On the Operational Feasibility of Autonomous Vehicle Crowdsourcing Service under Heterogeneous Supply Availability

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Short summary

Autonomous vehicle (AV) crowdsourcing service enables privately-owned AVs to rent out their vehicles to serve other travelers during idle periods. Existing literature suggests that this business model holds potential benefits for travelers, AV owners, and the operator, yet the analysis has mostly overlooked the heterogeneity in the spatiotemporal supply pattern. Motivated by this gap, we propose a time-expanded network model that jointly optimizes the AV rental price and vehicle dispatching, where the private AV supply is characterized by the idle periods and available locations of different classes of AV owners. With the proposed model, we numerically investigate the operational feasibility of an AV crowdsourcing service and identify key factors that influence service performance using a stylized two-region model. We further conduct a case study of Chicago based on the household travel survey and ride-hailing trip data. The results not only offer practical insights for service operators but also provide regulators with a better understanding of the potential impact of AV crowdsourcing on the citywide travel patterns and traffic dynamics.
Keywords: Autonomous vehicle crowdsourcing service; Heterogeneous travel patterns; Shared autonomous vehicles; Time-expanded network model.

1 Introduction

Autonomous driving technology is rapidly developing. Pilot programs and early-stage deployments have already emerged all over the world. The realization of fully autonomous driving is expected to fundamentally transform people's travel behavior, such as enhanced accessibility and different land use patterns. New mobility service models are likely to arise. One notable example is AV crowdsourcing services, in which privately owned vehicles are utilized for ride-hailing when not in use by their owners (X. Wang et al., 2021).

Compared with conventional human-driven ride-hailing services, the key modeling distinction of AV crowdsourcing services lies in the supply side. For ride-hailing services with human drivers, heterogeneity in driver preferences arises from factors such as working hours, activity schedules and home locations(Jaydarifard et al., 2024; Ashkrof et al., 2020). These factors are difficult to model mathematically, and much of the existing literature addresses them using data-driven approaches(Liu et al., 2022). Moreover, although platforms aim to optimize operational strategies, drivers do not always fully comply with dispatching decisions, thereby undermining the effectiveness of platform-level optimization. To mitigate this issue, several studies have proposed methods to infer driver preferences (T. Jiang et al., 2025; Urata et al., 2021), and incorporate these estimates into the optimization of service operations (L. Jiang et al., 2025).

With the transition from human-driven services to AV crowdsourcing services, supply-side heterogeneity would change. Supply is no longer influenced by driver preferences but is instead constrained by vehicle owners' spatiotemporal availability. In AV crowdsourcing services, vehicle owners report the locations and available time windows of their vehicles to the platform. Using this information, the platform manages the ride-hailing operations (Mourad et al., 2019). The primary requirement is that vehicles must be returned to their owners' locations within the specified time windows; within these periods, the platform retains full control over operational strategies

(S. Wang et al., 2019). Neglecting these constraints may prevent owners from using their vehicles as planned, potentially resulting in dissatisfaction and erosion of trust in the platform; thus, they must be explicitly incorporated into the model. Mourad et al. (2019) simulated service operations while incorporating these constraints; however, they assumed a fixed set of participating vehicle owners and did not account for the fact that participation is itself an endogenous decision influenced by platform pricing.

In the existing literature on AV crowdsourcing, research has either focused on optimizing service operations while neglecting pricing decisions (Mourad et al., 2019), or analyzed pricing incentives using aggregated models that neglect supply-side constraints (Z. Zhang et al., 2025; X. Wang et al., 2024). To the best of our knowledge, few studies have examined the joint design of pricing and operational strategies in the context of AV crowdsourcing services.

In this study, we model vehicle operations using a flow-based framework, in which vehicle movements across different time-space locations are represented as flows. This formulation enables operational constraints to be expressed as a set of linear equations (Pavone, 2016; R. Zhang et al., 2016; Zgraggen et al., 2019). We then evaluate service performance and platform costs under varying travel pattern metrics and cost factors. Finally, through a case study, we examine city-level service operations and illustrate the spatial and temporal distribution patterns of AV crowdsourcing service.

2 Model

To build the time-expanded network model, we divide the service area into regions and discretize the time horizon into intervals. The set of regions is denoted as $\mathcal{J}$ of size $J = |\mathcal{J}|$. AV owners are assumed to rent out their private AVs for multiple units of intervals Δ_s (e.g., $\Delta_s = 1$ hr). Accordingly, we use $h = 1, \ldots, H$ as the index of AV rental periods. For each rental period, the platform sets region-specific rental prices $P \in \mathbb{R}_+^{H \times J}$, with each element P_{hj} representing the payment made to an AV owner who rents out the private vehicle originating from region j during period h. On the demand side, the service horizon is divided into finer time slots of length Δ_t (e.g., $\Delta_t = 15$ min). Similarly, we introduce $t = 1, \ldots, T$ to denote each service period. To make the two time scales compatible, we assume Δ_s is a multiple of Δ_t (e.g., $\Delta_s = 4\Delta_t$). Besides, we assume the travel times between regions are constant and collectively denoted by matrix π, where π_{ij} is the travel time from region i to region j as multiples of Δ_t.

Vehicle supply

AV owners are categorized into a finite number of classes, denoted by Θ, according to their personal travel patterns during the day, where each class $\theta \in \Theta$ contains a total number of M^θ AV owners. We use an incidence matrix $\Omega^\theta \in \{0,1\}^{H \times J}$ to represent the spatiotemporal availability of supply of AV owners in class θ, where $\Omega^\theta_{hj} = 1$ if the vehicle can be rented out from region j for period h, and 0, otherwise.

We assume AV owners perceive heterogeneous opportunity costs ε that follow a known distribution with a positive finite support. To focus on the analysis of heterogeneous mobility pattners, we assume all AV owner classes share the same distribution of opportunity costs. In the context of AV crowdsourcing, the opportunity cost can be interpreted as the minimum acceptable compensation. Hence, AV owners would only rent out their AVs if the spatiotemporal rental price P_{hj} exceeds their opportunity costs, subject to availability. Accordingly, the spatiotemporal private AV supply of class θ from region j over time period h is given by

$$N^\theta_{hj} = M^\theta \mathbb{P}(P_{hj} \geq \varepsilon) \Omega^\theta_{hj}. \tag{1}$$

To convert the private AV supply from the rental periods to service periods, we introduce another incidence matrix $\Gamma \in \{0,1\}^{T \times H}$. The private AV supply of class θ measured by the service periods, denoted by $\tilde{N}^\theta \in \mathbb{R}^{T \times J}$, is thus given by

$$\tilde{N}^\theta = \Gamma N^\theta. \tag{2}$$

We further define $Z^\theta \in \mathbb{R}^{T \times J}$ as the difference between private AV supply between consecutive time periods, and assume all rentals start and finish within the same day. Hence, the net private AV supply of class θ is given by

$$Z^\theta_{t\cdot} = \tilde{N}^\theta_{t\cdot} - \tilde{N}^\theta_{t-1\cdot}, \tag{3}$$

where $Z^\theta_{t\cdot}$ denotes the t-th row in matrix Z^θ, and the same notation applies to other variables hereafter. A dummy vector $N_{0\cdot} = 0$ is introduced to avoid additional specification of $Z^\theta_{1\cdot}$.

Assume that all private AVs are rented and returned in the same region. Thus, a positive (negative) value in Z^θ indicates the number of newly rented (returned) private AVs of each region and time period. Besides renting private AVs, the platform also owns a fleet of N^ν AVs, which is treated as exogenous and serves the entire service region over the full planning horizon. Here, ν distinguishes these platform AVs from private AVs and collectively yields the set of vehicle classes $\mathcal{K} = \Theta \cup \{\nu\}$.

Vehicle dispatching strategies

The vehicle dispatching strategy is expressed as a set of matrices $Y^k \in \mathbb{R}_+^{T\times J\times J}$, each of which indicates the flows of AVs in class k. Specifically, each element Y^k_{tij} denotes the vehicle flow from region i to region j, departing during time period t. Before introducing the constraints on dispatching flows, we first introduce several intermediate variables. Firstly, since travel times between regions are not uniform, we construct the arrival matrix V^k in line with the departure matrix Y^k as follows:

$$V^k_{\tau(t)\cdot\cdot} = Y^k_{t\cdot\cdot}, \qquad \forall k \in \mathcal{K},\ \forall t, \tag{4}$$

where the mapping of time period $\tau : \mathbb{R}^{J\times J} \to \mathbb{R}^{J\times J}$ is defined as

$$\tau_{ij}(t) = \begin{cases} t + \pi_{ij}, & \text{if } t + \pi_{ij} \le T, \\ t + \pi_{ij} - T, & \text{otherwise.} \end{cases} \tag{5}$$

It thus allows us to consider periodic operations of AVs without specifying the starting and ending times. The inverse mapping τ^{-1} can be easily derived as per Eq. (5).

The vehicle dispatching flows Y are subject to several constraints. The first and shared among all vehicle classes is that the total dispatching flow from each region must not exceeds the total available vehicles. Let $E^k \in \mathbb{R}_+^{T\times J}$ denote the empty vehicle flow of class k at the beginning of each time period in each region. The first constraint is thus given by

$$Y^k_{t\cdot\cdot}\mathbf{1} \le E^k_{t\cdot}, \qquad \forall k \in \mathcal{K},\ \forall t, \tag{6}$$

where $\mathbf{1}$ denotes an all-ones vector of dimension J.
The second constraint expresses the flow dynamics of private AVs in each region between two consecutive time periods:

$$E^\theta_{t\cdot} = E^\theta_{t-1\cdot} + (V^\theta_{t-1\cdot\cdot})^\top\mathbf{1} - Y^\theta_{t\cdot\cdot}\mathbf{1} + Z^\theta_{t\cdot}, \qquad \forall \theta \in \Theta,\ \forall t > 1. \tag{7}$$

Since all private AV rentals complete within the same day, we also need to introduce the following constraints on the empty vehicles at the first and last time periods:

$$E^\theta_{1\cdot} = N^\theta_{1\cdot}, \qquad \forall \theta \in \Theta, \tag{8}$$

$$E^\theta_{T\cdot} + (V^\theta_{T\cdot\cdot})^\top\mathbf{1} - Y^\theta_{T\cdot\cdot}\mathbf{1} = N^\theta_{T\cdot}, \qquad \forall \theta \in \Theta. \tag{9}$$

It also enforces the zero vehicle dispatching at the end of service:

$$Y^\theta_{tij} = 0, \qquad \forall t > T - \pi_{ij},\ \forall i, j \in \mathcal{J}. \tag{10}$$

Similar constraints are defined for platform AVs, while a single fleet conservation is sufficient given that the platform AV supply remains the same over time:

$$E^\nu_{t\cdot} = E^\nu_{t-1\cdot} + (V^\nu_{t-1\cdot\cdot})^\top\mathbf{1} - Y^\nu_{t\cdot\cdot}\mathbf{1}, \qquad \forall t, \tag{11}$$

$$E^\nu_{T\cdot}\mathbf{1} + \mathbf{1}^\top U^\nu_T\mathbf{1} = N^\nu, \tag{12}$$

where $U^\nu_T \in \mathbb{R}_+^{J\times J}$ denotes the en-route platform AVs during the last time period T with each element computed as

$$U^\nu_{Tij} = \sum_{t'=\tau^{-1}(T)}^{T-1} Y^v_{t'ij}, \qquad \forall i, j \in \mathcal{J}. \tag{13}$$

Service capacity planning

We formulate the platform's service capacity planning as an optimization problem that aims to minimize the total supply cost, which comprises vehicle rental expenses and operational costs. The passenger demand and trip revenue are assumed exogenous in this study, whereas a penalty is introduced to the objective function to capture the loss of trip fare revenue when customer demand cannot be fully served. Let $D \in \mathbb{R}_+^{T\times J\times J}$ denote the demand across regions in time period t. Then, the demand loss $W \in \mathbb{R}_+^{T\times J\times J}$ is given by

$$W_{t\cdot\cdot} = \max\left\{0, D_{t\cdot\cdot} - \sum_{k\in\mathcal{K}} Y^k_{t\cdot\cdot}\right\}, \qquad \forall t. \tag{14}$$

Accordingly, the platform's optimization problem is formulated as follows:

$$\min_{P,Y} \quad \sum_{\theta\in\Theta}\langle P, N^\theta\rangle_F + c_0\sum_{k\in\mathcal{K}}\langle Y^k, \Pi\rangle_F + \langle c_\rho, W\rangle_F, \tag{15a}$$

$$s.t. \quad \text{Constraints (1)-(13)}, \tag{15b}$$

$$P, Y \geq 0 \tag{15c}$$

where $Y = (Y^\theta, Y^\nu)_{\forall\theta\in\Theta}$ denotes the full set of dispatching flows, $\langle\cdot,\cdot\rangle_F$ denotes the Frobenius inner product (i.e., sum of all element values of the element-wise product of two matrices), $c_0 \in \mathbb{R}_+$ represents the unit AV operation cost assumed equal between platform and private AVs, $\Pi \in \mathbb{R}_+^{T\times J\times J}$ stacks T times of travel time matrix π, and $c_\rho \in \mathbb{R}_+^{T\times J\times J}$ expresses the penalty of unit lost deman by time and OD pair (e.g., trip fare).

Assumption 1 *The opportunity cost of private AV owners follows a uniform distribution with support* $[\underline{\varepsilon}, \overline{\varepsilon}]$.

Proposition 1 *Under Assumption 1, the original capacity planning problem* (15) *can be reformulated as a convex quadratic problem.*

When the opportunity cost of AV owners is uniformly distributed, the original capacity planning problem (15) can be reformulated as a convex quadratic program, which can be efficiently solved using commercial solvers such as Gurobi for large-scale instances. The detailed reformulation is omitted due to the space limit.

3 Sensitivity analyses of influential factors

To explore key factors that affect the feasibility of AV crowdsourcing service, we first conduct numerical experiments on a stylized two-region network consisting of a residential area and a commercial area (see Figure 1). Accordingly, we construct the travel patterns of daily commutes for both passengers and AV owners, shown in Figure 2. Specifically, for passengers, all trips are from the residential area to the commercial area during the morning peak from 7 am to 10 am, whereas the opposite direction applies for the evening peak from 17 pm to 20 pm. The travel pattern of AV owners well mimics that of passengers but shifts either forward or backward (see two examples in Figure 2). Parameters include: the rental and trip time intervals are set to $\Delta_s = 1$ hr and $\Delta_t = 10$ min. The service horizon spans the entire 24 hours of a day. The intra-region trip duration is Δ_t while the inter-region trips take $3\Delta_t$. Following Assumption 1, we assign a uniform distribution of AV owners' opportunity cost with lower bound $\underline{\varepsilon} = 1$ and upper bound $\overline{\varepsilon} = 10$ (\$/hr). The operation cost is set as $c_0 = 0.6$ (\$/hr) (Wu et al., 2015). Finally, the fleet size of platform-owned AVs is assumed to be $N^\nu = 100$.



Figure 1: Stylized two-region network.

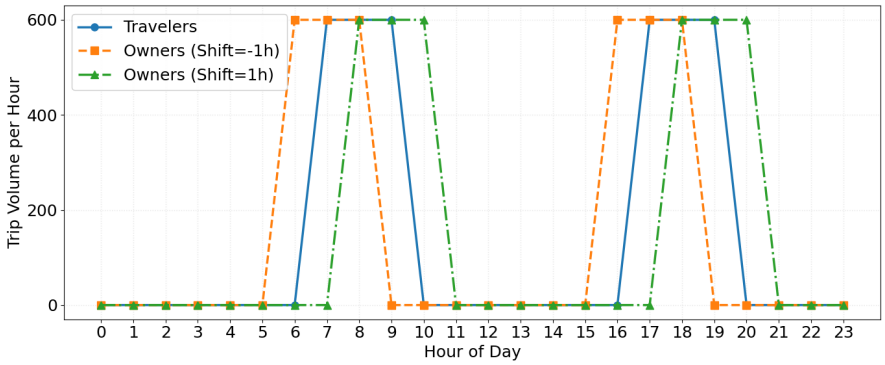
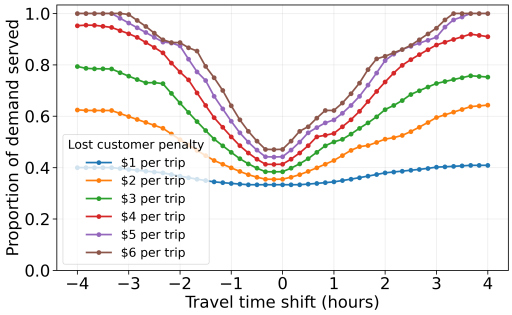


Figure 2: An example of travel time shift between owners and customers

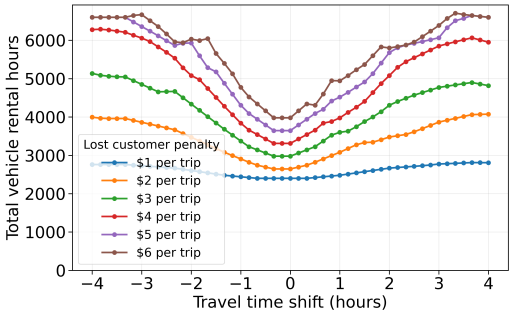
Lost demand penalty

We first investigate the service performance against the shift in travel pattern and the penalty of loss customer. As shown in Figure 3, the service achieves a higher efficiency with higher demand fulfillment and lower total service cost when the absolute difference in the travel pattern of passengers and AV owners expands. The direction of shift, however, does not make a significant difference, as all the results are mostly symmetric. These findings are generally expected because a significant supply-demand imbalance is likely to arise when passengers and AV owners simultaneously require vehicle access.

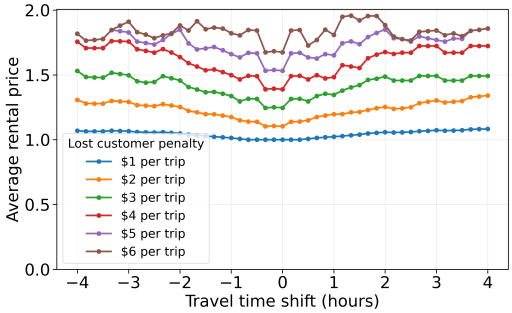
As expected, the higher the penalty, the more aggressive the private AV acquisition, which is reflected in both rental hours and price as per Figures 3 (b) and (c). The difference in rental hours and served demand grows significantly when the shift in travel pattern increases from zero and gradually saturates. Such a pattern is more noticeable in the high-penalty scenario. In contrast, the rental price remains relatively stable, implying that most additional rental hours are attributed to the larger potential supply. Overall, results in Figure 3 suggest that the success of AV crowdsourcing largely depends on the difference in travel patterns between private AV owners and passengers, particularly when the penalty of customer loss is considerable.



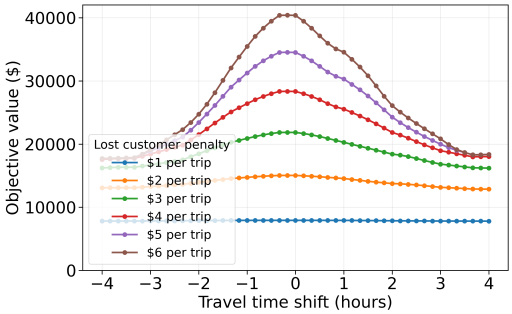
(a) Proportion of demand served



(b) Total vehicle rental hours



(c) Average rental price



(d) Objective value

Figure 3: Results under different travel pattern shifts and lost deman penalties.

Reliability buffer

To guarantee vehicle access for AV owners when needed, some buffer time shall be introduced before and after the AV owner's trip, as illustrated in Figure 4. Consequently, the available period for rent becomes shorter. The length of buffer time also reflects the AV owner's risk preference: a larger buffer indicates the owner is highly risk-averse and favors access to his/her own vehicle over the potential revenue of vehicle sharing.

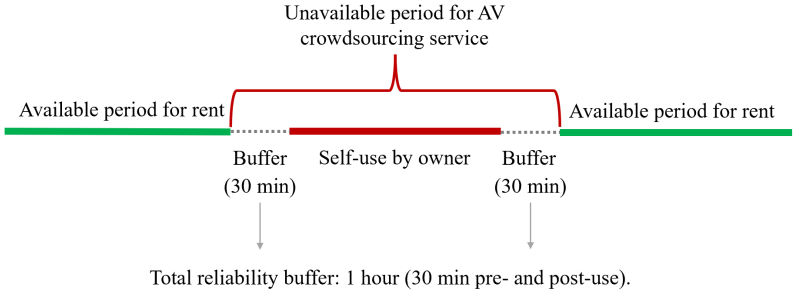
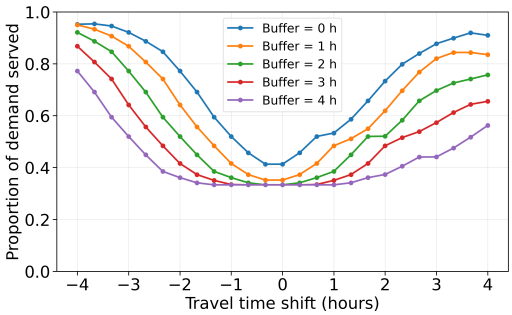
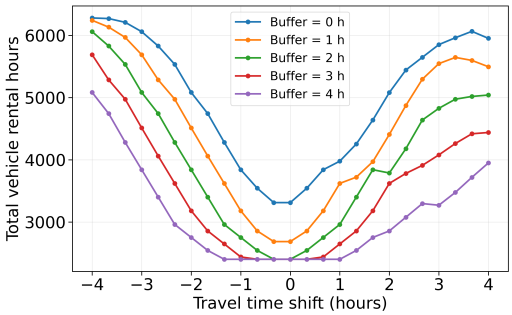


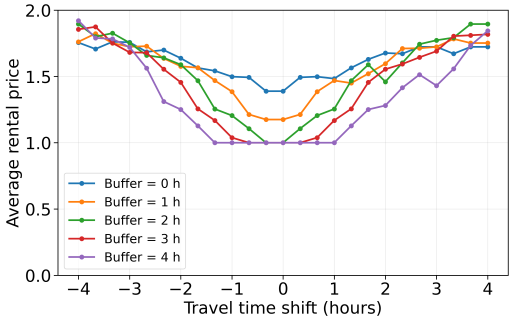
Figure 4: Illustration of one-hour reliability buffer



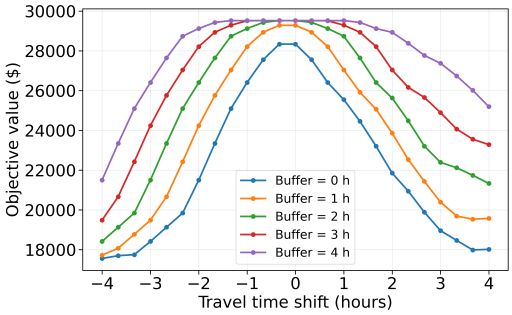
(a) Proportion of demand served



(b) Total vehicle rental hours



(c) Average rental price



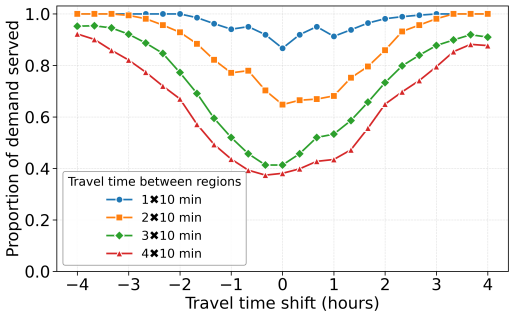
(d) Objective value

Figure 5: Results under different travel pattern shifts and reliability buffers.

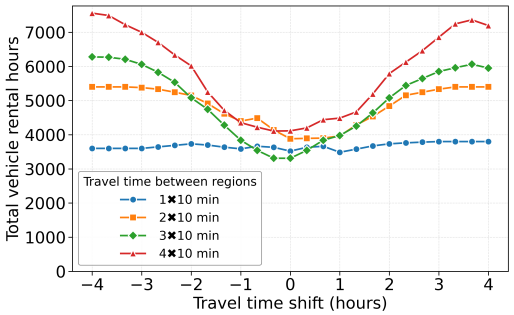
As shown in Figure 5, a larger buffer significantly compromises the service performance, but the negative impact can be largely offset by the shift in travel patterns. For instance, with a four-hour buffer, the service rate recovers from 40% to almost 80% when there is also a four-hour difference in the travel pattern between passengers and AV owners. However, with the same level of rental price, much fewer vehicle hours are obtained, as shown in Figures 5 (b) and (c). These results indicate that the reliability buffer could play a critical role in the design and operation of AV crowdsourcing services, which requires a deeper analysis considering the heterogeneity among AV owners.

Inter-region travel time

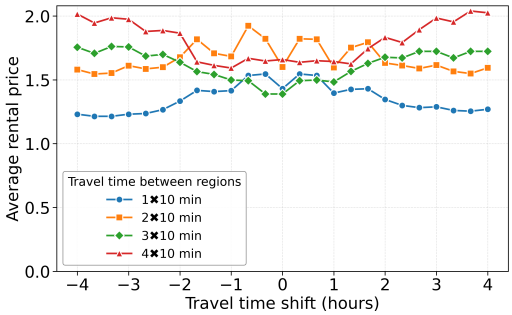
The inter-region travel time is particularly important when rented AVs are required to be returned to the same locations. If there are no passenger trips in the same direction as the vehicle return



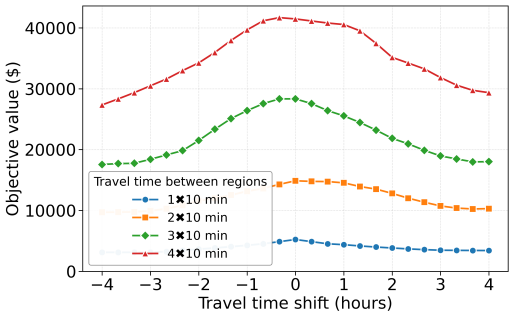
(a) Proportion of demand served



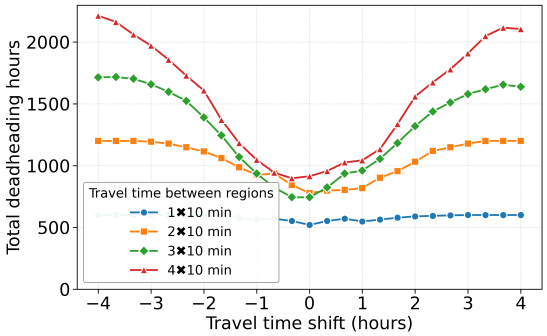
(b) Total vehicle rental hours



(c) Average rental price



(d) Objective value



(e) Total deadheading hours

Figure 6: Results under different travel pattern shifts and inter-region travel times.

trips and the inter-zone travel time is long, a large number of deadheading hours is expected. This result is indeed reflected in Figure 6 (e), especially when the travel pattern shift is large. In this case, more private AVs are available and also rented to fulfill the majority of passenger demand; see Figures 6 (a) and (b). In contrast, when inter-region travel time is sufficiently short, the benefit of travel pattern shifts diminishes because the platform can easily coordinate the movements of private AVs between regions. Furthermore, a slightly lower rental price is observed in Figure 6 (c), indicating an oversupply of private AVs.

4 Case study of Chicago

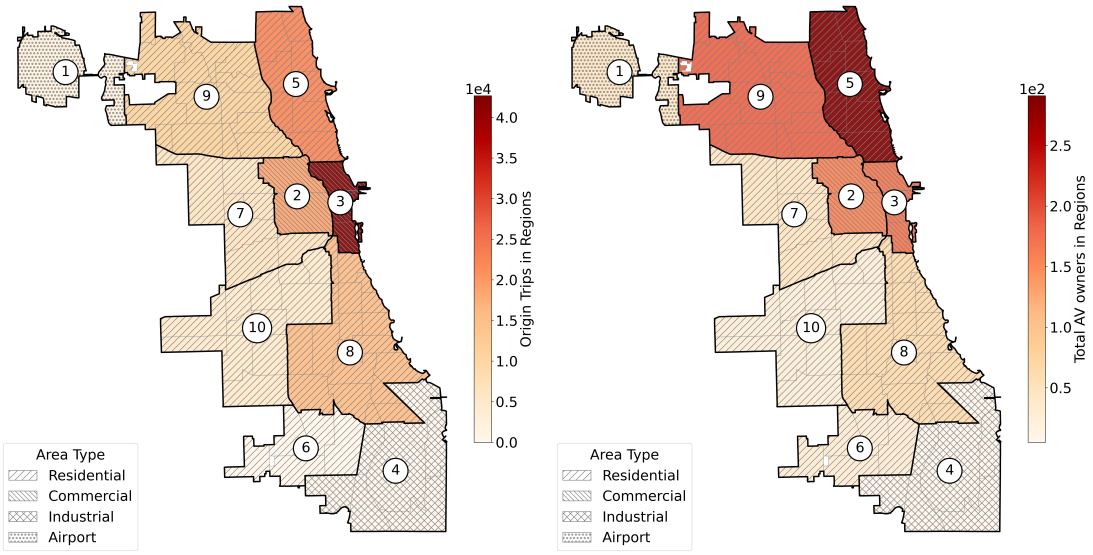
To further validate the operational feasibility of AV crowdsourcing services, we conduct a case study of Chicago based on the 2019 household travel survey by the Chicago Metropolitan Agency of Planning (Chicago Metropolitan Agency for Planning (CMAP), 2025), and the open-access ride-hailing data (City of Chicago, 2026).

Model setup

We combine the land use and geographical features to partition the Chicago city into 10 regions(City of Chicago, 2025). The time horizons are set to $\Delta_t = 15$ min and $\Delta_s = 1$ h. Due

to the lack of empirical data about private AV owners, we select high-income individuals with private vehicles in the survey as potential AV owners and group them into 669 classes according to their daily travel patterns. We assume the opportunity cost of AV owners follows a single uniform distribution while setting $\underline{\varepsilon} = 1$ (\$/hr) and $\overline{\varepsilon} = 25$ (\$/hr) (Valente et al., 2019). The number of platform-owned vehicles is $N^{\nu} = 100$. The spatial distribution of AV owners is shown in Figure 7 (b).

As for the passenger demand pattern, we extracted the ride-hailing trip data on November 20, 2024, filtered trips that both started and ended in the study region, and mapped them to time periods and regions specified in this case study. The spatial distribution of trip origin is shown in Figure 7 (b), while the temporal demand pattern is illustrated in Figure 8. Other parameters estimated from the ride-hailing trip data are the travel times between regions and the penalty of lost demand (as average trip fare).



(a) Passenger trip origin (b) AV owners

Figure 7: Potential demand and supply distribution.

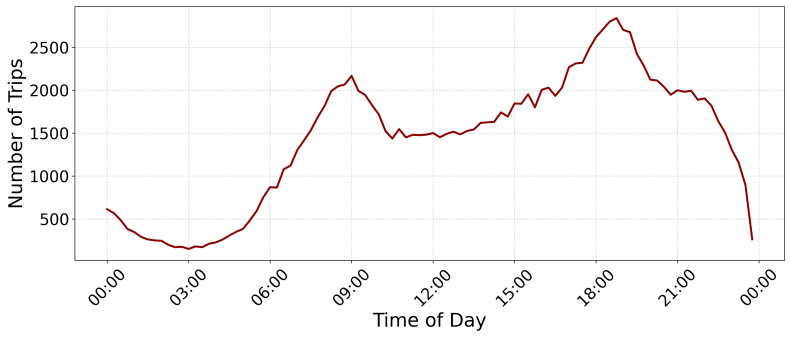


Figure 8: Temporal passenger demand over the day.

Main results

Due to the space limit, we only present the main results below. Figure 9 presents the average rental price, along with variance, over the day. It can be seen that the price closely follows the passenger demand pattern in Figure 8. The synchronization is due to two main factors. On the one hand, the platform-owned vehicles are not sufficient to serve the high passenger demand during peak hours, which forces the platform to increase the rental price to attract more AV owners. On the other hand, many AV owners also travel during the peaks, making it more expensive to rent private AVs.

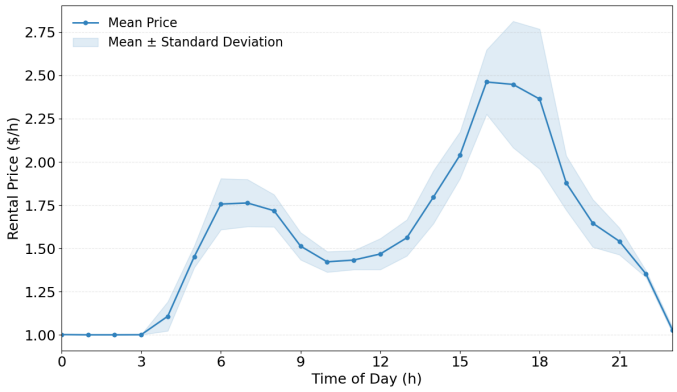
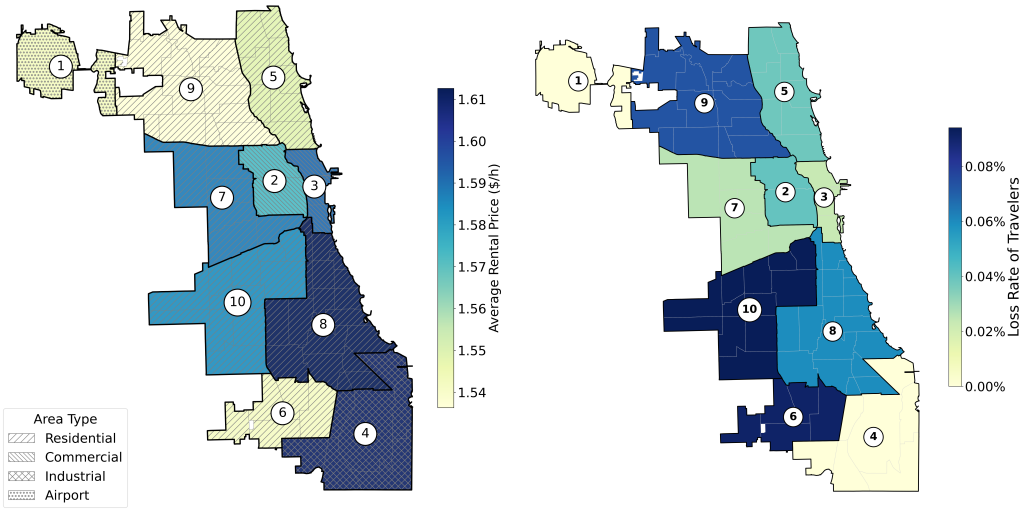


Figure 9: Average rental prices over the day with variability.

Figure 10 illustrates the spatial distribution of rental price and lost demand. Comparing Figure 7(b) and Figure 10(a), one can easily recognize that high rental prices are mostly associated with sparse private AV availability. Almost all passengers are served thanks to the well-coordinated operations of crowdsourced and fleet-owned AVs, which is further demonstrated in Figure 11.



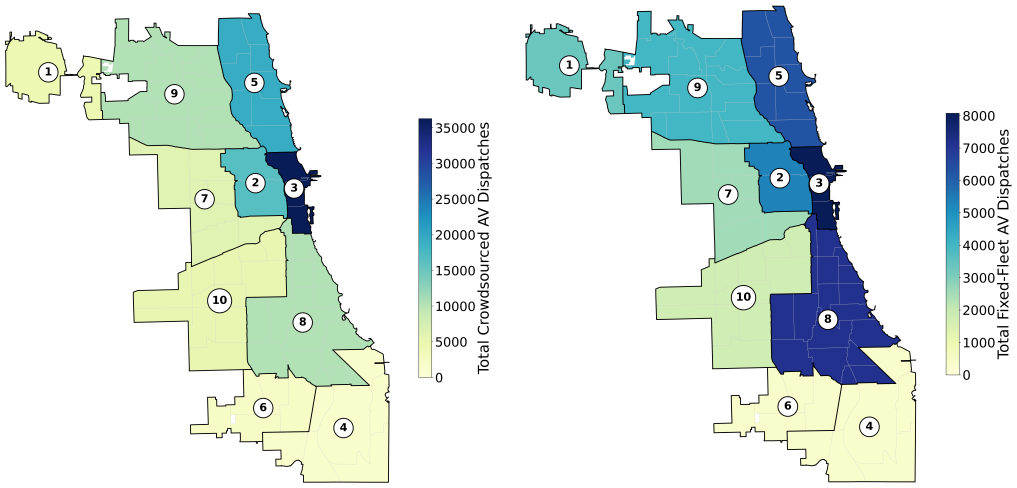
(a) Average rental price (b) Percentage of lost demand

Figure 10: Spatial distribution of rental price and demand loss.

As shown in Figure 11, the crowdsourced and platform-owned AVs have fairly different operational patterns. While the crowdsourced AVs are highly concentrated in central commercial areas, the platform-owned AVs are more spatially dispersed, covering both commercial and surrounding residential areas. Notably, the platform-owned AVs serve a larger share of trips originating at the airport, which could induce large deadheading hours for crowdsourced AVs. These results highlight the benefit of AV crowdsourcing in improving service efficiency and thus demonstrate its strong potential in real practice.

5 Conclusions

This paper investigates the operational feasibility of AV crowdsourcing services under heterogeneous travel patterns. Given private AV owners' spatiotemporal availability throughout the day, we develop a time-expanded network model to jointly optimize AV rental price and vehicle operations. With a stylized two-region model, we explore the sensitivity of service performance towards the difference in travel patterns between passengers and AV owners, along with the lost demand penalty, reliability buffer, and inter-region travel time. More practical insights are generated from a case study of Chicago based on real travel survey and ride-hailing trip data.



(a) Crowdsourced AVs (b) Platform-owned AVs

Figure 11: Spatial distribution of private and platform-owned AVs.

Future research can extend this work in multiple directions. First and foremost, strong assumptions on the opportunity cost, reliability buffer, and other parameters shall be relaxed to further investigate the impact of user heterogeneity and generate additional insights into practice. Besides, it has been assumed the travel pattern of AV owners is not affected by the AV crowdsourcing service, which may not be true in reality. Future research can explore how the vehicle sharing revenue could reshape the AV owners' activity patterns. Beyond strategic planning, it is also worthwhile to study the operational problems in AV crowdsourcing services.

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