Last-mile Collaboration: A Decentralized Mechanism with Performance Guarantees and its Implementation

Extended Abstract

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ABSTRACT

The last-mile urban freight market is characterised by soaring fragmentation, fierce competition and low profit margin. Horizontal collaboration could enable operators to exchange customers and coordinate routes, resulting in reduced costs and higher level of service. Previous research has focused on combinatorial auctions and scalable mechanisms are still limited. In this work, we propose an Iterative, Decentralized, and Auction-based Mechanism (IDAM) which is individually rational and budget balanced. It parallelizes several independent local auctions but still guarantees a bounded performance. When considering its best-case performance, IDAM could be as efficient as the centralized optimization while the worst-case performance depends on the fleet capacity and spatial distribution of customers. A case study of the Inner London Area, involving 50 companies and 1000 customers, showed that our approach achieves up to 76% cost savings.

KEYWORDS

Collaborative Vehicle Routing; Auction; Distributed Welfare Game; Price of Anarchy; Price of Stability

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1 INTRODUCTION

With the flourishing of e-commerce and home deliveries, there has been substantial growth in last-mile urban freight over recent years [6]. However, this growth is accompanied with the proliferation of logistic companies, causing additional fragmentation of the market, and fueling intense competition in the sector [5, 7]. Correspondingly, profit margins are extremely low so that operators struggle to survive, while the expectations of customers have increased [8]. Therefore, an efficient and fair collaboration framework could allow operators to remain competitive while providing satisfactorily level-of-service guarantees [19]. Combinatorial Auction (CA) techniques have been commonly used to coordinate decentralized decision makers [1, 4, 9, 11, 12]. However, they are known to incur significant computational challenges when seeking maximum profit gains, and are therefore limited to small and middle-scale instances. Since CA-based models allow companies to act as both buyers and sellers, existing mechanisms could provide allocations that violate the individually rationality requirement. Our work aims to address these gaps, by introducing a decentralized mechanisms that is individual rational, budget balanced and scalable to large-size instances.

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2 PROBLEM AND GAME FORMULATION

A Last-mile Collaboration Problem (LCP) comprises a set of logistics companies L and a set of customers O. Each company $l \in L$ possesses a set of depots D_l, a set of vehicles K_l and a set of customers O_l. One customer corresponds to a node on the urban network where a parcel must be delivered within a time window. Companies solve a vehicle routing problem [2] to plan vehicle routes, whose utility (revenue minus shipping cost) is denoted with $VRP(O_l, D_l, K_l) : O \times D \times K \to \mathbb{R}$, or simply $VRP_l(O_l)$ when the set of depots and vehicles are clear from the context. In the auction-based collaboration, companies retain some customers O_l^r while submitting the remaining $O_l^s = O_l \setminus O_l^r$ with reservation values $v_{l\omega}^r, \forall \omega \in O_l^s$ to an auctioneer, who determines the allocated customers O_l^a and the payment π_l to company $l \in L$, given its bids $b_{l\omega}, \forall \omega \in O_m^s, m \in L, m \neq l$. In this context, the utility received when participating in the auctions reads as $u_l = VRP_l(O_l^a \cup O_l^r) + \pi_l$. The objective of collaboration is to maximize the system-level profit $W = \sum_{l \in L} VRP_l(O_l^a \cup O_l^r)$.

We formulate the LCP as a special Distributed Welfare Game (DWG) [16], referred to as Freight Collaboration Game (FCG). A customer allocation in LCP corresponds to an action profile in FCG. As it is commonly assumed that a company values a customer by the marginal profit of including this customer into service [1, 9, 10], the FCG becomes a DWG with a marginal contribution protocol which is proven to be a potential game with potential function W [15, 16].

Definition 1 (Freight Collaboration Game). A freight collaboration game $G = (O, L, \{\mathcal{A}_\omega\}_{\omega \in O}, \{W_l\}_{l \in L}, \{f_l\}_{l \in L})$ consists of

- a set of players O and a set of resources L

- $\forall \omega \in O$, an action set $\mathcal{A}_\omega = \{a_\omega, a_\omega \in L\}$
- $\forall l \in L$, a local welfare function $W_l = VRP_l(O_l)$ where $O_l = \{\omega\}_{a_\omega = l}$ denotes the set of customers using the logistics company l.
- $\forall l \in L, \omega \in O_l$, a welfare sharing protocol or contribution protocol $f_l(\omega) = VRP_l(O_l) - VRP_l(O_l \setminus \{\omega\})$
- $\forall \omega \in O$, an utility $U_\omega = f_{a_\omega}(\omega)$

3 MODEL

In this section we formally introduce the IDAM, prove its termination, analyse its properties and quantify its performance bounds.

3.1 Iterative and Decentralized Auction-based Mechanism

IDAM is a repeated iteration of seven stages: submission, prebidding, platform select, company selection, bidding, allocation and payment. The execution of IDAM is as follows:

1. Initialize the allocated customer set $O_l^a := O_l^s, \forall l \in L$, cumulative payment $\pi_l := 0, \forall l \in L$, and $n_m, n_c, n_r := 1$.
2. (Submission Stage) Companies submit $\omega \in O_l^s$ to the platform with a reservation value $v_{l\omega}^r = VRP_l(O_l^a) - VRP_l(O_l^a \setminus \{\omega\})$.
3. (Pre-bidding Stage) The platform discloses all submitted customers and companies provide bids $b_{l\omega} = VRP_l(O_l^a \cup \{\omega\}) - VRP_l(O_l^a)$, which are estimated by insertion heuristics [3].
4. (Platform Selection Stage) For $\forall \omega \in O^s$, the platform calculates the potential profit increase $I_\omega = \max_{l \in L} b_{l\omega} - v_{m\omega}^r$, selects $n := \max(1, n_m(1 - n_r/n_c))$ customers with the highest I_ω from n different companies. These customers will be sold by n independent local auctions. The remaining customers are returned to the original owners.
5. (Company Selection Stage) Companies having customers selected become local auctioneers while others attend the local auction for which they provide their highest pre-bid.
6. (Bidding Stage) Companies recalculate their bids for the customer sold in the local auction by a more accurate method VRP'.
7. (Allocation Stage) Within a local auction managed by the company $m \in L$, the customer ω will be allocated to the bidder $l = \arg\max_{j \in L} b_{j\omega}$ if the highest bid $b_{l\omega}$ is higher than the reservation value $v_{m\omega}^r$. Otherwise, the customer is reserved by the auctioneer (company) m.
8. (Payment Stage) The winner l in a local auction pays $P_\omega = \max(\max_{i \in L, i \neq l} b_{i\omega}, v_{m\omega}^r)$ to the auctioneer (company) m.
9. Winners and corresponding auctioneers update their allocated customer sets O_l^a, submitted customer sets $O_l^s := O_l^s \cup O_l^a$ and cumulative payment π_l.
10. If there is no successful exchange and $n_r > n_c$, the iteration terminates. Otherwise, $n_r := n_r + 1$ and return to step 2.

3.2 IDAM Properties

THEOREM 1. *If companies truthfully bid their marginal profits, IDAM always terminates. The resulting customer allocation corresponds to an equilibrium of the corresponding FCG.*

PROOF. The reallocation of one customer from one company to another in the original LCP is effectively the change of a player's action in the corresponding FCG. After n_c iterations, only one customer will be reallocated to the company that provides the highest marginal profit if company bids truthfully. In the language of FCG, a player choose her best-response action. Therefore, IDAM simulates the best response dynamics and always terminates as any FCG is a potential game. Q.E.D.

THEOREM 2. *IDAM is individually rational and budget balanced.*

PROOF. IDAM requires that a company can only be either a bidder or a local auctioneer and that if the highest bid is lower than reservation value, the local auctioneer will reserve this customer. Consequently, one company will either win a profitable customer or receive his originally submitted customers. Therefore, companies (both bidders and local auctioneers) are incentivised in participating in the mechanism. Q.E.D.

3.3 Performance Guarantees

Price of Anarchy (PoA) and Price of Stability (PoS) are two common metrics for quantifying the efficiency of equilibria [13, 20]. The PoA measures the performance of the worst equilibrium against an allocation that maximizes W, while the PoS measures this ratio for the best-performing equilibrium. As IDAM terminates at an equilibrium of FCG, the PoA and PoS of FCG reveal the theoretic performance bounds of IDAM.

THEOREM 3. *For any FCG $G \in \mathcal{G}$, $PoS(G) = 1$.*

THEOREM 4. *When only travel cost is considered, for any FCG $G \in \mathcal{G}$*

$$PoA(G) \leq \frac{(|O| + |K|)c^{max}}{(|O| + |K|^{min})c^{min}} \quad (1)$$

where $|O|$ and $|K|$ are the total number of customers and vehicles respectively. $|K|^{min}$ is the minimum number of vehicles required to satisfies all customers. c^{max} (c^{min}) is the maximum (minimum) travel cost among all links $(i, j), i, j \in O \cup D$.

PROOF. As the potential function of FCG is W, any allocation maximising W is an equilibrium and therefore the PoS is 1. It can be observed that any feasible route plan using k vehicles requires travelling $k+|O|$ links. Accordingly, $|O|+|K|)c^{max}$ and $|O|+|K|^{min})c^{min}$ denotes the highest and lowest travel cost respectively. Then the PoA should be less than the ratio of these two values. In the instances of 2 customers, 2 companies and 1 shared depot, the PoA equals this ratio if customers and the depot are located at the vertices of an equilateral triangle. Q.E.D.

4 EXPERIMENTAL RESULTS

IDAM is validated on several LCP instances generated from a synthetic population of the Inner London Area (detailed information available at https://github.com/keyang-zhang/cvrp-data) [14, 17, 18]. As shown in Table 1, IDAM scales well with problem sizes and can achieve up to 76% cost savings.

Table 1: Results of large-scale instances (Total Travel Cost)

Instance	Companies	Customers	Do Nothing	IDAM	Cost Saving
P-400-20	20	400	8.50	3.20	62.35%
P-600-30	30	600	11.95	3.57	70.13%
P-800-40	40	800	14.00	3.84	72.58%
P-1000-50	50	1000	17.74	4.12	76.78%

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