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A Fast Simulated Annealing Heuristic for the Multi-Depot Two-Echelon Vehicle Routing Problem with Delivery Options

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Abstract

We study a variant of the vehicle routing problem (VRP) arising in last-mile distribution, called the multi-depot two-echelon vehicle routing problem with delivery options (MDTEVRP-DO). The MDTEVRP-DO involves two decision levels: (i) designing routes for a fleet of vehicles located in multiple depots to transport customer demands to a set of satellites, and (ii) routing a fleet of vehicles from the satellites to serve the final customers. A relevant feature of the problem characterizing nowadays delivering services is that the customers can collect their packages at pickup stations near to their home or workplace. For the problem, we design an effective simulated annealing (SA) heuristic. The new algorithm has been extensively tested on benchmark instances from the literature and its results compared with those of state-of-the-art algorithms. The results show that the proposed SA obtains several new best solutions for the MDTEVRP-DO benchmark instances. Moreover, its computation performance are greater than those of state-of-the-art algorithms for the MDTEVRP-DO.

Keywords: two-echelon vehicle routing problem, delivery option, simulated annealing

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1 Introduction

Last mile delivery is regarded as the most expensive, most polluting, and least efficient part of the e-commerce supply chain (Gevaers et al., 2009) and has drawn extensive concerns both in industry and academia. There is an increasing interested in implementing efficient, innovative, and ecological last mile delivery concepts (Hagen and Scheel-Kopeinig, 2021), such as urban consolidation centers (Allen et al., 2012), joint distribution (He et al., 2017), crowdsourced delivery (Archetti et al., 2016; Yu et al., 2021), electric or unmanned devices (Cattaruzza et al., 2017; Enthoven et al., 2020), drones (Carlsson and Song, 2018; Agatz et al., 2018), robots (Boysen et al., 2018; Chen et al., 2021) and autonomous vehicles (Yu et al., 2020)et al.

Despite the higher convenience for the recipient and the positive effects for logistics service providers through increasing business opportunities, direct package delivery to recipients' homes or workplaces (Home Delivery, HD) imposes a variety of social costs due to the increased number of delivery vehicles (e.g., vans and trucks) (Kapser and Abdelrahman, 2020). By providing customers an option to pick up their packages (Customer's Pickup, CP) at a pickup facility close to their homes or workplaces bring significant benefits for customers like flexibility and preferences, as well as operating cost saving for logistics operators. With providing CP option, customers may served either by HD service provided by a truck(electric or unmanned devices) or covered by pickup facilities where they can pick up their packages themselves (Zhou et al., 2016). Examples of such facilities include unattended parcel lockers and attended collection and delivery points located outside a consumer's home, or located at train or bus stations, local retail shops and other locations are currently being widely used in the world (Deutsch and Golany, 2018; Enthoven et al., 2020), and pickup-point systems is one promising concept to efficiently design last-mile delivery systems (Savelsbergh and Van Woensel, 2016).

Designing and optimizing the last mile delivery system considering the two alternative options has become an interesting work and has recently received considerable considerations (Zhou et al., 2016, 2019, 2018; Enthoven et al., 2020; Dumez et al., 2021; Yu et al., 2021). In urban scenario, the two-echelon logistics system plays a very important role nowadays in the management of urban freight activities (Baldacci et al., 2013; Perboli et al., 2021) and has received plenty of considerations since the work of Gonzales Feliu et al. (2007). In this distribution system, intermediate depots, named satellites, are placed between the central depot and the final customers, and the resulting distribution network is turned into a cost effective city logistics system underlying freight management and routing decisions in an integrated way.

Given the great value obtained by integrating alternative options and two-echelon distribution systems, in this paper, we focus on the multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution (MDTEVRP-DO) proposed by Zhou et al. (2018). The MDTEVRP-DO problem is highly important practical and complex problem involving several interconnected decisions (service options, facility locations, and two levels of vehicle routes).

To solve the MDTEVRP-DO effectively, we design a fast simulated annealing based heuristic together with a tailored solution representation scheme which always gives a solution without exceeding the capacity and working time constraint of the two-echelon vehicles. The new algorithm is extensively tested on benchmark instances of the MDTEVRP-DO and compared with state-of-the-art algorithms for the problem.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature. Section 3 describes the problem. The simulated annealing heuristic is detailed in Section 4. Section 5 develops the experiments and reports the computational results. Finally, conclusions are given in Section 6.

2 Literature review

To the best of authors' knowledge, Zhou et al. (2016) were the first to study the MDTEVRP-DO and to introduce alternative delivery options with alternative such as HD and CP. According to their definition, a customer should be served either by a truck with providing HD service or covered by an opened locker within acceptable distance. The decisions involve (i) where to open the lockers and (ii) how to route the visits to the opened lockers and customers that are not covered. A hybrid evolution search algorithm by combining genetic algorithm (GA) and local search (LS) is presented to solve this problem.

Several variants of delivery options appeared in previous studies, such as int the generalized vehicle routing problem (GVRP) where customers are grouped into clusters and exactly one customer from each cluster is visited (Ghiani and Improta, 2000; Bektaş et al., 2011; Pop et al., 2012; Hà et al., 2014; Yuan et al., 2021), the ring-star problem (RSP) where the customers be connected to a ring through transition points (Baldacci et al., 2007; Baldacci and Dell'Amico, 2010; Baldacci et al., 2017b,a), the covering tour problem (CTP) where a customer demand can be satisfied by visiting the customer along a tour or by visiting a location close to the customer (Naji-Azimi et al., 2012; Tricoire et al., 2012; Ha et al., 2013; Allahyari et al., 2015; Flores-Garza et al., 2017), roaming delivery locations(RDL) where a customer can be served at differen locations (Reyes et al., 2017; Ozbaygin et al., 2017; He et al., 2020), or multiple time windows (MTW) providing alternative time windows for customers (Souffriau et al., 2013; Belhaiza et al., 2014).

Below, we focus on the closely related problems to our problem. Veenstra et al. (2018) presented a locker location and vehicle routing problem where separate vehicle routes are used to serve the different delivery options and designed a hybrid variable neighborhood search(VNS) algorithm to solve the problem. Zhou et al. (2019) designed a probability and distance-based model to describe the customers' delivery options in customer clusters. By adopting an approximate continuous model to simulate the route in clusters, they proposed a multi-size locker location and vehicle routing problem with heterogeneous vehicles to perform separate routes of lockers and customers with HD service. To solve this problem, a hybrid GSA procedure combining genetic algorithm and simulated annealing (SA) was presented. Sitek and Wikarek (2019) and Sitek et al. (2021) considered post outlet, individual customer and locker as alternative delivery options and defined a capacitated vehicle routing problem with time windows. Hybrid approaches integrate constraint programming(CP), mathematical programming(MP) and heuristics were presented to solve this problem. Mancini and Gansterer (2021) expanded the alternative HD and CP options and formulated the vehicle routing problem with three delivery options considering customers' preferences. In this problem, customers can be served by home delivery with a specific time window (HDTW), or CP with preferred pickup lockers or either of the two options. A compensation is paid for customers when choosing CP as an alternative to receive the parcel at home. A large neighbourhood search (LNS)-based matheuristic and an iterated local search (ILS) procedure were presented. Based on the approach of Mancini and Gansterer (2021), where compensations may provide incentives for the customers to use lockers Grabenschweiger et al. (2021) addressed the vehicle routing problem with heterogeneous locker boxes, in which package size and locker box size were considered. An adaptive large neighborhood search (ALNS) was designed to solve this problem. Dumez et al. (2021) defined the vehicle routing problem with several alternatives delivery options, including customer's home, shared lockers and car's trunk. Delivery time window and customer's preference on these options are also considered to improve customer satisfaction. This problem was solved with an ALNS. Jiang et al. (2022) defined a covering salesman problem in which customers are classified into three groups, HD customers, CP customers and either HD or CP customers. A hybrid biogeography-based optimization(HBBO) was developed to solve this problem.

Table 1: Summary of the works considering alternative delivery options

Reference	Problem structure	Objective(minimization)	Deliver options	Main constraints	Solution
Zhou et al. (2016)	SE-MD	Locker open, fixed vehicle and arc cost	HD, CP with covering	Depot and locker capacity, route duration	GA&LS
Veenstra et al. (2018)	SE-SD	Locker open and arc cost	HD, CP with covering	Separate routes for HD and CP service	Hybrid VNS
Zhou et al. (2019)	SE-SD	Locker open, fixed vehicle, arc and secondary delivery cost due to HD failure	HD and CP are probability and cover distance based	Heterogeneous locks, separate routes for HD and CP service, heterogeneous vehicle	GA&SA
Sitek and Wikarek (2019) and Sitek et al. (2021)	SE-SD	arc cost, compensations for alternative delivery locations	Alternative delivery locations (without and with TW)	Locker capacity, heterogeneous vehicles	Hybrid with CP, MP and metaheuristics
Mancini and Gansterer (2021)	SE-SD	Fixed vehicle, arc cost and compensations with CP	HDTW, CP with covering, either HDTW or CP	Locker capacity	LNS-based matheuristic, ILS
Grabenschweiger et al. (2021)	SE-SD	Arc cost and compensations with CP	HDTW, CP with fixed compensation	Package size, box size of locker	ALNS
Dumez et al. (2021)	SE-SD	Number of vehicles and arc cost	CP, HDTW, alternative delivery locations	Locke capacity	LNS
Jiang et al. (2022)	SE-SD	Locker open and arc cost	HD, CP with covering, either HD or CP	Locker capacity	Hybrid biogeography -based optimization
Zhou et al. (2018)	TE-MD	Fixed vehicle, arc, connection and handling cost	HD, CP with connection cost	Limited vehicles of each satellite, route duration	Hybrid multi-population GA
Enthoven et al. (2020)	TE-SD	Arc and connections cost with CP	HD, CP with covering	CP occurs within covering distance, limited vehicles	ALNS
Yu et al. (2021)	TE-SD	Arc cost, connection cost with CP and compensation with occasional drivers	HDTW, CP with connection cost, occasional drivers	CP occurs within covering distance, lmited vehicles of each satellite	ALNS

Notion: SE-single echelon; TE-two echelon; SD-single deopt; MD-multiple depot; TW-time window.

The integration of delivery options into two-echelon systems has recently drawn the attention of the researchers. Zhou et al. (2018) introduced connection cost to describe the preference of CP service of a customer, and proposed MDTEVRP-DO where alternative delivery options are considered in the second echelon. A hybrid multi-population genetic algorithm(GA) is designed to solve this problem. By allowing splitting delivery in the first echelon and routing satellites and covering locations in a same route, Enthoven et al. (2020) defined the single depot two-echelon vehicle routing problem with CP and HD options and, designed a LNS for its solution. More recently, the single depot two-echelon vehicle routing problem with HDTW, CP options and occasional drivers is defined by Yu et al. (2021), where an ALNS algorithm is propose to solve the problem.

Table 1 provides a comparison of the features of closely related works.

3 Problem description

Based on the problem description presented by Zhou et al. (2018), we updated several parameters and describe the problem correctly and more concisely.

The MDTEVRP-DO can be formally described by a mixed graph $G = (N, A, C)$, where the node set N is partitioned as $N = N_D \cup N_S \cup N_P \cup N_C$. Set N_D represents n_d depots, N_S represents n_s satellites, N_P represents n_p pickup facilities and N_C represents n_c customers. The arc set A is defined as $A = \{(d, j), (j, d) : d \in N_D, j \in N_S\} \cup \{(i, j) : i, j \in N_S \cup N_P \cup N_C\}$. With each arc $(i, j) \in A$ is associated a routing cost t_{ij} and a travel time $r_{ij} > 0$.

Associated with the customer set N_C are n_c customer requests. Each customer request $i \in N_C$ has an associated depot node $o_i \in N_D$, demand q_j, and service time $s_i = u_{tc} \cdot q_i$, where $u_{tc} > 0$ is unit request service time. Accordingly, each depot $d \in N_D$ is associated with a set of customers denoted as $N_C(D)$, which means the requests of the customers are dispatched from depot d.

Each customer in N_C can be served by either a vehicle or picking up his/her packages from a pickup facility. Set C represents the possible connections between customers and pickup facilities, i.e., $C = \{(i, j) : i \in N_C, j \in N_P\}$. A non-negative connection cost c_{ip} is accounted whenever customer $i \in N_C$ picks up packages from pickup facility $p \in N_P$. c_{ip}, calculated as $d_{ip} \cdot q_i \cdot u_{cp}$, where d_{ip} is the distance between customer i and pickup facility p, and u_{cp} is a connection cost coefficient.

A fleet of m_d^1 identical vehicles with capacity Q_d^1 and fixed cost U_d^1 are located at depot $d \in N_D$ and used to transport goods to satellites. A maximum working time equal to L_d^1 is associated with each first-level vehicle of depot d. A fleet of m_s^2 identical vehicles with capacity Q_s^2 and fixed cost U_s^2 are available at satellite $s \in N_S$ to serve the customers.

The first-level consists of vehicle routes that start and end at the depot and deliver customer requests to a subset of satellites. Each satellite $s \in N_S$ can be served by more than one first-level route to consolidate the requests from depots in N_D. The cost of a first-level route is the sum of the costs of the traversed arcs plus the fixed vehicle cost of the associated depot d. Total working time is limited, i.e., the sum of travel time of arcs plus the handling time at satellites does not exceed the vehicle working time L_d^1. And the handling time at satellite s is noted as $q_s \cdot u_s$, where q_s is the requests delivered to s and u_s is the unit handling time.

At the second-level, the vehicles deliver the consolidated requests from the satellites to individual customers and pickup facilities. Each pickup facility $p \in N_P$ can be visited by more than one second-level route that providing sharing service for the customers from different depots.

If used, the cost of a second-level route is the sum of the traversed arcs, plus the fixed vehicle cost, plus the sum of the connection cost associated with the customers picking up the packages themselves. Total working time is limited, i.e., the sum of the travel time traversed arcs, plus the service time at customers and the service time at pickup facilities does not exceed the vehicle working time L_s^2. The service time at pickup facility p is noted as $q_p \cdot u_{tp}$, where q_p is the requests delivered to p and u_{tp} is the service time coefficient.

The problem seeks to design the vehicle routes of both levels so that each customer request is visited exactly once, the transportation requests delivered to customers from each satellite correspond to the transportation requests received from the depots, and the sum of the routing, connection, and handling costs is minimized.

4 Simulated annealing heuristic

Since the first development of simulated annealing by Gelatt (1983), SA has been successfully applied to solve numerous challenging combinatorial optimization problems (Lin and Shih-Wei, 2013; Lin and Ying, 2015; C and D, 2017; Lin and Ying, 2021). Although researchers have proposed rich algorithms to solve such issues, SA's capacity to enlarge the solution space by exploring worse solutions is promising in addressing problems like the MDTEVRP-DO. This study, therefore, proposes an SA-based heuristic for solving the MDTEVRP-DO.

4.1 Solution representation

An MDTEVRP-DO solution has two parts. The first part has a set of notation symbols used to record the service sequence of SEV. It consists of n_c customers indicated by the set $\{1, 2, \ldots, n_c\}$, n_s satellite stations represented by the set $\{S_1, S_2, \ldots, S_{n_s}\}$, $n_s/3$ dummy satellite stations (denoted as S_0), n_p pickup stations indicated by the set $\{P_1, P_2, \ldots, P_{n_p}\}$ and $n_p/3$ dummy pickup stations (denoted as P_0). Dummy satellite stations S_0 is used to separate routes in the second echelons, even though the capacity of the current vehicle is not exceeded. The second part has n_d set of notion symbols used to record the service sequence of the FEV for n_d deposits. Each set of notation symbols is used to record the service sequence of the FEV. It consists of n_s satellites indicated by the set $\{S_1, S_2, \ldots, S_{n_s}\}$ and $n_s/3$ dummy satellite stations S_0.

The first number in the first part of a solution must be in $\{S_1, S_2, \ldots, S_{n_s}\}$, indicating the first satellite under consideration. Each satellite serves customers (or pickup facilities) in the solution representation between the satellite and the next satellite. The first route of a satellite is started by serving the first customers (or pickup facilities) after the satellite station. Subsequent customers (or pickup facilities) are added to the current route one after the other. The current route is ended if including a customer (or pickup facilities) exceeds the current vehicle capacity or violates the working time constraint. The current SEV will go back to its starting satellite station. A new SEV route will then start by serving the next customer (or pickup facilities). Customers after the pickup facility indicate that the customer needs to pick up the goods at this pickup facility by themselves and P_0 indicates that the SEV will serve the customer directly. If a segment of successive pickup facilities exists in the solution representation, only the last pickup facility in this segment will be used. Similarly, if there is a segment of successive satellite stations exists in the solution representation, only the last satellite station in this segment will be used. If a SEV does not serve any customer or pickup facility, it does not need to be used, so there is no need to calculate the number of SEV vehicles used and their related costs.

After parsing the notation string of the first part solution representation, we can obtain the following information:

- Those customers or pickup facilities will be served by which satellite station.
- Which SEV will directly service customer.
- Which customers are going to pick up the goods at the pickup facility.
- If the pickup facility is used, the delivery volume it needs.
- The delivery volume, working time, and cost of each SEV.

After obtaining the related information from the first part of solution representation, the second of solution representation can be decoded in a similar way. The first route of a satellite station is started for each deposit by serving the first satellite after the deposit. Subsequent satellite stations are added to the current route one after the other. If a satellite station does not provide any goods to customers or pickup facilities, the FEV cannot serve the satellite station from the current depot.

The current route is ended if including a satellite will exceed the FEV capacity or violate the working time constraint, or the satellite station is S_0 The current FEV will go back to its starting deposit. A new FEV route will then start by serving the next satellite station.

This solution representation scheme always gives an MDTEVRP-DO solution without exceeding the capacity and working time constraint of FEVs or SEVs. However, the capacity of satellites may be exceeded, which will result in an infeasible solution whose objective value will be penalized. Furthermore, the number of FEVs or SEVs used may exceed the number of available FEVs or SEVs, which will result in an infeasible solution whose objective value will be penalized.

4.2 Illustration of solution representation

This study uses a small instance to illustrate the solution representation. The number of depots, satellite stations, pickup facilities, and customers is two, four, eight, and twenty, respectively. Due to the limit space, each cost and time data are not included in the tables. The capacity of FEVs and SEVs are 200 and 150, respectively. The maximal number of available FEVs and SEVs are 4 and 6, respectively.

The depots' coordinates and number of FEVs are shown in Table 2. Table 3 lists the coordinates, capacities, and number of SEVs of satellite stations. The coordinates of the pickup facility location are displayed in Table 4. Table 5 describes the coordinates, demands, and the provided depot nos. of customers.

Fig.1 illustrates an example of the solution representation. Fig.2 is a visual illustration of the distribution network corresponding to the sample solution representation shown in Fig.1.

By separating the symbol of real satellite station (S_1, S_2, S_3, S_4) in the first part, we can obtain the following substring:

S_4: $20 \rightarrow 9 \rightarrow 6$

Table 2: Depot Location Information

No.	X-cord	Y-cord	Number of FEV
D_1	4	32	2
D_2	32	10	2

Table 3: Satellite Station Information

No.	X-cord	Y-cord	Satellites Capacity	Number of SEV
S_1	14	23	200	2
S_2	25	17	250	2
S_3	28	17	200	2
S_4	12	26	280	2

Table 4: Pickup facility location Information

No.	X-cord	Y-cord
P_1	27	16
P_2	17	21
P_3	31	28
P_4	20	13
P_5	20	21
P_6	16	16
P_7	24	19
P_8	21	12

Table 5: Customer location, demand and the goods provided depot

No.	X-cord	Y-cord	Demand	Provided depot
1	27	16	15	1
2	31	28	20	2
3	24	20	25	1
4	17	23	20	2
5	18	23	20	1
6	14	31	45	2
7	27	15	30	1
8	18	22	20	2
9	16	33	35	1
10	22	14	35	2
11	17	7	20	1
12	23	12	20	2
13	17	23	35	1
14	31	28	30	2
15	24	20	20	1
16	18	19	15	2
17	24	22	20	1
18	18	23	30	2
19	18	21	25	1
20	20	30	20	2

S_2: 17 $\rightarrow$ 2 $\rightarrow$ 14 $\rightarrow$ P_8 $\rightarrow$ P_1 $\rightarrow$ 7 $\rightarrow$ 1 $\rightarrow$ S_0 $\rightarrow$ 10 $\rightarrow$ P_4 $\rightarrow$ 8 $\rightarrow$ P_0 $\rightarrow$ 11 $\rightarrow$ P_3 $\rightarrow$ P_0 $\rightarrow$ 12 $\rightarrow$ P_6 $\rightarrow$ P_7

S_1: 18 $\rightarrow$ 5 $\rightarrow$ 4 $\rightarrow$ 13 $\rightarrow$ 15 $\rightarrow$ 3 $\rightarrow$ 16 $\rightarrow$ 19 $\rightarrow$ P_2

S_3: P_5

A SEV from the satellite station (S_4) will directly go to customer 20, 9, and 6 one by one, and then go back to S_4. Only one SEV is needed of S_4, because the SEV route will not violate any constraint. There are two SEVs needed for the S_2. The first SEV route of S_2 serves customer 17, 2, 14, P1 and go back to S_2, while the second SEV route serves 10, P4, 11, 12, and then go back to S_2. Because customer 7 and 1 are directly followed P_1, customer 7 and 1 will go to P_1 to get their goods. Similarly, the customer 8 will go to P_4 to get goods. The first SEV route of S_2 does not continue after serving customer 1 (It is indeed pickup facility P_1, because customer 1 will go to P_1 to get goods), because the dummy satellite station S_0 is encountered.

First part																			
Seq.	S_4	20	9	6	S_2	17	2	14	P_8	P_1	7	1	S_0	10	P_4	8	P_0	11	P_3
	P_0	12	P_6	P_7	S_1	18	5	4	13	15	3	16	19	P_2	S_3	P_5	-	-	-
Second part																			
Seq.	D_1	S_3	S_4	S_2	S_1	S_0													
	D_2	S_2	S_0	S_1	S_3	S_4													

Figure 1: Example of solution representation.

There are two SEVs needed for S_1. The first SEV route of S_1 starts from S_1 and then serve customer 18, 5, 4, 13, and go back to S_1, while the second SEV route of S_1 starts from S_1 and then serve customer 15, 3, 16, 19, and then go back to S_1. Because it violates the constraint (maybe the capacity of SEV capacity or working time of SEV), the first SEV route of S_1 does not serve the customer 15 after serving customer 13, Because there is no customer will get goods at P_2, there is no need for the second SEV route of S_1 to go to P_2 after serving customer 19. Other pickup facilities, such as P_1, P_3, P_6, P_7, and P_8 are ignored because there is no customer directly following them. Because the satellite station (S_3) only has a pickup facility (P_5) to be considered and no customer will go to P_5 to get goods, there is no need to send out SEV for S_3. Therefore, five SEVs are used for all used satellite stations.

After parsing the first part of solution representation example, the route for FEVs can be constructed. According to the second part of solution representation example. Therefore, we have the following two substrings:

D_1: $S_3 \rightarrow S_4 \rightarrow S_2 \rightarrow S_1 \rightarrow S_0$

D_2: $S_2 \rightarrow S_0 \rightarrow S_1 \rightarrow S_3 \rightarrow S_4$

Because S_3 is no use for SEVs known from the first part solution representation, the S_3 can be ignored by FEVs of D_1 and D_2. The first FEV route ofD_1 starts from D_1 and then serve satellite station S_4, S_2, and go back to D_1. Because the first FEV route of D_1 will violate the constraint of vehicle capacity, it does not serve the satellite station S1 after serving satellite station S_2. So the second FEV of D_1 is needed to serve satellite station S1. Because there is no other satellite station symbol after S_1, the second FEV of D_1 is go back to D_1 after serve satellite station S_1.

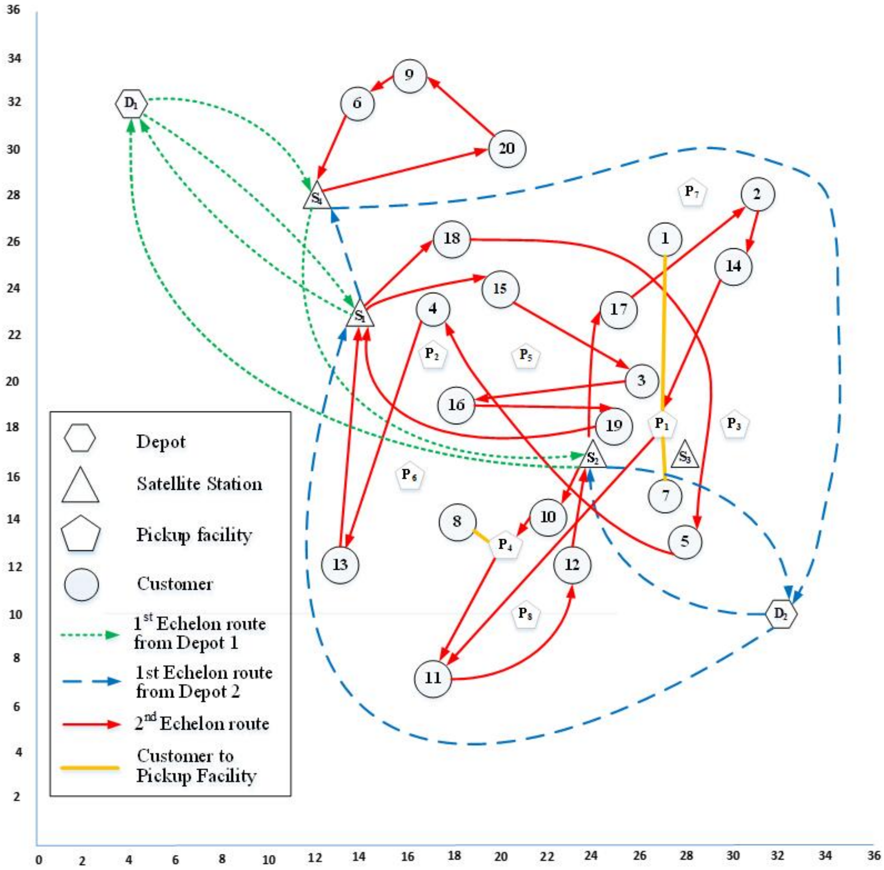

Figure 2: Visual illustration of the solution presented in Fig.1.

The first FEV route of D_2 starts from D_2 and the serve satellite station S_2. Because the next symbol followed by S_2 is S_0, the current FEV is terminated by go back to D_2 after serve satellite station S_2 . The second FEV route of D2 starts from D_2 and then S_1 and S_4 (S_3 is ignored), and the go back to D_2, because there is no other satellite station symbol after S_4. Therefore, four FEVs are used in total.

4.3 Initial solution and neighborhood

The initial solution is created by random. In order to generate the neighborhood solution from the current solution $\prod$, random moves are used, namely insert, swap, and invert. In each iteration, a new solution $\prod'$ is selected from $S(\prod)$. The insertion move is executed by arbitrarily selecting an element of $\prod$ and inserting it into the position immediately before another arbitrarily selected element of $\prod$. The swap move is performed by arbitrarily selecting two elements of and then swapping their positions. The inversion move involves arbitrarily selecting a subsequence of $\prod$ and then reversing the order of the subsequence. The probabilities for choosing these moves are 1/3, 1/3, and 1/3, respectively.

Since the solution represent consists of two parts and the first part is the most important in the developed algorithm, the probability of executing moves in the first part is increased. The probability that the first part is chosen to generate a neighborhood solution (using the chosen move) is $0.5+0.51/(n_d+1)$, while the probability that $\prod'$ is obtained by

```
Given: T_0, N_iter, N_non-improved, PF, β, and MD-TEVRP-DO instance;
Output: Π_best and OVF_best;
Begin
  Generate an initial solution Π randomly;
  T ← T_0; Π_best ← Π; N_non ← 0; OFV_best = OF(Π, M); UnitP = PF × OFV_best;
  While (N_non < N_non-improved) do
    For r=1 to N_iter do
        Generate ρ_1 =uniform(0,1);
         If (ρ_1 ≤ 1/3) move_type=Swap;
         If (ρ_1 > 1/3 and ρ_1 ≤ 2/3) move_type=Insertion;
         If (ρ_1 > 2/3 and ρ_1 ≤ 1) move_type=Inversion;
        Generate ρ_2 =uniform(0,1);
        If (ρ_2 <= 0.5 + 0.5 × 1/(n_d + 1)) then
           Π' is obtained by performing the chosen move_type on the first part of Π;
        Else
           Π' is obtained by performing the chosen move_type on one depot of the second part of
           Π;
        End If
        δ = OF(Π', UnitP) − OF(Π, UnitP);
        If (δ ≤ 0) then
           Π ← Π';
        Else
           Generate γ =uniform(0,1);
           If (γ ≤ e^(−δ/T)) then
              Π ← Π';
           End If
        End If
        If (Π' is feasible and OF(Π', UnitP) < OVF_best) then
           Π_best ← Π'; OVF_best ← OF(Π', UnitP); N_non ← 0; UnitP = PF × OFV_best;
        End If
    End for
    N_non ← N_non + 1; T ← Tβ;
  End while
  Return Π_best and OVF_best;
End
```

Figure 3: Pseudo code for the proposed SA heuristic.

performing the chosen move on one depot of the second part of $\prod$ is $0.51/(n_d+1)$. Note that the first symbol in the first part must be the satellite station. A move is discarded if the first symbol in the first part is not a satellite station. In this case, a new move is selected until a feasible solution is found.

4.4 The SA parameter and procedure

There are five parameters in the developed simulated annealing algorithm. T_0 is the initial temperature. N_{iter} denotes the number of iterations at a given temperature. $N_{non_improved}$ is the maximum number of successive temperature decreases at which the best solution is not improved; i.e., the algorithm terminates when the best solution is not improved after $N_{non-improved}$ successive temperature decreases. PF is the unit penalty factor to determine the unit penalty for violation of various constraints; β is the coefficient of the cooling schedule. The algorithm is described as follows.

The current temperature (T) is set to the initial temperature T_0 at the beginning of the proposed SA heuristic, while the best solution $\prod_{best}$ is set to be the current solution ($\prod$) and OFV_{best} is set to $OF(\prod, UnitP)$, while the $OF(\prod, UnitP)$ is the objective function used to calculate the objective function value of $\prod$ and $UnitP$ is unit penalty, computed as PFF_{best}. The $UnitP$ is calculated as a unit penalty multiplied by the degree of the restriction violation. If the volume of deliveries assigned to the satellite station exceeds the capacity of the satellite station, the penalty cost will be calculated as the amount of excess weight multiplied by the unit penalty cost. If the number of vehicles deployed exceeds the number of vehicles available, the penalty cost for each depot or satellite station shall be calculated as the excess number of vehicles multiplied by the unit penalty and the capacity of the vehicle. Each iteration at a given temperature generates a neighborhood search mechanism, as described in Section 4.3.

Let δ be the objective function difference between the new neighborhood solution and the current solution, i.e., $\delta = OF(\prod', UnitP) - OF(\prod, UnitP)$. If $\delta < 0$, then the new neighborhood solution will replace the current solution; otherwise, the new neighborhood solution is accepted if a random number ρ(between 0 and 1) is less than $e^{-\delta/T}$. If the new solution in the neighborhood satisfies these conditions, $\prod'$ is replaced as the current solution $\prod$. The current temperature drops to βT, $0 < \beta < 1$, after N_{iter} iterations at the current temperature T. The algorithm terminates when the best solution has not been improved after $N_{non-improved}$ consecutive temperature reductions. The best solution($\prod$) and its objective function value (OVF_{best})are updated when a better feasible solution is found. The best MDTEVRP-DO solution is derived from $\prod_{best}$ when the algorithm terminates. Fig. 3 is the pseudo code of the proposed SA heuristic.

5 Computational experiments

A computational experiment was conducted to evaluate the performance of the proposed SA algorithm in solving the MDTEVRP-DO problem. The following sections describe the benchmark problem set, parameter calibration, and computational results of HPGM compared with the state-of-the-art algorithm.

5.1 Test instances

This study adopts the MDTEVRP-DO dataset presented by Zhou et al. (2018). These instances are available at http://www.vrp-rep.org. (VRP-REP-ID=2017-0026). There are 36 instances in this data set. These test instances are generated based on $n_d = \{1, 2, 3\}$ depots, $n_s = \{4, 8, 12\}$ satellite stations, $n_p = \{10, 20, 30\}$ pickup facilities, and $n_c = \{50, 100, 150, 200\}$ customers. The detail method to set the location of nodes (depots, satellite stations, pickup facilities, and customers), capacity, cost, speed, and time parameters, number of vehicles, etc., can be found in Zhou et al. (2018).

5.2 Parameter setting

As shown in Table 6, there were four levels for each of the five parameters to calibrate; thus, there were 45 possible combinations of parameter values. The four levels for each of the five parameters were first determined by reference to several related studies (Lin and Shih-Wei, 2013; Lin and Ying, 2015; C and D, 2017; Lin and Ying, 2021), and then

Table 6: Parameters and Values Tested

Parameter	Values
T_0	10,15,20,25
N_{iter}	$1500L^*$,$2000L$, $2500L$, $3000L$
β	0.925, 0.95, 0.975, 0.99
$N_{non-improved}$	5,10,15,20
PF	$0.003B^!$, $0.005B$, $0.007B$, $0.008B$

L: The length of solution representation
B: Best objective function value

fine-tuned in a pilot experiment with six randomly generated test instances. To more efficiently determine the best combination of the five parameter values, Type B of the Taguchi L16 orthogonal experimental design, which includes 16 parameter combinations (see https://www.york.ac.uk/depts/maths/tables/l16b.htm), was applied to six additional randomly generated test instances. For each parameter combination, the proposed SA algorithm was run independently 10 times for each of the six generated test instances.

The average relative percentage deviation ($ARPD$) from the best solution of the six generated instances is given in Tables 7 and 8 as the response variable, in which the relative percentage deviation (RPD) was computed as follows:

$$RPD^i = (Obj^i_{ave} - Obj_{best})/Obj_{best} \times 100\%$$

where, Obj^i_{ave} denotes the average objective function value of a specific problem instance i ($i \in 1, 2, \cdots, 6$)obtained in 10 runs using the proposed SA algorithm with a specific parameter combination and the Obj_{best} is the minimum objective function value of a specific problem instance obtained in $10 \times 16 = 160$ runs using the proposed SA algorithm with all parameter combinations.

Table 7 shows the $ARPD$s obtained by different levels of each parameter. As can be seen in Table 8, the most important parameters among the five parameters is N_{iter} which had the largest $ARPD$ ranges. That is, when the number of solutions evaluated was increased, better solutions could be obtained at the cost of increased computation time. T_0 and β are the second an third important parameters. It is hard to separate the influence of T_0 and β. T_0 will determine the current temperature T in the algorithm. T affects the probability of accepting a worse solution. Generally, the higher the value of T, the larger the probability of accepting a worse solution will be. As a result, the convergence of the algorithm is slower. On the other hand, if the value of T is too small, the probability of accepting a worse solution will be small and the algorithm is more likely to be stuck at a local optimum. Smaller β will result in current temperature T reduced quickly, which larger β will result in current temperature reduced T slowly. $N_{non-improved}$ will influence of the termination of SA. Higher will $N_{non-improved}$ lead more solutions evaluated in the algorithm at the expense of computing time. The reason why PF is the least important parameter may be the tested values are all suitable. PF is too large, then the algorithm tends to reject infeasible solutions and is prone to being trapped in local optima. On the other hand, if PF is too small, then the algorithm is more likely to accept an infeasible solution.

To balance solution quality and computation time in this study, the parameter values of T_0, N_{iter}, β, $N_{non-improved}$ and PF were set to 15, $3000L$, 0.975, 20 and $0.003B$,

Table 7: Orthogonal array and the obtained $ARPD$s

Experiment No.	T_0	N_{iter}	β	$N_{non_improved}$	PF	$ARPD$
1	10	$1500L^*$	0.925	5	$0.003B$	10.0539
2	10	$2000L$	0.950	10	$0.005B$	10.2886
3	10	$2000L$	0.975	15	$0.007B$	5.1510
4	10	$3000L$	0.990	20	$0.009B$	4.2133
5	10	$1500L$	0.950	15	$0.009B$	6.8399
6	10	$2000L$	0.925	20	$0.009B$	7.2279
7	10	$2000L$	0.990	5	$0.005B$	4.7322
8	10	$3000L$	0.975	10	$0.003B$	3.8797
9	10	$1500L$	0.975	20	$0.005B$	6.1434
10	10	$2000L$	0.990	5	$0.003B$	5.6174
11	20	$2500L$	0.925	10	$0.009B$	5.2240
12	20	$3000L$	0.950	5	$0.007B$	4.0662
13	25	$1500L$	0.990	10	$0.007B$	8.3734
14	25	$2000L$	0.975	5	$0.009B$	5.5881
15	25	$2500L$	0.950	20	$0.003B$	3.9917
16	25	$3000L$	0.925	15	$0.003B$	4.3522

Table 8: $ARPD$s obtained by different levels of each parameter

Level	T_0	N_{iter}	β	$N_{non-improved}$	PF
1	7.4267	7.8527	6.7145	6.1101	5.8856
2	5.6699	7.1805	6.2966	6.9414	6.3791
3	5.2628	4.7747	5.1906	5.4901	6.2046
4	5.5763	4.1278	5.7341	5.3941	5.4663
Range	2.1639	3.7248	1.5239	1.5473	0.9128
Rank	2	1	4	3	5

respectively.

5.3 Results obtained

The performance of the proposed SA heuristic is compared with the HMPG proposed by Zhou et al. (2018). The HMPG was implemented using Visual Studio 2013 and run at PC with an Intel 4790, 3.60 GHz processor and 32 GB of memory running under the Windows 7 operating system. The proposed SA heuristic is implemented using Microsoft Visual C++ 2019 and runs on a computer equipped with an Intel(R) Xeon(R) CPU E3-1245 v6 @ 3.70GHz and 64 GB of RAM under the Windows 10 operating system.

Due to the different hardware used by the three solution methods, a conversion of the computational time is conducted in order to allow a fair comparison. Refer to https://www.cpubenchmark.net/singleThread.html, which shows that each different hardware has a different CPU single thread performance (STP). In line with the information on the website, Table 9 summarizes the STPs of the different hardware discussed in this paper. Note that the higher the STP value, the faster the hardware will operate.

Table 10 shows the comparison result of HMPG and SA. Even though the computer used for SA is a bit faster than that of HMPG, the computational time required for SA is much smaller than those of HMPG.

The new computational results of HMPG is obtained by modified some errors in computational of objective function values. And the termination condition is the original

Table 9: A summary of the STP of the different hardware discussed in this paper

Solution method	Hardware used	STP
The proposed SA	Intel(R) Xeon(R) CPU E3-1245 v6 @ 3.70GHz	2455
HMPG	Intel 4790, 3.60 GHz (8 Core) processor with 32 GB of memory	2230

maximal computational time and the maximum iteration with the best solution not improved and set it to be 100 iterations for HMPG.

The computational time of SA is longer than the those of HMPG only in two questions. The overall average time required by SA is almost only half of the by HMPG.

Furthermore, all 36 benchmark problems are improved by the SA. The improvement rate (IR) of the best solution obtained among 5 runs is computed as $IR^i_{best} = (HMPG^i_{best} - SA^i_{best} \times 100\%)$, where $HMPG^i_{best}$ and SA^i_{best} denote the best objective function value of a specific problem instance $i(i \in 1, 2, \cdots, 6)$ for HMPG and SA, respectively. Similarly, the improvement rate (AIR) of the average solution obtained among 5 runs is computed as $AIR^i_{ave} = (HMPG^i_{ave} - SA^i_{ave})/HMPG^i_{ave} \times 100\%$, where $HMPG^i_{ave}$ and SA^i_{ave} denote the average objective function value of a specific problem instance i for HMPG and SA, respectively. It be computed from the Table 10, the proposed SA can obtain $-4.39\% \sim 13.24\%$ and $-0.85\% \sim 11.63\%$ improvement rates (negative values denote that some solution obtained by SA is worse than that of HMPG) for the best solution and average solutions obtained among 5 runs, respectively.

In a final step of numerical analysis, one-tailed paired t-tests were performed on the best and mean IRs to check SA, and it was found to be significantly superior to HMPG. The statistical results are summarized in Table 11. From Table 11, it can be seen that at $\alpha = 0.05$ confidence level, the statistical tests prove that the proposed SA algorithm is significantly superior to HMPG algorithm in terms of best and mean IRs for test instances.

Analyzing the IRs from a different angle, Figure 4 graphically compares the IR values of SA over HMGP for different model parameters. The SA have higher improvement rates with the number of depot is one; the number of satellite stations is 8, the number of pickup facilities is 10, and the number of customer is 150.

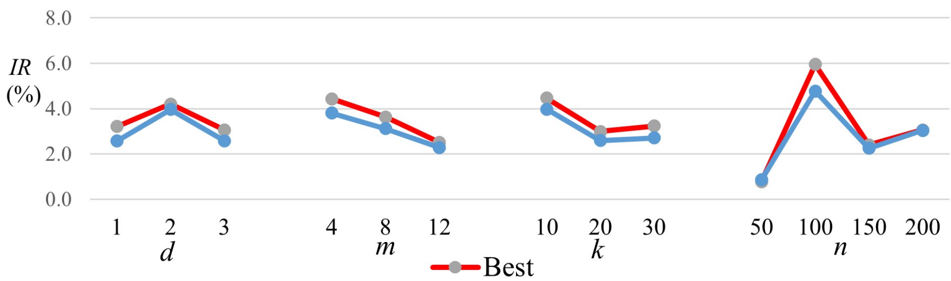

Figure 4: Visual representation of IRs under different problem parameters.

6 Conclusions and future research

In this paper, we considered the Multi-Depot Two-Echelon Vehicle Routing Problem with Delivery Options, a city logistics problem arising in the last mile distribution of

Table 10: Computational results for the problem sets (Zhou et al. (2018))

Instance	n_d	n_s	n_p	n_c	HMPG			SA		
					Best	Average	Time (min)	Best	Average	Time (min)
I1-4-10-50	1	4	10	50	2882.3	2896.6	4	2823.0	2839.0	0.6
I1-4-10-100	1	4	10	100	4920.3	5207.8	8.4	4851.6	4907.8	1.3
I1-4-20-50	1	4	20	50	3245.4	3249.5	7.9	3106.2	3163.4	0.9
I1-4-20-100	1	4	20	100	5110.1	5133.8	9.3	4568.3	4831.2	2.1
I1-8-10-100	1	8	10	100	4589.4	4608.6	6.5	4479.7	4557.2	1.6
I1-8-10-150	1	8	10	150	7063.8	7152.8	14.4	7027.1	7196.1	3.2
I1-8-20-100	1	8	20	100	5214.6	5268.3	9.1	5107.5	5202.4	2.9
I1-8-20-150	1	8	20	150	7602.9	7685.9	13.3	7354.1	7563.2	4.4
I1-12-20-150	1	12	20	150	7166.7	7288.3	9.2	7222.4	7311.7	6.5
I1-12-20-200	1	12	20	200	9824.2	9908.1	10.9	9811.2	10035.3	10.5
I1-12-30-150	1	12	30	150	7492.9	7900.4	15.4	7335.0	7643.4	11.4
I1-12-30-200	1	12	30	200	9881.0	10114.2	16.4	9548.6	9808.7	14.1
I2-4-10-50	2	4	10	50	2697.0	2730.0	4.4	2439.2	2485.4	0.7
I2-4-10-100	2	4	10	100	5252.6	5257.9	5.2	5495.7	5551.4	1.1
I2-4-20-50	2	4	20	50	3274.5	3407.3	8.4	2978.2	3041.0	1.1
I2-4-20-100	2	4	20	100	5911.5	5936.3	8.0	5444.7	5600.3	1.9
I2-8-10-100	2	8	10	100	5459.7	5499.5	11.5	5305.0	5388.3	1.6
I2-8-10-150	2	8	10	150	8795.2	8987.1	13.3	8398.0	8451.8	3.3
I2-8-20-100	2	8	20	100	4972.5	5071.0	9.7	4773.3	4873.0	2.9
I2-8-20-150	2	8	20	150	7909.7	8123.2	8.8	7871.5	8058.0	5.3
I2-12-20-150	2	12	20	150	7275.8	7476.5	9.5	7415.1	7524.9	7.5
I2-12-20-200	2	12	20	200	9947.6	10326.0	13.0	9614.6	9925.5	10.5
I2-12-30-150	2	12	30	150	7927.2	8186.8	18.2	7535.0	8104.9	9.3
I2-12-30-200	2	12	30	200	10148.9	10369.9	18.3	10187.9	10510.2	12.8
I3-4-10-50	3	4	10	50	3501.8	3549.1	5.5	3468.4	3530.5	0.8
I3-4-10-100	3	4	10	100	6315.2	6548.4	11.6	6257.5	6325.5	1.7
I3-4-20-50	3	4	20	50	3526.2	3573.4	5.8	3311.4	3355.4	1.3
I3-4-20-100	3	4	20	100	5902.5	5951.2	9.3	5249.0	5404.7	2.7
I3-8-10-100	3	8	10	100	4983.0	5305.0	10.4	4988.7	5050.5	2.3
I3-8-10-150	3	8	10	150	7384.8	7403.2	13.8	7574.5	7702.3	4.2
I3-8-20-100	3	8	20	100	5307.5	5378.3	12.4	5156.4	5215.3	3.6
I3-8-20-150	3	8	20	150	8001.7	8127.4	11.8	7645.9	7768.5	5.6
I3-12-20-150	3	12	20	150	7659.6	7804.7	13.8	7453.3	7543.8	9.2
I3-12-20-200	3	12	20	200	11671.6	11947.8	18.4	11106.3	11626.7	14.3
I3-12-30-150	3	12	30	150	8164.9	8357.5	18.7	7779.8	7941.3	11.4
I3-12-30-200	3	12	30	200	11106.5	11360.0	18.4	10174.8	10610.7	15.7
Average					6613.6	6752.5	11.2	6412.7	6573.6	5.3

Table 11: Statistical results from paired-t tests($\alpha = 0.05$)

Type	SA vs.	HMPG
Best RPD	Paired difference (IR)	3.6609
	t-value	-5.4074
	Degree of freedom	35
	P-value	0.0000
Mean RPD	Paired difference (IR)	3.1598
	t-value	-5.4335
	Degree of freedom	35
	P-value	0.0000

e-commerce. A feature of the problem is that customers may provide different delivery options, allowing them to pick up their packages at intermediate pickup facilities. The problem is complex and highly constrained as it involves a number of different, interconnected decisions (service options, facility locations, and two levels of vehicle routes). To solve the problem, a fast Simulated Annealing heuristic algorithm was proposed.

The algorithm was extensively tested on benchmark instances from the literature and compared with the Hybrid Multi-Population Genetic (HMPG) metaheuristic proposed by Zhou et al. (2018). The results obtained show that our SA heuristic is effective and efficient in solving the MDTEVRP-DO. In particular, it obtains 34 new best solutions for the 36 MDTEVRP-DO benchmark instances. Moreover, it requires a shorter computational time compared to the HMPG proposed by Zhou et al. (2018).

Finally, real-world last mile distribution services pose several challenging extensions, such as time window constraints, heterogeneous vehicle fleet, and time-dependent travel times, to name a few. Our future work will therefore go in the direction of considering these extensions and other important features of this class of problems.

References

Niels Agatz, Paul Bouman, and Marie Schmidt. Optimization approaches for the traveling salesman problem with drone. *Transportation Science*, 52(4):965–981, 2018.

Somayeh Allahyari, Majid Salari, and Daniele Vigo. A hybrid metaheuristic algorithm for the multi-depot covering tour vehicle routing problem. *European Journal of Operational Research*, 242(3):756–768, 2015.

Julian Allen, Michael Browne, Allan Woodburn, and Jacques Leonardi. The role of urban consolidation centres in sustainable freight transport. *Transport Reviews*, 32(4):473–490, 2012.

Claudia Archetti, Martin Savelsbergh, and M Grazia Speranza. The vehicle routing problem with occasional drivers. *European Journal of Operational Research*, 254(2):472–480, 2016.

Roberto Baldacci and Mauro Dell'Amico. Heuristic algorithms for the multi-depot ring-star problem. *European Journal of Operational Research*, 203(1):270–281, 2010.

Roberto Baldacci, Mauro Dell'Amico, and J Salazar González. The capacitated m-ring-star problem. *Operations research*, 55(6):1147–1162, 2007.

Roberto Baldacci, Aristide Mingozzi, Roberto Roberti, and Roberto Wolfler Calvo. An exact algorithm for the two-echelon capacitated vehicle routing problem. *Operations research*, 61(2):298–314, 2013.

Roberto Baldacci, Alessandro Hill, Edna A. Hoshino, and Andrew Lim. Pricing strategies for capacitated ring-star problems based on dynamic programming algorithms. *European Journal of Operational Research*, 262(3):879–893, 2017a. ISSN 03772217. doi: 10.1016/j.ejor.2017.04.025.

Roberto Baldacci, Sandra Ulrich Ngueveu, and Roberto Wolfler Calvo. The vehicle routing problem with transhipment facilities. *Transportation Science*, 51(2):592–606, 2017b. ISSN 0041-1655, 1526-5447. doi: 10.1287/trsc.2016.0711.

Tolga Bektaş, Güneş Erdoğan, and Stefan Røpke. Formulations and branch-and-cut algorithms for the generalized vehicle routing problem. *Transportation Science*, 45(3): 299–316, 2011.

Slim Belhaiza, Pierre Hansen, and Gilbert Laporte. A hybrid variable neighborhood tabu search heuristic for the vehicle routing problem with multiple time windows. *Computers & Operations Research*, 52:269–281, 2014.

Nils Boysen, Stefan Schwerdfeger, and Felix Weidinger. Scheduling last-mile deliveries with truck-based autonomous robots. *European Journal of Operational Research*, 271 (3):1085–1099, 2018.

Shih Wei Lin A B C and Vincent F. Yu D. Solving the team orienteering problem with time windows and mandatory visits by multi-start simulated annealing. *Computers & Industrial Engineering*, 114:195–205, 2017.

John Gunnar Carlsson and Siyuan Song. Coordinated logistics with a truck and a drone. *Management Science*, 64(9):4052–4069, 2018.

Diego Cattaruzza, Nabil Absi, Dominique Feillet, and Jesús González-Feliu. Vehicle routing problems for city logistics. *EURO Journal on Transportation and Logistics*, 6(1): 51–79, 2017.

Cheng Chen, Emrah Demir, and Yuan Huang. An adaptive large neighborhood search heuristic for the vehicle routing problem with time windows and delivery robots. *European Journal of Operational Research*, 2021.

Yael Deutsch and Boaz Golany. A parcel locker network as a solution to the logistics last mile problem. *International Journal of Production Research*, 56(1-2):251–261, 2018.

Dorian Dumez, Fabien Lehuédé, and Olivier Péton. A large neighborhood search approach to the vehicle routing problem with delivery options. *Transportation Research Part B: Methodological*, 144:103–132, 2021.

David LJU Enthoven, Bolor Jargalsaikhan, Kees Jan Roodbergen, Michiel AJ uit het Broek, and Albert H Schrotenboer. The two-echelon vehicle routing problem with covering options: City logistics with cargo bikes and parcel lockers. *Computers & Operations Research*, 118:104919, 2020.

David A Flores-Garza, M Angélica Salazar-Aguilar, Sandra Ulrich Ngueveu, and Gilbert Laporte. The multi-vehicle cumulative covering tour problem. *Annals of Operations Research*, 258(2):761–780, 2017.

S. Kirkpatrick C.D Gelatt, M.P.Vecchi. Optimization by simulated annealing. *Science*, 220(4598):671–680, 1983.

Roel Gevaers, Eddy Van de Voorde, and Thierry Vanelslander. Characteristics of innovations in last-mile logistics-using best practices, case studies and making the link with green and sustainable logistics. In *European Transport Conference, 2009*, 2009.

Gianpaolo Ghiani and Gennaro Improta. An efficient transformation of the generalized vehicle routing problem. *European Journal of Operational Research*, 122(1):11–17, 2000.

Jesús Gonzales Feliu, Guido Perboli, Roberto Tadei, and Daniele Vigo. The two-echelon capacitated vehicle routing problem. Technical report, 2007.

Jasmin Grabenschweiger, Karl F Doerner, Richard F Hartl, and Martin WP Savelsbergh. The vehicle routing problem with heterogeneous locker boxes. *Central European Journal of Operations Research*, 29(1):113–142, 2021.

Minh Hoang Ha, Nathalie Bostel, André Langevin, and Louis-Martin Rousseau. An exact algorithm and a metaheuristic for the multi-vehicle covering tour problem with a constraint on the number of vertices. *European Journal of Operational Research*, 226(2): 211–220, 2013.

Minh Hoàng Hà, Nathalie Bostel, André Langevin, and Louis-Martin Rousseau. An exact algorithm and a metaheuristic for the generalized vehicle routing problem with flexible fleet size. *Computers & Operations Research*, 43:9–19, 2014.

Tobias Hagen and Sabine Scheel-Kopeinig. Would customers be willing to use an alternative (chargeable) delivery concept for the last mile? *Research in Transportation Business & Management*, page 100626, 2021.

Yandong He, Xu Wang, Yun Lin, Fuli Zhou, and Lin Zhou. Sustainable decision making for joint distribution center location choice. *Transportation Research Part D: Transport and Environment*, 55:202–216, 2017.

Yandong He, Mingyao Qi, Fuli Zhou, and Jiafu Su. An effective metaheuristic for the last mile delivery with roaming delivery locations and stochastic travel times. *Computers & Industrial Engineering*, 145:106513, 2020.

Li Jiang, Xiaoning Zang, Ibrahim IY Alghoul, Xiang Fang, Junfeng Dong, and Changyong Liang. Scheduling the covering delivery problem in last mile delivery. *Expert Systems with Applications*, 187:115894, 2022.

Sebastian Kapser and Mahmoud Abdelrahman. Acceptance of autonomous delivery vehicles for last-mile delivery in germany–extending utaut2 with risk perceptions. *Transportation Research Part C: Emerging Technologies*, 111:210–225, 2020.

Lin and Shih-Wei. Solving the team orienteering problem using effective multi-start simulated annealing. *Applied Soft Computing Journal*, 13(2):1064–1073, 2013.

Shih Wei Lin and Kuo Ching Ying. A multi-point simulated annealing heuristic for solving multiple objective unrelated parallel machine scheduling problems. *International Journal of Production Research*, 53(4):1065–1076, 2015.

Shih-Wei Lin and Kuo-Ching Ying. Minimising makespan in job-shops with deterministic machine availability constraints. *International Journal of Production Research*, 59(14): 4403–4415, 2021. doi: 10.1080/00207543.2020.1764125. URL https://doi.org/10.1080/00207543.2020.1764125.

Simona Mancini and Margaretha Gansterer. Vehicle routing with private and shared delivery locations. *Computers & Operations Research*, 133:105361, 2021.

Zara Naji-Azimi, Jacques Renaud, Angel Ruiz, and Majid Salari. A covering tour approach to the location of satellite distribution centers to supply humanitarian aid. *European Journal of Operational Research*, 222(3):596–605, 2012.

Gizem Ozbaygin, Oya Ekin Karasan, Martin Savelsbergh, and Hande Yaman. A branch-and-price algorithm for the vehicle routing problem with roaming delivery locations. *Transportation Research Part B: Methodological*, 100:115–137, 2017.

Guido Perboli, Luce Brotcorne, Maria Elena Bruni, and Mariangela Rosano. A new model for last-mile delivery and satellite depots management: The impact of the on-demand economy. *Transportation Research Part E: Logistics and Transportation Review*, 145: 102184, 2021.

Petrică C Pop, Imdat Kara, and Andrei Horvat Marc. New mathematical models of the generalized vehicle routing problem and extensions. *Applied Mathematical Modelling*, 36(1):97–107, 2012.

Damián Reyes, Martin Savelsbergh, and Alejandro Toriello. Vehicle routing with roaming delivery locations. *Transportation Research Part C: Emerging Technologies*, 80:71–91, 2017.

Martin Savelsbergh and Tom Van Woensel. 50th anniversary invited article—city logistics: Challenges and opportunities. *Transportation Science*, 50(2):579–590, 2016.

Pawel Sitek and Jarosław Wikarek. Capacitated vehicle routing problem with pick-up and alternative delivery (cvrppad): model and implementation using hybrid approach. *Annals of Operations Research*, 273(1):257–277, 2019.

Paweł Sitek, Jarosław Wikarek, Katarzyna Rutczyńska-Wdowiak, Grzegorz Bocewicz, and Zbigniew Banaszak. Optimization of capacitated vehicle routing problem with alternative delivery, pick-up and time windows: A modified hybrid approach. *Neurocomputing*, 423:670–678, 2021.

Wouter Souffriau, Pieter Vansteenwegen, Greet Vanden Berghe, and Dirk Van Oudheusden. The multiconstraint team orienteering problem with multiple time windows. *Transportation Science*, 47(1):53–63, 2013.

Fabien Tricoire, Alexandra Graf, and Walter J Gutjahr. The bi-objective stochastic covering tour problem. *Computers & operations research*, 39(7):1582–1592, 2012.

Marjolein Veenstra, Kees Jan Roodbergen, Leandro C Coelho, and Stuart X Zhu. A simultaneous facility location and vehicle routing problem arising in health care logistics in the netherlands. *European Journal of Operational Research*, 268(2):703–715, 2018.

Shaohua Yu, Jakob Puchinger, and Shudong Sun. Two-echelon urban deliveries using autonomous vehicles. *Transportation Research Part E: Logistics and Transportation Review*, 141:102018, 2020.

Vincent F. Yu, Panca Jodiawan, Ming-Lu Hou, and Aldy Gunawan. Design of a two-echelon freight distribution system in last-mile logistics considering covering locations and occasional drivers. *Transportation Research Part E: Logistics and Transportation Review*, 154:102461, 2021.

Yuan Yuan, Diego Cattaruzza, Maxime Ogier, Frédéric Semet, and Daniele Vigo. A column generation based heuristic for the generalized vehicle routing problem with time windows. *Transportation Research Part E: Logistics and Transportation Review*, 152: 102391, 2021.

Lin Zhou, Xu Wang, Lin Ni, and Yun Lin. Location-routing problem with simultaneous home delivery and customer's pickup for city distribution of online shopping purchases. *Sustainability*, 8(8):828, 2016.

Lin Zhou, Roberto Baldacci, Daniele Vigo, and Xu Wang. A multi-depot two-echelon vehicle routing problem with delivery options arising in the last mile distribution. *European Journal of Operational Research*, 265(2):765–778, 2018.

Lin Zhou, Yun Lin, Xu Wang, and Fuli Zhou. Model and algorithm for bilevel multisized terminal location-routing problem for the last mile delivery. *International Transactions in Operational Research*, 26(1):131–156, 2019.