Dynamic vehicle routing problem considering simultaneous dual services in the last mile delivery

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Abstract

Purpose – This paper aims to study the vehicle routing problem with dynamic customers considering dual service (including home delivery [HD] and customer pickup [CP]) in the last mile delivery in which three decisions have to be made: determine routes that lie along the HD points and CP facilities; optimize routes in real time, which mode is better between simultaneous dual service (SDS, HD points and CP facilities are served simultaneously by the same vehicle); and respective dual service (RDS, HD points and CP facilities are served by different vehicles)?

Design/methodology/approach – This paper establishes a mixed integer linear programing model for the dynamic vehicle routing problem considering simultaneous dual services (DVRP-SDS). To increase the practical usefulness and solve large instances, the authors designed a two-phase matheuristic including construction-improvement heuristics to solve the deterministic model and dynamic programing to adjust routes to dynamic customers.

Findings – The computational experiments show that the CP facilities offer greater flexibility for adjusting routes to dynamic customers and that the SDS delivery system outperforms the RDS delivery system in terms of cost and number of vehicles used.

Practical implications – The results provide managerial insights for express enterprises from the perspective of operation research to make decisions.

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Originality/value – This paper is among the first papers to study the DVRP-SDS. Moreover, this paper guides the managers to select better delivery mode in the last mile delivery.

Keywords Dynamic programming, Vehicle routing problem, Simultaneous dual services, Dynamic customers, Hybrid heuristics

Paper type Research paper

1. Introduction

In recent years, e-commerce has become widely accepted and made rapid development. According to a survey from JD Morgan's annual Internet Investment Guide, the e-commerce sales have kept an annual growth rate of about 20 per cent (Hayel *et al.*, 2016). Business-to-consumer (B2C) e-commerce is more and more popular with customers with the popularity of personal computers and intelligent mobile phones, Oracle (2000) defines B2C as "a term describing the communication between businesses and consumers in the selling of goods and services" in their "Application Development Guide". While (IBM, 2001) defines it as "the use of Web-based technologies to sell goods or services to an end-consumer". Further, Jewels and Timbrell (2001) give a definition of B2C that B2C e-commerce is an exchange between producers and end consumers of goods, services and explicit knowledge about goods and services (or information about consumers) for available consumption in return for the actual or potential payment of monies. However, the rapid development of B2C e-commerce has brought serious challenges to express service providers (ESPs), especially in the last mile delivery, working as the last stage in delivering parcels to final customers (Huang, 2015; He *et al.*, 2016, 2017). Wining the last mile is the most crucial element of e-commerce on order-fulfillment operations, but many e-commerce enterprises found themselves unable to make timely, customized and cost-effective deliveries. It is common to have parcels shipped to pre-committed customers, but something always happens because of uncertainties arising from customers (such as the customers missed the deliveries), which makes companies have to reship the parcels, as a result, expenses can mount (Lee and Whang, 2001). According to the survey, the last mile delivery cost accounts for 13 per cent up to 75 per cent of total supply chain cost (Aized and Srai, 2014). In addition, according to a recent report from China (State Post Bureau, 2016), among these complaint cases filed by online shoppers, 48.3 per cent are due to delivery service, especially the delivery service of the last mile, 23 per cent are due to parcel delivery delays. Therefore, designing an efficient and sustainable last mile delivery system is the key issue for e-commerce.

There are currently two types of service modes in the last mile delivery, and they are called home delivery (HD) (Ahmadizar *et al.*, 2015) in which individual direct parcel delivery to customers' home or workplace and customer's pickup (CP) in which customers pick up their parcels at a terminal that is close to their home or work at the right time (Hayel *et al.*, 2016; Klein *et al.*, 2017; Zhou *et al.*, 2017, 2018). In this paper, we call them dual services. Note that customers with HD service are different from those customers with CP service in terms of their requirements: the delivery time for the customers with HD service are more critical than those for the customers with CP service; there are strict time windows for the customers with HD service, while there are few restrictions on time windows for the customers with CP service; the cost of delivery for these two kinds of customers differs, because several parcels can be delivered at the same time and location for CP service. By contrast, two parcels for the customers with HD service cannot be usually served simultaneously at the same location.

We focus on the last mile delivery with simultaneous dual services (SDS) in this paper, where customers with HD service and those with CP service can be served by a vehicle simultaneously which is different from (Zhou *et al.*, 2017) where these two kinds of customers would be served by two vehicles respectively which is called as respective dual services (RDS), as seen in Figure 1. Another important issue is that the deterministic vehicle routing problem (VRP) with respective dual services (VRP-RDS) described in (Zhou *et al.*, 2017) did not adequately cover real-life situations. Moreover, a sustainable and competitive delivery should be based on the positive user experiences. Improving the procedure in the last mile delivery can make the delivery service more desirable and attractive. In many real-life situations, especially in the last mile delivery, there exist many uncertainties resulting in the absence of customers. However, little research is available on the dynamic VRP with simultaneous dual services (DVRP-SDS) in the last mile delivery.

One of the characteristics of the last mile delivery is uncertain customer requirements which change frequently. These uncertainties further increase the complexity of the problem since the uncertainties have to be considered when coordinating each customer requirement in a delivery plan. Whereas schedules can be easily incorporated into the delivery plans if there are no uncertain customer requirements. They may lead to delivery in vain and customers are served with a second or even third delivery, therefore, the uncertainties of customer requirements play an important role as it can be also seen in Figure 2. In general, the courier will contact with the next customer by phone to see whether or not the next customer is present once the current

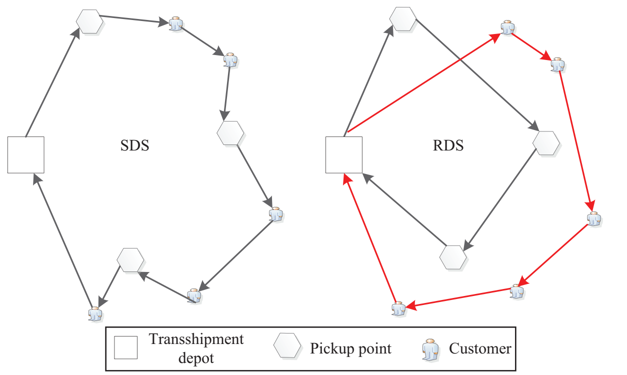

Figure 1.
Comparison of the SDS and RDS

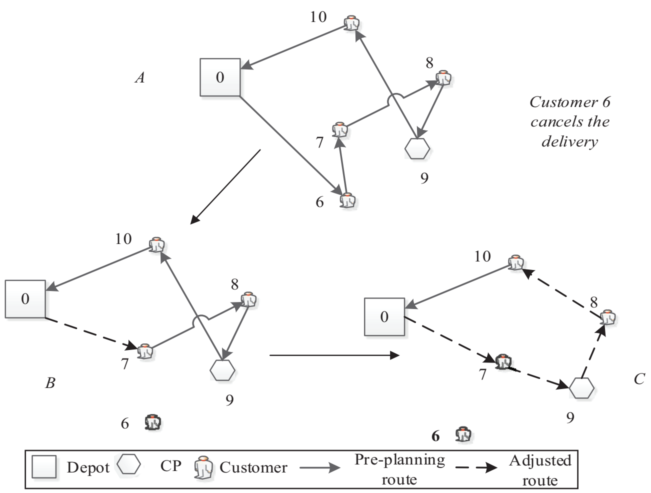

Figure 2.
DVRP-SDS in the last mile delivery

customer is served. If the next customer is not present (e.g. customer 6 is not present in Figure 2), the courier will delete customer 6 from the pre-planning route and continue serve customer 7 based on experience, the route changes from route A to route B (Figure 2). However, it is obvious that the route B is not the optimal one, for example, the route C is better than the route B. Therefore, it is necessary to explore a more scientific approach to generate the optimal route.

This paper presents a novel DVRP-SDS in the last mile delivery. Each vehicle serves both customers with HD requirements and customers with CP requirements simultaneously considering the time windows and service options of all customers on a route. The aim is to minimize the total delivery cost.

This remainder of the paper is organized as follows: the related literature is reviewed in Section 2. Section 3 displays problem statements. In Section 4, the mathematical model for the dynamic vehicle routing with SDSs is developed. A hybrid two-phase *matheuristic* is designed to solve the DVRP-SDS in Section 5. Section 6 designs numerical experiments to validate the effectiveness and superiority of the proposed model and designed algorithm. Finally, conclusions and future works are given in Section 7.

2. Literature review

2.1 The last mile of business-to-customer

The last mile of B2C is defined as "the final stretch in a B2C delivery service whereby the consignment is delivered to the recipient, either at the recipients' home or at a collection point" (Gevaers *et al.*, 2009; Zhou *et al.*, 2017). Practically, there are two kinds of last mile delivery including HD and CP (Dell'Amico and Hadjidimitriou, 2012; Ehmke and Mattfeld, 2012; Huang, 2015; Punakivi *et al.*, 2001; Tan, 2015; Zhou *et al.*, 2017). However, the HD has strict time window constraints and requiring the presence of the customer during delivery, or a second and even third delivery will occur (Ehmke and Mattfeld, 2012; Ehmke *et al.*, 2012). Besides HD, a direct delivery mode, some indirect modes in last mile delivery are popular with consumers; these indirect last mile delivery modes have removed constraints of receiving parcel at home and have decreased the delivery failure (Huang, 2015). Indirect delivery (e.g. reception box, delivery box, automated lockers) is also called unattended delivery which is similar to the last mile stops where vehicles can transport each passenger to the last mile stop closest to her final destination (Wang, 2017), the mode can combine profitability and high service level and simulations suggest that the mode can reduce HD costs considerably, by up to 60 per cent (Morganti and Dablanc, 2014; Punakivi *et al.*, 2001). Furthermore, the European Research project CityLog (part of Framework Programme 7) introduced the Modular BentoBox to avert the unnecessary driven kilometers when the customers is not home during the delivery, this mode aim at obtaining a balance between the logistics and customer's interests by delivering parcels to the BentoBox, instead that to the customer location (Dell'Amico and Hadjidimitriou, 2012). In addition to these unmanned devices, some manned facilities have been used for the last mile pickup and delivery services in China, these services support customers in choosing the ones they prefer to receive their parcels, such Cainiao Station provided by Alibaba Group and Postal Station provided by China Post (Zhou and Zhong, 2015; Zhou *et al.*, 2017).

2.2 Vehicle routing problem with dual services in the last mile delivery

The VRP in the last mile delivery has drawn wide attention in recent years. The description of the static VRP with dual services (HD and customer pickup [CP]) was proposed recently. Zhou *et al.* (2016) constructed the conceptual and mathematical models in which HD service and CP service exist in the same last mile delivery system. A hybrid solution combining a genetic algorithm (GA) and simulated annealing (SA) was proposed by Zhou *et al.* (2017) to solve the static VRP with dual services efficiently. As mentioned in Zhou *et al.* (2017), the

VRP with respective dual services is bi-level delivery in which customers with HD requirements and customers with CP requirements are served by two different vehicles which results in the crisscross delivery and more delivery vehicles are needed. Besides the characteristic, we mainly considered dynamic VRP in this paper. Dynamic VRP addressed in the real-world customer demands: the cancelation of parcel delivery and the changes of time windows, see e.g. Zhou *et al.* (2016, 2017) and Han *et al.* (2017).

Zhou *et al.* (2016) presented an integrated multiclass terminal location-heterogeneous vehicle routing optimization model for last mile delivery under online shopping, they proposed a two-phase heuristics SA algorithm named "multiclass terminal selection and location before heterogeneous vehicle routing". Moreover, Zhou *et al.* (2017) developed a further multi-sized terminal location-routing model with respective HD and CP services, due to the changes of customer locations which may result in the increasing distance between the customers and CP site, customers with initial CP requirements tend to choose HD service. Han *et al.* (2017) focused on the appointment scheduling and VRP with time windows in the last mile delivery. A tabu search-based hybrid heuristic algorithm was proposed, and random customer behaviors, e.g. no-show and random response time of customers, are considered to minimize the total penalty cost of the attended HD system by express delivery company. Most of the researches are about the VRP with hard or soft time window (Alvarez and Munari, 2017; Ibaraki *et al.*, 2005; Taş *et al.*, 2013), fuzzy time window (Tang *et al.*, 2009), and flexible time window (Hashimoto *et al.*, 2006; Taş *et al.*, 2014). However, in real-world situation of online shopping logistics, the upper bound and lower bound of time window have different impacts on ESPs and customers, e.g. in the early servicing case, waiting cost will occur which is a load for ESPs and means nothing for customers, in the late servicing case, late servicing may lead to a second or third delivery for ESPs and a bad service experience for customers. Therefore, different ways are applied to deal with them in the model in this paper.

When it comes to the methodology part, both exact and heuristic methods were applied to solve the VRP. Some small-scale instances can be solved by the exact algorithms with good performance (Baldacci *et al.*, 2012; Battarra *et al.*, 2014; Dayarian *et al.*, 2015; Desaulniers *et al.*, 2016; Roberti, 2012). For the heuristic method, many heuristics were applied to solve the real-life VRP under uncertainty, including tabu search (Taş *et al.*, 2014), local search (Dell'Amico *et al.*, 2016; Ibaraki *et al.*, 2005), GA (Ahmadizar *et al.*, 2015) and ant colony algorithm (Schyns, 2015). In addition, some hybrid heuristic algorithms were proposed as well: tabu search with local search (Liu *et al.*, 2014), GA with SA (Zhou *et al.*, 2017), hybrid GA with a heuristic algorithm (Bae and Moon, 2016; Yanik and Bozkaya, 2014), GA with local search (Derbel *et al.*, 2012).

To increase the practical usefulness and solve large instances, we propose a two-phase *matheuristic*, in the first phase, a construction heuristic to generate initial feasible solutions and an improvement heuristic that attempts to balance greediness and randomness to improve the initial feasible solution. In the second phase, the routes are adjusted to dynamic customers using dynamic programing.

3. Problem statements

An example of the dynamic vehicle routing in the last mile delivery with dual services is illustrated in Figure 2, which consists of one transshipment depot, two CP points, and thirteen customers with HD requirement. Customers can be served by either HD or CP service. Customers with HD requirement are served by vehicles directly, and those with CP requirement pick up their parcels themselves at the closest CP terminal. Moreover, the customers with HD requirement and those with CP requirement can be served by the same vehicle, which is different from the two levels of routes (Zhou *et al.*, 2017).

The present research mainly focuses on the following aspects to obtain the optimal dynamic vehicle routing:

- determine routes that lie along the HD points and CP facilities;
- optimize routes in real time; and
- which mode is better between SDS delivery system and RDS delivery system.

4. Model formulation

Table I.

4.1 Time window

From the perspective of customer, the parcels are desired to be delivered to the customers within the particular time window $[e_i, l_i]$. This is a strong constraint justified by the huge penalties encountered by the ESPs, such as in the context of the last mile delivery under online shopping. However, the vehicles sometimes served customers before or after the time window bounds which are called time window deviation (Taş *et al.*, 2014). Note that the constraint is essential restrictive at the upper bound l_i. In general, there are two kinds of time window deviations, one is that the vehicle arrives in advance but has to wait until the beginning of the time windows to start the service (Schyns, 2015); in this case, the total travel and waiting time of a delivery route does not exceed the planning period T. The other is that the vehicle arrives later which results in bad customer service experience, which is not allowed in this paper.

4.2 Mathematical model

Based on the analysis above, the mathematical model is constructed as follows.

$$Min\, Z = \sum_{i\in N}\sum_{j\in N}\sum_{k\in K} t_{ij}x_{ijk} \tag{1}$$

$$subject\ to \sum_{i\in N}\sum_{k\in K} x_{ijk} = 1, j \in N_I, \tag{2}$$

Sets	Description
N_o	Set of transshipment depots, $N_o = \{0\}$
N_h	Set of HD customers, $N_h = \{1, 2, \ldots, n_h\}$
N_c	Set of CP terminals, $N_c = \{1, 2, \ldots, n_c\}$
N_I	Set of both HD customers and CP customers $N_c \cup N_h$
N	Set of all nodes consists of $N_o \cup N_c \cup N_h$
K	Set of vehicles, $k \in K$
Parameters	
t_{ij}	Travel time between node i and node j
$[e_i, l_i]$	Time window for customer i with HD service
Q	Capacity of each vehicle
T	Planning period
q_i	Customer demand i $\in N_I$
U_{ik}	Remaining demand after service to node i on vehicle $k, i, j \in N, k \in K$
t_{ik}	Time of departure after vehicle k serves node $i \in N$
Decision variables	
x_{ijk}	Takes on 1 if vehicle k serves node j immediately after node i; 0, otherwise

Table I.
Parameters and variables for the model

$$\sum_{j \in N_I \backslash (i)} x_{ijk} = \sum_{j \in N \backslash (i)} x_{jik},\ i \in N\, k \in K, \tag{3}$$

$$\sum_{i \in N_o} \sum_{j \in N \backslash N_o} x_{ijk} = 1,\ k \in K, \tag{4}$$

$$\sum_{i \in N \backslash N_o} \sum_{j \in N_o} x_{ijk} = 1,\ k \in K, \tag{5}$$

$$\sum_{i \in N} x_{ijk} e_i \leq t_{jk} \leq \sum_{i \in N} x_{ijk} l_i,\ j \in N, k \in K, \tag{6}$$

$$t_{ik} + x_{ijk} t_{ij} \leq t_{jk} + T\left(1 - x_{ijk}\right),\ i \in N, j \in N, k \in K, \tag{7}$$

$$0 \leq U_{ik} \leq Q - q_i,\ i \in N_I, k \in K, \tag{8}$$

$$q_j + U_{jk} \leq U_{ik} + M\left(1 - x_{ijk}\right),\ i \in N_I, j \in N, k \in K, \tag{9}$$

$$x_{ijk} \in \{0,1\}, i,j \in N, k \in K \tag{10}$$

In above model, the objective is to minimize the total cost. The constraint (2) ensures that there is only one visit per customer, and constraint (3) guarantees the flow conservation for each node. Constraints (4) and (5) indicate that each vehicle starts and terminates at the transshipment depot. Constraints (6) and (7) represent time constraints. Constraints (8) and (9) ensure that the load of vehicle k does not exceed the capacity of vehicle. Constraint (10) declares the decision variables.

5. Solution methodology

The VRP is viewed as a NP-hard problem. The extended model in our paper further increases the complexity of the solution. Therefore, for the DVRP-SDS described above, we propose a two-phase *matheuristic* procedure. In the first phase, the computational efficient heuristic methods, which include construction heuristic and improvement heuristic, are designed (Reyes *et al.*, 2017). In the second phase, the solution is further real-time improved according to dynamic customers by means of forward dynamic programing.

5.1 Heuristics

5.1.1 Construction heuristic. The construction heuristic we design to generate initial feasible solution is inspired by the greedy rule. The procedure repeats the construction procedure N times and chooses the best initial solution. At each iteration in the construction, the next customer is inserted into the route in the following manner:

- For not yet visited customers, inserting them into each location at every route among the routes (including the empty route), evaluate the cost change induced by the insertion operation.

- Rank the insertion by non-decreasing cost and choose randomly one from the K most profitable ones.

At Step 2, we design K_greedy random insertion heuristic, inspired by greedy randomized adaptive search procedures (GRASP) (Feo and Resende, 1995; Jovanovic *et al.*, 2018; Jovanovic *et al.*, 2016), to insert customer into route. Repeat step 1 and 2 until all customers are inserted, and we generated $N = 100$ initial solutions; Algorithm 5.1 outlines the construction heuristic in pseudo-code.

Algorithm 5.1 Construction Heuristic

```
 Input: Solution size N. Customer data.
 Size of candidate list K
Output: the best initial feasible solution S.
 // the procedure returns the best initial feasible solution
    constructed using a random selection and K_greedy random
    insertion heuristic.

 Pool ← Ø
 for count ←1 to N do
     Unvisited customer set ← N_I
     Initial Solution IS ← Ø
     While Unvisited customer set ≠ Ø do
     if IS do not include empty route then
        IS is added an empty route
     end
    c, i, r ←K_GreedyRandomInsertion (IS, Unvisited customer
      set, K)
    // customer c is inserted into the ith location of route r
      among solution IS.
    Unvisited customer set ← Unvisited customer set \ c
 end
 Pool ←(append) IS
end
S ← arg min{cost(IS)|IS ∈ Pool}
Return S
```

5.1.2 Improvement heuristic. The improvement heuristic we design is inspired by the family of destroy-recreate paradigm; see e.g. Reyes *et al.* (2017). The destroy-recreate paradigm is composed of two phases. In the destroy phase, a feasible solution is destroyed L times using some special destroy rule. In the recreate phase, a new feasible solution is also recreated L times using some special recreate rule. In this paper, we use the following destroy-recreate rules:

- greedy destroy and K_greedy recreate (GDKGR); and
- random destroy and greedy recreate (RDGR).

To avoid local optima, we also adapt the greedy random rule in the greedy recreate procedure in the GDKGR to improve the solution (Feo and Resende, 1995; Jovanovic *et al.*, 2018). For each insertion during the recreate procedure, we select one randomly from K most profitable candidates. In addition, we switch between GDKGR and RDGR whenever an improvement is not found after ten iterations. Algorithm 5.2 details the improvement heuristic:

Algorithm 5.2 Improvement Heuristic

```
Input: the best initial feasible S
  The iteration number I
  Size of candidate list K
  The number of customers to be deleted and reinserted at each
  iteration N
  The numbers of unsuccessful improvement before switching
  neighborhoods switch

  Output: the improved feasible solution S.

  lastImprovement ← 0
  lastSwitch ← 0
  for iter ←1 to I do
      (R1, Unvisited customer set) ← Destroy(S)
      if R1 do not include empty route then
        R1 is added a empty route
      end
      R ← Recreate(R1, Unvisited customer set)
      if cost(R) >= cost(S) then
        if iter - lastImprovement >= switch then
          SwitchNerghborhood();
        end
      end
      else
      S ← R
      lastImprovement ← iter
      end
  end
  Return S
```

5.2 Conversion of dynamic customers

In the real world, the changes of customer requirements occur at several discrete time points. Suppose that the requirements change at $t_1^*, t_2^*, t_3^* \cdots$, it is obvious a static VRP during time periods $[0, t_1^*]$, $[t_1^*, t_2^*]$, $[t_2^*, t_3^*]$ . . .. In this paper, the VRP with dynamic customers is equally converted into static problem as follows.

In general, after a courier serves a customer, the courier will call the next customer to tell him/her to be served. In this case, when customer requirements change at the moment t_i^*, the customers who have been served have no effect to cost, so these customers are deleted from both HD customers and CP customers. In other words, the vehicle comes directly from the depot to the current customer at t_i^*, and the current customer is considered to be the first customer to serve, so it is a special TSP in which some node is firstly served. We adjust the route by applying forward dynamic programing (DP) (see 5.4).

5.3 Real time rolling plan

During the execution of delivery services, the vehicle routing needs to be re-optimized when customers change their requirements. For this purpose, the DP has to be repeatedly operated according to the present customers during a standard operation period. Here we apply an improved real time rolling plan approach (Ferrucci and Bock, 2014). Considering the execution and adjustment of vehicle routing, we draw planning horizon according to incoming changes. There are three types of vehicle routing plans applied during the whole period (see Figure 3). The *initial theoretical routing* at 0 obtained by the solution method is demoted as P_{it}^{0}. It may be replaced at the beginning of the following adjusting horizon. $P_r^i(i = 1, 2, \cdots)$ defines the *re-optimization routing* that is generated by the solution method after integrating the changes of customer requirements at $t_i^*(i = 1, 2, \cdots)$. Moreover, P_{br}^* denotes the *best rolling plan* that is actually executed by integrating all P_r^i. The procedure for updating the route in real time is as follows:

- For a given route r, after the vehicle serves the current customer i at the moment t_i^*, if the next customer cancels its delivery, then it is marked as a key time point.
- Delete these customers before the customer i in the route r, update information of the customer i, with demand $D_i = \sum_{c=0}^{i} d_i$ and travel time $T_{0i} = t_i^*$.
- Then the problem is regarded as a special TSP where the customer i is the first one to be served. It is solved by using DP as described in 5.4.
- Repeat step (1)-(30) if the next dynamic customer occurs until the vehicle return to the depot.

5.4 Dynamic programing

We adjust the route with dynamic customers using forward dynamic programing when the demands of customers change. Assume that there is a route $r = (c_0, c_1, \ldots, c_i, \ldots, c_v, c_0)$ with c customers, if the ith customer's demand changes; we adjust the route as follows:

We define $d(c_i, \tau, V)$ as the minimum cost of a partial route that vehicles start from the node c_i and go through each node of V and then come back the start point, and τ is the departure time from customer c_i. Then the recursion is given:

$$d(c_i, \tau, V) = \begin{cases} 2t_{c_0 c_i} & V = \varnothing \\ \min\left\{ t_{c_i c_k} + d\left(c_k, \tau^*, V/c_k\right)\right\} & V \neq \varnothing \end{cases}$$

In above recursion, the time window constraints are given: $\tau \in [e_i, l_i]$, $\tau^* \in \left[e_i, min\left\{l_i, \tau - t_{c_i c_k}\right\}\right]$, in particular, in this recursion, the first node to be served is the customer c_i.

6. Implementation and analysis

This section presents results of our computational experiments. The experiment is implemented in JAVA and executed on an Intel Xeon i5-3337U 1.8 GHz 2 core CPU 64 GB

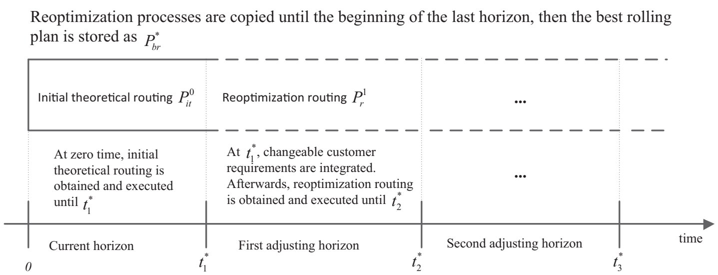

Figure 3.
The applied real time rolling plan

RAM computer. The instances are generated based on a real last mile delivery in Chongqing City from an express logistics enterprise that cooperates with our project team about a joint project (called City joint distribution under online shopping, No. 2015BAH46F01) which is funded by Ministry of science and technology of China. In this section, we first introduce the instance design for the DVRP-SDS model, and then report the computational results and the bi-level last mile delivery with respective dual services (Zhou *et al.*, 2017). Finally, a comparison between the different strategies is presented.

6.1 Instance design for the dynamic vehicle routing problem considering simultaneous dual services model

The location of transshipment depot is O (10.2 km, 7.4 km), and the locations of other nodes are given in Tables II and III. The vehicle travels at a speed of 30 km/h with working time 8:00-12:00. The capacity of each vehicle is 20. We explore three kinds of instances. More details can be found (https://pan.baidu.com/disk/home?fr=ibaidu#/all?vmode=list&path=%2FR.instance);

The first one is based on a real last mile delivery with 61 nodes (Tables II and III).

The second one is generated randomly and is characterized by a planning horizon $T = 240$ min, with 15, 20, 30, 60 and 120 customers, the demand d_c (for HD customers the demand is 1 with a percentage of 90 per cent and is 2 with a percentage of 10 per cent, for CP facilities the demand ranges from 1 to 5), a delivery location (x_i, y_i), $x_i \leq 26$, $y_i \leq 16$, and the time windows $[e_i, l_i]$, in order that each customer can be reachable, we set $t_{0i} \leq l_i$ in this kinds of instance, the percentage of both HD points and CP points is 50 per cent, we generate five instances for each group with 15, 20, 30, 60 and 120 customers.

The third one is generated the same way except that the percentage of CP points ranging from 10 to 50 per cent in five instances of each group.

6.2 Computational results of dynamic vehicle routing problem considering simultaneous dual services and DVRP-RDS

6.2.1 Computational results at the first phase. The results of the first stage for the realistic instance can be found in Table IV, where we report the model type, the cost and the number of vehicles of the schedule produced by the construction heuristic, the cost and the number

No.	X/km	Y/km	Demand	No.	X/km	Y/km	Demand
1	13.0	7.0	3	16	12.2	15.0	7
2	11.0	6.4	2	17	16.4	16.0	2
3	9.0	5.5	5	18	17.0	13.4	8
4	10.0	3.9	5	19	14.0	11.2	5
5	6.5	3.7	1	20	16.6	10.0	3
6	6.6	5.5	4	21	17.0	11.8	5
7	2.0	6.2	3	22	19.4	12.4	4
8	3.2	2.0	7	23	21.4	12.4	3
9	6.0	8.4	4	24	19.0	14.6	3
10	4.2	8.2	3	25	23.6	12.4	5
11	7.8	11.4	3	26	23.6	9.4	2
12	0.0	12.2	1	27	21.4	8.2	1
13	6.4	14.2	4	28	20.0	6.8	5
14	12.2	12.5	5	29	19.0	10.0	2
15	11.6	13.8	5	30	15.2	7.6	3

Table II. CP Service information

No.	X/km	Y/km	Demand	Time window
31	12.8	6.4	1	[0.00, 2.00]
32	14.2	6.8	2	[0.25, 0.83]
33	7.4	9.0	1	[0.33, 0.67]
34	8.6	6.4	1	[0.42, 0.67]
35	9.8	4.6	1	[0.42, 1.00]
36	12.2	4.2	3	[0.17, 0.50]
37	6.4	6.2	1	[0.00, 2.00]
38	8.6	2.2	1	[0.38, 0.72]
39	2.6	2.4	1	[0.00, 0.33]
40	4.2	5.4	1	[0.67, 1.00]
41	3.8	8.2	1	[0.75, 1.33]
42	6.6	10.8	1	[0.33, 0.67]
43	8.4	12.4	2	[0.67, 1.00]
44	5.8	13.6	2	[0.67, 1.00]
45	6.0	15.5	3	[0.00, 0.50]
46	10.4	14.0	1	[1.00, 1.50]
47	12.2	15.4	1	[1.67, 2.17]
48	12.0	12.2	1	[2.00, 2.67]
49	15.8	13.0	1	[2.00, 3.33]
50	15.4	10.2	2	[1.33, 2.58]
51	18.2	10.4	2	[2.00, 3.32]
52	18.0	13.0	1	[2.00, 3.33]
53	17.0	16.2	2	[0.00, 2.00]
54	20.0	14.8	1	[0.00, 2.00]
55	20.6	11.8	1	[2.50, 3.33]
56	21.4	8.8	1	[1.67, 2.17]
57	20.6	6.4	2	[2.00, 150]
58	25.0	8.0	1	[1.67, 2.17]
59	22.4	10.8	2	[2.33, 3.33]
60	24.2	12.8	1	[2.50, 3.34]

Table III.
HD Service information

Model	C_{init} Cost	C_{init} No. of vehicles	C_{impr} Cost	C_{impr} No. of vehicles	CPU
SDS	452.0	9.0	372.8	8.5	3.97
RDS	574.0	9.0	497.4	9.4	5.63
$\frac{(C_{RDS} - C_{SDS})}{C_{SDS}}$ %	27.0	0.0	33.4	10.6	41.8

Table IV.
Performance analysis on realistic instance

of vehicles of the schedule after it has been improved, and the relative difference in schedule cost and the number of vehicles (as a percentage). We run each model 10 times and calculate the average values, the results show that the SDS produced schedules of much better quality than the schedules produced by RDS, the cost is reduced by 33.4 per cent and the number of vehicles is reduced by 10.6 per cent. In terms of CPU time, the mean CPU time is 3.97 s for 10 times.

6.2.2 Computational results at the second phase. In this section, we analyze how dynamic customers affect the operation cost. To avoid random difference, we explore each customer's cancel with HD requirement and optimize the remaining partial route using DP described in

Section 5.2, then compare the total operation cost change with RDS delivery system. The results are shown in Table V where each line show 3 cost changes of dynamic customers of SDS and RDS delivery system, respectively. The last line shows the total cost change.

We can observe that the operation cost is decreased after optimizing the routes by using DP for 19 of 30 customers for SDS delivery system, and other 11 remain the same, whereas all routes are improved for SDS delivery system. In terms of total cost change, the SDS delivery system with a total cost decrease of 270 outperforms the RDS delivery system with a total cost decrease of 170, which shows that the SDS delivery system offers greater flexibility to adjust routes to dynamic customers.

6.3 Comparisons of the two strategies under different sizes

In this section, we analyze the two strategies under different sizes; we conducted computational experiments in which the percentages of CP service and HD service are 50 per cent respectively. We observe that the comparison between the SDS and RDS strategies shows that the SDS delivery system outperforms the RDS in the two aspects of cost and the number of vehicles used (Table VI). On average, the RDS delivery system is 36.7 per cent more expensive in the terms of cost, and 25.0 per cent more in the terms of the number of vehicles used, this results show the superiority of the SDS delivery system. In addition, the largest scale instance (the number of customers is not less than 120) can be solved within 10 s by our solution method, which validate the efficiency of our solution method (NoV represents the number of vehicles).

6.4 The benefits of customer pickup service

In this section, we explore the potential benefits of CP service in the two delivery systems. We conducted computational experiments with different percentages of CP service (ranging from 10 to 50 per cent). For each of these five variants of a group, we calculate total demand (total number of parcels) of each instance, then solve the problem using our method and compare the resulting unit delivery cost to the cost of a RDS delivery system. Table VII shows how these costs compare across instance variants.

We observe that the unit delivery cost is always gradually decreased with increasing percentage of CP service in each group (except for instance 3 and 24 in RDS delivery system) in the two delivery systems, even if the total cost is increased slightly when $N >= 60$ in the SDS delivery system, the unit delivery cost is still decreased, which shows that the CP service can reduce unit delivery cost in the last mile delivery and that the higher is the percentage of CP service, the more obvious is the advantage of SDS delivery system.

Customer no.		SDS			RDS	
31-33	0	−1	−1	−3	−8	−8
34-36	0	−4	0	−5	−3	−8
37-39	−1	−8	0	−5	−3	−5
40-42	−5	−34	−1	−5	−10	−8
43-45	−6	−12	−1	−8	−6	−3
46-48	0	0	−110	−8	−8	−8
49-51	−1	−69	−1	−8	−6	−1
52-54	−1	0	0	−8	−5	−1
55-57	0	−1	0	−8	−3	−3
58-60	0	−5	−8	−6	−1	−8
Sum		−270			−170	

Table V. Cost changes of solution with uncertainties

Table VI. Comparison analysis between SDS and RDS

		SDS			RDS			$\frac{(C_{RDS} - C_{SDS})}{C_{SDS}}$ %		
Instance	Nodes	Cost	NoV	CPU	Cost	NoV	CPU	Cost	NoV	CPU
1	15	145	2	1.59	224	4	2.39	54.5	100.0	50.3
2	15	166	2	1.75	268	3	2.53	61.4	50.0	44.6
3	15	121	3	1.72	198	3	2.63	63.6	0.0	53.0
4	15	165	2	1.66	264	3	2.40	60.0	50.0	44.6
5	15	126	2	1.77	206	4	2.39	63.5	100.0	35.0
Group mean		144.6	2.2	1.68	232	3.4	2.47	60.4	54.5	47.0
6	20	181	3	1.96	242	3	2.81	33.7	0.0	43.4
7	20	210	3	1.90	289	5	2.77	37.6	66.7	45.8
8	20	189	2	2.06	262	4	2.98	38.6	100.0	44.7
9	20	194	2	2.10	306	4	3.03	57.7	33.3	44.3
10	20	187	3	1.91	296	4	2.73	55.0	100.0	43.0
Group mean		192.2	2.6	1.99	279	4	2.86	45.2	53.8	30.4
11	30	238	4	3.01	337	4	3.57	41.6	0.0	18.6
12	30	262	4	3.08	357	6	3.70	36.3	50.0	20.1
13	30	253	4	2.99	384	6	3.52	51.8	50.0	17.7
14	30	238	4	3.23	357	6	3.95	50.0	50.0	22.3
15	30	251	4	3.19	365	6	3.26	45.4	50.0	8.5
Group mean		249.2	4	3.10	360	5.6	3.60	43.4	40.0	16.1
16	60	372	6	4.72	537	8	6.62	44.4	33.3	40.3
17	60	357	6	5.14	476	8	6.95	33.3	33.3	35.2
18	60	424	7	5.23	542	8	7.03	27.8	14.3	34.4
19	60	334	6	5.47	503	7	6.98	50.6	16.7	27.6
20	60	390	7	5.62	536	7	6.72	37.4	0.0	19.6
Group mean		375.4	6.4	5.24	518.8	7.6	6.86	38.2	11.8	30.7
21	120	641	12	10.93	780	14	11.57	21.7	16.7	5.9
22	120	631	13	9.97	837	15	11.25	32.6	15.4	12.8
23	120	693	13	9.43	879	15	10.42	26.8	15.4	10.5
24	120	666	12	9.93	870	13	11.05	30.6	8.3	11.3
25	120	708	13	9.61	820	15	10.82	15.8	15.4	12.6
Group mean		667.8	12.6	9.97	837.2	14.4	11.02	25.4	14.3	10.6
Overall mean		325.8	5.6	4.40	445.4	7.0	5.36	36.7	25.0	21.8

Another important one is that the total delivery cost of SDS delivery system are always much smaller than that of RDS delivery system no matter how the percentage of CP service changes in each instance in all groups. The third interesting point is that the total cost in the RDS delivery system increases with the increase in the proportion of CP services in each group, while the total cost in the SDS delivery system decreases ($N < 60$) or increases slightly ($N >= 60$). This result also shows the advantages of the SDS delivery system.

6.5 Performance analysis of solution method

To validate the effectiveness of our solution method, we solve the benchmark instances designed by Solomon (Solomon, 1987), 15 benchmark instances are solved in which the number of nodes ranges from 25 to 100. Compared with current best solutions obtained, the overall mean cost only increases 0.2 per cent, for small-scale instances, the optimal solutions are obtained by our solution method, which validate the effectiveness of our solution method (Table VIII).

Instance	Node	% for CP	Total demand (parcels)	SDS Cost	SDS Unit cost (per parcel)	RDS Cost	RDS Unit cost (per parcel)
1	15	10	22	116	5.27	128	5.82
2	15	20	29	109	3.76	127	4.38
3	15	30	29	103	3.55	133	4.59
4	15	40	32	95	2.97	126	3.94
5	15	50	40	90	2.25	140	3.50
Group mean			30.4	102.6	3.38	130.8	4.30
6	20	10	30	140	5.07	152	5.07
7	20	20	38	133	3.92	155	4.08
8	20	30	39	125	3.23	157	4.03
9	20	40	45	114	2.64	174	3.87
10	20	50	50	108	2.16	171	3.42
Group mean			40.4	124.0	3.07	169.4	4.19
11	30	10	48	218	4.54	226	4.71
12	30	20	54	195	3.61	209	3.87
13	30	30	64	185	2.89	225	3.51
14	30	40	66	172	2.61	228	3.45
15	30	50	77	167	2.17	234	3.04
Group mean			61.8	187.4	3.03	224.4	3.63
16	60	10	92	333	3.62	354	3.85
17	60	20	106	339	3.20	400	3.77
18	60	30	129	362	2.81	452	3.50
19	60	40	145	396	2.73	486	3.35
20	60	50	155	393	2.54	495	3.19
Group mean			125.4	364.6	2.91	437.4	3.49
21	120	10	168	631	3.76	722	4.30
22	120	20	206	638	3.10	802	3.89
23	120	30	233	656	2.82	847	3.64
24	120	40	246	662	2.69	897	3.64
25	120	50	267	677	2.54	946	3.54
Group mean			224	652.8	2.91	842.8	3.76
Overall mean			96.4	286.3	2.97	361.0	3.74

Table VII. Performance analysis CP service

7. Conclusions

In this paper, we introduced the DVRP-SDS for the type of VRP faced by companies deploying a CP delivery system, in which whether the customers with HD service and CP service can be served simultaneously by the same vehicle is a key issue. Our computational study suggests that SDS delivery system offers a significant opportunity for companies in the last mile delivery to reduce the delivery cost and the number of vehicles and thus reduce both emissions and congestion. In addition, it is the first time that our results show the potential benefits of CP service from a quantitative point of view.

In this assessment of the benefits of CP service, we have considered the schedules of single company. However, the utilization of CP facilities has a great effect on the potential benefits and this suggests significant avenues for future research, including the collaborative VRP in which many companies can share the CP facilities. In addition, more uncertainties about customers will be considered in future work.

Table VIII.
Performance analysis

Instance	No. of nodes	Current best solutions	Our method	Gap
R101_25	25	617.1	617.1	0.0%
R102_25	25	547.1	547.1	0.0%
R103_25	25	454.6	454.6	0.0%
R104_25	25	416.9	416.9	0.0%
R105_25	25	530.5	530.5	0.0%
Grout mean		*513.2*	*513.2*	*513.2*
R101_50	50	1,044	1,051.8	0.7%
R102_50	50	909.0	918.2	1.0%
R103_50	50	772.9	772.9	0.0%
R104_50	50	625.4	650	3.9%
R105_50	50	899.3	919.1	2.2%
Grout mean		850.1	862.4	1.4%
R101_100	100	1,645.8	1,644.4	−0.1%
R102_100	100	1,486.1	1,496.6	0.7%
R103_100	100	1,292.7	1,249.2	−3.4%
R104_100	100	1,007.2	1,005.6	−0.2%
R105_100	100	1,377.1	1,378.7	0.1%
Grout mean		1,361.8	1,354.9	−0.5%
Overall mean		908.4	910.2	0.2%

References

Ahmadizar, F., Zeynivand, M. and Arkat, J. (2015), "Two-level vehicle routing with cross-docking in a three-echelon supply chain: a genetic algorithm approach", *Applied Mathematical Modelling*, Vol. 39 No. 22, pp. 7065-7081.

Aized, T. and Srai, J.S. (2014), "Hierarchical modelling of last mile logistic distribution system", *The International Journal of Advanced Manufacturing Technology*, Vol. 70 Nos 5/8, pp. 1053-1061.

Alvarez, A. and Munari, P. (2017), "An exact hybrid method for the vehicle routing problem with time windows and multiple deliverymen", *Computers and Operations Research*, Vol. 83, pp. 1-12.

Bae, H. and Moon, I. (2016), "Multi-depot vehicle routing problem with time windows considering delivery and installation vehicles", *Applied Mathematical Modelling*, Vol. 40 Nos 13/14, pp. 6536-6549.

Baldacci, R., Mingozzi, A. and Roberti, R. (2012), "Recent exact algorithms for solving the vehicle routing problem under capacity and time window constraints", *European Journal of Operational Research*, Vol. 218 No. 1, pp. 1-6.

Battarra, M., Erdoğan, G. and Vigo, D. (2014), "Exact algorithms for the clustered vehicle routing problem", *Operations Research*, Vol. 62 No. 1, pp. 58-71.

Dayarian, I., Crainic, T.G., Gendreau, M. and Rei, W. (2015), "A branch-and-price approach for a multi-period vehicle routing problem", *Computers and Operations Research*, Vol. 55, pp. 167-184.

Dell'Amico, M. and Hadjidimitriou, S. (2012), "Innovative logistics model and containers solution for efficient last mile delivery", *Procedia – Social and Behavioral Sciences*, Vol. 48, pp. 1505-1514.

Dell'Amico, M., Díaz, J.C.D., Hasle, G. and Iori, M. (2016), "An adaptive iterated local search for the mixed capacitated general routing problem", *Transportation Science*, Vol. 50 No. 4, pp. 1223-1238.

Derbel, H., Jarboui, B., Hanafi, S. and Chabchoub, H. (2012), "Genetic algorithm with iterated local search for solving a location-routing problem", *Expert Systems with Applications*, Vol. 39 No. 3, pp. 2865-2871.

Desaulniers, G., Errico, F., Irnich, S. and Schneider, M. (2016), "Exact algorithms for electric vehicle-routing problems with time windows", *Operations Research*, Vol. 64 No. 6, pp. 1388-1405.

Ehmke, J.F. and Mattfeld, D.C. (2012), "Vehicle routing for attended home delivery in city logistics", *Procedia – Social and Behavioral Sciences*, Vol. 39, pp. 622-632.

Ehmke, J.F., Meisel, S. and Mattfeld, D.C. (2012), "Floating car based travel times for city logistics", *Transportation Research Part C: Emerging Technologies*, Vol. 21 No. 1, pp. 338-352.

Feo, T.A. and Resende, M.G. (1995), "Greedy randomized adaptive search procedures", *Journal of Global Optimization*, Vol. 6 No. 2, pp. 109-133.

Ferrucci, F. and Bock, S. (2014), "Real-time control of express pickup and delivery processes in a dynamic environment", *Transportation Research Part B: Methodological*, Vol. 63, pp. 1-14.

Gevaers, R., Van de Voorde, E. and Vanelslander, T. (2009), "Characteristics of innovations in last-mile logistics-using best practices, case studies and making the link with green and sustainable logistics", *Association for European Transport and Contributors*.

Hashimoto, H., Ibaraki, T., Imahori, S. and Yagiura, M. (2006), "The vehicle routing problem with flexible time windows and traveling times", *Discrete Applied Mathematics*, Vol. 154 No. 16, pp. 2271-2290.

Hayel, Y., Quadri, D., Jimenez, T. and Brotcorne, L. (2016), "Decentralized optimization of last-mile delivery services with non-cooperative bounded rational customers", *Annals of Operations Research*, Vol. 239 No. 2, pp. 451-469.

He, Y., Wang, X., Lin, Y. and Zhou, F. (2016), "Optimal partner combination for joint distribution alliance using integrated fuzzy EW-AHP and TOPSIS for online shopping", *Sustainability*, Vol. 8 No. 4, pp. 341.

He, Y., Wang, X., Lin, Y., Zhou, F. and Zhou, L. (2017), "Sustainable decision making for joint distribution center location choice", *Transportation Research Part D: Transport and Environment*, Vol. 55, pp. 202-216.

Huang, Z. (2015), *The Last Mile Delivery in China*.

Ibaraki, T., Imahori, S., Kubo, M., Masuda, T., Uno, T. and Yagiura, M. (2005), "Effective local search algorithms for routing and scheduling problems with general time-window constraints", *Transportation Science*, Vol. 39 No. 2, pp. 206-232.

IBM (2001), *Business to Business What is Business-to-Consumer (B2C)*?, IBM Corporation, available at: www1.ibm.com/servers/eserver/iseries/btob/b2c_definition.htm

Jewels, T.J. and Timbrell, G.T. (2001), "Towards a definition of B2C and B2B e-commerce", ACIS 2001 Proceedings, p. 56.

Jovanovic, R., Bayram, I.S. and Voß, S. (2018), " Solving the 2-connected m-dominating set problem using a GRASP approach for applications in power systems", *2018 IEEE 12th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG)*, pp. 1-6.

Jovanovic, R., Tuba, M. and Voss, S. (2016), "An ant colony optimization algorithm for partitioning graphs with supply and demand", *Applied Soft Computing*, Vol. 41, pp. 317-330.

Klein, R., Neugebauer, M., Ratkovitch, D. and Steinhardt, C. (2017), "Differentiated time slot pricing under routing considerations in attended home delivery", *Transportation Science*.

Lee, H.L. and Whang, S. (2001), "Winning the last mile of e-commerce", *MIT Sloan Management Review*, Vol. 42 No. 4, pp. 54-62.

Liu, R., Xie, X. and Garaix, T. (2014), "Hybridization of tabu search with feasible and infeasible local searches for periodic home health care logistics", *Omega*, Vol. 47, pp. 17-32.

Morganti, E. and Dablanc, L. (2014), "Recent innovation in last mile deliveries", *Non-technological Innovations for Sustainable Transport*, Springer, Cham, pp. 27-45.

Punakivi, M., Yrjölä, H. and Holmström, J. (2001), "Solving the last mile issue: reception box or delivery box?", *International Journal of Physical Distribution and Logistics Management*, Vol. 31 No. 6, pp. 427-439.

Oracle (2000), *Oracle8i Application Developer's Guide – XML Release 3 Glossary*, Oracle Corporation, available at: http://technet.oracle.com/docs/products/oracle8i/doc_library/817_doc/appdev.817/a86030/glossary.htm

Reyes, D., Savelsbergh, M. and Toriello, A. (2017), "Vehicle routing with roaming delivery locations", *Transportation Research Part C: Emerging Technologies*, Vol. 80, pp. 71-91.

Roberti, R. (2012), "Exact algorithms for different classes of vehicle routing problems", Doctoral dissertation, Alma.

Schyns, M. (2015), "An ant colony system for responsive dynamic vehicle routing", *European Journal of Operational Research*, Vol. 245 No. 3, pp. 704-718.

Solomon, M.M. (1987), "Algorithms for the vehicle routing and scheduling problems with time window constraints", *Operations Research*, Vol. 35 No. 2, pp. 254-265.

State Post Bureau (2016), "Report about express industry development", available at: www.spb.gov.cn/zxft_15555/gjyzjjgsj/whxfqy/bjzl/201603/t20160314_730249.html (accessed 1 January 2016).

Tan, K.C. (2015), "An innovation in last-mile delivery", *Ta-Q-Bin*, Springer, Singapore, pp. 45-57.

Tang, J., Pan, Z., Fung, R.Y. and Lau, H. (2009), "Vehicle routing problem with fuzzy time windows", *Fuzzy Sets and Systems*, Vol. 160 No. 5, pp. 683-695.

Taş, D., Jabali, O. and Van, Woensel, T. (2014), "A vehicle routing problem with flexible time windows", *Computers and Operations Research*, Vol. 52, pp. 39-54.

Taş, D., Dellaert, N., Van Woensel, T. and De Kok, T. (2013), "Vehicle routing problem with stochastic travel times including soft time windows and service costs", *Computers and Operations Research*, Vol. 40 No. 1, pp. 214-224.

Wang, H. (2017), "Routing and scheduling for a last-mile transportation system", *Transportation Science*.

Yanik, S. and Bozkaya, B. (2014), "A new VRPPD model and a hybrid heuristic solution approach for e-tailing", *European Journal of Operational Research*, Vol. 236 No. 3, pp. 879-890.

Zhou, J. and Zhong, X. (2015), "TAOBAO logistics model based on joint distribution", *Liss 2014*, Springer, Berlin, Heidelberg, pp. 29-33.

Zhou, L., Lin, Y., Wang, X. and Zhao, Q. (2016), "Integrated optimization for multiclass terminal location-heterogeneous vehicle routing of urban distribution under online shopping", *Computer Integrated Manufacturing Systems*, Vol. 22 No. 4, pp. 1139-1147.

Zhou, L., Lin, Y., Wang, X. and Zhou, F. (2017), "Model and algorithm for bilevel multisized terminal location-routing problem for the last mile delivery", *International Transactions in Operational Research*,

Zhou, L., Baldacci, R., Vigo, D. and Wang, X. (2018), "A multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution", *European Journal of Operational Research*, Vol. 265 No. 2, pp. 765-778.

Further reading

Jafari-Eskandari, M., Aliahmadi, A.R. and Khaleghi, G.H.H. (2010), "A robust optimisation approach for the milk run problem with time windows with inventory uncertainty: an auto industry supply chain case study", *International Journal of Rapid Manufacturing*, Vol. 1 No. 3, pp. 334-347.

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