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Negin Alisoltani, Mahdi Zargayouna. Assessing the Impact of Shared-Taxi Pricing on Congestion Using Agent-Based Modeling. Jezic, G., Chen-Burger, YH., Kusek, M., Šperka, R., Howlett, R., Jain, L. Agents and Multi-agent Systems: Technologies and Applications 2023, 354, Springer Nature Singapore, pp.119-128, 2023, Smart Innovation, Systems and Technologies, 978-981-99-3067-8. 10.1007/978-981-99-3068-5_11 . hal-04485508

HAL Id: hal-04485508

<https://hal.science/hal-04485508v1>

Submitted on 1 Mar 2024

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Assessing The Impact of Shared-Taxi Pricing On Congestion Using Agent-Based Modeling

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Abstract. The low car occupancy and the great demand for automobile transportation lead to traffic congestion in many urban areas. In large-scale networks with high shareability (opportunity for sharing the trips), a successful taxi-sharing program that increases vehicle occupancy may significantly save the roadway system's driving costs and alleviate traffic congestion. Pricing plays an essential role in this system, as the taxi provider always seeks to maximize his benefits, and the passenger prefers a cheaper fare if he is going to share his taxi. So pricing can impact the performance of a shared-mobility system and, consequently, the network traffic. In this research, we define a pricing scheme based on the shareability concept to consider the impact of trip fare on the traffic situation. To model the passengers' and taxi providers' behavior, we use an agent-based approach to model the taxi-sharing service. We use real-world data from the city of Lyon in France to assess the behavior of the proposed taxi-sharing system under different pricing conditions. We implement two scenarios with different maximum fares acceptable by the passengers to see the impact of pricing on congestion.

Keywords: Multi-agent System, Taxi-Sharing, Pricing Scheme, Simulation

1 Introduction

The significant travel demand for personal car transportation and low occupancy lead to traffic congestion, an increasingly important issue in many urban areas with rapid population and economic growth [1]. In [2], the authors show that in large-scale networks where the opportunity for sharing passengers' trips is high, a successful ride-sharing program that increases vehicle occupancy may significantly save the roadway system's driving costs and alleviate traffic congestion. Taxi-sharing is a type of ride-sharing where the driver is just a professional taxi driver. Recently, ride-sharing is expanding from traditional private car ride-sharing to taxi-sharing [3], and soon, to autonomous vehicle taxi-sharing [4] and big taxi providers around the world are becoming reputed for providing shared services.

In a taxi-sharing system, the passenger, the ride provider, and the dispatcher are the main parts. The passenger seeks a ride to pick her/him up at the origin

point and drop her/him off at the desired destination within a time interval. The ride provider has a fleet of taxis ready to serve the passengers' requests. The dispatcher receives the requests and the fleet information and tries to find the best matches on short notice. In such a system, provider and passenger criteria determine service efficiency and impact the service capability to reduce congestion. The impact of taxi-sharing and Uber-like services on traffic congestion has been studied in many pieces of research in different urban networks and contradictory conclusions have been claimed. The authors, in [5], define the concept of shareability and show that the ability of shared services to reduce congestion highly depends on this concept. Shareability is the potential for sharing trips, and it is different for different networks with different service demand conditions. They consider both passengers' and providers' objectives and constraints to model the service and cluster the ride requests based on the concept of shareability. However, they do not consider pricing a necessary criterion for both passengers and providers. In the current research, we define a pricing scheme based on the shareability concept defined in [5] to consider the impact of trip fare on the traffic situation.

The passengers expect to pay less when they share their ride, as their travel time would increase. So if the taxi-sharing fare is higher than a specific price, they will not be willing to use the service and may reject the offer. This behavior can have major impacts on the shareability in the system. In [6], passengers can communicate with multiple vehicles and choose the offer according to their individual preferences, such as the earliest starting time, lowest trip time, and lowest cost. So if the offered fare exceeds the lowest cost, they may reject it. In [7], the authors propose monetary constraints to model a more realistic taxi ride-sharing system. These constraints provide incentives for both passengers and taxi drivers. Passengers will not pay more compared to no ride-sharing and get compensated if their travel time is lengthened, and taxis will make money for all the rerouting distance due to ride-sharing. In this paper, we consider the maximum trip fare for the passengers. If the price of the shared taxi is higher than this maximum fare, the passenger may reject the offer. This maximum fare can depend on different parameters, such as the price of public transportation and traditional taxi services, the passenger's profile, and priorities.

Defining a pricing scheme that ensures both passengers' and providers' benefits is essential to consider these monetary constraints in modeling a taxi-sharing service. Various pricing schemes have been proposed for the taxi-sharing systems [8–10]. In a recent survey on taxi-sharing in [11], the authors classify the proposed pricing schemes in the literature into four categories: number of passengers-based, travel distance-based, trip urgency-based, and hybrid pricing schemes, which integrates the three previous categories. However, an important factor in this classification is missing. The time taken to cover the same distance can be different based on the traffic situation in the network. [12] consider a travel time-based road-pricing policy where all the major network links carry a toll based on travel time on the link for all road users during the morning and evening peak periods and assess the impact of this pricing on the mode

share. [13] presents a dynamic pricing strategy with a time-varying commission rate. [14] propose to impose a surcharge on taxi customers who take taxis during peak hours and/or travel towards congested areas. In our method, we propose a new pricing scheme to consider the travel distance and the number of passengers, considering the traffic situation in the taxi dispatching computations.

We use an agent-based approach to model passenger and taxi provider behavior. The agent-based approach offers a way to capture both supply and demand at a microscopic level, considering individual accessibility, available choices, and personal tastes and needs [15]. Therefore, this approach can make the possibility to evaluate our taxi-sharing system from the passengers' (transport cost, satisfaction, and service quality) and the providers' (operational cost, incomes, and fleet configuration) point of view [16,17]. In addition, it can easily assess the impacts on the transportation network criteria such as energy consumption and emissions, shifts between transport modes, network demand satisfaction level, and network congestion [18]. This paper uses an agent-based approach to model the taxi-sharing system, considering passengers, taxis, and dispatchers as agents.

Our previous study proposed a solution for the dynamic traffic conditions for a real-time ride-sharing service [19]. We use the same approach in this paper to consider large-scale network traffic. We define two models to deal with dynamic traffic conditions: the plant model and the prediction model. The current mean speed in the network will be used over the next 10 minutes to predict travel times for the dispatcher's calculations. Then, taxis and personal vehicle travel are simulated. The traffic situation is updated every 10 seconds using a trip-based MFD model as the plant model to represent the traffic dynamics. The remainder of the paper is organized as follows. First, section 2 proposes a multi-agent model for the taxi-sharing model. Then section 3 presents a pricing scheme for this system. Section 4 explains how we solve the dispatching problem. Section 5 presents the numerical experiment, and finally, section 6 concludes the paper.

2 Multi-agent system for the shared taxi service

The multi-agent system designed for the taxi-sharing service is shown in figure 1. The main components of this model are the passenger agents, the taxi agents, and the dispatching system. Each component is described as follows.

The passenger sends her/his request for a trip, defining the number of demanded seats, the time window (earliest pick-up time and latest drop-off time)

Passenger agent: The passenger sends his request for a trip via an application. This request contains the origin location, the destination point, the desired time window (earliest pick-up time and latest arrival time), and the number of demanded seats. Then he receives the dispatcher's choices, with different prices and waiting/travel times.

The passenger agent can choose one of the possible options, considering his behavioral rules and constraints. These constraints include the maximum fare he is willing to pay and the maximum number of sharing. The number of sharing

is a concept presented by [20], and it shows the maximum number of other passengers on board simultaneously with the current passenger.

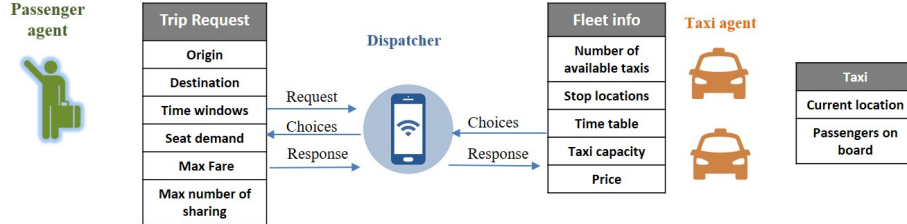


Fig. 1. Multi-agent system for taxi-sharing

Taxi agent: The taxi provider has a fleet of taxis, and the dispatcher has access to the fleet information, including the number of available taxis, the allowed stop locations, and the capacity of taxis at any time. The taxis are connected to the provider. They can have two situations, whether moving in the network to serve the onboard passengers or waiting in the allowed stop locations to be assigned to the new passengers. The dispatcher has access to the current location and the number of onboard passengers for each taxi at any time.

Dispatcher: As mentioned before, the dispatcher has access to the taxi fleet information. When it receives the new trip request, it calculates the best offer for the passenger and sends the choice(s) to the passenger. The passenger will choose one of the options (if more than one) and return his response to the dispatcher. Then the dispatcher updates the schedule of the selected taxi and sends the new schedule to the taxi. This component solves an optimization problem in real-time to find the best offers for the passengers. The performance of this solution method is explained in section 4.

3 Taxi pricing scheme

The taxi price calculation is shown in equation 1 where P_{Fixed} is the fixed price that each passenger should pay at the beginning, $P_{distance}$ is the price per distance, and D_t is the total travel distance for taxi t .

$$Price = P_{Fixed} + P_{distance} \times D_t \quad (1)$$

When every two passengers share a taxi trip, we can have two different situations for the ride [5]. In the first situation, which we call "shareable-FIFO", the taxi has to pick up the first passenger and then the second passenger, dropping them off at the destination point considering their pick-up sequence. In the second situation, which we call "shareable-FILO", the taxi drops off the second passenger before the first passenger.

We propose a pricing scheme based on these sharing situations.

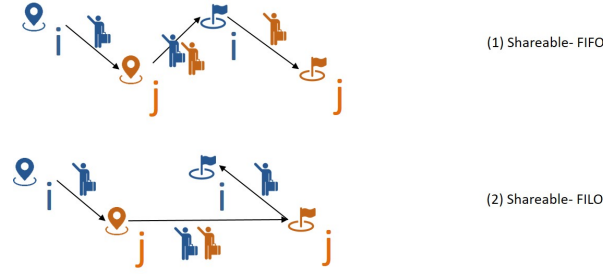


Fig. 2. The number of onboard passengers for different trip-sharing situations

1- Shareable-FIFO: The total travel distance for the taxi is $D_t = d_1 + d_2 + d_3$, where d_1 is the distance from the first origin to the second origin, d_2 is the distance from the second origin to the first destination and d_3 is the distance from the first destination to the second destination. For the first passenger, the travel distance is $d_1 + d_2$, and for the second passenger, it is $d_2 + d_3$. In this case, the fare for each passenger can be computed as follows:

$$fare_1 = P_{Fixed}/2 + P_{distance} \times (d_1 + d_2/2) \quad (2)$$

$$fare_2 = P_{Fixed}/2 + P_{distance} \times (d_2/2 + d_3) \quad (3)$$

2- Shareable-FILO: if we show the distance of each link by d_1 , d_2 and d_3 , the total travel distance is $d_1 + d_2 + d_3$ for the taxi, $d_1 + d_2 + d_3$ for the first passenger and d_2 for the second passenger. So for the second passenger, the travel distance is the same as without sharing. However, he/she is on board with another passenger. So to ensure equity, this passenger has to pay half of the fixed price, and the fare for each passenger is computed as below:

$$fare_1 = P_{Fixed}/2 + P_{distance} \times (d_1 + d_3) \quad (4)$$

$$fare_2 = P_{Fixed}/2 + P_{distance} \times (d_2) \quad (5)$$

It is important to mention that the shareable-FILO situation happens when the two origins or destinations are very close, and the system can serve the first passenger within her/his time window. A taxi trip, which starts from a stop location and ends at a stop location, can contain different combinations of these two situations. From equations 2 to 5, we can conclude that for any combination of the sharing situation, the trip fare for passenger k can be computed as:

$$fare_k = P_{Fixed}/N_t + P_{distance} \times (x_{org_k, des_k}^k \times d_{org_k, des_k} + \sum_{ij \in L, i, j \neq org_k, des_k} \frac{x_{ij}^k \times d_{ij}}{N_o^{ij}}) \quad (6)$$

Where N_t is the total number of passengers for taxi t , d_{ij} is the distance for the link between each two taxi stops i and j (to pick up or drop-off the passengers), x_{ij}^k is a binary variable which is equal to 1 if the passenger k is on board from

point i to point j , L is the set of links, org_k and des_k are the origin and destination points for passenger k , and N_o^{ij} is the number of onboard passengers when the taxi is taking link ij .

4 Dispatching algorithm

Using the pricing scheme presented in the previous section, we can compute the trip fare for each passenger. Each passenger agent can accept or reject an offer, considering her/his threshold for the shared taxi fare. Once the dispatcher receives the requests, it starts to find the best offer for the passengers that respects all their constraints, including the time window constraint, the maximum waiting time, the maximum number of sharing, and the maximum trip fare. Also, it has to ensure the taxi capacity constraint. The best schedule is the one that maximizes the revenue for the taxi provider and maximizes the number of assigned passengers. The dispatcher in our model uses the algorithm in Algorithm 1 to find the best offers. It has two main parts, to compute the new routes for taxis that are waiting at the stop locations and also for the moving taxis that are already serving passengers. For each group of received requests, it starts creating branches of in-sequence pick-up and drop-off points. For each point that will be added to the route, the dispatcher has to ensure that all the constraints are respected. Then when it finds the feasible branches, it puts them in a set called *Offers*. In the end, the dispatcher sends the optimal offer(s) to the passenger, and if the passenger accepts it, the dispatcher updates the taxi schedule and sends it to the taxi.

5 Experiments

The dispatcher uses estimates for the predicted travel time obtained from the "prediction model" [21]. When the rides are executed, a gap usually exists between the estimation and the real traffic condition. The "plant model" represents the real traffic condition. Distinguishing the prediction and the plant models can provide a realistic assessment of the system's functioning. We use real data from the Lyon network in our simulations. The prediction model is based on the last observed travel times. In contrast, the considered plant model is a trip-based Macroscopic Fundamental Diagram (MFD) model able to reproduce the evolution over time of mean traffic conditions for a full road network using the MFD as a global behavioral curve. The macroscopic fundamental diagram (MFD) overviews the network states [22, 23]. The origins/destination set contains 11,314 points. The network is loaded with travelers of all ODs with a given departure time representing the morning peak hour from 6 AM to 10 AM. The number of trips during this period is 484,690.

Algorithm 1: Dispatching algorithm

input: New requests, travel distances ($d_{i,j}$), travel times ($tt_{i,j}$) set of taxis (T), set of origin points (P), set of destination points (A), time windows (EP_i, LD_i), number of seats demanded (s_k) for passenger k , number of sharing (n_i^{share}), taxi capacity (Cap), weights of objective function (α, β)

output: Taxi schedules

for *origin* $p \in P$ **do**

- for** *c-schedule*, the schedule of taxi $t \in eT$ **do**
 - if** *Detour is possible from any of the remaining origins on c-schedule* **then**
 - Build the *re-schedule* by adding the p after *origin*;
 - if** p is feasible for time window, capacity, and number of sharing constraints on *c-schedule* **then**
 - if** *des* the destination of p is feasible for time window on *c-schedule* **then**
 - Create new schedule *n-schedule* by adding p and *des* to *c-schedule*;
 - Put *n-schedule* to the *Offers* set;
- Find the optimized route *optimal-schedule* \in *Offers*;

while *Not all the points in A are assigned* **do**

- Closest waiting taxi $t \in T$;
- Create initial routes set S from remaining origins in origin set P ;
- while** S is not empty **do**
 - Find the optimized route $s \in S$ (in terms of objective function);
 - Find the set of points SP that can be added to s ;
 - for** $sp \in SP$ **do**
 - if** sp is feasible for time constraints on s **then**
 - Compute new vehicle capacity ;
 - if** sp is feasible for capacity and number of sharing on s **then**
 - Create new route ns by adding the point sp to the route s ;
 - Add route ns to the routes set S ;
 - if** All $sp \in SP$ are non-feasible in route s **then**
 - if** number of route origins = number of route destinations **then**
 - Put route s in the offer set *Offers*;
 - else**
 - Remove route s from routes set S ;
- Find the optimized route *optimal-route* \in *Offers* that maximizes the taxi price;
- Compute $fare_k$ for the optimal solutions in *Offer* Send the pick-up and drop-off time of the optimal solution(s) with $fare_k$ for each solution to passenger k **if** *Passenger k accepts the offer* **then**
 - Assign the *optimal-route* for this offer to the taxi t ;
 - Remove pick-up points on *optimal-route* from P ;
- if** t is a waiting taxi **then**
 - Remove t from waiting taxi sets T and add it to the en-route vehicles set eT ;

Among these trips, the origin and destination points of 205,308 trips are inside the studied network. We assume that the demand for taxis is 40% of these trips. The taxi provider has 1000 taxis. To estimate the prices and taxi operators in Lyon, we use the information in [24]. If the passenger accepts the taxi provider’s offer, the trip will be made by a taxi-sharing service. Otherwise, we consider that the passenger uses a personal car (or a traditional taxi with the same functionality) to make the trip.

5.1 Results

We assess two scenarios. First, we set the maximum fare max_{fare}^k for each passenger agent equal to the taxi fare without sharing. So if the offered fare is more than this, the agent may reject the offer. In the second scenario, we assume that the passengers expect a cheaper fare equal to 75% of the fare in the first scenario and see the impact of the maximum fare on the taxi-sharing system in terms of changing traffic conditions.

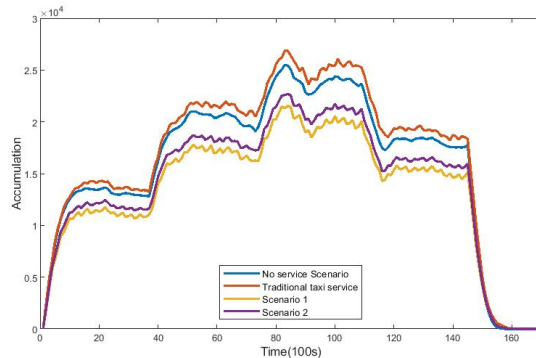


Fig. 3. Traffic situation comparison

The traffic situation for these two scenarios is shown in figure 3 compared to two other situations. "No service scenario" shows the situation when all the demand in the network is made by private vehicles. The traditional taxi service situation is when no passenger shares his ride. In this case, the taxi travel distance will increase, and the network will face more traffic. Our proposed taxi-sharing system can significantly reduce traffic congestion. However, this reduction highly depends on the passengers’ preferences. This reduction would be less when the passengers have more strict limitations on the maximum taxi fare.

Table 1. Simulation results for two pricing scenarios

Simulation	Rejected offers (%)	Total travel distance (km)	Average passenger waiting time (second)
Scenario 1	0.78	434004.8	76.46
Scenario 2	4.30	563385.9	49.36

Table 1 shows the simulation results for the taxi trips. As shown, when the passengers desire to pay a price that is less than 75% of the taxi price for a shared ride, the rejection rate is 3.52% more than when they accept to increase their desired maximum fare to be less than the taxi price. However, in both situations, the rejection rate is low as the pricing scheme and taxi-sharing system presented in this research can find the best fares to respect both passengers' and providers' expectations.

6 Conclusion

In this research, we defined a pricing scheme based on the shareability concept [5] to consider the impact of trip fare on the traffic situation. To model the passengers' and taxi providers' behavior, we used an agent-based approach to model the taxi-sharing service. We used real data from the city of Lyon in France to assess the behavior of the proposed taxi-sharing system under two scenarios with different maximum fares acceptable by the passengers to see the impact of pricing on congestion. The results show that a reasonable pricing scheme for the taxi-sharing system that can ensure both passengers and taxi providers can help reduce congestion in the network. In this research, we assessed the impact of pricing on network traffic. However, the trip fare is the same during different hours of the day. In future research, we will consider the impact of traffic on time-dependent pricing.

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