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A Travelling Salesman Problem With Carbon Emission Reduction in the Last Mile Delivery

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ABSTRACT The development of e-commerce has led to a surge in the number of online shopping parcels. However, given the lack of scale effect, last mile delivery is inefficient, expensive, and produces a considerable amount of carbon emissions, which has become an obstacle to the development of a sustainable economy. This work proposes a traveling salesman problem with carbon emission reduction in last mile delivery. The proposed problem aims to reduce the total costs and carbon emissions of last mile delivery by deciding on the allocation of parcel lockers while scheduling delivery routes. In addition, we take the customer self-collection intention into consideration and translate it into self-collection costs, which are included in the objective. An iterated local search (ILS) algorithm is proposed, and four new local search operators are designed to improve customer allocation. The proposed method is tested on a set of scattered and clustered instances, including a real-world instance. The computational results show the superiority and competitiveness of the proposed algorithm.

INDEX TERMS Sustainable economy, carbon emission, parcel lockers, customer pickup, last mile, ILS.

I. INTRODUCTION

The development of e-commerce, especially C2C e-commerce (Taobao), has overcome geographical restrictions on sales and realised a surge in online transaction volume. According to the National Bureau of Statistics of China, in 2017, the number of online shopping users in the country reached 533 million, online retail sales reached 7.1 trillion yuan and the number of parcels of online shopping reached 40.06 billion. In 2017, an average of more than 100 million parcels per day flowed from merchants to customers.

Home delivery (HD), the process of delivering parcels directly to customer homes, used to be common in last mile delivery. Meanwhile, with the increase in parcel volume, last mile delivery, which lacks 'economic scale' [1], has become the most ineffective, expensive and carbon-emitting part of e-commerce logistics [2]. It has also increased the pressure on its actors [3] and become a bottleneck in the development of e-commerce [4]. Research on improving the efficiency of last mile delivery and reducing its carbon emissions has become a key issue for the sustainable economy.

Customer pickup (CP), which allows customers to self-collect parcels from nearby parcel lockers (PLs) at their convenience, has recently become popular in last mile delivery. CP has many benefits, including improved delivery efficiency [5], reduced delivery costs [6], [7] and minimised failed deliveries [8]. Moreover, PLs in last mile delivery are close to customers, who are willing to walk to pick up their parcels. CP can also considerably reduce the carbon emissions of last mile delivery [9].

At present, most research works on CP focus on case studies [1], [6], [9]; investigations of its routing problems are scarce. This study proposes a novel travelling salesman problem (TSP) with carbon emission reduction (TSPCER) in last mile delivery to address practical issues and fill the aforementioned research gap. The proposed problem aims to reduce the total costs and carbon emissions of last mile delivery by deciding on the allocation of PLs whilst scheduling delivery routes. We translate the customer self-collection intention into self-collection costs and incorporate it into the objective.

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Meanwhile, we propose an iterated local search (ILS) algorithm to solve the problem.

The study is organized as follows. Section 2 includes a review of related literature on last mile delivery. Section 3 provides a detailed description and formulation of TSPCER, and Section 4 presents the proposed ILS heuristic. Section 5 displays the computational experiments and discussions. Finally, Section 6 presents the conclusions and future works.

II. LITERATURE REVIEW

TSP is a classical problem in the field of combinatorial optimisation. Given a set of cities, the TSP aims to find a minimum-length Hamiltonian cycle of the cities in which each city has to be visited exactly once [10]. Many variations of the standard TSP, including TSP with time window [11], [12], TSP with pickup-and-delivery [13], [14], asymmetric TSP [15], [16], family TSP [17], [18], the travelling purchaser problem (TPP) [19], [20] and the covering salesman problem (CSP) [21], [22], have been introduced in the literature.

Amongst these studies, CSP research is the most closely related to the current work. CSP is a generalisation of TSP and aims to construct a minimum-length tour over a subset of the given customers such that each customer not visited on the tour is within the covering distance of at least one visited customer [22]. Many papers have discussed the application of this problem in the fields of emergency management and disaster planning. Interested readers are referred to [23]–[25].

The proposed problem is similar to CSP, but some differences exist. CSP has two kinds of nodes: the depot and customers. The objective of CSP is to find a minimum-length tour. In TSPCER, three types of nodes, namely, the depot, customers and PLs, are available. The goal of TSPCER is to find not only a minimum-length tour but also the best usage of the PLs.

Another research topic related to this study is PLs. Studies on PL focus on two areas, namely, case studies and self-collection network optimisation. In case studies, Punakivi *et al.* [6] and Kämäräinen [7] stated that allowing customers to pick up parcels from PLs could reduce the delivery costs of last mile delivery by more than 55% and 42%, respectively. Edwards *et al.* [9] emphasised that carbon emission could be reduced by 83% by having customers collect parcels from PLs. In addition, Agatz *et al.* [5], Chen *et al.* [26], Van Duin *et al.* [27] and Morganti *et al.* [28] proposed that PLs play important roles in the improvement of urban liveability and reduction of road congestion, demand for curb-side parking and emissions of greenhouse gases.

In self-collection network optimisation, Park *et al.* [29] proposed an optimisation methodology that analyses the effects of logistics collaboration in the last mile network in Seoul, South Korea. Deutsch and Golany [1] proposed a location–allocation problem of PLs to build an efficient self-collocation network in last mile delivery. Zhou *et al.* [2] and Zhou *et al.* [30] introduced two location routing problems

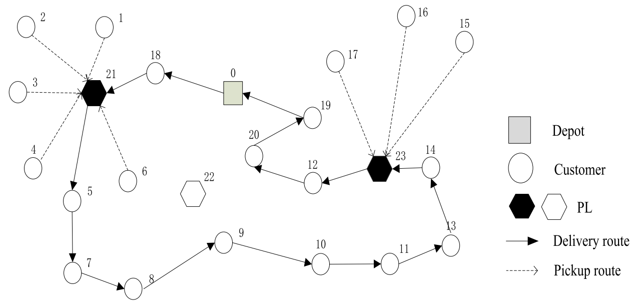

FIGURE 1. Last mile delivery network with PLs.

with delivery options to minimise the total costs of last mile delivery.

Some existing studies have found that the total delivery costs and carbon emissions of last mile delivery could be evidently reduced by using PLs. However, some studies [8], [31] have shown that most consumers prefer to use PLs near their homes; the farther the customers are from PLs, the lower their self-collection intentions. Furthermore, we take the customer self-collection intention into consideration and then translate it into self-collection costs, which are incorporated into the objective. We aim to find the minimum-length tour and best usage of PLs to reduce the total delivery cost and carbon emission of last mile delivery.

III. PROBLEM DESCRIPTION AND FORMULATION

A. PROBLEM DESCRIPTION

The problem is defined on a network $G = (V, A)$, where the node set V is partitioned as $V = V_D \cup V_C \cup V_P$. $V_D = \{0\}$ represents the depot, $V_C = \{1, 2, 3, \ldots, N\}$ represents N customers and $V_P = \{N+1, N+2, \ldots, N+M\}$ represents M PLs. The arc set A is defined as $A = A_1 \cup A_2$. $A_1 = \{\langle m, n\rangle | m, n \in V\}$ is a set of delivery arcs connecting each pair of nodes in V, and each arc $\langle m, n\rangle$ is associated with a delivery cost d_{mn}. $A_2 = \{\langle i, p\rangle | i \in V_C, p \in V_P\}$ represents a set of pickup arcs from customer i to PL p, and each arc $\langle i, p\rangle$ is associated with a pickup cost c_{ip}. In addition, the unit open cost, capacity and service radius of the PLs are u, v and R, respectively.

In the network, a courier starts from the depot, delivers parcels to N customers and then returns to the depot. During the delivery process, the courier can deliver each parcel directly to the customer's home or to a PL near the customer. The aim of this process is to minimise the total costs, included route, customer pickup and PL opening costs.

Figure 1 depicts an example of a last mile delivery system with 1 depot, 3 PLs, and 21 customers.

B. FORMULATION

In this section, we provide a formal definition of the TSPCER, and the decision variables of the model are defined as follows.

Binary variable x_{mn}

$$x_{mn} = \begin{cases} 1 & \textit{if arc}(m, n) \textit{ is visited by the tour} \\ 0 & \textit{otherwise} \end{cases}$$

Binary variable y_{ip}

$$y_{ip} = \begin{cases} 1 & \text{if customer } i \text{ is allocated to PL } p \\ 0 & \text{otherwise} \end{cases}$$

1) GENERAL TSP FORMULATION

The model of the general TSP can be described as follows:

$$\min \sum_{i,j \in V_D \cup V_C} d_{ij} x_{ij}, \tag{1}$$

$$\sum_{j \in V_D \cup V_C} x_{ij} = 1 \quad \forall i \in V_D \cup V_C, \tag{2}$$

$$\sum_{i \in V_D \cup V_C} x_{ij} = 1 \quad \forall j \in V_D \cup V_C, \tag{3}$$

$$u_i - u_j \leq N * (1 - x_{ij}) - 1 \quad \forall i,\ j \in V_D \cup V_C, \tag{4}$$

$$u_i = \{1, 2, \ldots, N\} \quad \forall i \in V_D \cup V_C. \tag{5}$$

The objective function (1) minimises the route cost. Constraint (2) ensures that each customer is served only once. Constraint (3) guarantees that if customer i is visited, then an arc leaving it must be observed. Constraints (4) and (5) ensure that the delivery route has only one closed loop.

2) TSPCER FORMULATION

Compared with general TSP, TSPCER in last mile delivery increases PL allocation in the constraints and PL opening and customer pickup costs in the objective, which can be stated as follows:

$$\min z = \sum_{m,n \in V} d_{mn} x_{mn} + \sum_{i \in V_C, p \in V_P} c_{ip} y_{ip} + \sum_{i \in V_C, p \in V_P} u y_{ip} \tag{6}$$

$$\text{subject to} \sum_{m \in V} x_{0m} = 1, \tag{7}$$

$$\sum_{m \in V} x_{im} + \sum_{p \in V_P} y_{ip} = 1 \quad \forall i \in V_C, \tag{8}$$

$$\sum_{n \in V} x_{mn} = \sum_{h \in V} x_{hm} \quad \forall m \in V, \tag{9}$$

$$y_{ip} \leq \sum_{m \in V} x_{mp} + \sum_{m \in V} x_{pm} \quad \forall i \in V_C,\ \forall p \in V_P, \tag{10}$$

$$\sum_{i \in V_C} y_{ip} \leq v \quad \forall p \in V_P, \tag{11}$$

$$c_{ip} y_{ip} \leq R \quad \forall i \in V_C, p \in V_P, \tag{12}$$

$$x_{mn} = \{0, 1\} \quad \forall m, n \in V, \tag{13}$$

$$y_{ip} = \{0, 1\} \quad \forall p \in V_P, \forall i \in V_C. \tag{14}$$

The objective function (6) minimises the route, customer pickup and PL opening costs. Constraint (7) shows that the tour starts from the depot. Constraint (8) ensures that each customer is served only once by either tour or PL. Constraint (9) guarantees that if a customer or PL is visited by the tour, then the tour must leave from it. Constraint (10) ensures that a customer i could be allocated to PL p only if PL p is visited by the tour. Constraints (11) and (12) are the capacity and server radius constraints for the PL, respectively. Constraints (13) and (14) define all variables.

IV. ILS ALGORITHM

The popular ILS algorithm is a heuristic involving an LS heuristic and a perturbation process. At each iteration, a new initial solution, which is used by the local search (LS) heuristic as a new starting point for improvement, is generated by the perturbation. The ILS algorithm has been proven to be a successful approach to solving combinatorial optimisation problems [4], [32].

We propose the heuristic ILSTSPCER, which is based on the widely known ILS, for TSPCER. In ILSTSPCER, we improve the perturbation process, including add_PL, drop_PL and shaking processes, to generate a new initial solution. In addition, four new LS operators are proposed to improve customer allocation.

In the following subsections, we comprehensively discuss the proposed ILSTSPCER heuristic, including the general procedure, solution representation, perturbation and LS.

A. STSPCER PROCEDURE

ILSTSPCER starts from a random initial solution S0. S represents the current best solution. At each iteration, a new solution S', which retains part of the structure of the current best solution S, is generated by the perturbation process. Then, LS is applied to the solution S' to yield a new solution, which is used to update the solution S'. If the new solution S' is better than the current best solution S, then the current best solution S is updated by the new solution S', and the same steps are repeated. Meanwhile, we add an intra-parameter called iterLevel to enlarge the search space. The steps of ILSTSPCER are presented in Algorithm 1.

Algorithm 1 Proposed Ilstspcer Procedure

Input: *kMax, iterMax,* S_0
Output: *S*
$k \leftarrow 1$; $iterLevel \leftarrow 0$;
$S \leftarrow S_0$;
whilst $k < kMax$ ***do***
  $S' \leftarrow perturb(S,k)$;
  $S' \leftarrow VND(S')$;
  if $obj(S') < obj(S)$ ***then***
   $S \leftarrow S'$; $k \leftarrow 1$;
  else
   if $iterLevel > iterMax$ ***then***
    $iterLevel \leftarrow 0$; $k \leftarrow k + 1$;
   $iterLevel \leftarrow iterLevel + 1$;
 end

B. SOLUTION REPRESENTATION

In ILSTSPCER, a solution is represented by two strings of numbers. $S_{allocation}$ represents customer allocation. As shown in Figure 1, $S_{allocation}(1) = 10$ illustrates that customer 1 is

$S_{allocation}$	0	10	10	0	0	0	11	0	11	0
	0	1	2	3	4	5	6	7	8	9

S_{route}	0	3	4	5	10	7	11	9	0	0	0

FIGURE 2. **Example of solution representation.**

allocated to PL 10; otherwise, $S_{allocation}(3) = 0$ emphasises that customer 3 is served by a courier rather than a PL. S_{route} indicates the delivery route, which is a permutation of *1* depot denoted by $\{0\}$, N customers denoted by the set $\{1, 2, \ldots, N\}$ and M potential PLs denoted by the set $\{N+1, N+2, \ldots, N+M\}$. For example, the delivery route in Figure 2 is 0-3-4-5-10-7-11-9-0.

C. PERTURBATION

A feature of ILSTSPCER is that we add two processes (*add_PL* and *drop_PL*) to the perturbation to enlarge the solution space. In the perturbation, *add_PL* is responsible for adding a PL into the current best solution S, and the role of *drop_PL*is to close the PL in the current best solution S. Additional details of the perturbation are shown in Algorithm 2.

Algorithm 2 Details of Perturbation

```
Input: S,k
r = rand(0,1);
if r < 0.3 then
   S' ← add_PL(S, openNum);
elseif r < 0.6 then
   S' ← drop_PL(S, closNum);
else
   S' ← shaking(S,k);
end
```

1) ADD_PL PROCESS

The *add_PL* process produces a new solution by adding a PL to the current best solution S. The process steps are as follows.

Step 1: Randomly select a PL. Select a closed PL from the current best solution S.

Step 2: Allocate customers to the selected PL. In the allocation method, when the customer is close to the selected PL, the PL is allocated early until the termination condition is met.

Step 3: Locate the PL in the route. Randomly select a position in the route, and then, locate the PL to the selected position.

Step 4: Repeat the preceding steps openNum times. Notably, in openNum = random(0,L), L is the maximum number of closed PLs in the current best solution S.

Step 2 has three kinds of termination conditions, namely, maximum, minimum and random allocations. (i) The maximum allocation is that the customers meeting the PL capacity and service distance constraints are all allocated to the PL. (ii) The minimum allocation is that no customer is allocated to the PL. (iii) The random allocation is that the number of customers allocated to the PL is randomly generated but between the minimum and the maximum.

2) DROP_PL PROCESS

The *drop_PL* process yields a new solution by dropping a PL from the current best solution *S*. The process steps are as follows.

Step 1: Select a PL. Randomly select an opened PL from the current best solution S.

Step 2: Close the selected PL. Delete the selected PL from the route, and re-insert the customers allocated to the selected PL to the route. Similar to step 3 of the *add_PL* process, this re-insertion is random.

Step 3: Repeat the aforementioned steps *closNum* times. Notably, in *closNum* = *random*(0,H), H is the maximum number of the opened PL in the current best solution S.

3) SHAKING PROCESS

The shaking process is responsible for generating a new solution by perturbing the current best solution S. In this study, the perturbation is performed by randomly exchanging two nodes in the current best solution S.

The number of exchanged customers is the parameter that defines the size of the perturbation. This number is a key factor of the ILS algorithm in that it determines the portion of the locally modified optimal solution. In this study, this parameter is set to k, and the benefit of the setting is that the best solution space expands with the increase in iteration.

Notably, the exchange must satisfy the service distance constraints. In addition, the two nodes (a customer allocated to a PL, and a PL) cannot be exchanged.

4) LOCAL SARCH

Variable neighbourhood descent (VND), as detailed in Algorithm 3, is used as LS in the proposed ILSTSPCER algorithm to improve the new solution generated by the perturbation process.

The neighbourhood structure used in VND comprises well-known operators [33], [34], namely, (i) intra- and inter-route customer relocation and (ii) intra- and inter-route customer exchange. Some improvements were made to solve the proposed problem. Additional details are as follows.

Algorithm 3 VND Process

Input: S'; *a set of neighbourhood structures* $\mathcal{N}_l$

$l \leftarrow 1$;
repeat
  $S'' \leftarrow$ *find the best solution in* $\mathcal{N}_l(S')$;
  if $obj(S'') < obj(S')$
    $S' \leftarrow S''$; $l \leftarrow 1$;
  else
    $l \leftarrow l + 1$;
  until $l < l_{max}$

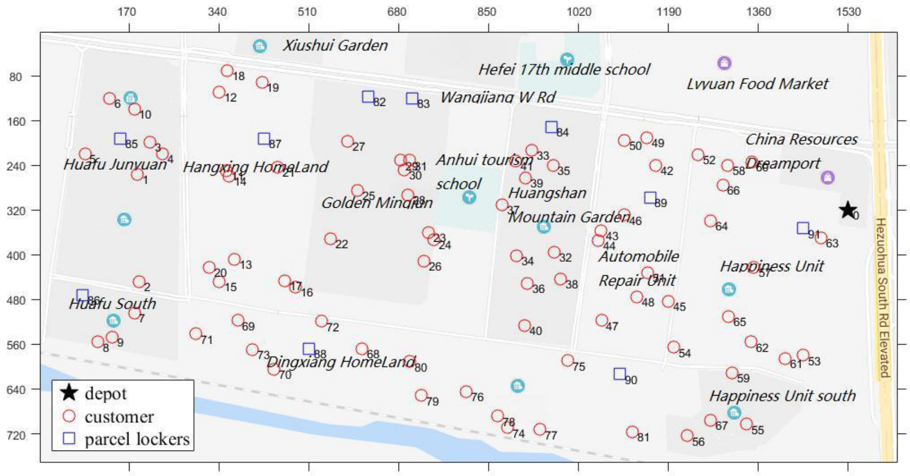

FIGURE 3. Network of the real-world instance.

a: INTRA-ROUTE

$\mathcal{N}_1$ – relocation_R2R: A customer i or an opened PL p in the route is relocated to the best new position in the route.

$\mathcal{N}_2$ – exchange_R2R: Two nodes (customer or PL) in the route exchange their positions.

b: INTER-ROUTE

$\mathcal{N}_3$ – relocation_R2P: A customer i in the route is relocated to the best PL p. Notably, the relocation must follow the PL capacity and service distance constraints; otherwise, the relocation is not allowed.

$\mathcal{N}_4$ – relocation_P2R: A customer i allocated to PL p is relocated to the best new position in the route. Notably, PL p must be deleted from the route if the capacity of PL p becomes 0 after the deletion.

$\mathcal{N}_5$ – exchange_R2P: Two customers i and j (one in the route and one allocated to a PL) exchange their positions. Notably, the exchange must follow the distance constraints.

$\mathcal{N}_6$ – exchange_P2P: Two customers i and j (both allocated to PLs) exchange their positions. Notably, the exchange must comply with the service distance constraints.

V. COMPUTATION EXPERIMENTS

We present a real-world example and propose two sets of comparative experiments to verify the effectiveness and competitiveness of the proposed method and algorithm. The proposed algorithm is compiled with C++ and runs on a PC with an Intel i5-7500 CPU (3.40 GHz) and 8 GB memory.

A. REAL-WORD INSTANCE

This section presents a last mile delivery test based on a real-world example of Shushan District in Hefei City. The area is 1620 m × 810 m. The depot (No. 0) has subcontracted the area to a courier, who is paid by piece to improve the delivery efficiency and reduce the 'finding cost'. Ten PLs (No. 82–91) are distributed in the area, and 81 customers (No. 1–81) must be served in half a day. The locations of the depot, PLs and customers are shown in Figure 3. The distance between every two nodes is set as a straight-line distance to simplify the calculation.

TABLE 1. Result of PL locations and customer allocation.

PLs	Customers
87	1,3,4,5,6,10,12,18,19o,25
88	2,7,8,9,16,17,22,71,72
89	33,35,37,39,41,49,50,51,64,66
90	40,45,47,48,55,56,59,67,75,81
91	53,61,62,63

TABLE 2. Result of delivery route.

0-60-58-52-42-89-64-66-51-50-41-37-39-49-35-33-46-43-44-32-38-36-34-26-24-23-28-30-31-29-27-21-87-4-3-10-12-1-6-18-5-25-19-11-84-83-82-85-86-14-13-20-15-69-73-70-88-17-16-71-72-7-22-2-8-9-68-80-79-76-78-74-77-90-81-40-56-45-67-48-55-59-75-47-54-65-57-91-63-62-61-53-0

The main parameters are as follows: $c_{ip} = w \times d_{ip}$, $w = 0.2$, $u = 10$, $R = 500$ m and $v = 10$. The best solution is obtained by five runs. The results are shown in Tables 1 and 2.

We use $w = c_{ip}/d_{ip}$ to analyse the impact of customer intention to use PLs on total cost, which is set from 0.0 to 1.0. $w = 0.0$ means that the customers are very likely to use PLs; $w = 0.2$ means fairly likely; $w = 0.4$ means likely; $w = 0.5$ means neither likely nor unlikely; $w = 0.6$ means unlikely; $w = 0.8$ means fairly unlikely; $w = 1.0$ means very unlikely. The other parameter settings are the same as above. As shown in Table 3, the best solutions of the proposed method (PM) are obtained by five runs, and the total costs of

TABLE 3. Comparison of HD and PM.

w	Proposed method (PM)				HD	GAP1	GAP2
	Total cost	Route cost	Pickup cost	Opening cost	Total cost		
0.0	3270.0	2570	0.0	700	6700	51.2%	51.2%
0.2	5577.8	3421	1726.8	430	6700	42.5%	16.7%
0.4	6398.4	5244	954.4	200	6700	18.7%	4.5%
0.5	6571.5	5948	523.5	100	6700	9.7%	1.9%
0.6	6645.4	6435	170.4	40	6700	3.4%	0.8%
0.8	6686.6	6549	117.6	20	6700	2.0%	0.2%
1.0	6700.0	6700	0.0	0	6700	0.0%	0.0%

TABLE 4. Comparisons of ILS and SA on clustered instances.

Instance	N	M	SA		ILS		GAP
			obj	time	obj	time	(%)
C-1-1	20	2	314.0	0.07	314.0	0.05	0.0
C-1-2	20	2	281.0	0.07	281.0	0.04	0.0
C-1-3	20	2	347.0	0.07	347.0	0.05	0.0
C-1-4	20	2	257.6	0.06	257.6	0.04	0.0
C-2-1	40	4	284.6	1.24	277.4	0.73	2.5
C-2-2	40	4	392.8	1.33	389.8	0.74	0.8
C-2-3	40	4	394.0	1.25	392.0	0.72	0.5
C-2-4	40	4	297.6	1.27	297.2	0.85	0.1
C-3-1	60	6	455.4	7.12	448.6	6.22	1.5
C-3-2	60	6	373.8	6.88	365.8	5.68	2.1
C-3-3	60	6	406.2	7.19	376.6	6.01	7.3
C-3-4	60	6	371.6	7.05	359.8	6.02	3.2
C-4-1	100	10	503.6	68.01	478.0	42.66	5.1
C-4-2	100	10	529.8	67.85	511.0	45.32	3.5
C-4-3	100	10	523.0	63.71	509.0	47.51	2.7
C-4-4	100	10	557.6	65.94	516.0	52.70	7.5
C-5-1	200	20	788.0	223.71	714.8	184.30	9.3
C-5-2	200	20	677.2	266.11	653.0	205.63	3.6
C-5-3	200	20	761.2	201.32	699.6	241.08	8.1
C-5-4	200	20	783.4	215.32	739.2	227.42	5.6
AVG			465.0	60.28	446.37	53.69	3.2

HD are obtained by CPLEX 12.7.1 within 3600 s. Notably, GAP1 = (total cost_{HD} − route cost_{PM} − opening cost_{PM}) / total $\text{cost}_{\text{HD}} \times 100\%$ and GAP2 = (total cost_{HD} − total cost_{PM}) / total $\text{cost}_{\text{HD}} \times 100\%$.

GAP2 presents the total cost savings in last mile delivery. The comparison clearly shows that total cost savings are large when the customers' intention to use PLs is strong. The highest total cost savings reach 51.2%, which is basically consistent with the 55% of Punakivi *et al.* [6] and 42% of Kä mä rä inen [7]. GAP1 presents the carbon emission reduction in last mile delivery. In reality, customers prefer to walk to PLs within 500 m to pick up their parcels. In areas where PLs are highly accepted ($w = 0.0 - 0.4$), the carbon emission reduction of last mile delivery can reach 18.7%–51.2%.

B. COMPARISON WITH OTHER HEURISTICS

Given that no similar examples are presented in this section, we design two sets of instances (scattered and clustered instances) to test the proposed algorithm. Twenty instances, divided into five groups, are available in each set of instances. The data of the depot, PLs and customers in the instances are generated as follows. (i) The location area is (0, 100) × (0, 100); (ii) the depot is located in (50, 50); (iii) the locations of the PLs are randomly generated in the location area; (iv) all the customers for the scattered instances are randomly distributed in the location area; (v) N customers for the clustered instances are equally divided into M groups, which are randomly distributed around M PLs.

For checking the competitiveness of the proposed ILS, it is compared with simulated annealing (SA), which was

TABLE 5. Comparisons of ILS and SA on scattered instances.

Instance	N	M	SA obj	SA time	ILS obj	ILS time	GAP (%)
R-1-1	20	2	403.2	0.07	403.2	0.04	0.0
R-1-2	20	2	310.8	0.08	310.8	0.04	0.0
R-1-3	20	2	413.2	0.08	413.2	0.04	0.0
R-1-4	20	2	344.6	0.07	344.6	0.05	0.0
R-2-1	40	4	472.8	1.28	471.8	0.71	0.2
R-2-2	40	4	495.6	1.41	491.8	0.69	0.8
R-2-3	40	4	477.6	1.37	471.0	0.74	1.4
R-2-4	40	4	440.4	1.24	437.6	0.71	0.6
R-3-1	60	6	541.2	8.85	532.4	7.36	1.6
R-3-2	60	6	582.6	8.21	569.2	5.90	2.3
R-3-3	60	6	583.3	8.38	547.2	6.81	6.2
R-3-4	60	6	569.2	8.89	552.0	6.80	3.0
R-4-1	100	10	783.6	77.02	720.2	50.42	8.1
R-4-2	100	10	787.8	76.61	732.8	47.38	7.0
R-4-3	100	10	732.4	76.75	696.4	49.02	4.9
R-4-4	100	10	793.8	74.64	742.4	46.30	6.5
R-5-1	200	20	1062.6	210.95	1003.0	184.32	5.6
R-5-2	200	20	1036.0	235.94	988.0	233.29	4.6
R-5-3	200	20	1137.0	234.87	1065.4	237.53	6.3
R-5-4	200	20	1110.6	238.72	1069.8	212.26	3.7
AVG			653.9	63.27	628.14	54.52	3.1

proposed by Yu *et al.* [35] and proven suitable for solving location routing problems. The main parameters are set as follows: $c_{ip} = 0.2 \times d_{ip}$, $u = 2.0$, $R = 30.0$, $v = 5$. $kMax_{ILS} = N$, $iterMax_{ILS} = M$; $T_{SA} = N \times N$, and $alpha_{SA} = 0.96$. The results are shown in Tables 4 and 5. Notably, N presents the number of customers, M is the number of PLs, GAP = $(\mathrm{obj_{SA}} - \mathrm{obj_{ILS}})$ / $\mathrm{obj_{SA}} \times 100$ and the best solutions of ILS and SA are obtained by 10 runs.

Tables 4 and 5 show that all the clustered and scattered instances are solved by the proposed ILS with average results of 446.37 and 628.14, respectively. The average gaps to SA are 3.2% and 3.1%, respectively. In addition, the proposed ILS effectively solves all 40 instances with average CPU times of 53.69 and 54.52 s, respectively, which are suitable for this daily problem.

VI. CONCLUSIONS

This research introduces TSPCER in last mile delivery. A feature of the problem is that the total delivery costs and carbon emissions of last mile delivery can be considerably reduced by using PLs. In addition, we incorporate the pickup costs, which represent the self-service intention of customers, into the objective. The results of a real-world instance show that the total costs and carbon emissions of last mile delivery can be reduced to 4.5%–51.2% and 18.7%–51.2%, respectively, by using PLs in areas where they are highly accepted. In addition, we propose an ILS algorithm for solving the given problem; the algorithm is tested on scattered and clustered instances. Computational results and comparisons show that the proposed ILS algorithm performs well with quite a reasonable computational time for the proposed problem, which must be solved every day.

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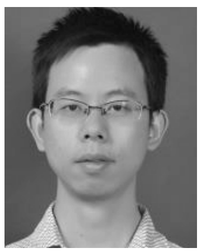

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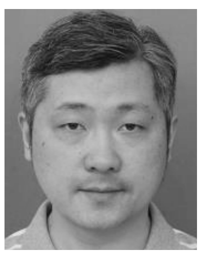

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