12-2020

Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading-unloading zones

Vincent F. YU

WINARNO

Shih-Wei LIN

Aldy GUNAWAN
Singapore Management University, aldygunawan@smu.edu.sg

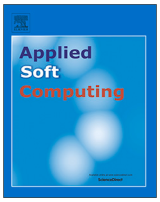
Citation

YU, Vincent F.; WINARNO; LIN, Shih-Wei; and GUNAWAN, Aldy. Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading-unloading zones. (2020). *Applied Soft Computing*. 97, (B),.
Available at: https://ink.library.smu.edu.sg/sis_research/7126

Contents lists available at ScienceDirect

Applied Soft Computing Journal

journal homepage: www.elsevier.com/locate/asoc



Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones

Vincent F. Yu [a], Winarno [a,b], Shih-Wei Lin [c,d,e,*], Aldy Gunawan [f]

[a] Department of Industrial Management, National Taiwan University of Science and Technology, Taipei, Taiwan
[b] Department of Industrial Engineering, Universitas Singaperbangsa Karawang, Karawang, Indonesia
[c] Department of Information Management, Chang Gung University, Taoyuan, Taiwan
[d] Department of Industrial Engineering and Management, Ming Chi University of Technology, Taipei, Taiwan
[e] Department of Neurology, Linkou Chang Gung Memorial Hospital, Taoyuan, Taiwan
[f] School of Information Systems, Singapore Management University, Singapore

ARTICLE INFO

Article history:
Received 3 March 2019
Received in revised form 13 January 2020
Accepted 5 September 2020
Available online xxxx

Keywords:
Two-echelon freight distribution system
Third-party logistics
Loading–unloading zones
Simulated annealing

ABSTRACT

This research examines the problem of designing a two-echelon freight distribution system in a dense urban area that considers third-party logistics (TPL) and loading–unloading zones (LUZs). The proposed system takes advantage of outsourcing the last mile deliveries to a TPL provider and utilizing LUZs as temporary intermediate facilities instead of using permanent intermediate facilities to consolidate freight. A mathematical model and a simulated annealing (SA) algorithm are developed to solve the problem. The efficiency and effectiveness of the proposed SA heuristic are verified by testing it on existing benchmark instances. Computational results show that the performance of the proposed SA is comparable with that of another state-of-the-art algorithm. The model and algorithm are then used to design a two-echelon freight distribution system in Taipei City, Taiwan. Results of the case study indicate that the proposed model and algorithm provide a better distribution system.

1. Introduction

A two-echelon freight distribution system (FDS) is an efficient strategy for freight delivery in urban areas, in which the freight is consolidated at an intermediate facility before arriving at its destination. Two-echelon FDSs can be applied in express delivery companies, grocery and hypermarket product distribution, spare parts distribution companies and newspaper distribution companies. However, the design of a two-echelon FDS in urban areas cannot be separated from existing business strategies and city developments. One business strategy for increasing the competitiveness of a company is to collaborate with third-party logistics (TPL) [1] and the literature has reported TPL involvement in designing a two-echelon FDS model [2].

Providing loading–unloading zones (LUZs) in a city is also one form of city development to facilitate freight loading–unloading activities, however few studies have explored LUZs. Dezi et al. [3] and Pinto et al. [4] optimized the distribution and size of LUZs according to the demand and location of business activities. The application of an LUZ system was also studied by Muñuzuri et al. [5], Alho and Silva [6] and Gardrat and Serouge [7].

To the authors' knowledge, no study has considered TPL and LUZs simultaneously in designing a two-echelon FDS. This study fills this gap by proposing a two-echelon open location routing problem (2E-OLRP) considering TPL and LUZs. The proposed 2E-OLRP differs from that described by Pichka et al. [2]. Fig. 1 illustrates the difference between the two problems. Fig. 1(a) shows how the TPL is involved in both echelons in the problem proposed by [2], while it can be seen from Fig. 1(b), that the TPL is involved only in the second echelon, meaning that only the second echelon vehicles (SEVs) arrive at customers.

This study considers the use of LUZs as temporary satellites in a 2E-OLRP. When a company utilizes a usual (permanent) satellite to connect its depot and customers, the activation cost of the permanent satellite increases the total distribution cost. Therefore, utilizing LUZs reduces the total distribution cost for the company because these facilities can be accessed freely.

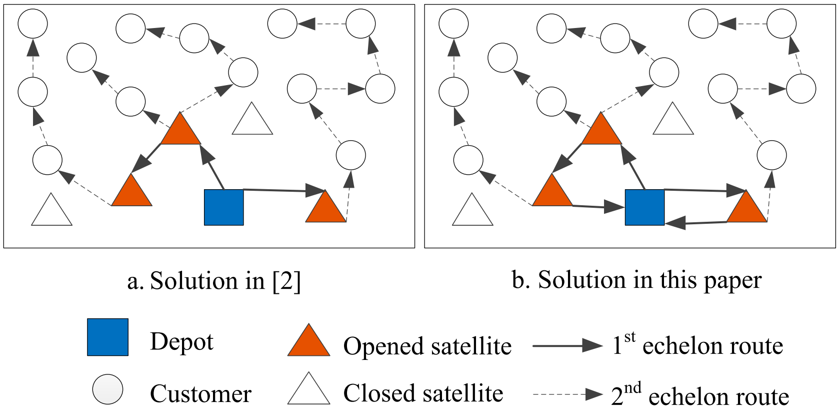
There may be conflicting cost components in the system. For example, more satellites may result in smaller traveling cost of the second level vehicles, while increase the traveling cost of the first level vehicles. Therefore, the objective of the 2E-OLRP is to minimize the total costs of the distribution system consisting of the satellites' set-up cost, the activation cost of vehicles and routing cost for both first and second echelon vehicles. The 2E-OLRP is an NP-hard problem because it generalizes

---

[*] Corresponding author at: Department of Information Management, Chang Gung University, Taoyuan, Taiwan.
E-mail address: swlin@mail.cgu.edu.tw (S.-W. Lin).

https://doi.org/10.1016/j.asoc.2020.106707
1568-4946/© 2020 Published by Elsevier B.V.

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.



a. Solution in [2]

b. Solution in this paper

Fig. 1. Illustration of the 2E-OLRP solution in [2] and in this paper.

(23)	(21)	0	16	15	14	(22)	0	(25)	20	*	13	5	3	7	*	0	10	9	17	2	(24)	12	1	4	18	19	8	6	11

Fig. 2. Example of solution representation.

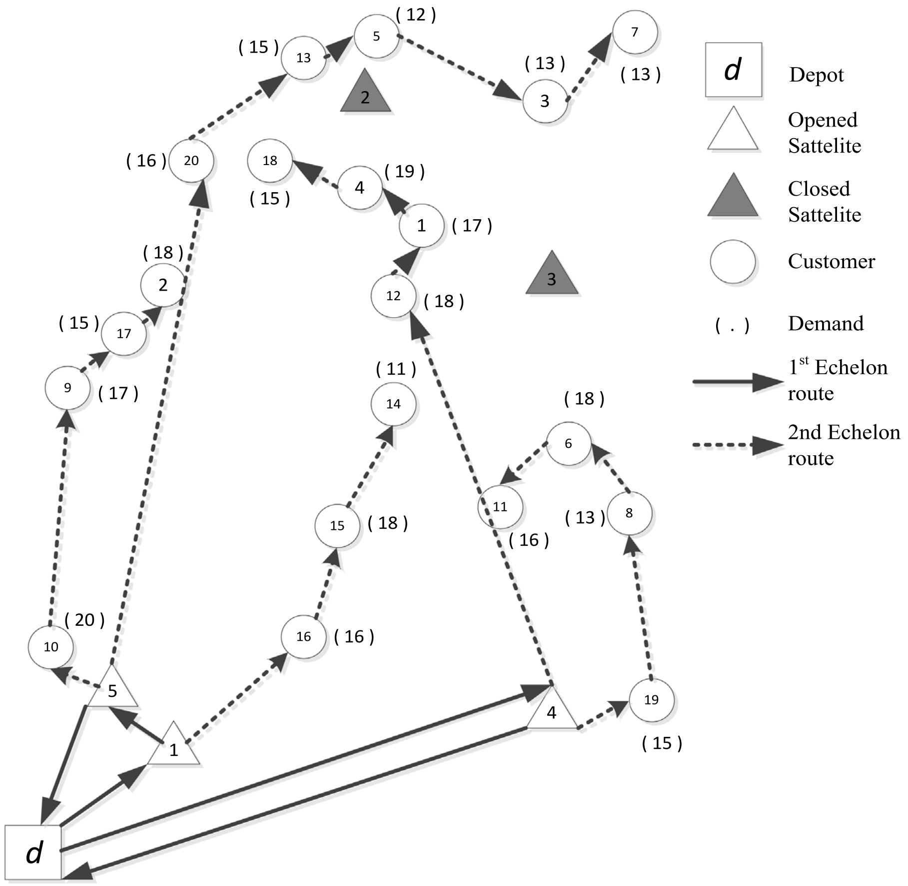


Fig. 3. Visual illustration of the solution presented in Fig. 2.

several known NP-hard problems: the two-echelon facility location problem, the two-echelon vehicle routing problem and the capacitated location-routing problem. Therefore, heuristic solution approaches are efficient and effective alternatives for solving medium- and large-scale 2E-OLRPs.

The main contributions of this paper are summarized as follows. First, this paper proposes a 2E-OLRP that considers TPL in the second echelon. Second, it proposes an efficient and effective SA heuristic to solve the 2E-OLRP. In addition, SA has been used successfully by many researchers to solve distribution system problems [8–12]. Finally, a case study of designing a two-echelon FDS in Taipei City, Taiwan is presented to illustrate the advantage of utilizing LUZs.

The remainder of this paper is structured as follows. Section 2 summarizes the related literature. Section 3 presents a mathematical model for the 2E-OLRP. Section 4 discusses the proposed SA heuristic for the 2E-OLRP. Section 5 presents the

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

computational study. Section 6 discusses the case study. Finally, Section 7 offers conclusions and suggestions for future research.

2. Literature review

The two-echelon open location routing problem is a variant of the two-echelon location routing problem (2E-LRP). The 2E-LRP was introduced by Jacobsen and Madsen [13]. Cuda et al. [14] surveyed papers for the 2E-LRP before 2012. Jacobsen and Madsen [13] designed a heuristic algorithm for the 2E-LRP in a newspaper distribution system. They proposed three sequential heuristics for the problem. These three heuristics were then analyzed in depth [15]. Lin and Lei [16] considered a two-level routing-location problem in the design of a national finished goods distribution system for a Taiwanese label-stock manufacturer. They proposed a hybrid genetic algorithm embedded with a routing heuristic to solve the problem. These authors reported that customers with larger demand should be served directly from the depot.

Boccia et al. [17] designed a two-echelon FDS as a 2E-LRP model. The authors reported the basic assumptions of the 2E-LRP. A tabu search (TS) was proposed to solve the problem for small-, medium- and large-scale instances. The study was continued in Boccia et al. [18] by providing three mixed integer linear programming models using one-, two- and three-index formulations. The authors solved only the of two- and three-index models using XPRESS-MP for small- and medium-scale instances.

Nguyen et al. [19] presented a multi-start evolutionary local search to solve the 2E-LRP. They examined the method on three sets of instances with up to 200 customers. Nguyen et al. [20] subsequently introduced two new sets of instances for the 2E-LRP and implemented a greedy randomized adaptive search procedure (GRASP) with path relinking. In Nguyen et al. [21], they improved their findings on the same instances by using a multi-start iterated local search with tabu list and path relinking.

Crainic et al. [22] tackled the 2E-LRP using a TS heuristic. Their objective was to define the location and number of two kinds of capacitated facilities: the size of two different vehicle fleets and the related routes in each echelon. Contardo et al. [23] solved the two-echelon capacitated location routing problem (2E-CLRP) using a branch-and-cut algorithm and an adaptive large neighborhood search. Schwengerer et al. [24] presented a variable neighborhood search (VNS) for the 2E-LRP, adapted and extended VNS for the location routing problem [25].

Winkenbach et al. [26] solved the 2E-LRP in order to guide the strategic decision making of postal operators. The problem was addressed using a heuristic that splits the optimization problem into two interdependent subproblems. Breunig et al. [27] proposed a large neighborhood search (LNS) to solve the two-echelon vehicle routing problem (2E-VRP) and the 2E-LRP.

Furthermore, several researchers have added other aspects to the 2E-LRP in order to bring it closer to real-world application. Nikbakhsh and Zegordi [28] presented a 2E-LRP with soft time windows. They proposed four-index formulation to model the problem. A heuristic consisting of neighborhood search and an Or-opt heuristic was proposed to solve the problem and tested on five classes of instances with up to 100 customers. Time windows were also considered by Govindan et al. [29] in designing a 2E-LRP for a sustainable supply chain network of perishable food. The problem was solved using a hybrid of multi-objective particle swarm optimization and adapted multi-objective variable neighborhood search. The algorithm was tested on small-, medium- and large-scale instances. The performance of the algorithm was compared with genetic algorithm based methods.

Dalfard et al. [30] considered vehicle fleet capacity and maximum route length constraints in the 2E-LRP. A hybrid of genetic algorithm and SA was applied to solve the problem. The effectiveness of the algorithm was compared with that of LINGO on their own five instances with up to 100 customers.

Rahmani et al. [31] formulated a multi-product with pickup and delivery system as a 2E-LRP. They proposed two types of local search to improve the routing and the processing center locations. A 2-opt was extended to tackle the pickup demand, delivery demand and multi-product constraints. A local search, called product merging, was especially designed for the problem. The performance of the algorithm was tested on five groups of instances with up to 200 customers.

Vidović et al. [32] presented a variant of the 2E-LRP considering a collection of non-hazardous recyclables under a profit and distance-dependent collection rate. The model defines the collection of non-hazardous recyclables from end users to transfer points, passing through collection points. The authors proposed a two-phase heuristic to address the problem. The number and location of collection points, end user allocation and quantities collected are determined in the first phase, while optimal routes of collection vehicles and transfer station locations are determined in the second phase. The proposed heuristic was tested on small-, medium- and large-scale instances.

Pichka et al. [2] proposed a 2E-LRP considering TPL in the first and second echelons. The concept of closed and open routes was defined in both echelons of the model. The authors introduced the 2E-OLRP term to model the problem and proposed a two-phase algorithm to solve it. The first phase sets opened satellites, assigns customers to those opened satellites and constructs the first echelon vehicle routes, while the second phase constructs vehicle routes in the second echelon. To improve solutions in the first phase, an SA heuristic was proposed and another SA heuristic was used to improve solutions in the second phase.

3. Mathematical model

The components of the 2E-OLRP include a depot with unlimited capacity, a set of customers with given coordinates and demands, a set of potential satellites with known coordinates and capacities and a set of homogeneous vehicles in the first and the second echelons. This study defines 2E-OLRP on a complete undirected graph $G = (V, A)$. The node-set V is partitioned into a depot (node 0), a set $M = \{1, 2\dots n\}$ of potential satellite locations and a set $T = \{n{+}1, n{+}2\dots n{+}r\}$ of customers. Each arc (i, j) in the arc-set A has a traveling cost c_{ij}. W_m and σ_m denote capacity and set-up cost of satellite $m \in M$, respectively. Each customer $t \in T$ has a demand d_t. F is a set of identical first echelon vehicles (FEVs) based at the main depot, each with capacity H and activation cost K. E is a set of smaller identical second echelon vehicles (SEVs), each with capacity L and activation cost B. A_1 and A_2 are the arcs in the first and second echelon, respectively.

This study formulates 2E-OLRP as a mixed integer linear program using the following variables:

$x_{ij}^{f} = 1$ if FEV f traverses (i, j), 0 otherwise;
$y_{ij}^{e} = 1$ if SEV e traverses (i, j), 0 otherwise;
$z_m = 1$ if satellite m is opened, 0 otherwise;
$q_{mt} = 1$ if satellite m serves customer t;
$b_m^f \geq 0$: amount delivered to satellite m by FEV f;
u_m^f, s_t^e:auxiliary variables.

The mathematical model of the 2E-OLRP is as follows:

$$\text{Min} \sum_{m\in M} \sigma_m z_m + \sum_{m\in M}\sum_{f\in F} K x_{0m}^{f} + \sum_{m\in M}\sum_{t\in T}\sum_{e\in E} B y_{mt}^{e} + \sum_{(i,j)\in A_1}\sum_{f\in F} c_{ij} x_{ij}^{f} + \sum_{i\in A_2 j\in T}\sum_{e\in E} c_{ij} y_{ij}^{e} \tag{1}$$

$$\sum_{i\in M\cup T}\sum_{e\in E} y_{ti}^{e} = 1, \forall t \in T \tag{2}$$

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

$$\sum_{j\in M\cup T} y^e_{ji} = \sum_{j\in M\cup T} y^e_{ij}, \forall i \in M\cup T, e\in E \tag{3}$$

$$\sum_{m\in M}\sum_{t\in T} y^e_{mt} \le 1, \forall e\in E \tag{4}$$

$$\sum_{t\in T}\sum_{j\in M\cup T} d_t y^e_{tj} \le L, \forall e\in E \tag{5}$$

$$s^e_t - s^e_j + r y^e_{tj} \le r-1, \forall e\in E, [t,j]\in T : t\ne j \tag{6}$$

$$\sum_{i\in T} y^e_{mi} + \sum_{i\in M\cup T} y^e_{it} \le 1 + q_{mt}, \forall m\in M, t\in T, e\in E \tag{7}$$

$$\sum_{m\in M} q_{mt} = 1, \forall t\in T \tag{8}$$

$$\sum_{t\in T} d_t q_{mt} \le W_m z_m, \forall m\in M \tag{9}$$

$$\sum_{i\in M\cup\{0\}}\sum_{f\in F} x^f_{mi} = z_m, \forall m\in M \tag{10}$$

$$\sum_{j\in M\cup\{0\}} x^f_{ji} = \sum_{j\in M\cup\{0\}} x^f_{ij}, \forall f\in F, i\in M\cup\{0\} \tag{11}$$

$$u^f_m - u^f_j + n x^f_{mj} \le n-1, \forall f\in F, [m,j]\in M : m\ne j \tag{12}$$

$$\sum_{f\in F} b^f_m = \sum_{t\in T} d_t q_{mt}, \forall m\in M \tag{13}$$

$$\sum_{m\in M} b^f_m \le H, \forall f\in F \tag{14}$$

$$b^f_m \le H \times \sum_{i\in M\cup\{0\}} x^f_{mi}, \forall m\in M, f\in F \tag{15}$$

$$x^f_{ij} \in \{0,1\}, \forall (i,j)\in A_1, f\in F \tag{16}$$

$$y^e_{ij} \in \{0,1\}, \forall (i,j)\in A_2, e\in E \tag{17}$$

$$z_m \in \{0,1\}, \forall m\in M \tag{18}$$

$$q_{mt} \in \{0,1\}, \forall m\in M, t\in T \tag{19}$$

$$b^f_m \ge 0, \forall m\in M, f\in F \tag{20}$$

$$s^e_t \ge 0, \forall e\in E, t\in T \tag{21}$$

$$u^f_m \ge 0, \forall m\in M, f\in F \tag{22}$$

The objective function (1) includes satellite set-up costs, vehicles activation costs and vehicle travel costs. Constraint (2) ensures that each customer is visited once. The second echelon route continuity constraint (3) guarantees that a vehicle returns to its satellite of origin. Constraint (4) ensures that each SEV leaves one satellite at most. Constraint (5) is an SEVs' capacity constraint. Constraint (6) is the sub-tour elimination constraint. Constraint (7) ensures that satellite m serves customer t if an SEV e leaves satellite m and arrives at customer t. Constraint (8) assigns each customer to a single satellite. Constraint (9) ensures that no customer is assigned to a closed satellite and the total demand served by an opened satellite cannot exceed its capacity.

Constraint (10) states that each opened satellite must be visited by one FEV. Constraint (11) ensures trip continuity for each FEV used. Constraint (12) prevents sub-tours. Constraint (13) is flow conservation constraint. Constraint (14) is the FEV capacity constraint. Constraint (15) ensures that if FEV f does not visit satellite m, then the amount brought by FEV f to satellite m must be zero. Constraints (16)–(22) define decision variables.

4. Simulated annealing heuristic for 2E-OLRP

Metropolis et al. [33] introduced SA and Kirkpatrick et al. [34] popularized SA by applying it to combinatorial optimization problems. SA has been successfully applied to solve numerous hard combinatorial optimization problems [11,12,35–43]. Although rich algorithms [2,21,25,27,30,44] have been proposed by researchers to solve such problems, SA's capacity to enlarge the solution space by exploring worse solutions is promising in addressing problems like the 2E-OLRP. This study therefore proposes an SA-based heuristic for solving the 2E-OLRP.

4.1. Solution representation

A set of number strings is employed to represent a 2E-OLRP solution. It consists of n customers indicated by the set $\{1, 2, \ldots, n\}$, m potential satellites indicated by the set $\{n+1, n+2, \ldots, n+m\}$ and N_{dummy1} stars (*) and N_{dummy2} zeros (0). These dummy stars and zeros are used to separate routes in the first and second echelons, respectively, even though the capacity of the current vehicle is not exceeded. N_{dummy1} and N_{dummy2} are calculated as $\left\lceil \sum_i \frac{d_i}{Q_1} \right\rceil$ and $\left\lceil \sum_i \frac{d_i}{4Q_2} \right\rceil$ respectively, where d_i is the demand of customer i, Q_1 and Q_2 are the capacities of the vehicle in the first and second echelons, respectively and $\lceil \bullet \rceil$ denotes the smallest integer bigger than or equivalent to the enclosed number. The ith number in $\{1, 2, \ldots, n\}$ indicates the ith customer to be served. The first number in a solution is always in $\{n+1, n+2, \ldots, n+m\}$, indicating the first satellite under consideration.

Each satellite serves customers between the satellite and the next satellite in the solution representation. The first route of a satellite is started by serving the first customer after the satellite. Subsequent customers are added to the current route one after the other. If including a customer will exceed the current SEV's capacity, the current route is ended. In the event that the next number in the solution representation is a dummy zero, the current route is ended. A new route will then start by serving the next customer after the dummy zero. It should be noted that the vehicles in the second echelon do not need to return to the satellite from which they start.

After determining the satellites to be opened and the service sequence of customers, the visiting sequence to the used satellites can be obtained as follows. The FEV departs from the depot to the first used satellite. If including a used satellite exceeds the FEV's capacity, then the current route ends and the FEV returns to the depot. A new route is then started from the depot to serve the remaining used satellites. The current route also ends if the next entry in the solution representation is a dummy star. After serving the last used satellite, the FEV returns to the depot.

This solution representation scheme always gives a 2E-OLRP solution without exceeding the capacity 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.

4.2. Illustration of solution representation

This study uses the 20-5-1 instance of Prodhon's 2E-LRP dataset to illustrate the solution representation. The number of depots, satellites and customers are one, five and twenty, respectively. Each satellite has the same capacity but different activation costs. The capacities and activation costs of FEVs and SEVs are homogeneous. The customers' demands and coordinates of the depot, satellites and customers are known.

Fig. 2 illustrates an example of the solution representation. In the first echelon, the solution consists of two routes. The routes start and terminate at node d (depot). Because satellites 1 (21), 4 (24) and 5 (25) have customers to be served, they will be opened, then the visiting sequence of the FEV is satellites 1, 5 and 4. Because there is a dummy star between satellite 5 and satellite 4, the FEV returns to the depot after visiting satellite 5, then the

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

second FEV route starts from the depot to satellite 4. After visiting satellite 4, the FEV returns to the depot.

In the second echelon, there are five routes. The first route starts from satellite 1 and terminates at customer 14, because the next element after customer 14 in the solution string is satellite 2. Note that the dummy zero following satellite 1 has no effect because there is no customer to be served. In the fourth route, visiting customer 19 will violate the vehicle's capacity. Consequently, the fourth route terminates at customer 18 and the fifth route starts from satellite 4 by visiting customer 19 as its first customer and terminates at customer 11. New routes are built until all customers are served. Fig. 3 is a visual illustration of the distribution network corresponding to the sample solution representation illustrated in Fig. 2.

4.3. Initial solution and neighborhood

The initial solution is randomly constructed. This study uses a standard SA procedure with a random neighborhood structure that uses three types of move, namely insertion, swap and 2-opt. $\mathscr{N}(X)$ denotes the set of neighboring solutions of X. In every iteration, a new solution Y is chosen from $\mathscr{N}(X)$ either by insertion, swap, or 2-opt moves as follows.

The insertion move is carried out by arbitrarily choosing an element of X and inserting it into the position immediately before another arbitrarily selected element of X. The swap move is carried out by arbitrarily choosing two elements of X and then switching their positions. The 2-opt move is carried out by arbitrarily choosing a substring of X and then reversing the order of the substring. The probabilities of choosing these moves will be self-tuned.

Let P_i be the probability of choosing the ith move, computed as $f_i/\sum_{j=1}^{3} f_j$, where f_i is the average score of the ith move. f_i is calculated as $\sum_{j=1}^{C_i} \frac{1}{Obj(x_j)}/C_i$, where C_i is the number of times that the ith move is used and $Obj(x_j)$ denotes the jth objective function value obtained by the ith move.

A move will be discarded if it results an infeasible solution. In this case, a new move will be selected until a feasible solution is obtained.

Because the impact of satellites on solution quality are more significant than that of customers, the probability of choosing a satellite in the insertion and swap moves are set to 20%.

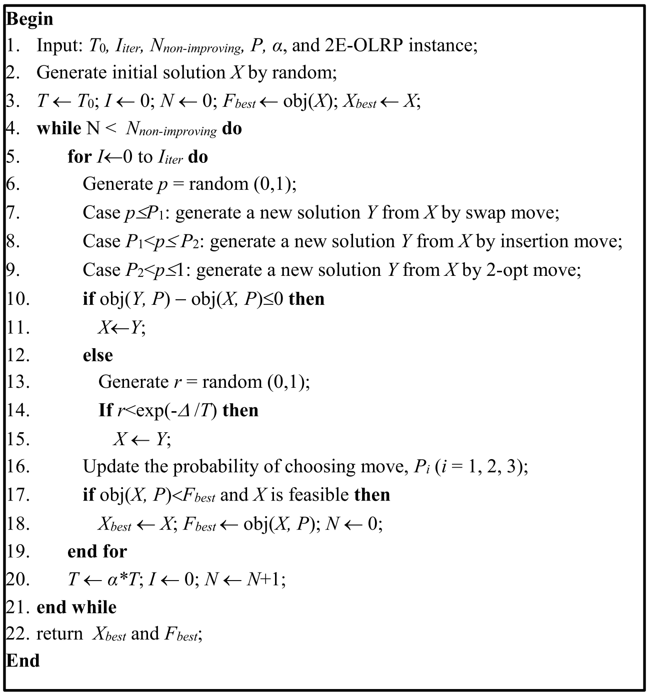
4.4. The SA procedure

Table 1 summarizes the five parameters used in the algorithm. The algorithm is described as follows. The current temperature (T) is set to be the initial temperature T_0 at the onset of the proposed SA heuristic, whereas the best solution (X_{best}) and the current solution (X) are set to obj(X, P). Each iteration at a certain 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., $\Delta = \text{obj}(Y, P) - \text{obj}(X, P)$. If $\Delta \leq 0$, then the new neighborhood solution is better than the current solution; otherwise, the new neighborhood solution is accepted if a random number r between 0 and 1 is smaller than $\exp(-\Delta/\text{T})$. If the new neighborhood solution satisfies these conditions, then Y replaces X as the current solution; next, the probability of choosing different moves is re-calculated.

The current temperature declines to αT, $0<\alpha<1$, after running I_{iter} iterations at the current temperature T. The algorithm ends if the best solution has not been improved after $N_{non\text{-}improving}$ consecutive temperature reductions. The best solution (X_{best}) and its objective function value (F_{best}) are updated when a better feasible solution is found. The best 2E-OLRP solution is derived from X_{best} when the heuristic ends. Fig. 4 depicts a pseudo code explaining the proposed SA heuristic.

Table 1
Five parameters that are used in the proposed SA heuristic.

Parameter	Definition
T_0	The initial temperature
I_{iter}	Total number of iterations that the perturbation should repeat at a certain temperature
$N_{non\text{-}improving}$	The maximum allowable number of consecutive temperature reductions without improvement in the solution value
P	The unit penalty cost associated with the violation of satellite capacity
α	The coefficient of the cooling schedule



```
Begin
Input: $T_0$, $I_{iter}$, $N_{non\text{-}improving}$, $P$, $\alpha$, and 2E-OLRP instance;
Generate initial solution $X$ by random;
$T \leftarrow T_0$; $I \leftarrow 0$; $N \leftarrow 0$; $F_{best} \leftarrow$ obj($X$); $X_{best} \leftarrow X$;
while N < $N_{non\text{-}improving}$ do
    for $I \leftarrow 0$ to $I_{iter}$ do
        Generate $p$ = random (0,1);
        Case $p \leq P_1$: generate a new solution $Y$ from $X$ by swap move;
        Case $P_1 < p \leq P_2$: generate a new solution $Y$ from $X$ by insertion move;
        Case $P_2 < p \leq 1$: generate a new solution $Y$ from $X$ by 2-opt move;
        if obj($Y$, $P$) – obj($X$, $P$) $\leq 0$ then
            $X \leftarrow Y$;
        else
            Generate $r$ = random (0,1);
            If $r < \exp(-\Delta/T)$ then
                $X \leftarrow Y$;
        Update the probability of choosing move, $P_i$ ($i$ = 1, 2, 3);
        if obj($X$, $P$) < $F_{best}$ and $X$ is feasible then
            $X_{best} \leftarrow X$; $F_{best} \leftarrow$ obj($X$, $P$); $N \leftarrow 0$;
    end for
    $T \leftarrow \alpha * T$; $I \leftarrow 0$; $N \leftarrow N+1$;
end while
return $X_{best}$ and $F_{best}$;
End
```

Fig. 4. Pseudo code for the proposed SA heuristic.

5. Computational study

The 2E-OLRP model is solved by CPLEX 12.8.0.0 on a computer equipped with an Intel Xeon E5-1620v2 CPU at 3.70 GHz and 40 GB of RAM running Windows 10. The proposed SA heuristic is implemented using Microsoft Visual C++ 6.0 and run on a computer equipped with an Intel Core i7-920 CPU at 2.67 GHz and 8 GB of RAM running Windows 10.

5.1. Test instances

This study adopts two well-known 2E-LRP datasets presented by Nguyen et al. [21] as 2E-OLRP instances. These instances are available at http://prodhonc.free.fr/Instances/instances0_us.htm. Table 2 summarizes the datasets. As in Breunig et al. [27], the first echelon distance has a higher weight than the second echelon distance.

The 8 small 2E-OLRP instances are solved by CPLEX and the results are compared with those achieved by the proposed SA heuristic. Furthermore, the performance of the proposed SA heuristic is compared with that of the state-of-the-art algorithm on the two well-known 2E-LRP instances.

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

Table 2
Summary of test instances.

Instance name	Number of instances	Number of depots	Number of satellites	Number of customers
Nguyen's 2E-LRP Instances	24	1	5, 10	25, 50, 100, 200
Prodhon's 2E-LRP Instances	30	1	5, 10	20, 25, 50, 100, 200

Table 3
A summary of the STP of the different hardware discussed in this paper.

Solution method	Hardware used	STP
CPLEX	Intel Xeon E5-1620v2 CPU at 3.70 GHz	1.973
The proposed SA	Intel Core i7-920 CPU at 2.67 GHz	1.166
LNS	Intel Xeon E5-2670v2 @2.5 GHz	1.606

Table 4
Comparison of CPLEX and SA heuristic based on Nguyen's and Prodhon's instances.

	m	n	CPLEX				SA		
			Obj.	RPD	Time	Time-c[a]	Obj.	RPD	Time
25-5N	5	25	68,376	0.00	1,467.6	2,483.3	68,376	0.00	15.8
25-5Nb	5	25	53,845	0.00	9.8	16.6	54,056	0.39	14.6
25-5MN	5	25	61,424	0.00	2,121.0	3,589.0	61,424	0.00	15.0
25-5MNb	5	25	48,585	0.00	503.4	851.8	48,585	0.00	14.4
20-5-1	5	20	76,988	0.16	18,000.0	30,458.0	76,864	0.00	14.6
20-5-1b	5	20	53,476	0.00	82.7	139.9	53,476	0.00	11.5
20-5-2	5	20	73,274	0.24	18,000.0	30,458.0	73,096	0.00	15.9
20-5-2b	5	20	55,515	0.00	1,793.6	3,035.0	55,515	0.00	11.3
Average				0.05	5,247.3	8,878.9		0.05	14.1

[a] Time-c $=$ Time $*$ 1.973/1.166.

Table 5
Computational results for the first dataset adopted from Nguyen's datasets.

Instance	m	n	LNS				SA		
			Ave	Best	Time	Time-c[a]	Ave	Best	Time
25-5N	5	25	80,370.00	80,370	60	83	80,479.90	80,370	17
25-5Nb	5	25	64,562.00	64,562	60	83	64,562.00	64,562	16
25-5MN	5	25	78,947.00	78,947	60	83	78,947.00	78,947	17
25-5MNb	5	25	64,438.00	64,438	60	83	64,438.00	64,438	17
50-5N	5	50	137,815.00	137,815	60	83	137,904.09	137,815	50
50-5Nb	5	50	110,981.85	110,094	60	83	110,863.35	110,094	47
50-5MN	5	50	123,484.00	123,484	60	83	123,512.90	123,484	48
50-5MNb	5	50	105,783.45	105,401	60	83	105,875.60	105,401	45
50-10N	10	50	117,325.55	115,725	60	83	116,307.20	115,725	59
50-10Nb	10	50	88,212.00	87,520	60	83	87,574.05	87,315	54
50-10MN	10	50	138,241.35	135,519	60	83	136,237.25	135,519	58
50-10MNb	10	50	111,520.80	110,613	60	83	110,627.30	110,613	56
100-5N	5	100	193,806.85	193,229	900	1240	195,647.55	193,228	172
100-5Nb	5	100	159,064.10	158,927	900	1240	159,273.00	158,987	139
100-5MN	5	100	204,876.10	204,682	900	1240	208,014.09	204,941	168
100-5MNb	5	100	165,795.35	165,744	900	1240	166,964.05	166,115	151
100-10N	10	100	216,265.50	210,799	900	1240	215,043.30	210,499	186
100-10Nb	10	100	161,273.30	155,489	900	1240	156,235.80	155,581	177
100-10MN	10	100	204,396.15	201,275	900	1240	205,870.00	202,314	192
100-10MNb	10	100	172,202.45	170,625	900	1240	172,910.05	170,625	161
200-10N	10	200	359,948.65	350,680	900	1240	353,142.84	349,081	741
200-10Nb	10	200	260,698.20	257,191	900	1240	259,391.34	257,288	661
200-10MN	10	200	329,486.45	324,279	900	1240	337,574.00	326,842	714
200-10MNb	10	200	297,857.50	293,339	900	1240	294,489.31	290,849	609
Average			164,472.98	162,531	480	661	164,245.17	162,526	190

[a] Time-c $=$ Time * 1.606/1.166.

5.2. *Parameter setting*

The proposed algorithm uses five parameters and the Taguchi method of experimental design [45] is applied to obtain the best parameter combination. Each of the five parameters has four levels. The SA algorithm is executed five times for each of the 10 randomly selected instances. The relative percentage deviation (RPD) from the best solution is obtained using the design of the experiment. The RPD is calculated as RPD $= (Obj^{Method} - Obj^{Best})/Obj^{Best} \times 100\%$, where Obj^{Method} is the average objective value of five replications obtained using a certain parameter combination and Obj^{Best} is the minimum objective value among five replications obtained using all parameter combinations.

This study performed sensitivity analysis to observe the effect of parameter values on solution quality and computational time. Fig. 5 shows the results of the sensitivity analysis. Solid and dash curves in the subfigures indicate the average relative percentage deviation (ARPD) values and the computational times, respectively. As shown in the figure, I_{iter} and $N_{non\text{-}improving}$ significantly affect the computational time.

It is further noted that T_0, I_{iter} and $N_{non\text{-}improving}$ significantly influence solution quality. If these three parameters are high, solution quality will be better. However, increasing the values of

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

Table 6
Computational results for the second dataset adopted from Prodhon's datasets.

Instance	m	N	LNS				SA		
			Ave	Best	Time	Time-c[a]	Ave	Best	Time
20-5-1	5	20	89,075.00	89,075	60	83	89,075.00	89,075	16
20-5-1b	5	20	61,863.00	61,863	60	83	61,986.25	61,863	13
20-5-2	5	20	84,478.00	84,478	60	83	84,478.00	84,478	16
20-5-2b	5	20	60,838.00	60,838	60	83	60,910.05	60,838	13
50-5-1	5	50	131,454.00	131,085	60	83	131,422.00	130,843	54
50-5-1b	5	50	101,669.20	101,530	60	83	101,704.50	101,530	48
50-5-2	5	50	131,827.00	131,825	60	83	131,877.00	131,825	57
50-5-2b	5	50	110,332.00	110,332	60	83	110,364.25	110,332	48
50-5-2BIS	5	50	122,599.00	122,599	60	83	122,647.25	122,599	56
50-5-2bBIS	5	50	105,707.85	105,696	60	83	105,747.75	105,696	49
50-5-3	5	50	128,614.50	128,379	60	83	128,404.30	128,379	53
50-5-3b	5	50	104,006.00	104,006	60	83	104,073.50	104,006	46
100-5-1	5	100	319,268.60	318,399	900	1240	320,040.81	319,463	177
100-5-1b	5	100	257,686.40	256,991	900	1240	259,442.25	256,938	160
100-5-2	5	100	231,488.85	231,305	900	1240	232,536.80	231,475	172
100-5-2b	5	100	194,800.35	194,763	900	1240	194,887.45	194,784	140
100-5-3	5	100	245,178.75	244,071	900	1240	244,975.91	244,319	171
100-5-3b	5	100	195,123.20	194,110	900	1240	195,426.16	194,580	146
100-10-1	10	100	362,648.70	354,525	900	1240	364,647.06	362,246	206
100-10-1b	10	100	312,451.60	299,758	900	1240	313,080.91	311,190	168
100-10-2	10	100	307,937.60	304,909	900	1240	305,880.09	304,773	191
100-10-2b	10	100	265,814.85	264,173	900	1240	264,571.34	263,876	166
100-10-3	10	100	318,952.10	311,699	900	1240	325,977.06	314,579	194
100-10-3b	10	100	265,442.40	262,932	900	1240	270,938.31	262,598	183
200-10-1	10	200	564,159.80	550,672	900	1240	555,421.81	553,307	669
200-10-1b	10	200	456,952.40	448,188	900	1240	453,879.31	451,220	512
200-10-2	10	200	499,499.45	498,486	900	1240	505,198.75	499,415	664
200-10-2b	10	200	428,912.35	422,967	900	1240	427,812.69	425,089	577
200-10-3	10	200	568,539.15	534,271	900	1240	536,451.44	532,024	837
200-10-3b	10	200	425,078.20	417,686	900	1240	421,522.50	418,602	608
Average			248,413.28	244,720	564	777	247,512.68	245,731	214

[a] Time-c = Time * 1.606/1.166.

these parameters, especially I_{iter} and $N_{non\text{-}improving}$, will increase computational time drastically, as shown in Figs. 5(b) and 5(d). For α, as shown in Fig. 5(c), 0.975 is the best value.

Computational time is not significantly affected by α, while the value of P influences the probability of accepting an infeasible solution during the execution of the algorithm. As shown in Fig. 5(e), if P 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 P is too small, then the algorithm is more likely to accept an infeasible solution.

In order to obtain a comparable computational time with the previous method, parameter values are set based on the average computational time (ACT) of LNS in solving the 2E-LRPs of the Nguyen and Prodhon datasets [27]. The result shows that the ACT for the former dataset is 480 s, while the latter is 564 s. The faster ACT of the two datasets is chosen as the computational time upper bound (λ) for parameter setting. As long as the computational time of the smallest ARPD does not exceed λ, the parameter value used will be chosen as the final parameter values. Otherwise, the parameter values are chosen from the next smallest ARPD in the same manner and so on. Fig. 5 shows that using the final parameter values, $T_0 = 5$, $\alpha = 0.975$, I_{iter} =12000L, $N_{non\text{-}improving} = 15$ and $P = 0.003B$, chosen in this way, the computational time is smaller than λ.

5.3. Computational results

The performance of the proposed SA heuristic is compared with those of CPLEX and LNS proposed by [27]. 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 3 summarizes the STPs of the different hardware discussed in this paper. Note that the higher the STP value, the faster the hardware will operate.

5.3.1. Results for 2E-OLRP instances

The CPLEX results of the 2E-OLRP model are compared with those obtained by the proposed SA heuristic on 8 small instances of Nguyen et al. [21]. As shown in Table 4, CPLEX obtains 6 optimal solutions in an average of about 1686 s, whereas the proposed SA heuristic obtains 5 out of 8 optimal solutions in 14.1 s, on average. CPLEX cannot solve two of the problems within 8.46 h. Note that the computational times listed in the Time-c column of the table have been converted from the original computational times in the Time column using the STP values in Table 3.

5.3.2. Results for 2E-LRP instances

To verify its effectiveness, the proposed SA heuristic is tested on two sets of 2E-LRP instances and the results can be found at http://web.ntust.edu.tw/~vincent/lrp/. The results are then compared with those obtained by LNS [27]. Tables 5 and 6 list the average solution value, the best solution value and the running time of 20 runs for LNS and the proposed SA heuristic. The Time-c column lists the computational times converted from the original computational times in the Time column using the STP values in Table 3. It can be seen that the performance of the proposed SA heuristic is comparable with that of LNS, with lower computing time. The time complexity of the proposed SA heuristic is $O((n^2+n)\log n)$. The determination of the SA time complexity can be seen in [46]. The LNS consists of three nested loops at most, thus, its time complexity is $O(n^3)$.

Statistical tests are conducted to determine whether the proposed SA heuristic outperforms LNS. For each test, the performances of SA and LNS are compared on the same dataset, thus,

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

Table 7
Results of the Wilcoxon signed-rank tests on average solution value, the best solution value and the running time.

	SA vs.	LNS
Nguyen's dataset	Test on average solution value	
	W	463.5
	p-value	0.4238
	Test on best solution value	
	W	445.5
	p-value	0.5295
	Test on running time	
	W	684
	p-value	0.0002206*
Prodhon's dataset	Test on average solution value	
	W	298
	p-value	0.4223
	Test on best solution value	
	W	287
	p-value	0.5123
	Test on running time	
	W	432
	p-value	0.001322*
All datasets	Test on average solution value	
	W	1484.5
	p-value	0.4365
	Test on best solution value	
	W	1452.5
	p-value	0.5147
	Test on running time	
	W	2196
	p-value	<0.0000001*

*Indicates that significant difference exists.

two related samples are observed. The Wilcoxon signed-rank test can be used to test the related samples [47]. The Wilcoxon signed-rank tests are conducted on average solution value, the best solution value and the running time. Table 7 shows the statistical test results at the confidence level of $\alpha = 0.05$. The P-values of average solution value and the best solution value for Nguyen's, Prodhon's and all datasets are all more than α implying that the proposed SA heuristic and the LNS have the same performance in terms of solution quality. Whereas, the P-values of the running time for Nguyen's, Prodhon's and all datasets are all less than α. It implies that the running time for the two algorithms are different. Based on the running times shown in Tables 5 and 6, the proposed SA is faster than LNS in solving 2E-LRP.

5.3.3. *Sensitivity analysis*

This subsection presents the sensitivity analysis results. In particular, (i) the varying cost of satellite set-up and (ii) the varying activation cost of SEVs are considered. For both analyses, experiments were conducted on 100-10MN and 100-10-2b instances, consisting of 100 customers and 10 satellites. A summary of the abbreviations used in tables of this section can be found in Table 8.

The results of the first analysis are presented in Tables 9 and 10, showing the effects of varying satellite set-up costs and cost percentages, respectively. As shown in Table 9, the number of satellites used is influenced by satellite set-up cost. If satellite set-up cost is less than 100%, then the number of satellites used tends to increase. This means that some potential satellites with normal cost (100%) are close to customers, but are not chosen by the algorithm, because the satellite set-up cost is high. When the satellite set-up cost is zero, more potential satellites can be opened close to customers. In addition, both instances show an increase in the number of satellites used when satellite costs drop to zero.

Table 10 shows that the percentage of satellite set-up costs negatively affects the percentage of all other components' distribution costs. If the percentage of satellite set-up costs decreases, then the percentage of all other components' distribution costs increases. It can thus be concluded that designing a two-echelon distribution system in urban areas is strongly influenced by the satellite set-up cost, because property prices in urban areas is very high. Thus, free LUZs support more efficient and less expensive distribution systems in urban areas.

The second analysis's results are presented in Tables 11 and 12, showing the effects of varying SEV activation costs and SEV cost percentages, respectively. As shown in Table 11, if the SEV activation cost decreases, then the number of SEVs used increases. Variation of SEV activation cost does not significantly affect the number of vehicles used in the first echelon for both instances, but does exhibit different effects on other components of the total distribution cost. Variation of SEV activation cost does not affect the vehicle travel cost in the first echelon and the satellite set-up cost in 100-10-2b, but does affect those in the 100-10MN instance. For the 100-10MN instance, if the vehicle activation cost of the second echelon increases, then the satellite set-up cost tends to increase; whereas when the vehicle activation cost of the second echelon is less than or greater than 100%, the vehicle travel cost of the second echelon decreases in 100-10MN and remains steady in 100-10-2b.

As shown in Table 12, the proportion of SEV activation cost affects all cost components in 100-10-2b. When the SEV activation cost proportion increases, all other cost components decrease, whereas in 100-10MN, the proportion of SEV activation cost only affects the FEV activation cost proportion and SEV travel cost proportion. When the SEV activation cost proportion increases, the proportion of both these cost components decreases.

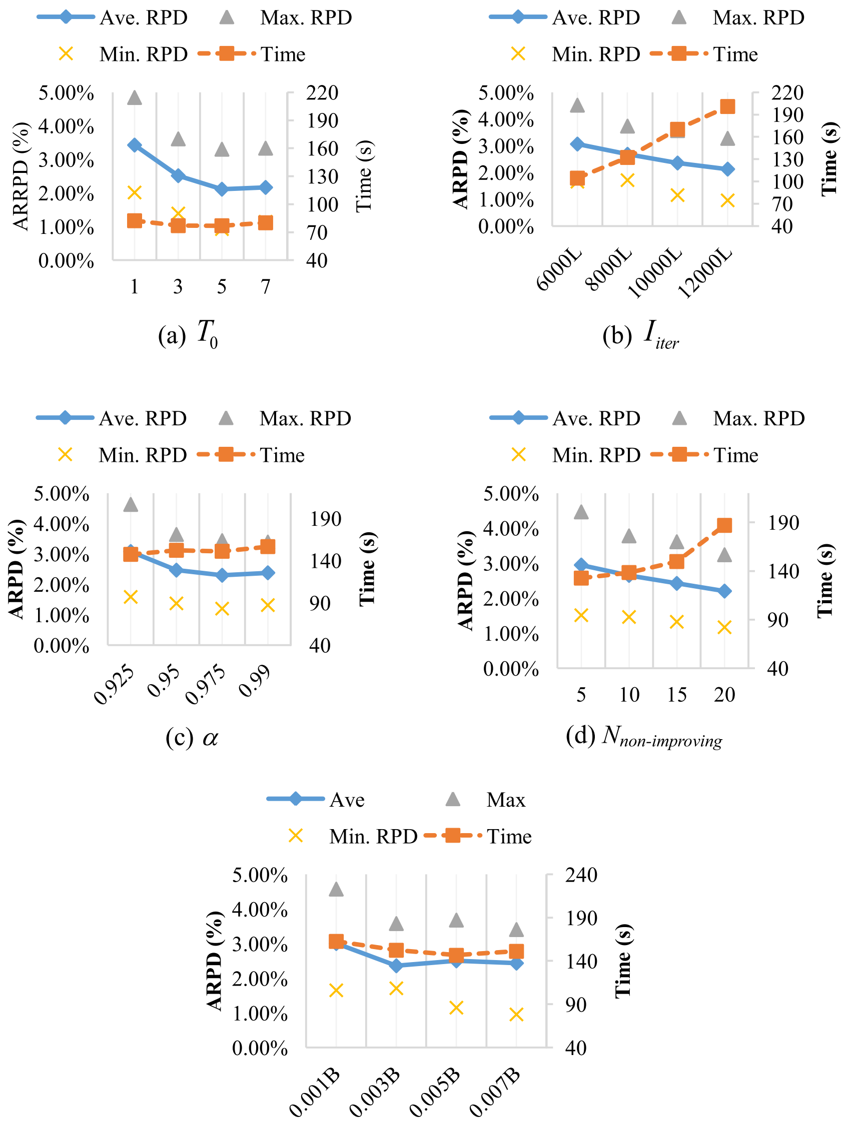
6. Case study

This case study presents the design of a two-echelon FDS in Taipei City, Taiwan considering TPL and LUZs. The LUZs were provided by the Taipei City government along some major roads in commercial areas. Trucks could park temporarily in these facilities while loading or unloading. Fig. 6 shows an employee of a logistics company unloading packages from a box van to a courier motorcycle at an LUZ. The LUZs can be used for free by anyone, including logistics companies. As described in Section 1, the LUZs function as temporary satellites.

In this case study, a logistics company has one depot located at the outskirts of Taipei City and customers are located throughout the Taipei City area. A number of potential permanent (temporary) satellites are located in the Taipei City area. The company uses a two-echelon system to deliver freight from the depot to customers. The freight is delivered from the depot to satellites by a truck (first echelon). Afterwards, from the satellites the freight is shipped to customers by a motorcycle (second echelon). The company's objective is to minimize the total distribution cost by optimizing the number and locations of the selected permanent (temporary) satellites as well as delivery routes in both echelons. In addition, the total distribution cost of using permanent satellites is compared with that of using temporary satellites.

Tables 13 and 14 summarize the data from the permanent and temporary satellites, respectively. Here, "PR" and "TR" in Tables 13 and 14, respectively denote permanent satellites and temporary satellites. The tables show that the numbers of permanent and temporary satellites are 12 and 24, respectively. 402 customers are spread throughout the districts of Taipei City. The

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.



(a) T_0 (b) I_{iter}

(c) α (d) $N_{non\text{-}improving}$

(e) P

Fig. 5. The effect of each parameter on the solution quality.

Table 8
A summary of the abbreviations used in the tables of this section.

Using a satellite (vehicle)	Name of the cost component
NS: Number of satellites opened	VAC-1: Vehicle activation cost of the first echelon
NV-1: Number of vehicles used in the first echelon	VTC-1: Vehicle travel cost of the first echelon
NV-2: Number of vehicles used in the second echelon	SC: Satellite set-up cost
	VAC-2: Vehicle activation cost of the second echelon
	VTC-2: Vehicle travel cost of the second echelon
	TC: Total distribution cost

customer demands, depot coordinates (X,Y), permanent satellite, temporary satellite and customer data are provided at http://web.ntust.edu.tw/~vincent/lrp/. Table 15 presents truck and motorcycle data. Note that all costs in the table are daily costs. In addition, the trucks are owned by the logistics company, whereas the motorcycles are owned by the delivery persons of a TPL company.

In this case study, the two-echelon distribution network operations as follows. The first echelon routes start from the depot, visit each of the selected permanent (temporary) satellites exactly once and return to the depot without violating the capacity constraint. Each selected permanent (temporary) satellite receives the number of packages requested by the customers assigned to the satellite. Second echelon routes start from a permanent (temporary) satellite and visit each of the customers exactly once without violating the capacity constraint. Each motorcycle serves one route. After serving the final customer on the route, the motorcycle does not return to the TPL company. The freight delivery process in the second echelon finishes when all customers have been served.

This case study is solved by the proposed SA heuristic and the results can be accessed at http://web.ntust.edu.tw/~vincent/lrp/. The routes obtained using permanent and temporary satellites are depicted in Figs. 7 and 8, respectively. A solution results comparison between permanent satellite utilization (PSU) and

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

Table 9
Effects of the use of varying cost of satellite set-up.

Instance	Cost	0%	25%	50%	75%	100%	125%	150%	175%	200%
100-10MN	VAC-1 (NV-1)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)
	VTC-1	31758	27006	33282	34337	27006	37621	34185	34185	34185
	SC (NS)	0 (5)	8160.75 (4)	18970 (5)	25398 (5)	32643 (4)	35257.5 (4)	41095.5 (4)	47944.75 (4)	54794 (4)
	VAC-2 (NV-2)	15000 (15)	16000 (16)	16000 (16)	16000 (16)	16000 (16)	17000 (17)	16000 (16)	16000 (16)	16000 (16)
	VTC-2	79933	82592	77149	79301	85884	80693	84704	86447	86433
	TC	134691	141758.8	153401	163036	169533	178571.5	183984.5	192576.8	199412
100-10-2b	VAC-1 (NV-1)	10000 (2)	10000 (2)	15000 (3)	15000 (3)	15000 (3)	15000 (3)	15000 (3)	15000 (3)	15000 (3)
	VTC-1	26709	26709	31404	39006	39006	39006	39006	39006	48700
	SC (NS)	0 (4)	52341.5 (4)	77224.5 (3)	112455 (3)	149940 (3)	187425 (3)	224910 (3)	262395 (3)	282102 (3)
	VAC-2 (NV-2)	12000 (12)	11000 (11)	11000 (11)	12000 (12)	11000 (11)	12000 (12)	11000 (11)	11000 (11)	12000 (12)
	VTC-2	33171	33636	38380	33129	34026	33632	34295	34119	38181
	TC	81880	133686.5	173008.5	211590	248972	287063	324211	361520	395983

Table 10
Effects of the use of varying cost of satellite set-up (in percentage).

Instance	Cost	0%	25%	50%	75%	100%	125%	150%	175%	200%
100-10MN	VAC-1	5.94%	5.64%	5.22%	4.91%	4.72%	4.48%	4.35%	4.15%	4.01%
	VTC-1	23.58%	19.05%	21.70%	21.06%	15.93%	21.07%	18.58%	17.75%	17.14%
	SC	0.00%	5.76%	12.37%	15.58%	19.25%	19.74%	22.34%	24.90%	27.48%
	VAC-2	11.14%	11.29%	10.43%	9.81%	9.44%	9.52%	8.70%	8.31%	8.02%
	VTC-2	59.35%	58.26%	50.29%	48.64%	50.66%	45.19%	46.04%	44.89%	43.34%
	TC	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
100-10-2b	VAC-1	12.21%	7.48%	8.67%	7.09%	6.02%	5.23%	4.63%	4.15%	3.79%
	VTC-1	32.62%	19.98%	18.15%	18.43%	15.67%	13.59%	12.03%	10.79%	12.30%
	SC	0.00%	39.15%	44.64%	53.15%	60.22%	65.29%	69.37%	72.58%	71.24%
	VAC-2	14.66%	8.23%	6.36%	5.67%	4.42%	4.18%	3.39%	3.04%	3.03%
	VTC-2	40.51%	25.16%	22.18%	15.66%	13.67%	11.72%	10.58%	9.44%	9.64%
	TC	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 11
Effects of the use of varying activation cost of SEVs.

Instance	Cost	25%	50%	75%	100%	125%	150%	175%	200%
100-10MN	VAC-1 (NV-1)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)	8000 (2)
	VTC-1	34185	37169	34337	27006	35001	34337	35001	34337
	SC (NS)	27397 (4)	28206 (4)	33864 (5)	32643 (4)	33864 (5)	33864 (5)	33864 (5)	33864 (5)
	VAC-2 (NV-2)	4250 (17)	8500 (17)	12000 (16)	16000 (16)	18750 (15)	22500 (15)	26250 (15)	30000 (15)
	VTC-2	81787	77976	79074	85884	79277	80237	78541	80265
	TC	155619	159851	167275	169533	174892	178938	181656	186466
100-10-2b	VAC-1 (NV-1)	15000 (3)	15000 (3)	15000 (3)	15000 (3)	15000 (3)	15000 (3)	15000 (3)	15000 (3)
	VTC-1	39006	39006	39006	39006	39006	39006	39006	39006
	SC (NS)	149940 (3)	149940 (3)	149940 (3)	149940 (3)	149940 (3)	149940 (3)	149940 (3)	149940 (3)
	VAC-2 (NV-2)	3250 (13)	6000 (12)	9000 (12)	11000 (11)	13750 (11)	16500 (11)	19250 (11)	22000 (11)
	VTC-2	32829	33485	33534	34026	33967	33698	34062	34210
	TC	240025	243431	246480	248972	251663	254144	257258	260156

temporary satellite utilization (TSU) is summarized in Table 16 and analyzed below.

In the first echelon, because temporary satellites have smaller capacities than those of permanent satellites, the number of opened satellites in TSU is greater than that of PSU. However, the number of opened temporary satellites does not affect the satellite set-up cost because they are free, thus a satellite set-up cost reduction of 100% is compared with that of PSU. Furthermore, even though the number of temporary satellites visited is greater than that of permanent satellites, distances between temporary satellites are smaller than those among permanent satellites, thus the truck travel cost of TSU is smaller (8.69%) than that of PSU.

In the second echelon, the use of temporary satellites can maximize the motorcycle load, so the number of motorcycles used is

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

Table 12
Effects of the use of varying activation cost of SEVs (in percentage).

Instance	Cost	25%	50%	75%	100%	125%	150%	175%	200%
100-10MN	VAC-1	5.14%	5.00%	4.78%	4.72%	4.57%	4.47%	4.40%	4.29%
	VTC-1	21.97%	23.25%	20.53%	15.93%	20.01%	19.19%	19.27%	18.41%
	SC	17.61%	17.65%	20.24%	19.25%	19.36%	18.92%	18.64%	18.16%
	VAC-2	2.73%	5.32%	7.17%	9.44%	10.72%	12.57%	14.45%	16.09%
	VTC-2	52.56%	48.78%	47.27%	50.66%	45.33%	44.84%	43.24%	43.05%
	TC	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
100-10-2b	VAC-1	6.25%	6.16%	6.09%	6.02%	5.96%	5.90%	5.83%	5.77%
	VTC-1	16.25%	16.02%	15.83%	15.67%	15.50%	15.35%	15.16%	14.99%
	SC	62.47%	61.59%	60.83%	60.22%	59.58%	59.00%	58.28%	57.63%
	VAC-2	1.35%	2.46%	3.65%	4.42%	5.46%	6.49%	7.48%	8.46%
	VTC-2	13.68%	13.76%	13.61%	13.67%	13.50%	13.26%	13.24%	13.15%
	TC	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 13
The data of the permanent satellites.

PR	Capacity (kg)	Set-up cost (NT$)	District	PR	Capacity (kg)	Set-up cost (NT$)	District
1	1650	1000	Songshan	7	1000	900	Xinyi
2	1000	750	Zhongshan	8	1650	1000	Zhongzheng
3	1650	1000	Shilin	9	2300	750	Datong
4	2300	750	Wanhua	10	2300	1000	Nangang
5	1000	900	Daan	11	1650	1000	Neihu
6	1650	800	Wenshan	12	1650	800	Beitou

Table 14
The data of the temporary satellites.

TR	Capacity	District	TR	Capacity	District
1	540	Zhongzheng	13	540	Neihu
2	360	Songshan	14	540	Wanhua
3	540	Songshan	15	540	Datong
4	720	Zhongshan	16	540	Datong
5	540	Wenshan	17	540	Zhongshan
6	540	Daan	18	540	Shilin
7	360	Daan	19	720	Beitou
8	540	Daan	20	540	Wenshan
9	720	Xinyi	21	720	Shilin
10	720	Xinyi	22	540	Nangang
11	540	Xinyi	23	540	Zhongshan
12	540	Wanhua	24	540	Neihu

Fig. 6. A temporary satellite in a free loading–unloading zone in Taipei City, Taiwan.

smaller than that of a scenario of using permanent satellites. As a result, the cost of motorcycle activation and motorcycle travel are also decreased by 4.00% and 7.17%, respectively. Finally, the last row of Table 16 shows that the utilization of temporary satellites can reduce the total distribution cost by up to 21.75%.

Table 15
The data of truck and motorcycle.

Vehicle	Capacity (kg)	Activation cost (NT$)	Variable cost (NT$)
Truck	1500	1000	6
Motorcycle	90	110	1.2

7. Conclusions and future research

This paper presents a design for a two-echelon freight distribution system in an urban area considering third-party logistics (TPL) by formulating a mathematical programming model of the problem and developing an efficient SA heuristic for the problem. Small instances taken from two well-known 2E-LRP datasets are solved by CPLEX and the proposed SA heuristic, showing that the proposed SA heuristic outperforms CPLEX in terms of computational time. In addition, the proposed SA heuristic was tested on two well-known 2E-LRP datasets. According to the computational results, the performance of the proposed SA heuristic is comparable with that of another state-of-the-art algorithm in terms of solution quality, while using less computational time.

A case study of a 2E-OLRP utilizing LUZs (temporary satellites) was conducted in Taipei City, Taiwan. The proposed SA heuristic was used to solve the case study problem. The case study shows

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

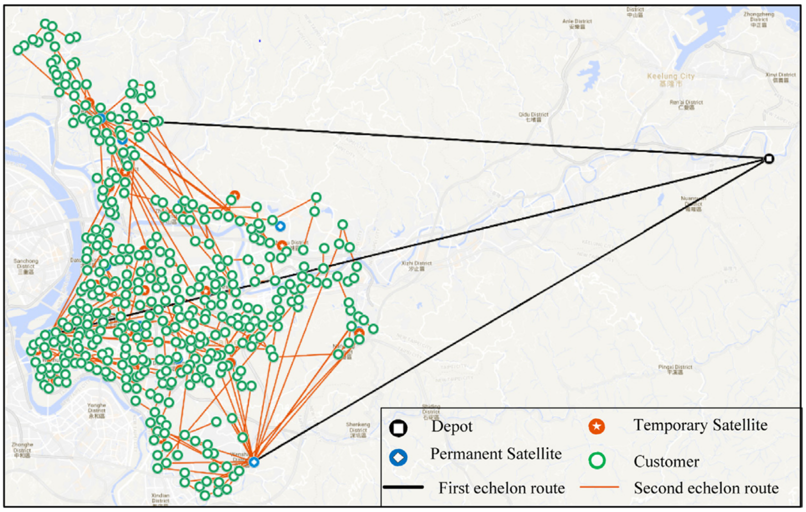


Fig. 7. Visualization of routes by using permanent satellites.

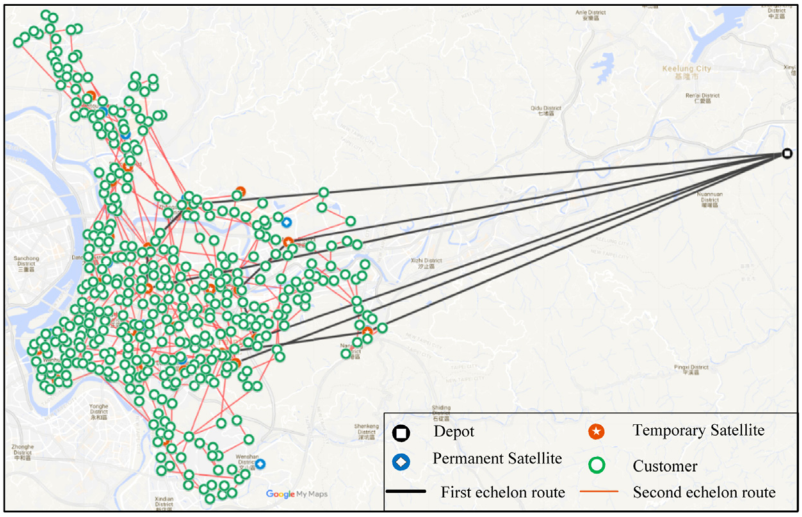


Fig. 8. Visualization of routes by using temporary satellites.

Table 16
A solution results comparison of two-echelon FDS by permanent and temporary satellites utilization.

Parameter	Permanent satellites utilization	Temporary satellites utilization	Cost gap (%)
Facilities(vehicles)			
Number of satellites opened	3	9	–
Number of trucks used	3	3	–
Number of motorcycles used	50	48	–
Cost			
Satellite set-up cost (NT$)	2350.00	0.00	100.00
Truck activation cost (NT$)	3000.00	3000.00	0.00
Truck travel cost (NT$)	951.00	868.32	8.69
Motorcycle activation cost (NT$)	5500.00	5280.00	4.00
Motorcycle travel cost (NT$)	585.86	543.85	7.17
Total distribution cost (NT$)	12386.86	9692.17	21.75

that the utilization of LUZs reduces the total distribution cost by up to 21.75%.

Future research may consider a 2E-OLRP with more practical constraints, such as time windows, multiple depots, allowing for two-level routes and simultaneous pickup and delivery to bring the problem closer to real-world application. Uncertainties in customer demands, as well as travel and service times are common in real-world applications, considering these aspects in a 2E-OLRP will be interesting. More effective and efficient heuristic methods and multi-objective optimization can also be developed for the 2E-OLRP.

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.

CRediT authorship contribution statement

Vincent F. Yu: Conceptualization, Writing - review & editing, Supervision. **Winarno:** Data curation, Writing - original draft, Visualization. **Shih-Wei Lin:** Supervision, Software, Validation. **Aldy Gunawan:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The work of the first author was supported in part by the Ministry of Science and Technology of the Republic of China (Taiwan) under grants MOST 106-2410-H-011-002-MY3 and MOST 108-2745-8-011-004. The second author would like to acknowledge to the Ministry of Research, Technology and Higher Education of the Republic of Indonesia, which grants a beneficial opportunity and supports his study in the doctoral program at National Taiwan University of Science and Technology, Taiwan. The work of the corresponding author was supported in part by the Ministry of Science and Technology of the Republic of China (Taiwan) under grant MOST 107-2410-H-182-005-MY2.

References

[1] D. Simchi-Levi, P. Kaminsky, E. Simchi-Levi, Designing and Managing the Supply Chain: Concepts, Strategies, and Case Studies, McGraw-Hill, 2009, p. 498.
[2] K. Pichka, A.H. Bajgiran, M.E. Petering, J. Jang, X. Yue, The two echelon open location routing problem: mathematical model and hybrid heuristic, Comput. Ind. Eng. 121 (2018) 97–112.
[3] G. Dezi, G. Dondi, C. Sangiorgi, Urban freight transport in bologna: Planning commercial vehicle loading/unloading zones, in: The Sixth International Conference on City Logistics, 2010.
[4] R. Pinto, R. Golini, A. Lagorio, Loading/unloading lay-by areas location and sizing: A mixed analytic-monte carlo simulation approach, IFAC-Papers OnLine 49 (12) (2016) 961–966.
[5] J. Muñuzuri, M. Cuberos, F. Abaurrea, A. Escudero, Improving the design of urban loading zone systems, J. Transp. Geogr. 59 (2017) 1–13.
[6] A.R. Alho, J.d.A. e Silva, Utilizing urban form characteristics in urban logistics analysis: A case study in Lisbon, Portugal, J. Transp. Geogr. 42 (2015) 57–71.
[7] M. Gardrat, M. Serouge, Modeling delivery spaces schemes: Is the space properly used in cities regarding delivery practices? Transp. Res. Procedia 12 (2016) 436–449.
[8] H.-C. Chang, C.-C. Kuo, Network reconfiguration in distribution systems using simulated annealing, Electr. Power Syst. Res. 29 (3) (1994) 227–238.
[9] Y.-J. Jeon, J.-C. Kim, J.-O. Kim, J.-R. Shin, K.Y. Lee, An efficient simulated annealing algorithm for network reconfiguration in large-scale distribution systems, IEEE Trans. Power Deliv. 17 (4) (2002) 1070–1078.
[10] S.-W. Lin, V.F. Yu, S.-Y. Chou, Solving the truck and trailer routing problem based on a simulated annealing heuristic, Comput. Oper. Res. 36 (5) (2009) 1683–1692.
[11] V.F. Yu, S.-W. Lin, W. Lee, C.-J. Ting, A simulated annealing heuristic for the capacitated location routing problem, Comput. Ind. Eng. 58 (2) (2010) 288–299.
[12] V.F. Yu, S.-Y. Lin, A simulated annealing heuristic for the open location-routing problem, Comput. Oper. Res. 62 (2015) 184–196.
[13] S.K. Jacobsen, O.B. Madsen, A comparative study of heuristics for a two-level routing-location problem, European J. Oper. Res. 5 (6) (1980) 378–387.
[14] R. Cuda, G. Guastaroba, M.G. Speranza, A survey on two-echelon routing problems, Comput. Oper. Res. 55 (2015) 185–199.
[15] O.B. Madsen, Methods for solving combined two level location-routing problems of realistic dimensions, European J. Oper. Res. 12 (3) (1983) 295–301.
[16] J.-R. Lin, H.-C. Lei, Distribution systems design with two-level routing considerations, Ann. Oper. Res. 172 (1) (2009) 19.
[17] M. Boccia, T.G. Crainic, A. Sforza, C. Sterle, A metaheuristic for a two echelon location-routing problem, in: International Symposium on Experimental Algorithms, 2010, pp. 288–301.
[18] M. Boccia, T.G. Crainic, A. Sforza, C. Sterle, Location-Routing Models for Designing a Two-Echelon Freight Distribution System, Rapport Technique, CIRRELT, Université de Montréal, 2011, p. 91.
[19] V.-P. Nguyen, C. Prins, C. Prodhon, A multi-start evolutionary local search for the two-echelon location routing problem, in: International Workshop on Hybrid Metaheuristics, 2010, pp. 88–102.
[20] V.-P. Nguyen, C. Prins, C. Prodhon, Solving the two-echelon location routing problem by a grasp reinforced by a learning process and path relinking, European J. Oper. Res. 216 (1) (2012) 113–126.
[21] V.-P. Nguyen, C. Prins, C. Prodhon, A multi-start iterated local search with tabu list and path relinking for the two-echelon location-routing problem, Eng. Appl. Artif. Intell. 25 (1) (2012) 56–71.
[22] T.G. Crainic, A. Sforza, C. Sterle, Tabu Search Heuristic for a Two-Echelon Location-Routing Problem, CIRRELT, 2011.
[23] C. Contardo, V. Hemmelmayr, T.G. Crainic, Lower and upper bounds for the two-echelon capacitated location-routing problem, Comput. Oper. Res. 39 (12) (2012) 3185–3199.
[24] M. Schwengerer, S. Pirkwieser, G.R. Raidl, A variable neighborhood search approach for the two-echelon location-routing problem, in: European Conference on Evolutionary Computation in Combinatorial Optimization, 2012, pp. 13–24.
[25] S. Pirkwieser, G.R. Raidl, Variable neighborhood search coupled with ilp-based very large neighborhood searches for the (periodic) location-routing problem, in: International Workshop on Hybrid Metaheuristics, 2010, pp. 174–189.-.
[26] M. Winkenbach, P.R. Kleindorfer, S. Spinler, Enabling urban logistics services at la poste through multi-echelon location-routing, Transp. Sci. 50 (2) (2015) 520–540.
[27] U. Breunig, V. Schmid, R. Hartl, T. Vidal, A large neighbourhood based heuristic for two-echelon routing problems, Comput. Oper. Res. 76 (2016) 208–225.
[28] E. Nikbakhsh, S. Zegordi, A heuristic algorithm and a lower bound for the two-echelon location-routing problem with soft time window constraints, Sci. Iran. Trans. E Ind. Eng. 17 (1) (2010) 36–47.
[29] K. Govindan, A. Jafarian, R. Khodaverdi, K. Devika, Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food, Int. J. Prod. Econ. 152 (2014) 9–28.
[30] V.M. Dalfard, M. Kaveh, N.E. Nosratian, Two meta-heuristic algorithms for two-echelon location-routing problem with vehicle fleet capacity and maximum route length constraints, Neural Comput. Appl. 23 (7–8) (2013) 2341–2349.
[31] Y. Rahmani, W.R. Cherif-Khettaf, A. Oulamara, A local search approach for the two–echelon multi-products location–routing problem with pickup and delivery, IFAC-Papers OnLine 48 (3) (2015) 193–199.
[32] M. Vidović, B. Ratković, N. Bjelić, D. Popović, A two-echelon location-routing model for designing recycling logistics networks with profit: Milp and heuristic approach, Expert Syst. Appl. 51 (2016) 34–48.
[33] N. Metropolis, A.W. Rosenbluth, M.N. Rosenbluth, A.H. Teller, E. Teller, Equation of state calculations by fast computing machines, J. Chem. Phys. 21 (6) (1953) 1087–1092.
[34] S. Kirkpatrick, J.C. Gelatt, M.P. Vecchi, Optimization by simmulated annealing, Science 220 (4598) (1983) 671–680.
[35] A. Van Breedam, Improvement heuristics for the vehicle routing problem based on simulated annealing, European J. Oper. Res. 86 (3) (1995) 480–490.
[36] W.-C. Chiang, R.A. Russell, Simulated annealing metaheuristics for the vehicle routing problem with time windows, Ann. Oper. Res. 63 (1) (1996) 3–27.
[37] V. Jayaraman, A. Ross, A simulated annealing methodology to distribution network design and management, European J. Oper. Res. 144 (3) (2003) 629–645.
[38] Y. Kuo, Using simulated annealing to minimize fuel consumption for the time-dependent vehicle routing problem, Comput. Ind. Eng. 59 (1) (2010) 157–165.
[39] V.F. Yu, S.-W. Lin, S.-Y. Chou, The museum visitor routing problem, Appl. Math. Comput. 216 (3) (2010) 719–729.
[40] E.H. Grosse, C.H. Glock, R. Ballester-Ripoll, A simulated annealing approach for the joint order batching and order picker routing problem with weight restrictions, Int. J. Oper. Quant. Manage. 20 (2) (2014) 65–83.
[41] J.C. Goodson, A priori policy evaluation and cyclic-order-based simulated annealing for the multi-compartment vehicle routing problem with stochastic demands, European J. Oper. Res. 241 (2) (2015) 361–369.
[42] S.-W. Lin, V.F. Yu, A simulated annealing heuristic for the multiconstraint team orienteering problem with multiple time windows, Appl. Soft Comput. 37 (2015) 632–642.
[43] K.M. Ferreira, T.A. de Queiroz, Two effective simulated annealing algorithms for the location-routing problem, Appl. Soft Comput. 70 (2018) 389–422.

[44] V.C. Hemmelmayr, J.-F. Cordeau, T.G. Crainic, An adaptive large neighborhood search heuristic for two-echelon vehicle routing problems arising in city logistics, Comput. Oper. Res. 39 (12) (2012) 3215–3228.

[45] D.C. Montgomery, Design and Analysis of Experiment, sixth ed., John Wiley & Sons, Inc., 2005.

[46] P.B. Hansen, Simulated Annealing, Syracuse University, School of Computer and Information Science, 1992.

[47] R.E. Walpole, R.H. Myers, S.L. Myers, K. Ye, Probability & Statistics for Engineers & Scientists, ninth ed., Prentice Hall, 2011, p. 812.

Please cite this article as: V.F. Yu, Winarno, S.-W. Lin et al., Design of a two-echelon freight distribution system in an urban area considering third-party logistics and loading–unloading zones, Applied Soft Computing Journal (2020) 106707, https://doi.org/10.1016/j.asoc.2020.106707.