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A Profit-Aware Negotiation Mechanism for On-Demand Transport Services

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Abstract. As new markets for transportion arise, on-demand transport services are set to grow as more passengers seek affordable personalized journeys. To reduce passenger prices and increase provider revenue, these journeys will often be shared with other passengers. As such, new negotiation mechanisms between passengers and the service provider are required to plan and price journeys. In this paper, we propose a novel profit-aware negotiation mechanism: a multi-agent approach that accounts for both passenger and service provider preferences. Our negotiation mechanism prices each passenger's journey, in addition to providing vehicle routing and scheduling. We prove a stability property of our negotiation mechanism using a connection to hedonic games. This connection yields new insights into the link between vehicle routing and passenger pricing. We also show via simulations the dependence of the service provider profit and passenger prices on the number of passengers as well as passenger demographics. In particular, our key observation is that increasing the number of passengers has the effect of increasing passenger diversity, which in turn increases the service provider's profit.

1 Introduction

On-demand transportation services are initiated at the request of passengers, between flexible origins and destinations. In current transport systems, on-demand transport plays an important role in the form of taxi services, and transportation for the elderly and disabled [6]. Looking to the near future, on-demand services are set to grow dramatically with advances in online markets, increased data collection and analysis in transport systems, and near-ubiquitous mobile communication services. Even now, numerous public (e.g. SUPERHUB [4]) and private (e.g. Lyft[2] and Cabforce[3]) organizations have begun R&D projects to implement open transport markets, supported by intelligent data aggregation.

The traditional formulation of the journey planning problem for on-demand transport is the dial-a-ride problem (DARP); a constrained version of the classical traveling salesman problem [9]. In the DARP, a fleet of vehicles services passengers with pick-up and drop-off time constraints. Importantly, the fleet of vehicles is operated by a single provider. The optimal solution of the DARP is then the minimum cost vehicle routes that satisfy all passenger constraints. An extensive collection of optimal and heuristic algorithms have been proposed within the operations research literature to solve the DARP, which are comprehensively summarized in [6].

Despite the improved efficiency of the traditional DARP over unprincipled heuristics, it remains a centralized approach–well-known to scale poorly as the size of the transport system increases. To overcome the scaling problems in the traditional DARP, distributed approaches have been proposed. In particular, multi-agent techniques have been employed, where passengers and vehicles are treated as autonomous agents. For instance, multi-agent taxi scheduling was proposed in [11, 1, 14] and multi-agent DARP (and related vehicular routing problems) in [12, 7, 3, 2, 13].

Unfortunately, the state-of-the-art multi-agent DARP approaches in [12, 7, 3, 2, 13] have largely focused on finding the minimum cost routes for each vehicle (subject to passenger pick-up and delivery time constraints). In near-future transport markets, the optimal vehicle routes will be determined by what passengers are prepared to pay–hidden from the service provider–in addition to the cost of vehicle routes. These price preferences were partially addressed in [10] via a cost sharing mechanism; however, the intimate connection between passenger pricing and journey planning was not considered.

In this paper, we propose a novel profit-aware negotiation mechanism for the DARP, to obtain vehicle routes, as well as passenger allocations and prices. In particular, we develop a four-stage negotiation between each passenger and the service provider; passenger preferences, vehicle capacities, and route costs are all accounted for. Our negotiation mechanism fundamentally differs from previous approaches to the multi-agent DARP as our focus is on the service provider *profit*–explicitly accounting for the individual preferences of both the provider and passengers–instead of costs that lump preferences together. As such, our negotiation mechanism should in fact be viewed as a market mechanism–a protocol to exchange services for monetary payment. Our approach opens the way for the outcomes of our negotiation to reflect the behaviors and motivations of service providers and passengers in the real world.

In order to efficiently route and price each passenger's journey, we cluster passengers into feasible trips. Each vehicle's route is then found by routing through a subset of the passenger clusters. To ensure that the clusters are stable–i.e., no bias against any passenger–we introduce the passenger cluster game and show that it is in fact a type of hedonic game. We then prove that the stability of passenger clusters (analogous to coalitions) is determined by the cost of travelling between clusters and the price each passenger is offered. Our result has the surprising implication that minimizing the cost for the initial clustering is not necessarily optimal when cluster stability is also required.

We then show via Monte Carlo simulations that the service provider profits and passenger prices are highly dependent on the number of potential passengers and the passenger demographic. In particular, increasing the number of potential passengers increases

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diversity, which in turn increases the profit of the service provider. We also show that our negotiation mechanism has the desirable property that the service provider charges more when passengers are prepared to pay more.

2 System Model

Consider an on-demand transportation network consisting of a single service provider and N passengers. The service provider owns a fleet of K vehicles, each with a capacity of C passengers. Passenger pick-up and drop-off locations, and direct routes between locations are represented by the graph $G = (V, E)$. In particular, the pick-up and drop-off locations are represented by vertices in the set V, while the direct routes between locations in V are represented by the edges in the set E. We assume that all passengers to be serviced are known before the negotiation begins[4] and that each vehicle starts and finishes at the same depot.

Associated to each vertex $v \in V$ (corresponding to pick-up/drop-off locations) is a service time s_v, which represents the time required for the vehicle to board passengers. Moreover, associated to each edge $e \in E$ (corresponding to direct routes between locations) are:

1. a start location $u \in V$;
2. an end location $w \in V$;
3. a cost $c_e \in [0, \infty)$ to the service provider to traverse edge $e \in E$;
4. and an edge traversal time $t_e \in \{0, 1, 2, \ldots\}$.

The edge cost c_e and the edge traversal time t_e are found during pre-processing where the service provider solves the shortest path problem between u and w on the underlying road network.

2.1 Passenger Preferences

Before the passenger allocation is performed via our negotiation mechanism, each passenger provides the following information to the service provider:

1. pick-up and drop-off locations, denoted by $v_{i,p} \in V$, $v_{i,d} \in V$ for passenger i's pick-up and locations, respectively;
2. pick-up time interval, denoted by $(a_i, b_i) \in \{0, 1, 2 \ldots\} \times \{0, 1, 2, \ldots\}$ with $a_i \leq b_i$ for the i-th passenger;
3. latest drop-off time, $l_i \in \{0, 1, 2, \ldots\}$ with $l_i > b_i$ for the i-th passenger.

In addition to the travel requirements, each passenger also has preferences for the amount she is willing to pay. In particular, we assume that passenger i is prepared to pay a maximum price of $p_{i,\max} = r_{i,\max} R_i$, where R_i is the distance as the crow flies between passenger i's pick-up and drop-off locations[5] and $r_{i,\max} \in (0, \infty)$ is a price rate in €/km, which converts the distance traveled into euros.

To account for differences in price preferences between passengers, we model $r_{i,\max}$ as a random variable (independently and identically distributed for each passenger) distributed according to the generalized Beta distribution on support $[0, r_{\max}]$. In particular, the cumulative distribution function (CDF) for the price rate $r_{T,i}$ is

$$F_{r_{i,\max}}(x) = \frac{1}{B(\alpha, \beta)} \int_0^{\frac{x}{r_{\max}}} t^{\alpha-1}(1-t)^{\beta-1} dt \qquad (1)$$

for all $i \in \{1, 2, \ldots, N\}$, where $B(\alpha, \beta)$ is the Beta function. We have chosen the generalized beta distribution as it has a large number of distributions with bounded support as special cases, which means that our model can be tailored to a variety of demographics.

Importantly, the actual maximum price, $p_{i,\max}$ that passenger i is prepared to pay is known *only* to passenger i. The service provider only knows the *distribution* of $p_{i,\max}$, for each passenger. This has important consequences in the negotiation as the service provider cannot initially be sure whether or not a passenger will accept an offer.

2.2 Service Provider Preferences

The objective of the service provider is to maximize its *profit*; i.e the difference between the total revenue obtained from all the passengers it services, and the total cost of all vehicle journeys. This is fundamentally different from the traditional DARP, where the service provider minimizes the total cost, which does not reflect passenger price preferences. We note that the profit maximization problem is always subject to the route feasibility constraints, as passengers will not accept the service if pick-up or drop-off time constraints are not satisfied.

There are two notions of profit maximization in this paper. The first notion is that of the maximum expected revenue, which is applicable when the service provider does not have any side information about each passenger's maximum price. On the other hand, the second notion is that of the maximum minimum (maximin) revenue; that is, the vehicle routes and passenger pricing that maximizes the minimum possible profit under the given routing and pricing policy. We use the maximin approach when the service provider does have side information about each passenger's maximum price. As detailed in Section 3, the maximum expected revenue is employed to generate an initial offer to each passenger. Later in the negotiation, the service provider uses the maximin revenue in the final offer to ensure that passengers are guaranteed to accept.

3 Proposed Negotiation Mechanism

In this section, we propose our negotiation mechanism for the on-demand transport network detailed in Section 2. Our negotiation mechanism proceeds in four stages, which ends with a feasible journey plan for each vehicle and prices for each passenger. The stages are summarized as follows:

1: The service provider offers each passenger a journey along with a price.
2: Each passenger makes an initial decision whether to reject the offer or to conditionally accept.
3: The service provider makes final offers to the passengers that conditionally accepted.
4: Each remaining passenger makes its final decision whether to reject or unconditionally accept the offer.

3.1 Stage 1: Initial Service Provider Offers

In the first stage of the negotiation, the service provider constructs possible routes for each vehicle and prices the journey for each passenger; summarized in Algorithm 1. It is important to note that the passenger journeys are coupled, even though all passengers negotiate independently of each other. This is due to vehicle capacity and passenger pick-up/drop-off time constraints, which mean that the optimal vehicle allocation for a given passenger depends on which other

[4] This scenario is known as the static DARP and is known to be realistic for several types of on-demand services [6].

[5] Although the distance travelled may be significantly further than R_i, it is often difficult for passengers to estimate the actual distance to be travelled. As such, the distance as the crow flies is a reasonable estimate, on which passengers can make price-related decisions.

passengers are also allocated to the vehicle. As the service provider does not know a priori which passengers will ultimately accept their offer, it must first enumerate multiple feasible journey plans for each vehicle.

Algorithm 1 Summary of Stage 1

1. **Group passengers into feasible clusters** subject to constraints on vehicle capacity, passenger pick-up interval, and passenger drop-off time. This is illustrated in Fig. 1.

2. **Enumerate journeys via the cluster tree** (illustrated in Fig. 2). Each branch is a feasible journey for a single vehicle. Vehicles are allocated a single branch, each with distinct passengers.

3. **Price each journey for each passenger**. This is achieved by solving the optimization problem in (7) to maximize the expected profit for the service provider.

In practice, both the number of vehicles in the service provider's fleet and the number of potential passengers can be very large. As such, it is not computationally feasible to enumerate all possible routes for each vehicle through each subset of passengers. To overcome this problem, we instead use a principled heuristic approach based on passenger clustering.

3.1.1 Passenger Clustering and Journey Enumeration

Our journey enumeration algorithm first clusters passengers together into (minimum cost) clusters and then enumerates feasible vehicle routes between different clusters. As noted in [8, 9], minimum cost clustering is a type of set partition problem[6], which partitions the passengers into routes, with the k-th vehicle route (chosen from the set of all routes Ω) denoted y_k and passengers in route y_k (with edges $E_k \subset E$) given by $\{i|\delta_{ki} = 1\}$. The minimum cost partition is then the solution to

$$\begin{aligned} \underset{\delta, y_k}{\text{minimize}} \quad & \sum_{k \in \Omega} \sum_{a \in E_k} c_a y_k \\ \text{subject to} \quad & \sum_{k \in \Omega} \delta_{ki} y_k = 1, \quad i \in \{1, 2, \ldots, N\} \\ & y_k \in \{0, 1\}, \qquad\qquad\quad k \in \Omega, \end{aligned} \tag{2}$$

where a trip through cluster k (with passengers $\{i|\delta_{ki} = 1\}$) is feasible with respect to vehicle capacity and passenger pick-up/drop-off constraints.

For large on-demand transport networks, it is not practical to solve (2) optimally. Instead, we adopt a heuristic clustering approach based on [8], where the clustering is based on the locations of the passengers. The output of the passenger clustering is a set of clusters $C_1, C_2, \ldots$, each with an initial pick-up interval (corresponding to the first passenger in the cluster) and final drop-off time (corresponding to the last passenger in the cluster). The result of the passenger clustering algorithm is illustrated in Fig. 1.

Once the clustering has been performed, feasible journeys between clusters are enumerated. This is achieved by forming a tree (illustrated in Fig. 2), with each branch corresponding to a feasible route between clusters. As each vehicle begins and ends at the same depot, it is only necessary to enumerate the tree for a single vehicle.

[6] We note that the set partitioning problem in (2) cannot be solved using standard set partitioning approaches for coalition formation due to the constraints from vehicle capacities and passenger pick-up/drop-off times.

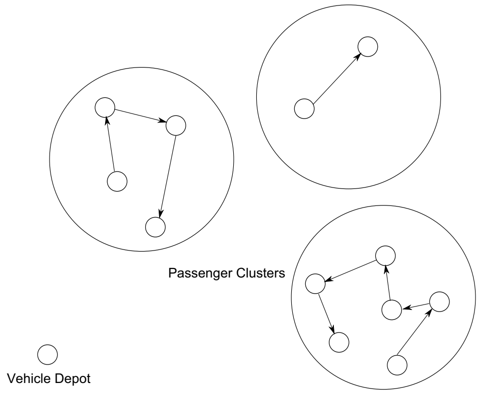

Figure 1: Illustration of passenger clustering. The small circles represent passenger pick-up and drop-off locations. If a given passenger is a member of a cluster, then the cluster contains both the pick-up and drop-off locations.

This is because the multiple vehicle routes are obtained by allocating vehicles branches with distinct passengers.

At the end of the journey enumeration step in Stage 1, the service provider obtains the potential routes for each vehicle in its fleet, with each journey enumeration corresponding to a different subset of the potential users. In addition, the cost (to the service provider) of each route is also given, which is used to compute passenger prices.

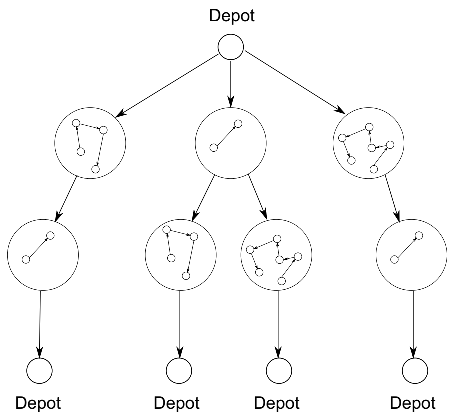

Figure 2: Illustration of the journey enumeration tree.

3.1.2 Journey Pricing

The next step in Stage 1 in the negotiation is to allocate prices to each passenger. As the service provider only knows the distribution of the passengers' maximum price, it maximizes its expected profit.

To formulate the optimization problem, we first define the profit conditioned on the acceptance of a set $S \subset \{1, 2, \ldots, N\}$ (and all other passengers rejecting the offer), denoted by $P_S(r)$ at price rate r. There are two scenarios to consider: S consists of passengers that can be served simultaneously by the K vehicles; and S consists of passengers that cannot be served simultaneously. In the first scenario, P_S is given by

$$P_{S,1}(r) = \sum_{k \in S} r R_k - c_S, \tag{3}$$

where c_S is the cost to the provider of servicing passengers S and R_k is the distance as the crow flies between passenger k's pick-up and drop-off locations, as detailed in Section 2.1.

On the other hand, if the passengers in S cannot be served simultaneously then the service provider must choose the subset $S_c \subset S$ that can be served and maximizes the operators profit over S. As the price rate is not known yet (it is the solution to the optimization problem in (7)), we obtain S_c by solving

$$S_c = \arg\max_{S_c \subset S} \sum_{k \in S_c} R_k - c_{S_c}, \tag{4}$$

where c_{S_c} is the cost to the provider to service the passengers in S_c. The conditional profit in the second scenario is then given by

$$P_{S,2}(r) = \sum_{k \in S_c} rR_k - c_{S_c}. \tag{5}$$

Finally, the conditional profit for the service provider when the set S of passengers accept their offers is given by

$$P_S(r) = \begin{cases} P_{S,1}(r), & \text{if the service provider can simultaneously} \\ & \text{serve all passengers in } S; \\ P_{S,2}(r), & \text{otherwise.} \end{cases} \tag{6}$$

The total profit P_{T1} is then obtained using the law of total probability.

We find the passenger price rate, r, via the following optimization problem.

$$\max_r \mathbb{E}[P_{T1}] = \max_r \sum_{S \in \mathcal{P}} P_S(r) F_{r_T}(r)^{|S|} \left(1 - F_{r_T}(r)\right)^{N-|S|}, \tag{7}$$

where $\mathcal{P}$ is the power set of $\{1, 2, \ldots, N\}$ and F_{r_T} is the Beta distribution CDF in (1). In general, the optimization problem (7) is nonconvex. As such, the problem is numerically solved to find local maxima.

At the end of the first stage, each passenger k is offered their desired journey at a price p_k based on the price rate obtained in (7). In particular, the offer price for passenger k is $p_k = rR_k$ for $k \in \{1, 2, \ldots, N\}$[7].

3.2 Stage 2: Initial Passenger Decisions

In the second stage of the negotiation, each passenger i makes a preliminary decision based on the price p_i that it has been quoted by the service provider. The passenger can respond to the service provider's quote in one of two ways: *conditionally accept*; or *reject*.

If passenger i conditionally accepts, it means that she has formed a contract with the service provider, which ensures that the service must be paid for unless the service provider increases the price. On the other hand, if passenger i rejects the offer then she no longer is interested in a journey with the service provider.

3.3 Stage 3: Final Service Provider Offers

In the third stage of the negotiation, the service provider has additional information. In particular, the service provider knows: what the users that conditionally accept are prepared to pay; and which users have rejected the offer.

As not all passengers will usually accept their offer, the service provider must update the passenger clusters. Although the cluster sizes will change if not all passengers accept, we assume that the service provider does not change the passenger clusters. The consequences of this assumption are examined further in Section 4. We emphasize that the journey enumeration from Stage 1 is still feasible, even with changes in the cluster sizes.

To obtain final prices for each passenger, the service provider solves the maximin profit problem over the passengers that have accepted in the previous stage. Let S^* be the passengers that accepted their offers in the previous stage and P_{T2} the final profit obtained from our negotiation. The maximin profit problem is then

$$\max_r \min P_{T2}. \tag{8}$$

As we have a lower bound on the maximum price each user is prepared to pay, the maximin profit problem in (8) is equivalent to

$$S_c^* = \arg\max_{S_c \subset S^*} \sum_{k \in S_c} rR_k - c_{S_c}, \tag{9}$$

where the passengers in S_c^* are charged $rR_k,\ k \in S_c^*$ and the other passengers are priced out.

The service provider uses the pricing in Stage 3 to ensure that the passengers in desirable clusters accept, which in turn maximizes the service provider's profit. That is, the service provider will raise the price of passengers that have conditionally accepted so that they reject the final offer[8]. This means that Stage 3 is equivalent in concept to the maximum determination problem in auctions (see e.g. [15]).

3.4 Stage 4: Final Passenger Decisions

In the fourth stage of the negotiation, the remaining passengers make their final decision based on the latest offer from the service provider. Each passenger either *unconditionally accepts* the final offer, or *rejects* it; i.e, passengers that conditionally accepted in Stage 2 now either accept the offer if the maximum price did not rise above p_i or reject otherwise.

4 Passenger Cluster Stability

So far, we have focused on how the service provider can perform pricing and journey planning in order to maximize its profits. We now take the perspective of the passengers. Although the passengers are not directly part of the service provider's clustering algorithm in Stage 1 (see Section 3.1.1), it is highly desirable from the perspective of fairness–an additional means for passengers to discriminate between providers–that the clustering is not biased against any given passenger; that is, the passenger cannot find a cluster where both the passenger and the new cluster are better off. In order to avoid this bias after Stage 2, the fact that some passengers are likely to have rejected their offer must be accounted for in the original clustering and passenger pricing.

In this section, we prove a new relationship between the stability of the passenger clusters (defined precisely in Definition 2) and the price each passenger is charged after the initial passenger decisions in Stage 2. Our main result is a sufficient condition for the stability of the passenger clusters, which guarantees that each passenger cannot unilaterally find a different cluster that will improve her chance of being serviced, while also improving the chance that the cluster she seeks to join will be serviced.

[7] Although we consider a common price rate for each passenger (largely for the purposes of exposition), it is possible to extend to different price rates for each passenger and even different price rates for each possible route (for the same passenger).

[8] We note that it is possible that passengers may accept service, even after the price is raised. In this case the service provider can subcontract the journey with no financial loss.

To begin, we define the passenger cluster game, which naturally arises from the notion of passenger clusters and is closely related to a coalitional game.

Definition 1 *The passenger cluster game is the set of players* $N = \{1, 2, \ldots, n\}$ *and preference relation over the clusters* $\succeq$ *(analogous to the payoff function), which for passenger* i

$$\{i\} \cup C_j \succeq_i \{i\} \cup C_k, \tag{10}$$

if

$$\sum_{m \in \{i\} \cup C_j} p_m - c_{C_j \cup \{i\}} \geq \sum_{m \in \{i\} \cup C_k} p_m - c_{C_k \cup \{i\}}, \tag{11}$$

where p_m *is the price offered to passenger* m *and* c_{C_k} *is the total cost to the service provider of servicing cluster* k *(excluding the cost of traveling to the cluster from another cluster or the depot).*

Intuitively, a passenger i prefers cluster C_j over C_k if the profit generated by $\{i\} \cup C_j$ for the service provider is greater than the profit generated by $\{i\} \cup C_k$. As neither the passengers nor the service provider ultimately know the passengers that will accept, this means that the service provider is more likely to route through cluster $\{i\} \cup C_j$ than $\{i\} \cup C_k$ and hence passenger i is more likely to be serviced.

Importantly, the passenger cluster game is a hedonic game[9]. A practical notion of stability in hedonic games is individual stability, which we state in terms of the passenger cluster game.

Definition 2 *Suppose that the passengers have formed clusters* $\Pi = \{C_1, C_2 \ldots\}$*. Then,* Π *is individually stable if for every passenger* i *and for all* $C_k \in \Pi$*,* $C_i \succeq_i C_k \cup \{i\}$ *or* $C_k \succeq_j C_k \cup \{i\}$ *for all* $j \in C_k$*.*

Intuitively, the clusters are individually stable if no passenger can unilaterally find a new cluster that both the passenger and the cluster it seeks to join prefer over the original clusters.

As we show in Theorem 1, the stability of passenger clusters is intimately linked to the price each passenger is offered for its journey.

Theorem 1 *All passengers are individually stable in their allocated clusters if* $p_i < c_{r,k}$ $\forall k \neq i$*, where* $c_{r,k}$ *is the minimum cost path between cluster* C_k *and cluster* C_i *(containing passenger* i*).*

Proof of Theorem 1: Observe that if passenger i is to pay p_i, then the profit of the new cluster, $P_{C_k \cup \{i\}}$, is bounded by

$$P_{C_k \cup \{i\}} \leq \sum_{j \in C_k} p_j + p_i - c_{C_k} - c_{r,k} \tag{12}$$

since the cost of servicing passenger i is at least the cost of travelling from a passenger in cluster k to the pick-up location of passenger i. As such, when $p_i < c_{r,k}$ it follows that

$$P_{C_k \cup \{i\}} < P_{C_k} \tag{13}$$

and the result follows. □

The main consequence of Theorem 1 is that the price the service provider charges must be bounded by the cost of traveling between clusters, to ensure cluster stability. Surprisingly, this means that initial clustering based on minimum cost is not necessarily optimal when stability is required, even if the set partitioning problem in (2) is solved optimally. In fact, both the cost of each cluster and the distance between clusters must be taken into account[10].

[9] A hedonic game is a coalitional game where the preference relation for each player over coalitions depends only on the members of the coalitions and nothing else.

[10] We leave the design of clusters to optimally tradeoff between cost and distance for future work.

5 Simulation Results

In this section, we perform a Monte Carlo simulation study of the influence of the number of passengers as well as passenger demographics on pricing and service provider profits. To the best of our knowledge, this is the first study on the effect of the on-demand transport network on service provider *profits* (as opposed to costs) and actual passenger prices.

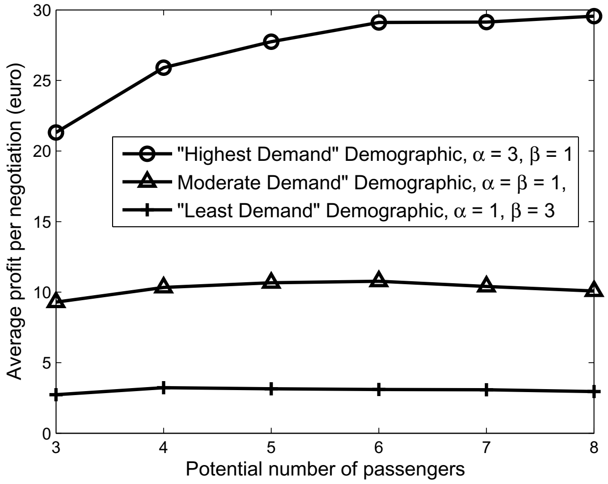

Figure 3: Plot of the average profit per negotiation for a varying number of potential passengers. Three passenger demographics are considered: "highest demand" ($\alpha = 3$, $\beta = 1$); "moderate demand" ($\alpha = \beta = 1$); and "least demand" ($\alpha = 1$, $\beta = 3$).

Consider the on-demand transport network consisting of a service provider with $K = 3$ unit capacity vehicles and N potential passengers. This is a realistic fleet size when (as we consider) the passenger pick-up and drop-off locations are placed randomly according to the uniform distribution on $[0, L] \times [0, L]$, where $L = 4$ km, which along with the direct routes between locations forms the graph G (see Section 2). We also expect that the insights we obtain approximately hold for larger scale networks with a similar vehicle density (≈ 5 vehicles/km^2). We also assume that:

1. the start of the pick-up interval is uniformly distributed on $\{1, 2, \ldots, 60\}$;
2. the duration of the pick-up interval is uniformly distributed on $\{5, 6, \ldots, 20\}$;
3. the average vehicle velocity is $v = 20$ km/hour;
4. the maximum journey time is uniformly distributed on $\{\lfloor 3R_i/v \rceil, \lfloor 6R_i/v \rceil, \ldots, \lfloor 7R_i/v \rceil\}$;
5. and the standard cost of vehicle journeys is $c_s = €\,0.3$/km.

As detailed in Section 2, the maximum price rate for passenger i is distributed according to the generalized Beta distribution on $[0, 10]$ with parameters α, β. To model different passenger demographics, we vary α and β, which in turn changes the shape of the corresponding distribution function. In particular, we define a passenger demographic in terms of demand for services; for example, passengers at peak hour typically have higher demand, and as such are prepared to pay more. More precisely, we consider the following demand demographics:

1. $\alpha = 3$ and $\beta = 1$ corresponds to the Beta distribution with the largest proportion of the probability mass above €5 (half of the

maximum possible price rate), which means that the demographic has a high proportion of “high-demand” passengers.
2. $\alpha = \beta = 1$ corresponds to the Beta distribution with half the probability mass above €5, which means that the demographic has a moderate proportion of “high-demand” passengers.
3. $\alpha = 1$ and $\beta = 3$ corresponds to the Beta distribution with the largest proportion of the probability mass below €5, which means that the demographic has a low proportion of “high-demand” passengers.

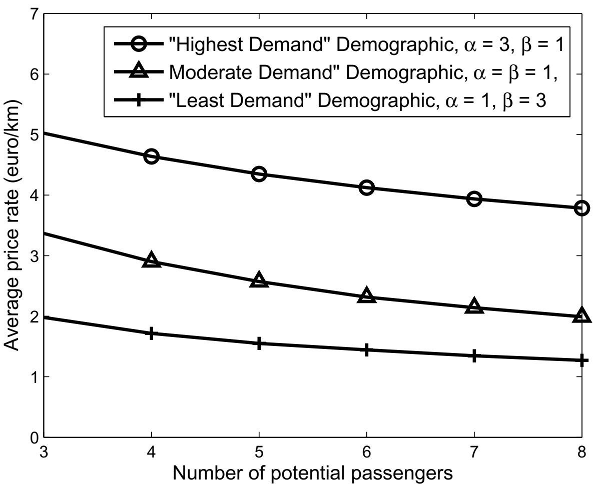

Figure 4: Plot of the average price rate for a varying number of potential passengers. Three passenger demographics are considered: “highest demand” ($\alpha = 3$, $\beta = 1$); “moderate demand” ($\alpha = \beta = 1$); and “least demand” ($\alpha = 1, \beta = 3$).

Fig. 3 shows the relationship between the average profit the service provider makes from a single negotiation as the number of potential passengers increases. We observe that for all passenger demographics (corresponding to different α, β) the average profit increases and the number of potential passengers increases. This is due to the fact that increasing the pool of potential passengers also increases the diversity, until the profit saturates. As such, it is possible to find cheaper routes with passengers that pay more. We also observe that the demographic with the lowest proportion of the high demand passengers ($\alpha = 1$, $\beta = 3$) also yields the lowest average profit. As the proportion of wealthier passengers increases further ($\alpha = \beta = 1$ and $\alpha = 3$, $\beta = 1$), the average profit also increases, for all sizes of the potential passenger pool.

Fig. 4 shows the relationship between the average price rate paid by each passenger as the number of potential passengers increases. Observe that the average price rate reduces for a larger number of passengers. This can be explained by noting that it is not always possible to find low cost passengers with only a small number to choose from, which means that the price must be higher for the service to be profitable. Also observe that as the proportion of the passengers that have high demand increases, so does the average price rate. As such, when the passengers are prepared to pay more for a journey, the service provider will charge more.

6 Conclusions and Future Work

On-demand services are set to play an important role in transport markets. In light of this, we have developed a negotiation mechanism between passengers and the service provider to obtain vehicle routes, as well as passenger allocation and pricing. In contrast with previous work, we focus on the profit of the service provider instead of the cost, which allows us to account for both service provider and passenger preferences. Future extensions will account for larger scale networks (using the testbed in [5]), dynamic passenger arrivals and more complex passenger decision making processes.

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