Mechanism design for Mobility-as-a-Service platform considering travelers’ strategic behavior and multidimensional requirements

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1 INTRODUCTION

Mobility-as-a-Service (MaaS) is an emerging transport model which provides access to any combination of travel modes through a single platform. A MaaS operator sits between travelers and TSPs, acting as a broker who purchases mobility resources from individual TSPs, constructs seamless transport services, then sells them to travelers in response to their demand. To ensure the sustainability of such platforms, the key challenge lies in matching travelers to TSPs so that travelers’ individual needs are satisfied, TSPs gain nonnegative profits and system efficiency is achieved. However, individual travelers’ travel requirements and valuations are not readily available and difficult to obtain. In this study, we develop an auction-based mobility resource allocation and pricing mechanism to elicit travelers’ true requirements and valuations, and solve this matching problem within the transport network context. The mechanism takes travelers’ strategic behavior into account and applies VCG-based pricing scheme to ensure incentive compatibility, individual rationality and system efficiency. We adopt a column-generation based solution algorithm to solve the offline (static) matching and pricing problem. For the online (dynamic) problem, we develop a dynamic learning algorithm to obtain near optimal solution and compare it to the classic greedy-based algorithm. The efficiency of the proposed mechanisms is tested through a case study.

2 METHODOLOGY

2.1 Offline auction mechanism with column generation

We start by formulating and solving the offline (static) mobility resource matching problem. Consider a multimodal network $G(\mathcal{N},\mathcal{L})$ operated by a MaaS platform where $\mathcal{N}$ denotes node set and $\mathcal{L}$ denotes mode-specific link set. Each link is associated with length $L_{ij}, \forall i,j \in \mathcal{N}, i \neq j$, travel time T_{ij}, capacity W_{ij}, the maximum number of riders sharing a vehicle on that link R_{ij} and operational cost C_{ij}. These links construct $\mathcal{K}$ multimodal paths with heterogeneous performance, measured by travel time T_k, operational cost C_k and weighted number of shared riders R_k, where T_k and C_k are the summation of T_{ij} and C_{ij} of all links on path k. R_k is the weighted average number of allowable shared riders of all links on path k. Let $\mathcal{S}$ denote the set of travelers who bid for mobility service. A bid from traveler s includes his or her origin O_s, destination D_s, requested travel time $\mathcal{T}_s$, preferred number of shared riders $\mathcal{R}_s$ and bidding price $\mathcal{B}_s$. Traveler's requested travel time and number of shared riders are regarded as soft constraints, which means violation on these requirements are allowed but will lead to a loss in the value they can obtain. The true valuation of traveler s towards path k can be calculated as:

$$V_{sk} = V_s - \gamma_s \max\{T_k - \mathcal{T}_s, 0\} - \beta_s \max\{R_k - \mathcal{R}_s, 0\} \qquad \forall s \in \mathcal{S}, k \in \mathcal{K} \tag{1}$$

where V_s is the true willingness-to-pay of traveler s and it equals to $\mathcal{B}_s$ only if traveler bids truthfully. γ_s and β_s represent the unit monetary penalty of traveler s due to late arrival and exceeding the preferred number of shared riders. Our goal is to maximize social welfare, defined as the total utility of all travelers and TSPs. Travelers' utility u_s equals to his or her true valuation obtained from traveling on the allocated path k minus the payment, denoted by p_s, i.e., $u_s = V_{sk} - p_s$. TSPs' utility equals the total payments received from travelers minus the total operational costs. The social welfare maximization problem is then formulated as follows:

$$\max_{x_{sk}} \sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} (V_{sk} - C_k) x_{sk} \tag{2}$$

subject to

$$\sum_{k\in\mathcal{K}} x_{sk} \le 1 \qquad \forall s \in \mathcal{S} \tag{3}$$

$$\sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}} x_{sk} \delta_{ij}^k \le W_{ij} R_{ij} \qquad \forall i, j \in \mathcal{N}, i \ne j \tag{4}$$

$$x_{sk} \in \{0,1\} \qquad \forall s \in \mathcal{S}, k \in \mathcal{K} \tag{5}$$

where $x_{sk} = 1$ if traveler s is assigned to path k. Note that path k is feasible for traveler s only if it is between O_s and D_s. Constraints (3) guarantee that each traveler can be allocated to at most one path. Constraints (4) ensure that the number of travelers on each link does not exceed the link capacity. Constraints (5) set the feasible domains of decision variables.

Considering that number of decision variables associated with paths are much larger than number of capacity constraints of links, we adopt column generation algorithm, which has been widely applied in solving combinatorial optimization problems (e.g., Akyüz, et al., 2016; Gendron, et al., 2014). The idea is to start by solving a linear restricted master problem (RMP) with only a subset of paths, then iteratively we find paths that have the potential to increase the objective function and add them to the network until no such paths exist. Finally, we conduct the branch-and-bound process to obtain the integer solution.

To determine the payment for each traveler, we have to ensure incentive compatibility and individual rationality, which means travelers bid truthfully and gain non-negative utility from using the MaaS service. We adopt the VCG-like payment rule:

$$p_s = Z_{X_{-s}^*} - \left(Z_{X_s^*} - v_s(X_s^*) \right) \qquad \forall s \in \mathcal{S} \tag{6}$$

where X_s^* and X_{-s}^* are optimal solutions to the social welfare maximization problem with and without the request of traveler s and $Z_{X_s^*}$ and $Z_{X_{-s}^*}$ denote corresponding social welfare. $v_s(X_s^*)$ is the valuation of traveler s obtained under solution X_s^*. Such payment rule prevents travelers from misreporting since the payment of traveler s does not depend on his or her reported bidding price.

2.2 Online auction mechanism with dynamic learning algorithm

When setting the problem in online (dynamic) scenario, column generation algorithm and VCG-like payment rule will take exponential time with the increase of travelers, and thus cannot give immediate response. To this end, we propose a dynamic learning algorithm to solve the online resource allocation problem, which is extended from a general version (Agrawal, et al., 2014). The idea is to use some initial inputs to solve a small-scale partial linear programing, obtain the optimal shadow (dual) price of mobility resources and treat that shadow price as a threshold price such that only travelers whose bids are above the threshold price will be accepted. The threshold price is updated continuously.

We assume travelers' arrival order follows the random permutation model, which lies between the worst case and a known distribution. We also need to know the total number of travelers a priori to decide the proper quantity of requests for learning threshold price. The competitive ratio of this algorithm is then theoretically proved. In general, we solve shadow price of each link from history bids and determine the allocation for future bids subject to capacity constraints. The payment of allocated traveler is the shadow price of the matched path, which equals to the summation of shadow prices of all link on that path.

2.3 Online auction mechanism with greedy algorithm

For comparison purpose, we propose another online algorithm based on the classic greedy algorithm. Greedy algorithm is a popular solution method to online (dynamic) resource allocation problems due its time efficiency and satisfactory competitive ratio (e.g., Zhang, et al., 2018). The basic idea is to rank travelers based on their bids and determine allocation according to this rank. Our ranking criteria is bid density ω_{sk}, defined to be the social welfare contributed by traveler s if he or she is allocated to path k divided by his or her integrated travel requirements.

In each time slot, the greedy algorithm first sorts requesting travelers according to their bid density in a non-ascending order. Then following this rank, the algorithm greedily processes travelers' requests considering the capacity constraint. Travelers' payment is calculated based on the critical bid density, defined to be the lower bound that the traveler's bid density must exceed to be accepted in the auction. Since this critical bid density is independent from the traveler's own bid information, such payment rule also guarantees truthfulness.

3 RESULTS

We demonstrate the performance of our proposed offline and online mechanisms using a numerical study on Sioux-Falls network as is shown in Figure 1. We assume there are three origins (O_1 to O_3) and seven destinations (D_1 to D_7) with two TSPs operating in this network: a ridesourcing company and an on-demand bus company.

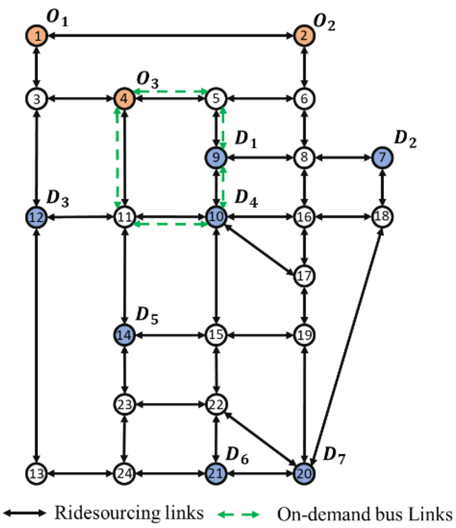

Figure 1 Sioux-Falls network

In the offline numerical experiment, we simulate 50 travelers requesting for mobility service from the MaaS platform. Our mechanism accepts 35 travelers' requests, achieving a matching rate of 70%. Incentive compatibility and individual rationality are confirmed in this case.

For the online case, we use the same network setting and set the total time span to be 120 minutes (which will be divided to 20 time slots for the greedy algorithm). We compare the performance of the proposed dynamic learning algorithm and the customized greedy algorithm to the first-arrive-first-serve (FAFS) matching rule, which simply assigns travelers based on their arriving order. The result obtained from the offline scenario is treated as benchmark to calculate two major metrics: ratio of social welfare (RSW) and ratio of matching rate (RMR). Both uniform and Poisson distributions are applied to generate the arrival order of travelers. Table 1 summarizes results of 50 generated instances with 800 travelers. As is shown, both greedy algorithm and dynamic learning algorithm can achieve high approximation ratios on social welfare and matching rate (above 0.85). In terms of RSW, dynamic learning algorithm performs the best in both uniform and Poisson distributions. Though it takes the longest computation time (CT), compared to the operation time span, it is acceptable for the online matching problem.

Table 1 Performance of Online Solution Algorithms with 800 Travelers

Arriving Distribution	Measure	Statistic	FAFS	Greedy Algorithm	Dynamic Learning Algorithm
Uniform	RSW	Mean (Std)	0.804(0.010)	0.875(0.012)	0.898(0.034)
	RMR	Mean (Std)	0.929(0.008)	0.856(0.008)	0.922(0.041)
	CT	Mean	266.757s	561.160s	979.782s
Poisson	RSW	Mean (Std)	0.807(0.013)	0.874(0.011)	0.900(0.036)
	RMR	Mean (Std)	0.927(0.009)	0.854(0.010)	0.925(0.038)
	CT	Mean	267.263s	554.440s	987.616s

We also tested other demand scenarios: 200, 400, 600, and 1000 travelers and found that no matter under which demand scenario, the dynamic learning algorithm always outperforms the other two algorithms, which demonstrates its robustness and effectiveness.

4 DISCUSSION

In this paper, we present an auction-based mobility resource allocation and pricing mechanism for the MaaS platform under transport network context. To provide seamless and personalized services for travelers, our proposed mechanisms allow travelers to report their multidimensional travel requirements (bidding price, travel time, preferred number of shared riders). All proposed offline and online mechanisms can ensure incentive compatibility and individual rationality of travelers, system efficiency and payment non-negativity of the platform.

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