https://doi.org/10.1016/j.tra.2020.11.010

Shared mobility oriented open vehicle routing with order radius decision

Lu Zhen [1], Zheyi Tan [1*], Shuaian Wang[2], Wen Yi [3], Junyan Lyu [1]

[1] *School of Management, Shanghai University, Shanghai, China*

[2] *Department of Logistics and Maritime Studies, The Hong Kong Polytechnic University, Kowloon, Hong Kong*

[3] *School of Built Environment, College of Sciences, Massey University, Auckland, New Zealand*

Abstract: In the era of sharing economy and the mobility-as-service, the last mile delivery system is undergoing revolutionary changes with emerging a lot of new operation modes and policies. The crowdsourced delivery mode has become a novel and popular practice in the last mile delivery industry. This mode brings a novel way for facilitating the efficiency of last mile delivery on the basis of the shared mobility. This paper studies an open vehicle routing problem (OVRP) for the shared mobility based last mile delivery mode, in which parcel delivery orders are disseminated within a circle to attract occasional vehicles (or couriers) to fulfill these orders. Different from the traditional OVRP, this study further considers the decision of the above mentioned circle's radius, which should be balanced between attracting enough vehicles and reducing additional cost (reward) for covering vehicles' empty trips to the pickup location. This paper proposes a nonlinear mixed-integer programming model for the problem. A column generation based solution method is implemented to solve the model. Some numerical experiments are also conducted to validate the efficiency of the solution method and draw out some managerial implications for the practitioners. The proposed methodology in this paper may be potentially benefit not only for reducing the last mile delivery cost but also for promoting the modern transportation paradigm revolution to ridesharing and mobility-as-service.

Keywords: Shared mobility; Emerging delivery mode; Open vehicle routing problem; Order dissemination radius; Column generation.

[*] Corresponding author. Email: zytan_shu@163.com; Tel: +86-21-66137925; Fax: +86-21-66134284.

1.Introduction

The last-mile delivery as a critical part in logistics has attracted more and more attention in both the academia and practitioners. With the rapid increase of sales in online shopping, logistics service providers especially parcel delivery companies are undergoing great pressure to operate their last-mile delivery activities. For facilitating the operations of the last-mile delivery, some new ways have been implemented or invented, for example, shared mobility, express delivery cabinets, self-built community convenience stores, drone based delivery, express robots, and so on (Li et al., 2019). Among them, the shared mobility (delivery by using social logistics) based on MassS (mobility as a service) may be one of the most efficient and cost-saving ways for parcel delivery companies to implement in reality, especially during the era of sharing economy (Alonso-González et al., 2020; Benjaafar and Hu, 2020). It is not only a business mode innovation benefit for parcel delivery companies but also could reduce the social cost and increase welfare for society (Hyland and Mahmassani, 2020; Gao et al., 2020)

When a parcel delivery company does not possess the own dedicated fleet, or the vehicle quantity is insufficient, for the sake of satisfying the customer demands, the company is bound to gain available vehicles for hiring. Due to the mode of one-way car-sharing, the sharing vehicles do not necessarily go back to the depot after completing the service, therefore, the vehicles routes are open (Mounce and Nelson, 2019). Therefore, for the last-mile delivery based on the shared mobility, the scheduling of the occasional vehicles (or couriers) is an open vehicle routing problem (OVRP) in nature. Compared to the traditional vehicle routing problem (VRP), vehicles in the OVRP are not required to return to the depot after finishing their delivery tasks.

Although the OVRP as well as its variants have been well investigated in literature, an important issue on attracting occasional vehicles (or couriers) is usually neglected. More specifically, given a batch of customer orders (delivery tasks) that are assigned to occasional vehicles, a parcel delivery company needs disseminate these orders in a circle area and attract enough vehicles to grab the orders; the circle's center is the depot where the delivered goods are picked up by the occasional vehicles. As the usual practice, a vehicle is paid according to its laden trip length, i.e., the route length of the order that the vehicle fulfills. However, for the empty trip of a vehicle from its original location to the depot where the goods are picked up, it also needs to be considered and given some reward otherwise the vehicle is not willing to travel if the empty trip is long and the laden trip is short. Due to interest of the easy management, the additional reward for covering the vehicles' empty trip cost is usually identical for all the vehicles involved in the fulfillment of the batch of orders. The identical reward should be determined according to the longest empty trip among all the vehicles; it is related to the radius (denoted by r) of the circle, in which the orders are disseminated. In this case, each vehicle inside the circle with the radius r could be attracted to fulfill an order because the reward is no less than the cost of its empty trips. Based on the above analysis, we can see that the order dissemination radius determines the additional reward, and further affects the total cost for fulfilling all the orders. In addition, it is easy to understand that the decision of the radius also influences whether enough vehicles could be attracted to fulfill the orders. Therefore, the OVRP should be combined with the decision on the order dissemination radius so as to fit the realistic environment of last mile delivery based on the shared mobility. A simple example is illustrated in Figure 1 to explain the above problem context.

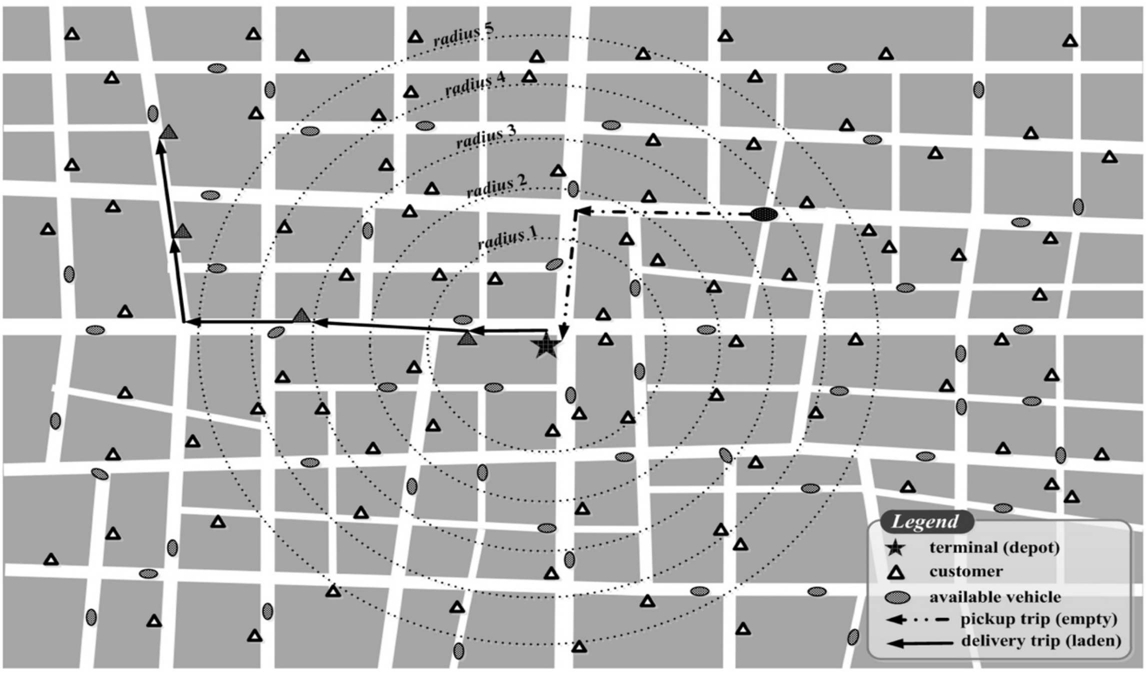

Figure 1: An illustration of OVRP with order dissemination circles

This paper conducts an exploratory study on this OVRP considering the order dissemination radius. The objective of the new problem studied in this paper is to minimize the total cost of fulfilling a batch of customer orders. A nonlinear mixed-integer programming (MIP) model is constructed. Then we linearize it and propose a column generation (CG) based solution method to solve the model. Efficiency of the algorithm and the effectiveness of the model are validated by some numerical experiments. The proposed model as well as the algorithm could pave the way for developing some decision support systems for facilitating the goal of smart mobility (Ho et al., 2020).

The remainder of this paper is organized as follows. Section 2 reviews the related works. Section 3 describes the problem background. Section 4 presents the model and its linearization. Section 5 elaborates a CG based solution method. Section 6 reports numerical experiment results. The conclusions are then outlined in the last section.

2.Literature review

This study is related to the shared mobility and the OVRP. Thus the related works are reviewed mainly through the above mentioned two streams.

Shared mobility is a hot topic in the fields of operations research (OR) during recent years. Two main directions related to shared mobility are ride sharing and vehicle sharing (Wei et al. 2018). The first concept “ride sharing” means individuals share their vehicles for others with the same trip; and the costs such as fuel, toll, and parking fees are also shared with others (Wang and Qu 2017; Wang et al. 2018). Ride sharing is not only beneficial for participants, which saves transportation cost, but also beneficial to environment, which reduces the pollution (Xiang et al. 2008). For a comprehensive overview on ride sharing, see the review work provided by Cordeau et al. (2007) and Doerner et al. (2014). Here some recent works on ride sharing are elaborated. Qu and Bard (2015) designed an exact algorithm based on branch-and-price-and-cut (B&P&C) for solving a new variant of ride sharing problem, which considers time windows, heterogeneous vehicle fleet and demand. Cachon et al. (2017) investigated several pricing schemes for ride sharing platform; their research results validated that welfare of providers and consumers could be improved and generally achieved near optimal welfare. Wang et al. (2018a) proposed some integer programming models to generate near stable matches between riders and drivers for system-wide performance improvement. Timo and Michael (2019) designed an adaptive large neighborhood search (ALNS) algorithm for solving a dial-a-ride problem considering vehicle capacity, time windows, maximum route duration, and maximum user ride times. Besides ride sharing, the concept "vehicle sharing" has also been well studied. Vehicle sharing means people access the available vehicles without ownership for temporary usage. He et al. (2017) studied a service region design problem for free-float electric vehicles sharing systems; they investigated a lower bound on the expected profit for the problem. He et al. (2019) further used the distributional robust optimization (DRO) methodology to study a fleet repositioning problem for a free-float vehicle sharing system with minimizing the total cost of repositioning and lost sales.

As aforementioned in the introduction, the studied problem in this paper belongs to variants of the OVRP, which has been widely investigated in recent years. For solving the OVRPs, scholars have developed various algorithms such as the tabu search algorithm (Brandão 2004), the ant colony optimization (ACO) algorithm (Li et al. 2009), the variable neighborhood search (VNS) algorithm (Krzysztof et al. 2009), the particle swarm optimization (PSO) algorithm (MirHassani et al. 2011), the tailored iterated local search algorithm (Atefi et al. 2018). The OVRP also has some variants such as OVRP with capacity constraint (COVRP), OVRP with time window (OVRPTW) and OVRP with multiple depots (MDOVRP). Sariklis and Powell (2000) proposed a two-stage algorithm for the COVRP. Brando (2001) proposed genetic algorithm (GA) and Letchford (2006) presented branch and cut (B&C) to solve the COVRP. For the OVRPTW, Repoussis et al. (2007) proposed a greedy look-ahead route construction heuristic. Brandão (2018) developed an iterated local search algorithm for the OVRPTW. Niu et al. (2018) further considered some environmental friendly issue and proposed a green OVRPTW, for which a tabu search based heuristic was developed. For the third type of variant, i.e., the MDOVRP, Tarantilis and Kiranoudis (2002) designed a list-based threshold accepting algorithm. Liu et al. (2014) conducted a hybrid GA to derive the routes with minimizing the traveling cost of the vehicles for the MDOVRP. Based on the previous study, Lalla-Ruiz et al. (2016) constructed a new MIP model to improve the performance of solving the problem. Soto et al. (2017) developed a general multiple neighborhood search hybridized with a tabu search (MNS-TS) strategy which was proved to be efficient for the MDOVRP. In this paper, we also settled a unified view of ejection chains for constructing several neighborhoods in a simple but efficient manner. A brief summary on the algorithms used for solving OVRP variants is shown in Table 1.

Although the shared mobility and the OVRP have been well studied in recent years, this study differs from these related works significantly. First, this study further considers the decision of the order dissemination radius, which influences attracting enough vehicles to fulfill the delivery orders. Second, a new algorithm based on CG is developed for solving the new OVRP variant. This study may contribute to the literature on the share mobility oriented OR studies and OVRP studies.

Table 1: Brief summary of algorithms for OVRP variants in recent years

Algorithms	**Problems**	**Other issues**	**Related works**
ACO	OVRP	——	Li et al. (2009)
VNS	OVRP	——	Krzysztof et al. (2009)
PSO	OVRP	——	MirHassani et al. (2011)
local search	OVRPTW	——	Atefi et al. (2015)
tabu search	OVRPTW	low carbon	Niu et al. (2018)
list-based threshold heuristic	MDOVRP	——	Tarantilis and Kiranoudis (2002)
hybrid GA	MDOVRP	——	Liu et al. (2014)
MNS-TS	MDOVRP	——	Soto et al. (2017)
two-stage heuristic	COVRP	penalties	Sariklis and Powell (2000)
branch and cut	COVRP	——	Letchford et al. (2006)

3.Problem description

There is a logistics company who utilizes public shared vehicles to deliver goods from a depot to customers within a service region. The shared vehicles are evenly and randomly distributed in the region. The company disseminates the customers' delivery orders to the available vehicles located in a circle with the depot as the center and a radius r. The vehicles in the circle have the opportunity to take the order and fulfill the delivery tasks. The planning of these used vehicles' routes for fulfilling the tasks from the depot to distributed customers belongs to a classic VRP variant – the OVRP, in which vehicles need not return to depot. However, the problem studied in this paper differs from the OVRP in the "order dissemination", in which vehicles are attracted to take the orders; because the company usually needs to pay additional reward to vehicles for their empty trips from their locations to the depot besides paying the fee according to the laden trips' length. Without paying the additional reward, the company may not attract enough vehicles to undertake the batch of orders.

As aforementioned, the total fee for the vehicles' laden trips is considered by the VRPs including the OVRP; but the additional reward, which is usually ignored in the VRPs, is related to the radius r of the order dissemination circle. The larger is the radius r, more vehicles could be attracted, and then more reward should be paid by the company for the vehicles. According to the usual practice of the crowdsourced logistics service platforms, the reward to the vehicles in the circle is identical no matter their distance from the depot for the interest of the simple management and fairness. Another reason for the identical reward is that if a crowdsourced logistics service platform gives the additional award to occasional drivers based on their empty trips' length, it may attract some drivers who are very far way from the depot, which is not only uneconomical for the platform but also cause a waste of social labor resource. A driver travels a long distance of empty-trip, but may just fulfill a laden trip with relatively short distance, which is actually a waste of social labor resource. In addition, the identical reward is also convenient for the platform to manage the fulfillment process of the batch of tasks, edit the task message disseminated to the drivers within a certain circle. Given a batch of delivery tasks that the platform needs to arrange immediately, an identical message could be formed swiftly and disseminated to drivers. The identical message just contains the identical information on the depot's location and the additional reward besides the payment for drivers' actual fulfilled delivery trips, which depends on the laden trips' length as usual practice. It should be noted that this study assumes the occasional vehicles inside the order dissemination circle will not be attracted by some other unforeseen orders once they have accepted fulfilling delivery tasks. The uncertainty issue is not considered in this study; while, more challenging issues will be brought in by the uncertainty issue (Zhen, 2015).

This study aims at designing a mathematical model embedded in a decision support system that helps the platform determine the radius of the order dissemination and the tasks for each drivers. The objective of the mathematical model proposed in this study contains one part on the total travelling distance considered in VRPs and the other part related to the multiplication of the number of used vehicles and the radius r. Based on the above analysis, it is obvious that the radius r is an important decision variable, which affects the number of used vehicles in the OVRP and the cost of attracting them. For the interest of simplicity on model formulation, the radius variable is discretized into a set of values $r \in R$. The R is the set of possible radiuses chosen for order message dissemination.

A simple example with five possible radiuses of order dissemination is illustrated in Figure 1 to explain the above problem context. The fulfillment process of a vehicle is also illustrated in Figure 1, in which a dark ellipse denotes the vehicle, solid line and dashed line denote the vehicle's laden and empty trips, respectively.

4. Model formulation

In this section, a MIP model for the problem is constructed. Some nonlinear forms are also linearized. This model is the basis for the further investigations.

4.1 Notations

Before presenting the model, notations on parameters and variables used in the model are listed as follows. For the convenience of understanding the notations, we use Roman letters and Greek letters to denote the parameters (indices, sets) and the decision variables respectively.

Indices and sets:

R set of radiuses, indexed by r. Customer orders are disseminated to the available vehicles in a circle with radius as r.

K set of available vehicles, indexed by k.

N set of customers, indexed by i, j; $N = \{1,2,\cdots,n\}$.

N^0 set of customers and the depot "0"; $N^0 = N \cup \{0\}$.

N^+ set of customers and the virtual destination "$n+1$"; $N^+ = N \cup \{n+1\}$. The virtual destination is used for flow conservation in a vehicle's route.

Parameters:

Q capacity of each vehicle.

$o_{k,r}$ binary, equals one if vehicle k is in the order dissemination radius r, and zero otherwise.

$l_{i,j}$ distance between customer i and customer j.

Decision variables:

ε integer, chosen radius of the order dissemination circle.

α_k binary, equals one if vehicle k is used, and zero otherwise.

$\beta_{i,j,k}$ binary, equals one if vehicle k visits node j immediately after node i, and zero otherwise.

4.2 Mathematical model

Based on the above definition, a MIP model on OVRP with deciding order dissemination radius is formulated as follows.

$$Minimize \quad \varepsilon \sum_{k\in K} \alpha_k + \sum_{k\in K} \sum_{i\in N^0} \sum_{j\in N^+} l_{i,j}\beta_{i,j,k} \tag{1}$$

Subject to:

$\sum_{j \in N} \beta_{0,j,k} = \alpha_k$ $\forall k \in K$ (2)

$\sum_{i \in N} \beta_{i,N+1,k} = \alpha_k$ $\forall k \in K$ (3)

$\sum_{i \in N^0} \sum_{j \in N} \beta_{i,j,k} \leq Q$ $\forall k \in K$ (4)

$\sum_{i \in N^0} \beta_{i,j,k} = \sum_{i \in N^+} \beta_{j,i,k}$ $\forall j \in N, \forall k \in K$ (5)

$\sum_{k \in K} \sum_{j \in N^+} \beta_{i,j,k} = 1$ $\forall i \in N$ (6)

$\alpha_k \leq o_{k,\varepsilon}$ $\forall k \in K$ (7)

$\beta_{i,j,k} \leq \alpha_k$ $\forall i \in N^0, \forall j \in N, \forall k \in K$ (8)

$\beta_{i,j,k} + \beta_{j,i,k} \leq 1$ $\forall i \in N^0, \forall j \in N^+, \forall k \in K$

(9)

$\sum_{i \in M} \sum_{j \in M} \beta_{i,j,k} \leq |M| - 1$ $M \subseteq N, 2 \leq |M| \leq |N|, \forall k \in K$ (10)

$\sum_{i \in N^0} \sum_{j \in N^+} l_{i,j} \beta_{i,j,k} \geq \sum_{i \in N^0} \sum_{j \in N^+} l_{i,j} \beta_{i,j,s}$ $\forall k, s \in K, k < s$

(11)

$\alpha_k \in \{0,1\}$ $\forall k \in K$ (12)

$\beta_{i,j,k} \in \{0,1\}$ $\forall i \in N^0, \forall j \in N^+, \forall k \in K$ (13)

$\varepsilon \in R$ (14)

The objective function (1) minimizes the total travel distance of vehicles, which includes two parts. The first part is about the additional cost (reward) for attracting enough vehicles to fulfill the orders; it is related to the pickup distance (empty trips) which depends on the chosen radius. The second part is about the cost for delivery which is the sum of all vehicles' laden trips' distance from the depot to orders' destinations. For the interest of simplicity, we sum up the above two parts directly by assuming the unit cost is identical for both the empty trip and the laden trip. If the unit costs (fees) for the two parts are not identical in reality, we just need define two more unit cost parameters for each part. However, this does not change the structure (and the complexity) of the model. Constraints (2) and (3) guarantee that each vehicle must depart from the depot if it is used and finish the process at a virtual point. The distance from any node to a virtual point is zero. Constraints (4) ensure that the number of customers served by each vehicle cannot exceed its capability limit. Constraints (5) are flow conservation constraint to make sure each customer only has one predecessor and one successor. Constraints (6) confirm that each customer is visited exactly once by one vehicle over the whole process. Constraints (7) illustrate that the used vehicles are in the circle with the chosen radius. Constraints (8) and (9) link two variables related to the usage of a vehicle and visiting sequence of the vehicle. Constraints (10) are utilized to eliminate subtours. Constraints (11) are to refrain from the symmetry generated by the homogenous vehicles which is achieved by matching long routes with small index vehicles that arrive early. On one hand, it can guarantee that long-distance customers can acquire service in a relatively short time. At the same time, the total distance and the consumed time of each driver are roughly balanced. On the other hand, it also provides an effective incentive mechanism for drivers to get to the depot more quickly after receiving orders, so as to deliver cargo to customers. Constraints (12)~(14) define the domain of decision variables.

4.3 Linearization

The first part of objective (1), i.e., $\varepsilon \sum_{k\in K} \alpha_k$, is nonlinear. Therefore, we define a binary variable δ_r to replace the primal variable ε. δ_r equals one if ε is r, and zero otherwise. Two more constraints are defined as follows:

$$\sum_{r\in R} r\delta_r = \varepsilon \tag{15}$$

$$\sum_{r\in R} \delta_r = 1 \tag{16}$$

Then, we define another binary variable $\xi_{k,r}$ to denote the product of α_k and δ_r; $\xi_{k,r}$ equals one if the vehicle k is used and the radius is r, and zero otherwise. The nonlinear part "$\varepsilon \sum_{k\in K} \alpha_k$" in the objective is replaced by "$\sum_{r\in R} \sum_{k\in K} r\xi_{k,r}$". And three more constraints are added as follow:

$$\xi_{k,r} \geq \alpha_k + \delta_r - 1 \qquad \forall k \in K, \forall r \in R \tag{17}$$

$$\xi_{k,r} \leq \alpha_k \qquad \forall k \in K, \forall r \in R$$

(18)

$$\xi_{k,r} \leq \delta_r \qquad \forall k \in K, \forall r \in R \qquad (19)$$

In addition, constraints (7) are also nonlinear because the variable ε is in the subscript of $o_{k,\varepsilon}$. The constraint is replaced by the following constraint.

$$\sum_{k \in K} \alpha_k \leq \sum_{k \in K} \sum_{r \in R} o_{k,r} \delta_r \qquad (20)$$

$$\alpha_k \leq \sum_{r \in R} o_{k,r} \delta_r \qquad \forall k \in K \qquad (21)$$

Eventually, the linearized model is:

$$\textit{Minimize} \ \sum_{r \in R} \sum_{k \in K} r \xi_{k,r} + \sum_{k \in K} \sum_{i \in N^0} \sum_{j \in N^+} l_{i,j} \beta_{i,j,k} \qquad (22)$$

Subject to: Constraints (2)~(6); (8)~(21).

5. CG based heuristics solution method

Commercial solvers such as CPLEX can hardly solve the above MIP model for large-scale problem instances. Thus this study should develop some algorithm to solve it. From the perspective of algorithm design, heuristics can obtain solution in a short time with less precision; while exact algorithms can obtain precise solutions with a relatively long time. According to the usual practice of algorithm design for solving large-scale MIPs, the CG is a suitable methodology that could solve better solutions than heuristics and use less time than exact algorithms (Wang et al., 2018b; Zhen, 2016; Zhen et al., 2017; Zhen et al., 2018). Therefore, this study employs the CG as the methodology to design an algorithm to solve the new OVRP studied in this paper, which may contribute to the related works on the algorithms for OVRP variants.

5.1 Weighted set cover master problem

According to the usual practice of the CG, this section reformulates the problem as a master problem (MP) model first by Dantzig-Wolfe decomposition. We define $\mathcal{P}_k$ as the set of all routing plans for vehicle k, $k \in K$; each routing plan for vehicle k in set $\mathcal{P}_k$ is indexed by p_k; a binary decision variable λ_{p_k} is defined for each feasible routing plan, $k \in K$, $p_k \in \mathcal{P}_k$. When plan p_k

is chosen for vehicle k, λ_{p_k} equals one, otherwise zero. A binary parameter z_{i,p_k} is defined to denote whether customer i is served by plan p_k. Total costs of each plan p_k are denoted by C_{p_k}. Based on the above definition, the MP model is formulated as follows.

[**MP**] *Minimize* $\sum_{k \in K} \sum_{p_k \in \mathcal{P}_k} C_{p_k} \lambda_{p_k}$ (23)

Subject to:

$\sum_{k \in K} \sum_{p_k \in \mathcal{P}_k} z_{i,p_k} \lambda_{p_k} = 1$ $\forall i \in N$ (24)

$\sum_{p_k \in \mathcal{P}_k} \lambda_{p_k} = 1$ $\forall k \in K$ (25)

$\lambda_{p_k} \in \{0,1\}$ $\forall k \in K, \forall p_k \in \mathcal{P}_k$ (26)

Objective (23) minimizes the total costs of routing plans. Constraints (24) guarantee each customer is served by only one vehicle. Constraints (25) indicate that each vehicle has only one routing plan. Constraints (26) define decision variables.

In order to reduce the solution space and solving time, a subset of all feasible routing plans is defined to build a restricted master problem (RMP) in the CG procedure. The subset is denoted by $\mathcal{P}'_k \subseteq \mathcal{P}_k$. It should be noted that there is at least one feasible solution that should exist in the RMP. The initial feasible solution for the RMP could be constructed according to a greedy heuristic, which obtains a set of feasible assignment plans. In the heuristic, a pick-up order is greedily assigned to the closest vehicle first. Last but not the least, the RMP should be relaxed to a linear programming model by replacing the integrality constraints (26) by $\lambda_{p_k} \geq 0, \forall k \in K, \forall p_k \in \mathcal{P}'_k$. The linear relaxed model of RMP (LR-RMP) is formulated as follows.

[**LR-RMP**] *Minimize* $\sum_{k \in K} \sum_{p_k \in \mathcal{P}'_k} C_{p_k} \lambda_{p_k}$ (27)

Subject to:

$\sum_{k \in K} \sum_{p_k \in \mathcal{P}'_k} z_{i,p_k} \lambda_{p_k} = 1$ $\forall i \in N$ (28)

$\sum_{p_k \in \mathcal{P}'_k} \lambda_{p_k} = 1$ $\forall k \in K$ (29)

$\lambda_{p_k} \geq 0$ $\forall k \in K, \forall p_k \in \mathcal{P}'_k$ (30)

In each iteration of the algorithm, the dual variables of the LR-RMP are added into the pricing problem (PP) as input parameters so as to generate a new feasible routing plan. The dual variables π_i and φ_k are defined to denote the dual variables corresponding to Constraints (28) and (29), respectively.

5.2 Pricing problems

The purpose of PP is to generate columns with the negative reduced cost and then add them into the RMP. In each iteration of the CG procedure, there are $|K|$ number of PPs to be solved; each PP derives one plan for each vehicle in each iteration. Then we select plans and assemble a whole solution with $|K|$ vehicles' plans so as to obtain the optimal one with the minimal total cost. Each PP is related to a vehicle k and generates a feasible routing plan for the vehicle. The PP model for each vehicle k (denoted as PP_k) is defined as follows.

Decision variables in PP_k:

$\beta_{i,j}$ binary, equals one if vehicle k visits node j immediately after node i, and zero otherwise.

α binary, equals one if vehicle k is used, and zero otherwise.

σ_r binary, equals one if vehicle k is used and the radius is r, and zero otherwise.

ϑ Integer, the additional cost (reward) for attracting enough vehicles to fulfill the orders

[PP_k] *Minimize* $\sigma_k = C_{p_k} - \sum_{i\in N}\tau_i \sum_{j\in N^+}\beta_{i,j} - \varphi_k$ (31)

Subject to:

$$\sum_{j\in N}\beta_{0,j} = \alpha \quad (32)$$

$$\sum_{i\in N}\beta_{i,N+1} = \alpha \quad (33)$$

$$\sum_{i\epsilon N^0}\sum_{j\epsilon N}\beta_{i,j} \le Q \quad (34)$$

$$\sum_{i\epsilon N^0}\beta_{i,j} = \sum_{i\epsilon N^+}\beta_{j,i} \qquad \forall j \in N \quad (35)$$

$$\beta_{i,j} \le \alpha \qquad \forall i \in N^0, \forall j \in N^+ \quad (36)$$

$$\beta_{i,j} + \beta_{j,i} \le 1 \qquad \forall i \in N^0, \forall j \in N^+ \quad (37)$$

$$\sum_{i\epsilon M}\sum_{j\epsilon M}\beta_{i,j} \le |M| - 1 \qquad M \subseteq N, 2 \le |M| \le |N| \quad (38)$$

$$\max_{r\in R}\{\sigma_r\} \geq \alpha \quad (39)$$

$$r \leq \vartheta + M(1-\sigma_r) \qquad \forall r \in R \quad (40)$$

$$\sigma_r \leq o_{k,r}\alpha \qquad \forall r \in R \quad (41)$$

$$C_{p_k} = \sum_{i\in N^0}\sum_{j\in N^+} l_{i,j}\beta_{i,j} + \vartheta \quad (42)$$

$$\beta_{i,j} \in \{0,1\} \qquad \forall i \in N^0, \forall j \in N^+ \quad (43)$$

$$\alpha \in \{0,1\} \quad (44)$$

$$\sigma_r \in \{0,1\} \qquad \forall r \in R \quad (45)$$

$$\vartheta \in N \quad (46)$$

The objective (31) minimizes the reduced cost. Constraints (32)~(38) correspond to Constraints (2)~(5) and (8)~(10), respectively. Constraints (39)~(41) ensure the relationship among $\alpha, \sigma_r, \vartheta$. Constraints (42) represents the calculation of the cost of a column, which is the sum of the vehicle's delivery cost and the minimum possible pickup cost. Here the minimum possible pickup cost is some sort of additional cost (reward) for attracting enough vehicles to fulfill the orders. Constraints (43)~(46) define the decision variables.

It should be noted that the CG based method is a heuristic which cannot guarantee to obtain an optimal solution. The RMP as well as PPs does not correspond to the original model proposed in Section 4 precisely. The reason lies in that the part "$\varepsilon \sum_{k\in K} \alpha_k$" in Objective (1) is hardly decomposable into individual columns. More specifically, the combination of the parts "ϑ" in Constraints (42) does not match the above mentioned part "$\varepsilon \sum_{k\in K} \alpha_k$" precisely. Therefore, the proposed solution method in this study needs to recalculate the final objective value based on the solution provided by the traditional CG procedure according to Objective (1); the final objective value cannot be calculated by summing up all the selected columns' costs. As the traditional CG method is naturally a heuristic rather than an exact solution method, the above handling tactics may be applicable in the design of a heuristic solution method for the problem in this study.

5.3 Procedure of CG based solution method

This section elaborates the framework of our proposed CG-based solution method. The outer procedure is the selection heuristic used to obtain an integer solution, i.e., the binary solution on selecting columns. The inner procedure is the CG procedure for generating columns. Before elaborating on the algorithm, we define three sets: the unserved customer set Ω_1, the unused vehicles set Ω_2 and Θ_0 column pool.

Step 0. Initialize an unserved customer list Ω_1 for the N. Initialize a vehicle waiting list, which includes all of the vehicle that have not been designated with an assignment plan p_k, that is Ω_2 for the K.

Step 1. Execute the CG procedure of generating columns.

Sub-step 1.0. Run a greedy heuristic to obtain a set of feasible assignment plans. In the heuristic, a pick-up order is greedily assigned to the closest vehicle first. Then, input the initial set to the LR-RMP formulated in Section 5.1.

Sub-step 1.1. Solve the LR-RMP by solver (e.g., CPLEX) and acquire a dual vector π_i and φ_k.

Sub-step 1.2. Input the dual vector to the PP_k and solve it to obtain the optimal assignment plan for each vehicle $k \in K$. The $|K|$ pricing problem models are solved in a parallel way; each model corresponds to one vehicle.

Sub-step 1.3. Add the optimal assignment plans with negative reduced cost to the LR-RMP. If all assignment plans have a non-negative reduced cost, cease the CG procedure; otherwise, go to *Sub-step 1.1*.

Step 2. When the CG procedure ends, an LP solution is obtained by solving the LR-RMP. Update column pool Θ_0 with assignment plans whose corresponding decision variables λ_{p_k} are not equal to zero.

Step 3. Check whether the assignment plans in the column pool Θ_0 satisfy Constraints (28)~(29) with the current LR-RMP. If not, delete these assignment plans.

Step 4. Test whether the column pool Θ_0 contains elements. If $\Theta_0 \neq \emptyset$, select one assignment plan p_k from Θ_0 based on the selection strategy below and update the unserved customer set Ω_1, the unused vehicles set Ω_2; otherwise, go to *Step 6*.

Selection strategy: Select from the column pool Θ_0 the assignment plan corresponding to the largest fractional value of the decision variables λ_{p_k}. If there are two assignment plans with the same fractional value, select the one with the lower cost of plan. The principle behind this strategy is that the assignment plan with the highest fractional value is more likely to be part of an optimal solution.

Step 5. Update LR-RMP based on Ω_1 and Ω_2, only for unserved customers and vehicles not used. Go to *Step 2*.

Step 6. Test whether unserved customer list Ω_1 contains elements. If $\Omega_1 \neq \emptyset$, Update LR-RMP based on Ω_1 and Ω_2 and go to *Step 1*; otherwise, calculate objective value F_{CG} based on equation (22). It should be noted that as the objective of the RMP is a bit different from the original model, thus the final objective value F_{CG} is calculated according to the original model's objective, i.e., equation (22); the calculation is based on the solution provided by the CG solution method. In addition, the decision on the radius of the order dissemination is also determined on the basis of the solution provided by the CG solution method rather than being outputted directly by the CG method. At the end of the algorithm, an integer solution and objective value F_{CG} for the problem is outputted.

The flowchart of the above procedure is demonstrated in Figure 2.

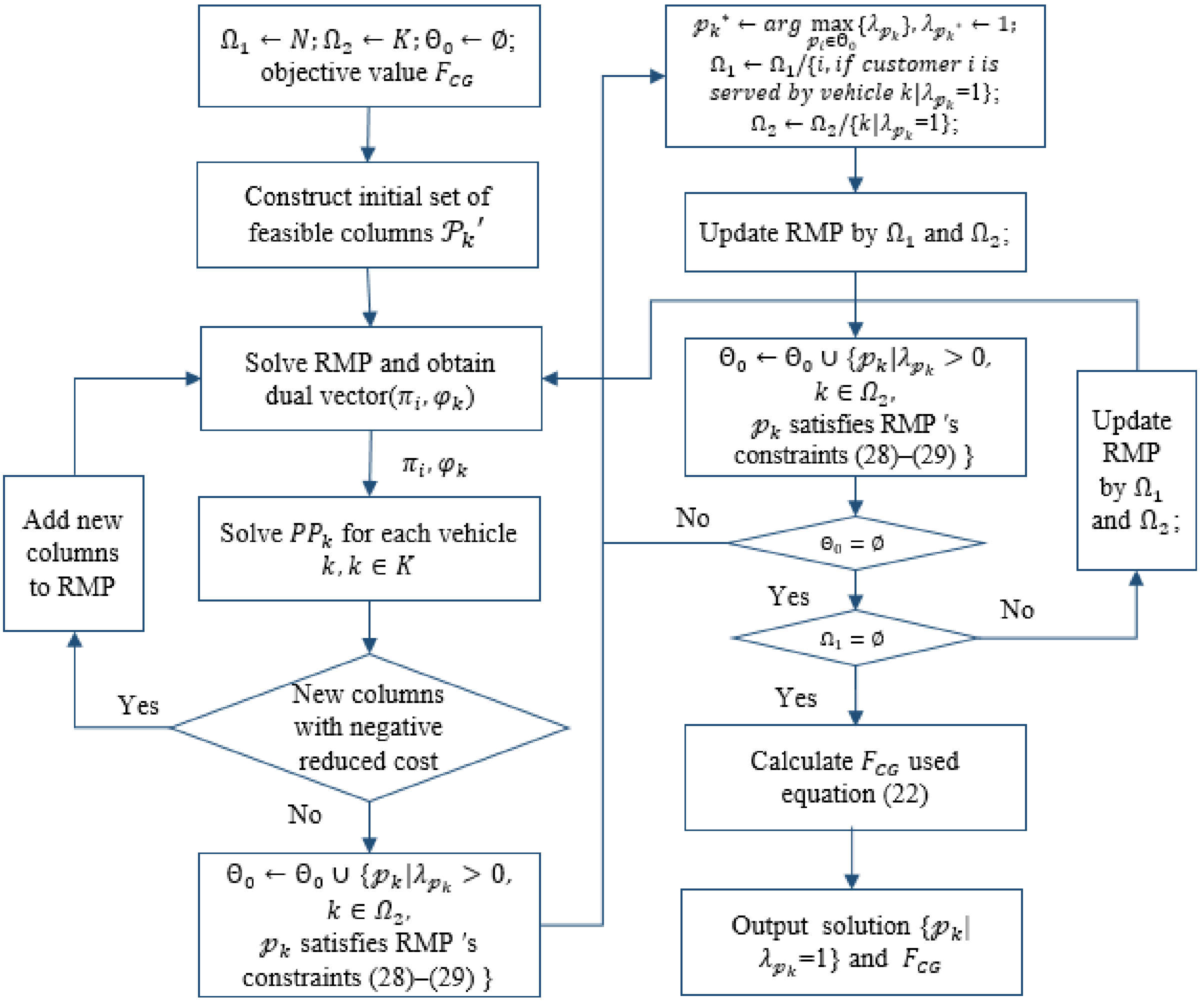

Figure 2: Flowchart of the CG-based solution method

6. Numerical experiments

6.1 Data set description

Some numerical experiments are conducted on Inter(R) Core(TM) i7-8565U CPU, 1.8 GHz processing speed and 20 GB of memory. The algorithms are implemented in C# (Visual Studio 2019). The CPLEX version 12.6.1 is utilized to solve the RMP and the PP models.

For investigating the influence of the vehicle and customer quantity on the performance, we set the vehicle capacity remains the same ($|Q| \in [3,5]$) and the largest radius remains the same ($|R| \in [6,8]$) in the experiments. The scale of six instance groups (ISGs) is shown in Table 2 as follows.

Table 2: Scale of instance groups in experiments

	vehicle numbers $|K|$	customer points $|N|$
ISG1	6	12
ISG2	8	18
ISG3	10	24
ISG4	11	30
ISG5	12	40
ISG6	13	50

6.2 Performance evaluation of the CG based solution method

For evaluating the performance of the CG based solution method, we compare the results solved by the CG method and the optimal result solved by the CPLEX directly for some small-scale problem instance groups. The results in Table 3 show that the CPLEX cannot solve some instances with relatively large scale such as ISG3 in two hours. For the instances that both the CPLEX and the CG method can solve, the gap of their objective value is not very significant; the average gap value is 0.87%, as shown in the column "Gap (CG)" of Table 3.

Table 3: Performance evaluation in small scale problem instances

Instance		CPLEX		CG		LB	GAP	
scale	number	F_{Cplex}	t_{Cplex}(s)	F_{CG}	t_{CG}(s)	F_{LB}	Gap (CG)	Gap (LB)
ISG1	1	37.74	1	37.74	10	36.75	0.00%	2.62%
	2	31.14	2	31.14	7	30.08	0.00%	3.40%
	3	34.21	1	34.21	14	32.85	0.00%	3.98%
	4	27.96	1	28.88	19	26.68	3.29%	4.58%
	5	22.25	3	22.25	15	21.15	0.00%	4.94%
	6	22.18	2	22.31	13	21.69	0.59%	2.21%
	7	20.03	1	20.03	11	19.11	0.00%	4.59%
	8	20.91	2	21.13	13	20.78	1.05%	0.62%
	9	30.47	3	31.27	21	29.38	2.63%	3.58%
	10	28.76	1	28.76	17	27.26	0.00%	5.22%
ISG2	11	62.40	482	62.40	64	58.79	0.00%	5.79%
	12	64.94	489	64.94	92	62.56	0.00%	3.66%
	13	47.60	224	47.60	25	44.98	0.00%	5.50%
	14	50.96	463	50.96	93	47.97	0.00%	5.87%
	15	25.74	32	26.38	62	24.36	2.49%	5.36%
	16	54.00	1659	54.00	98	51.05	0.00%	5.46%
	17	46.30	72	47.01	172	44.69	1.53%	3.48%
	18	42.65	103	43.98	135	40.85	3.12%	4.22%
	19	37.72	21	39.14	60	36.01	3.76%	4.53%
	20	51.20	76	51.20	29	48.73	0.00%	4.82%
ISG3	21	52.64	3672	52.64	234	50.50	0.00%	4.07%
	22	47.32	1214	47.66	291	45.36	0.72%	4.14%
	23	——	——	29.18	94	26.13	——	——
	24	——	——	29.18	94	26.13	——	——
	25	——	——	48.37	122	45.61	——	——
	26	——	——	22.82	75	19.87	——	——
	27	——	——	31.80	131	28.06	——	——
	28	——	——	35.55	197	32.32	——	——
	29	——	——	57.40	242	54.48	——	——
	30	——	——	43.06	282	40.85	——	——
Average							0.87%	4.21%

Notes: F_{Cplex}, F_{LB}, F_{CG} represent the objective obtained by CPLEX, LB, and CG; t_{Cplex}, t_{CG} represent the computation time of CPLEX and CG. "Gap (CG)" and "Gap (LB)" are the optimality gaps between the optimal solution obtained by CPLEX and the solutions obtained by the CG method and the LB, respectively.

For the purpose of evaluating performance of the CG method in large-scale instances that the CPLEX cannot solve, we calculate a lower bound (LB) for the problem by relaxing the binary variables $\beta_{i,j,k}$ to continuous variables. The LB and its gap from the optimal objective value solved by the CPLEX are listed in the columns "LB" and "Gap (LB)" of Table 3. The average optimality gap of the LB is 4.21%, which will be used later in the performance evaluation for large-scale instances.

For further evaluating performance of the CG method in large-scale instances, the comparative experiments are conducted between the CG method and the LB for the instance groups ISG4, ISG5 and ISG6. The results in Table 4 show that the CG based method could solve these large scale problem instance within two hours. The average gap of the results solved by the CG based method from the LB is about 5.19%. Recall that the optimality gap of the LB is about 4.21%, it implies the optimality gap of the CG method should be significantly smaller than the "5.19%" in the large scale problem instances because the compared LB is much lower (4.21%) than the optimal value. The optimality gap of the CG method for the large-scale instances may be estimated as about 0.98%, which is an estimated value and cannot be proved theoretically due to the complexity of the model. These results in Table 3 and Table 4 validate the efficiency of our proposed CG based solution method.

Table 4: Performance evaluation in large scale problem instances

Instance		CG		LB	Gap
scale	number	F_{CG}	t_{CG}(s)	F_{LB}	
ISG4	1	41.91	675	38.48	8.18%
	2	43.88	516	41.10	6.34%
	3	52.30	356	47.66	8.87%
	4	78.43	302	74.16	5.44%
	5	54.14	384	50.17	7.33%
	6	36.63	423	34.52	5.76%
	7	59.19	261	56.12	5.19%
	8	42.41	852	38.75	8.63%
	9	45.68	484	41.74	8.63%
	10	49.55	587	46.49	6.18%
ISG5	11	68.50	2961	64.97	5.15%
	12	100.73	3062	96.32	4.38%
	13	71.43	2402	68.28	4.41%
	14	55.20	2293	52.68	4.57%
	15	73.43	2019	71.00	3.31%
	16	68.85	2061	64.96	5.65%
	17	62.06	1586	59.89	3.50%
	18	71.99	2040	68.81	4.42%
	19	58.12	1892	55.44	4.61%
	20	69.61	2633	65.01	6.61%
ISG6	21	71.19	7050	67.31	5.45%
	22	117.92	6252	112.68	4.44%
	23	119.35	3174	115.06	3.59%
	24	129.46	5418	125.89	2.76%
	25	91.62	3071	88.45	3.46%
	26	129.70	4411	123.82	4.53%
	27	126.49	3134	121.81	3.70%
	28	128.04	3167	124.67	2.63%
	29	131.23	4581	127.44	2.89%
	30	128.29	5220	121.90	4.98%
Average					5.19%

Notes: F_{LB}, F_{CG} represent the objective value obtained by LB and CG; t_{CG} represent the computation time of CG. "Gap" lists the objective gap between LB and the solution obtained by the CG based method.

6.3 Sensitivity analysis

The total number of available vehicles and the largest radius for order dissemination may have influence on the final cost incurred for the logistics company. Therefore, some sensitive analysis is performed with respect to the above mentioned parameters.

6.3.1 Sensitivity analysis on available vehicle quantity

The first sensitivity analysis is conducted by changing the quantity of available vehicles in a certain of circle. Table 5 shows a series of nine experiments with 30 customer points, identical region radius and vehicle capacity; the quantity of available vehicles increases from 10 to 18 with step one. The values in the column of the pick-up cost decrease gradually because more vehicles are available, it is easier to find a closer vehicle to undertake a deliver order. While, the values in the column of the delivery cost seems not change very significantly; the reason is that the delivery cost mainly depends on the region radius of a circle in which customers are dispersed. Then the final objective, i.e., the sum of the pick-up cost and delivery cost, also decreases gradually.

Table 5: Sensitivity analysis of available vehicle quantities

ID	vehicle numbers $\|K\|$	$F_{pick-up}$	$F_{delivery}$	F_{CG}
5-1	10	48	38.36	86.36
5-2	11	48	37.38	85.38
5-3	12	40	39.10	79.10
5-4	13	40	38.72	78.72
5-5	14	40	36.97	76.97
5-6	15	32	38.32	70.32
5-7	16	32	36.82	68.82
5-8	17	32	37.55	69.55
5-9	18	24	38.20	62.20

6.3.2 Sensitivity analysis on the largest radius of order dissemination

The second sensitivity analysis is conducted on the three group of instances with different numbers of vehicles, different largest order radius, and the same number of customers. Table 6 lists the parameters of the three instance groups.

Table 6: Scale of instance groups of region radius

	vehicle numbers $\lvert K \rvert$	largest region radius Max_r	customer points $\lvert N \rvert$
ISG7	13	7	30
ISG8	16	8	30
ISG9	20	9	30

Table 7: Sensitivity analysis of region radius

Instance	ID	$F_{pick-up}$	$F_{delivery}$	F_{CG}
ISG7	7-1	48.00	24.83	72.83
	7-2	40.00	42.83	82.83
	7-3	40.00	35.93	75.93
	7-4	40.00	44.82	84.82
	7-5	40.00	22.35	62.35
	7-6	40.00	27.65	67.65
	7-7	40.00	34.53	74.53
	7-8	40.00	31.25	71.25
	7-9	40.00	28.90	68.90
	7-10	40.00	30.70	70.70
ISG8	7-11	40.00	29.07	69.07
	7-12	40.00	24.61	64.61
	7-13	32.00	29.09	61.09
	7-14	32.00	45.43	77.43
	7-15	40.00	43.29	83.29
	7-16	40.00	29.21	69.21
	7-17	32.00	27.74	59.74
	7-18	32.00	30.17	62.17
	7-19	40.00	42.92	82.92
	7-20	40.00	42.73	77.73
ISG9	7-21	24.00	30.83	54.83
	7-22	24.00	28.24	52.24
	7-23	32.00	30.55	62.55
	7-24	32.00	25.11	57.11
	7-25	32.00	32.98	64.98
	7-26	32.00	39.09	71.09
	7-27	32.00	41.53	73.53
	7-28	32.00	23.39	55.39
	7-29	32.00	32.32	64.32
	7-30	32.00	40.04	72.04

The values in the last column of Table 7 show that the total cost may decrease with the numbers of available vehicles and radius growing; but this decreasing trend is not very significant. When comparing the instance groups ISG7, ISG8 and ISG9, the average value gradually decreases. This result implies that the largest radius of the order dissemination may have impact on the operation cost of a logistic company. The long term trend of the cost reducing with the largest order radius growing exists. The reason may lie in the increase of regions and available vehicles, which makes the logistics company have more space for trade-offs. Therefore, the logistics company should try to expand the region radius as far as possible under the reasonable regional scope. In addition, determining a proper order dissemination radius still matters for the company's operation. The proposed model as well as algorithm may be potentially useful for the decision makers in logistic companies adopting the crowdsourced delivery operation mode.

6.3.3 Sensitivity analysis on densities of vehicle and customer distributions

Given a fixed area (a circle with a fixed radius $\mathcal{R}$), we investigate the influence of vehicle and customer densities as well as the ratio between them on the objective function and the decision on the order dissemination radius. The results are listed in Table 8 and Table 9.

In these tables, ρ_j and ρ_k denote the density of uniform distribution of customers and vehicles, respectively. It means $\rho_j = |N|/\pi\mathcal{R}^2$ and $\rho_j = |K|/\pi\mathcal{R}^2$. Then values in the "$\rho_j/\rho_k$" column denote the distribution density ratio of customers to vehicles. The values in the "ε" column denote the solved decision variable on the order dissemination radius. And the values in the "F_{CG}" column denote the objective value solved by CG.

Table 8 shows two series of cases under two regions with $\mathcal{R}$ as three and four kilometers. From the results in Table 8, we can see that the order dissemination radius (ε) mostly depends on the distribution density ratio (ρ_j/ρ_k). For the instances with the same ratio in a region, the order dissemination radius is almost the same except for just one of the ten instances. Another important finding is that with the distribution density ratio increasing, the order dissemination radius shows a non-decreasing trend, which is validated by the instances in Table 8.

Table 8: Sensitivity analysis on ratio of the densities of customers to vehicles

$\mathcal{R}(km)$	ρ_j	ρ_k	ρ_j/ρ_k	$\varepsilon(km)$	F_{CG}
3	0.50	0.14	3.50	2.50	28.02
	0.74	0.21		2.50	35.86
	0.99	0.28		2.50	46.64
	1.24	0.35		2.50	60.38
	1.49	0.42		2.50	68.68
	0.50	0.46	1.08	1.00	22.65
	0.74		1.61	1.00	25.25
	0.99		2.15	1.50	41.41
	1.24		2.69	1.50	46.06
	1.49		3.23	2.00	58.75
	1.24	0.32	3.89	2.50	57.32
		0.35	3.50	2.50	55.40
		0.39	3.18	2.00	51.23
		0.42	2.92	2.00	50.15
		0.46	2.69	1.50	48.15
4	0.30	0.12	2.50	2.67	33.39
	0.40	0.16		2.67	47.39
	0.50	0.20		2.67	53.48
	0.60	0.24		2.67	59.80
	0.70	0.28		2.67	59.96
	0.34	0.30	1.13	1.33	30.90
	0.48		1.60	2.00	45.08
	0.62		2.07	2.00	59.30
	0.76		2.53	2.67	76.45
	0.90		3.00	2.67	84.59
	0.76	0.24	3.17	3.33	80.01
		0.28	2.71	2.67	73.41
		0.32	2.38	2.67	73.08
		0.36	2.11	2.00	70.02
		0.40	1.90	2.00	66.71

Three series of cases under three different combinations of customers and vehicles are conducted. For each case, we increase the region's size (i.e., the region radius $\mathcal{R}$) under the same density ratio of customers to vehicles (ρ_j/ρ_k). We can see the larger is the region's size ($\mathcal{R}$), the order dissemination radius (ε) is larger. More important finding is that the increasing rate of the above two values ($\mathcal{R}$ and ε) is the same, which is reflected by the ratio of $\mathcal{R}$ to ε is the same. This phenomenon is validated in all the three cases in Table 9.

Table 9: Sensitivity analysis on density ratio under different region size

Instances	$\mathcal{R}(km)$	ρ_j/ρ_k	$\varepsilon(km)$	F_{CG}
	2	1.5	0.67	46.38
	3	1.5	1.00	54.82
$\lvert N\rvert = 40, \lvert K\rvert = 27$	4	1.5	1.33	63.22
	5	1.5	1.67	79.28
	6	1.5	2.00	84.05
	2	2.0	0.67	46.38
	3	2.0	1.00	54.82
$\lvert N\rvert = 40, \lvert K\rvert = 20$	4	2.0	1.33	63.22
	5	2.0	1.67	79.28
	6	2.0	2.00	84.05
	2	2.5	1.33	52.54
	3	2.5	2.00	63.15
$\lvert N\rvert = 40, \lvert K\rvert = 16$	4	2.5	2.67	79.13
	5	2.5	3.33	94.78
	6	2.5	4.00	103.03

The results in Table 8 and Table 9 demonstrate the order dissemination radius is proportional to the region radius; and the proportional ratio depends on the density ratio of customers to vehicles. Moreover, the larger is the density ratio of customers to vehicles, the proportional ratio (i.e., $\varepsilon/\mathcal{R}$) is larger. In reality, it means a larger order dissemination radius should be adopted for a larger density ratio of customers to vehicles. It should be noted that the above implications are mainly observed from the numerical experiments. Due to the solving capability of the solver and algorithm, the numbers of customers and vehicles cannot be set as a very large number or even be assumed to approach infinity so as to derive some analytical results on the calibration of the above mentioned ratios. However, the above experiments may predict these ratios or proportional relationships exist in this problem context. It could not only provide managerial implications for decision makers in reality but also pave the way for some future theoretical studies by analytical way.

7. Conclusions

In the era of sharing economy, the shared mobility may provide the logistics industry a new mode for parcel delivery. This study investigates an essential theoretical problem on OVRP which influences the cost efficiency of this shared mobility based parcel delivery industry. Different from the classic OVRP and its existing variants, this study further considers the deciding the radius of the parcel delivery order dissemination circle. This newly considered decision is related to the trade-off between attracting enough occasional vehicles and reducing the total cost, which includes the reward (additional cost) for attracting (covering) the vehicles' empty trip cost from their original location to the depot. Moreover, different from the widely used methodologies for solving OVRPs such as GA, Tabu, PSO, VNS, this study employs the CG as the methodology to design solution method for solving this new problem, which may contribute the literature on algorithm studies of OVRPs. Some numerical experiments are also conducted to validate the efficiency of the CG based solution method. Managerial implications are also obtained on the basis of numerical experiments.

It should be noted that this study may also contain limitations. For example, the solved problem instance scale may not be very large in some realistic application environment. In the future we will further investigate the acceleration techniques to accelerate the solving speed of the PPs so that the solvable instance scale could be increased. On the other hand, we should also pursue developing some exact solution algorithm by extending the current CG to the branch and price framework. In addition, more social and cultural issues could be involved in the shared mobility related optimization models (Karlsson et al., 2020); the possibility of the occasional vehicle rejecting the assigned orders could also be considered on the basis of this study. All of the above mentioned issues could be our potential research directions in the future.

Acknowledgement

This research is supported by the National Key R&D Program of China (Grant numbers 2018YFE0102700) and the National Natural Science Foundation of China (Grant numbers 71831008, 71671107)

References

Alonso-González M.J., Hoogendoorn-Lanser S., van Oort N., Cats O., Hoogendoorn S. (2020) Drivers and barriers in adopting Mobility as a Service (MaaS) – A latent class cluster analysis of attitudes. *Transportation Research Part A: Policy and Practice* 132, 378-401.

Atefi R., Salari M., Coelho L.C., Renaud J. (2018) The open vehicle routing problem with decoupling points. *European Journal of Operational Research* 265, 316-327.

Benjaafar S., Hu M. (2020) Operations management in the age of the sharing economy: what is old and what is new? *Manufacturing & Service Operations Management* 22, 93-101.

Brandão J. (2004) A tabu search algorithm for the open vehicle routing problem. *European Journal of Operational Research* 157, 552-564.

Brandão J. (2018) Iterated local search algorithm with ejection chains for the open vehicle routing problem with time windows. *Computers & Industrial Engineering* 120, 146-159.

China industrial planning network, (2018). Research on the last mile of logistics industry. http://www.chanyeguihua.com/2917.html/ 2018-7-13. Accessed by 13 November 2019.

Cordeau J.F., Laporte G. (2007) The dial-a-ride problem: models and algorithms. *Operations Research* 153, 29-46.

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.

Doerner K.F., Salazar J.J. (2014) Pickup-and-delivery problems for people transportation. *Vehicle Routing: Problems, Methods and Applications* 32, 193-212.

Gao, K., Yang, Y., Sun, L., Qu, X. (2020) Revealing psychological inertia in mode shift behavior and its quantitative influences on commuting trips. *Transportation Research Part F*, 71, 272-287

He L., Mak H.Y., Rong Y., Shen Z.J.M. (2017) Service region design for urban electric vehicle sharing systems. *Manufacturing & Service Operations Management* 19, 309-327.

He L., Hu Z., Zhang M. (2019) Robust repositioning for vehicle sharing. *Manufacturing & Service Operations Management*, in press, doi: 10.1287/msom.2018.0734.

Ho C.Q., Mulley C., Hensher D.A. (2020) Public preferences for mobility as a service: Insights from stated preference surveys. *Transportation Research Part A: Policy and Practice* 131, 70-90.

Hyland M., Mahmassani H.S. (2020) Operational benefits and challenges of shared-ride automated mobility-on-demand services. *Transportation Research Part A: Policy and Practice* 134, 251-270.

Karlsson I.C.M., Mukhtar-Landgren D., Smith G., Koglin T., Kronsell A., Lund E., Sarasini S., Sochor J. (2020) Development and implementation of Mobility-as-a-Service – A qualitative study of barriers and enabling factors. *Transportation Research Part A: Policy and Practice* 131, 283-295.

Krzysztof F., Hindi K.S. (2009) A variable neighborhood search algorithm for the open vehicle routing problem. *European Journal of Operational Research* 195, 803-809.

Li X., Yuan T.P., Ling S.C.H. (2009) An ant colony optimization metaheuristic hybridized with tabu search for open vehicle routing problems. *Journal of the Operational Research Society* 60, 1012-1025.

Li, X., Medal, H., Qu, X., (2019) Connected Heterogeneous Infrastructure Location Design under Additive Service Utilities. *Transportation Research Part B*, 120, 99-124

Letchford A.N., Lysgaard J., Eglese R. (2006) A branch-and-cut algorithm for the capacitated open vehicle routing problem. *Journal of the Operational Research Society* 56, 588-596.

Liu R., Jiang Z.B., Geng N. (2014) A hybrid genetic algorithm for the multi-depot open vehicle routing problem. *OR Spectrum* 36, 401-421.

Lalla-Ruiz E., Exposito-Izquierdo C., Taheripour S., Voss S. (2016) An improved formulation for the multi-depot open vehicle routing problem. *OR Spectrum* 38, 175-187.

MirHassani S.A., Abolghasemi N. (2011) A particle swarm optimization algorithm for open vehicle routing problem. *Expert System with Applications* 38, 11547-11551.

Mounce R., Nelson J.D. (2019) On the potential for one-way electric vehicle car-sharing in future mobility systems. *Transportation Research Part A: Policy and Practice* 120, 17-30.

Niu Y., Yang Z., Chen P., Xiao J. (2018) Optimizing the green open vehicle routing problem with time windows by minimizing comprehensive routing cost. *Journal of Cleaner Production* 171, 962-971.

Qu Y., Bard J.F. (2015) A branch-and-price-and-cut algorithm for heterogeneous pickup and delivery problems with configurable vehicle capacity. *Transportation Science* 49, 254-270.

Repoussis P.P., Tarantilis C.D., Ioannou G. (2007) The open vehicle routing problem with time windows. *Journal of the Operational Research Society* 58, 355-367.

Sariklis D., Powell S. (2000) A heuristic method for the open vehicle routing problem. *Journal of the Operational Research Society* 51, 564-573.

Soto M., Sevaux M., Rossi A., Reinholz A. (2017) Multiple neighborhood search, tabu search and ejection chains for the multi-depot open vehicle routing problem. *Computer & Industrial Engineering* 107, 211-222.

Timo G., Michael D. (2019) Adaptive large neighborhood search with a constant-time feasibility test for the dial-a-ride problem. *Transportation Science* 53, 480-491.

Tarantilis C.D., Kiranoudis C.T. (2002) Distribution of fresh meat. *Journal of Food Engineering* 51, 85-91.

Wei Q., Li L.F., Liu S., Jun Z., Shen M. (2018) Shared mobility for last-mile delivery: design, operational prescriptions, and environmental impact. *Manufacturing & Service Operations*

Management 20, 737-751.

Wang X., Agatz N., Erera A. (2018a) Stable matching for dynamic ride-sharing systems. *Transportation Science* 52, 850-867.

Wang, S., Qu, X. (2017) Station choice for Australian commuter rail lines: equilibrium and optimal fare design. *European Journal of Operational Research*, 258, 144-154.

Wang, S., Zhang, W., Qu, X. (2018) Trial-and-error train fare design scheme for addressing boarding/alighting congestion at CBD stations. *Transportation Research Part B*, 118, 318-335

Wang K., Zhen L., Wang S., Laporte G. (2018b) Column generation for integrated berth allocation, quay crane and yard assignment problem. *Transportation Science* 52, 812-834.

Xiang Z., Chu C., Chen H. (2008) The study of a dynamic dial-a-ride problem under time-dependent and stochastic environments. *European Journal of Operational Research* 185, 534-551.

Zhen L. (2015) Tactical berth allocation under uncertainty. *European Journal of Operational Research* 247, 928-944

Zhen L. (2016) Modeling of yard congestion and optimization of yard template in container ports. *Transportation Research Part B* 90, 83-104.

Zhen L., Liang Z., Zhuge D., Lee L.H., Chew E.P. (2017) Daily berth planning in a tidal port with channel flow control. *Transportation Research Part B* 106, 193-217.

Zhen L., Wang K., Wang S., Qu X. (2018) Tug scheduling for hinterland barge transport: a branch-and-price approach. *European Journal of Operational Research* 265, 119-132.