Green Location-Routing Problem with Delivery Options

Mengtong Wang, Lixin Miao, and Canrong Zhang

1 Introduction

Due to the discrete temporal and spatial distribution of customer demands that results in a high delivery failure and a low vehicle utilization, the last-mile delivery has become a time-consuming and uncertain process. As a result, parcel logistics companies are exploring and implementing innovative tools such as drones and pavement-based droids to optimize last-mile deliveries. However, such solutions are difficult to be widely adopted due to significant public acceptability and regulatory barriers (https://www.nic.org.uk/publications/better-delivery-the-challenge-for-freight/). Recently, lockers for self-service collection and return of parcels have received positive feedback from both customers and industries by improving the user experience for the former and providing scale benefits for the latter (Vakulenko et al., 2017). Furthermore, contactless delivery has become a new hotspot in the context of COVID-19, bringing new opportunities for the development of lockers. Therefore, a crucial issue for a parcel logistics company is to redesign its pick-up and delivery operations to include lockers as an option.

The first author is a student and we would like to compete for the Best Student Paper award.

M. Wang
Department of Industrial Engineering, Tsinghua University, Beijing, China

Division of Logistics and Transportation, Shenzhen International Graduate School, Tsinghua University, Shenzhen, China

L. Miao · C. Zhang (✉)
Division of Logistics and Transportation, Shenzhen International Graduate School, Tsinghua University, Shenzhen, China
e-mail: crzhang@sz.tsinghua.edu.cn

H. Yang et al. (eds.), *AI and Analytics for Public Health*, Springer Proceedings in Business and Economics, https://doi.org/10.1007/978-3-030-75166-1_14

In addition, there is a rising awareness of the need for alleviating the environmental consequences of logistics operations by deploying low-emission vehicles, e.g., electric vehicles (EVs) (Shen et al., 2019). For example, FedEx has expanded the size of its EV fleets to minimize environmental impacts (http://csr.fedex.com/pdf/FedEx_GCR_FINAL_4.17.19_144dpi.pdf). EVs are now sufficient to meet the needs of short- and medium-distance transportation, and do not need to be charged during the trip. Consequently, there are two delivery options that parcel logistics companies can choose to serve customers. The first delivery option is the direct-to-customer delivery where EVs transport parcels to customers' homes or workplaces. Another delivery option is the direct-to-locker delivery where EVs transport parcels to lockers and customers pick up them at their own convenience.

In this paper, we first address a green location-routing problem with delivery options (GLRP-DO) where a parcel logistics company needs to simultaneously determine the location of lockers and the routing plans for EVs from a single depot. Routes for the replenishment of lockers and routes for the delivery of parcels to customers are separated due to several practical considerations. Hence, we consider two types of EV fleets with different load capacities and battery driving ranges, where large EVs are dedicated to replenishing lockers by providing the round-trip service and small EVs are dedicated to servicing the customers. A locker can serve customers within its pre-specified coverage range and has an accommodation capacity limitation. Each customer must be served by either a locker or a small EV. The goal is to minimize the total cost from the perspective of a parcel logistics company, including the opening cost and handling cost of lockers, as well as the routing costs of EVs. Figure 1 shows a schematic example of the GLRP-DO distribution system.

Despite receiving considerable attention in the last-mile distribution system, research on lockers appears to be scarce. The most related problem is the multi-depot two-echelon vehicle routing problem with delivery options in (Zhou et al., 2018). In this problem, the delivery option for each customer is pre-set by giving

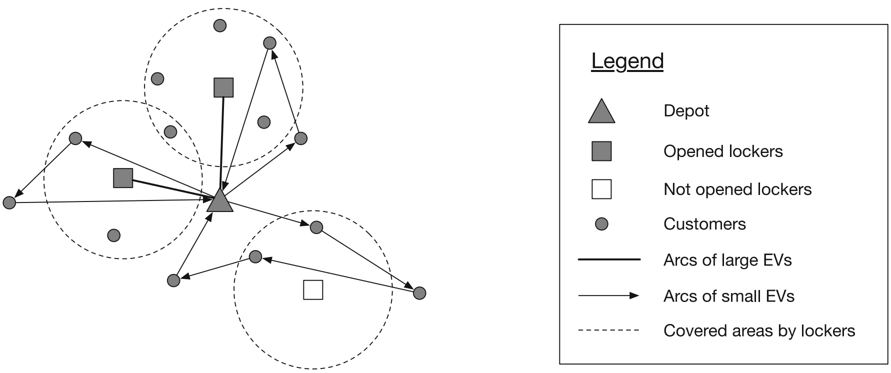

Fig. 1 A schematic example of the GLRP-DO distribution system

a node set including three cases (only served by direct delivery, only served by pick-up facilities, served by either-or). Another related problem is a simultaneous facility location and vehicle routing problem in (Veenstra et al., 2018). In contrast to our problem where a patient within a service range may not be assigned to the corresponding locker (probably due to the limitation of its accommodation capacity), a patient in (Veenstra et al., 2018), is forced to be served by an open locker if it is within the coverage distance of the locker, leading to an un-capacitated locker. Then, a recent study extended the above research to a two-echelon system and developed an efficient adaptive large neighbourhood search heuristic to provide high-quality solutions for large-sized instances (Enthoven et al., 2020).

Different from the above literature, some studies have investigated a similar locker network with the objective of maximizing the company's overall profit. It is not necessary to satisfy all customer demands in these studies. Deutsch and Golany (2018) designed a parcel locker network as a solution to the last-mile distribution system, and used discounts in the delivery cost for customers who choose the locker service. Hosseini et al. (2019) developed a generalization of the capacitated location-routing problem from the perspective of a company engaged in collecting used products from customer zones to maximize its overall profit. A financial incentive is defined to help determine the quantity of used products which are returned by customers. In this problem, the idea of collection centers is similar to our lockers. However, our study focuses on minimizing the total cost and satisfying the total customer demand. Moreover, there is no limit on the accommodation capacity of collection centers and the driving range of vehicles in Hosseini et al. (2019).

According to the above review, although the above studies have mentioned lockers or delivery options in various contexts, they have not totally regarded delivery options as decision variables and have not considered both coverage ranges of lockers and battery driving ranges of EVs. Furthermore, so far, there has been no research to develop exact algorithms for similar problems, but this is very important to obtain available benchmark solutions for larger instances. To address practical issues and fill the research gap, we use an integrated modelling approach to assist in the planning process to deploy a new last-mile distribution system with two delivery options (i.e., the GLRP-DO) and propose an effective branch-and-price (B&P) algorithm that can solve to optimality instances with moderately larger size.

2 Model Formulation

We apply a Danzig-Wolfe decomposition (Dantzig & Wolfe, 1960), to formulate the GLRP-DO as a set partitioning formulation and treat it as a master problem (MP) that links the columns generated through pricing subproblems. In this study, two types of pricing subproblems are proposed for providing feasible columns. The first type of pricing subproblems is the locker coverage service subproblem (LCSP) that generates a pattern of service customers with negative reduced cost for each locker, and the second type of pricing subproblems is the shortest path problem with battery driving range constraints (SPPBDRC) that helps generate a negative reduced-cost small EV route.

2.1 Problem Statement

In this paper, the GLRP-DO is defined in a graph $G = (V, A)$, where $V = \{0\} \cup V_l \cup V_c$ is the set of vertices, $\{0\}$ represents the depot, V_l is the set of potential lockers, and V_c is the customer set. Let the arc set $A = \{(i,j) : i,j \in V, (i,j) \notin V_l \times V_l\}$, which comprises the arcs connecting the depot to the customers and lockers, and those connecting pairs of customers. Associated with a locker $l \in V_l$ are, the fixed open cost f_l (per day), the handling cost a_l (per parcel), the accommodation capacity Q_l and the coverage range r_l. For replenishing lockers, the set of large EVs K^0 with load capacity Q_e^0 and battery driving range B^0 is available at the depot, and provides the round-trip service due to the high volume transported between the depot and lockers. For serving customers, the set of small EVs K with load capacity Q_e and battery driving range B is available at the depot and provides the direct delivery service. The distance, the travel cost of arc $(i,j) \in A$ and the charging consumption rate are given as d_{ij}, c_{ij} and h, respectively. It is assumed that the distance and travel cost observe the triangle inequality. Each customer $i \in V_c$ has a known and deterministic demand q_i, and can be served by a small EV or an open locker. We also assume that no customer demand is greater than the capacity of small EVs and lockers, and no accommodation capacity of lockers is greater than the load capacity of large EVs. Therefore, only one round-trip service is needed for each open locker. Let ϕ be a factor that represents the economies of scale of the round-trip service, then $\overline{f_l} = f_l + \phi\,(c_{0l} + c_{l0})$ can be treated as the fixed cost of locker l, consisting of the opening cost f_l of locker l and the routing cost $\phi(c_{0l} + c_{l0})$ of large EVs.

2.2 Master Problem

We redefine the set V_l as $\{l|\, d_{0l} + d_{l0} \leq B^0, l \in V_l\}$ to ensure that lockers can be visited by large EVs. Let P be the set of all feasible patterns. Each pattern $p \in P_l$ means a set of customers served by locker l within its coverage range and accommodation capacity, and $\cup_{l \in V_l} P_l = P$. Let R be the set of all feasible routes. Each route $r \in R$ starts from the depot, visits one or several customers in V_c, and ends at the depot. Moreover, each route does not violate the load and battery capacities of small EVs by construction. Let $\alpha_{ip} \in \{0, 1\}$ be a binary parameter that equals 1 if customer i is assigned to pattern p, and 0 otherwise. Let $\beta_{ir} \in \{0, 1\}$ be a binary parameter that equals 1 if customer i is visited by route r, and 0 otherwise. The costs of each pattern $p \in P$ and route $r \in R$ are c_p and c_r, respectively. Then, let v_l be a binary variable that takes value 1 if locker l is opened, and 0 otherwise. Let z_p be a binary variable that takes value 1 if pattern $p \in P$ belongs to the solution, and 0 otherwise. Let x_r be a binary variable that equals 1 if route $r \in R$ belongs to the solution, and 0 otherwise. Finally, the MP is formulated as follows:

$$\min_{v,z,x} \sum_{l \in V_l} \overline{f}_l v_l + \sum_{p \in P} c_p z_p + \sum_{r \in R} c_r x_r \tag{1}$$

$$\text{s.t.} \quad \sum_{p \in P} \alpha_{ip} z_p + \sum_{r \in R} \beta_{ir} x_r = 1 \qquad \forall i \in V_c \tag{2}$$

$$\sum_{p \in P_l} z_p = v_l \qquad \forall l \in V_l \tag{3}$$

$$v_l \in \{0, 1\} \qquad \forall l \in V_l \tag{4}$$

$$z_p \in \{0, 1\} \qquad \forall p \in P \tag{5}$$

$$x_r \in \{0, 1\} \qquad \forall r \in R \tag{6}$$

The objective function (1) minimizes the total cost including the fixed cost of opened lockers (the opening cost of opened lockers and the large EV routing cost for these lockers), the handling cost of opened lockers, and the small EV routing cost for customers. Constraint (2) ensures that each customer is served by exactly one route or one pattern, thereby achieving a partitioning scheme for customers. Constraint (3) guarantees that at most one pattern will be chosen for each locker. To introduce the subsequent two types of pricing subproblems, let $\boldsymbol{\mu}$ and $\boldsymbol{\tau}$ be the dual variables of the constraints (2) and (3), respectively. Constraints (4), (5) and (6) specify the domains of the decision variables.

2.3 The Locker Coverage Service Subproblem

Let z_i^l be a binary variable that takes value 1 iff customer i is served by locker l. Then all pricing subproblems for each locker are identical except for the dual price τ_l considered in the objective function. Hence, the LCSP- l is simply dedicated to each open locker l and is presented as follows:

$$\min_{z} \sum_{i \in V_c} (a_l q_i - \mu_i) z_i^l - \tau_l \tag{7}$$

$$\text{s.t.} \quad d_{il} z_i^l \leq r_l \qquad \forall i \in V_c \tag{8}$$

$$\sum_{i \in V_c} z_i^l = Q_l \tag{9}$$

$$z_i^l \in \{0, 1\} \qquad \forall i \in V_c \tag{10}$$

In this formulation, the objective function (7) is to minimize the reduced cost of a pattern for locker l. Constraints (8) and (9) are implemented to define the coverage range and the accommodation capacity constraints of locker l, respectively. The binary requirement of the solution is ensured by constraint (10). The LCSP- l is essentially a variant of knapsack problem that can be solved in pseudo-polynomial time. Considering that commercial MIP solvers can easily solve instances of the knapsack problem with thousands of variables (Poss, 2013). We call the CPLEX solver to find the exact solution of the LCSP-l.

2.4 The Shortest Path Problem with Battery Driving Range Constraints

Let x_{ij} be equal to 1 iff a small EV traverses arc (i,j). b_i represents the remaining battery of a small EV when it arrives at node $i \in \{0\} \cup V_c$. Then, the SPPBDRC is presented as follows:

$$\min_x \sum_{i \in \{0\} \cup V_c} \sum_{j \in \{0\} \cup V_c, j \neq i} \bar{c}_{ij} x_{ij} \tag{11}$$

$$\text{s.t.} \sum_{j \in V_c} x_{0j} = 1 \tag{12}$$

$$\sum_{j \in V_c} x_{j0} = 1 \tag{13}$$

$$\sum_{j \in \{0\} \cup V_c, j \neq i} x_{ji} = \sum_{j \in \{0\} \cup V_c, j \neq i} x_{ij} \qquad \forall i \in V_c \tag{14}$$

$$\sum\nolimits_{i \in V_c} \sum_{j \in \{0\} \cup V_c, j \neq i} q_i x_{ij} \leq Q_e \tag{15}$$

$$b_i \leq B - h * d_{0i} x_{0i} \qquad \forall i \in V_c \tag{16}$$

$$b_j \leq b_i - h * d_{ij} x_{ij} + B\left(1 - x_{ij}\right) \qquad \forall i \in V_c, \forall j \in \{0\} \cup V_c, j \neq i \tag{17}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i \in V_c, \forall j \in \{0\} \cup V_c, j \neq i \tag{18}$$

$$b_i \geq 0 \qquad \forall i \in \{0\} \cup V_c \tag{19}$$

The objective function (11) minimizes the reduced cost of the constructed route. Constraints (12) and (13) are associated with the routing decision, and constraint (14) ensures the flow balance. Constraint (15) relates to the total small EV load capacity. Constraints (16) and (17) enforce sub-tour elimination using the cumulative battery capacity consumed upon visiting a node for each small EV. Constraints (18) and (19) define the domains of decision variables. Note that the new arc cost $\overline{c}_{ij}$ is defined as $\overline{c}_{ij} = c_{ij} - \mu_i, \forall i \in V_c, \forall j \in \{0\} \cup V_c, j \neq i$ and $\overline{c}_{0j} = c_{0j}, \forall j \in V_c$.

It can be shown that the SPPBDRC is modeled as an elementary shortest path problem with resource constraints which is NP-hard (Dror, 1994), but it can be solved by dynamic programming in pseudo-polynomial time. Therefore, we employ the label setting algorithm to generate the optimal route of the SPPBDRC. Labels are attached to each node to identify the state of the resources (reduced cost, load capacity and battery capacity) when a corresponding feasible path is found from the depot to the present node. In addition, we extend labels and accelerate the solution procedure by adopting the method proposed by Feillet et al. (2004).

3 Methodology

First, the linearly relaxed version of MP (LMP) is solved to obtain dual values for defining reduced costs. Considering that a restricted LMP (LRMP) involves a small subset of columns at each branch node, then the column generation is called to identify the subsets of patterns and routes with negative reduced costs. These patterns and routes as new columns are added to the LMP and resolved iteratively. This procedure is repeated until no new column exists and then we can obtain the optimal solution of LMP. If it is fractional, some branching rules are applied hierarchically in the B&P algorithm and the detail is described later. The best-first strategy is implemented to explore the branch-and-bound tree, which guarantees that the child node with the best lower bound will be explored first.

3.1 Branching Rules

In this study, two types of pricing subproblems are proposed for constructing feasible columns. In order to create adequate branching rules that are compatible with these pricing subproblems, we consider four-layer hierarchical branching rules in the proposed B&P algorithm.

The first branching rule branches on the location variable v_l. Fixing $v_l = 1$ enforces the use of locker l with its LCSP- l solved, and fixing $v_l = 0$ is achieved by imposing a value of $z_p = 0$ for all of the patterns $p \in P_l$ in the RMP.

The second branching rule restricts the service assignment for each customer. We define $\rho_i = \sum_{p \in P} \alpha_{ip} z_p$ as the value of choosing the locker service for customer i. We branch on the value of ρ_{i^*} that is most fractional (whose fractional part is closest to 0.5). Fixing $\rho_{i^*} = 1$ means that customer i^* is only visited by the locker service, and can be achieved by deleting all routes that visit customer i^* and no longer allowing small EVs to visit customer i^* in its corresponding subproblems. Fixing $\rho_{i^*} = 0$ ensures that customer i^* cannot be satisfied by the locker service. We delete all patterns that visit customer i^* and prohibit any locker to serve customer i^* in its pricing subproblems.

The third branching rule branches on the arc (i,j). Let R_{ij} be the set of all routes that visit the arc (i,j), and we select the arc (i^*,j^*) such that $\varphi_{i^*j^*} = \sum_{r \in R_{i^*j^*}} x_r$ is most fractional. Then, we impose $\varphi_{i^*j^*} = 0$ by removing the arc (i^*,j^*) from the network for small EVs and dropping all routes that include arc (i^*,j^*) in one branch. In the other branch, we impose $\varphi_{i^*j^*} = 1$ by removing all arcs (i',j^*) and (i^*,j') such that $i' \neq i^*$ and $j' \neq j^*$, and dropping all route-related columns that do not satisfy this constraint.

The fourth branching rule restricts the locker assignment for each customer. We define $\theta_{il} = \sum_{p \in P_l} \alpha_{ip} z_p$ as the value of choosing locker l for serving customer i. We branch on the value of $\theta_{i^*j^*}$ that is most fractional. Fixing $\theta_{i^*j^*} = 1$ means that customer i^* is only visited by locker l^*, and can be achieved by deleting all patterns from locker $l \neq l^*$ that visit customer i^* and no longer allowing locker $l \neq l^*$ to visit customer i^* in its corresponding subproblems. Fixing $\theta_{i^*j^*} = 0$ ensures that customer i^* cannot be satisfied by locker l^*. We delete all patterns from locker l^* that visit customer i^* and prohibit locker l^* to serve customer i^* in its pricing subproblems.

3.2 A Tight Upper Bound

Through numerical experiments, we find that in most cases, the best lower bound has reached the optimal value after the first three steps of branching rules. It means that the best routes have been found but the best patterns haven't been identified. To reduce the number of branching, we propose an acceleration technique with the aim of finding a better feasible solution and thus improving the performance of our B&P algorithm.

If a solution of RLMP satisfies the first three branching rules, we can obtain a feasible small EV routing plan and its cost $z_{EV} = \sum_{r \in R} c_r x_r$. In addition, the set of lockers to open V_l' and the set of customers served by lockers V_c' can also be acquired. Then, we develop the following locker assignment problem (LAP) to find a feasible solution for assigning remaining customers to the opened lockers.

$$z_{Locker} = \min_{v,z} \sum\nolimits_{l \in V_l'} \overline{f}_l v_l + \sum_{i \in V_c'} \sum\nolimits_{l \in V_l'} a_l q_i z_i^l \tag{20}$$

$$\text{s.t.} \quad \sum_{l \in V_l'} z_i^l = 1 \qquad \forall i \in V_c' \tag{21}$$

$$z_i^l d_{il} \leq r_l v_l \qquad \forall i \in V_c', \forall l \in V_l' \tag{22}$$

$$\sum_{i \in V_c'} q_i z_i^l \leq Q_l v_l \qquad \forall l \in V_l' \tag{23}$$

$$v_l \in \{0, 1\} \qquad \forall l \in V_l' \tag{24}$$

$$z_i^l \in \{0, 1\} \qquad \forall i \in V_c', \forall l \in V_l' \tag{25}$$

Once the first three branching rules are met and the fourth branching rule is violated, we first solve the LAP to obtain a new upper bound $z^{'} = z_{Locker} + z_{EV}$ to update the best upper bound, rather than implementing the fourth branching rule. In the computational experiments section, we will test that the above acceleration strategy to observe its impact on the reduction of running time.

4 Computational Experiments

We conduct numerical experiments with two aims. First, we assess the performance of our B&P algorithm in comparison with the original MIP model using the branch-and-cut algorithm implemented via CPLEX with version 12.7. Second, the sensitivity analysis and managerial insights are given to consider the impact of delivery options of the GLRP-DO. All experiments are coded by JAVA and run on a computer with a 16GB RAM and 4.0 GHz CPU.

4.1 Description of Problem Instances

For the GLRP-DO, we construct our instances by extending three well-known sets of benchmark instances (Perboli et al., 2011), namely “Set 2” and “Set 3”. Moreover, some new information is added and summarized in Table 1, which includes the name of sets (Set), the number of instances (#), the numbers of customers (N_c), lockers (N_l) and EVs (N_e), and other values of related parameters. Note that we assume the parameter settings of EVs are sufficient to ensure the feasibility of testing instances.

Table 1 Characteristics of the GLRP-DO instances

Set	#	N_c	N_l	N_e	f_l	ϕ	a_l	Q_l	Q_e^0	R	B^0	B	h
2/3	6	21	3	16	60	0.1	0.001	6000	3000	30	180	120	1
	6	21	4	16	60	0.1	0.001	4500	3000	30	180	120	1
	6	50	5	23	100	0.1	0.01	90	45	50	300	200	1
	6	50	6	23	100	0.1	0.01	75	45	50	300	200	1

4.2 Computational Performance of the B&P Algorithm

Partial results of performance comparison between our B&P algorithm and CPLEX are shown in Table 2. The first and second columns show the name and the set of potential lockers of each instance, respectively. For CPLEX, Columns 3–5, respectively, represent the objective value (optimal solutions or best upper bound found) obtained with CPLEX (Best), the solver optimality gap within 3600 seconds (Gap(%)), and the computing time of CPLEX (T(seconds)). The remaining columns relate to the B&P algorithm. Columns 6–9 report the following: (i) the optimal objective value or the upper bound obtained within 3600 seconds (Best); (ii) the optimality gap at termination or within 3600 seconds (Gap(%)); (iii) total CPU time of the B&P algorithm without the tight upper bound described in Sect. 3.2 (T_{no}(seconds)); (iv) total CPU time of the B&P algorithm with the tight upper bound (T(seconds)).

The results show that the superior performance of the B&P algorithm over the B&B/C algorithm implemented with CPLEX mainly comes from the following two aspects: (i) The proposed tight upper bound presented in previous section is beneficial for accelerating the B&P procedure. For large-size instances, the substantial CPU time savings achieved by this acceleration technique are about 30% on average for the instances in Set 2, and about 12% on average for the instances in Set 3. For medium-size instances, the performance of the tight upper bound is not outstanding, or even worse. The reason may be that this upper bound cannot provide a tighter upper bound but increases the redundant upper bound calculation. (ii) The proposed B&P algorithm is both effective and efficient in solving the GLRP-DO. In fact, CPLEX failed to solve the GLRP-DO for 50% of instances to provable optimality within 3600 seconds. In contrast, the proposed B&P algorithm solved all testing instances to optimality in an average of 5 seconds for instances with three lockers and 21 customers, an average of 18 seconds for instances with four lockers and 21 customers, an average of 186 seconds for instances with five lockers and 50 customers, and an average of 572 seconds for instances with six lockers and 50 customers.

Table 2 Comparative results for CPLEX vs. B&P algorithm

	Description	CPLEX			B&P algorithm			
Inst.	Lockers	Best	Gap (%)	T (seconds)	Best	Gap (%)	T_{no} (seconds)	T (seconds)
Set 2								
En51s5-1	2,4,5,17,46	841.61	1.21	3623.45	841.61	0.00	194.83	163.24
En51s5-2	6,12,27,32,37	843.83	1.38	3625.53	843.83	0.00	219.72	159.10
En51s5-3	7,11,19,27,47	835.19	1.33	3630.36	835.19	0.00	305.66	202.33
Average			1.31	3626.45		0.00	240.07	174.89
En51s6-2	6,12,27,32,37,45	951.17	3.07	3614.81	945.46	0.00	325.15	271.91
En51s6-4	3,4,8,17,39,46	953.12	3.25	3621.27	946.95	0.00	1000.23	743.30
En51s6-5	2,13,22,27,32,37	954.74	3.28	3624.18	946.03	0.00	396.15	327.12
Average				3620.08			573.84	447.44
Set 3								
En51s5-1	12,18,39,41,43	841.94	1.53	3622.92	841.94	0.00	274.58	188.78
En51s5-2	13,19,40,41,42	844.97	1.39	3623.22	844.97	0.00	292.15	186.50
En51s5-3	13,40,41,42,44	848.95	1.22	3617.99	848.95	0.00	198.19	155.89
Average				3621.37		0.00	254.97	177.06
En51s6-1	12,18,21,39,41,43	951.66	3.03	3608.38	945.41	0.00	423.17	399.12
En51s6-2	13,19,20,40,41,42	955.79	3.24	3618.43	948.33	0.00	514.64	447.49
En51s6-4	16,22,24,28,41,43	959.05	3.78	3618.56	947.26	0.00	407.94	355.05
Average				3615.12		0.00	448.58	400.55

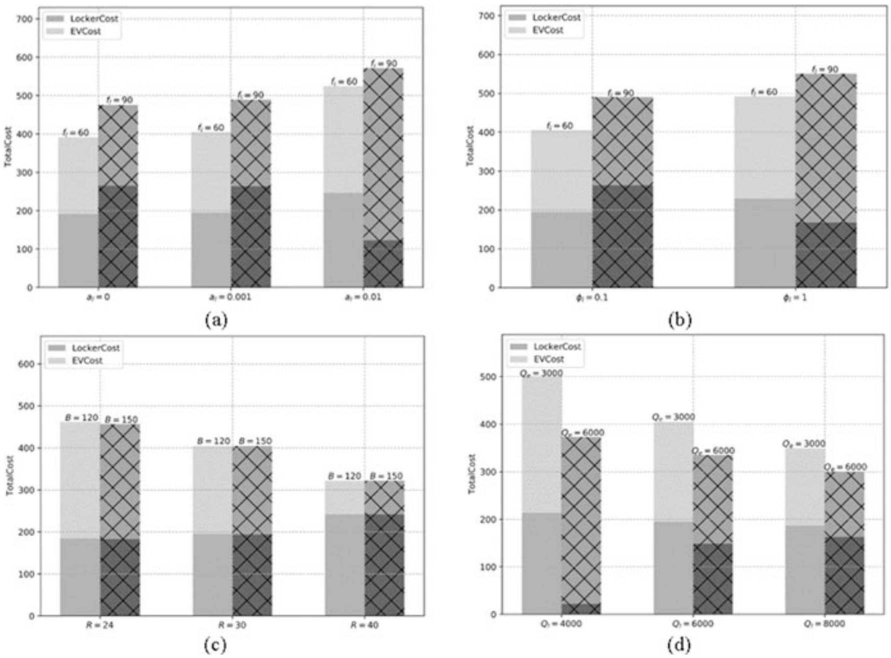

Fig. 2 Sensitivity analysis of the GLRP-DO

4.3 Sensitivity Analysis for the GLRP-DO

In this section, we investigate three sets of model parameters that may affect the solutions of the GLRP-DO. The first one is the sensitivity of the result to the cost of lockers including the opening cost, the handling cost and economies of scale factor. The second one is the impact of the coverage range of lockers and the battery driving range of small EVs, and the third one is the effect of the accommodation capacity of lockers and the load capacity of small EVs.

Examples of such lockers that provide self-service options can include lockers and self-built service stations. As a result, the costs of these lockers and the realization of economies of scale may be very different. Figure 2a and 2b contrast the composition of the optimal total cost under different opening cost f_l, holding cost a_l and economies of scale factor ϕ settings. The results show that when the opening cost is high, as the holding cost or economies of scale factor increases, the total cost increases, where the cost of locker service decreases and the cost of small EVs increases. In addition, we observe the GLRP-DO system is more sensitive to the handling cost than the opening cost.

Given a depot, a set of customers and a set of potential lockers can be opened, the changes in the coverage range R and the battery driving range B may result in different delivery solutions for serving all the customers. Figure 2c illustrates that with the increase in the coverage range of lockers, the total cost decreases, and the delivery proportion of lockers increases. Furthermore, when the battery driving range of EVs reaches a certain level, it will not have much impact on the choice of delivery options and cost.

Indeed, different types of lockers or EVs can provide different accommodation/load capacities. Thus, planning an efficient GLRP-DO system requires examining the impact of the accommodation capacity Q_l of lockers and the load capacity Q_e of small EVs. As can be seen in Fig. 2d, the accommodation capacity and load capacity can provide better competitive advantages for their corresponding delivery options (lockers and EVs). Moreover, the solutions of the GLRP-DO are more sensitive to the accommodation capacity than to the load capacity.

5 Summary

In this paper, we introduce the GLRP-DO, a practical last-mile delivery problem, that can deal with the presence of delivery options (lockers or direct delivery) and the application of EVs. We develop an effective B&P algorithm for the GLRP-DO, where two types of pricing subproblems are solved exactly and some useful acceleration techniques are proposed. Due in part to the tighter upper bound, the computing time of the algorithm is reduced by 20% on average for large-size testing instances. Furthermore, the B&P algorithm greatly outperforms the commercial solver CPLEX over all testing instances. Our computational study also illustrates how the GLRP-DO can support parcel logistics companies to make better decisions in the relevant context. First, it is very important to improve the utilization rate of locker accommodation capacity as much as possible if companies consider including lockers as a delivery option, as the comparative advantage of using lockers depends largely on the economies of scale. In addition, experimental results demonstrate that the GLRP-DO system is more sensitive to the handling cost than to the opening cost of lockers. Second, EVs are suitable for such hybrid delivery systems and mixed-fleet policies for the management of EVs are profitable in such a delivery network. Consequently, interesting extensions on this research consist of involving customer participation in decision-making process to maximize the utilization rate of the opened lockers, and investigating the GLRP-DO with special aspects such as multi-trips or customer time windows.

Acknowledgements This work was supported by the National Key R&D Program of China under grant No. 2018AAA0101705, and the National Natural Science Foundation of China under grants 71771130 and 71872092.

References

Dantzig, G. B., & Wolfe, P. (1960). Decomposition principle for linear programs. *Operations Research, 8*(1), 101–111.

Deutsch, Y., & Golany, B. (2018). A parcel locker network as a solution to the logistics last mile problem. *International Journal of Production Research, 56*(2), 251–261.

Dror, M. (1994). Note on the complexity of the shortest path models for column generation in VRPTW. *Operations Research, 42*(5), 977–978.

Enthoven, D. L. J. U., Jargalsaikhan, B., Roodbergen, K. J., et al. (2020). The two-echelon vehicle routing problem with covering options: City logistics with cargo bikes and parcel lockers. *Computers & Operations Research, 118*.

Feillet, D., Dejax, P., Gendreau, M., et al. (2004). An exact algorithm for the elementary shortest path problem with resource constraints: Application to some vehicle routing problems. *Networks, 44*(3), 216–229.

Hosseini, M. B., Dehghanian, F., & Salar, M. (2019). Selective capacitated location-routing problem with incentive-dependent returns in designing used products collection network. *European Journal of Operational Research, 272*(2), 655–673.

Perboli, G., Tadei, R., Vigo, D., et al. (2011). The two-echelon capacitated vehicle routing problem: Models and math-based heuristics. *Transportation Science, 45*(3), 364–380.

Poss, M. (2013). Robust combinatorial optimization with variable budgeted uncertainty. *A Quarterly Journal of Operations Research, 11*(1), 75–92.

Shen, Z. M., Feng, B., Mao, C., et al. (2019). Optimization models for electric vehicle service operations: A literature review. *Transportation Research Part B-methodological, 128*, 462–477.

Vakulenko, Y., Hellstrom, D., Hjort, K., et al. (2017). What's in the parcel locker? Exploring customer value in e-commerce last mile delivery. *Journal of Business Research, 88*, 421–427.

Veenstra, M., Roodbergen, K. J., Coelho, L. C., et al. (2018). 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.

Zhou, L., Baldacci, R., Vigo, D., et al. (2018). 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.