$, $\mathcal{I}^{\text{ser}}$, $\mathcal{I}^{\text{re}}$, $\mathcal{I}^{\text{cha}}$, $\mathcal{I}^{\text{stop}}$, $\mathcal{F}$, $\mathcal{T}$, and $\mathcal{G}$. The decision variables of the model include x_i^{re}, x_i^{cha}, x_i^{ser}, x_i^{stop}, $x_{\text{ori,des},t}^{\text{drop}}$, e_n, and $p_{f,t}^{\text{EV}}$. And the parameters of the model include Δt, $\pi_{f,t}^{\text{CSO}}$ (from the perspective of the AMoD fleet, it is a parameter), λ^{dist}, r^{in}, $o_{\text{ori,des},t}$, s_n, V_g, c^0, $C_f^{\max}$, P^{cha}, and $t^{\max}$. Among them, s_n provides the initial condition of the system at $t=0$, as calculated by (1).

$$s_n = \begin{cases} V_g & n_{\text{loc}}=g, n_{\text{time}}=0, n_{\text{soc}}=c^0 \\ 0 & \text{otherwise} \end{cases} \quad \forall n \in \mathcal{N} \tag{1}$$

The basic formulation of the AMoD fleet scheduling model is as follows, where R^{AMoD} is the net revenue of the AMoD fleet.

$$\max R^{\text{AMoD}} = -\Delta t \sum_{f\in\mathcal{F}} \sum_{t\in\mathcal{T}} \pi_{f,t}^{\text{CSO}} p_{f,t}^{\text{EV}} - \lambda^{\text{dist}} \sum_{i\in\mathcal{I}^{\text{ser}}} x_i^{\text{ser}} d_i - \lambda^{\text{dist}} \sum_{i\in\mathcal{I}^{\text{re}}} x_i^{\text{re}} d_i + r^{\text{in}} \sum_{i\in\mathcal{I}^{\text{ser}}} x_i^{\text{ser}} d_i \tag{2}$$

s.t.

$$\forall x_i^{\text{re}}, x_i^{\text{cha}}, x_i^{\text{ser}}, x_i^{\text{stop}}, x_{\text{ori,des},t}^{\text{drop}}, e_n \geq 0 \tag{3}$$

$$\sum_{\substack{i\in\mathcal{I}^{\text{ser}} \\ i_{\text{ori,loc}}=\text{ori} \\ i_{\text{des,loc}}=\text{des} \\ i_{\text{ori,time}}=t}} x_i^{\text{ser}} = o_{\text{ori,des},t} - x_{\text{ori,des},t}^{\text{drop}} \quad \forall \text{ori, des} \in \mathcal{G}, \forall t \in \mathcal{T} \tag{4}$$

$$\sum_{\text{type}\in\{\text{ser, re, cha, stop}\}} \left(\sum_{\substack{i\in\mathcal{I}^{\text{type}} \\ i_{\text{ori}}=n}} x_i^{\text{type}} - \sum_{\substack{i\in\mathcal{I}^{\text{type}} \\ i_{\text{des}}=n}} x_i^{\text{type}} \right) = s_n - e_n \quad \forall n \in \mathcal{N} \tag{5}$$

$$C_f^{\max} \geq p_{f,t}^{\text{EV}} = P^{\text{cha}} \sum_{\substack{i\in\mathcal{I}^{\text{cha}} \\ i_{\text{ori,loc}}=f \\ i_{\text{ori,time}}=t}} x_i^{\text{cha}} \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T} \tag{6}$$

$$e_n = 0 \quad n_{\text{time}} < t^{\max} \text{ or } n_{\text{soc}} < c^0, \forall n \in \mathcal{N} \tag{7}$$

$$\sum_{n \in \mathcal{N}} e_n = \sum_{n \in \mathcal{N}} s_n \tag{8}$$

In the objective function (2), the first term represents the charging cost, the second term represents the distance cost caused by order services, the third term represents the distance cost caused by rebalancing, and the fourth term represents the income from order services.

Constraint (3) specifies that the decision variables are non-negative. Constraint (4) describes the behavior of meeting passenger orders. Passenger demand at time slot t from origin "ori" to destination "des" corresponds to service edges in the augmented network. The total service flow of the AMoD fleet on the corresponding edges is less than or equal to the passenger demand $o_{\text{ori, des}, t}$, and the difference between them represents the abandoned passenger demand $x^{\text{drop}}_{\text{ori, des}, t}$. Constraint (5) describes the flow conservation of the nodes in the augmented network. Constraint (6) limits the charging power within the maximum capacity. Constraint (7) specifies that the external outflow from nodes in the augmented network that have not reached the last time slot $t^{\max}$ and have insufficient SOC c^0 is 0. Constraint (8) ensures that the sum of all external outflows is equal to the initial total number of vehicles. Combined constraints (7) and (8) require that all flows must flow out of a node with SOC of at least c^0 in the last time slot $t^{\max}$. This physically implies that all vehicles should maintain a battery level of at least c^0 at the end of the schedule.

It should be noted that given the charging prices $\left\{\pi^{\text{CSO}}_{f,t}\right\}$, the objective function and all constraints of the AMoD scheduling model are linear, and the model can be formulated as a linear programming (LP). In subsequent research on charging pricing strategies based on game theory, the decisions of the CSO will impact the behavior of the AMoD fleet through $\left\{\pi^{\text{CSO}}_{f,t}\right\}$.

B. Charging Pricing

From a practical perspective, for the CSO, pricing decisions are often divided into several discrete levels [22]. Based on historical experience and any available data, the CSO can provide a general range for charging prices and discretize them into multiple levels from high to low. The time scale of charging pricing is generally not overly detailed and may be different from that of AMoD fleet scheduling. In addition, the cost of electricity procurement is determined by the electricity prices of the distribution system and the charging demands, and this paper assumes that the CSO is a price taker for the electricity prices of distribution system.

The model uses sets $\mathcal{F}$ and $\mathcal{T}$ with the same meaning as the AMoD scheduling model. $\mathcal{T}^{\text{price}} \subset \mathcal{T}$ represents the time slots in $\mathcal{T}$ where pricing decisions need to be made, while the prices in other time slots remain unchanged and consistent with them.

The decision variables of the model include $\pi^{\text{CSO}}_{f,t}$ and $\theta_{f,t}$. The parameters of the model include Δt, $\alpha_{f,t}$, $p^{\text{EV}}_{f,t}$ (from the perspective of the CSO, it is a parameter), $\Delta\pi_{f,t}$, and t^{price}.

The basic description of the pricing model for the CSO is as follows, where R^{CSO} is the net revenue of the CSO.

$$\max R^{\text{CSO}} = \sum_{t \in \mathcal{T}} \Delta t \sum_{f \in \mathcal{F}} \left(\pi^{\text{CSO}}_{f,t} - \alpha_{f,t}\right) p^{\text{EV}}_{f,t} \tag{9}$$

s.t.

$$\pi^{\text{CSO}}_{f,t} = \alpha_{f,t} + \theta_{f,t} \Delta\pi_{f,t} \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T} \tag{10}$$

$$\theta_{f,t} = \theta_{f,t+\tau} \quad \tau = 1, 2, \ldots, t^{\text{price}} - 1, \forall f \in \mathcal{F}, \forall t \in \mathcal{T}^{\text{price}} \tag{11}$$

$$\theta_{f,t} \in \{0, 1, 2\} \quad \forall f \in \mathcal{F}, \forall t \in \mathcal{T} \tag{12}$$

The objective function (9) represents the revenue of the CSO after subtracting the electricity fees paid to the power system.

Constraint (10) calculates the value of the charging price, which represents the pricing decision made by the CSO based on the electricity price from the distribution system. The adjustable part is the additional fees set by the CSO such as service charges. Constraint (11) specifies the time scale for pricing, indicating that the price cannot change for a continuous period of t^{price} multiplied by Δt. Constraint (12) discretizes the charging pricing into three levels: high, medium, and low, for each time slot.

It should be noted that $\left\{p^{\text{EV}}_{f,t}\right\}$ is determined by the behavior of the AMoD fleet, and according to the AMoD fleet scheduling model, $\left\{p^{\text{EV}}_{f,t}\right\}$ is influenced by $\left\{\pi^{\text{CSO}}_{f,t}\right\}$.

III. Game Frameworks

A. Non-cooperative Game Framework

Regardless of the type of object it is facing, pricing-related studies on charging stations inevitably involve the process of modeling the service objects of the charging stations. The decision-making process for pricing requires taking into account the behavior of the service objects. Therefore, Stackelberg game naturally becomes an effective tool to adapt to this characteristic [25], [26], [30] - [33]. Considering that price signals can be quickly and widely disseminated through information platforms, it is reasonable to establish a sequential order of charging pricing and AMoD fleet scheduling, making Stackelberg game framework applicable.

As shown in Fig. 2, the basic elements of the game are described as follows.

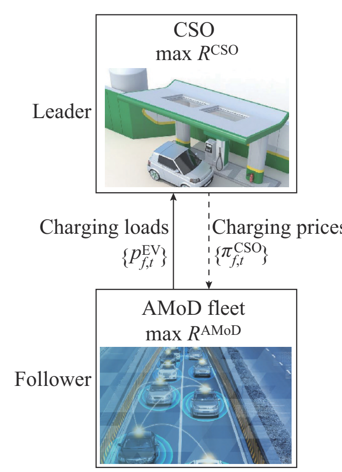

Fig. 2. Illustration of Stackelberg game between CSO and AMoD fleet.

1) Players: the AMoD fleet is the follower, and the CSO is the leader.

2) Payoffs: the payoff functions for players are (2) and (9), respectively.

3) Strategy sets: the strategy sets for players are the feasible dispatch region of the AMoD fleet determined by (3)-(8) and the feasible pricing region of the CSO determined by (10)-(12). It should be noted that the two strategy sets are not coupled. In other words, regardless of the opponent's decision, their respective feasible regions do not change.

The key to solving the sub-game perfect Nash equilibrium lies in representing the optimal response function of the AMoD fleet under various charging prices. Let $\left[x_i^{\text{re}}, x_i^{\text{cha}}, x_i^{\text{ser}}, x_i^{\text{stop}}, x_{\text{ori,des},t}^{\text{drop}}, e_n, p_{f,t}^{\text{EV}}\right]$ be the decision variable vector $\boldsymbol{x}$. The scheduling problem of the AMoD fleet and its dual problem can be restated in the following compact form.

$$\begin{cases} \max \boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} \\ \text{s.t. } \boldsymbol{A}_1\boldsymbol{x}=\boldsymbol{b}_1 : \boldsymbol{v} \\ \quad \boldsymbol{A}_2\boldsymbol{x} \le \boldsymbol{b}_2 : \boldsymbol{w} \\ \quad \boldsymbol{x} \ge \boldsymbol{0} \end{cases} \xrightarrow{\text{Dual}} \begin{cases} \min \left(\boldsymbol{b}_1^{\mathrm{T}}\boldsymbol{v}+\boldsymbol{b}_2^{\mathrm{T}}\boldsymbol{w}\right) \\ \text{s.t. } \boldsymbol{A}_1^{\mathrm{T}}\boldsymbol{v}+\boldsymbol{A}_2^{\mathrm{T}}\boldsymbol{w} \ge \boldsymbol{c} \\ \quad \boldsymbol{w} \ge \boldsymbol{0} \end{cases} \tag{13}$$

where vector $\boldsymbol{c}$ contains the influence of charging pricing $\left\{\pi_{f,t}^{\text{CSO}}\right\}$; $\boldsymbol{A}_1, \boldsymbol{A}_2, \boldsymbol{b}_1, \boldsymbol{b}_2$ are all constant matrices; and $\boldsymbol{v}$ and $\boldsymbol{w}$ are dual variables.

It has been noticed that the optimality condition for optimization problems can be determined using the Karush-Kuhn-Tucker (KKT) condition. For the problems with good properties, the KKT condition can be both a necessary and sufficient condition for the optimal solution [22]. However, for problem (13), both the inequality constraint $\boldsymbol{A}_2\boldsymbol{x} \le \boldsymbol{b}_2$ and the non-negativity constraint $\boldsymbol{x} \ge \boldsymbol{0}$ require the corresponding complementary constraints to be introduced. This is especially important considering the high dimensionality of $\boldsymbol{x}$ in the AMoD fleet scheduling problem, as too many complementary constraints will burden the computation.

For LP, it can be proven that the primal-dual condition is also both sufficient and necessary for optimality. The primal-dual condition replaces complementary slackness with strong duality, thus overcoming the challenges of dealing with too many complementary slackness conditions.

$$\begin{cases} \boldsymbol{A}_1\boldsymbol{x}=\boldsymbol{b}_1 \\ \boldsymbol{A}_2\boldsymbol{x} \le \boldsymbol{b}_2 \\ \boldsymbol{x} \ge \boldsymbol{0} \\ \boldsymbol{A}_1^{\mathrm{T}}\boldsymbol{v}+\boldsymbol{A}_2^{\mathrm{T}}\boldsymbol{w} \ge \boldsymbol{c} \\ \boldsymbol{w} \ge \boldsymbol{0} \\ \boldsymbol{c}^{\mathrm{T}}\boldsymbol{x}=\boldsymbol{b}_1^{\mathrm{T}}\boldsymbol{v}+\boldsymbol{b}_2^{\mathrm{T}}\boldsymbol{w} \end{cases} \tag{14}$$

Backtracking to the charging pricing stage, the equivalent optimization problem is described as:

$$\begin{cases} \max R^{\text{CSO}} = \sum_{t \in \mathcal{T}} \Delta t \sum_{f \in \mathcal{F}} \left(\pi_{f,t}^{\text{CSO}} - \alpha_{f,t}\right) p_{f,t}^{\text{EV}} \\ \text{s.t. Charging pricing constraints (10)-(12)} \\ \quad \text{AMoD optimality condition (14)} \end{cases} \tag{15}$$

In the objective function (9) and the strong duality condition $\boldsymbol{c}^{\mathrm{T}}\boldsymbol{x}=\boldsymbol{b}_1^{\mathrm{T}}\boldsymbol{v}+\boldsymbol{b}_2^{\mathrm{T}}\boldsymbol{w}$, there are non-linear terms resulting from the multiplication of charging price $\pi_{f,t}^{\text{CSO}}$ with other decision variables. Since constraint (10) discretizes the charging price, it actually introduces a product of integer variables and continuous variables, which can be linearized using Big-*M* method. Therefore, the optimization problem (15) is essentially mixed-integer linear programming (MILP) and can be solved by mature commercial solvers.

B. Cooperative Game Framework

The AMoD mode will bring about centralized rationality in large-scale fleets, implying that EVs may no longer be only charging price takers but rather qualify for equal interaction (e.g., cooperation and negotiation) with CSOs. The rational decision-making exhibited by a centralized dispatching fleet makes it possible for the CSO and the AMoD manager to potentially determine charging prices through friendly negotiations, which is almost impossible in a scenario where the transportation system is still dominated by decentralized and disordered private cars. The cooperation between the two parties would bring greater potential profits to the transportation system.

The key to breaking the non-cooperative dilemma is that when all charging stations, as available resources, cooperate with vehicles, the order acceptance and route arrangement of the AMoD fleet could be further optimized, reducing inefficient movements and facilitating the completion of more passenger orders, thus increasing the total revenue. The non-cooperative equilibrium is an inefficient equilibrium. From the perspective of future urban transportation, negotiations and cooperation between these two types of stakeholders may be more likely to occur.

As shown in Fig. 3, this paper uses Nash bargaining as a negotiation tool, which provides a cooperative game solution that satisfies the properties of Pareto optimality, symmetry, independence of irrelevant alternatives, and affine transformation invariance. The breaking point of the bargaining $\left(R_0^{\text{AMoD}}, R_0^{\text{CSO}}\right)$ is the equilibrium solution of Stackelberg game described in Section III-A. In other words, if the net income given to either the AMoD fleet or the CSO in the bargaining is less than the net income in Stackelberg game, the player will not accept the cooperative result, and cooperation cannot be achieved. It is precisely because both parties have the potential to increase their profits that cooperation and negotiation have a basis.

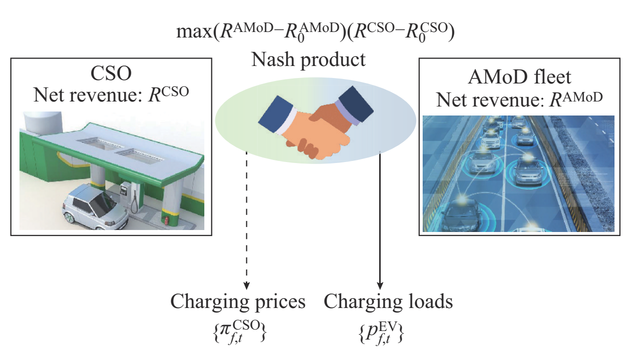

Fig. 3. Illustration of Nash bargaining between CSO and AMoD fleet.

According to Nash bargaining, the objective is to maximize Nash product $\left(R^{\text{AMoD}}-R_0^{\text{AMoD}}\right)\left(R^{\text{CSO}}-R_0^{\text{CSO}}\right)$. It should be noted that even ignoring the issue of integer variables, the objective function is a non-convex function with bilinear terms, which will bring difficulty to the computation. By using the monotonicity property of the logarithmic function, it is possible to take the logarithm of the objective function, which converts the product into a sum of logarithms.

The final formulated Nash bargaining problem is given as:

$$\begin{cases} \max\ \left(\ln\left(R^{\text{AMoD}}-R_0^{\text{AMoD}}\right)+\ln\left(R^{\text{CSO}}-R_0^{\text{CSO}}\right)\right) \\ \text{s.t. } R^{\text{AMoD}}\geq R_0^{\text{AMoD}} \\ \quad R^{\text{CSO}}\geq R_0^{\text{CSO}} \\ \quad \text{AMoD scheduling constraints (3)-(8)} \\ \quad \text{Charging pricing constraints (10)-(12)} \end{cases} \tag{16}$$

Problem (16) is a mixed-integer convex optimization problem with linear constraints, or can be transformed into linear constraints using Big-M method.

In the solution of problem (16), the net benefits of both the CSO and the AMoD fleet will increase compared with the non-cooperative game framework, which is a prerequisite for cooperation between both parties. On this basis, there are still natural obstacles to betraying the Nash bargaining solution for both parties based on the principles of game theory, which is the key to overcoming the non-cooperative dilemma.

1) The pricing problem inherently involves a decision order, which creates resistance for the leader (i.e., CSO) to deviate from the Nash bargaining solution. This is because any betrayal actions by the leader will be observed by the follower (i.e., AMoD fleet), and the AMoD fleet will make the optimal response to the deviated prices. Therefore, the CSO can at most revert to the equilibrium of Stackelberg game, as this is the maximum benefit it can get in the case of non-cooperation. However, this benefit is not as high as the one obtained from the Nash bargaining solution.

2) The follower (i.e., AMoD fleet) can indeed betray and achieve higher payoffs than the Nash bargaining solution after the leader’s decision is made. However, the resistance to betraying cooperation comes from the deterrence created by the repeated nature of the game. Pricing and scheduling take place every day, and a single act of betrayal in one day will trigger punishments from the leader in subsequent rounds (e.g., tit for tat or cruel strategy) [34]. Considering long-term benefits with a discount factor $0<\delta<1$, betrayal would lead to a loss in long-term benefits.

IV. Numerical Experiments

A. Data Overview and Parameter Settings

The passenger travel demand data are based on the ride-hailing order dataset of Didi in Chengdu [35], China. After preprocessing more than 0.22 million raw data entries, some orders with inappropriate timestamps and locations too far from the city center have been removed, resulting in approximately 0.17 million retained travel orders. It is believed that this data range can describe the distribution of passenger travel demand in the city. Figure 4 shows the heat map distribution of the origin locations for passenger travel demands. From practical calculation standpoint, the area is divided into grids, each measuring approximately 5 km in length. The specified area in this paper covers a total of 5×5 grids. The CSO operates eight charging stations within specific grids, i.e., charging stations #6, #9, #10, #11, #12, #13, #19, and #22, according to their corresponding grid numbers. Each charging station within a grid can be considered an aggregate of all charging facilities within that grid.

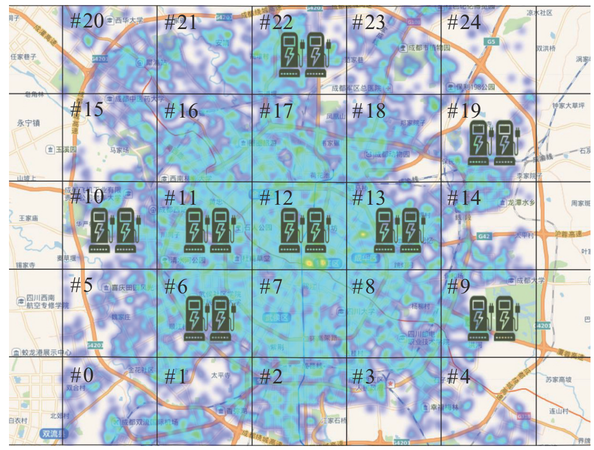

Fig. 4. Heat map distribution of origin locations for passenger travel demands.

In addition to spatial distribution characteristics, travel orders also have temporal distribution characteristics. As shown in Fig. 5, there is less demand for nighttime travel, and the number of passenger orders increases from around 08:00 in the morning until 23:00 in the evening.

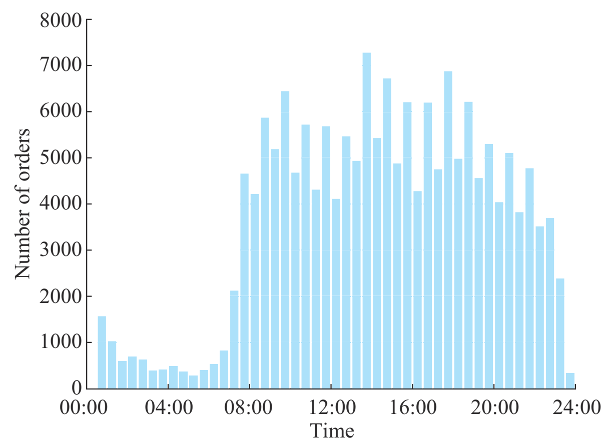

Fig. 5. Distribution of time for passenger orders.

Assuming that within the 5×5 grids, the power load of each grid has different electricity prices, reflecting the differential characteristics of time and space. The electricity price data shown in Fig. 6 is sourced from the electricity market in [36]. Each grid corresponds to a randomly selected node from the data.

The configuration parameters of the AMoD fleet and charging stations are shown in Table I.

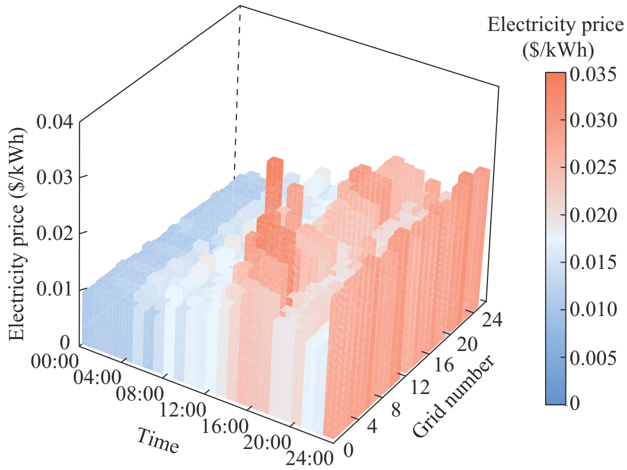

Fig. 6. Electricity price data in each grid.

TABLE I
CONFIGURATION PARAMETERS OF AMOD FLEET AND CHARGING STATIONS

Parameter	Value
Fleet size	5000 vehicles [13]
Vehicle range	300 km [37]
Battery capacity	76 kWh [38]
Limits for SOC	10%-90% [39]
Initial SOC of vehicles	50% [3]
Average speed	50 km/h [38]
Unit distance order revenue	0.22 $/km
Unit distance cost	0.0165 $/km [38]
Time discretization for AMoD	30 min [17]
SOC discretization for AMoD	10%
Charging power	30 kW [37]
Charging efficiency	95% [40]
Charging station capacity	15 MW
Difference between price levels	0.056 $/kWh
Time scale for charging pricing	1 hour [3]

A fleet size of 5000 vehicles represents approximately 3% of the total number of daily orders, which is a normal proportion for the AMoD system [13], [18], [19]. The dispatch time range is from 0 to 24 hours within a day. The initial distribution of the AMoD fleet is randomly and uniformly generated.

All numerical experiments are conducted in a Python 3.9.13 environment. The optimization problems are solved using Gurobi 11.0.0.

B. Non-cooperative Scenario

The Stackelberg game problem is solved to obtain the optimal pricing strategy for the CSO, resulting in a total net revenue of $69380.11.

As shown in Fig. 7, the results demonstrate two trends. On the temporal scale, there is a higher charging load during periods of lower pricing and a lower charging load during periods of higher pricing. On the spatial scale, charging stations located in the city center and hotspots receive more visits. For example, charging stations #6 and #12 in the central area have high charging power, and charging station #22 at the northern end also receives a number of visits since many passenger orders are involved. However, unpopular and remote charging stations such as charging stations #9 and #19 have very few users. These results reflect the profit-driven behavior of the AMoD fleet, namely fully utilizing the temporal and spatial differences in charging prices.

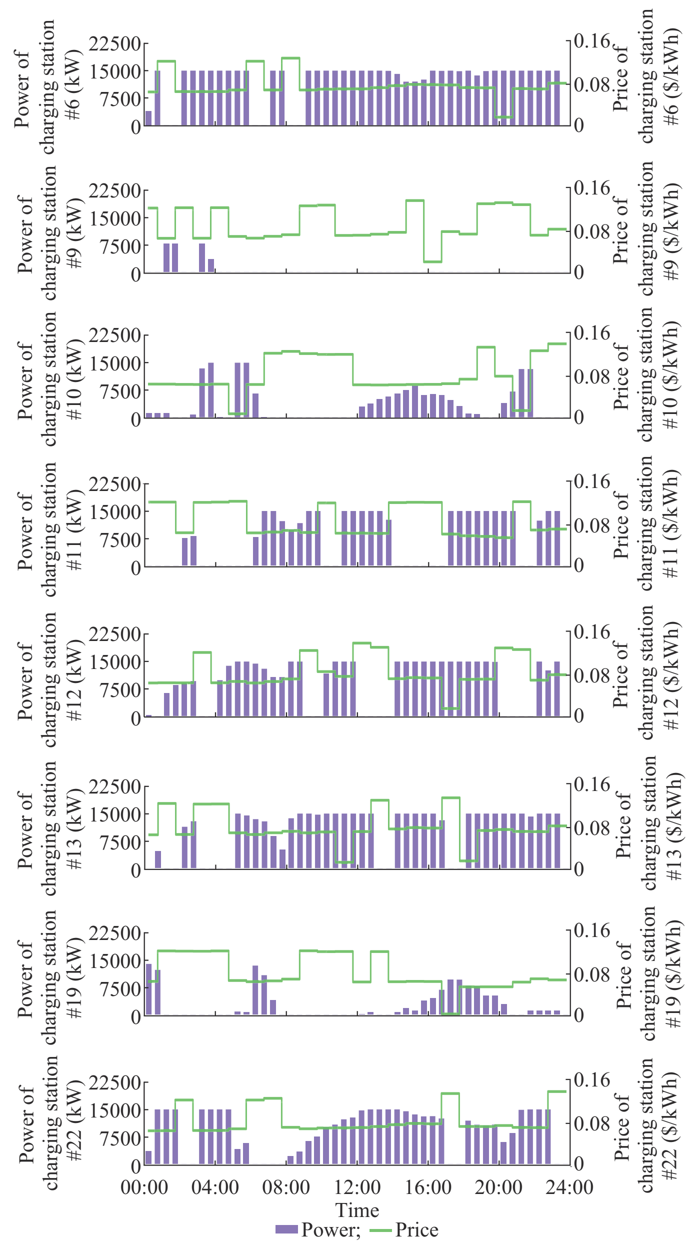

Fig. 7. Pricing results and charging power of each charging station (Stackelberg game).

In the equilibrium solution, the total net revenue of the AMoD fleet is $84429.66. Out of the 172926 passenger orders completed in a day, 116369 are served while 56557 are abandoned, resulting in a total abandoned order value of $95517.78.

The optimal scheduling result of the AMoD fleet reflects its response to the charging pricing. Figure 8 shows the distribution of vehicle locations at different time. Throughout the entire operation, the result shows the influence of passenger travel demand. The central area of the city has abundant charging stations and high travel demand of passengers, and most passengers still have destinations in the central area, leading to a concentration of vehicle activity in the city center.

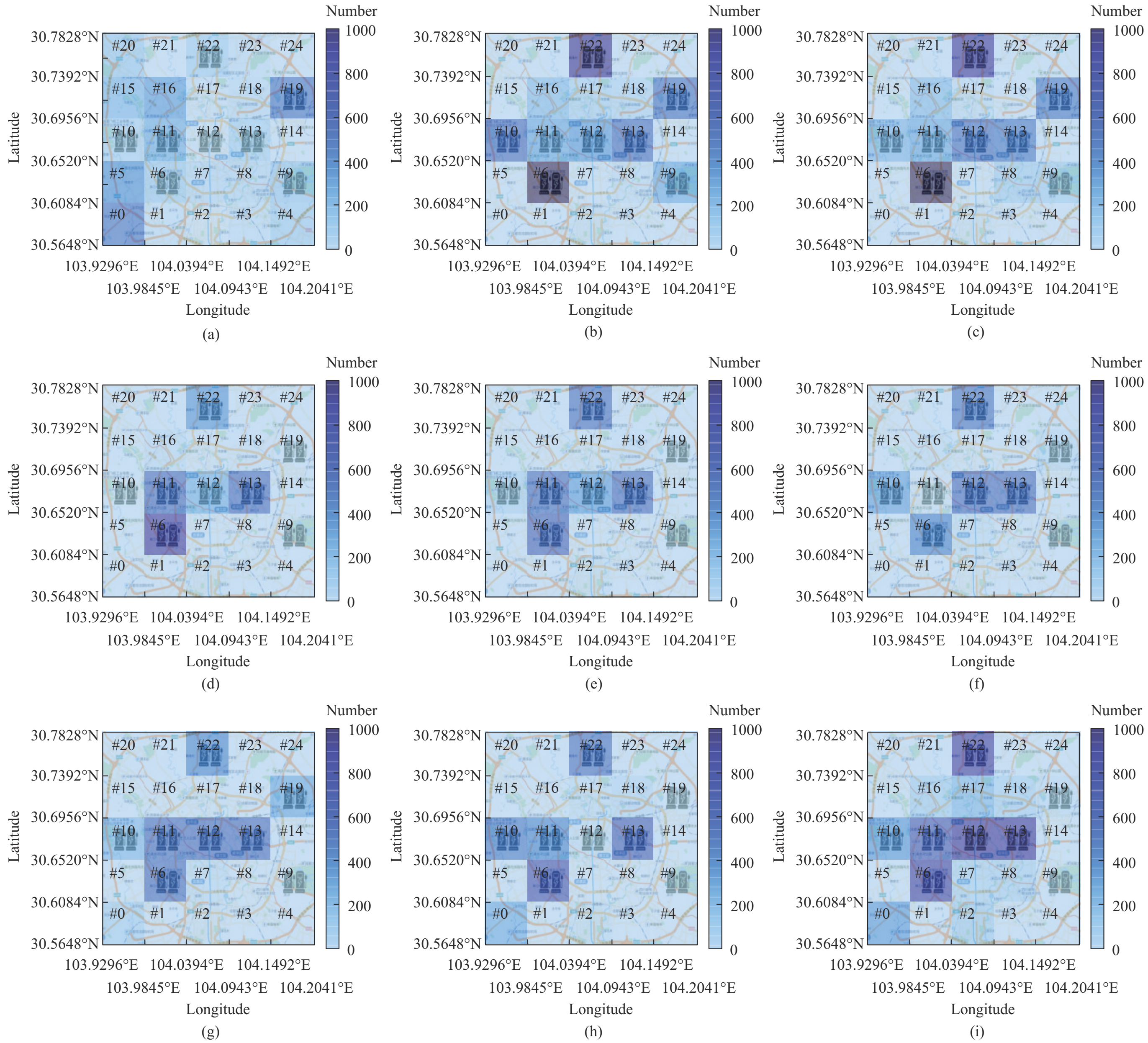

Fig. 8. Distribution of vehicle locations at different time (Stackelberg game). (a) 00:00. (b) 03:00. (c) 06:00. (d) 09:00. (e) 12:00. (f) 15:00. (g) 18:00. (h) 21:00. (i) 24:00.

Figure 9 presents the variations in the number of vehicles in different states at each time slot. Initially, due to random initial distributions and vehicles with only 50% SOC, some vehicles start charging and rebalancing to prepare for the morning peak of travel. During the operation, the trend in the number of vehicles in service closely follows the time distribution characteristics of passenger demand as shown in Fig. 5.

C. Cooperative Scenario

According to Nash bargaining, the pricing results implemented by the CSO are shown in Fig. 10. The total net revenue for the CSO is \$75142.76.

It can be seen that overall, the charging prices are relatively low, mostly at the middle or low level. This reflects the compromises and concessions made by the CSO to attract vehicles for charging. In response to this, the number of vehicles going to charging stations has indeed increased. Therefore, even with the trend of price reduction, the net revenue of CSO has increased.

At the same time, it is also important to note that the AMoD fleet also makes compromises. Figure 10 shows that if the AMoD fleet decides to betray, it can take full advantage of the low-price period to significantly reduce charging costs, but it refuses to do so to avoid harming its partner.

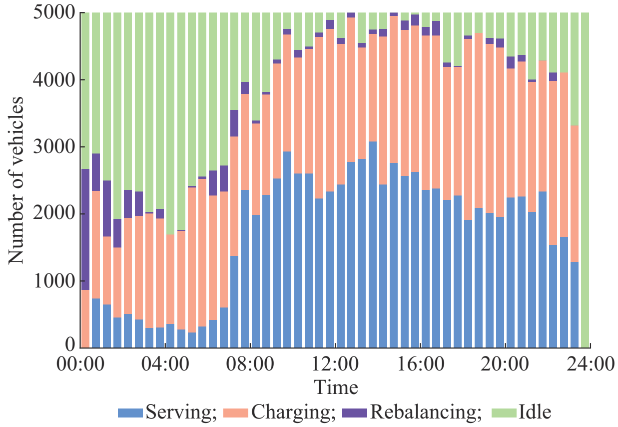

Fig. 9. Number of vehicles in different states at each time slot (Stackelberg game).

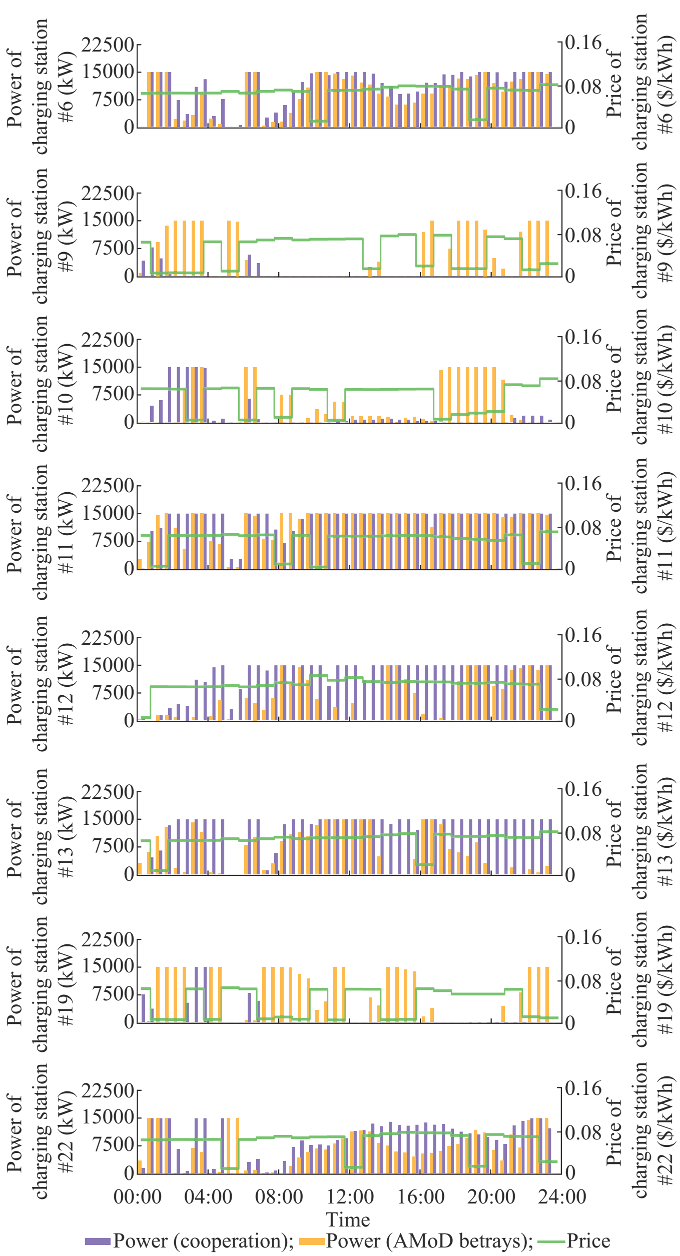

Fig. 10. Pricing results and charging power of each charging station (Nash bargaining).

Instead, the AMoD fleet focuses its main efforts on completing more passenger orders (126459 out of a total of 172926) and achieving an increase in net profits ($91048.91).

D. Comparison and Discussion

Table II summarizes the calculation results of certain indicators for different cases, considering various possible situations for comparison.

1) Case 1: complete central optimization. There exists a single entity that has full control over both the CSO and the AMoD fleet, making decisions with the goal of optimizing overall benefits.

2) Case 2: non-cooperative game. The CSO and the AMoD fleet consider each other's actions as adversaries, aiming to maximize their own interests and reach Stackelberg equilibrium.

3) Case 3: cooperative bargaining. Building upon the non-cooperative baseline, the CSO and the AMoD fleet engage in joint negotiations to reach a solution that increases the benefits for both parties while maintaining relative fairness (from the perspective of Nash bargaining theory).

4) Case 4: cooperative bargaining, but the AMoD fleet betrays the negotiation agreement.

It is worth noting that in cooperative bargaining (Case 3), the AMoD fleet is the second mover, and its betrayal corresponds to Case 4. As the first mover, the CSO's betrayal would be observed by the second mover, leading to a return to Stackelberg game (Case 2).

Firstly, complete central optimization (Case 1) determines the upper limit of the sum of net incomes for the CSO and the AMoD fleet to be $166198.49 ($91623.53 + $74574.96).

In the non-cooperative solution (Case 2), even if the average charging price set by the CSO is high, the AMoD fleet is not very proactive in charging and tries to avoid high-priced periods as much as possible. As a result, the CSO does not receive a significant net profit after settlement. Due to the concerns about charging costs, the AMoD fleet must carefully plan routes, potentially abandoning a substantial number of passenger orders. With a decrease in the fulfillment rate of passenger orders, the net revenue of the AMoD fleet also experiences a decline. In summary, compared with Case 1, Case 2 demonstrates an overall efficiency loss resulting from the adversarial nature and competition, amounting to approximately 7.45%.

In the bargaining solution (Case 3), the CSO adjusts the charging prices according to the cooperation requirements. This allows the AMoD fleet to be less concerned about charging costs and further optimize their routes to serve more passengers and generate more revenue. With the increase of distance traveled, the charging demand of the AMoD fleet also increases, resulting in higher total charging energy and increased net income for the CSO. From Table II, it can be observed that even though the average charging price set by the CSO is lower, the actual settlement price is higher. This phenomenon highlights the progress of Case 3 compared with Case 2, where the charging station assists the AMoD fleet in earning additional passenger revenue, and the fleet transfers a portion of their earnings to the CSO by increasing their charging behaviors.

TABLE II
CALCULATION RESULTS OF CERTAIN INDICATORS FOR DIFFERENT CASES

Entity	Indicator	Case 1	Case 2	Case 3	Case 4
AMoD fleet	Net revenue	$91623.53	$84429.66	$91048.91	$102605.02
	Total service distance	916745.93 km	844173.61 km	916724.11 km	837770.23 km
	Total rebalancing distance	74416.69 km	64919.63 km	74497.38 km	112375.93 km
	Completed passenger order	126470	116369	126459	115889
	Abandoned passenger order	46456	56557	46467	57037
CSO	Net revenue	$74574.96	$69380.11	$75142.76	$48920.00
	Charging station income	$96712.89	$89057.02	$97281.67	$68774.13
	Fees paid to power system	$22137.93	$19676.91	$22138.90	$19854.13
	Total charging energy	1435.66 MWh	1272.80 MWh	1435.62 MWh	1352.40 MWh
	Average charging pricing	0.050 $/kWh	0.083 $/kWh	0.057 $/kWh	0.057 $/kWh
	Average charging settlement price	0.067 $/kWh	0.070 $/kWh	0.068 $/kWh	0.051 $/kWh

Meanwhile, when comparing Case 3 with Case 1, there is hardly loss in the total net revenue. There is just a slight adjustment in revenue distribution, reflecting the nature of Pareto efficiency in Nash bargaining.

Additionally, it can be observed that the negotiation cooperation between the two parties enhances the overall benefits for various stakeholders in urban transportation. In addition to increasing the net profits of the two major players, the travel demands of passengers are also better met, resulting in a win-win situation for the CSO, the AMoD fleet, and the passengers. Furthermore, increasing the charging energy during the daytime with high photovoltaic generation in the power system is beneficial for accommodating renewable energy sources.

Regarding the possibility of betrayal in the negotiation, clear conclusions can be drawn from Table II. The comparison between Cases 2 and 3 indicates that the CSO, as the first mover, has no incentive to actively betray and return to the Stackelberg equilibrium. The comparison between Cases 3 and 4 shows that the AMoD fleet, as the second mover, would indeed significantly increase net income by choosing betrayal. However, this increase in income does not come from passenger orders, but from the unjust pursuit of low-priced periods, which will seriously damage the revenue of the CSO. At the same time, from the perspective of the entire transportation system, this scenario reduces the number of completed passenger orders and considerably increases the distance of rebalancing movements. Compared with Case 1, this results in a serious efficiency loss (approximately 8.83%), even more severe than the normal non-cooperative game (Case 2).

Fortunately, the betrayal of the AMoD fleet is not rational in terms of long-term interests. Considering the repeated game played daily, a sudden betrayal on one day will trigger the cruel strategy of the CSO in the following days. Even if the AMoD fleet can earn an extra $11556.11 (from $91048.91 to $102605.02) in one day, assuming that the CSO adopts an unforgiving strategy in the subsequent days, the AMoD fleet would essentially earn $6619.25 less every day (from $91048.91 to $84429.66). As long as the AMoD fleet considers long-term interests with a not-too-small discount factor δ $(0<\delta<1)$, it will realize that betrayal is not profitable. It should be noted that these discussions are only at the theoretical level of game theory and do not consider the complexities of the real-world business environment or government regulations.

The above analysis indicates that the game frameworks designed in this paper capture the decision-making characteristics of both the CSO and the AMoD fleet. Game equilibrium helps guide and explain the operation of the future urban transportation system.

V. CONCLUSION

The AMoD system provides a revolutionary and promising solution for future urban transportation. The charging behavior of AMoD fleets, as a critical link connecting future power and transportation systems, requires a well-guided charging demand management method. This paper investigates the charging pricing strategy for the AMoD fleet based on game theory. Firstly, an optimization scheduling model is established to describe the spatio-temporal action patterns of the AMoD fleet. Subsequently, charging pricing strategies are studied using Stackelberg game and Nash bargaining. Then, interaction trends between the two entities and the mechanism of charging price formation are discussed, along with an analysis of the game implications for breaking out of the non-cooperative dilemma and moving towards cooperation. Finally, numerical experiments based on real-world city-scale data are provided to validate the rationality of the proposed frameworks. The results show that the AMoD fleet has profit-driven action patterns and can capture and utilize the spatio-temporal distribution of charging prices. By leveraging this behavior, the CSO can formulate optimal profit-oriented charging prices based on Stackelberg game. Furthermore, if the negotiation between the AMoD fleet and the CSO can be conducted, the net incomes of both parties can increase. The fulfillment of passenger's travel demands and the comprehensive benefits of stakeholders in urban transportation can be enhanced.

This paper only involves a single CSO and a single AMoD fleet. In general, there may be multiple CSOs and multiple AMoD platforms in a city. In such cases, multiple

CSOs may compete for the charging demands of vehicles to seize market share and earn more profits, while multiple AMoD fleets may also compete with each other due to charging capacity limitations, traffic congestion effects, etc. It may be necessary to introduce complex game architectures (such as Nash-Stackelberg-Nash game) to describe the interactions between various entities. Moreover, considering the uncertainties involved in traffic networks and passenger orders, dynamic pricing for charging stations and real-time online scheduling for AMoD fleets will be more challenging research topics.

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