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Dynamic pricing and penalty strategies in a coupled market with ridesourcing service and taxi considering time-dependent order cancellation behavior

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Abstract

Time-dependent order cancellation behavior affects ridesourcing platform operation and overall system performance. This paper models impacts of time-dependent order cancellation behavior on the driver-rider matching efficiency and examines ridesourcing platform operation strategies, where taxi is the alternative to the ridesourcing mode. A time-dependent matching model is developed to characterize the complex interaction among participants (drivers and riders) considering ridesourcing order cancellation behavior, where the impact of the cancelled orders on the numbers of drivers and riders is explicitly modeled. In particular, we formulate the time-dependent order cancellation rates before and after the matching stage (i.e., cancellation of unconfirmed and confirmed orders). Under the proposed model, a platform profit maximization problem is formulated and three pricing strategies are examined. Our numerical studies demonstrate that the dynamic pricing (i.e., customer/rider fare and driver wage) can well accommodate time-dependent system inputs (e.g., demand rates) and thus enable the platform to increase profit via better market segmentation. We also investigate the objective of maximizing the number of completed trips and examine the trade-off between the platform profit and the number of completed trips. In addition, we show that the relaxation of upper bounds of the ridesourcing fare and order cancellation penalty can increase the ridesourcing platform's profit and indirectly improve the utilization rate of taxis as well as the taxi company's profit.

Keywords: Ridesourcing, Taxi, Order cancellation, Pricing, Penalty

1. Introduction

The widespread popularity of smartphones has promoted the usage of app-based on-demand ridesourcing services and made them attractive and affordable for general travel groups. Ridesourcing customers (or riders) send travel requests to the platform via the mobile ridesourcing app, and then the platform matches these customers in real-time with the drivers who are providing ridesourcing service. Thanks to many advantages provided by ridesourcing platforms, such as reduced spatial barriers in the process of matching customers and vehicles, ridesourcing service has become a powerful competitor to the taxi service (Rayle et al., 2016; Nie, 2017).

Although the app-based ridesourcing service eases the matching of customers and ridesourcing vehicles, and attracts considerable customers, not all trip orders or travel requests are completed as scheduled. While waiting for matching with vehicles or pick-up, some customers may cancel the placed orders. The cancellation of confirmed orders may save ridesourcing customers' waiting time, but will waste the drivers' efforts to pick up the customers (for example, the time and fuel cost from the order is confirmed to the cancellation) and reduce the platform's ridesourcing supply, as mentioned in He et al. (2018) and Wang et al. (2020). The cancellation of unconfirmed orders also wastes the efforts of the platform, because after customers place orders, the platform will dispatch vehicles based on algorithms to meet customers, and even attract drivers to provide services with high wages when the availability of vehicles is limited (e.g., Hall et al., 2015; Chen, 2016). To the best of our knowledge, there is rather limited literature on

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ridesourcing order cancellation. He et al. (2018) first incorporated order cancellation behavior into a market with street-hailing and e-hailing taxi services, and designed pricing strategies based on the proposed equilibrium model for the maximization of platform revenue or social welfare. Wang et al. (2020) further considered order cancellation behavior in a market with hybrid modes of street-hailing and ridesourcing service, and developed an equilibrium model to characterize the interaction among different participants in the two-sided market. These studies arouse attention to ridesourcing trip order cancellation behavior, but they are based on steady-state equilibrium analysis and only focus on the cancellation of confirmed orders. In the actual ridesourcing market, drivers are free to enter and exit the market (only self-employed private car owners are considered) and customers can also place and cancel orders at any time, which will affect the supply and demand of ridesourcing service (thus affecting matching time, fleet size and order cancellation, etc.), which in turn will further affect subsequent driver and customer decisions. This time-dependent dynamic interaction cannot be characterized by the steady-state equilibrium models. Therefore, it is necessary to establish a time-dependent ridesourcing system model to better capture the process of interaction between drivers, customers and the platform, and at the same time contribute to the design of the platform's operation/pricing strategy. In addition to the confirmed order cancellation behavior described in previous studies that is harmful to drivers and ridesourcing market efficiency, the cancellation of unconfirmed orders in reality usually does not involve any penalty, and the cancellation of unconfirmed orders by customers in the matching pool will affect the matching efficiency of the platform. The above motivates the current study to model time-dependent order cancellation behavior, including cancellations of both confirmed and unconfirmed orders.

Implementing appropriate pricing and penalty strategies is one way to manage order cancellation behavior (He et al., 2018; Wang et al., 2020), and dynamic pricing has been adopted by platforms and plays an important role in transportation network companies (TNCs), such as Uber and Didi (e.g., Hall et al., 2015). The pricing can affect customers' travel choices and service fleet size, while the penalty (on customers) and compensation (to drivers), respectively, increase the cost of order cancellation and make up for the loss of related drivers. Due to the limited research on order cancellation, the penalty and compensation strategy in relation to order cancellation is also limited to the work of He et al. (2018) and Wang et al. (2020). They both explore the penalty strategy under the objective of maximizing platform profit and/or social welfare. With the boom of ridesourcing service, there is a large and growing amount of studies on platform pricing. Proponents believe that dynamic pricing strategy can help platforms to gain more profits and reduce inefficiency, see, e.g., Hall et al. (2015), Cachon et al. (2017), Castillo et al. (2017), Nourinejad & Ramezani (2020). On the contrary, some scholars pointed out that dynamic pricing may not necessarily improve the system performance or even worsen the system. For example, the forward-looking behavior of customers and drivers induced by dynamic pricing can worsen the system performance (Chen & Hu, 2020). The performance of Uber's dynamic pricing on New Year's Eve in New York and Sydney was also criticized by the public (Lowrey, 2014; Han & Robertson, 2016). Besides, there are many pricing strategies from other perspectives, such as spatial pricing (e.g., Zha et al., 2018) and optimal pricing considering congestion (e.g., Li et al., 2021), while inappropriate pricing or fleet sizing strategy may result in inefficient ridesourcing service and additional congestion (Beojone & Geroliminis, 2021).

In this paper, we make an attempt to portray the dynamic matching process between customers and drivers, and the interplay between different participants in the coupled market of taxi and ridesourcing service considering time-dependent order cancellation behavior, and also investigate the impacts of different pricing strategies on the system performance. We discretize the study period into multiple time intervals of equal length. In each time interval, the customer-vehicle matching rate is determined by the numbers of waiting customers and vacant vehicles at both ends in the matching pools for taxi and ridesourcing services. The numbers of waiting customers and vehicles in each time interval are endogenously related to the arrival and departure rates of customers and vehicles, which are governed by the total demand, supply, matching efficiency in each time interval, and also the number of cancelled orders. For this reason, we propose a model to depict the time-dependent order cancellation behavior, where we model cancellations before and after matching, i.e., cancellations of both confirmed and unconfirmed orders. Based on the proposed dynamic matching model, we further explore the impact of order cancellation behavior on the market and examine the system performance of different pricing strategies in consideration of platform profit, as well as the influence of the government's deregulation of ridesourcing service pricing/penalty strategies on the coupled market. While this paper focuses on private platform operators to maximize profits, we also investigate alternative objectives, i.e., a public operator that maximizes the number of completed (or serviced) trips (for social benefit) and a regulated operator that concerns both profit and the number of completed trips (the bi-objective problem). Note that the number of trips completed is particularly relevant to the order cancellation behavior.

The remainder of this paper is organized as follows. Section 2 presents a literature review on taxi/ridesourcing market modelling and pricing strategy. Section 3 firstly models the numbers of passengers and vehicles waiting to be matched for taxi and ridesourcing service, and then formulates the passenger-vehicle matching efficiency and matching time for both taxi and ridesourcing service. This is followed by formulating the time-dependent order cancellation behavior of ridesourcing customers before and after matching (i.e., unconfirmed and confirmed orders). Section 4 proposes three pricing strategies and presents the optimization problem of the ridesourcing platform. Section 5 conducts numerical studies to illustrate the proposed model. Section 6 concludes the paper and provides further discussions.

2. Literature review

The studies on the taxi market originated in the 1970s and Douglas (1972) provided a first look at an aggregate taxi model to characterize the supply-demand relationships and market equilibrium. After that, many researchers extended the taxi model proposed by Douglas to various different types of taxi market (e.g., Beesley, 1973; Schroeter, 1983). In a taxi market, the number of vacant taxis is an important factor in determining the level of service and waiting time of customers; and the supply, demand and waiting time are interactive (e.g., De Vany, 1975; Foerster & Gilbert, 1979). In the 1990s, to elaborate how taxis circulate in the market to find customers and provide services, Yang & Wong (1998) incorporated the spatial structure of the road network to the equilibrium model of taxi service. The taxi market model in Yang & Wong (1998) has been further extended in many ways, such as considering congestion effects and customer demand elasticity (e.g., Wong et al., 2001), multiple customer classes and taxi modes (e.g., Wong et al., 2008), nonlinear fare structures (e.g., Yang et al., 2010) and friction in the vehicle-customer matching process (e.g., Yang & Yang, 2011).

The meeting function is often utilized to measure the efficiency when waiting customers and vacant vehicles search for each other. Schroeter (1983) first introduced a meeting function into the taxi market in which telephone ordering radio dispatch service and airport taxi are the main operating modes. The meeting function was further applied by Yang & Yang (2011) to a traditional taxi market, with the purpose of depicting the searching and meeting friction for street-hailing customers and vehicles, where the meeting function reflects how the matching rate changes with the numbers of waiting customers and vacant vehicles. Since then, the meeting function has been widely used in studies on the taxi market and the ridesourcing/ridesharing market to describe searching friction or characterize the difference in matching efficiency when there is more than one travel mode (He & Shen, 2015; Zha et al., 2016; Ramezani & Nourinejad, 2018; Nourinejad & Ramezani, 2020; Chen et al., 2020; Wei et al., 2020).

Pricing is often regarded as an effective management tool in the transportation sector, such as congestion pricing (e.g., de Palma & Lindsey, 2011; Meng & Liu, 2012; Gu et al., 2018; Zheng & Geroliminis, 2020; Chen et al., 2021), and parking pricing (e.g., Qian et al., 2012; Qian & Rajagopal, 2014; Zheng & Geroliminis, 2016; Liu & Geroliminis, 2016, 2017; Liu, 2018; Gu et al., 2020; Zhang et al., 2020; Wu et al., 2021). With the emergence of on-demand ridesourcing service in the past decade, TNCs like Uber and Didi have reshaped traditional taxi market and has attracted considerable attention. The ridesourcing market is a classic two-sided market (e.g., Armstrong, 2006; Weyl, 2010), and many researchers pay attention to the impact of pricing strategies on the system and the interaction among participants (Ke et al., 2020). In particular, Chen (2016) pointed out that the surge pricing can stimulate more e-hailing drivers to provide longer service, complete more trips and improve the efficiency of the ridesourcing platform. Cachon et al. (2017) implemented different pricing strategies and found that dynamic pricing strategy with fixed commission rate can reach a higher platform profit than the pricing scheme with a fixed fare collected from passenger and a fixed wage offered to drivers. Yang et al. (2020) suggested that range constraints for dynamic pricing may lead to a failure in balancing supply and demand, and they proposed a new reward scheme where customers pay extra fares to a reward account during rush hour and use them during off-peak hours as compensation, and then all participants will be better off under certain conditions. An analytical model was developed by Bai et al. (2019) based on queuing model, where the platform gains more revenue by time-based payout ratio (i.e., the ratio of wage to price) than fixed payout ratio. They also noted that when the payout ratio exceeds one, the platform will suffer losses and attract more customers and drivers to enter the market, and this strategy may be adopted in the early stage when one wants to promote the platform. Wang et al. (2016) proposed an equilibrium model with single taxi-hailing service and investigated the impact of pricing strategy disturbance on system performance. Zha et al. (2018) explored the impact of spatial pricing on ridesourcing system and found that flat pricing strategy may yield higher prices in order to maintain sufficient supply, which reduces the utility of users, while flexible spatial pricing can benefit multiple participants.[1]

The emerging ridesourcing services grow rapidly and occupy a considerable market share, but also have experienced severe competition with other transportation modes. Taxis and ridesourcing service are competing modes (e.g., Rayle et al., 2016; Nie, 2017). Specifically, Nie (2017) found that taxis can compete more effectively with ridesourcing service during peak hours and in high population density area. In addition, the competitions among different ridesourcing platforms are also studied. For instance, Cohen & Zhang (2017) considered multiple platforms not only to compete for customers, but also for drivers who can provide services. Based on the proposed model, they studied both the competition and coopetition between platforms, and designed profit-sharing contracts to benefit each party. Mo et al. (2020) explored the competition of two different ridesourcing platforms, and studied the impact of the government's two subsidy strategies under the equilibrium of non-cooperative competition to improve social welfare. This study is related to the above in the sense that taxi is modeled as the travel alternative to ridesourcing service, while this study focuses on time-dependent ridesourcing order cancellation behaviors.

3. Modelling the dynamic matching process and time-dependent order cancellation behavior

In this section, we establish a dynamic matching model that considers time-dependent order cancellation behavior, which includes four main subsections: (i) traveler's mode choice and the numbers of customers waiting to be matched for taxis and ridesourcing services; (ii) the numbers of ridesourcing vehicles and taxis waiting to be matched in each time interval; (iii) the matching efficiency and waiting times of ridesourcing service and taxi service; (iv) time-dependent order cancellation rate and the number of cancelled orders. In addition, the dynamic matching model with embedded time-dependent order cancellation behavior is summarized in the last (fifth) subsection (of this section).

We adopt a discrete-time formulation, where we discretize the study period $[T_0, T]$ into T^* time intervals of equal length Δt and $T^* = (T - T_0)/\Delta t$. Each time interval is denoted as t, $t \in \{1, ..., T^*\}$. To facilitate reading, major notations are summarized below.

Table 1: Glossary of Notations

Notation	Interpretation
a_{rs}, a_{tx}	Starting fees of ridesourcing and taxi service (A\$)
$A_{rs}^{t_i,t_j}(t)$	Number of customers who place, match and wait to board ridesourcing vehicles at time t_i, t_j and t
b_{rs}	Starting wage of ridesourcing drivers (A\$)
c_g	Average fuel cost per kilometer (A\$/km)
c_0	Fixed cost per trip (A\$/trip)
c_p	Parking cost per hour (A\$/hour)
d	Average trip distance (km)
D, D_{rs}, D_{tx}	Total demand, ridesourcing demand and taxi demand
G_{rs}, G_{tx}	Trip completion rates of ridesourcing vehicle and taxi
h_{rs}	Estimated monetary cost for ridesourcing drivers (A\$)
H_{rs}, H_{tx}	Positive meeting constants of meeting rate
k_{rs}, k_{tx}	Distance-based fare rates of ridesourcing and taxi service (A\$/km)
K_{rs}, K_{tx}	Trip fares of ridesourcing and taxi service (A\$)
$\widehat{k}_{rs}$	Penalty charged to customers cancelling matched orders (A\$/trip)
$[\underline{k}_{rs}, \underline{s}_{rs}, \underline{\widehat{k}}_{rs}, \underline{\widehat{s}}_{rs}]$	Lower bounds of fare, wage, penalty and compensation
$[\overline{k}_{rs}, \overline{s}_{rs}, \overline{\widehat{k}}_{rs}, \overline{\widehat{s}}_{rs}]$	Upper bounds of fare, wage, penalty and compensation
m	Flag-fall distance (km)

[1]The successful implementation of the pricing strategy relies on the platform's accurate forecasting and/or understanding of demand. Substantial efforts have been dedicated to demand forecasting in the ridesourcing markets (Ke et al., 2017; Kontou et al., 2020; Ke et al., 2021).

M_{rs}, M_{tx}	Meeting rates of customers with ridesourcing and taxi service
$M_{rs}^{t_i}(t)$	Actual matching amount at time t for orders placed at time t_i
$M_{rs}^{'t_i}(t)$	Pre-allocated matching amount at time t for orders placed at time t_i
n	Duration of each pricing decision step
N_{rs}^{c}, N_{tx}^{c}	Numbers of customers waiting to be matched for ridesourcing and taxi service
N_{rs}^{en}, N_{rs}^{ex}	Numbers of ridesourcing vehicles entering and exiting the market
$N_{rs}^{\max}$	Potential maximum number of ridesourcing vehicles
N_{rs}^{v}, N_{tx}^{v}	Numbers of vacant waiting ridesourcing vehicles and taxis
N_{rs}^{o}	Number of occupied ridesourcing vehicles
N_{rs}^{pk}, N_{tx}^{pk}	Numbers of orders that customers are successfully picked up by ridesourcing vehicles or taxis in a time interval
$N_{rs}^{c,t_i}(t)$	Number of unmatched customers who place orders at time t_i and wait to be matched at time t
$\overline{P}_{oc1}^{c}$, $\overline{P}_{oc2}^{c}$	Estimated order cancellation rates before and after matching
P_{in}, P_{out}	Probabilities of ridesourcing drivers entering and exiting the market
$P_{oc1}^{t_i}(t)$	Time-dependent order cancellation rate before matching at time t
$P_{oc2}^{t_i,t_j}(t)$	Time-dependent order cancellation rate after matching at time t
$P_{oc1}(t)$, $P_{oc2}(t)$	Total order cancellation rates before and after matching for orders placed at time t
q	Operating cost of ridesourcing platform (A$/trip)
r_{rs}	Expected revenue of ridesourcing drivers (A$)
R_{oc1}, R_{oc2}	Numbers of cancelled orders before and after matching in a time interval
s_{rs}	Distance-based wage rate of ridesourcing drivers (A$/km)
$\widehat{s}_{rs}$	Compensation paid to the drivers whose orders are cancelled (A$/trip)
TC_{rs}, TC_{tx}	Perceived generalized trip costs of ridesourcing and taxi customers
$t \in \{1, ..., T^*\}$	Time-step t belongs to the set of discrete time interval $\{1, ..., T^*\}$
t_s, t_e	Start time and end time of a time period
U_{rs}, U_{tx}	Perceived disutilities of ridesourcing and taxi service
v_0	Average speed of taxi and ridesourcing vehicle (km/h)
$\overline{w}_{oc1}^{c}$, $\overline{w}_{oc2}^{c}$	Estimated cancellation times for customers to cancel orders before and after matching (min)
$\overline{w}_{rs}^{c}$, $\overline{w}_{tx}^{c}$	Expected matching times of customers for ridesourcing and taxi service(min)
$\overline{w}_{rs}^{pk}$	Average pick-up time for customers and vehicles of matched orders (min)
α_{rs}, β_{rs} $(\alpha_{tx}, \beta_{tx})$	Constant elasticities of meeting rate of ridesourcing (taxi) service
γ	Value of time
θ_1, θ_2	Positive parameters
$\eta\overline{w}_{rs}^{c}(t_i)$	A proportion of the expected waiting time for orders placed at time t_i
$[\sigma_{k_{rs}}, \sigma_{s_{rs}}, \sigma_{\widehat{k}_{rs}}, \sigma_{\widehat{k}_{rs}}]$	Lower bounds of fare, wage, penalty and compensation adjustment between adjacent pricing decision steps
$[\tau_{k_{rs}}, \tau_{s_{rs}}, \tau_{\widehat{k}_{rs}}, \tau_{\widehat{s}_{rs}}]$	Upper bounds of fare, wage, penalty and compensation adjustment between adjacent pricing decision steps

3.1. Numbers of taxi and ridesourcing customers waiting to be matched

Consider a region where customers can choose ridesourcing and taxi services. The total travel demand generated in each discretized time interval is divided into ridesourcing demand and taxi demand based on customers' perceived disutilities of the two modes. With the flag-fall fee of taxi a_{tx}, fare rate of taxi k_{tx} and expected matching time for taxi $\overline{w}_{tx}^{c}$, the mean perceived generalized trip cost of taxi customers at time t can be given as

$$TC_{tx}(t) = a_{tx} + k_{tx}(t)\max(d - m, 0) + \gamma\overline{w}_{tx}^{c}(t - 1) \tag{1}$$

where d and m denote the average trip distance and flag-fall distance, respectively; γ is the customers' value of time. $K_{tx} = a_{tx} + k_{tx}(t)\max(d-m, 0)$ represents the average trip fare charged to taxi customers, where $k_{tx}(t)\max(d-m, 0)$ means that when the average trip distance exceeds the flag-fall distance, customers will be charged at $k_{tx}(t)$ A\$/km. The last term is the expected waiting cost for matching of taxi customers, where $\overline{w}_{tx}^{c}(t-1)$ indicates that the real information at the previous moment (i.e., $t-1$) is used to estimate the matching time (wait for being matched) when making mode choice (this might be provided by the platform).

As for ridesourcing customers, possible order cancellations at two stages, i.e., before and after the order is confirmed or matching is completed, are considered. With the estimated cancellation rates before matching $\overline{P}_{oc1}$ (cancellation of unconfirmed orders) and after matching $\overline{P}_{oc2}$ (cancellation of confirmed orders), the matching time for ridesourcing vehicle $\overline{w}_{rs}^{c}$ and pick-up time $\overline{w}_{rs}^{pk}$, the perceived cancellation times before matching $\overline{w}_{oc1}$ and after matching $\overline{w}_{oc2}$, the average trip fares of taxi customer K_{tx} and ridesourcing customer K_{rs}, the mean perceived generalized trip cost of ridesourcing customers at time t can be given as:

$$\begin{aligned} TC_{rs}(t) = &\left[1-\overline{P}_{oc1}(t)\right]\left\{\gamma\overline{w}_{rs}^{c}(t-1) + (1-\overline{P}_{oc2}(t))\left[\gamma\overline{w}_{rs}^{pk}(t-1) + K_{rs}(t)\right] + \overline{P}_{oc2}(t)\left[\gamma\overline{w}_{oc2}(t-1) + K_{tx} + \widehat{k}_{rs}(t)\right]\right\} \\ &+ \overline{P}_{oc1}(t)\left[\gamma\overline{w}_{oc1}(t-1) + K_{tx}\right] \end{aligned} \tag{2}$$

where $K_{rs}(t) = a_{rs} + k_{rs}(t)\max(d-m, 0)$; a_{rs} is the flag-fall fee of ridesourcing service; k_{rs} is the distance-based fare rate of ridesourcing service; $\widehat{k}_{rs}$ is the penalty charged on ridesourcing customers who cancel confirmed orders. Similar to Eq. (1), information at the previous moment (i.e., $t-1$) is used to calculate trip costs. The perceived cancellation time is assumed to be proportional to the waiting time (wait for matching and pick-up). The first term of Eq. (2) represents the expected cost of keeping orders before matching. Specifically, the first term in curly brackets represents the waiting cost for matching of ridesourcing customers; the second term is the cost of completing orders by ridesourcing vehicles after matching, including the waiting cost for pick up and trip fare of ridesourcing service; and the third term is the cost of completing orders by taxis when customers cancel orders after matching, including the waiting cost from matching to cancellation, taxi trip fare and penalty. The second term of Eq. (2) represents the expected cost of completing orders by taxis when customers cancel orders before matching, including the time cost from placing orders to the cancellation time point and taxi trip fare.

Based on the generalized trip cost, the perceived disutility of each mode can be given as: $U_{tx}(t) = \theta_1 TC_{tx}(t) + \varepsilon_{tx}(t)$ for taxi customers and $U_{rs}(t) = \theta_1 TC_{rs}(t) + \varepsilon_{rs}(t)$ for ridesourcing customers, where $\theta_1 > 0$ is the scale parameter; ε_{tx} and ε_{rs} are the error terms following certain identical and independent Gumbel distribution. Hence, given the total demand $D(t)$ at time t and based on the disutilities of both modes, the modal-split of customers can be obtained with the following binary Logit function:

$$D_{tx}(t) = \frac{D(t)}{1 + \exp\left[\theta_1(TC_{tx}(t) - TC_{rs}(t))\right]}, D_{rs}(t) = D(t) - D_{tx}(t) \tag{3}$$

where $D_{tx}(t)$ and $D_{rs}(t)$ are the numbers of customers choosing taxi and ridesourcing services respectively at time t. We have $\frac{\partial D_{tx}(t)}{\partial TC_{tx}(t)}<0$ and $\frac{\partial D_{rs}(t)}{\partial TC_{rs}(t)}<0$ from Eq. (3), because the demand rate decreases with the generalized trip cost for both modes. The total demand rate $D(t)$ is exogenous while the demand rates of taxi and ridesourcing are affected by the fare rate, waiting time and possible order cancellation cost.

The searching and meeting efficiency between customers and vehicles (either taxis or ridesourcing vehicles) depends on the numbers of waiting participants at both ends of the matching pool. On the customer side, the number of customers waiting to be matched needs to consider the arrival and departure rates of customers. Specifically, for taxi customers, the arrival rate includes not only newly generated taxi demand $D_{tx}(t)$, but also the cancelled orders of ridesourcing service before and after matching, denoted by R_{oc1} and R_{oc2}, respectively; the departure rate is determined by the meeting rate M_{tx}. Following the functional form describing changes in the number of customers in Nourinejad & Ramezani (2020), and based on the number of waiting customers in the last time interval, the number of taxi customers waiting to be matched can be given as:

$$N_{tx}^{c}(t) = N_{tx}^{c}(t-1) + D_{tx}(t) - M_{tx}(t-1) + R_{oc1}(t-1) + R_{oc2}(t-1) \tag{4}$$

Note that the departure rate of ridesourcing customers includes the meeting rate M_{rs} and the cancelled orders before matching R_{oc1}; the arrival rate is determined by the newly generated ridesourcing demand $D_{rs}(t)$. Similar to Eq. (4), the number of ridesourcing customers waiting to be matched can be given as:

$$N_{rs}^{c}(t) = N_{rs}^{c}(t-1) + D_{rs}(t) - M_{rs}(t-1) - R_{oc1}(t-1) \tag{5}$$

Eq. (4) and Eq. (5) respectively reflect the positive and negative effects of ridesourcing customers' order cancellation on the numbers of taxis and ridesourcing customers waiting to be matched. Besides, by comparing Eq. (4) and Eq. (5), one can see that the cancelled orders before and after matching have asymmetric effects on the numbers of taxi/ridesourcing customers waiting to be matched. In particular, the order cancellation after matching will increase the number of taxi customers waiting to be matched without affecting the counterpart of ridesourcing customers.

3.2. Numbers of vacant taxis and ridesourcing vehicles waiting to be matched

In the coupled two-sided market, taxis and ridesourcing vehicles provide mobility service. We discuss the supply of taxi and ridesourcing service and the number of vehicles waiting to be matched at each interval in this subsection. Assuming that the number of taxis is regulated by a taxi company with a fixed fleet size in this market, the state of the taxi will switch between vacant and occupied. Specifically, a vacant taxi will be occupied immediately after picking up customers; on the contrary, if the trip is completed, the occupied taxi will become vacant again. The taxi will re-enter the market after completing the trip and then wait to be matched with customers. We first formulate the trip completion rate of taxi as follows:

$$\int_{t_s}^{t_e+d/v_0} G_{tx}(u)du = \int_{t_s}^{t_e} N_{tx}^{pk}(u)du \tag{6}$$

where G_{tx} is the trip completion rate of taxi; t_s and t_e are the start time and end time of a time period; v_0 is the average speed of taxi and ridesourcing vehicle; N_{tx}^{pk} is the number of orders that customers are successfully picked up by taxis. The above equation ensures that the number of taxis picking up customers during the period $[t_s, t_e]$ is equal to the number of taxis dropping off customers during the period $[t_s, t_e + d/v_0]$. Given the average trip distance d and average speed of taxi v_0, customers who board taxis during $[t_s, t_e]$ will complete their trips at time $(t_e + d/v_0)$ at the latest. The arrival rate of taxi is determined by the completion rate of taxi G_{tx}, while the meeting rate of taxi determines the departure rate M_{tx}. Then, following similar formulations describing changes in the number of vacant vehicles in Nourinejad & Ramezani (2020), the number of vacant taxis, denoted by $N_{tx}^{v}(t)$, can be given as follows

$$N_{tx}^{v}(t) = N_{tx}^{v}(t-1) + G_{tx}(t) - M_{tx}(t-1) \tag{7}$$

For ridesourcing vehicles, we assume that ridesourcing drivers can freely decide their working hours, so the fleet size of ridesourcing vehicle in the market is not fixed. Moreover, how many ridesourcing drivers provide mobility services is related to their expected revenue. Hence, the expected revenue of ridesourcing drivers at time t is first formulated below:

$$r_{rs}(t) = (1 - \overline{P}_{oc2}(t))(b_{rs} + s_{rs}(t)\max(d-m, 0)) + \overline{P}_{oc2}(t)\widehat{s}_{rs}(t) \tag{8}$$

where $r_{rs}(t)$ is the expected revenue rate based on the order cancellation for ridesourcing drivers at time t; b_{rs} and $s_{rs}(t)$ are the starting wage and the distance-based wage rate of ridesourcing drivers; $\widehat{s}_{rs}$ is the compensation paid to drivers whose orders are cancelled. The first term represents the expected revenue of completed trips, and the second term is the compensation of cancelled trips.

The drivers' driving distance for the completed trips includes the pick-up distance and the trip distance, and for the cancelled orders, the driving distance is a part of the pick-up distance (the vehicles are assumed to park when waiting for matching). Therefore, the estimated monetary cost $h_{rs}(t)$ based on order cancellation for drivers who provide service at time t is given by

$$h_{rs}(t) = \overline{w}_{rs}^{v}(t-1)c_p + \overline{P}_{oc2}(t)\overline{w}_{oc2}(t-1)v_0c_g + (1 - \overline{P}_{oc2}(t))(\overline{w}_{rs}^{pk}(t-1)v_0 + d)c_g + c_0 \tag{9}$$

where $\overline{w}_{rs}^{v}$ is the ridesourcing vehicles' matching time with customers; c_p is the parking cost per unit time; c_g is the average fuel cost per kilometer; v_0 is the average speed; c_0 is the fixed cost (e.g., costs related to vehicle insurance and depreciation that are converted into the fixed cost per trip). The first term on the right hand side of above equation is the parking cost, the second term is the fuel cost of vehicles from matching to order cancellation, and the third term is the fuel cost for picking up customers and delivering them to the destinations.

The numbers of ridesourcing vehicles/drivers entering and exiting the market at time t, similar to Nourinejad & Ramezani (2020), can be modelled as

$$N_{rs}^{en}(t) = \left(N_{rs}^{\max} - N_{rs}^{v}(t-1) - N_{rs}^{o}(t-1)\right) P_{in}\left(r_{rs}(t), h_{rs}(t)\right) \tag{10}$$

$$N_{rs}^{ex}(t) = \left(N_{rs}^{v}(t-1) + G_{rs}(t) - M_{rs}(t-1) + R_{oc2}(t-1)\right) P_{out}\left(r_{rs}(t), h_{rs}(t)\right) \tag{11}$$

where $N_{rs}^{en}(t)$ and $N_{rs}^{ex}(t)$, respectively, denote the numbers of ridesourcing vehicles entering and exiting the market at time t; $N_{rs}^{\max}$ is the potential maximum number of ridesourcing vehicles in the market; $N_{rs}^{v}(t-1)$ denotes the number of vacant ridesourcing vehicles at time $(t-1)$; $N_{rs}^{o}(t-1)$ denotes the number of occupied ridesourcing vehicles at time $(t-1)$; $G_{rs}(t)$ is the trip completion rate of ridesourcing vehicles at time t; P_{in} and P_{out} respectively represent the probabilities of ridesourcing drivers entering and exiting the market, which are governed by the expected revenue and monetary cost. The above formulations provide an estimate of ridesourcing supply, where if the expected income is higher and the expected monetary cost is lower, more drivers will provide service and fewer drivers will leave the market. The above formulations have to be calibrated with real-world data in order to produce realistic estimations.

Eqs. (10) and (11) also indicate that the numbers of ridesourcing vehicles entering and exiting the market are part of the vehicles outside the market and part of the unoccupied vehicles in the market, respectively. The arrival rate of ridesourcing vehicles includes the newly entering vehicles, trip completion rate of ridesourcing vehicles and cancelled trips after matching, while the departure rate is determined by the newly exiting vehicles and meeting rate. Thus, similar to Eq. (7), the number of vacant ridesourcing vehicles at time t can be given by Eq. (12), and the number of occupied ridesourcing vehicles at time t can be given by Eq. (13).

$$N_{rs}^{v}(t) = N_{rs}^{v}(t-1) + N_{rs}^{en}(t) - N_{rs}^{ex}(t) - M_{rs}(t-1) + G_{rs}(t) + R_{oc2}(t-1) \tag{12}$$

$$N_{rs}^{o}(t) = N_{rs}^{o}(t-1) + M_{rs}(t-1) - G_{rs}(t) - R_{oc2}(t-1) \tag{13}$$

We assume that the ridesourcing vehicles being matched with customers or having picked up customers are occupied. Accordingly, Eq. (12) and Eq. (13) indicate that the order cancellation after matching enlarges the number of vacant vehicles and reduces the number of occupied vehicles. Similar to Eq. (6), Eq. (14) below indicates the flow conservation of ridesourcing vehicles whose order is not cancelled:

$$\int_{t_s}^{t_e+d/v_0} G_{rs}(u)du = \int_{t_s}^{t_e} N_{rs}^{pk}(u)du \tag{14}$$

where N_{rs}^{pk} is the number of orders that customers are successfully picked up by their reserved ridesourcing vehicles.

3.3. Matching efficiency and waiting time for customers and vehicles

The numbers of customers and vacant vehicles waiting to be matched formulated respectively in Subsection 3.1 and Subsection 3.2 together will determine the matching rates, while the matching/meeting rates in turn affect the numbers of waiting participants at both ends of the matching pool in the form of departure rates for both taxi and ridesourcing services, which have been expressed in Eqs. (4), (5), (7) and (12). We now further formulate the dynamic matching process of customers and vehicles with the consideration of the time-dependent order cancellation behavior. Due to the physical distance barrier between vehicles and customers for both taxi and ridesourcing modes, there always exists searching friction between customers and vehicles. To measure this searching friction, the meeting function can be used to approximate the efficiency of matching customers and vehicles within a time interval. The meeting rate is a function of the numbers of customers and vacant vehicles waiting to be matched, which is widely used in studies on traditional taxi market or ridesourcing market (e.g., Yang & Yang, 2011; He & Shen, 2015). The meeting/matching rates for taxi and ridesourcing market at time t are both formulated to characterize the matching process of waiting customers and vacant vehicles, which can be given as

$$M_{rs}(t) = H_{rs}(N_{rs}^{c}(t))^{\alpha_{rs}}(N_{rs}^{v}(t))^{\beta_{rs}} \tag{15}$$

$$M_{tx}(t) = H_{tx}(N^c_{tx}(t))^{\alpha_{tx}}(N^v_{tx}(t))^{\beta_{tx}} \tag{16}$$

where H_{rs} and H_{tx} are positive meeting constants related to the size of meeting area and travel modes; α_{rs} and β_{rs} (α_{tx} and β_{tx}) respectively indicate the constant elasticities of meeting rate with respect to the numbers of customers and vacant vehicles waiting to be matched, with $0 < \alpha_{rs} \leq 1$ and $0 < \beta_{rs} \leq 1$ ($0 < \alpha_{tx} \leq 1$ and $0 < \beta_{tx} \leq 1$). The meeting function (Eqs. (15)-(16)) of each mode is homogeneous of degree (α_{rs}+β_{rs}) or (α_{tx}+β_{tx}), which shows increasing, constant, decreasing returns to scale if the value of α_{rs}+β_{rs} is $> 1, = 1, < 1$ or α_{tx}+β_{tx} is $> 1, = 1, < 1$, respectively, for each mode. Since the matching efficiency of ridesourcing service based on smartphone app is expected to be more advantageous than that of cruising taxi service, the meeting rate of ridesourcing is greater than that of taxi when the number of waiting customers and the number of vacant vehicles in the matching pool are identical for the two modes, that is, $H_{rs}(N^c(t))^{\alpha_{rs}}(N^v(t))^{\beta_{rs}} > H_{tx}(N^c(t))^{\alpha_{tx}}(N^v(t))^{\beta_{tx}}$ where $H_{rs} \geq H_{tx}$, $\alpha_{rs} \geq \alpha_{tx}$ and $\beta_{rs} \geq \beta_{tx}$ with at least one inequality strictly holding. Besides, the meeting rate at time t increases with the numbers of customers and vacant vehicles waiting to be matched, i.e., $\dfrac{\partial M_{rs}(t)}{\partial N^c_{rs}(t)} > 0$, $\dfrac{\partial M_{rs}(t)}{\partial N^v_{rs}(t)} > 0$, $\dfrac{\partial M_{tx}(t)}{\partial N^c_{tx}(t)} > 0$ and $\dfrac{\partial M_{tx}(t)}{\partial N^v_{tx}(t)} > 0$. The meeting rate of each mode at time t cannot exceed the numbers of customers and vehicles waiting to be matched at time t and thus we have $M_{rs}(t) \leq N^c_{rs}(t)$ and $M_{rs}(t) \leq N^v_{rs}(t)$ for customer-ridesourcing vehicle matching and $M_{tx}(t) \leq N^c_{tx}(t)$ and $M_{tx}(t) \leq N^v_{tx}(t)$ for customer-taxi matching.

Based on the meeting rates at time t given by Eqs. (15)-(16) and the numbers of customers waiting to be matched given by Eqs. (4)-(5), the expected matching times of customers for ridesourcing vehicles and taxis can be expressed as Eqs. (17)-(18).

$$\overline{w}^c_{rs}(t) = \frac{N^c_{rs}(t)}{M_{rs}(t)} = H^{-1}_{rs}(N^c_{rs}(t))^{1-\alpha_{rs}}(N^v_{rs}(t))^{-\beta_{rs}} \tag{17}$$

$$\overline{w}^c_{tx}(t) = \frac{N^c_{tx}(t)}{M_{tx}(t)} = H^{-1}_{tx}(N^c_{tx}(t))^{1-\alpha_{tx}}(N^v_{tx}(t))^{-\beta_{tx}} \tag{18}$$

In parallel to Eqs. (17)-(18), together with Eqs. (15)-(16) and the numbers of vacant vehicles waiting to be matched given by Eqs. (7) and (12), the expected matching times of ridesourcing vehicles and taxis for customers can be formulated as Eqs. (19)-(20).

$$\overline{w}^v_{rs}(t) = \frac{N^v_{rs}(t)}{M_{rs}(t)} = H^{-1}_{rs}(N^c_{rs}(t))^{-\alpha_{rs}}(N^v_{rs}(t))^{1-\beta_{rs}} \tag{19}$$

$$\overline{w}^v_{tx}(t) = \frac{N^v_{tx}(t)}{M_{tx}(t)} = H^{-1}_{tx}(N^c_{tx}(t))^{-\alpha_{tx}}(N^v_{tx}(t))^{1-\beta_{tx}} \tag{20}$$

From Eqs. (17)-(20), one can identify the relationship between the matching time of customers/vehicles and the number of waiting customers/vehicles at both ends of the matching pool. The numbers of customers and vacant vehicles waiting to be matched have opposite effects on the expected matching times of customers and vehicles, i.e., $\dfrac{\partial \overline{w}^c_{rs}(t)}{\partial N^c_{rs}(t)} > 0$, $\dfrac{\partial \overline{w}^c_{rs}(t)}{\partial N^v_{rs}(t)} < 0$, $\dfrac{\partial \overline{w}^v_{rs}(t)}{\partial N^c_{rs}(t)} < 0$ and $\dfrac{\partial \overline{w}^v_{rs}(t)}{\partial N^v_{rs}(t)} > 0$ for ridesourcing service, and $\dfrac{\partial \overline{w}^c_{tx}(t)}{\partial N^c_{tx}(t)} > 0$, $\dfrac{\partial \overline{w}^c_{tx}(t)}{\partial N^v_{tx}(t)} < 0$, $\dfrac{\partial \overline{w}^v_{tx}(t)}{\partial N^c_{tx}(t)} < 0$ and $\dfrac{\partial \overline{w}^v_{tx}(t)}{\partial N^v_{tx}(t)} > 0$ for taxi service.

In addition to the matching time, ridesourcing drivers and customers have to experience pick-up time to cover the physical distance. The function of pick-up time follows that in Wang et al. (2020), i.e.,

$$\overline{w}^{pk}_{rs}(t) = l_{rs}\left(N^c_{rs}(t), N^v_{rs}(t)\right)/v_0 \tag{21}$$

where l_{rs} indicates the average distance between drivers and customers and is assumed to be a function of $N^c_{rs}(t)$ and $N^v_{rs}(t)$. The average distance decreases with the numbers of customers and vehicles waiting to be matched, i.e., $\partial l_{rs}\left(N^c_{rs}(t), N^v_{rs}(t)\right)/N^c_{rs}(t) < 0$, $\partial l_{rs}\left(N^c_{rs}(t), N^v_{rs}(t)\right)/\partial N^v_{rs}(t) < 0$. Combining the number of waiting customers and the number of vacant vehicles at time t in the previous subsections, we can substitute Eqs. (4), (5), (7) and (12) into Eqs. (15) and (16) to obtain the exact formulae of the matching functions incorporating the numbers of cancelled orders before and after matching as follows:

$$\begin{aligned} M_{rs}(t) =& H_{rs}(N^c_{rs}(t-1) + D_{rs}(t) - M_{rs}(t-1) - R_{oc1}(t-1))^{\alpha_{rs}} \cdot \\ & (N^v_{rs}(t-1) + N^{en}_{rs}(t) - N^{ex}_{rs}(t) + G_{rs}(t) - M_{rs}(t-1) + R_{oc2}(t-1))^{\beta_{rs}} \end{aligned} \tag{22}$$

$$
\begin{aligned}
M_{tx}(t) =&H_{tx}(N_{tx}^{c}(t-1)+D_{tx}(t)-M_{tx}(t-1)+R_{oc1}(t-1)+R_{oc2}(t-1))^{\alpha_{tx}}\cdot \\
&(N_{tx}^{v}(t-1)+G_{tx}(t)-M_{tx}(t-1))^{\beta_{tx}}
\end{aligned} \tag{23}
$$

3.4. Time-dependent order cancellation rate and cancelled orders

After customers choose ridesourcing and request a ride, they either wait for being matched with a driver or wait for pick up if the order is already confirmed (i.e., matched with a driver). During the waiting, ridesourcing customers may encounter vacant taxis, and thus they may cancel orders and switch to taxi service. Whether customers cancel orders or not is affected by the costs to be incurred, as discussed in Wang et al. (2020).

Order cancellation before and after matching (i.e., unconfirmed and confirmed orders) involves customers' different considerations on penalty and remaining waiting time, which affects the customers' order cancellation behavior, so the order cancellation rates before and after matching are formulated separately. For the order cancellation before matching, the total cost for orders placed at time t_i and cancelled at time t is equal to the taxi fare, while the total cost of keeping orders includes the ridesourcing trip fare, remaining matching time cost and pick-up time cost. The time-dependent order cancellation rate before matching $P_{oc1}^{t_i}(t)$ can be modelled as Eq. (24) below. For the order cancellation after matching at time t and ridesourcing customers whose e-hailing orders are placed at time t_i and matched at time t_j, if they cancel orders at time t, the total remaining cost includes the taxi fare and penalty charged by the platform and if they continue their orders, the total remaining cost includes the ridesourcing trip fare and the pick-up time cost. For orders placed at time t_i, matched at time t_j and then cancelled at time t, the time-dependent order cancellation rate after matching $P_{oc2}^{t_i,t_j}(t)$ can be modelled as Eq. (25) below.

$$
P_{oc1}^{t_i}(t)=\left(1-e^{-\dfrac{\Delta t}{\overline{w}_{tx}^{c}(t)}}\right)\frac{1}{1+\exp\left\{\theta_2\left[K_{tx}-K_{rs}\left(t_i\right)-\gamma\left(\max(\overline{w}_{rs}^{c}(t_i)-(t-t_i),\eta\overline{w}_{rs}^{c}(t_i))+\overline{w}_{rs}^{pk}(t_i)\right)\right]\right\}} \tag{24}
$$

$$
P_{oc2}^{t_i,t_j}(t)=\left(1-e^{-\dfrac{\Delta t}{\overline{w}_{tx}^{c}(t)}}\right)\frac{1}{1+\exp\left\{\theta_2\left[\ K_{tx}+\widehat{k}_{rs}(t)-K_{rs}\left(t_i\right)-\gamma\left(t_j+\overline{w}_{rs}^{pk}(t_j)-t\right)\right]\right\}} \tag{25}
$$

The first term on the right hand side of Eq. (24) or Eq. (25) indicates the probability of meeting vacant taxis for ridesourcing customers who are waiting for responses or their matched vehicles with the assumption that the customers' waiting time for taxi service follows an exponential distribution with the mean of $\overline{w}_{tx}^{c}(t)$ (Du & Gong, 2016; Wang et al., 2020) during the time interval with a length of Δt; the second terms on the right-hand side of Eqs. (24) and (25) are the Logit-based choices to decide whether to cancel the order or not, depending on the perceived costs to be incurred for different choices. Note that while waiting, we consider customers' perceived remaining matching time is always no smaller than a proportion of the mean matching time, i.e., $\eta\overline{w}_{rs}^{c}(t_i)$.

Based on the time-dependent order cancellation rate, we can estimate the numbers of cancelled orders before and after matching at each time interval. Except for the customers who are matched or picked up with the corresponding vehicles, the remaining customers either continue to wait or cancel their orders and board taxis. It is assumed that the matching between the customers and the vehicles follows the first-come-first-served principle, that is, matches are performed according to the sequence in which customers place orders. Hence, the number of unmatched customers at time t who place orders at time t_i, denoted by $N_{rs}^{c,t_i}(t)$, can be expressed as

$$
N_{rs}^{c,t_i}(t)=\max(N_{rs}^{c,t_i}(t-1)-M_{rs}^{'t_i}(t-1),0)(1-P_{oc1}^{t_i}(t-1)) \tag{26}
$$

where $M_{rs}^{'t_i}(t)$ represents the pre-allocated matching amount at time t for orders placed at time t_i, and $M_{rs}^{'t_i}(t)=M_{rs}(t)$ if $t_i=1$; $N_{rs}^{c,t_i}(t)=D_{rs}(t)$ if $t_i=t$. This equation indicates that $N_{rs}^{c,t_i}(t)$ is equal to the number of remaining unmatched customers after some have switched to taxi service in the previous time interval. The pre-allocated successful matching amount for orders with different order placing times can be recursively determined by

$$
M_{rs}^{'t_i+1}(t)=M_{rs}^{'t_i}(t)-\min(N_{rs}^{c,t_i}(t),M_{rs}^{'t_i}(t)) \tag{27}
$$

where $M^{t_i}_{rs}(t) = \min\left(N^{c,t_i}_{rs}(t), M'^{t_i}_{rs}(t)\right)$ indicates the actual matching amount at time t for orders placed at time t_i. The above equation indicates that after the customers who place orders at time t_i are matched, the remaining matching amount will be pre-allocated to the customers who place orders at time $(t_i + 1)$. If the customers placing orders at time t_i are not fully matched with vehicles, i.e., $M^{t_i}_{rs}(t) = M'^{t_i}_{rs}(t)$, zero matching amount at time t will be allocated to customers placing orders after time t_i. Combining Eqs. (24), (26) and (27), the total number of cancelled orders before matching for orders placed at different times no later than time t can be calculated by

$$R_{oc1}(t) = \sum_{\forall t_i \le t} \max(N^{c,t_i}_{rs}(t) - M'^{t_i}_{rs}(t), 0) P^{t_i}_{oc1}(t) \tag{28}$$

Eq. (28) means that the number of cancelled orders before matching at time t is determined by the number of unmatched customers placing orders no later than time t and their corresponding time-dependent order cancellation rate before matching. After the matching is completed, the customers may experience being picked up, cancelling the order and switching to a taxi, or continuing to wait. Assuming that the customers matched at time t_j can be picked up at time t, we have $t \le t_j + \overline{w}^{pk}_{rs}(t_j) \le t + 1$, and the total number of ridesourcing customers being successfully picked up at time t can be calculated as follows:

$$N^{pk}_{rs}(t) = \sum_{\forall t_i \le t} \sum_{\forall t_i \le t_j \le t} A^{t_i,t_j}_{rs}(t), t \le t_j + \overline{w}^{pk}_{rs}(t_j) \le t + 1 \tag{29}$$

where $A^{t_i,t_j}_{rs}(t)$ denotes the number of customers who place orders at time t_i, are matched with vehicles at time t_j and wait to board at time t. Since when vehicles are matched with customers, the platform can obtain the real-time location information of both and further obtain a reliable pick-up time, we assume that the vehicles can pick up customers according to that time for simplicity. If customers are not picked up at the current interval, we have $t_j + \overline{w}^{pk}_{rs}(t_j) > t + 1$, and thus the total number of cancelled orders after matching can be calculated by

$$R_{oc2}(t) = \sum_{\forall t_i \le t} \sum_{\forall t_i \le t_j \le t} A^{t_i,t_j}_{rs}(t) P^{t_i,t_j}_{oc2}(t), t_j + \overline{w}^{pk}_{rs}(t_j) > t + 1 \tag{30}$$

Similar to Eq. (28), the above equation indicates that the number of cancelled orders after matching at time t is determined by the number of customers not picked up yet from previous matched customers and the corresponding time-dependent order cancellation rate after matching. The number of customers who continue to wait to board their matched vehicles can be expressed by

$$A^{t_i,t_j}_{rs}(t) = A^{t_i,t_j}_{rs}(t-1)(1 - P^{t_i,t_j}_{oc2}(t-1)), t_j + \overline{w}^{pk}_{rs}(t_j) > t \tag{31}$$

This equation describes the recurrence relationship regarding the number of customers who have not been picked up. If $t_j + \overline{w}^{pk}_{rs}(t_j) < t$, $A^{t_i,t_j}_{rs}(t) = 0$. According to the order placing time and matching time, combining the time-dependent order cancellation rates in Eqs. (24)-(25), and following the first-come-first-served principle, the state variables such as the number of cancelled orders shown in Eqs. (26)-(31) can be obtained.

The potential order cancellation and its impacts on user cost are perceived by customers when they make choices between ridesourcing and taxi. Assuming that customers will estimate the order cancellation rate based on available information before their own trips, the estimated order cancellation rate before matching $\overline{P}_{oc1}$ and estimated order cancellation rate after matching $\overline{P}_{oc2}$ for customers at time $(t + 1)$ can be modeled as follows

$$\overline{P}_{oc1}(t+1) = \sum_{\forall t_i \le t} \frac{\max(N^{c,t_i}_{rs}(t) - M'^{t_i}_{rs}(t), 0) P^{t_i}_{oc1}(t)}{D_{rs}(t_i)} \tag{32}$$

$$\overline{P}_{oc2}(t+1) = \sum_{\forall t_i \le t} \frac{\sum_{\forall t_j \le t} A^{t_i,t_j}_{rs}(t) P^{t_i,t_j}_{oc2}(t)}{D_{rs}(t_i)} \tag{33}$$

In Eqs. (32)-(33), we consider that the customers rely on the time-dependent cancellation rates of orders placed at different times in the past to predict the order cancellation rates for upcoming trips. The numerators of Eqs. (32)-(33) respectively represent the numbers of cancelled orders before and after matching at time t for orders placed at time t_i.

Corresponding to the customers' estimated order cancellation rate at time t, the time-dependent order cancellation rate can be utilized to obtain the cancellation rate of orders placed at time t, which can be expressed as Eqs. (34)-(35).

$$P_{oc1}(t) = \frac{\sum_{\forall t'_i \geq t} \max(N_{rs}^{c,t}(t'_i) - M'^{t}_{rs}(t'_i), 0) P^{t}_{oc1}(t'_i)}{D_{rs}(t)} \tag{34}$$

$$P_{oc2}(t) = \frac{\sum_{\forall t'_j \geq t} \sum_{\forall t'_i \geq t'_j} A_{rs}^{t,t'_j}(t'_i) P_{oc2}^{t,t'_j}(t'_i)}{D_{rs}(t)} \tag{35}$$

where $P_{oc1}(t)$ and $P_{oc2}(t)$ are respectively the total order cancellation rates before and after matching for customers who choose ridesourcing service at time t; t'_i and t'_j are the cancellation time and matched time, respectively, for orders placed at time t. Similar to Eqs. (32)-(33), the numerators of Eqs. (34)-(35) respectively represent the numbers of cancelled orders before and after matching at time t'_i for orders placed at time t.

3.5. Summary of matching process and order cancellation

The dynamic matching process of taxis and ridesourcing service with the consideration of time-dependent order cancellation behavior are summarized in this subsection to facilitate reading, as shown in Fig. 1. The two large dashed boxes (above and below) represent the matching processes between drivers and customers of taxi and ridesourcing services, respectively. In the two dashed boxes, the numbers of customers and vehicles waiting to be matched at each time interval with dynamic matching are updated, where the cancelled orders before and after matching in the dashed box below are one of the sources of the number of waiting customers in the dashed box above (for the taxi market).

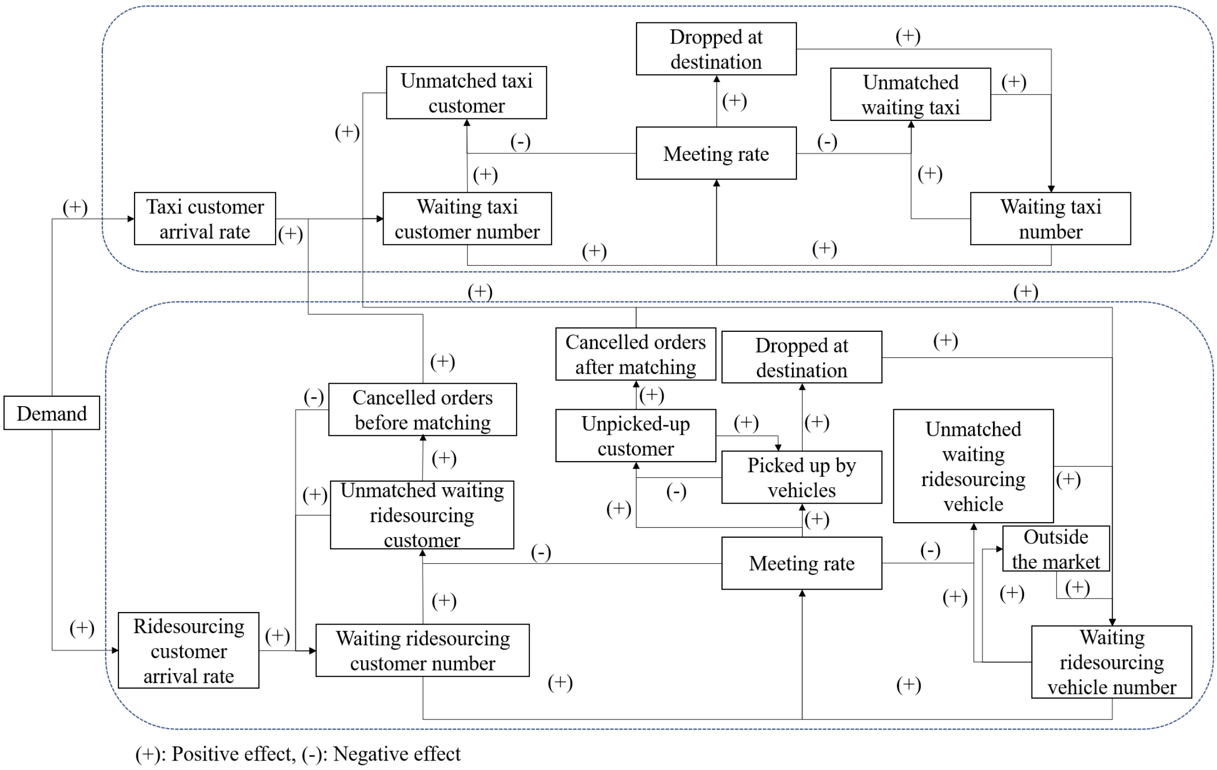


Fig. 1. Dynamic matching process and order cancellation in a coupled market with both taxi and ridesourcing services

4. Pricing and penalty strategies of the ridesourcing platform

In a coupled market with taxis and ridesourcing service, the platform's pricing and penalty strategies will affect the customers' mode choices, ridesourcing vehicle fleet size, rider-driver matching efficiency, ridesourcing order cancellation behavior and further the entire system. Therefore, we now further discuss the pricing and penalty strategies of the ridesourcing platform, subject to the dynamic matching process of customers and vehicles as well as the time-dependent order cancellation behavior. Generally speaking, dynamic pricing depends on the level of supply and demand in the system, while static pricing is in nature less capable of accommodating changes in supply and demand. For example, when demand changes, a fixed fare may cause loss of customers or a longer matching time, which will reduce system efficiency and platform profits. We examine and compare dynamic and static pricing in the time-dependent system we proposed. In addition, order cancellation, as a factor that affects matching efficiency in this time-dependent system, may also perform differently under dynamic pricing and static pricing. For this reason, three pricing strategies are examined: dynamic pricing with time-varying commission rate (TCR), dynamic pricing with fixed commission rate (FCR) and static pricing. The commission rate refers to the proportion of the money obtained by the platform to the fare charged on customers. Additional constraints are required for different pricing strategies, which will be introduced separately below.

(i) Dynamic (TCR) pricing: This pricing strategy with time-varying commission rate does not require any additional constraints, which indicates there is no constraint between fare and wage.

(ii) Dynamic (FCR) pricing: The fixed commission rate requires that the ratios of the money obtained by the platform to the fare charged to customers are equal at all times, and this constraint is equivalent to the ratios of wage to fare being equal at all times, with any two different times t, t^* in the study period, given by

$$\frac{s_{rs}(t)}{k_{rs}(t)} = \frac{s_{rs}(t^*)}{k_{rs}(t^*)}, \forall t, t^* \in [1, T^*], t \neq t^* \tag{36}$$

(iii) Static pricing: This pricing strategy requires constant fare k^*_{rs}, wages^*_{rs}, penalty $\widehat{k}^*_{rs}$ and compensation $\widehat{s}^*_{rs}$ during the study period, which can be given by

$$k_{rs}(t) = k^*_{rs}, s_{rs}(t) = s^*_{rs}, \widehat{k}_{rs}(t) = \widehat{k}^*_{rs}, \widehat{s}_{rs}(t) = \widehat{s}^*_{rs}, \forall t \in [1, T^*] \tag{37}$$

Ridesourcing platform designs pricing strategies based on its objectives under given taxi services. In this section, we formulate the optimization of pricing and penalty strategies in order to maximize platform profit while considering time-dependent order cancellation. The total profit of ridesourcing platform is from the difference between collected fare and operating cost for completed trips and the difference between penalty and compensation for cancelled trips. The optimization problem for the maximum profit of ridesourcing platform can be modelled as

$$\begin{aligned} \max Z_1 = &\sum_{\forall t \in [1,T^*]} \left\{ \left[(a_{rs} + k_{rs}(t) \max(d-m,0) - q) - (b_{rs} + s_{rs}(t) \max(d-m,0)) \right] N^{pk}_{rs}(t) \right\} + \\ &\sum_{\forall t \in [1,T^*]} \left[\widehat{k}_{rs}(t) - \widehat{s}_{rs}(t) \right] R_{oc2}(t) \end{aligned} \tag{38}$$

where q denotes the operating cost of ridesourcing platform. The first term on the right-hand side represents the profit from completed trips and the second term indicates the profit from cancelled trips. The above optimization problem is subject to the system conservation and dynamics defined in Section 3, i.e., the state variables defined by Eqs. (1)-(14) and (17)-(33) should be set as constraints of the optimization problem.

Pricing and penalty strategies affect the choices of customers and drivers, customer-driver matching efficiency, time-dependent order cancellation and further the operation of the two-sided market. In addition, under dynamic pricing, over-frequently changing prices may affect the decision-making of customers and drivers and even annoy them, resulting in a poor user experience, which in turn affects users' loyalty to the platform and affects platform profits in the long run (e.g., Dholakia, 2015; Chen et al., 2015). In order to alleviate the defects of over-frequently changing prices and be practical, we set additional constraints in Eqs. (39)-(42).

$$k_{rs}(t) = k_{rs}(t'), t' = \lceil \frac{t}{n} \rceil, t' \in [1, T^*/n] \tag{39}$$

$$s_{rs}(t) = s_{rs}(t'), t' = \lceil \frac{t}{n} \rceil, t' \in [1, T^*/n] \tag{40}$$

$$\widehat{k}_{rs}(t) = k_{rs}(t'), t' = \lceil \frac{t}{n} \rceil, t' \in [1, T^*/n] \tag{41}$$

$$\widehat{s}_{rs}(t) = k_{rs}(t'), t' = \lceil \frac{t}{n} \rceil, t' \in [1, T^*/n] \tag{42}$$

where symbol $\lceil\ \rceil$ means rounding up to the nearest integer. Note that T^* is the total number of time steps in the modelled operation time horizon (the time step length reflects the time resolution in the model after discretization of the time horizon). We consider that for every n time steps, we keep the same pricing and penalty strategies, where the choice of n should avoid over-rapid changes. Thus, n consecutive time steps constitute one pricing decision step and t' denotes the pricing decision step corresponding to t, as defined in Eqs. (39)-(42).

We also consider that the price fluctuation between adjacent pricing decision step cannot be drastic (so is bounded). For example, suppose the fare that a customer observes while waiting for match is 1 A\$/km, and when the customer is picked up in the next pricing decision step, the fare becomes 10 A\$/km. In this context, customers may strategically wait for a better price in this situation, making the dynamic pricing strategy under-performing (Chen & Hu, 2020). For this reason, we impose restrictions on the fluctuations of price strategy as follows:

$$\sigma_{k_{rs}} \leq k_{rs}(t') - k_{rs}(t'+1) \leq \tau_{k_{rs}}, t' \in [1, T^*/n] \tag{43}$$

$$\sigma_{s_{rs}} \leq s_{rs}(t') - s_{rs}(t'+1) \leq \tau_{s_{rs}}, t' \in [1, T^*/n] \tag{44}$$

$$\sigma_{\widehat{k}_{rs}} \leq \widehat{k}_{rs}(t') - \widehat{k}_{rs}(t'+1) \leq \tau_{\widehat{k}_{rs}}, t' \in [1, T^*/n] \tag{45}$$

$$\sigma_{\widehat{s}_{rs}} \leq \widehat{s}_{rs}(t') - \widehat{s}_{rs}(t'+1) \leq \tau_{\widehat{s}_{rs}}, t' \in [1, T^*/n] \tag{46}$$

where $[\sigma_{k_{rs}}, \sigma_{s_{rs}}, \sigma_{\widehat{k}_{rs}}, \sigma_{\widehat{k}_{rs}}]$ and $[\tau_{k_{rs}}, \tau_{s_{rs}}, \tau_{\widehat{k}_{rs}}, \tau_{\widehat{s}_{rs}}]$ are the lower and upper bounds of fare, wage, penalty and compensation adjustment between adjacent pricing decision steps, respectively.

Finally, even if the pricing strategy of ridesourcing platform is more flexible than that of taxi which is regulated by the government, the price of ridesourcing service is usually restricted within a certain range, and these constraints can be given by

$$\underline{k}_{rs} \leq k_{rs}(t') \leq \overline{k}_{rs}, t' \in [1, T^*/n] \tag{47}$$

$$\underline{s}_{rs} \leq s_{rs}(t') \leq \overline{s}_{rs}, t' \in [1, T^*/n] \tag{48}$$

$$\underline{\widehat{k}}_{rs} \leq \widehat{k}_{rs}(t') \leq \overline{\overline{\widehat{k}}}_{rs}, t' \in [1, T^*/n] \tag{49}$$

$$\underline{\widehat{s}}_{rs} \leq \widehat{s}_{rs}(t') \leq \overline{\overline{\widehat{s}}}_{rs}, t' \in [1, T^*/n] \tag{50}$$

where $[\underline{k}_{rs}, \underline{s}_{rs}, \underline{\widehat{k}}_{rs}, \underline{\widehat{s}}_{rs}]$ and $[\overline{k}_{rs}, \overline{s}_{rs}, \overline{\overline{\widehat{k}}}_{rs}, \overline{\overline{\widehat{s}}}_{rs}]$ are the lower bound and upper bound of pricing scheme (i.e., fare, wage, penalty and compensation) respectively.

In summary, the optimization problem in Eq. (38) will be subject to the constraints in Eqs. (1)-(14), (17)-(33), and (39)-(50). We adopt the Genetic Algorithm (GA) to solve the optimization problem since designing algorithms to solve optimization problem is not the focus of this study. In particular, constraints Eqs. (39)-(42) are first used to determine the number of variables; constraints Eqs. (47)-(50) are set as the bounds of variables; constraints Eqs. (43)-(46) are transformed into linear inequality constraints; constraints Eqs. (1)-(14) and (17)-(33) are utilized to calculate the objective function Z_1, and the optimization terminates when the pre-determined tolerance is reached (the convergence curves of the objective values of some scenarios in the numerical study are shown in the Appendix A for illustration).

Note that here we focus on the optimization of profit given that the ridesourcing company is often private and profit-driven. In the numerical studies, we will also explore the objective of maximizing the number of completed trips (i.e., more social welfare oriented that is dependent on number of passengers served), and the trade-off between the profit and number of completed trips (refer to Section 5.4).

5. Numerical study

We consider a city area served by both a ridesourcing company and a taxi company. Fig. 2 shows the high and low demand levels in this numerical study. The taxi company has a fixed fleet size N_{tx}=2.4×10^4, the taxi flag-fall fare is a_{tx}=5 A\$ and taxi fare rate is k_{tx}=4 A\$/km. For ridesourcing service, the number of potential ridesourcing vehicles is N_{rs}=1.4×10^4, the ridesourcing service flag-fall fare is a_{rs}=5 A\$ as well and the number of vacant vehicles initially in the market is N^v_{rs}=1.5×10^3. The unit cost for fuel is c_g=0.5 A\$/km, the fixed cost per trip is c_0=10 A\$ and the parking fee c_p=0 (varying parking fees are considered in the sensitivity analysis). The pick-up time is assumed to be $\overline{w}^{pk}_{rs}(t) = \left(2 \times 10^5/N^c_{rs}(t)\right)^{0.5}\left(3 \times 10^5/N^v_{rs}(t)\right)/1800$, i.e., inversely proportional to the number of customers and vehicles waiting to be matched. The average speed is v_0=28 km/h. The average trip distance is d=10 km and the distance within the flag-fall fare is m=2 km. The value of time is γ=0.5 A\$/min. The time interval (for time horizon discretization) is Δt=1 min. The pricing decision step is 10 min. Other parameters are assumed as follows: θ_1=0.1, θ_2=1 and η=0.2. The operating cost of platform company is q=0.05 A\$/trip. In the meeting function of the two modes, we assume H_{rs}=H_{tx}=1/300. Since the rider-vehicle matching of the app-based ridesourcing service is generally more efficient than the taxi service, we assume α_{rs}=0.84, β_{rs}=0.84, α_{tx}=0.76, β_{tx}=0.76, where both modes exhibit increasing returns to scale. Note that the aforementioned parameters should be carefully calibrated with real-world data in practice.

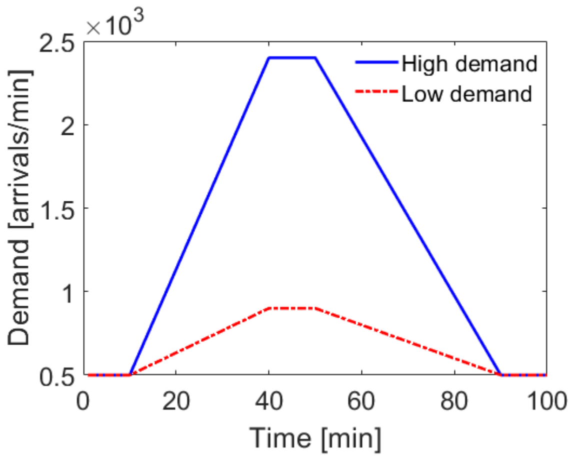
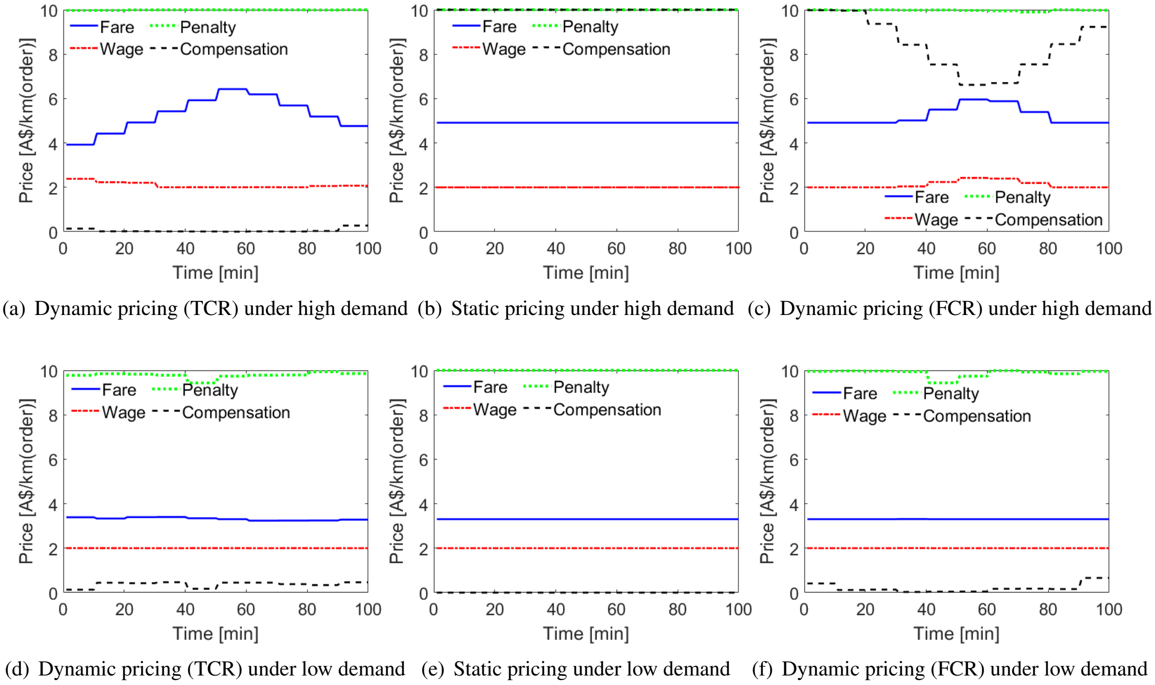


Fig. 2. Demand distribution over time: high and low demand levels

5.1. Comparison of different pricing strategies

We first examine dynamic TCR and FCR pricing and static pricing strategies in the coupled market of ridesourcing and taxi under ridesourcing order cancellation. We consider both high and low demand levels presented in Fig. 2. Note that we will further compare the case with trip order cancellation and the case with no order cancellation in Section 5.2 in order to illustrate the impact of order cancellation.

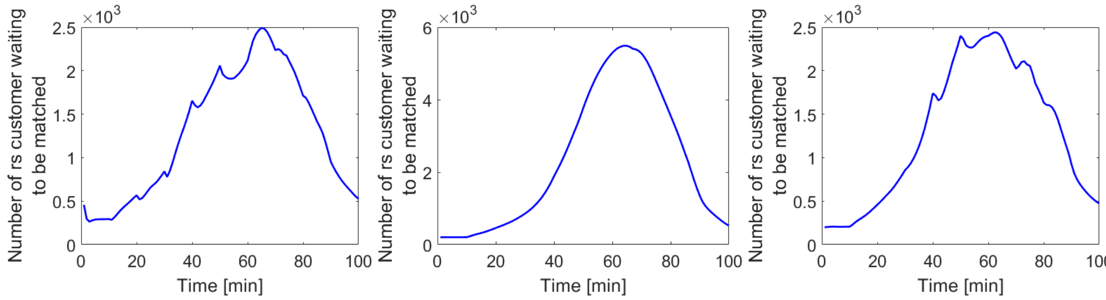
As shown in Fig. 3(a) and Fig. 3(d), the difference between the fare and the wage under high demand is greater than that under low demand. This relationship is consistent with that in static pricing (see Fig. 3(b) and Fig. 3(e)) and dynamic FCR pricing (see Fig. 3(c) and Fig. 3(f)), which suggests that the profit obtained by the platform for each completed order under high demand is larger. The fare for the ridesourcing service under high demand is generally higher than that of taxi (4 A\$/km), while the fare under low demand is lower than the taxi fare. A higher ridesourcing



(a) Dynamic pricing (TCR) under high demand (b) Static pricing under high demand (c) Dynamic pricing (FCR) under high demand

(d) Dynamic pricing (TCR) under low demand (e) Static pricing under low demand (f) Dynamic pricing (FCR) under low demand

Fig. 3. Optimal prices under high and low demand levels in three pricing scenarios: (a, d)TCR; (b,e)Static; (c,f)FCR

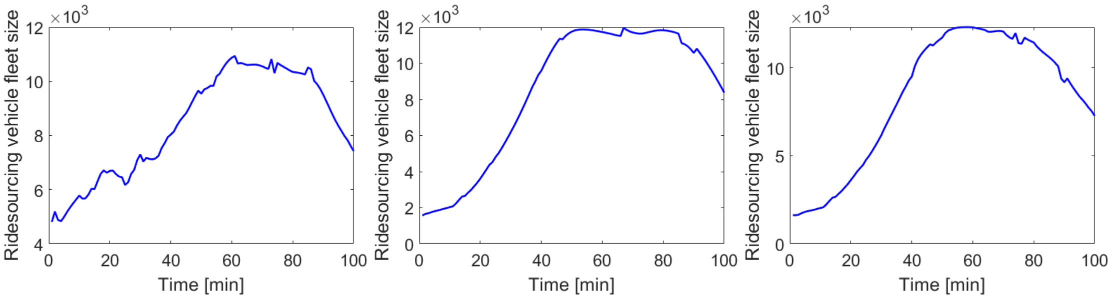


(a) TCR (b) Static (c) FCR

Fig. 4. Number of ridesourcing customers waiting to be matched in three pricing scenarios: (a) TCR; (b) Static; and (c) FCR.

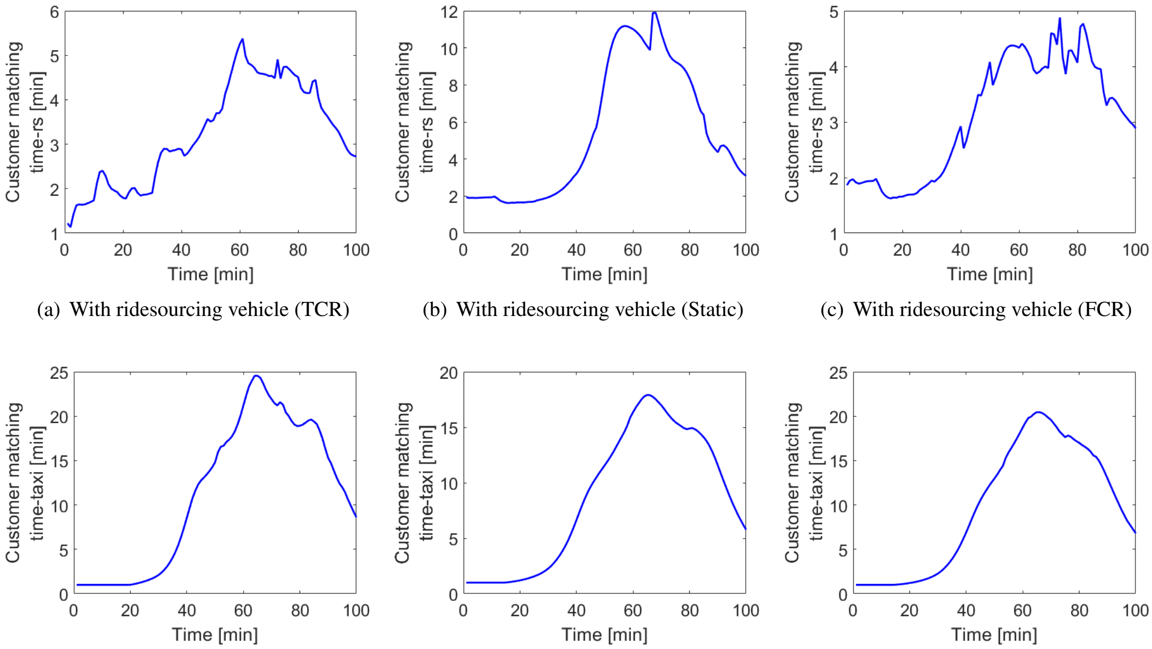
fare under high demand helps prevent too many customers from choosing the service, and reduce customers' matching time with ridesourcing vehicles. Fig. 6(a)-(c) and Fig. 6(d)-(f), respectively, show the customers' matching times with ridesourcing vehicles and taxis under high demand. The customers' matching time with taxis is longer while ridesourcing service is more expensive. Differently, there are sufficient taxis in the market under the low demand. The ridesourcing service does not have the advantage of a shorter matching time, and the platform adopts a relatively low fare (lower than taxi fare) in order to attract more users and thus maximize its profit.

We further have the following observations for the three different pricing strategies. Under high demand, the platform profits under dynamic TCR, dynamic FCR and static pricing are 1.02×10^6A$, 9.17×10^5A$ and 8.70×10^5A$, respectively. The profit under dynamic TCR pricing is 10.93% and 16.89% greater than that under dynamic FCR and static pricing. Under low demand, the platform profits under dynamic TCR, dynamic FCR and static pricing are 4.51×10^5A$, 4.48×10^5A$ and 4.48×10^5A$. The profit under dynamic TCR pricing is 0.60% and 0.69% larger than that under dynamic FCR and static pricing. This means that under both high and low demand levels, the platform earns



(a) TCR (b) Static (c) FCR

Fig. 5. Ridesourcing vehicle fleet size in three scenarios: (a) TCR; (b) Static; and (c) FCR.



(a) With ridesourcing vehicle (TCR) (b) With ridesourcing vehicle (Static) (c) With ridesourcing vehicle (FCR)

(d) With taxi (TCR) (e) With taxi (Static) (f) With taxi (FCR)

Fig. 6. Customer's matching time with ridesourcing vehicle and taxi in three scenarios: (a, d) TCR; (b, e) Static; and (c, f) FCR

a larger profit through dynamic TCR pricing when compared to dynamic FCR and static pricing, and this advantage is more significant under high demand.

We now focus on the scenario with high demand as the efficiency gaps among the three different pricing strategies are larger and more observable (see Fig. 3). As can be seen from Fig. 3(a)-(c), when compared to dynamic FCR and static pricing, the fare of dynamic TCR pricing is more refined over time, which makes it more capable to accommodate time-dependent demand conditions and segment customers with different purchasing power, and therefore yields a larger profit. In particular, the fare under dynamic TCR pricing is lower than the taxi fare in the beginning when demand is low, but higher at demand peak times (higher even compared to the other two pricing strategies). The wage under dynamic TCR pricing is higher in the first 30 minutes, corresponding to the larger fleet size compared to that under the other two pricing strategies at this stage, as shown in Fig. 5. However, the fleet size at demand peak times under dynamic TCR pricing is smaller than that under the other two pricing strategies because the higher fare at the peak times suppresses demand for the ridesourcing service, which is consistent with the number of waiting customers shown in Fig. 4. In summary, when compared to static and dynamic FCR pricing, dynamic TCR pricing enables the ridesourcing platform to attract more customers to choose the ridesourcing service through lower fare when the initial demand is small, and yield a larger profit per completed trip through a higher fare when demand is high.

5.2. Impacts of order cancellation

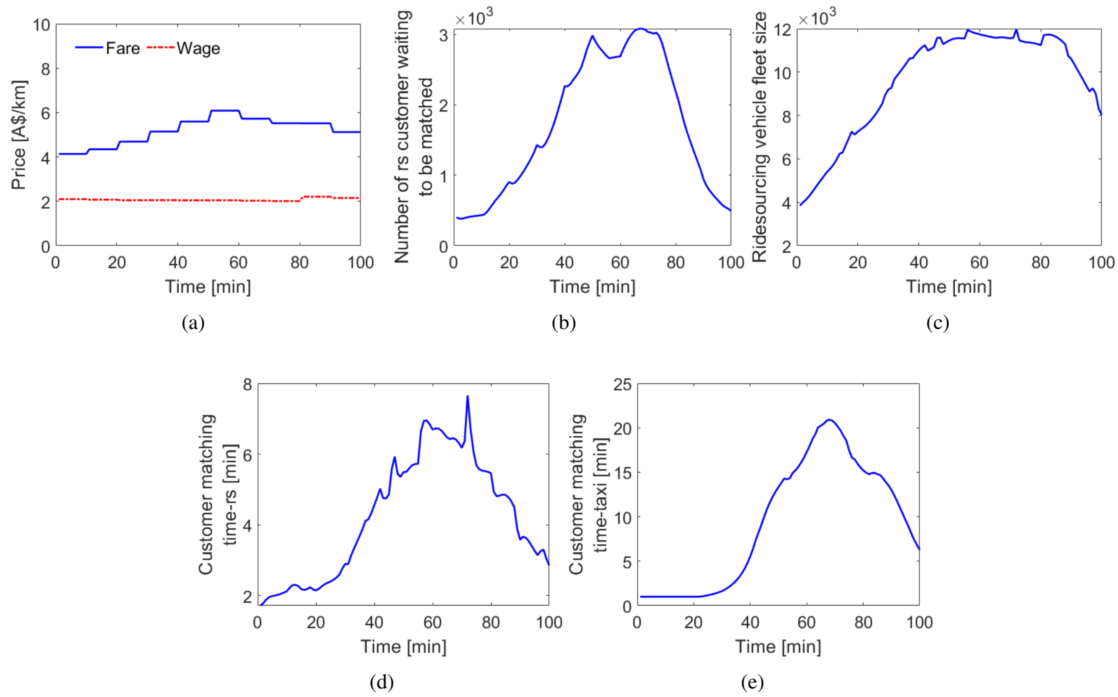


Fig. 7. System performance under benchmark case: (a) Dynamic pricing (TCR) under high demand; (b) Number of ridesourcing customers waiting to be matched; (c) Ridesourcing vehicle fleet size; (d) Customer's matching time with ridesourcing vehicle; and (e) Customer's matching time with taxi.

We now compare the case with order cancellation and the case with no order cancellation. To ease the presentation, we define the case with no order cancellation as the "benchmark case" (i.e., customers do not cancel orders once they send ride requests), and compare it to the case with order cancellation, i.e., "OC case".

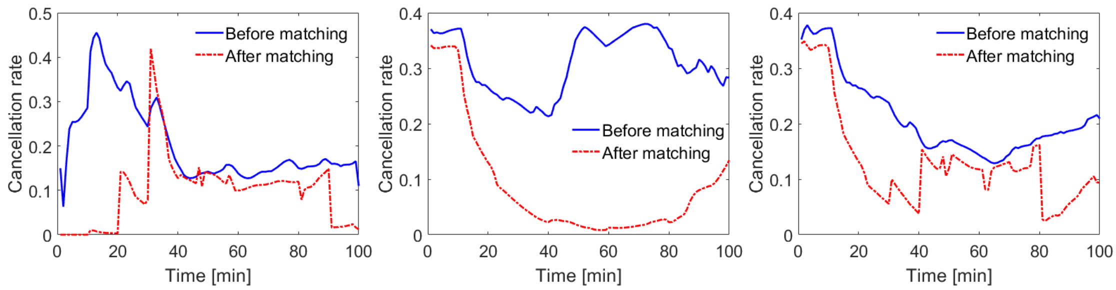
For illustration we only summarize and compare the benchmark case and OC case under dynamic TCR pricing and high demand level, where Fig. 7 shows several efficiency metrics for the benchmark case. The number of ridesourcing customers waiting to be matched in the benchmark case is higher than that in the OC case (see Fig. 7(b) and Fig. 4(a)). In particular, in the OC case, the number of waiting customers is peaked at 2500 and the peak duration is very short (less than 5 minutes), while the peak in the benchmark case is about 3000 and lasts about 25 minutes (i.e., 50th-75th minute in Fig. 7(b)). It follows that the matching time of ridesourcing customers in the benchmark case is higher than that in the OC case. By comparing Fig. 7(d) and Fig. 6(a), we can see that in the benchmark case, the matching time for ridesourcing customers can be up to approximately 8 minutes and is more than 5 minutes for a duration over 40 minutes (i.e., 40th-80th minute in Fig. 7(d)), while in the OC case, the matching time of the ridesourcing customers is peaked at 5.5 minutes and the duration with a matching time longer than 5 minutes is very short. Correspondingly, the matching time of taxi customers is shorter in the benchmark case than in the OC case (see Fig. 7(e) and Fig. 6(d)). The above differences are due to the fact that in the benchmark case, ridesourcing customers do not cancel their orders, while in the OC case, ridesourcing customers may cancel their orders and take taxis while waiting for the service. In addition, platform profits are 1.08×10^6A\$ and 1.02×10^6A\$ in the benchmark case and OC case, respectively. The profit of the former is 6.25% larger than that of the latter, which is consistent with the intuition that the order cancellation leads to the loss of platform profit. At the same time, this is also reflected in the number of completed ridesourcing trips and ridesourcing fleet size. Specifically, the number of completed ridesourcing trips in the benchmark case is 4.16×10^4, which is 15.56% larger than that in the OC case (3.60×10^4). The ridesourcing fleet size in the benchmark case is larger than that in the OC case (see Fig. 7(c) and Fig. 5(a)).

In a short summary, when compared to the benchmark case, under the OC case, the matching time is shorter for ridesourcing customers and longer for taxi customers, and the optimal ridesourcing fleet size is smaller. Besides, order cancellation may hurt platform profit and the number of completed ridesourcing trips.

5.3. Order cancellations before and after matching (unconfirmed and confirmed orders)

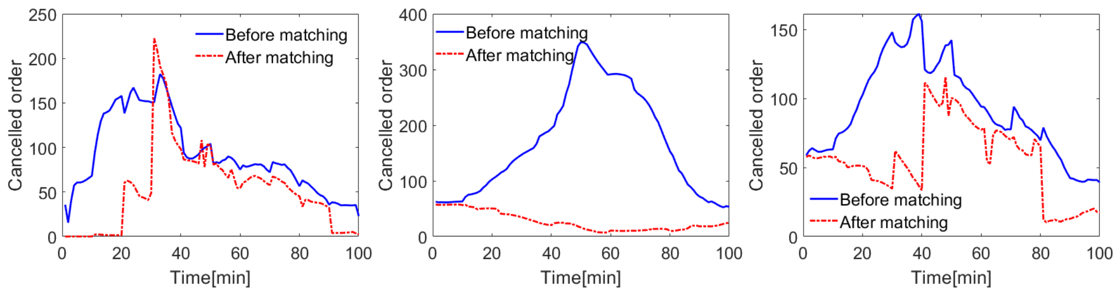
We now study cancellations of unconfirmed and confirmed orders. Fig. 8 and Fig. 9 show the cancellation rates and the numbers of cancelled orders (before and after matching) over time. The order cancellations before and after matching exhibit different patterns during the study period, which is further explained below.

We start with discussing the order cancellation before matching (cancellation of unconfirmed orders). The cancellation rate is larger at both ends of the study period and smaller in the middle under dynamic TCR and FCR pricing strategies. This is because customers have a greater chance of meeting vacant taxis at both ends of the study period but less during the peak period. The corresponding customers' matching times with ridesourcing vehicles and taxis indeed reflect the likelihood of the customers to meet vacant taxis, as shown in Fig. 6(a), Fig. 6(c), Fig. 6(d) and Fig. 6(f). The order cancellation rate under static pricing is higher when compared to the other two pricing strategies, and it can be observed that even at peak times, there is no significant advantage of the customers' matching time with ridesourcing vehicles (see Fig. 6(b)) when compared to the customers' matching time with taxis (see Fig. 6(e)), because the number of ridesourcing customers waiting to be matched at peak times is larger under static pricing (about twice that under dynamic TCR and FCR pricing, one can refer to Fig. 4).



(a) TCR (b) Static (c) FCR

Fig. 8. Cancellation rate in three scenarios: (a) TCR; (b) Static; and (c) FCR.



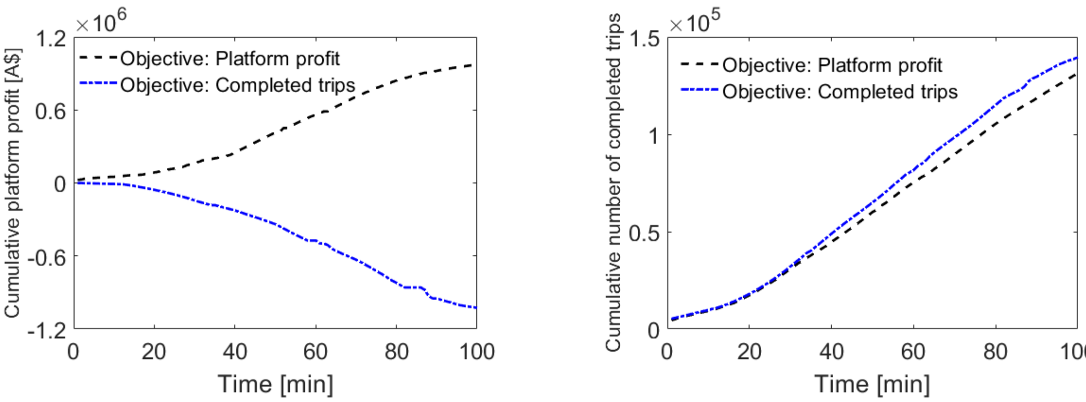
(a) TCR (b) Static (c) FCR

Fig. 9. Cancelled orders in three scenarios: (a) TCR; (b) Static; and (c) FCR.

We further discuss the order cancellation after matching (cancellation of confirmed orders), where the cancellation rate and cancelled orders behave differently from those before matching. Fig. 8(a) and Fig. 9(a) show that the order cancellation under dynamic TCR pricing is considerably higher in the middle of study time period. The reason is that the ridesourcing fare is lower at either end of the period, and the penalty for cancelling orders is about 10 A$/trip (see Fig. 3(a)), where the cost of cancelling orders is relatively high (compared to the fare) and thus, reduces order cancellation; while the ridesourcing fare rate exceeds 5 A$/km during the period with relatively significant order cancellation (i.e., 30th-90th minute under dynamic TCR pricing), combining the average trip distance 10 km and the taxi fare rate 4 A$/km, the total fare for completing the trip by ridesourcing vehicle exceeds the taxi fare and penalty combined, which in turn increases order cancellation. Hence, the penalty enforced under lower fares is more effective in restricting cancellation of confirmed orders. Besides, customers are more likely to meet vacant taxis during off-peak hours, which may incentivize order cancellation behavior, and vice versa during peak periods. Specifically, under static pricing (see Fig. 8(b) and Fig. 9(b)) when the fare remains fixed, there are more order cancellations during periods with larger probabilities of taxi appearance and the order cancellation is higher at off-peak times than peak times. The order cancellation under dynamic FCR pricing is similar to that under dynamic TCR pricing in the middle of the study period, and it is similar to that under static pricing at both ends of the study period.

In summary, the order cancellations before and after matching present different patterns, which are governed by the cost and the possibilities of the customers meeting vacant taxis. For order cancellation before matching, customers are more concerned about being matched to vehicles, especially during peak periods when the matching time is a dominating factor in order cancellation. For the order cancellation after matching, the cost of completing the trip dominates more the occurrence of order cancellation. In addition, the penalties imposed under lower fares are more effective in suppressing the order cancellation after matching than under higher fares.

5.4. Alternative objective functions

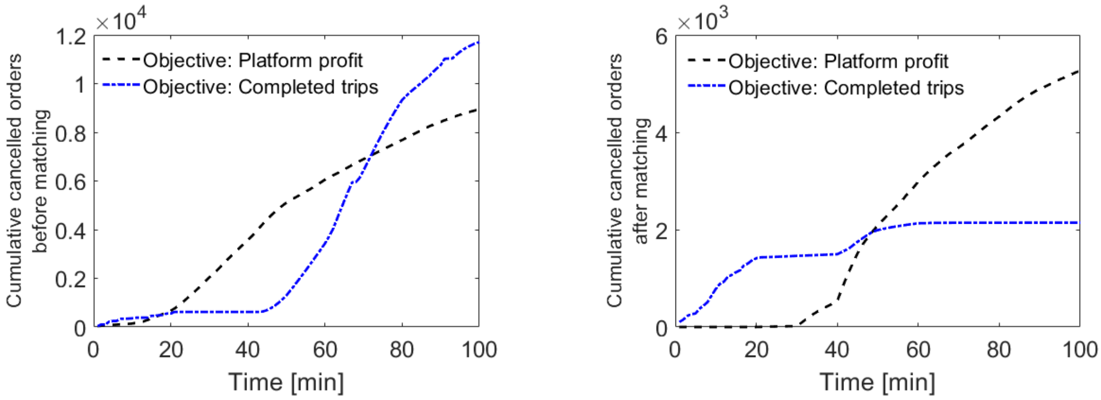


(a) Cumulative platform profit (b) Cumulative number of completed trips

Fig. 10. Cumulative platform profit and completed trips under different objectives

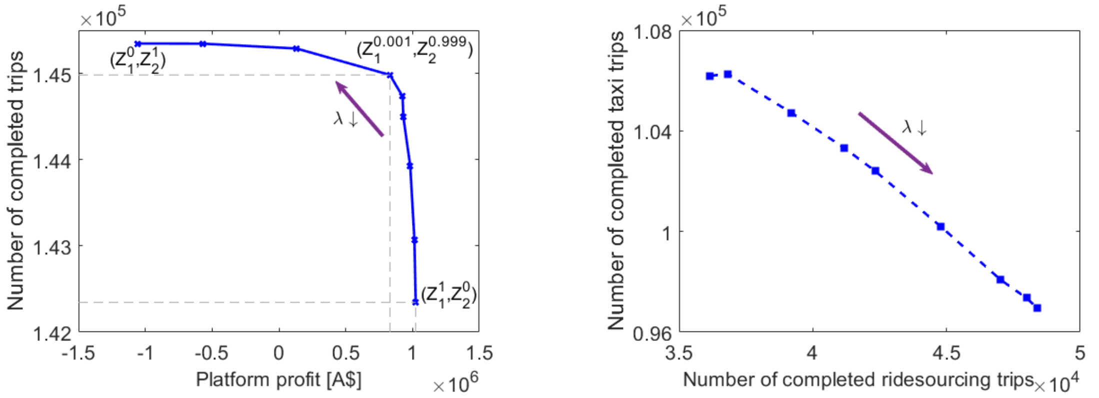
The previous analysis focused on the objective of profit maximization (for a private ridesourcing platform). A public operator may concern more the number of completed trips. Moreover, patterns of (unconfirmed and/or confirmed) order cancellations can be different under the maximization of profit and the maximization of number of completed trips. We now explore the number of completed trips as the objective (e.g., the platform is operated by public agency or subject to regulation) and examine the trade-off between the platform profit and the number of completed trips. For illustration we only discuss the results based on dynamic TCR pricing under high demand (if other scenarios are discussed, they will be specified).

We start with discussing the objective of maximizing the number of completed trips, where the number of completed trips can be formulated as $Z_2 = \sum_{\forall t\in[1,T^*]} \left(N_{rs}^{pk}(t) + N_{tx}^{pk}(t)\right)$. Fig. 10 illustrates the cumulative platform profit and the cumulative number of completed trips over time under the two different objectives. The profit maximization



(a) Cumulative cancelled orders before matching (b) Cumulative cancelled orders after matching

Fig. 11. Cumulative cancelled orders before and after matching



(a) Pareto frontier (b) Number of completed taxi and ridesourcing trips

Fig. 12. Pareto frontier and corresponding performance

and the maximization of completed trips are in general conflicting with each other. As presented in Fig. 10(b), the completed trips under profit maximization is lower than that under the other objective. As shown in Fig. 10(a), the cumulative platform profit under the maximization of completed trips is much smaller than that under the other objective, and the profit can be even negative, which suggests that the platform to maximize the number of completed trips is not financially sustainable without government subsidies.

We also compare differences in terms of order cancellation under the two different objectives (maximization of profit and maximization of the number of completed trips). The cumulative cancelled orders before and after matching (i.e., unconfirmed and confirmed order cancellation) under the two different objectives are summarized in Fig. 11. It can be seen that the number of cancelled orders before matching is larger under the maximization of the number of completed trips than that under profit maximization. Differently, the number of cancelled orders after matching is smaller under the maximization of the number of completed trips. This is because, under the objective of maximizing the number of completed trips, the operator adopts lower fares to attract more customers and higher wages to attract drivers (which leads to a negative profit, see Fig. 10(a)), resulting in longer waiting time for customers and more cancelled orders before matching. After customers being matched, lower fares mean that overall it is less costly for customers to continue waiting and thus there are fewer cancelled orders after matching.

We now further illustrate the trade-off between the two different objectives by examining the following weighted objective:

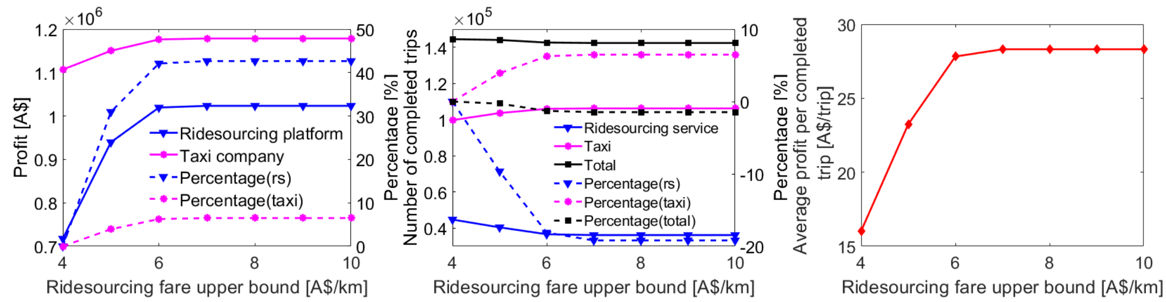
$$\max \tilde{Z} = \lambda Z_1 + (1 - \lambda) Z_2 \tag{51}$$

where Z_1 represents the platform profit; Z_2 indicates the number of completed trips. λ denotes the weight of platform profit (where $\lambda \in[0,1]$). The above can be regarded as the case where the private platform has a certain agreement with the government. When λ increases, platform profit becomes more dominant in the agreement. If λ=1, $\tilde{Z}$ degenerates into Z_1 (i.e., platform profit maximization), and if λ=0, $\tilde{Z}$ degenerates into Z_2 (i.e., maximization of the number of completed trips).

What follows here is an analysis of the Pareto-optimal result of the agreement between the platform and the government. Fig. 12(a) shows the Pareto frontier in relation to the two objectives, i.e., maximization of the number of completed trips and maximization of platform profit, and the corresponding numbers of completed taxi and ridesourcing trips is shown in Fig. 12(b). The platform profit and the number of completed trips change in opposite directions when the weight λ changes (see Fig. 12(a)), and no one solution is better than another one (where both objectives can improve) on the Pareto frontier. This implies that improving (decreasing) the number of completed trips will sacrifice (increase) platform profit. As shown in Fig. 12(a), when there is no agreement between the platform and government, the corresponding profit is obtained at point (Z_1^1, Z_2^0), where the superscript in the point (Z_1^1, Z_2^0) represents the weight of each objective, and the platform profit and the number of completed trips reach the maximum and minimum value at this point, respectively. As shown in Fig. 12(a), when λ is close to 0, the platform profit loss to the increase of the number of completed trips is large, which is not cost-effective. We can find a solution on the Pareto frontier that observably increases the number of completed orders by slightly reducing profits, e.g., point $(Z_1^{0.001}, Z_2^{0.999})$, where the increase in the number of completed trips accounts for 87.86% of the increase in the number of completed trips from Z_2^0 to Z_2^1, and the reduced profit only accounted for 9.26% of the profit reduction from Z_1^1 to Z_1^0. Hence, we claim, under certain regulation/agreement, there is a solution on the Pareto frontier that yields both considerable platform profit and trip completion. Besides, as shown in Fig. 12(b), when λ decreases, the completed ridesourcing trips increase, while the completed taxi trips generally decrease, which implies that the increase in completed ridesourcing trips will result in a decrease of completed taxi trips. The profit of taxi company is positively correlated with the number of completed taxi trips, and therefore, in this experiment, increasing the number of completed ridesourcing trips on the Pareto frontier sacrifices both the profits of taxi company and ridesourcing platform.

5.5. Sensitivity Analysis

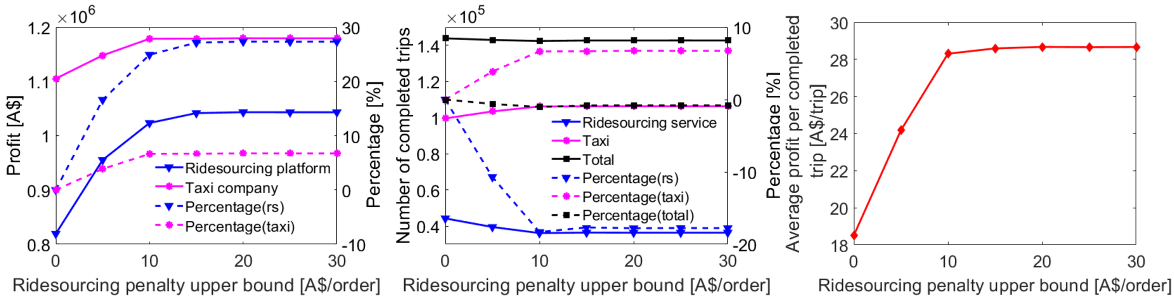
We now examine how varying the bounds of ridesourcing fare and cancellation penalty, and parking fee may affect several system efficiency metrics. In particular, we first vary the bound of ridesourcing fare or cancellation penalty and explore how the platform/taxi company profits and the numbers of completed ridesourcing/taxi trips may vary. Second, we vary the parking fee and examine how the platform profit and the number of completed ridesourcing trips vary against the parking fee.



(a) Platform profit (b) Number of completed trips (c) Average profit per completed trip

Fig. 13. Optimization with different ridesourcing fare upper bound

We now examine relaxing the ridesourcing fare bound (can be regarded as the government's deregulation of ridesourcing fare), while the (cancellation) penalty remains capped at 10 A$/trip. In particular, Fig. 13 displays the



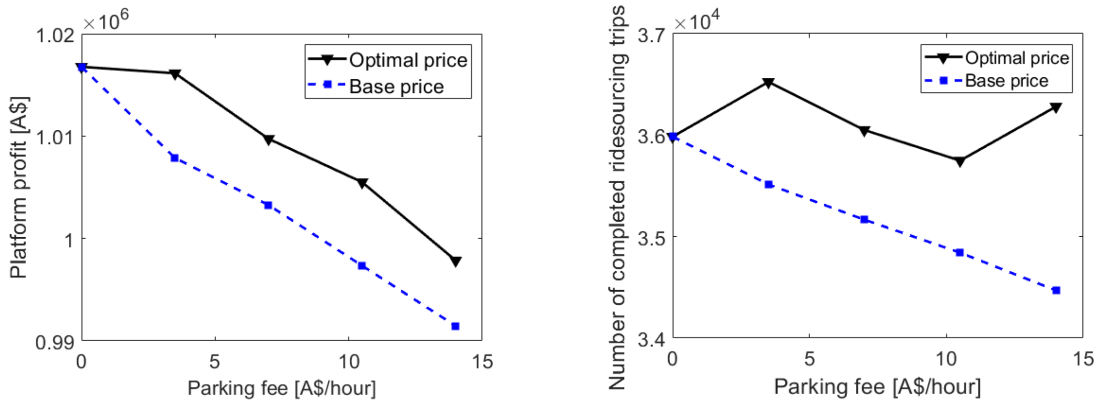
(a) Platform profit (b) Number of completed trips (c) Average profit per completed trip

Fig. 14. Optimization with different ridesourcing penalty upper bound

changes in terms of the platform profit and taxi company's profit (see Fig. 13(a)), the number of completed trips (see Fig. 13(b)), and the changes in the average platform profit per completed trip (see Fig. 13(c)) after the deregulation of the ridesourcing fare. When optimizing the ridesourcing platform profit, relaxing the fare bound/cap within a certain range will allow the platform to be more profitable, while further relaxing the fare bound/cap after the critical value does not further improve the profitability. As shown in Fig. 13(a), when the upper bound of the fare increases from 4 A\$/km to over 7 A\$/km, the platform profit increases by 43% and then remains constant, as indicated by the blue dotted line (triangle marker), while the number of completed ridesourcing trips decreases by about 19%, as shown by the blue dotted line (triangle marker) in Fig. 13(b). Furthermore, the average profit per completed trip increases from 16 A\$/trip to 28 A\$/trip by nearly 12 A\$/trip (see Fig. 13(c)), suggesting that a larger profit per trip at a higher fare yields a larger platform profit, which is consistent with the discussions in Section 5.1. When the platform profit increases (after relaxing the fare bound), the profit of the taxi company and the number of completed taxi trips also increase by about 6% under the same conditions (see Fig. 13(a) and Fig. 13(b)). This is because when the upper bound of ridesourcing fare increases, ridesourcing service becomes more expensive, where more travelers shift to taxi and the number of completed taxi trips and the taxi company's profit both increase. The total number of completed trips is reduced by about 1.5%, which implies that appropriate fare regulation in place can help (slightly) increase the number of completed trips even if it will reduce platform profit and taxi company's profit. These are consistent with the discussions on the bi-objective Pareto Frontier in Section 5.4.

Similar to the relaxation of the ridesourcing fare bound, the relaxation of the penalty bound is also examined while keeping the fare bound/cap at 10 A\$/km (see Fig. 14). A larger penalty bound allows the platform to yield a larger profit as there is more flexibility in setting the penalty. Specifically, when compared to the scenario with no penalty as shown in Fig. 14(a), relaxing the penalty upper bound to above 15 A\$/trip will contribute about 27% increase in the total platform profit, while the number of completed ridesourcing trips decreases by about 17% (see Fig. 14(b)), and the average profit per completed trip can rise from around 18 A\$/trip to 29 A\$/trip (see Fig. 14(c)). Under the same conditions, the taxi company's profit and the completed taxi trips increase by about 7%, while the total completed trips decreases by about 0.8%. Moreover, the platform profit and the number of completed ridesourcing trips at a fare of around 4 A\$/km in Fig. 13 are close to those under no penalty in Fig. 14. This is because when there is no penalty, the corresponding optimal fare is around 4 A\$/km (similar to the taxi fare), while if a higher fare is designed and no penalty is imposed, the order cancellation after matching will increase, which results in a lower platform profit. The penalty is an indispensable element for the successful implementation of the ridesourcing platform's pricing strategy to avoid over-cancellation and thus maximize its profit (by setting a relatively high fare).

We also vary the parking fee c_p and examine its effects. In the analysis below, the parking fee increases from zero to 14 A\$/hour (if cruising cost is considered, it can be converted to a monetary equivalent). Given the parking cost variation, we consider two scenarios for ridesourcing pricing scheme, i.e., (i) we fix the ridesourcing pricing scheme which is the optimal when the parking fee c_p is zero (corresponding to "base price" in Fig. 15); (ii) we optimize the ridesourcing pricing scheme in response to the parking cost variation (corresponding to "optimal price" in Fig. 15). A higher parking fee means a higher cost to the driver while waiting for matching, and therefore when the platform's pricing scheme remains unchanged, the ridesourcing fleet size decreases, and the number of completed ridesourcing



(a) Platform profit (b) Number of completed ridesourcing trips

Fig. 15. Platform profit and completed ridesourcing trips against the parking fee

trips also decreases. As presented in Fig. 15(b), the number of completed ridesourcing trips decreases with the parking fee under base price and the corresponding platform profit has a same trend when parking fee varies (see Fig. 15(a)). A similar trend of platform profit is observed even if the platform pricing is optimized in response to the parking cost variation in Fig. 15(a), which suggests that lower parking fees allow the platform to be more profitable. However, as shown in Fig. 15(b), the number of completed ridesourcing trips is not monotonous under the optimal pricing. This is because the optimal price is obtained by optimizing the platform profit, which involves the trade-off between the completed ridesourcing trips and the profit per trip like as discussed earlier. Moreover, it is noted that given the parking cost variation, allowing the platform pricing scheme to be optimized can yield both a larger profit and a larger number of completed ridesourcing trips.

In summary, the government's deregulation of the upper bound on the ridesourcing fare and penalty allows the platform profit to be increased (as there is more pricing flexibility), and indirectly improves the taxis utilization and increases the taxi company's profit, while it may reduce the number of completed trips. Setting higher fares under high demand to pursue a greater platform profit will be more effective with the help of penalty (to avoid over-cancellation). In addition, a smaller parking cost (due to vehicles' waiting for matching) allows the platform to achieve a higher profit while it does not necessarily yield more completed trips.

6. Conclusions

This paper studies a market that provides mobility services by ridesourcing vehicles and taxis while taking into account the time-dependent order cancellation behavior of customers. We propose models for the order cancellations before and after matching to characterize the time-dependent order cancellation behavior of ridesourcing customers, and incorporate the number of cancelled orders into the numbers of customers and vacant vehicles waiting to be matched for both the ridesourcing and taxi services. The proposed dynamic matching model captures the variation of exogenous factors as well as the influence of endogenous order cancellation on the matching efficiency. Based on the proposed dynamic matching model, we explore ways for designing different pricing strategies. Three pricing strategies are proposed and compared, i.e., dynamic TCR pricing, dynamic FCR pricing, and static pricing. Then we conducted numerical experiments to understand the impact of order cancellation and examine the system performance in different scenarios. We highlight the main findings below:

- For the ridesourcing platform, there is a trade-off between the number of completed trips and the profit per completed trip. In particular, the platform achieves the maximum profit through a larger profit per trip under high demand, while under low demand the platform profit is more dependent on completing more trips. When compared to the other two pricing strategies, dynamic TCR pricing can achieve better market segmentation and help the platform yield a larger profit.

- This paper also explores the difference in order cancellations before and after matching (i.e., cancellations of unconfirmed and confirmed orders), discusses the main factors that dominate occurrence of order cancellations at different stages. It is also observed that penalty is more effective in controlling the order cancellation after matching (cancellation of confirmed orders) when ridesourcing fare is lower.

- When the platform is operated by a public agency (government authority) who aims to maximize the number of completed ridesourcing trips, the platform may receive a negative profit. If the objectives of the platform profit and the number of completed ridesourcing trips are considered at the same time, a Pareto-efficient solution can be found where we have considerable platform profit and trip completion.

- The government's deregulation of ridesourcing fare and penalty can increase the platform profit within a certain range, and indirectly improve the taxi utilization as well as the taxi company's profit. In addition, doing so will increase the accessibility of ridesourcing, and decrease the accessibility of taxi in terms of customers' matching times.

Although the proposed model characterizes the coupled market with ridesourcing and taxi considering time-dependent order cancellation, some features are also ignored in the model and are worth exploring in the future.

Firstly, this paper only considers ridesourcing and taxi for simplicity (and no other mode). This allows us to focus on the complex time-dependent interaction between the two modes that exhibit certain similarities. Besides, we assume that the ridesourcing vehicles take e-hailing customers, and taxis take street-hailing customers. However, nowadays taxis can also provide e-hailing service through smartphone-based platform (e.g., He & Shen, 2015; Wang et al., 2016), which may increase the e-hailing fleet size and reduce the waiting time of e-hailing customers, thereby attracting more customers to choose e-hailing through the platform. On the other hand, vacant taxis can take either e-hailing customers or street-hailing customers, which will increase the chance of taxis finding customers (especially when customer demand is low) and may bring taxis directly increase in utilization and profit. At the same time, it is of our interest to consider the order cancellation of taxi drivers who accept e-hailing orders during the pick-up process, in which they may meet street-hailing customers. It is also noteworthy that expanding the coupled market of taxi and ridesourcing modes considered in this paper to multi-modal or even multi-platform complex systems, in which customers may no longer choose ridesourcing or taxi after cancelling their orders, but cancel trips or switch to public transportation can be further studied in the future.

Secondly, this study assumes that the ridesourcing vehicles park when waiting for matching and numerically investigates the effects of different parking fees/costs. In reality, it may be difficult to find a parking space, so the vacant ridesourcing vehicle will cruise until finding a parking space or being matched with a customer, as discussed in Xu et al. (2017). A future study may incorporate the cruising-for-parking process of ridesourcing vehicle into the model proposed in this paper. In addition, in this paper we assume that the parking fee is constant, while in practice the parking fees may vary over time and space (e.g., Zheng & Geroliminis, 2016; Liu & Geroliminis, 2017). The time-and-space-dependent parking fees should be further incorporated when the proposed model is extended to the network level in future studies.

Thirdly, this paper assumes that the trip distance and the vehicle speed are fixed, while endogenous traffic congestion is ignored. The model in this paper can be further extended to include heterogeneous customers and traffic congestion (e.g., Lamotte & Geroliminis, 2018; Beojone & Geroliminis, 2021). Besides, the proposed model only considers a single region, while supply and demand not only change in time, but also in space. Therefore, it is of our interest to extend the proposed model to multiple regions in order to capture the characteristics of order cancellation behavior in different regions and design corresponding spatial-temporal pricing strategies. Moreover, we may consider order cancellation from not only the customer side, but also from the supply side (e.g., driver's order cancellation due to the long deadhead time for picking up customers).

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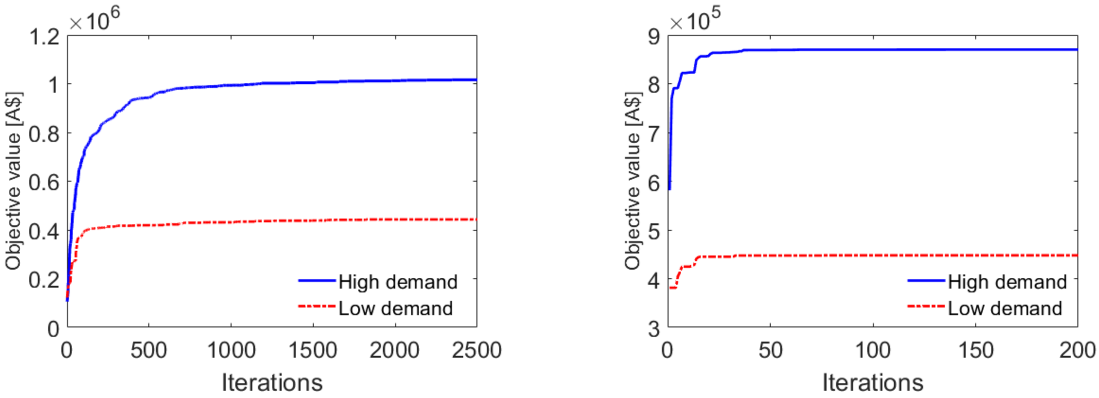
Appendix A. Illustration for the convergence of GA



(a) Dynamic TCR pricing (b) Static pricing

Fig. 16. The convergence of GA for dynamic TCR and static pricing under high and low demand levels

We used the genetic algorithm (GA) in this paper to solve the pricing problems (which are highly nonlinear problems). We now illustrate the convergence of the GA. In particular, we examined four scenarios, i.e., dynamic and static pricing under high and low demand levels, corresponding to those in Fig. 3(a)-(b) and Fig. 3(d)-(e) in Section 5.1. Fig. 16 shows how the objective value converges for the above four scenarios. It is noted that the objective values converged faster under static pricing when compared to the dynamic TCR pricing, which is due to that a smaller number of variables are involved under static pricing.

References

Armstrong, M. (2006). Competition in two-sided markets. *The Rand Journal of Economics*, *37*, 668–691.

Bai, J., So, K. C., Tang, C. S., Chen, X., & Wang, H. (2019). Coordinating supply and demand on an on-demand service platform with impatient customers. *Manufacturing & Service Operations Management*, *21*, 556–570.

Beesley, M. E. (1973). Regulation of taxis. *The Economic Journal*, *83*, 150–172.

Beojone, C. V., & Geroliminis, N. (2021). On the inefficiency of ride-sourcing services towards urban congestion. *Transportation Research Part C: Emerging Technologies*, *124*, 102890.

Cachon, G. P., Daniels, K. M., & Lobel, R. (2017). The role of surge pricing on a service platform with self-scheduling capacity. *Manufacturing & Service Operations Management*, *19*, 368–384.

Castillo, J. C., Knoepfle, D., & Weyl, G. (2017). Surge pricing solves the wild goose chase. In *Proceedings of the 2017 ACM Conference on Economics and Computation* (pp. 241–242).

Chen, L., Mislove, A., & Wilson, C. (2015). Peeking beneath the hood of uber. In *Proceedings of the 2015 Internet Measurement Conference* (pp. 495–508).

Chen, M. K. (2016). Dynamic pricing in a labor market: Surge pricing and flexible work on the uber platform. In *Proceedings of the 2016 ACM Conference on Economics and Computation* (pp. 455–455).

Chen, X. M., Zheng, H., Ke, J., & Yang, H. (2020). Dynamic optimization strategies for on-demand ride services platform: Surge pricing, commission rate, and incentives. *Transportation Research Part B: Methodological*, *138*, 23–45.

Chen, Y., & Hu, M. (2020). Pricing and matching with forward-looking buyers and sellers. *Manufacturing & Service Operations Management*, *22*, 717–734.

Chen, Y., Zheng, N., & Vu, H. L. (2021). A novel urban congestion pricing scheme considering travel cost perception and level of service. *Transportation Research Part C: Emerging Technologies*, *125*, 103042.

Cohen, M., & Zhang, R. P. (2017). Competition and coopetition for two-sided platforms. *Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=3028138*, .

De Vany, A. S. (1975). Capacity utilization under alternative regulatory restraints: an analysis of taxi markets. *Journal of Political Economy*, *83*, 83–94.

Dholakia, U. M. (2015). Everyone hates uber's surge pricing–here's how to fix it. *Harvard Business Review*, *21*.

Douglas, G. W. (1972). Price regulation and optimal service standards: The taxicab industry. *Journal of Transport Economics and Policy*, *6*, 116–127.

Du, L., & Gong, S. (2016). Stochastic poisson game for an online decentralized and coordinated parking mechanism. *Transportation Research Part B: Methodological*, *87*, 44–63.

Foerster, J. F., & Gilbert, G. (1979). Taxicab deregulation: economic consequences and regulatory choices. *Transportation*, *8*, 371–387.

Gu, Z., Liu, Z., Cheng, Q., & Saberi, M. (2018). Congestion pricing practices and public acceptance: A review of evidence. *Case Studies on Transport Policy*, *6*, 94–101.

Gu, Z., Najmi, A., Saberi, M., Liu, W., & Rashidi, T. H. (2020). Macroscopic parking dynamics modeling and optimal real-time pricing considering cruising-for-parking. *Transportation Research Part C: Emerging Technologies*, *118*, 102714.

Hall, J., Kendrick, C., & Nosko, C. (2015). The effects of uber's surge pricing: A case study. *The University of Chicago*, .

Han, E., & Robertson, J. (2016). Uber says most new year's eve passengers not hit with massive surge pricing. `https://www.smh.com.au/national/nsw/uber-says-most-new-years-eve-passengers-not-hit-with-massive-surge-pricing-20160102-gly2v9.html`.

He, F., & Shen, Z.-J. M. (2015). Modeling taxi services with smartphone-based e-hailing applications. *Transportation Research Part C: Emerging Technologies*, *58*, 93–106.

He, F., Wang, X., Lin, X., & Tang, X. (2018). Pricing and penalty/compensation strategies of a taxi-hailing platform. *Transportation Research Part C: Emerging Technologies*, *86*, 263–279.

Ke, J., Qin, X., Yang, H., Zheng, Z., Zhu, Z., & Ye, J. (2021). Predicting origin-destination ride-sourcing demand with a spatio-temporal encoder-decoder residual multi-graph convolutional network. *Transportation Research Part C: Emerging Technologies*, *122*, 102858.

Ke, J., Yang, H., Li, X., Wang, H., & Ye, J. (2020). Pricing and equilibrium in on-demand ride-pooling markets. *Transportation Research Part B: Methodological*, *139*, 411–431.

Ke, J., Zheng, H., Yang, H., & Chen, X. M. (2017). Short-term forecasting of passenger demand under on-demand ride services: A spatio-temporal deep learning approach. *Transportation Research Part C: Emerging Technologies*, *85*, 591–608.

Kontou, E., Garikapati, V., & Hou, Y. (2020). Reducing ridesourcing empty vehicle travel with future travel demand prediction. *Transportation Research Part C: Emerging Technologies*, *121*, 102826.

Lamotte, R., & Geroliminis, N. (2018). The morning commute in urban areas with heterogeneous trip lengths. *Transportation Research Part B: Methodological*, *117*, 794–810.

Li, S., Yang, H., Poolla, K., & Varaiya, P. (2021). Spatial pricing in ride-sourcing markets under a congestion charge. *Transportation Research Part B: Methodological*, *152*, 18–45.

Liu, W. (2018). An equilibrium analysis of commuter parking in the era of autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *92*, 191–207.

Liu, W., & Geroliminis, N. (2016). Modeling the morning commute for urban networks with cruising-for-parking: An mfd approach. *Transportation Research Part B: Methodological*, *93*, 470–494.

Liu, W., & Geroliminis, N. (2017). Doubly dynamics for multi-modal networks with park-and-ride and adaptive pricing. *Transportation Research Part B: Methodological*, *102*, 162–179.

Lowrey, A. (2014). Is uber's surge-pricing an example of high-tech gouging? `https://www.nytimes.com/2014/01/12/magazine/is-ubers-surge-pricing-an-example-of-high-tech-gouging.html?_r=0`.

Meng, Q., & Liu, Z. (2012). Impact analysis of cordon-based congestion pricing on mode-split for a bimodal transportation network. *Transportation Research Part C: Emerging Technologies*, *21*, 134–147.

Mo, D., Yu, J., & Chen, X. M. (2020). Modeling and managing heterogeneous ride-sourcing platforms with government subsidies on electric vehicles. *Transportation Research Part B: Methodological*, *139*, 447–472.

Nie, Y. M. (2017). How can the taxi industry survive the tide of ridesourcing? evidence from shenzhen, china. *Transportation Research Part C: Emerging Technologies*, *79*, 242–256.

Nourinejad, M., & Ramezani, M. (2020). Ride-sourcing modeling and pricing in non-equilibrium two-sided markets. *Transportation Research Part B: Methodological*, *132*, 340–357.

de Palma, A., & Lindsey, R. (2011). Traffic congestion pricing methodologies and technologies. *Transportation Research Part C: Emerging Technologies*, *19*, 1377–1399.

Qian, Z. S., & Rajagopal, R. (2014). Optimal dynamic parking pricing for morning commute considering expected cruising time. *Transportation Research Part C: Emerging Technologies*, *48*, 468–490.

Qian, Z. S., Xiao, F. E., & Zhang, H. (2012). Managing morning commute traffic with parking. *Transportation Research Part B: Methodological*, *46*, 894–916.

Ramezani, M., & Nourinejad, M. (2018). Dynamic modeling and control of taxi services in large-scale urban networks: A macroscopic approach. *Transportation Research Part C: Emerging Technologies*, *94*, 203–219.

Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? a survey-based comparison of taxis, transit, and ridesourcing services in san francisco. *Transport Policy*, *45*, 168–178.

Schroeter, J. R. (1983). A model of taxi service under fare structure and fleet size regulation. *The Bell Journal of Economics*, *14*, 81–96.

Wang, X., He, F., Yang, H., & Gao, H. O. (2016). Pricing strategies for a taxi-hailing platform. *Transportation Research Part E: Logistics and Transportation Review*, *93*, 212–231.

Wang, X., Liu, W., Yang, H., Wang, D., & Ye, J. (2020). Customer behavioural modelling of order cancellation in coupled ride-sourcing and taxi markets. *Transportation Research Part B: Methodological*, *132*, 358–378.

Wei, B., Saberi, M., Zhang, F., Liu, W., & Waller, S. T. (2020). Modeling and managing ridesharing in a multi-modal network with an aggregate traffic representation: A doubly dynamical approach. *Transportation Research Part C: Emerging Technologies*, *117*, 102670.

Weyl, E. G. (2010). A price theory of multi-sided platforms. *American Economic Review*, *100*, 1642–72.

Wong, K.-I., Wong, S. C., & Yang, H. (2001). Modeling urban taxi services in congested road networks with elastic demand. *Transportation Research Part B: Methodological*, *35*, 819–842.

Wong, K.-I., Wong, S. C., Yang, H., & Wu, J. (2008). Modeling urban taxi services with multiple user classes and vehicle modes. *Transportation Research Part B: Methodological*, *42*, 985–1007.

Wu, W., Liu, W., Zhang, F., & Dixit, V. (2021). A new flexible parking reservation scheme for the morning commute under limited parking supplies. *Networks and Spatial Economics*, *21*, 513–545.

Xu, Z., Yin, Y., & Zha, L. (2017). Optimal parking provision for ride-sourcing services. *Transportation Research Part B: Methodological*, *105*, 559–578.

Yang, H., Fung, C., Wong, K. I., & Wong, S. C. (2010). Nonlinear pricing of taxi services. *Transportation Research Part A: Policy and Practice*, *44*, 337–348.

Yang, H., Shao, C., Wang, H., & Ye, J. (2020). Integrated reward scheme and surge pricing in a ridesourcing market. *Transportation Research Part B: Methodological*, *134*, 126–142.

Yang, H., & Wong, S. C. (1998). A network model of urban taxi services. *Transportation Research Part B: Methodological*, *32*, 235–246.

Yang, H., & Yang, T. (2011). Equilibrium properties of taxi markets with search frictions. *Transportation Research Part B: Methodological*, *45*, 696–713.

Zha, L., Yin, Y., & Xu, Z. (2018). Geometric matching and spatial pricing in ride-sourcing markets. *Transportation Research Part C: Emerging Technologies*, *92*, 58–75.

Zha, L., Yin, Y., & Yang, H. (2016). Economic analysis of ride-sourcing markets. *Transportation Research Part C: Emerging Technologies*, *71*, 249–266.

Zhang, F., Liu, W., Wang, X., & Yang, H. (2020). Parking sharing problem with spatially distributed parking supplies. *Transportation Research Part C: Emerging Technologies*, *117*, 102676.

Zheng, N., & Geroliminis, N. (2016). Modeling and optimization of multimodal urban networks with limited parking and dynamic pricing. *Transportation Research Part B: Methodological*, *83*, 36–58.

Zheng, N., & Geroliminis, N. (2020). Area-based equitable pricing strategies for multimodal urban networks with heterogeneous users. *Transportation Research Part A: Policy and Practice*, *136*, 357–374.