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A Reverse Auction-Based Individualized Incentive System for Transit Mobility Management

Wenhua Jiang, Haris N. Koutsopoulos, and Zhenliang Ma

***Abstract*— Urban rail transit systems in many cities are experiencing crowding during peak periods due to rapid population growth. Incentive-based demand management strategies aim to better utilize the available capacity by shifting peak travel to off-peak periods. Various deployments have demonstrated the crowding-reduction potential of incentives in reducing crowding but they have also shown that such strategies are inefficient with many passengers receiving the incentives but relatively few contributing to crowding reduction. This paper proposes a reverse auction-based, individualized incentive strategy to encourage individual passengers to switch travel from peak to off-peak periods. The proposed approach is individualized, participatory, and explicitly accounts for individual characteristics and the potential contribution of their behavior changes to the system. Extensive experiments are conducted to demonstrate the approach using AFC data from Hong Kong's urban rail network. The results indicate that auction-based individualized incentives can enhance the system efficiency by strategically selecting passengers as winners whose behavioral changes contribute to the system performance. It also highlights the importance of correcting the information bias of perceived travel behavior between bidders and the population when operators select bid winners.**

***Index Terms*— Reverse auction design, individualized incentives, mobility management, transit systems.**

I. Introduction

URBANIZATION is increasing globally, and 55% of the world's population now lives in urban areas. By 2050, this is projected to further increase to 68% (notably 83% for upper-middle-income countries like North America, Europe, and Oceania) [1]. Growing population densities have led to a rise in urban congestion and crowding in public transport systems during peak hours. Delivering good service is a crucial problem that transit agencies face. Usually, increasing capacity in urban rail systems, such as extending networks or updating signaling systems, is a direct way to deal with the increasing demand. However, such improvements are often difficult and expensive. Instead, transit demand management strategies in urban rail systems, aiming at better utilization of available capacity through influencing customers' mobility behavior, are a promising alternative.

Providing incentives, such as free trips, off-peak discounts, lottery/rebates, etc., are commonly used demand management strategies in public transit systems [2]. Researchers have reported that 2-5% of travelers shift from peak to lower demand periods in response to incentives [4], [5]. Depending on the implementation, incentive programs can be categorized as generic or individualized.

Generic incentive programs provide the same incentive to all passengers regardless of their characteristics and contributions to system performance. Generic incentives are not very efficient. For instance, passengers who usually travel during off-peak do not contribute to the load on critical links (ineffective passengers) during the peak period but may benefit from generic off-peak incentives without having to change behavior [2]. In addition, generic incentives are static and not effective in inducing long-term behavior change. For example, two studies investigated passengers' longitudinal behavior in response to a fare discount promotion over two years in Hong Kong [6], [7]. They found that 35-40% of passengers who initially adopted the promotion eventually reverted to their previous travel time periods. Individualized incentive programs aim at rewarding beneficial behavior changes by providing incentives at the individual level (targeted passengers) according to, for example, their travel characteristics (i.e. commute time, travel distance) and contributions to the system [8], [9]. Compared to generic incentives, individualized incentives account for user heterogeneity and potential contribution to system goals, such as load reduction. However, existing individualized incentives are passive and, to some extent, static as the decision process is not participatory. A participatory program allows passengers to specify the incentives required to offset the inconvenience of changing their habitual behavior. Individualized but passive incentives are likely to be ineffective in retaining passengers' long-term interest and induce habitual behavior change. Studies also found that passengers' willingness to participate and the reward they are expecting for changing their habitual behavior vary widely across individuals [10]. An effective and efficient incentive mechanism should be participatory, individualized, and dynamic and reward good behavior changes that contribute to the system performance improvements.

This paper proposes a reverse auction-based individualized, participatory, incentive mobility management system aiming to nudge passengers to shift their peak hour travel to off-peak

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periods. In this context, participatory means that the system gives ownership of decisions to both individual passengers and the agency to find effective options for both sides. The unique characteristic of the system is that it allows passengers to actively interact with the system by submitting bids based on their own choices (rather than passively accepting system offers) for changing their departure times. Enhancing user interaction can result in a more efficient and user-friendly transportation experience [11]. Airlines use a similar approach to manage overbooking, a common practice of selling more seats than what are available for a specific flight [12], [13]. The airline seeks volunteers to leave the overbooked flight by offering passengers increasing reward amounts until the available capacity is satisfied. Overcrowding in transit is, to some extent, like overbooking in airlines. The transit agency controls the capacity and its use. Passengers with tickets are allowed to enter the station, but if there is no capacity available on arriving trains, they are automatically bumped to the next train with available space.

The proposed system selectively invites passengers to participate and provides varied discount options for passengers to choose from, for example, through a mobile app or web interface. Passengers who decide to participate submit the reward they want to change departure times that fit their schedules. The transit agency collects bids and selects the auction winners. The selection is based on the agency's assessment of which bidders are most likely to change their behavior and benefit the system. The assessment is based on historical travels of bidders as captured by trip transactions in the AFC database. The auction winners decide whether to travel in the committed time periods for the next commuting trip. Finally, the auction winners who actually travel in the committed time receive bid payments. AFC data enables the deployment of such a system effectively. The trip entry/exit information provides a detailed understanding of the spatiotemporal characteristics of individual movements [14]. The AFC data facilitates the optimal auction design by targeting passengers whose behavior change would contribute to reducing crowding in the urban railway system. The main advantages of the proposed concept include:

- It retains passengers' interest in participating and is more likely to promote sustainable behavior change by directly involving passengers in the mobility management process. Passengers interact with the incentive system by a) deciding whether to participate (e.g., depending on their schedule flexibility); and b) how much reward they would accept (within limits) to offset the inconvenience of changing their planned trip times.
- It is effective and efficient in managing peak travel by targeting "promising" passengers. It adjusts to individuals' characteristics and trip contexts, and rewards behavior changes that most likely contribute to the system goals, e.g., load reduction on critical links.
- Because it is participatory, passengers who submit a bid are more likely to change departure times, since, if selected, they will receive the reward they actually requested. For the same reason, it is also more likely to sustain its performance in the long run, as passengers are continuously engaged in the process.

The proposed strategy is a completely new strategy that hasn't been discussed or tested before and designed to address the major limitations of current approaches. The key contributions of the paper are:

- Proposes a reverse auction-based individualized incentive mechanism in which individuals are invited to set their 'reward' for travelling during the off-peak period and agencies offer requested rewards to those most likely to have effective behavior changes, within the constraint of available budgets.
- Formulates an optimization problem to select auction bid winners with system performance target, budget constraints, and considering the heterogeneous and uncertain passenger travel behavior, their bidding amount, and their behavior change contribution to the system performance.
- Evaluates the potential of the proposed scheme using a real-world urban railway network and conducts extensive experiments to explore the impact of design/implementation factors, including different numbers of invited passengers and bidding participation levels.

The remainder of the paper is organized as follows: Section II provides a brief review of related work. The proposed incentive system framework, together with the main design aspects is described in Section III. In Section IV, the potential of the system is illustrated in a case study using data from Hong Kong's MTR system. The final section summarizes the main findings and future research directions.

II. Related Work

In the literature, many incentive based strategies have been proposed for transit demand management (TDM) in peak periods, including free tickets, off-peak discounts, lottery rewards [2], [3]. In this section, we discuss various transit related incentive mechanisms and review the reverse auction-based incentives that have been applied in industries.

A. Incentive-Based Transit Demand Management

Various studies have demonstrated the positive impact of incentives on reducing peak travel in public transit. As discussed in the previous section, incentive schemes can be generic or individualized.

1) Generic Schemes: [4] studied an 'early bird' program in Melbourne which offered passengers free travel before 7:00 a.m., and reported that it reduced peak train loads by around 3%. Reference [15] conducted a survey exploring rail passengers' willingness to change travel times in Sydney. They reported that by offering a 30% discount, 15% of peak travel passengers would be willing to change their habitual departure times by 30 minutes and 4% by 60 minutes, with most traveling earlier. Reference [16] conducted a survey exploring the impact of a variety of incentives (e.g. fare discounts, coupons, free WIFI) on commuters' travel behavior in the Beijing Subway system. They found that incentives have a positive impact by reducing the morning peak trips.

Reference [5] investigated the impacts of MTR's Early Bird discount promotion on crowding reduction during morning peak periods in Hong Kong. They found that the promotion impacted commuters' behavior with 3% switching to off-peak travel. Reference [2] proposed a general methodology for optimal promotion designs. It targets the passengers based on their expected behavioral change and the degree of their contribution to congested sections of the system. Using empirical data from MTR system in Hong Kong, they evaluated the crowding-reduction potential of various strategies along with temporal (e.g., pre-peak/after-peak), spatial (e.g., station/OD), and fare discount (e.g., flat/step) dimensions. The analysis highlighted the importance of designs that target passengers who directly contribute to crowded hotspots. Reference [17] designed a hybrid fare scheme (HFS) for reducing peak-hour congestion in the urban transit systems which combines a fare-reward component (H-FRS) and a uniform fare component (H-UFS). Commuters can choose to join either of the sub-schemes according to their scheduling flexibility. In the H-FRS, a commuter is rewarded with one free trip during a prescribed shoulder peak interval after a certain number of paid trips during the peak period within the peak hours. In the H-UFS, a commuter pays a marginally higher but pre-determined uniform fare during the peak period. The authors concluded that the HFS can maintain the transit operator's revenue and achieve at least a 25% reduction of the total trip time costs for commuters.

2) Individualized Schemes: Different from generic incentives, individualized schemes provide incentives to targeted individuals. For example, the lottery/rebate reward scheme INSINC was implemented in Singapore to manage peak crowding in its Mass Rapid Transit system (MRT). Commuters who participate in the program earn 3 credits per kilometer they travel during the off-peak shoulder period and 1 credit per kilometer traveled in any other time period (weekday trips). Passengers can redeem the credits for, for example, cash rewards or a raffle prize. It is estimated that the INSINC scheme reduced peak trips by 7.49% during the six-month pilot [8]. A similar program, 'BART perks', has been deployed in San Francisco by the Bay Area Rapid Transit (BART) system to encourage riders to travel outside peak periods by offering redeemable points for cash rewards with three options (Autoplay, Spin-to-Win game or cash buyout). The results showed that 10% of the participants switched to off-peak travel due to the program [18]. 'BART perks-Phase II' improved upon Phase I by providing redeemable points to participants based on their travel history, i.e. entry station, average departure time, etc. [9]. It reported that passengers who received offers increased their off-peak travel by 6-20% (depending on the type of offer) compared to those who did not receive offers to shift their commutes. Reference [19] using laboratory experiments examined the choices made by passengers under a lottery-based incentive scheme to promote public transit usage during off-peak periods. They concluded that higher expected lottery rewards do help in increasing the shift to off-peak travel. The risk attitudes of the passengers play a significant role in explaining the choices they make. Recently, [20] developed an integrated incentive scheme for energy-saving and congestion reduction in a mobility system. The scheme consists of a system model (SM) and an incentive optimizer. The SM combines personalized behavioral modeling, traffic, and energy use simulators, and the incentive optimizer allocates incentives to each user based on SM-generated feasible alternatives, travel intent prediction, budget constraints, responses received from scheme users and non-users. The numerical simulation demonstrated that the proposed scheme was able to reach a system-wide energy savings of 12.5% with 7.5% of the passengers taking the reward points. Reference [21] introduced an incentive system that offers a series of recommended travel alternatives to travelers in a multi-modal transportation system. The system updates users' travel preferences by keeping track of their past choices and provides travelers with a corresponding amount of tokens as incentives to reduce energy consumption.

B. Reverse Auction-Based Incentive Mechanisms

Reverse auction-based incentives have been used in the airline industry to manage overbooking which is a common practice of selling more tickets than the available capacity [12]. The scheme works as follows: when the number of ticketed passengers showing up exceeds the flight capacity, the airline looks for volunteers willing to give up their seats by inviting them to bid the amount of money (e.g. travel vouchers) that they will accept as compensation for switching to another flight. The 'overbooking auction scheme' was first proposed by [22]. It involved asking each passenger to write a sealed 'bid' of the lowest amount they are willing to accept in return for transferring to a later flight. Reference [13] conducted a survey and concluded that the overbooking auction plan was sound and practical, given that there may be a good number of passengers who are willing to accept relatively small amounts of money to wait for the next available flight. Reference [23] studied the auction bumping strategy using airline data for a period over 14 years. The author found that there is usually a fair proportion of ticketed passengers who are willing to accept small amounts of money or other benefits in exchange for giving away their seats. Reference [24] compared a reverse auction mechanism with a fixed-price compensation for overbooked flights in terms of costs involved. They concluded that the auction can lead to higher profit for the airlines in most cases.

C. Discussion

Different types of incentives for transit demand management have been used in practice, including free tickets, fare discounts, credit/lottery. They have different characteristics in terms of implementation complexity, cost efficiency, and behavior change.

The free ticket program is easy to implement using AFC systems. However, it has a low cost-efficiency as it has limited flexibility to differentiate the heterogeneous travel patterns of passengers. Fare discount-based incentives can be designed considering spatial, temporal, and discount structures. In practice, most discount incentives use a flat discount structure over a single time period. Similar to the free ticket incentive,

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flat-rate discount promotions are not personalized and have low cost-efficiency. An early evaluation of a 25% discount promotion in Hong Kong's MTR system found a 3% reduction in peak hour trips. The results demonstrated that different users have different responses suggesting that the incentives may be improved by accounting for user heterogeneity. Both the free and discount schemes are attractive to passengers. However, if they need to shift their typical departure times by a considerable amount to take advantage of the promotion, these schemes are not desirable. Empirical studies show that the impact of fare savings is not the same for all users. The magnitude of savings is less important for users who need to shift by more than 15 min to receive a discount [25].

Credit-based incentives allow passengers to earn points which could be redeemed for cash or used for playing online games. It is relatively complicated to implement compared to free tickets or fare discount incentives, as points are offered to participants according to different rules, depending on their travel status (e.g., number of trips, departure time). The field experiment with the INSISC system in Singapore demonstrated that it takes four weeks for passengers to form a habit of behavior change, resulting in a consistent 7% of peak trips shifted.

Implementations of these incentive strategies in practice are mostly generic and passive. They do not take into consideration passenger heterogeneity in response to incentives, as well as the impact of passenger behavior changes on system performance. This paper proposes an auction-based approach to nudge passengers to shift to off peak travel. The approach allows passengers to participate in the mobility management process through auctions and maximize the rewards to those passengers whose behavior change most likely benefits the system.

There are two challenges in a reverse auction-based system in general: a) retaining passenger interests in participating and b) modeling the bidding behavior evolution. For example, in a recurring reverse auction-based incentive system, passengers may lose interest in future participation and drop out if the chance of winning is very low. Various studies have proposed strategies to deal with this problem. For example, bidders who failed in previous rounds of auctions may be assigned higher weights to increase their winning probability in subsequent auctions [26]. Bidding behavior may also evolve over time. Passengers who are risk-neutral, if they are not selected in previous auctions, may decrease their bid prices in order to increase their probability of winning [27]. Reversely, passengers who won in previous rounds are likely to increase their bid price to increase their expected reward. Incorporating the learning phase where bidders change their bid behavior in the design of the incentive system is beyond the scope of this study. This paper focuses on the steady state case in order to explore the potential of auction-based incentive systems.

III. Methodology

A. A Reverse Auction-Based Individualized Incentive System

We model the interactions between the system and passengers as an online reverse auction. In reverse auctions, there is

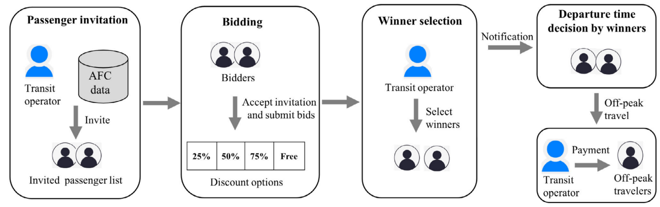

Fig. 1. A reverse auction based individualized incentive system.

one buyer and many potential sellers who compete to sell their products or services. In the proposed system, the transit operator is the buyer targeting a number of passengers to change their departure time. The passengers are the sellers bidding their asking prices for changing their departure behavior. The operator selects winners and rewards them with their submitted bids.

Fig. 1 illustrates the system framework. It consists of the following processes: 1) the operator sends invitations to all (or selected) passengers; 2) individual passengers decide whether to submit a bid or not. If they submit one, it is in the form of fare discounts which are the options provided by the operator; 3) the operator selects winners among the bidders and notifies them of the bidding results; 4) winners make decisions to travel during the off-peak period or not; 5) winners who travel during the off-peak receive the fare discount they requested.

The system (using for example a mobile app) works as follows. Passengers register and create an account for auction participation using the unique identification number of their AFC card. The operator identifies candidate passengers according to their contribution to the critical link load and sends them invitations to join the auction, for example, the previous day. The invited passengers make decisions to participate or not. Their decision may be based on their past experience with the system, their original intended travel time flexibility, etc. Passengers who decide to participate in the auction, choose a bid option and submit it. Their choice may be based on the expected reward, considering prior experience with the system. After the bidding process, the operator selects a subset of bidders as winners based on their potential contribution to the critical link load and available budget. The system informs the results to all bidders. After that, the winners make their decision whether to travel during the off-peak period. Since they decided to participate in the bidding process and won the requested reward, the likelihood of switching to the off-peak period is relatively high (even if they originally intended to travel during the peak), especially compared to the probability of switching under the typical (static and generic) promotion schemes. Finally, the system rewards the winners who actually travel during the off-peak period, according to their bid.

There are several challenges when designing such a system, including:

- In the auction invitation process, the number of invited passengers should be carefully considered. If all passengers are invited, those who make little or no contribution to the critical link loads may join the system. Although based on the proposed design, the likelihood of them being selected is small, they may still become winners, leading to a low crowding-reduction potential in reducing congestion with a constrained budget. If inadequate passengers are invited, there is a risk that not enough passengers will join the auction and switch to off-peak travel, and hence fail to achieve a specified system performance target (e.g., load reduction on critical links).

- In the winner selection process, the operator decides to select winners among the bidders. The selection is based on their claimed discounts given a budget constraint and desired overall load reduction level on critical links. At this stage, however, the operator does not know the actual travel plans of passengers on the target day. Thus, passengers' crowding-reduction potential (their potential contribution to reduce the load on critical links) should be taken into account in the winner selection process.

There are also several key economic properties that characterize the performance of a mechanism: computational efficiency, individual rationality, budget-balance, and truthfulness [28]. A mechanism is computationally efficient if the outcome can be computed in a polynomial time. An auction mechanism is individually rational if the utility is non-negative for each bidder and no deficit for the mechanism if budget balance. Finally, in a truthful mechanism, if no bidder can improve his utility by bidding a value deviating from his true value, regardless of what other bidders announce.

Note that in practice, passengers and operators may update their strategies often based on experience. For example, passengers may change decisions with respect to participation and their bidding strategy, while operators update the invited passengers set and winner selection strategies based on their understanding of the expected passengers' behavior. Gradually, the system is expected to converge to a steady state under which both sides have their perceived 'optimal' strategies. This paper focuses on exploring the performance of the system under steady-state conditions, in which, we assume the auction incentive system has been run for a sufficient large number of rounds, bidders will not experiment with their bids as they will have no extra payoff by changing their bids. These are the same conditions as in various steady-state reverse auction studies [29], [30].

Table I summarizes the notation used in the following sections.

TABLE I
NOTATION

Index	
i	an individual passenger
j	an OD pair
l	a critical link
p	peak period
k	a path used by passengers
off	off-peak period
Set	
J	Set of passengers in decreasing order of crowding-reduction potential e_i
I	Set of invited passengers
B	Set of passengers who participate in the auction
W	Set of auction winners
L	Set of critical links
R_i	Set of OD pairs that bidder i uses
K_i	Set of paths for OD pair j
D	Set of discount options to bid for
Parameters	
e_i	The crowding-reduction potential of individual i (the expected contribution to the load reduction on critical links)
π_i	Habitual probability of travel of bidder i
π_{ip}	Habitual probability of bidder i traveling during the peak period given that bidder i travels
π_{ijp}	Habitual probability of bidder i uses OD pair j given the bidder travels in the peak period p
π_{ij}^{off}	Habitual probability of bidder i uses OD pair j given the bidder travels in the off-peak period op
π_{ijp}^{k}	Habitual probability of bidder i using path k given that the bidder uses OD path k pair j in the peak given that the bidder uses OD pair j in the peak
δ_{kl}	1 if path k includes link l; 0, otherwise
ϖ_i^{off}	Operators' estimated probability that bidder i will shift to off-peak travel (if they win the bid)
ω_i^{off}	Actual probability of winner i shifting to off-peak travel (if they win the bid)
F_j	Trip fare of OD pair j
d_{ij}^{m}	Discount d^m submitted by bidder i given that they travel on OD pair j
C	Total budget
N_l^*	Minimum number of passengers required to switch to off-peak travel to achieve the target load reduction on critical link l

B. Auction Invitation Process

The selection of the passengers to be invited to the auction is based on the following steps: OD pairs contribution ranking, passenger identification, and passenger crowding-reduction potential calculation.

- OD pairs contribution ranking. All OD pairs in the system are ranked in descending order according to their contribution to the critical link loads during the congested period, i.e., 8:30-9:00 am. The contribution of an OD pair demand to a critical link load is a function of the OD demand, and expected path choices [2].
- Passenger identification. Passengers traveling on the selected OD pairs and using the system during the critical period are identified from the AFC data.
- Passenger crowding-reduction potential calculation. For each passenger i, their habitual probabilities, including travel probability π_i, probability π_{ij} to use OD pair j, and probability π_{ijp} to travel during the peak period can be derived according to their travel history based on AFC data. The crowding-reduction potential of each passenger is calculated using Eq. (1).

The system invites N passengers to participate in the auction based on their potential to reduce the load on critical links (crowding-reduction potential). The crowding-reduction potential of passenger i is defined as their likelihood to contribute to the reduction of the load on critical links if they decide to travel during the off-peak period. Using the AFC system, the transit operator has knowledge of past behavior of the passengers using smart cards.

$$e_{il} = \pi_i \times \sum_{j \in R_i} \sum_{k \in K_i} \pi_{ip} \times \pi_{ijp} \times \pi_{ijp}^{k} \times \delta_{kl} \times \varpi_i^{off}, \quad \forall l \in L \tag{1}$$

The crowding-reduction potential of an individual passenger on critical link l depends on the probability of passenger i changing their habitual behavior in response to the incentive system. A passenger's crowding-reduction potential with respect to a specific critical link l, e_{il}, is the probability that an individual shifts to off-peak travel if they win, multiplied by the contribution to the load of the critical link during the peak, see Eq. (1). The potential contribution of an individual passenger to the load of critical link l during peak periods can be inferred from their past habitual behavior recorded by smart cards in the AFC system. The calculation of crowding-reduction potential involves considering the travel probability of passenger i, probability of traveling during peak given i travels, probability of using OD pair j during peak, probability of selecting path k within OD pair j during peak, path k includes link critical link l or not and the probability of i shifting to off-peak travel if they win the bid. For the path fractions π_{ijp}^{k} associated with a specific OD pair j, the travel paths between OD pairs are provided by MTR, which are used in the MTR journey planner. It includes information on OD pairs, path ID, and path details (a sequence of tuples of [line, direction, station]).

A passenger's overall crowding-reduction potential e_i is the sum of its crowding-reduction potential contributing to the load of a link over all critical links Eq. (2).

$$e_i = \sum_{l \in L} e_{il} \tag{2}$$

The set of users invited to participate in the auction is defined as:

$$I = \{i \in J | n_i \leq N\} \tag{3}$$

where n_i is the index of individual i in set I with passenger order decreasing on their crowding-reduction potential e_i. Note that all passengers or a subset of passengers could be considered for invitation.

C. Passenger Bidding Process

An individual passenger i who receives the auction invitation makes plans for their next day's travel, including whether to travel or not, whether they will travel in the peak or off-peak, and which OD pair they will travel on. Based on their plans, they respond to the auction invitation. The invited passengers are provided a set of discount options to bid Fig. 2(a). Upon invitation, passengers make decisions on whether to bid and which bid to submit out of these options. With no loss of generality, we assume passengers who have no plan to travel for the next day will not participate in the auction as they do not qualify for the reward without traveling. Passengers who plan to travel, may decide to bid or not. The system is tailored for individuals who demonstrate a high level of crowding-reduction potential for adjusting their departure behaviors. Users who do not find the incentive of bidding appealing and are unlikely to make the effort to participate can simply choose to ignore the auction invitation, which wouldn't pose inconvenience to them in any way. On the other hand, for users who are flexible and motivated by rewards, engaging in the bidding process is likely to be a non-burdensome experience. In a participatory system, users who are willing to submit a specific bid are more likely to change their behavior, which is tailor to their preferences, in contrast to a system that generates bids automatically. Passenger i who decides to participate in the auction submit their requested reward (discount) selected from the provided options $d^m \in D$. Their choice represents the discount they are willing to accept in order to switch to travel during the off-peak period. Fig. 3 shows the bidding decision process of passenger i. Note that passengers planning to travel off-peak the next day are assumed to participate in the auction with probability 1, as they do not have to alter their plans.

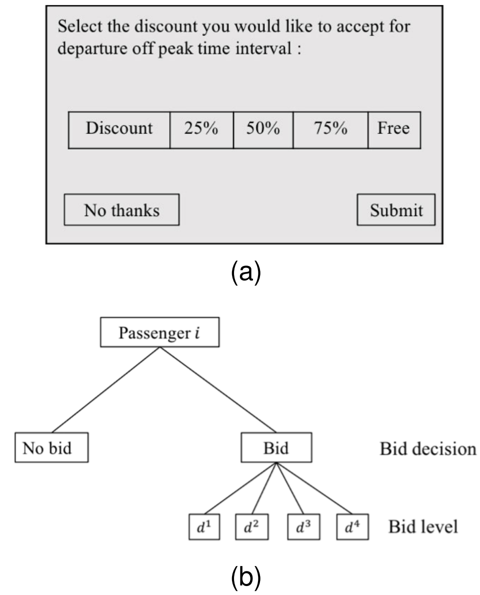

Fig. 2. Bidding behavior of passengers. (a) Bid options; (b) Two-level nested logit choice model.

A nested logit model is developed to model the passenger bidding behavior [31], [32]. Fig. 2(b) shows a tree diagram describing the nesting structure. There are two levels: the probability of submitting a bid; and the probability of choosing a certain discount level for their bid.

The lower-level models the probability that individual i traveling on OD pair j will submit a bid d^m:

$$P\left(d_{ij}^{m} \middle| D\right) = \frac{e^{V_{ij}^{m}}}{\sum_{d^m \in D} e^{V_{ij}^{m}}} \tag{4}$$

where V_{ij}^{m} is the utility of passenger i submitting a bid d^m. Without loss of generality, the utility V_{ij}^{m} is defined as a function of the discount that passenger i will receive and the probability of winning the bid (expected reward).

$$V_{ij}^{m} = \beta * d_{ij}^{m} * F_j * P\left(w_{ij}^{m}\right) \tag{5}$$

where $P\left(w_{ij}^{m}\right)$ is the perceived probability of winning, and β is a parameter.

The likelihood of winning the auction depends on two key factors, the characteristics of the auction process; and the bid discount that a bidder would like to receive. For two submissions with the same bid price, the winning likelihood depends on attributes, such as the number of bidders, the characteristics of the trip and prior travel behavior exhibited by the individual. The requested bid price also affects the winning rate, i.e., the lower the bid, the more likely the bidder will win the auction. Various studies have proposed a logistic regression to model the winning probability [33], [34]:

$$P\left(w_{ij}^{m}\right) = \frac{1}{1 + e^{z}} \tag{6}$$

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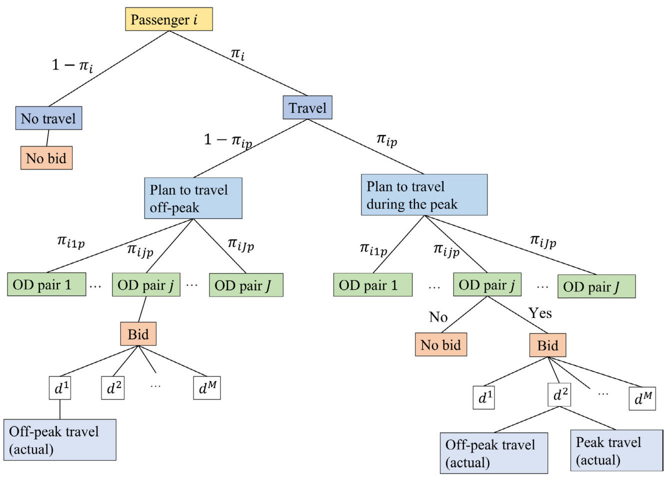


Fig. 3. Travel plan and bidding behavior of passengers.

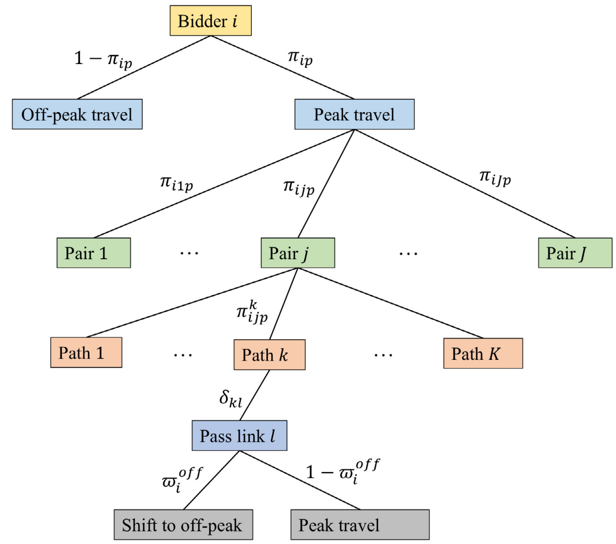


Fig. 4. Bidder 's habitual behavior as inferred by the system using AFC transaction data.

where, $z = \sum_i \theta_i * g_i$. g_i represents the characteristics of the individual and the bid, and θ_i is the corresponding weights. Given that the paper focuses on steady-state conditions, the participating passenger is aware of previous outcomes of their bids. They are also aware that price impacts the chances of winning. We, therefore, model z as a function of the bid amount, i.e., $z = \theta * d_{ij}^m * F_j$, where F_j is the fare for OD pair j.

The upper-level logit model models the probability of passenger i deciding to participate in the bidding process given that they travel on OD pair j [34].

$$P\left(b_{ij}\right) = \frac{e^{V_{b_{ij}}}}{e^{V_{b_{ij}}} + e^{V_{\bar{b}_{ij}}}} \tag{7}$$

$V_{b_{ij}}$ is the utility of passenger i if they participate in the auction $V_{\bar{b}_{ij}}$ is the utility if they do not):

$$V_{b_{ij}} = \alpha E\left[\max\left(V_{ij}^m + \varepsilon_{ij}^m\right), \forall d^m\right] = \alpha \log\left(\sum_{d^m \in D} e^{V_{ij}^m}\right) \tag{8}$$

where α is a coefficient, and ε_{ij}^m is the error term.

After being notified of their bid results, the bid winners decide whether they will switch to off-peak travel. We assume that bid winners will actually switch to the off-peak travel with a probability ω_i^{op} (habitual behavior, for example, calibrated from their travel histories) given that they win their requested bids.

D. Winner Selection Process

After the bidding process, the system collects all the bidders B with their submitted discounts and selects winners based on the available information. It is worth noting that the system does not know the actual travel plans of passengers on the target day at this stage. It knows the passengers' claimed discounts (bids) and their habitual travel behavior which can be extracted from the AFC data (in terms of traveling during the peak and OD pair used based on historical AFC transactions of the bidder), the path choice probability is based on information about path choice fractions (e.g. from surveys). The probability of shifting to off-peak travel if they win, could be based on observation from past behavior of the passenger. Fig. 4 shows an example of bidder i's travel behavior information known to the system. Based on their habitual travel behavior and the submitted bid, the system selects a subset of bidders from set B as winners. The goal is to maximize the expected load reduction on critical links given the available budget.

We formulate the winner selection process as an optimization problem. The objective is the maximization of the expected crowding-reduction potential of the selected winners, subject to a budget constraint C and desired load reductions (number of passengers shifted to the off-peak) on critical links. The decision variables x_i is:

$$x_i = \begin{cases} 1, & if\ bidder\ i\ is\ selected \\ 0, & otherwise \end{cases} \tag{9}$$

Hence, the winner selection problem can be written as:

$$\max_B \sum_{i \in B} e_i x_i \tag{10}$$

Subject to:

$$\sum_{i \in B}\left\{\sum_{j \in R_i} \pi_{ip} \times F_j \times d_{ij}^m \times \left[\pi_{ijp} \times \varpi_i^{off} + \left(1 - \pi_{ijp}\right)\right]\right\} \times x_i \leq C \tag{11}$$

$$\sum_{i \in B} \left(e_{il} \cdot x_i\right) \geq N_l^*, l \in L \tag{12}$$

$$x_i \in \{0, 1\}, \ \forall i \tag{13}$$

Eq. (10) maximizes the total expected crowding-reduction potential over all bidders, e_i was originally defined by Eq. (1) and (2), taking into account the probability of travel π_i. However, in Eq. (10), it is used without the term π_i. It is assumed that since passenger i submitted a bid, their plan is to travel on the target day. Eq. (11) guarantees that the expected fare revenue loss because of incentive discounts paid

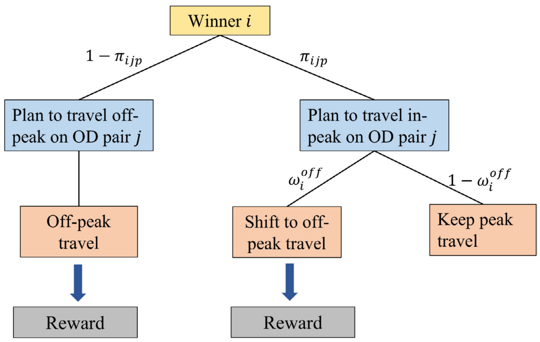


Fig. 5. Winners' decision whether to shift to off-peak or not.

to the winners does not exceed the budget. Eq. (12) ensures that the total load reduction on a critical link is no less than the minimum required load reduction on that link. We use the Gurobi Optimizer to solve the optimization problem presented in Eqs. (10)-(13). Gurobi is a robust optimization solver known for its utilization of advanced algorithms, including linear programming, mixed-integer programming, quadratic programming, and constraint programming, to address a wide range of optimization problems [35].

E. Actual Travel Behavior of Bid Winners

After the winner selection process, the system informs all bidders of the bidding results. Winners make decisions on whether to travel off-peak for the next day. Winner i who originally planned to travel during the peak, will shift to the off-peak travel with an actual probability ω_i^{off}. If winner i originally planned to travel off-peak will travel as planned. Fig. 5 shows winner i's decision process on traveling off-peak. The system will pay the reward to the winners who travel during the off-peak period.

Algorithm 1 summarizes the simulation process of the incentive system.

Algorithm 1 The Reverse Auction-Based Incentive System

Input: Passenger set J in decreasing order of crowding-reduction potential e_i
Output: Winner set W
Invite top N passengers from J based on e_i in Eq. (1)
  $I = \{1, \ldots, i, \ldots, N | i \in J\}$
For $i \in I$ **do**
  i responds to the auction invitation
  If $R_i = \{b, d^m\}$ **then** $B \leftarrow B \cup i$
For $i \in B$ **do**
  $W \leftarrow$ select winners by solving Eq. (5) - Eq. (8)
For $i \in W$ **do**
  i decides to switch to off-peak or not

F. Properties of the Proposed Incentive Mechanism

There are several properties of the proposed incentive system. First, in Algorithm 1, the complexity of the crowding-reduction potential sorting operation (line 3-4) is O(N), and the for loop in the bidding process (line 5-7) also has a computational complexity of O(N). Additionally, the computational complexity of the for loop in the winner selection process (line 8-9) is O(B). Therefore, the time complexity of Algorithm 1 is in polynomial time order. Second, there are two kinds of bidding results for each bidder i. If passenger i traveling on OD pair j participates in the auction and fails to bid, then the utility of the bidder $V_{(b_{ij})}$ equals to 0. If passenger i is successful, the rewards he will be paid equals to the requested discount d_{ij}^m multiplied by the trip fare F_j, then the utility of the bidder $V_{(b_{ij})}$ is greater than 0. According to the above mentioned analysis, the user utility is non-negative, satisfying individual rationality. In terms of the bidding process, two cases need to be considered for the system during the bidding process. First, if there are no passengers participate in the auction, the utility of the transit operator equals to 0. Second, if there are passengers participate in the auction, Eqs. (11)-(12) ensures that the payment to the winners will not exceed the available budget and the load reduction is not less than the desired load reduction. Hence, the utility of the transit operator is non-negative, and the mechanism is balanced in budget. Finally, in the auction formulation, as all the bidders are rational, the natural behavior of the losing bidders would be to decrease their bids (if bidders overbidding). Similarly, winning bidders will increase their bids by certain amount in the next round to increase their payoffs (if bidders underbidding). Eventually, the system reaches the steady state in which all the bidders have their corresponding fixed bids and bidders cannot improve their utilities by deviating their true valuation, no matter what bids the other users submit. Thus, in this study, the incentive mechanism is truthful.

IV. Case Study

Hong Kong's Mass Transit Railway (MTR) system is used as a case study. We consider two critical links (Fig. 6) which operate close to capacity in the peak of the peak time period 8:30-9:00 am. MTR has a closed AFC system requiring users to tap their cards at both entry and exit gates, thus the complete trip details are known. We used AFC data from 24 weekdays (April 9 to May 11, 2018) for the analysis.

A. Experimental Setup

Previous studies have suggested that incentivizing passengers to change their exit times is effective at reducing crowding during peak periods [25]. Reference [2] proposed a generic optimization approach to design such strategies. They formulate the optimal promotion design problem to target 'effective' users whose behavioral response to the promotion contributes to the reduction of crowding in the system. In this study, we use a reverse auction-based strategy to encourage passengers, who habitually exit the system during the peak period, to shift to the off-peak period. For the purpose of this application, we assume that the auction system is designed to invite a subset of metro passengers based on their crowding-reduction potential in reducing the critical link loads rather than inviting all passengers. Different ways can be used to select these passengers, including station/OD

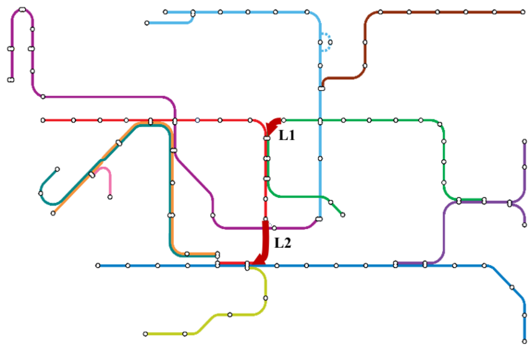


Fig. 6. Subway network and critical links (red arrows).

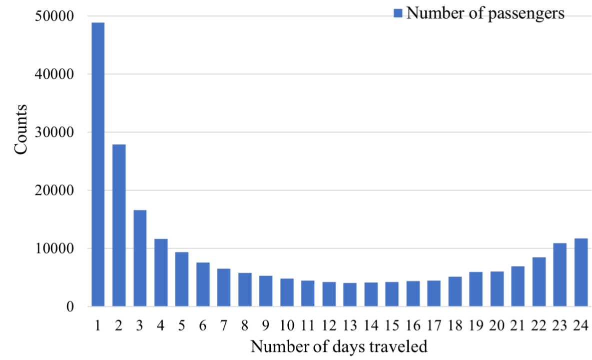
pair based (passengers using certain stations/OD pairs are invited), and individual based (targeted passengers are invited). Compared to other selection methods, inviting passengers by their crowding-reduction potential can better target passengers who will likely contribute to the reduction of the load at critical links.

To reduce the computation burden, the selection of the passengers to be invited to the auction is based on the following steps: OD pairs contribution ranking, passenger identification, and passenger crowding-reduction potential calculation.

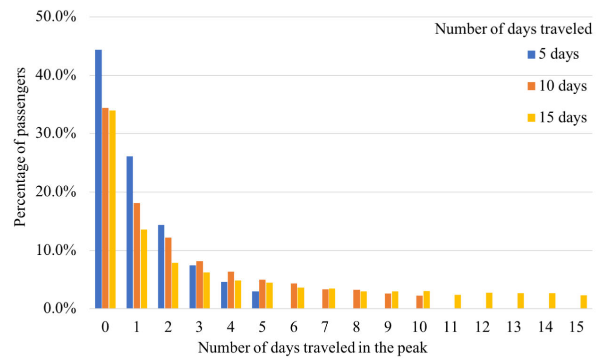
- OD pairs contribution ranking. All OD pairs in the system are ranked in descending order according to their contribution to the critical link loads during the congested period, i.e., 8:30-9:00 am. The contribution of an OD pair demand to a critical link load is a function of the OD demand, and expected path choices [2].
- Passenger identification. Passengers traveling on the selected OD pairs and using the system during the critical period are identified from the AFC data.
- Passenger crowding-reduction potential calculation. For each passenger i, their habitual probabilities, including travel probability π_i, probability π_{ij} to use OD pair j, and probability π_{ijp} to travel during the peak period can be derived according to their travel history based on AFC data. The crowding-reduction potential of each passenger is calculated using Eq. (1).

The top 200 OD pairs contribute 65% of the load on the critical links. Fig. 7 shows the distribution of all passengers from these OD pairs in terms of the number of days they use the MTR network and the number of days traveled during the peak period. Fig. 7(a) shows that around 40% of the passengers travel over 10 days and 20% of the passengers travel at least 18 out of the 24 weekdays.

Fig. 7(b) shows the distribution of passengers traveled during the peak period when the total number of traveled days is 5, 10 and 15 days. The blue, orange and yellow bars describe the distribution of passengers who traveled 5 days, 10 days and 15 days, respectively, during the study period. For example, the second blue bar (x = 1) means that approximately 26% passengers traveled only one day in peak, considering that they traveled for a total of 5 days. Likewise, we can observe that roughly 18% (the second orange bar) passengers traveled one day at the peak when they traveled for a total of 10 days.The



(a)



(b)

Fig. 7. Distribution of passengers. (a) Number of days traveled; (b) Number of days traveled during the peak.

results show that, depending on the number of travel days, 55-65% of the passengers travel at least one day during the peak. Generally, Fig. 7 shows that there is large heterogeneity in passengers' travel behavior in terms of number of days traveled and days with trips during the peak. This heterogeneity should be taken into account in the incentive system design.

B. Scenario Parameter Settings

Using the Hong Kong MTR system data, we validate the performance of the proposed auction across a number of scenarios. The scenarios represent key factors affecting performance, including the number of invited passengers, the bidding participation level, and the budget level. In the experiments, we vary the number of invited passengers from 10,000 to 100,000 (0.2% - 2.1% daily ridership) with an increment of 10,000 [36]. For each passenger, we simulate their travel and bidding behavior, including the probability of traveling, probability of traveling during the peak, probability of traveling during the peak period using OD pair j, probability of bidding, and probability of submitting a bid with a value d^m.

To explore the impact of different bidding participation levels, we examine two bidding scenarios: high and low participation. We assume an average participation rate of 65% in the high participation scenario and a rate of 10% in the low participation case. To achieve these, we reversly estimate the distribution of model parameters α, β, θ in Eqs. (5)-(8) by enumerating different parameter combinations.

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TABLE II
PARAMETERS USED TO REPRESENT PASSENGER BEHAVIOR IN THE EXPERIMENT

Parameters	High probability of bidding	Low probability of bidding
α	$U(0.1, 0.5)$	$U(-1.6, -1.4)$
β	$U(0, 1)$	$U(0, 0.3)$
θ	$U(-0.3, -0.1)$	$U(-0.3, -0.1)$

Table II shows the parameters used in the experiment. According to Eqs. (5)-(8), we obtain: (1) the high probability bidding case (the participation rate ranges between 53.5% and 86.6% with an average 64.5%); and (2) low probability bidding case(the participation rate ranges between 3.6% and 12.5% with an average 8.7%). The probability of submitting a bid amount by each bidder is calculated by Eq. (4).We also explore the influence of budget levels by varying it from HK$10, 000 to 250, 000 (0.02%- 0.47% daily revenue) with an increment of HK$20, 000 [36]. The (habitual) probability of winner i shifting to off-peak travel ω_i^{off} and that perceived by the agency π_i^{off} are uniformly distributed over $U(0.8, 1)$.

The rationale behind setting parameters is as follows: initially, Eq. (6) models the perceived probability of winning, denoted as $P\left(w_{ij}^m\right)$, which requires the setting of the parameter θ. As $P\left(w_{ij}^m\right)$ represents a probability, it must fall within the range of [0, 1]. Hence, we define the range of θ within the range. Similarly, the setting for β is associated with the probability that an individual submits a bid when travelling on OD pair j, denoted as d^m, in Eq. (4)-(5). The range for α is established based on the probability of an individual's decision to participate in the bidding, as illustrated in Eq. (7)-(8). Following the same principles, we also determine the appropriate ranges for β and α.

We demonstrate the computational efficiency and convergence of our optimization by presenting an example. We consider winner selection with a HK $150,000 budget and 90,000 invitations, assuming high participation. Using Gurobi v9.1.1 on macOS 64-bit, with 6 cores and 12 logical processors, our optimization completed in 1.21 seconds over 327 iterations. This problem falls under Mixed Integer Programming, solved using Gurobi's Branch-and-Bound algorithm with an optimality tolerance of 1e-4 (0.01%) [37]. After 327 iterations, the gap narrows to 0.0002%, indicating near-optimal solution convergence.

C. Results

1) Overall Potential: We discuss results initially for the low response rate case which is the pessimistic scenario. Fig. 8(a) shows the average load reduction at the critical links as a function of the budget and the number of invited passengers for the low participation rate scenario. Each line shows the optimal auction solution for the corresponding number of invitations and budget levels. For example, with 50,000 invited participants and a budget of HK$30,000 per day, the load reduction is 3.8%. As the budget increases the load reduction also increases and finally stabilizes at 4.1% when the budget exceeds HK $50,000. Similar trends can be observed for other numbers of invited passengers. The results also show that the auction performance is bounded in terms of load reduction regardless of the amount of budget invested. Increasing the budget above a threshold does not further improve the performance. This threshold depends on the number of passengers invited to participate. This is as expected as all the bidders become winners when the budget value is beyond a critical point (which is a function of the number of invitations). Increasing the budget beyond this point does not reduce the peak loads. Fig. 8(b) shows the number of winners as a percentage of all bidders. It shows that with a certain budget level that is not sufficient to reward all bidders (e.g. HK$20,000), the average winning probability of the bidders decreases as the number of invitations increases, which suggests that a relatively small number of invitations can encourage long-term loyalty as the chances of being rewarded is high.

Fig. 8(a) also illustrates a portfolio of schemes that can be used by operators given certain budget constraints and implementation considerations. For example, in the case of low participation rate and a budget of HK$90,000 per day, load reduction at the critical links ranges from 2.6% to 5.4%. If the goal is to reach a specific load reduction level, e.g., 5.0%, the results show that the system cannot achieve this level if the number of invited passengers is 70,000. At least 80,000 passengers have to be invited to reach the goal of 5% load reduction on critical links.

Compared to the OD pair based incentives with a flat fare discount in [2], the efficiency of the auction-based incentive system is much higher by directly targeting individuals. For example, the OD based incentive scheme achieves a maximum load reduction of 2.4% with a budget of HK$383,560 per day using 2300 candidate OD stations, while the auction system can achieve a similar reduction level (2.6%) with 30,000 passengers invited and HK$30,000 per day for the low participation scenario.

2) Impact of the Number of Invited Passengers and Bidding Participation Level: Fig. 9 shows the percent load reduction as a function of the budget and number of invitations for high and low participation scenarios. The results indicate that for a given budget, the percent load reduction increases as the number of passengers invited increases. It is also observed that the marginal contribution of additional budget on the load reduction diminishes as the budget increases. Compared to the low participation scenario, the magnitude of load reduction is significantly higher for the high participation scenario. For example, to achieve a 5% load reduction under the high bidding participation scenario a budget of HK$10,000 is needed if 10,000 passengers are invited. The minimum needed budget in the low participation case to achieve the same reduction is HK$ 70,000 and require at least 90,000 individuals.

Fig. 10 shows the average cost per effective passenger for the high and low participation rates with varied budget levels and number of invitations. We define effective passengers as the winners who change their original peak travel plans to off-peak and contribute to critical link load reduction. Fig. 10(a) shows the average cost per effective passenger for the high participation scenario. Given the same number of invitations, the average cost per effective passenger increases

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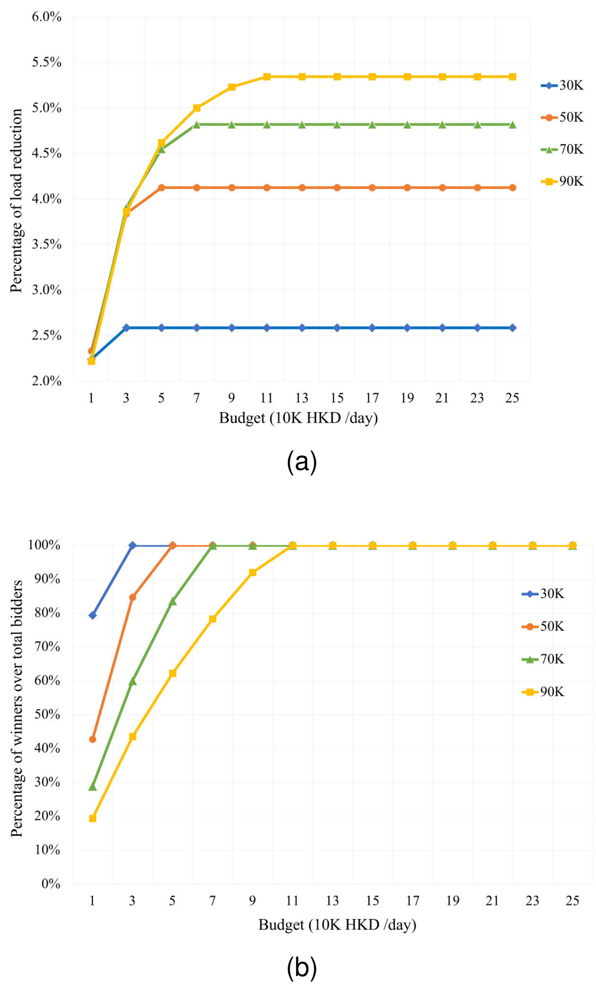

Fig. 8. Performance of the system in the low participation case. (a) average load reduction; (b) percentage of winners over the total number of bidders.

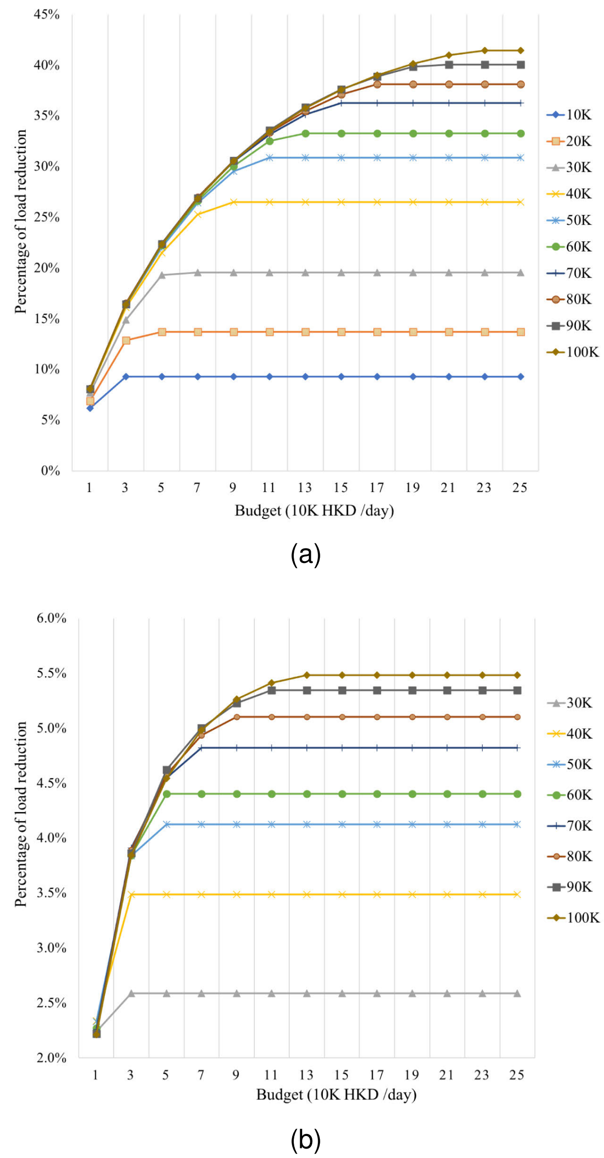

Fig. 9. Average load reduction with various invitation and budget levels. (a) High participation rate; (b) Low participation rate.

firstly, and then stabilizes at a fixed amount when the budget is sufficient for rewarding all bidders (all bidders become winners). We also observe that, for a certain budget level which is not sufficient for rewarding all bidders (e.g. HK$50,000), the average cost per effective passenger decreases as the number of invitations increases. This is expected as the system has more opportunities to select better bidders as winners considering the trade-off between crowding-reduction potential and reward. The pattern is gradually reversed when the budget is not a constraint for rewarding winners (e.g. HK$170,000). That is, the average cost per effective passenger increases with the increasing invitations for a certain budget level sufficient for offering rewards to all bidders. That is because, when the available budget is large enough, adding more invitations means more low effective passengers are rewarded, leading to the decrease in the cost efficiency. Similar patterns are observed for the low participation rate scenario in Fig. 10(b).

3) Characteristics of Winning Bids: Fig. 11 shows the distribution of various characteristics among the bidders and selected winners in the case where 30,000 passengers are invited with a budget of HK$10,000 for both low and high bidding participation. Fig. 11(a) and 11(c) show the distribution of the reward received. Each bar represents the percentage of bidders/winners who received the reward they bid on (fare reduction) in HK$.

The results show that bidders submitting lower bids are more likely to be selected by the system. Fig. 11(b) and 11(d) show the distribution of the crowding-reduction potential (expected reduction in critical load) of bidders and winners. Each bar indicates the percentage of bidders/winners with the corresponding expected number of critical links. A value close to 2 means that a passenger is very likely to go through two critical links. The results show that bidders with higher crowding-reduction potential in contributing to critical load reduction are more likely to be selected as winners.

4) Improving Decision Making in Selecting Winners: We define as off-peak travelers the passengers who are invited to the auction but they actually plan to travel off-peak on the target day. The ratio of off-peak travelers is the number of invited off-peak travelers over the total number of invited travelers. Similarly, off-peak bidders are the bidders who

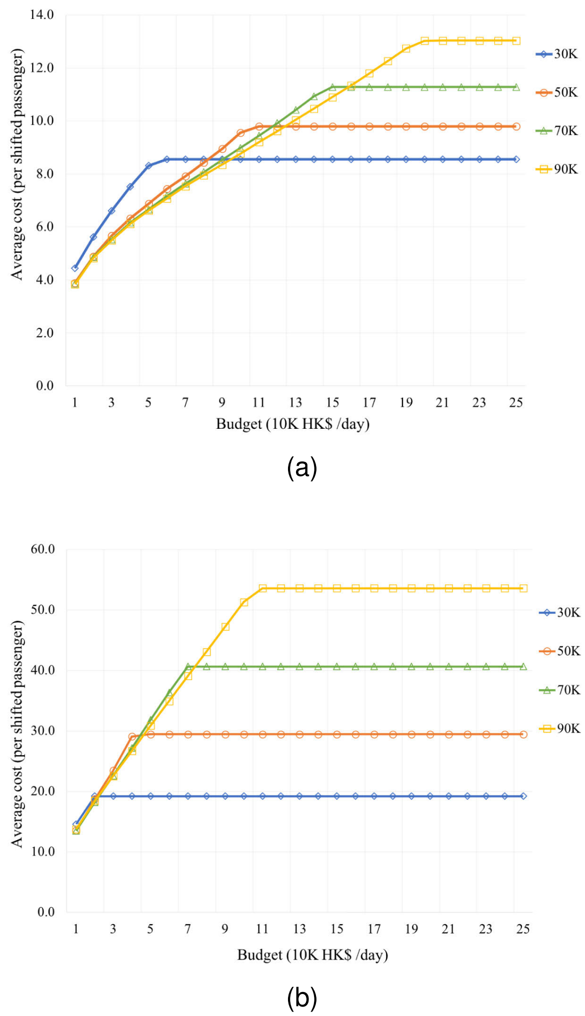

Fig. 10. Average cost per effective passenger for different participation rates. (a) High; (b) Low.

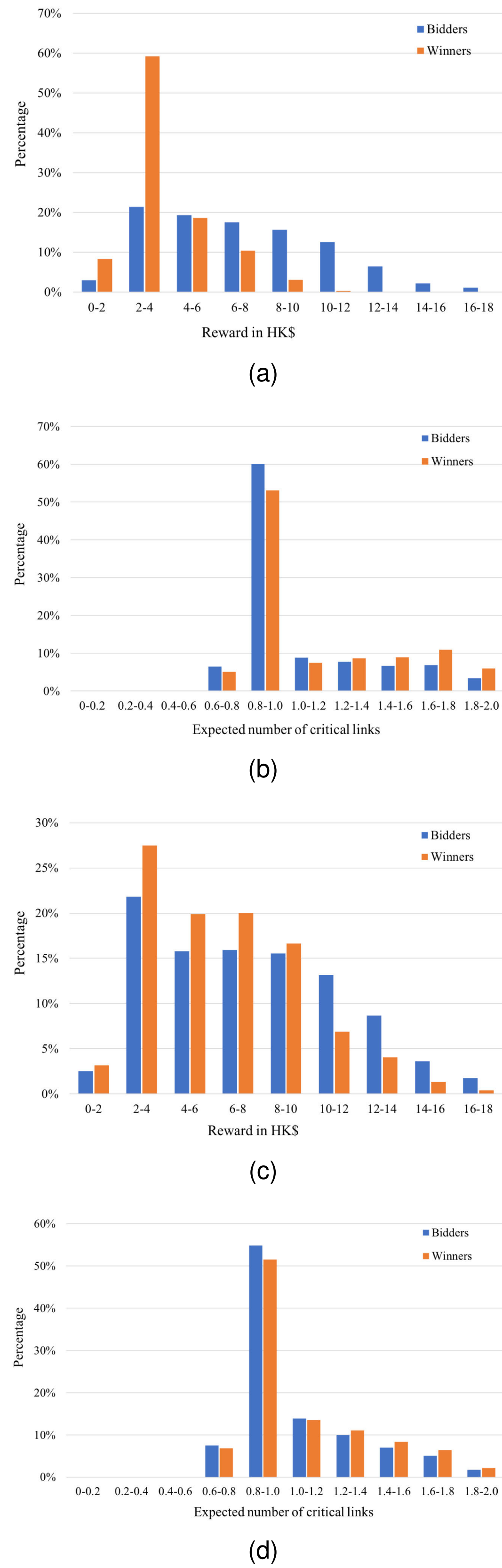

Fig. 11. Distribution of the amount of reward and passenger crowding-reduction potential. (a-b) high; (c-d) low.

actually plan to travel in the off-peak. The ratio of off-peak bidders is defined as the number of off-peak bidders over the total number of bidders (invited travelers who participate in the auction). Fig. 12(a) and 12(b) show the ratio of off-peak travelers and off-peak bidders for the case of high and low participation rates, respectively. The percentage of off-peak bidders is consistently higher than the percentage of off-peak travelers. This is actually expected as invited passengers who were planning to travel off-peak are more likely to bid (if they win, they do not have to change their plans) in order to receive the requested discount. The difference between the two ratios is larger in the low participation case, since for the same number of invitations, the proportion of off-peak bidders among the bidders is higher in the low participation case. This is because for the same number of invitations, the number of passengers planning to travel off-peak is the same in both scenarios. Hence, these passengers will submit a bid as explained before. Furthermore, in the low participation case, the number of passengers who plan to travel during the peak and decide to bid is much lower, resulting in a much higher ratio of off-peak bidders. However, off-peak travelers ratio is the same in the low and high participation scenarios as it represents the same population.

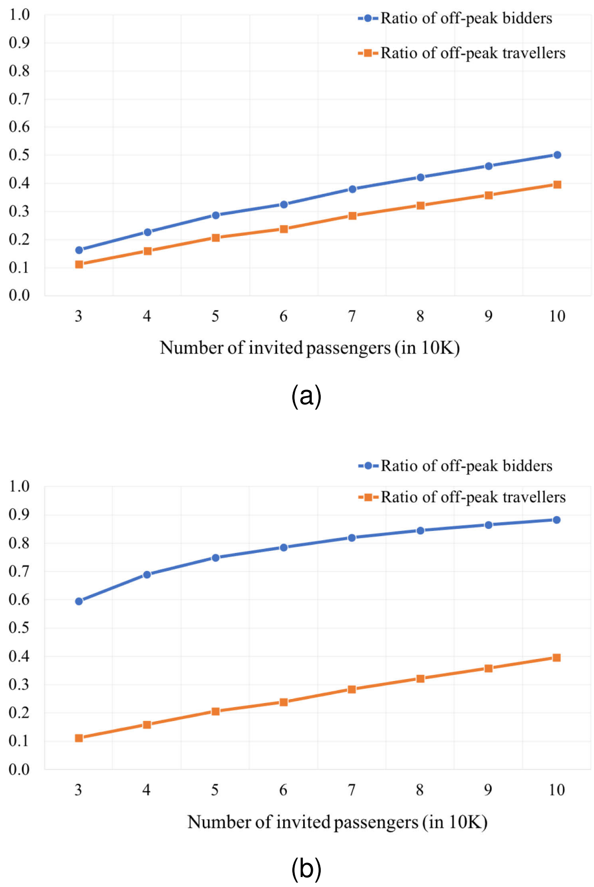

Fig. 12. Ratio of off-peak travelers and off-peak bidders. (a) High participation rate; (b) Low participation rate.

The difference between these two ratios indicates the level of information bias when operators select winners. In the approach used earlier, operators assume that the probability that a bidder plans to travel off-peak is given by the historical data (red line in Fig. 12). However, in the sample of bidders, passengers who actually plan to travel off-peak are more likely to participate in the auction (as they do not have to alter their behavior to receive the reward if selected). Therefore, the percentage of off-peak bidders in the bidder set is higher than the percentage of off-peak travelers in the invited set, but this is not taken into account in the formulation. Consequently, the winner selection process uses biased information, underestimating the probability of actually traveling off-peak. This likely leads to suboptimal solution. This can be avoided if the probability π_{ijp} of an individual travelling during the peak in calculating the crowding-reduction potential of an individual in Eq. (1) assumed by the agent, takes into account the expected higher participation of off-peak travelers in the set of bidders. However, the estimation of this probability is not straightforward.

While developing methods to correct for the habitual information bias is out of this paper's scope, a simple experiment is used to illustrate its impact on the winner selection process. We assume 30,000 passengers are invited and the available budget is HK$30,000 for high and low participation scenarios. In the high participation case, the results show that using the habitual π_{ijp} as estimated by the historical data, the expected load reductions (as estimated by Eq. (1)) is 15.8%. However, the actual reduction (based on the simulation experiments) is 14.9%, leading to a 0.9% overestimation. By increasing the probability of bidders traveling during the off-peak period by 10% (average difference between these two ratios is around 10% in Fig. 12(a)), that is, using a modified $\hat{\pi}_{ijp}$, the discrepancy between the expected and actual load reduction decreases to 0.7%. In the low participation case, the discrepancy between the expected and actual load reduction decreases from 3.1% to 2.3% with the modified $\hat{\pi}_{ijp}$.

5) Impact of Personalization: To assess the significance of personalization, we conducted a comparison between the proposed incentive system and a benchmark scenario in which passengers are randomly selected from the top 200 OD pairs with fixed incentives. The probability of inducing actual individual behavior change remains consistent with the primary experiment. For the random selection of passengers, we performed 50 iterations and report the average performance.

In the benchmark, where incentives are provided to all randomly selected passengers, it can be considered that all the selected passengers participate in the system and are winners. This setting is more analogous to a high participation scenario in the proposed system. Thus, we compare the performance of the benchmark with that of the proposed system assuming a high participation rate. For simplicity, a 25% discount is applied, revealing that with HK$ 30,000, approximately 13,000 passengers are selected, resulting in a 4.7% load reduction. In contrast, the proposed system achieved 9.3% load reduction under the same conditions. When using HK$ 50,000, the load reduction increases to 7.8% with around 20,000 passengers selected, which still falls short of the efficiency achieved by the proposed system with a 13.7% load reduction.

V. Conclusion

In this paper, we propose a reverse auction-based individualized incentive mechanism for alleviating peak period crowding in public transit systems by incentivizing passengers to change their departure times. Instead of deploying generic, fixed-amount discount incentives for all passengers, as is common practice, the system allows passengers to reflect their preferred incentive level (bid). The system considers the heterogeneity among passengers, including passengers' potential contributions to the crowded links, and habitual travel patterns. The selection of the auction winners is formulated as an optimization problem rewarding those whose behavioral change is likely to contribute to the reduction of the crowding in the system considering budget constraints. A real-world transit network is used to evaluate the performance of the system. The case study also explores the impact of design/implementation and passenger factors, including the number of passengers invited to participate in the auction, the available budget, and the level of participation (fraction of invitees who decide to bid).

The results show that the system can effectively shift demand from the peak period to the off-peak. In addition, it is cost-efficient by targeting potentially valuable passengers (high crowding-reduction potential and low bids). The results also show that the system performance gradually increases and then becomes stabilized with an increasing number of invited passengers and budget, regardless of the bidding participation level. We also point out that there is bias in the estimation of the probability of traveling during the off-peak period (used by the system for winner selection), if historical data based on the general user population is used, as opposed to the bidder set. The bidder set is not representative of the users as passengers who plan to travel in the peak are more likely to bid.

Future research will focus on passengers' day-to-day adjustments of their behavior, as passengers might change their bidding decisions after several auction rounds, and correct for the bias discussed in the previous section. Additionally, extensive surveys will be conducted to calibrate parameters for modeling bidders' behavior. The personalized incentive system can be coupled with the proactive information recommendation system for more efficient individual mobility management [38], [39].

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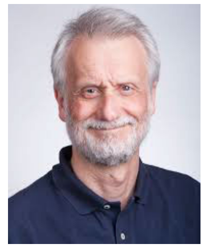

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