An Efficient Dispatch and Decision-making Model for Taxi-booking Service

Cheng Qiao*‡, Mingming Lu†, Yong Zhang* and Kenneth N. Brown‡
* Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, China
mcheng.qiao@gmail.com, zhangyong@siat.ac.cn
† School of Information Science and Engineering, Central South University, China
mingminglu@csu.edu.cn
‡ Insight Centre for Data Analytics, Department of Computer Science, University College Cork, Ireland
k.brown@cs.ucc.ie

***Abstract*—Taxi-booking services have recently gained attention to address congestion and sustainability. However, current booking services have a low success rate, due to uncooperative behaviours of passengers and drivers. In this paper, we propose a centralized Carrying Reservation System (CRS) to exchange real-time information for drivers and passengers and support a taxi dispatch mechanism to balance real-time supply and demand. Evolutionary game theory is applied to analyze behaviour and optimize the utility for taxi drivers and passengers. Global Position System (GPS) trajectory data from the Transport Commission of Shenzhen Municipality is used to evaluate the performance of proposed system. Results show that our model could reduce locating time as much as 46%, which will in turn lower passengers' waiting times. With our game theory model, drivers' profit could be increased by over 18%. Compared with an off-line mining and online recommendation method (OMOM), our method improves the gain of drivers during non-rush hours.**

***Keywords*—Algorithm, Recommend System, Evolutionary Game Theory, GPS data**

I. Introduction

Taxis play a prominent role in the transportation system of metropolitan city areas [1], due to their personalized direct door-to-door service. In China, cities such as Shenzhen and Shanghai in particular suffer from a pressing problem: it is difficult for passengers to find vacant taxis during rush hours, but hard for drivers to locate passengers during non-rush hours. The main reason for the problem is the contradiction between demand and supply: limited taxicabs versus crowded service-needed passengers during rush hours while abundant taxicabs against few urgent passengers during Non-rush hours[2].

To solve this problem, many local governments introduced a taxi-booking service that enable passengers to reserve a taxi in real time or in advance[3, 4, 5]. However, the system has been deemed to be ineffective, due to its high costs to the taxi drivers, cumbersome maintenance and low response rate. Drivers are reluctant to bear the cost of picking up distant passengers, partly because of the risk of those passengers breaking the appointment. The advance of communications technology means it is now possible to maintain location traces and to extract patterns from historical data. Recommender systems have been proposed to exploit this data. Such systems recommend a sequence of pick-up points or a sequence of potential parking positions to drivers.

Although various recommender systems have been proposed, none of the existing work has systematically studied real-time demand in the taxi market. Real-time demand was discussed [6, 7, 8], although the systems make their recommendations mostly by relying on historical GPS traces that recorded similar information, such as similar location, similar time schedules and similar itineraries. Focusing on historical information means the systems cannot exploit the latest dynamic information in a city taxi market.

Our research aims to provide a solution to balance the supply and demand of taxi-service market. We propose an evolutionary game approach to maximize drivers' profit and minimize passengers' cost. With the aid of widely deployed Global Position System(GPS) technology, we assume that the true location of taxis and passenger smartphones are already available. By considering the incentive to drivers and the true location of all participants, we develop a taxi dispatch mechanism. We show the existence of stable equilibrium. Finally, we use real-world data to evaluate the performance of the proposed system.

The major contributions of this paper are summarized below.

1) A systematic study about driver and passengers' preference is presented, and we extract the key characteristics of participants' behaviors. Cooperating with taxi drivers and passengers, we identify several facts that contribute to the low success rate of current booking service.
2) With the aid of GPS technology, we present an efficient dispatch model, in which we consider both the willingness of drivers and the locations of all participants.
3) Using the routes of the drivers, we propose a evolutionary game approach to optimize the driver revenue passenger cost. To the best of our knowledge, it is the first solution to the taxi problem that consider participants to be bounded rational. We set parameters according to the key characteristics extracted from the behaviour study and construct a game model.

This work was mainly done when the first author worked in Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences.

GPS trajectory data (WGS84 geodetic system) from the Transport Commission of Shenzhen Municipality, which recorded about 20,000 taxis in Shenzhen and 13,000 taxis in Dongguan, was used to evaluate the performance of the system. Comparing with the ground truth, our reservation system can (i) reduce at least 52% of drivers' locating time and the improved scaled will be at most 46%; (ii) increase at least 18% of the driver profit; (iii) lower the passenger waiting time.

The paper is organized in the following fashion. In Section 2 we discuss related work and in Section 3 define the methods used in the system. Section 4 shows the simulation model, and Section 5 shows the results obtained from the simulation to estimate the effectiveness of the proposed method. Conclusions are given in Section 6.

II. Related Works

Supply and demand interaction in the taxi market is the most challenge issue. Yang et al.[9] introduced a network model to describe the demand and supply equilibrium of taxi services under fare structure and fleet size regulation in either competitive or monopoly markets. Results showed that it could determine a number of system performance measures at equilibrium such as utilization rate for taxis and level of service quality, and predict the effects of alternative regulations on system performance. The nature of equilibrium in the market for taxi services was given by Manski et al.[10]. They showed that in the taxi market supply generates demand, and vice versa. This supply-demand interaction can be explosive but eventually must stabilise. Yang et al.[11] developed a simultaneous equation system for passenger demand, taxi utilization and level of services based on a taxi service situation found in the urban area of Hong Kong over the last ten years. Yang et al.[12] developed a meeting function to model search and meeting frictions and established the existence of a stationary competitive equilibrium achieved at fixed fare prices, which is determined when the demand of the customers matches the supply of taxis. However, the supply-demand interaction is still vague for the unpredictable nature of passengers and their destinations.

Under the condition of dynamic imbalance of supply and demand, recommender systems[13] have been proposed to reduce cost and maximise income for both drivers and passengers. Many recommender system[14, 15, 16] that refer to useful knowledge mined from massive amounts of accumulated travel data, providing real-time decision making service for people in travel, have been proposed. Ge et al.[17] proposed an cost-aware tour recommendation, which aims to mine the cost preferences and user interests simultaneously from the large scale of tour logs. Balan et al.[18] introduced a real-time trip information system that provides passengers with the expected fare and trip duration of the taxi ride they are planning to take. Ge et al.[19] developed a mobile recommender system which has the ability to recommend a sequence of pick-up points for taxi drivers or a sequence of potential parking positions. Jason et al.[20] presented a simple yet practical method, which refers to a derived Spatio-Temporal Profitability(STP) map, to reduce cruising miles by suggesting profitable locations to taxicab drivers. Chen et al.[21] showed that vacant taxis' search strategies are based on drivers' experience and information and gave a simulation model for cruising taxis.

However, the detail of taxi dispatch systems has received little attention. Currently, Global Positioning System(GPS) technology is widely applied for automatic vehicle location[1, 22]. An alternative dispatch system and a novel trip-chaining strategy for taxi advance booking has been proposed by Wang et al.[1], where the dispatch of taxis is determined by real-time traffic conditions and the taxi assigned the booking job is the one with the shortest-time path. A novel trip-chaining strategy means that several bookings with demand time points which are spread out within a reasonable period of time are chained together, and with each pick-up point being within close proximity to the previous drop-off location. However, there is little work to target the following problem: when two and more taxis are in close proximity according to GPS information, which taxi should be dispatched?

III. Behaviour Analysis

In most cities, taxis are operated by many different companies. Jiaotong, Guangjun, Huayuan and many other small companies. Even worse, booking numbers are different even between two nearby taxi companies in the same city, not to mention companies in different cities.

We analyze participants' behaviours to learn their key preferences. A random survey was applied to collect participants' information. Fig 1 gives a short description of our process to extract the key characteristics.

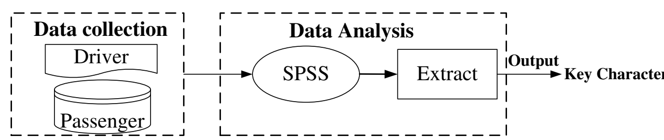

Fig. 1: Extract the key characteristics

Having cooperated with taxi driver and passenger, we identified several factors that lead to the low success rate of current booking services. Drivers are reluctant to bear the cost of picking up assigned passengers, mainly due to the risk of passengers breaking the appointment. Passengers are more willing to phone for taxi service

1) during rush hours, and
2) when their location is remote and few taxis are accessible.

However, in both cases, taxi drivers are reluctant to pick up the passenger. Taxi drivers do not need to worry about booking passengers during rush hours and do not have enough motivation to pick up passengers from a remote place. In both cases, passengers are also liable to take a vacant taxi that is passing by. To account for this, we propose that passengers' utility functions can best be represented by the expected waiting time.

For drivers, they prefer passengers that

1) that request a long-distance ride, or
2) whose destination area is one of the driver's preferred areas.

Both cases will decrease the time required to locate passengers, which could increase the revenue of drivers in turn. Thus, we formulate drivers' utility based on the current destination and the next trip after arriving at the destination.

IV. Reservation system

CRS provides a platform through which, passengers can reserve a taxi service. There are mainly four major steps in CRS: 1) passengers send a request to Process Centre(PC), including information about location, departure time and destination. 2) PC broadcasts this information to nearby taxis. 3) drivers notify their willingness to pick up which passengers. 4) PC works as an auctioneer to compute the best match, so as to maximize the utility for both passengers and taxi drivers, and inform the result to both sides.

We give a detail description of the architecture. Passengers send a request to the process center, including the information of starting place, departure time and destination. Then the Transmit-and Receive Modules(TR Module) broadcast the information to nearby taxi drivers. Passengers that willing to pick up the passengers will inform his willing to PC. Based on both short-path allocation rules and willingness of drivers, the Compute module will compute a route and a match to dispatch a taxi to pick up the passenger. Another vital responsibility of compute module is calculate some important parameters(e.g., average waiting time, average driving distance at certain time in certain place). The clock is setting to handle the situation that drivers do not respond within a time range. When the waiting time exceed the setting time, this request information will be ignored. Analysis module can verify that whether your choosing action is the most optimal.

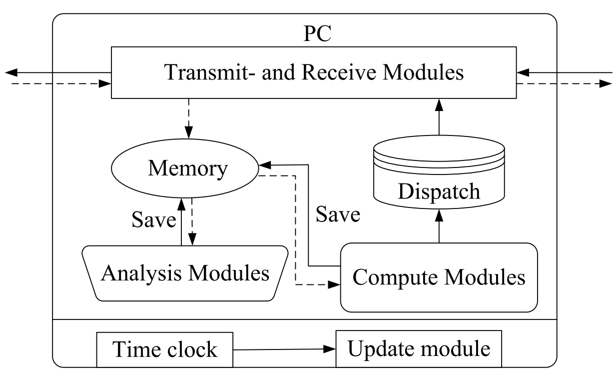

Fig. 2: Reservation Architecture

V. Model

The proposed model consists of three major components: the knowledge and utility definition, the dispatch model and and evolutionary game model. Once the utility is designed for all participants, standard game theoretical methods are applied to calculate the optimal strategies for the actors.

A. Knowledge and utility definition

It is important to note that drivers knows where and when to locate passengers based on their experience. We define E as the assertion of a quantitative measure of knowledge, which reflect preference for an area. Higher E means that driver will locate another passengers in the destination with a high probability.

From the study, it appears that the most optimal situation for a driver is that a long-distance ride and destination is located within one of his/her favourite areas. After reaching the destination, drivers have to locate another passenger for the next driving, so a favorite area will decrease the expected time to locate passengers. Consequently, the utility function mainly contains three aspects: the time cost to locate passengers, the current trip and the next trip after reaching the destination. More formally:

$$U_D = U_{tim} + U_{cur} + U_{nex} \tag{1}$$

where $U_{tim} = CT$, and the unit time cost C is defined as

$$C = \frac{G - C_c}{T} \tag{2}$$

where G, C_c, T denote the expected gain, total cost, the total riding time respectively.

B. Dispatch model

We will address the problem of how to dispatch a taxi when two or more taxis are in close proximity according to GPS information in this section. Our dispatch principle is to find a driver-passenger match that maximizes the utility function of driver and minimizes the time consumption of passenger.

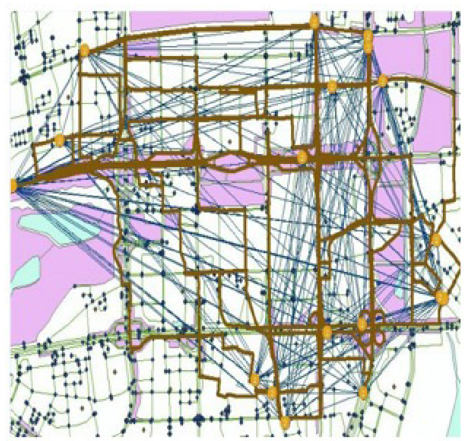

Fig. 3: Compute the Shortest Path by Arcgis

As the GPS location and city map information are available, we can compute the accurate time consumption $T_{D_k P_i}$ of driver D_k on the way to pick up the passenger P_i. The MDP(Match for Driver-Passenger)algorithm is summarized as follows:

C. Evolutionary game model

We have still to answer the question of under what circumstances are the drivers willing to pick up passengers and passengers willing to wait for reserved taxi? In this section, we will address this under the assumption that all drivers and passengers know that each of them attempts to maximize his or her own utility, and they are fully aware of the impact on

Algorithm 1 MDP

Let I_{ij} be shortest distance of unoccupied taxi i to available passenger j (refer to figure 3).
Let $W_{ij} \in [0, 1]$ be the willingness of driver i to pick up the passenger j.
Let $s = argmin(I_{ij} + \alpha W_{ij})$ that α is a parameter that balance the magnitude unit.
if no such s exists **then**.
    random assign the chance to a driver .
else
    assign the chance to the driver that subject to s.
end if

their own utilities from any combination of their individual choices.

Such a strategic interaction can be modeled as a game $G = [N, S, U]$, where N, S, and U denote the set of players (drivers and passengers), the set of available strategies, and the set of payoff functions, respectively. We consider two pure strategies for driver and passenger respectively:

The driver has two pure strategies:

S_{D_1} Driver pick up the passenger within the limited time.
S_{D_2} Driver ignore the service request and stick by his driving plan.

Note that in reality drivers could choose to pick up passenger at the beginning but then change their mind when they see another passenger on the way. However, the original choice was chosen as the driver's optimal action (and searching for a passenger was a possible action). If the driver sticks to the strategy, they can expect to pick up a passenger in the next few minutes and locate another passenger easily after that trip. However, picking up a passenger waiting on the roadside may lead to an undesirable destination.

The passenger has two pure strategies:

S_{P_1} Waiting until the taxi come.
S_{P_2} Getting in a taxi that pass by.

We use an evolutionary game model[23, 24], instead of classical game theory[25], to analyze this problem. Classical game theory requires the assumption of rational players, while evolutionary game theory only requires bounded rationality. With the rationality assumption, driver (passenger) should select the best strategy according to the strategy selected by passenger (driver), which requires the driver (passenger) having rational awareness, analytical reasoning ability, memory capacity, and accuracy requirements[26]. It emphasizes that the driver (passenger) must not make mistakes and must believe that other drivers (passengers) also will not make mistakes through the process of the game at any times.

However, it is unreasonable in reality, as driver (passenger) might not choose the optimal strategy for himself. For evolutionary game theory, driver (passenger) could continually adjust their strategies by observing the other players according to the payoff. It is a constant learning and evolution process with dynamic adjustment.

TABLE I: parameter setting

L_1	Average occupied driving distance when follow experience
L^*	Driving distance provided by passenger
L_2	Expected occupied driving distance after deal has completed
L	Average driving distance to pick up passengers
C_1	Time cost per unit time
P_1	The probability of taxi come across available passenger per unit time
w_e	Time consumption on the way to pick up the passenger
w	The average waiting time in certain region
f	Regulatory unit fare
E'	Preference of a random destination area

We assume some payoff parameters in our model.

Thus, we can get the probability P_C of passenger finding an available taxi during time w_e:

$$\begin{aligned} P_C &= P_1 + (1-P_1)P_1 + (1-P_1)^2 P_1 + (1-P_1)^3 P_1 \\ &\quad + \cdots + (1-P_1)^{w_e-1} P_1 \\ &= \frac{P_1 - P_1(1-P_1)^{w_e}}{1-(1-P_1)} \\ &= 1-(1-P_1)^{w_e} \end{aligned} \tag{3}$$

Let x denote the proportion of the drivers who wish to play strategy D_1 and the rest $1-x$ refer to those drivers play strategy D_2. Likewise, y denote the proportion of the passengers play the strategy P_1 and strategy P_2 is being tried by the rest passengers. Based on the above parameters and assumptions, we give the payoff matrix:

TABLE II: Game model encompassing the strategies

Driver	Passenger	
	$P_1(y)$	$P_2(1-y)$
$D_1(x)$	(U_{11}, V_{11})	(U_{12}, V_{21})
$D_2(1-x)$	(U_{21}, V_{12})	(U_{22}, V_{22})

- Driver's payoff function by employing strategy D_1 when passenger play strategy P_1 :

$$U_{11} = EL_2 f - LC_1 + fL^* \tag{4}$$

- Passengers's payoff function of employing P_1 when driver play strategy D_1:

$$V_{11} = -w_e \tag{5}$$

Likewise,

- U_{12}: $U_{12} = (1-P_c)(EL_2 f + fL^*) + P_c(E' f L_2 + fL_1) - LC_1$
- V_{21}: $V_{21} = -P_c w_e - (1-P_c)w$
- U_{21}: $U_{21} = E' f L_2 + fL_1$
- V_{12}: $V_{12} = -w_e$
- U_{22}: $U_{22} = E' f L_2 + fL_1$
- V_{22}: $V_{22} = -P_c w_e - (1-P_c)w$

The goal of the analysis module in the reservation system is to learn a set of key characteristics and then set appropriate parameters to model drivers' and passengers' behaviour. The block diagram of the analysis process is given by Fig 4, in which game theory is applied to calculate the conditions to improve the success rate of reservation system.

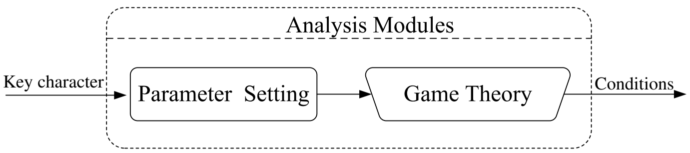

Fig. 4: Analysis Model

VI. Analysis

We use the standard Jacobian Matrix (J) evaluated at the equilibrium for evaluating the asymptotic stability of an equilibrium strategy pair and obtain the ESS values here. Any solution pair that satisfies the Eqnarray 6 is an ESS of the game.

$$Tr(J) < 0, det(J) > 0 \tag{6}$$

Theorem VI.1 *No matter what actions the passengers will make, the driver's optimal actions are picking up the passengers if the following formula holds:*

$$E \geq max(\frac{(1-P_c)(E'fL_2 + fL - fL^*) + LC_1}{L_2 f(1-P_c)}, \tag{7}$$

$$\frac{L_1 - L^* + E'L_2}{L_2} - \frac{LC_1}{fL_2}) \tag{8}$$

where E, P_c denote the preference and the probability of a taxi finding an available passenger during time w_e respectively. This theorem shows that there is some interactive relationship among these parameters. This also provides guidance information for drivers to adjust their current strategies.

Theorem VI.2 *Without outside incentive, when shortest-path matching is applied by the driver, the passenger's optimal action is waiting until the taxi comes, if the following formula holds:*

$$w \geq w_e \tag{9}$$

where w, w_e denote the average waiting time and time consumption to pick up passengers, respectively.

VII. Performance Evaluation

A. Preparatory phase

It is easy to confirm the true location of passengers while it is difficult to confirm the exact arriving time. We assume that a passenger was already waiting there when a taxicab switched from cruising to occupied, and thus the occupation index switching from 0 to 1 should be recorded. We set the observation time to be 5 minutes, for two reasons. Firstly, the sparseness and low-sampling-rate of the taxi trajectories[27] discourage us from computing less than 5 minutes flow(e.g.,$1 \sim 5$ *minute*, $2 \sim 6$ *minute*.). Secondly, although on-the-call system is used by passengers, they still appear to be unwilling to wait longer than 5 minutes.

For the nature of the service and the driver's desire for short-term profitability[20], we focus on some regions(e.g, conference center, shenzhen university etc). Figure 5 gives a detail description of the method. The green solid line is the GPS trip of the taxi with ID number $94P79$ and $02T46$. When passengers' information is included, taxi $94P79$ and $02T46$ will choose the red dotted line routing instead, which could decrease the locating time. It is reasonable to use shortest-past matching and find passengers as soon as possible.

Fig. 5: Methodology

B. Result

1) Time consumption to locate passenger: Firstly, we need to confirm whether passengers' information involved will increase some aspects of the on-the-call system. With the aid of Arcgis and map information, we calculate the real distance of the drivers' route. Figure 6 shows the improvement since shortest-path matching was applied during the five different periods. It illustrates some observations: firstly, taxi drivers could gain more profit when they use the shortest-path allocation strategy during Non-rush hour. Secondly, driving by experience is almost as good as driving by shortest-path allocation rules. Since drivers' locating time reduces, that will decrease passengers' waiting time.

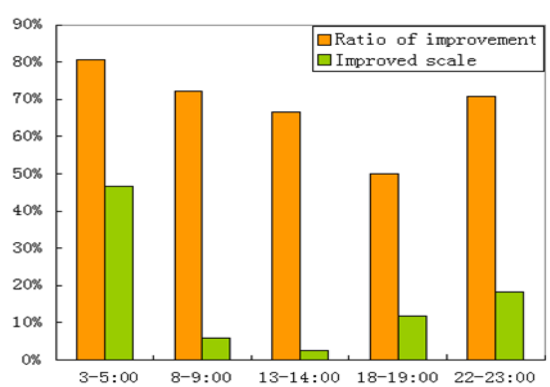

Fig. 6: Time consumption to locate passengers

2) Convergence of participant : The PC broadcasts passenger's information to nearby taxi drivers (here we set the broadcast range as 1 kilometer). The regulatory unit fare is 2.4 yuan per Kilometer. Suppose that a passenger send a request in 22:00 and his/her destination is 12 kilometer away.

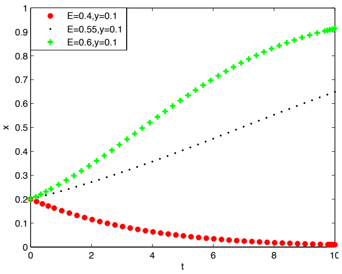

Fig. 7: Time vs. rate change

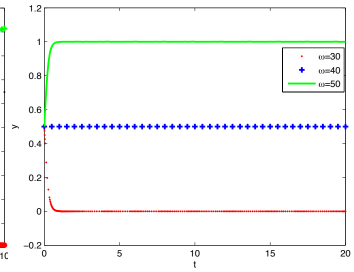

Fig. 8: Time vs. rate change

Figure 7 shows the rate change of the driver. Whether the percentage of drivers playing S_{D_1} will converge to 1 relies on driver's preference E. Moreover, driver's preference E that satisfies theorem VI will converge to 1 finally.

We select a time period for which the time consumption to pick up passengers w_e is 40s, and choose different average waiting times w to imitate the convergence of passengers. Figure 8 illustrate that the percentage will converge to 1 only when $w \geq w_e$ holds. This is consistent with the analysis in the former section. It implies that passengers are not patient and prefer actions that keep waiting times shorter.

3) Optimal actions: But how should drivers handle this situation to maximize their profit? Fig 9 describes the critical convergence line with respect to different preferences E and average occupied driving distance L_1 when driving by experience. The figure denotes that personal drivers that locate in the area between the line and x axis will converge to 1, i.e, is willing to pick up the passengers and gain more profit. In other words, the optimal action for those drivers is choosing the strategy "pick up". However, the optimal actions will turn to be the strategy "ignore" when above this line.

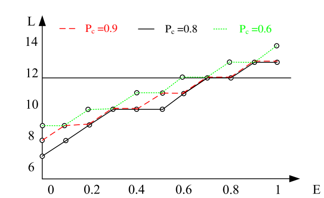

Fig. 9: Distance vs. Preference

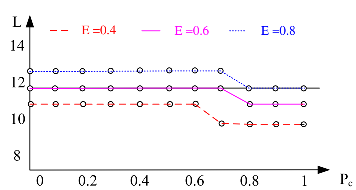

Fig. 10: Distance vs. probability

The higher the preference E of the destination, the more driver is willing to pick up the passengers, until the average occupied driving distance L_1 greatly exceeds the distance passengers requested. Moreover, it will guide drivers to choose their optimal actions. For a driver with a preference $E = 0.8$ and average occupied driving distance $L_1 = 12$, the optimal strategy is to follow CRS's guide and pick up the passenger.

Fig 11 presents the game approach profit compared with the ground truth, which could increase at least 18% of the drivers' profit. As the percentage of drivers who accept a match increases, the profit the drivers will gain increases. It shows that drivers will optimize their profit when all drivers choose to pick up the passengers. The Non-game approach profit fluctuates mainly because of its random destinations, i.e., the preferences fluctuate between 0 and 1, while the game approach profit fluctuates mainly for preference of destination and percentage of cooperative drivers. The most probable reason for this is that passengers choose their actions mainly according to their evaluation of drivers' behavior. When they think the probability that the driver will pick them up is high, they are more willing to wait, which will reduce the risk of failing to meet the passengers and in turn increase the profit of drivers.

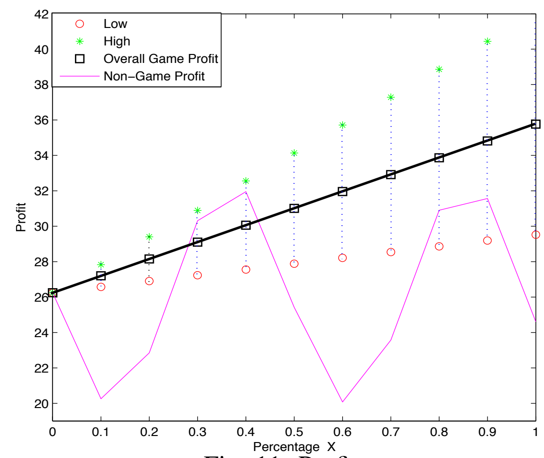

Fig. 11: Profit

4) Evaluation on Online Dispatch: We compare our dispatch method with the OMOR[8], which proposed that taxi could earn more by waiting in parking places, rather than cruising. The OMOR method first detected parking places and then proposed a probabilistic model to calculate how likely the driver would be to pick up a passenger in a parking place. Here we denote Δ as the waiting time in parking places, and we set $\Delta = 30$ *secs* and $\Delta = 60$ *secs* here. Intuitively, drivers could be more likely to pick up a passenger when waiting more time. We randomly select more than 20 places and compute the time consumption and profit.

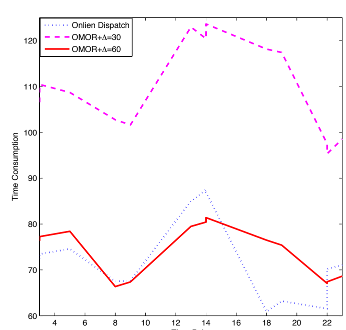

Fig. 12: favorite area

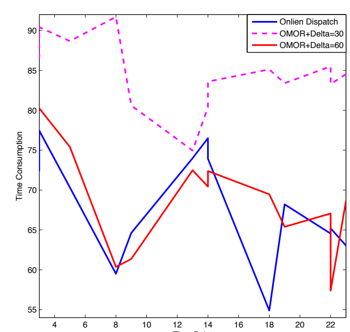

Fig. 13: unfavorite area

Figure 12 and 13 showed that drivers could gain more when waiting in parking places for 60 secs rather than 30 secs. However, online dispatch could help idle drivers to locate passengers more quickly in non-rush hours than in rush hours. The most possible conclusion is that heavy demand for taxi service always exist during rush hour. Also, the time consumption to locate passengers during rush hour is longer than during non-rush hour, because of high traffic congestion and more rival drivers.

VIII. Conclusions

We proposed an efficient dispatch and decision model for taxi-booking service and used evolutionary game theory to optimize the behaviour of taxi drivers and passengers. GPS trajectory data from Transport Commission of Shenzhen Municipality was used to evaluate the performance of the proposed system.

Our contributions are: i) a systematic study of participants' behaviour, which shows that passengers' natural unwillingness to wait and drivers' uncooperative behaviour contributes to the low success rate of current booking services; ii) an efficient dispatch and decision model to balance real-time supply and demand which can reduce the time to find passengers by between 2% and 46%; iii) an evolutionary game approach for optimizing the revenue of drivers and costs of passengers, for which results shows that we could increase driver profit by at least 18%.

Acknowledgment

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