Two-Echelon Dispatching Problem With Mobile Satellites in City Logistics

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***Abstract*—At present, city logistics mostly adopts a two-echelon dispatching model which combines distribution centers located in suburbs and fixed satellites located in urban areas for distribution. However, both expensive rental fees and daily changes of customer demand in metropolitan areas make dispatching route generated by fixed satellites inefficient. Moreover, the existing mobile depot model needs a large investment for facilities. In this paper, we propose a two-echelon city dispatching model with mobile satellites (2ECD-MS) which locations of mobile satellites change according to demands of customers to ensure the efficiency of delivery routes in every day. A cluster-based variable neighborhood search scheduling algorithm is proposed to determine locations of mobile satellites and dispatching routes of trucks and tricycles. Then, the 2ECD-MS is extended to 2ECD-MS-TDD to allow trucks dispatching directly (TDD) for further cost reduction. Experimental results show that the 2ECD-MS significantly reduces the total cost against the model using fixed satellites mode by 3.5% while the 2ECD-MS-TDD further reduces the total cost against the 2ECD-MS significantly by 3.25% in 54 cases with different customer scales, geographical scopes, and distribution types. These show the superiority of the proposed methods in cost reduction for city logistics in comparison to the traditional fixed model.**

***Index Terms*—City logistics, mobile satellite, two-echelon, variable neighborhood search.**

I. Introduction

THE primary purpose of city logistics [1] is to transport goods in urban areas in an efficient way, taking into account traffic congestion, safety, and environments. With the rapid development of e-commerce and the increasing demand of consumers for the speed of delivery, city logistics faces enormous challenges. Major logistics companies have changed their urban warehousing and distribution strategies to meet the growing demand for distribution better. At present, a two-echelon distribution system is the most commonly used system for urban distribution by logistics enterprises such as JD.com and SF-express. The two-echelon distribution system [2] uses different types of vehicles on various echelons and satellites to consolidate and transship parcels. In the two-echelon dispatching, parcels 1) are loaded on the truck of the first-echelon transportation; 2) arrive the satellite located in the urban area; 3) are delivered to customers by the second-echelon distribution vehicles.

The two-echelon distribution has many advantages. Firstly, using different types of vehicles at different levels effectively solves the problems of urban traffic restrictions and environmental pollution [3]. Secondly, the two-echelon distribution system has a strong flexibility [4], and can be well combined with innovative concepts to provide the last mile distribution, such as electric vehicles, unmanned aerial vehicles, parcel locker, and autonomous robots.

The existing two-echelon dispatching system adopts fixed satellite (FS) which located in a fixed location. However, dispatching routes generated based on FS is not efficient because demands of customers vary every day. Moreover, the high rental cost in metropolitan areas makes the FS costly. Therefore, we propose the concept of mobile satellite (MS) to adjust MS locations and delivery routes every day in this work.

Fig. 1 (a) and (b) show typical two-echelon distribution examples with FS and MS, respectively. These examples have one distribution center (DC), one truck, and one satellite. As shown in Fig. 1, the location of satellite in (a) is fixed while that in (b) changes every day flexibly according to customers' geographical locations and demands in different days. Subfigures ① and ② show customer demands in two different days for the same area. Total travel distances of both truck and tricycle in two days using the MS model, i.e. (b), are significantly smaller than that of the FS model's. Therefore, given the unavoidable changes of customer demands in every day, the proposed MS model is more efficient than using the FS model.

Therefore, a two-echelon city dispatching model with mobile satellite (2ECD-MS) for package distribution is proposed. In the 2ECD-MS, the MS only needs a small area and

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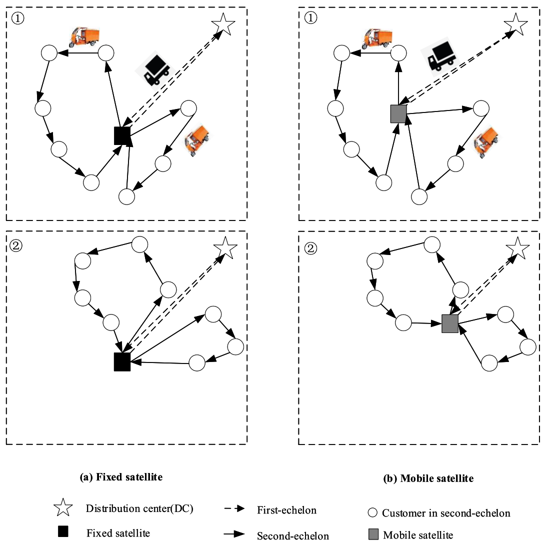

Fig. 1. Examples of two-echelon dispatching with FS and MS in two days with different customer demands.

does not need any storage equipment. In the first-echelon, trucks leave the DC and serve as the MS, of which the location changes every day depending on the daily needs of customers. In the second-echelon, parcels are transferred to tricycles and delivered to consumers. A cluster-based variable neighborhood search (VNS) algorithm is proposed for scheduling in the 2ECD-MS, which optimizes both locations of MSs and delivery routes according to different customer demands. Meanwhile, the 2ECD-MS is extended to 2ECD-MS-TDD to allow trucks dispatching directly (TDD) for further cost reduction.

The main contributions of this paper are as follows:

1) We propose a two-echelon city dispatching model with mobile satellite (2ECD-MS) to plan delivery routes efficiently for daily-change customer demands. The existing two-echelon dispatching system with fixed satellites cannot optimize delivery routes according to different daily demands (as shown in Fig. 1). Moreover, expensive rental fees in metropolitan areas further increase the total cost for using distribution model with fixed satellites. Therefore, optimal delivery routes with lower cost are achieved by the 2ECD-MS.

2) The 2ECD-MS is extended to the 2ECD-MS-TDD to allow trucks dispatching directly (TDD) for further cost reduction.

3) The proposed models are compared with the traditional model using FS to show the superiority in cost reduction for city logistics by using the MS. Experimental results show that the 2ECD-MS significantly reduces the total cost against the FS model by 3.5% while the 2ECD-MS-TDD further reduces the total cost significantly against the 2ECD-MS by 3.25% in 54 cases with different customer scales, geographical scopes, and distribution types.

The organization of the paper is as follows. Section II summarizes related works. Problem definition and mathematical formulation are provided in Section III. Section IV proposes the 2ECD-MS and its extension 2ECD-MS-TDD. Experimental results and discussions are shown in Section V. We conclude this work in Section VI.

II. Related Works

According to the use of intermediate facilities, city logistics can be broadly divided into two categories: direct dispatching and indirect dispatching [2]. Direct dispatching is delivered directly from DC to customers while indirect dispatching is transferred through some intermediate facilities (e.g. satellites) before arriving at customers. Indirect dispatching is becoming increasingly prevalent in urban distribution due to the city traffic restrictions and environmental pollution. Two-echelon (2E) dispatching system is a typical case of indirect dispatching, which implies to use different types of vehicles on various echelons and to use satellites to consolidate and transship cargoes.

The most representative two-echelon dispatching problems are the two-echelon location-routing problem (2E-LRP) [5], and the two-echelon vehicle routing problem (2E-VRP) [6]. The 2E-LRP aims at finding the optimal set of location sites for the DCs and the satellites from the given fixed location set as well as the optimal set of vehicle routes [7]. 2E-VRP can be seen as special cases of 2E-LRP where the location of the DCs and the satellites to use is given.

Recently, some papers propose variants and extensions of 2E dispatching problems. 2E-LRP with multi-sized terminals for last mile delivery are modeled in [8]. In [9], two-echelon, three-echelon, and four-echelon dispatching problems are studied. The optimization of the 2E logistics network through integrated cooperation and transportation fleet sharing is researched in [10]. The 2E dispatching problem with customer grouping is considered in [11], [12]. The 2E-LRP problem considering the real-time capacity varying of satellite is studied in [13], [14]. Considering that in 2E-LRP, the second-echelon distribution is usually provided by the third-party logistics and does not need to return to the satellites, a mathematical model of 2E open LRP problem is established in [15]. In [16], a new concept of truck-based autonomous robots for last-mile deliveries is studied. The 2E-LRP problem of heterogeneous fleet for joint delivery is studied in [17]. Reference [18] focused on the 2E-LRP with time windows for optimization of a sustainable supply chain network of perishable food. The 2E-CVRP-E issue of the impact of urban distribution on the environment is studied in [19]. The 2E-VRP with time window, synchronization, and multi trips constraints is studied in [20]. However, these works are based on the premise of fixed satellites, which will lead to higher costs due to high rents in metropolitan areas.

From the point of view of the algorithm, heuristic algorithms and evolutionary algorithms are mainly used for solving two-echelon dispatching problems. The heuristic algorithms include tabu search [21], simulated annealing [22], adaptive large neighborhood search [23], variable neighborhood search [24], etc. The common evolutionary algorithms include genetic algorithm [25], ant colony algorithm [26], particle swarm optimization [27]. At present, the research trend of literature is to mix multiple algorithms. References [28] and [29] proposed hybrid meta-heuristic algorithms, mixing greedy random adaptive search, evolutionary iteration local search, learning process, and path relink strategy. Reference [30] incorporated genetic algorithm with simulated annealing algorithm. Reference [31] combines several local search strategies with some problem-specific operators to design a hybrid meta-heuristic algorithm. The combination of particle swarm optimization and ant colony algorithm is proposed in [10]. Also, a clustering algorithm combined with an evolutionary algorithm is proposed in [11]. VNS combines with a saving algorithm is proposed in [14].

The literatures related to the concept of mobile satellite is scarce. One of the similar concepts is mobile depot [32], which is first proposed by TNT Express Company in 2014 to deal with narrow roads, traffic congestion, and complex conditions in cities. After that, there are only two literatures evaluates the concept of mobile depot from the perspective of sustainable development [33], [34]. The advantage of this mode is that it can reduce urban congestion and pollution emissions. However, the investment of equipment is relatively high, and appropriate space is needed for transshipment operation [35]. Also, the practice of these innovative concepts is generally concentrated in Europe. The main feature of Europe is that it is sparsely populated, but this kind of equipment is inappropriate in developing countries with many people and less land.

Another similar concept is the transshipment network [36] proposed by the MIT logistics laboratory. It includes two types: transshipment center and transshipment point, corresponding to different operating space sizes. The transshipment center only needs some parking space and necessary weather protection facilities but does not need storage facilities. The transshipment point is usually on the street without any facilities, which makes the implementation of mobile satellites possible.

At present, there is no literature on the combination of two-echelon dispatching and mobile satellite concept. Therefore, this paper proposes a two-echelon city dispatching model with mobile satellite to fill the gap.

III. Problem Definition and Mathematical Formulation

A. Problem Description

The 2ECD-MS is a two-echelon city dispatching model with a DC and multiple MSs. A MS means a satellite (a truck in our model) which location is uncertain and needs to be determined according to customers' geographical locations and demands in each planning day. The location of city distribution center (DC) is known. On the first-echelon, MSs are served by multiple available homogeneous trucks and the last mile delivery is completed by tricycles on the second-echelon. Truck delivers parcels to MSs from the DC and transfers parcels to tricycles at MSs. The overall objective of the 2ECD-MS model is to minimize the cost which involves the number of vehicles, distances traveled in the first- and the second-echelons, and the number of MSs. Factors affecting the cost are used as optimization objectives and being optimized simultaneously.

Assumptions of our mathematical model are as follows:

- The truck exclusively acts as a mobile satellite depot which stores parcels temporarily and also can deliver to customers directly. Customers are divided into two types: the first level truck dispatching directly (TDD) customers and the tricycle dispatching customers through MS. We evaluate this alternative mode of operation in the experiment section.
- Items to be delivered are small express parcels. Route optimization includes routes both on the first-echelon and the second-echelon.
- Due to the widespread use of parcel locker, customer time window is not considered and each customer can only be allocated to one MS and split-up distribution is not allowed.
- Both the DC location and customers' demands and locations are known. MSs have no storage capacity and no open cost. Each MS has its service area and assigned customers.
- The DC has several homogeneous trucks and each MS has some tricycles. On the first-echelon, a MS can be served more than once by different trucks. Each customer can be served only once by one vehicle (either truck or tricycles). Vehicles are not bottleneck resources. Any route in the model is closed.

B. Problem Formulation

We consider a DC V_0, a set of satellites V_s, a set of customers V_c, which divided into two types: truck direct dispatching customers V_c^0 and second-echelon serviced customers $V_c^m (m \in V_s)$, and two homogeneous fleets of vehicles K_1 and K_2 with capacity Q_1 and Q_2. The 2ECD-MS is defined on a directed graph $G = (V, A)$, which reflects the two-echelon system. The first-echelon is defined by $G_1 = (V_1, A_1)$ with $V_1 = V_0 \cup V_c^0 \cup V_s$ and $A_1 = \{(0, i) | i \in V_s \cup V_c^0\} \cup \{(i, j) | i, j \in V_s \cup V_c^0\} \cup \{(i, 0) | i \in V_s \cup V_c^0\}$. The second-echelon is defined by $G_2 = (V_2, A_2)$ and $A_2 = \{(i, j) | i \in V_S, j \in V_c^m\} \cup \{(i, j) | i, j \in V_c^m\} \cup \{(i, j) | i \in V_c^m, j \in V_S\}$. Each arc $(i, j) \in A = A_1 \cup A_2$ is associated with a travel cost (equal to the travel distance d_{ij}). Solving the 2ECD-MS involves locating MSs and allocating customers to MSs as well as planning both first-echelon and second-echelon routes, such that capacity constraints are satisfied. Parameters and decision variables of the model are summarized in Table I.

Optimization Objectives:

Objectives for 2ECD-MS are defined as follows:

1) Minimizing the total travel distance of truck:

$$\min f_1 = \sum_{i \in V_0 \cup V_s \cup V_c^0} \sum_{j \in V_s} \sum_{t \in K_1} d_{ij} x_{ij}^t \tag{1}$$

2) Minimizing the total travel distance of tricycle:

$$\min f_2 = \sum_{m \in V_s} \sum_{i \in \{m\} \cup V_c^m} \sum_{j \in \{m\} \cup V_c^m} \sum_{k \in K_2^m} d_{ij}^m y_{ij}^k \tag{2}$$

3) Minimizing the number of mobile satellites:

$$\min f_3 = |V_s| \tag{3}$$

4) Minimizing the number of tricycles used:

$$\min f_4 = \sum_{m \in V_s} \sum_{k \in K_2^m} e_m^k \tag{4}$$

TABLE I
PARAMETER AND VARIABLE DEFINITIONS

Parameters	Explanations
V_0	Distribution center (DC)
V_s	Set of mobile satellites
V_c	Set of customers
V_c^m	Set of customers served by mobile satellite m,$m \in V_s$
V_c^0	Set of customers served by truck in first-echelon
A_1	First-echelon arc set
A_2^m	Set of arcs between satellite m and its customers, and arcs between the customers served by satellite m
Q_1	Capacity of each truck in the first-echelon
Q_2	Capacity of each tricycle in the second-echelon
q_i	Demand required by customer i, $i \in V_c$
d_{ij}	Distance of a truck traveling on the arc $(i,j) \in A_1$
d_{ij}^m	Distance of a tricycle traveling on the arc $(i,j) \in A_2^m$
K_1	Set of first-echelon available trucks
K_2^m	Set of tricycles used at mobile satellite m
Decision Variables	
x_{ij}^t	1, if first-echelon truck t travels directly from node i to j 0, otherwise $\left(i,j \in V_0 \cup V_s \cup V_c^0, t \in K_1, i \neq j\right)$
y_{ij}^k	1, if second-echelon tricycle k travels directly from node i to j 0, otherwise $(i,j \in V_s \cup V_c^m, k \in K_2^m, i \neq j)$
f_i^t	1, the tth truck loads cargoes for customer i,$i \in V_C^m \cup V_c^0,\ t \in K_1$ 0, otherwise
o_m^t	1, the tth truck serves satellite m 0, otherwise $(t \in K_1)$
u_t	1, if the tth truck is used 0, otherwise
e_m^k	1, if the kth tricycle is used 0, otherwise $(m \in V_s, k \in K_2^m)$

5) Minimizing the number of trucks used:

$$\min f_5 = \sum_{t \in K_1} u_t \tag{5}$$

Five objectives are used to provide more detailed information to decision-makers for deciding the distribution plan according to the actual situation of the company by optimizing factors that affect the cost instead of optimizing the overall cost only.

Subject to

$$\sum_{i \in V_0 \cup V_s \cup V_c^0} x_{ij}^t = 1, \quad \forall j \in V_c^0, \forall t \in K_1 \tag{6}$$

$$\sum_{t \in K_1} f_i^t = 1, \quad \forall i \in V_c \tag{7}$$

$$\sum_{i \in V_c} f_i^t q_i \leq Q_1, \quad \forall t \in K_1 \tag{8}$$

$$\sum_{i \in V_0 \cup V_s \cup V_c^0} x_{ij}^t = o_j^t, \quad \forall j \in V_s, \forall t \in K_1 \tag{9}$$

$$\sum_{j \in V_s \cup V_c^0} x_{0j}^t = u_t, \quad \forall t \in K_1 \tag{10}$$

$$\sum_{i \in V_0 \cup V_s \cup V_c^0} x_{ij}^t = \sum_{i \in V_0 \cup V_s \cup V_c^0} x_{ji}^t, \ \forall j \in V_c^0 \cup V_s, \forall t \in K_1 \tag{11}$$

$$\sum_{i \in \{m\} \cup V_c^m} y_{ij}^k = 1, \quad \forall j \in V_c^m, \forall k \in K_2^m \tag{12}$$

$$\sum_{i \in V_C^m} \sum_{j \in V_C^m \cup \{m\}} y_{ij}^k \cdot q_i \leq Q_2, \forall m \in V_s, \quad \forall k \in K_2^m \tag{13}$$

$$\sum_{j \in V_c^m} y_{mj}^k = \sum_{j \in V_c^m} y_{jm}^k, \quad \forall m \in V_s, \forall k \in K_2^m \tag{14}$$

$$\sum_{i \in \{m\} \cup V_c^m} y_{ij}^k = \sum_{i \in \{m\} \cup V_c^m} y_{ji}^k, \ \forall j \in V_c^m, \forall k \in K_2^m \tag{15}$$

Constraint (6) ensures that exactly one truck arrives at first-echelon customers once. Constraint (7) ensures that customer demand is served by used trucks. Constraints (8) and (13) provide capacities of each truck and each tricycle, respectively. Constraints (9), (10), and (11) ensure the degree balance in the first-echelon. Constraint (12) guarantees that each customer served by satellite is visited exactly once by one tricycle. we stipulate that each node is served by only one route. Constraint (14) guarantees the degree balance of satellites in the second-echelon. Constraint (15) guarantees the degree balance of customers in the second-echelon.

IV. 2ECD-MS

Optimization procedures of the 2ECD-MS are shown in Fig.2. It mainly includes four parts: population generation, MS location optimization, delivery routes optimization, and elite solutions selection. Firstly, the size of population is determined according to the customers demand and the number of MSs. The initial population is then generated accordingly. Secondly, a clustering algorithm is used to optimize the location of MS and assign customers to an appropriate MS. Then, to optimize the delivery route, five neighborhoods operators are used in the VNS method to obtain global optimal solutions on the first- and the second-echelons. Finally, the environment selection strategy based on reference point is used to select elite multi-objective solutions. The algorithm outline is shown in **Algorithm 1**.

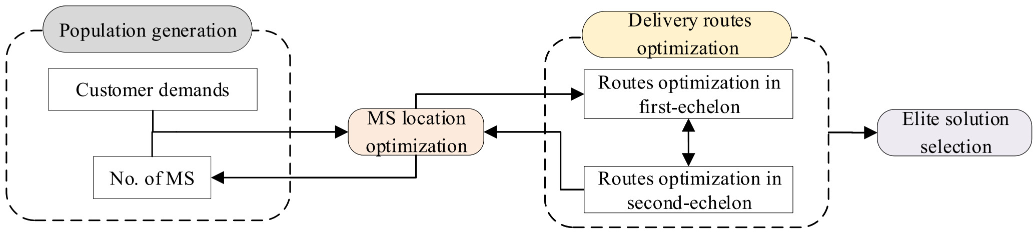

Fig. 2. The optimization procedures of 2ECD-MS.

Algorithm 1 Overall Algorithm Framework

Input:
1) A 2ECD-MS instance C;
2) The maximum number of mobile satellites: l_{max};
Output: A representative solution set $\mathbb{S}$.

$l \leftarrow 1$
while $l \leq l_{max}$ **do**
  for $iter = 1$ to $iter_{max}$ **do**
    $(MSLocation, CustomerIndex)$ ←MSLocationOpt (C, l); /***Algorithm 2***/
    Obj ←RouteOpt$(MSLocation, CustomerIndex)$; /***Algorithm 3***/
  end for
end while
$\mathbb{S}$ = elite solution selection from Obj by well-spread reference point.

Algorithm 2 MSLocationOpt(C, l)

Randomly select l cluster centers $MSLocation$.
repeat
  $Sim \leftarrow$ SimilarityCalculate$(C, MSLocation)$;
  $CustomerIndex \leftarrow$ AssignCustomers(Sim);
  Update $MSLocation$;
until Clusters are steady

Algorithm 3 RouteOpt$(MSLocation, CustomerIndex)$

According to $MSLocation$, $CustomerIndex$ randomly initialize a solution x_1, x_2 for first- and second-echelon respectively;
$x_1'' \leftarrow$ VNS(x_1); /*first-echelon route schedule*/
$x_2'' \leftarrow$ VNS(x_2); /*second-echelon route schedule*/
$Obj \leftarrow evaluate(x_1'', x_2'')$;

A. Population Generation

The 2ECD-MS is a multi-objective optimization problem. As the number of MSs l is not fixed for all problems, l is taken as a parameter to be optimized. Due to the randomness of approximation algorithm, each l is carried out $iter_{max}$ times. Therefore, the population size is set to be $l_{max} iter_{max}$, where l_{max} and $iter_{max}$ denote the maximum number of MS and the maximum number of iteration, respectively. According to the customer demands and the number of MSs, the initial population is randomly generated.

B. MS Location Optimization

Locations of MSs are optimized via a customer clustering which groups customers to maximize their geographical distances in different groups while to minimize geographical distances of customers within the same group. The k-means clustering algorithm is used. Firstly, locations of MSs are randomly selected within the geographical range. Distances between customers and MSs are calculated and each customer is assigned to the nearest MS. Then, the center location of all customers in a cluster is used as the MS location of this group of customers. These procedures are repeated until the locations of MSs converge. Procedures are summarized in **Algorithm 2**.

C. Delivery Routes Optimization

The two-echelon dispatching includes two kinds of route planning: truck's route on first-echelon and tricycle's route on the second-echelon. We adopt the VNS with five neighborhood operators to optimize routes and evaluation results are stored in Obj. Processes are outlined in **Algorithm 3**. Components of the route scheduling will be introduced in following subsections.

1) Neighborhood Operators: Neighborhood operators are designed to find local optimum in different neighborhoods and ultimately obtain global optimum solutions. For the purpose of scheduling a two-echelon problem, we adopt two types of neighborhood operators: basic neighborhood operators and problem-specific neighborhood operators. Basic neighborhood operators include relocate, 2-opt, and CrossExchange while problem-specific neighborhood operators include ShortestRemoval and WorstRemoval operators. The description of each operator is as follows.

N_1(relocate): Randomly select a customer from a route to remove and insert to the best position of all possible routes.

N_2(2-opt): Randomly exchange two edges and their corresponding customers inside a route.

N_3(CrossExchange): Exchange a segment from each of two routes.

N_4(ShortestRemoval): Select the route with the least number of customers. Insert all customers in the selected route to other routes and delete the selected route.

N_5(WorstRemoval): Select the route with the largest ratio of the travel distance to the total demands. Insert all customers in the selected route to other routes and delete the selected route. We believe that a route with few loading rates but a large travel distance should be considered as a bad route.

N_1-N_3 are the basic operators that optimize all the objectives implicitly. N_4 and N_5 are two problem-specific

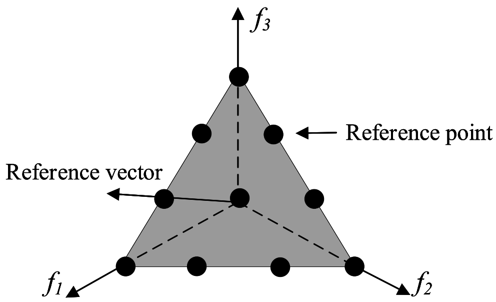

Fig. 3. An example of three-objective problem with ten structured reference points.

neighborhood operators corresponding to optimize the number of vehicles and distance.

2) VNS: The VNS mainly includes two parts: shaking and local search. The primary purpose of shaking is to obtain a new initial solution x' by randomly selecting one of the five neighborhood operators to perturb the initial solution x. The local search adopts the strategy of variable neighborhood descent to obtain the local optimal solution x''. Procedures are summarized in **Algorithm 4**.

Algorithm 4 VNS(x)

Define $N_k (k = 1, 2, \ldots, 5)$ neighborhood operators.
$k \leftarrow 1$
$x'' \leftarrow x$
while $k \leq 5$ **do**
  Shaking: generate a solution x' from the randomly selected neighborhood;
  Local search: $x^* \leftarrow argmin_{x' \epsilon N_k(x)} f\left(x'\right)$;
  if $f\left(x^*\right) < f\left(x''\right)$ **then**
    $x'' \leftarrow x^*$
    $k \leftarrow 1$
  else
    $k \leftarrow k + 1$
  end if
end while
return x''.

D. Elite Solution Selection

To obtain representative solutions, we use the environment selection strategy based on reference points to select the elite solutions. Firstly, uniform reference points are generated according to the number of objectives. Taking three objectives as an example, uniform reference points are well-spread in objective space, as shown in Fig. 3. Then, solutions are sorted according to different nondomination levels. The key is to select the solution in the last selection level. The strategy of selection is to calculate pairwise perpendicular distances between population members and reference vectors. Reference points are associated with a population member if its reference vector is closest to that population member in the normalized objective space [37]. Finally, the solution associated reference vector with the minimum number of solutions is selected.

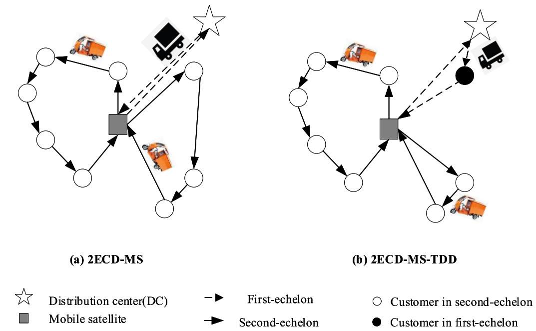

Fig. 4. Two dispatching strategies in 2ECD-MS.

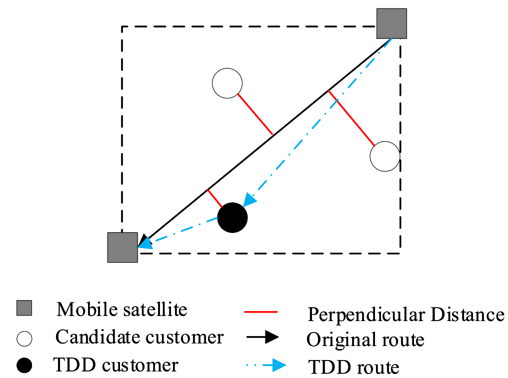

Fig. 5. An example of TDD strategy.

E. 2ECD-MS-TDD

The 2ECD-MS-TDD is an extension of the 2ECD-MS which allows trucks dispatching directly (TDD). Fig. 4 shows the two distribution strategies: 1) truck only serves a MS as in the 2ECD-MS (Fig. 4(a)); 2) truck serves a MS and also dispatches to customers directly as in the 2ECD-MS-TDD(Fig. 4(b)). As shown in Fig. 4, when some customers are very close to the first-echelon truck route, the TDD strategy reduces the total travelling distances, i.e. total cost.

The TDD strategy selects customers mainly by calculating the perpendicular distance from customers' locations to the truck route. Customers with distances from the route less than a preselected maximum distance d_m are selected as TDD customers. An example of the TDD strategy is shown in Fig. 5. The grey rectangle, the black hollow circle, black solid circle, and the red line represent a MS, a candidate customer, a TDD customer, and the perpendicular distance from a customer to the driving route of the truck, respectively. As shown in Fig. 5, a rectangular box of two mobile satellites (dotted box) is drawn and customers located within this box are selected as candidates. The black line is the original MS dispatching route while the blue dotted line is the TDD dispatching route. According to the triangle Pythagorean theorem and scaling rules of the trigonometric inequality, truck travel distance increases by up to $2d_m$ for each TDD customer in the first-echelon of distribution.

V. Experimental Analysis

In this section, we first introduce experimental settings including dataset instances, the performance indictor, and parameter settings. Next, we compare three different distribution

TABLE II
THE CHARACTERISTICS AND SPECIFIC VALUES IN THE DATASETS

	No. of instances	n	l_{max}	β	Q_1	Q_2	q	R
Prodhon2E	30	{20,50,100,200}	{5,10}	{1,2,3}	{210,450,525,630,840,1155,1260,1785,1890}	{70,150}	[11,20]	50×50
Ngunye2E	24	{25,50,100,200}	{5,10}	{N,MN}	{750,850}	{100,150}	N(15,25)	1000×1000

modes with fixed satellite, mobile satellite, and mobile satellite with TDD.

A. Instances

Since 2ECD-MS is a new problem, there are no instances for it. We modify two 2E datasets, Prodhon2E and Nguyen2E, to fit the problem in this paper. Our modification consists of two parts: we modify the number of potential satellites in each instance as the maximum number of MS l_{max} in each instance; the location of DC of each instance in the original Nguyen2E dataset is different, and we set it uniformly at coordinates (0,0). Since the 2ECD-MS is a new problem, there are no dedicated instances for problems with mobile satellites. Two 2E datasets, Prodhon2E and Nguyen2E [29], are modified to fit the MS problem. Modification consists of two parts: the number of potential satellites in each instance is modified to be equally to the maximum number of MS l_{max} in each instance; the location of DC of each instance in the Nguyen2E is set to be located at coordinates (0,0) instead of being different in every instance.

Each instance in the dataset is a combination of six characteristics: number of customers n, customer demand q, the maximum number of MS l_{max}, customer distribution characteristics β, first-echelon vehicle capacity Q_1, and second-echelon vehicle capacity Q_2. The characteristics and specific values of the dataset are shown in Table II. There are 30 instances in the Prodhon2E dataset, $\beta = 1, 2, 3$ represents three different types of customer distribution: uniform distribution, aggregate distribution, and mixed distribution; customers demand in [11,20] and customers are distributed in the range of 50×50. The format of instance name is n-l_{max}-β. For example, 20-5-1 means that there are 20 customers in the instance, the maximum number of MSs is 5, the customer distribution type is type 1, and instances with the additional b means that the second-echelon vehicle's capacity is 150.

There are 24 instances in the Nguyen2E dataset. Customer distribution N and MN represent normal distribution and multimodal normal distribution, respectively. The demands follow a normal distribution with mean 15 and variance 25. Customer distribution is in the range of 1000×1000. Instances are named in the same way as Prodhon2E.

B. Performance Indicator

In order to evaluate costs yielded by different distribution modes, we use formulas and values in literature [29] to transfer the multi-objective values into total costs:

$$cost = 2Mf_1 + Mf_2 + F_2 f_4 + F_1 f_5 + O \tag{16}$$

For different datasets, values of parameters in (16) are different, as shown in Table III. M is a positive integer, F_1 represents the fixed cost incurred by a first-echelon vehicle, and a second-echelon vehicle incurs a fixed cost F_2. For different distribution modes, the open cost O of each satellite in the fixed mode is set to the average of the potential satellite open cost of the existing instances in the dataset; the open cost of the mobile mode is 0.

TABLE III
PARAMETER DESCRIPTION AND VALUES IN COST EQUATION

Symbol	Description	Prodhon2E	Nguyen2E
M	A positive integer	100	10
F_1	Fixed cost incurred by a first-echelon vehicle	5000	4000
F_2	Fixed cost incurred by a second-echelon vehicle	1000	1000

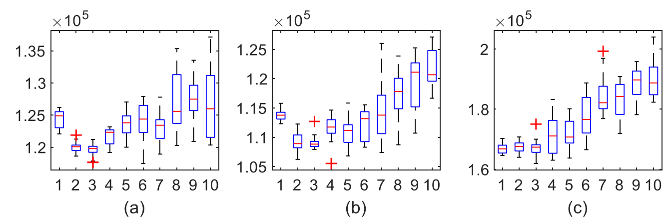

Fig. 6. Sensitivity tests for parameter d_m in three instances of Prodhon2E dataset. (a) 100-5-1b (b) 100-10-2b (c) 200-10-2b.

C. Parameter Settings

According to existing empirical experiments, we set $iter_{max} = 20$ and the size of solution set $\mathbb{S} = 20$. For the TDD mode, a preliminary experiment test is carried out to set the truck coverage parameter d_m. From the Prodhon2E dataset, three instances of 100-5-1b, 100-10-2b, and 200-10-2b are selected, and d_m is set in [1,10] with step=1. As shown in box diagrams in Fig. 6, minimum costs are achieved when $d_m = 2$ or 3. The larger the d_m is, the more customers the first-echelon vehicles will be served directly, the driving distance will increase, and the number of parking will increase. Meanwhile, parking requires additional costs. Therefore, $d_m = 2$ is used for the Prodhon2E dataset in our experiments. Given the range of Nguyen2E dataset is twenty times larger than that of the Prodhon2E dataset's, $d_m = 40$ for Nguyen2E dataset.

D. Comparison Between Fixed Satellite and Mobile Satellite

Comparison results of fixed (FS) and mobile (MS) distribution modes on the two datasets are summarized in Tables IV and V. The two tables list the best cost, the mean, and the standard deviation of the two modes. The CPU time of the MS mode and the percentage gap between the best costs obtained by the FS and the MS, i.e., $GAP = 100\% \times (best_{FS}/best_{MS} - 1)$ are also listed in Tables IV and V.

TABLE IV
FS MODE VERSUS 2ECD-MS ON THE PRODHON2E DATASET

Prodhon2E instances	FS					2ECD-MS				
	best	mean	std.	p-value	sig.	best	mean	std.	GAP	CPU time(s)
20-5-1	74101.12	75093.24	827.61	6.50E-08	1	**69226.47**	**70228.23**	1388.75	7.04%	0.66
20-5-1b	47179.39	47898.62	524.71	6.15E-08	1	**43736.52**	**44149.12**	535.09	7.87%	0.45
20-5-2	71273.26	72644.66	1121.23	6.26E-08	1	**68164.02**	**69462.61**	911.22	4.56%	0.36
20-5-2b	44134.02	44274.61	287.61	2.90E-08	1	**41433.44**	**41673.31**	326.89	6.52%	0.51
50-5-1	116528.67	117733.36	862.63	5.23E-07	1	**113960.71**	**115611.66**	946.76	2.25%	6.83
50-5-1b	88295.01	90147.10	2367.06	7.49E-06	1	**85266.09**	**86937.69**	1638.36	3.55%	6.68
50-5-2	113591.78	114666.07	721.46	1.66E-07	1	**110419.62**	**111556.27**	919.73	2.87%	6.37
50-5-2b	83840.65	84106.23	306.82	6.61E-08	1	**80412.22**	**80931.49**	411.18	4.26%	6.71
50-5-2bBIS	83421.48	84537.40	473.52	1.06E-07	1	**82127.44**	**83020.75**	542.31	1.58%	5.06
50-5-2BIS	119364.34	121037.47	1734.52	2.08E-01	0	**117080.97**	**119819.40**	2081.43	1.95%	4.53
50-5-3	113311.08	115035.52	1156.85	6.80E-08	1	**108969.49**	**111144.62**	1238.42	3.98%	8.21
50-5-3b	85881.08	87618.57	1038.09	7.87E-08	1	**82165.07**	**83422.41**	870.98	4.52%	5.17
100-5-1	188413.62	190416.61	1319.99	1.05E-06	1	**184313.89**	**187281.99**	1372.90	2.22%	69.69
100-5-1b	126831.44	132349.88	3157.22	1.06E-07	1	**122439.67**	**125355.46**	1421.43	3.59%	37.25
100-5-2	170049.84	172199.66	1611.35	1.23E-07	1	**165017.93**	**167707.93**	1424.25	3.05%	99.87
100-5-2b	114551.77	116217.01	1370.64	6.80E-08	1	**110462.52**	**112293.91**	957.08	3.70%	95.98
100-5-3	176587.81	179574.01	1932.70	2.36E-06	1	**171582.34**	**175360.42**	1950.53	2.92%	75.22
100-5-3b	117253.20	119902.85	1460.30	1.05E-06	1	**112366.17**	**115844.14**	1745.07	4.35%	78.11
100-10-1	187856.60	191109.40	2106.12	2.07E-02	1	**186463.59**	**189329.81**	1821.92	0.75%	74.53
100-10-1b	126899.08	128664.96	1184.28	9.75E-06	1	**122650.61**	**126140.12**	1489.94	3.46%	78.92
100-10-2	173068.65	174945.46	1449.89	1.81E-05	1	**169786.97**	**172254.93**	1557.18	1.93%	83.30
100-10-2b	115958.78	119449.32	3015.16	6.80E-08	1	**111635.32**	**113300.68**	914.01	3.87%	78.92
100-10-3	170325.25	174033.20	1968.06	1.23E-07	1	**165119.27**	**169063.64**	1565.77	3.15%	88.40
100-10-3b	115497.74	118637.83	1680.88	6.80E-08	1	**110467.07**	**112610.18**	1377.06	4.55%	82.08
200-10-1	313526.85	316903.60	2171.82	8.60E-06	1	**309567.00**	**312931.37**	1759.19	1.28%	703.04
200-10-1b	189783.89	192246.82	1703.94	6.67E-06	1	**186887.25**	**189305.28**	1404.40	1.55%	493.57
200-10-2	282696.13	286612.63	2002.47	4.68E-02	1	**282368.65**	**285411.97**	1598.76	0.12%	850.49
200-10-2b	175657.04	178612.24	1466.70	2.92E-05	1	**174045.97**	**176251.28**	1466.72	0.93%	947.85
200-10-3	298800.44	300936.17	1318.82	6.80E-08	1	**288828.36**	**292269.47**	1602.95	3.45%	1051.09
200-10-3b	181212.09	183639.53	1559.37	2.22E-07	1	**174691.30**	**177368.95**	2225.55	3.73%	802.69
+/−/≈	**0/29/1**									

The optimal value is shown in bold. In addition, the Wilcoxon sum-test is used to detect whether there is a significant difference between the two modes. At the end of tables, "+", "−−", and "≈" indicate that costs yielded by the FS mode are significantly better than, worse than, and near that of the MS mode. The p-values obtained from statistical tests are also listed.

Table IV (for the Prodhon2E dataset) shows that the proposed 2ECD-MS yields better solutions than the FS mode in all instances. According to p-values, the cost of the 2ECD-MS is significantly lower than that of the FS mode in 29 instances and has no significant difference in one instance. Table V (for the Nguyen2E dataset) also shows that the 2ECD-MS is significantly better than the FS mode in all instances. Compared with the FS mode, the total cost yielded by the 2ECD-MS is 3.3% and 3.7% less than that of FS's in Prodhon2E and Nguyen2E datasets, respectively. Overall, the 2ECD-MS is better than the FS mode in total economic cost, reducing cost by 3.5% on average in 54 instances with different customer scales, geographical scope, and distribution types.

E. Effectiveness of TDD Strategy

The 2ECD-MS-TDD is compared with the other two distribution strategies in this section. The comparison results of three distribution modes: FS, 2ECD-MS, and 2ECD-MS-TDD on two datasets are summarized in Tables VI and VII. In Tables VI and VII, GAP means the percentage gap between the best costs obtained by the 2ECD-MS and the 2ECD-MS -TDD, i.e., $GAP = 100\% \times (best_{MS}/best_{MS-TDD} - 1)$. The 2ECD-MS-TDD is superior to the FS mode in both the optimal solution and the significance analysis for all instances. The 2ECD-MS-TDD yields better solutions than the 2ECD-MS for Prodhon2E dataset (Table VI). According to p-values, the cost yielded by the 2ECD-MS-TDD is significantly lower than that of the 2ECD-MS in 29 instances. The same optimal solution is obtained in one instance, so there is no significant difference between them. For the Nguyen2E dataset (Table VII), the 2ECD-MS-TDD yields the optimal solution in most cases. According to p-values, it is significantly better than the 2ECD-MS in 16 cases and no significant difference in the remaining

TABLE V
FS MODE VERSUS 2ECD-MS ON THE NGUYEN2E DATASET

Nguyen2E instances	FS					2ECD-MS				
	best	mean	std.	p-value	sig.	best	mean	std.	GAP	CPU time(s)
25-5MN	88083.59	89354.26	1889.67	3.36E-06	1	**85903.73**	**86450.81**	1162.38	2.54%	0.44
25-5MNb	86634.90	87963.86	1629.47	2.67E-02	1	**82672.57**	**85392.38**	2227.85	4.79%	0.94
25-5N	86558.21	88555.13	1269.97	6.65E-08	1	**82173.75**	**84470.01**	866.87	5.34%	0.78
25-5Nb	78423.74	78909.67	522.61	8.11E-04	1	**75278.27**	**76655.21**	1559.16	4.18%	0.52
50-5MN	135811.21	137881.27	1430.73	9.27E-05	1	**131979.80**	**134836.65**	2629.25	2.90%	9.09
50-5MNb	115264.11	118588.26	3154.80	2.51E-07	1	**111055.30**	**113297.37**	1531.55	3.79%	3.01
50-5N	161727.63	165803.22	1668.33	6.79E-08	1	**153249.56**	**157192.15**	2181.25	5.53%	8.81
50-5Nb	103307.56	106946.87	2252.66	3.29E-05	1	**98105.07**	**102395.85**	2371.12	5.30%	3.33
50-10MN	170942.62	175118.36	2818.92	1.43E-07	1	**164322.52**	**166995.50**	2301.12	4.03%	8.23
50-10MNb	152179.12	154135.36	1121.19	6.77E-08	1	**142656.39**	**147866.22**	1720.84	6.68%	2.90
50-10N	131185.51	133777.97	1727.39	6.80E-08	1	**122377.44**	**123976.00**	1795.33	7.20%	9.46
50-10Nb	102400.03	105476.14	2390.95	7.90E-08	1	**94878.84**	**98912.81**	1651.16	7.93%	3.29
100-5MN	245285.53	248825.04	2377.51	6.04E-03	1	**241460.64**	**246216.90**	2963.41	1.58%	71.50
100-5MNb	199275.53	203008.44	2099.80	7.41E-05	1	**194126.95**	**199344.23**	2677.53	2.65%	31.95
100-5N	217116.93	221845.32	2667.90	1.01E-03	1	**211506.75**	**218118.78**	3265.36	2.65%	71.74
100-5Nb	179401.81	180990.73	1164.72	6.80E-08	1	**174159.89**	**176576.48**	1645.07	3.01%	41.24
100-10MN	242397.25	248588.00	1997.02	5.23E-07	1	**239145.95**	**242698.59**	1948.84	1.36%	82.05
100-10MNb	206050.64	211679.16	2834.40	2.36E-06	1	**198274.42**	**204291.00**	3835.85	3.92%	63.67
100-10N	232741.76	236803.41	2725.57	6.80E-08	1	**223683.96**	**228200.92**	2030.69	4.05%	74.59
100-10Nb	182864.68	185594.60	1847.21	6.80E-08	1	**175422.60**	**177666.94**	1334.84	4.24%	43.70
200-10MN	436056.57	442240.86	2576.20	2.96E-07	1	**428505.28**	**434422.94**	3087.73	1.76%	846.26
200-10MNb	373812.22	377774.17	3027.83	6.80E-08	1	**365507.64**	**370564.95**	1773.14	2.27%	561.30
200-10N	398720.39	405364.84	3923.71	2.56E-03	1	**395602.28**	**401424.73**	3477.53	0.79%	797.25
200-10Nb	337105.68	342504.43	2803.28	1.43E-07	1	**329054.91**	**333356.49**	2900.21	2.45%	787.92
$+/-/\approx$	**0/24/0**									

8 cases. Compared with the 2ECD-MS, costs obtained by the 2ECD-MS-TDD are reduced by 4.7% and 1.8% on average for Prodhon2E and Nguyen2E datasets, respectively. Overall, the effectiveness of the 2ECD-MS-TDD on further optimizing economic costs is remarkable, i.e. reducing cost by 3.25% on average in 54 instances with different customer scales, geographical scope and distribution types.

F. Analysis of the Relations Among Multiple Objectives

To visualize the relation between the various objectives, this paper uses the thermodynamic diagram to show the changing trend of solutions between multiple objectives in the 2ECD-MS-TDD. In the thermodynamic diagram, the obtained non-dominant solutions with f_1, f_2, f_3, and f_4 are projected onto a 2D plane, where a row and a column represent a solution and an objective, respectively. Each objective value is normalized to the [0,1] interval and expressed by the color from light (minimum) to dark (maximum). To explore the relation between multiple objectives on the solution, we select six test instances of different customer scales and distribution types from Prodhon2E and Nguyen2E datasets. The visualized solution of each dataset is shown in Fig. 7 and Fig. 8, respectively. Each instance in the figure is rearranged in ascending order according to the first objective. The four columns in figures correspond to the objective f_1 to f_4.

As shown in figures, the second-echelon vehicle traveling distance (f_2) shows an increasing trend with the decrease of the first-echelon vehicle traveling distance (f_1), which is obviously in accordance with the two-echelon distribution vehicle driving pattern in practice. Due to the number of customers affects traveling distances of distribution vehicles directly, this trend becomes more pronounced as the customer size increases, as shown in Fig. 7(d), (e), and (f) and Fig. 8(e) and (f). The number of MSs (f_3) is positively correlated with f_1 in general, which means that the increase of driving distance on the first-echelon may be caused by the rise in the number of MSs. There is no direct relationship between the number of vehicles used on the second-echelon (f_4) and the change of f_1.

From the perspective of cost, the number of vehicles being used and the distance traveled should be minimized. Distances traveled in the two echelons are conflicting and the cost of the distance traveled on the first-echelon (f_1) is twice that of the second-echelon's (f_2). Therefore, minimizing f_1 is more important. However, the increment of f_1 may be caused by the increment of the number of vehicles used on the second-echelon (f_4). Therefore, objectives f_1, f_2, and f_4 are in conflict with each other.

To further explore the relation between the number of MS and the cost, the statistics of the number of MS when each instance obtains the optimal cost are shown in Fig. 9.

TABLE VI

COST COMPARISON WITH FS, 2ECD-MS, AND 2ECD-MS-TDD ON THE PRODHON2E DATASET

Prodhon2E instances	FS					2ECD-MS					2ECD-MS-TDD				
	best	mean	std.	p-value	sig.	best	mean	std.	p-value	sig.	best	mean	std.	GAP	CPU time(s)
20-5-1	74101.12	75093.24	827.61	6.50E-08	1	**69226.47**	**70228.23**	1388.75	1	0	**69226.47**	**70228.23**	1388.75	0.00%	0.64
20-5-1b	47179.39	47898.62	524.71	6.05E-08	1	43736.52	44149.12	535.09	3.25E-06	1	**41102.66**	**42072.79**	1115.19	6.41%	0.63
20-5-2	71273.26	72644.66	1121.23	6.00E-08	1	68164.02	69462.61	911.22	2.26E-03	1	**67844.46**	**68519.53**	754.96	0.47%	0.92
20-5-2b	44134.02	44274.61	287.61	2.30E-08	1	41433.44	41673.31	326.89	3.95E-08	1	**38875.76**	**39194.86**	360.61	6.58%	0.53
50-5-1	116528.67	117733.36	862.63	6.78E-08	1	113960.71	115611.66	946.76	1.06E-07	1	**109440.97**	**111019.98**	1313.74	4.13%	3.88
50-5-1b	88295.01	90147.10	2367.06	7.42E-06	1	85266.09	86937.69	1638.36	5.09E-03	1	**81471.13**	**84834.17**	2671.01	4.66%	3.72
50-5-2	113591.78	114666.07	721.46	6.80E-08	1	110419.62	111556.27	919.73	6.80E-08	1	**104010.25**	**104907.71**	495.49	6.16%	5.25
50-5-2b	83840.65	84106.23	306.82	6.49E-08	1	80412.22	80931.49	411.18	6.68E-08	1	**75745.49**	**76271.54**	255.83	6.16%	6.91
50-5-2bBIS	83421.48	84537.40	473.52	6.78E-08	1	82127.44	83020.75	542.31	6.78E-08	1	**77890.06**	**78303.53**	363.64	5.44%	4.58
50-5-2BIS	119364.34	121037.47	1734.52	6.77E-08	1	117080.97	119819.40	2081.43	6.77E-08	1	**105550.05**	**107383.75**	1994.58	10.92%	5.61
50-5-3	113311.08	115035.52	1156.85	6.80E-08	1	108969.49	111144.62	1238.42	6.80E-08	1	**103834.70**	**104959.13**	738.38	4.95%	8.78
50-5-3b	85881.08	87618.57	1038.09	6.77E-08	1	82165.07	83422.41	870.98	1.99E-04	1	**78842.00**	**81518.18**	1702.51	4.21%	2.92
100-5-1	188413.62	190416.61	1319.99	6.80E-08	1	184313.89	187281.99	1372.90	6.80E-08	1	**172775.98**	**175469.37**	1240.86	6.68%	45.22
100-5-1b	126831.44	132349.88	3157.22	6.80E-08	1	122439.67	125355.46	1421.43	6.80E-08	1	**115647.45**	**119533.52**	1500.46	5.87%	57.99
100-5-2	170049.84	172199.66	1611.35	6.80E-08	1	165017.93	167707.93	1424.25	6.80E-08	1	**158467.79**	**160170.22**	1391.62	4.13%	90.63
100-5-2b	114551.77	116217.01	1370.64	6.80E-08	1	110462.52	112293.91	957.08	9.17E-08	1	**107016.30**	**108796.81**	858.03	3.22%	89.17
100-5-3	176587.81	179574.01	1932.70	6.80E-08	1	171582.34	175360.42	1950.53	6.80E-08	1	**163402.68**	**166551.27**	1566.03	5.01%	57.86
100-5-3b	117253.20	119902.85	1460.30	6.80E-08	1	112366.17	115844.14	1745.07	2.96E-07	1	**108819.43**	**111571.55**	1464.30	3.26%	39.52
100-10-1	187856.60	191109.40	2106.12	6.80E-08	1	186463.59	189329.81	1821.92	6.80E-08	1	**178363.00**	**181867.26**	1482.12	4.54%	48.09
100-10-1b	126899.08	128664.96	1184.28	6.80E-08	1	122650.61	126140.12	1489.94	5.23E-07	1	**119064.34**	**121542.32**	1723.16	3.01%	45.28
100-10-2	173068.65	174945.46	1449.89	6.80E-08	1	169786.97	172254.93	1557.18	6.80E-08	1	**162805.54**	**165021.84**	1322.06	4.29%	97.30
100-10-2b	115958.78	119449.32	3015.16	6.80E-08	1	111635.32	113300.68	914.01	7.58E-04	1	**106291.69**	**110536.12**	2594.17	5.03%	94.08
100-10-3	170325.25	174033.20	1968.06	6.80E-08	1	165119.27	169063.64	1565.77	1.41E-05	1	**162262.83**	**165569.25**	1996.73	1.76%	76.09
100-10-3b	115497.74	118637.83	1680.88	1.06E-07	1	110467.07	112610.18	1377.06	2.39E-02	1	**106444.16**	**111448.58**	1816.99	3.78%	33.22
200-10-1	313526.85	316903.60	2171.82	6.80E-08	1	309567.00	312931.37	1759.19	6.80E-08	1	**294734.81**	**298537.76**	1642.28	5.03%	608.89
200-10-1b	189783.89	192246.82	1703.94	6.80E-08	1	186887.25	189305.28	1404.40	6.80E-08	1	**177977.06**	**182361.94**	1789.10	5.01%	716.67
200-10-2	282696.13	286612.63	2002.47	6.80E-08	1	282368.65	285411.97	1598.76	6.80E-08	1	**260798.62**	**263463.45**	1647.97	8.27%	697.16
200-10-2b	175657.04	178612.24	1466.70	6.80E-08	1	174045.97	176251.28	1466.72	6.80E-08	1	**163189.51**	**166945.28**	2383.79	6.65%	750.63
200-10-3	298800.44	300936.17	1318.82	6.80E-08	1	288828.36	292269.47	1602.95	6.80E-08	1	**277141.72**	**280869.68**	1993.95	4.22%	756.49
200-10-3b	181212.09	183639.53	1559.37	6.80E-08	1	174691.30	177368.95	2225.55	6.01E-07	1	**169487.06**	**175520.23**	1784.91	3.07%	738.57
+/−/≈	**0/30/0**					**0/29/1**									

TABLE VII

COST COMPARISON WITH FS, 2ECD-MS, AND 2ECD-MS-TDD ON THE NGUYEN2E DATASET

Nguyen2E instances	FS					2ECD-MS					2ECD-MS-TDD				
	best	mean	std.	p-value	sig.	best	mean	std.	p-value	sig.	best	mean	std.	GAP	CPU time(s)
25-5MN	88083.59	89354.26	1889.67	5.60E-08	1	85903.73	86450.81	1162.38	5.50E-08	1	**84018.79**	**84197.08**	359.55	2.24%	0.61
25-5MNb	86634.90	87963.86	1629.47	2.00E-03	1	**82672.57**	85392.38	2227.85	9.23E-01	0	**82672.57**	**84993.35**	2139.36	0.00%	0.72
25-5N	86558.21	88555.13	1269.97	7.65E-08	1	82173.75	84470.01	866.87	1.17E-06	1	**80308.25**	**81690.27**	1304.44	2.32%	0.62
25-5Nb	78423.74	78909.67	522.61	5.46E-06	1	**75278.27**	**76655.21**	1559.16	6.75E-02	0	75431.55	76976.09	839.63	-0.20%	0.54
50-5MN	135811.21	137881.27	1430.73	6.79E-08	1	131979.80	134836.65	2629.25	4.99E-02	1	**131455.91**	**133222.75**	1002.85	0.40%	6.39
50-5MNb	115264.11	118588.26	3154.80	6.78E-07	1	**111055.30**	**113297.37**	1531.55	9.68E-01	0	111641.21	113667.92	1327.42	-0.52%	4.23
50-5N	161727.63	165803.22	1668.33	6.79E-08	1	153249.56	157192.15	2181.25	9.13E-07	1	**149558.26**	**152304.36**	1856.91	2.47%	4.21
50-5Nb	103307.56	106946.87	2252.66	2.06E-06	1	98105.07	102395.85	2371.12	2.50E-01	0	**95345.98**	**101394.18**	2739.38	2.89%	5.97
50-10MN	170942.62	175118.36	2818.92	6.80E-08	1	164322.52	166995.50	2301.12	1.00E+00	0	**163213.80**	**166698.35**	2063.44	0.68%	4.79
50-10MNb	152179.12	154135.36	1121.19	6.78E-08	1	142656.39	147866.22	1720.84	3.28E-05	1	**138811.92**	**143677.51**	2734.15	2.77%	3.84
50-10N	131185.51	133777.97	1727.39	6.80E-08	1	122377.44	123976.00	1795.33	6.80E-08	1	**113002.50**	**117681.64**	1753.07	8.30%	4.68
50-10Nb	102400.03	105476.14	2390.95	2.21E-07	1	**94878.84**	98912.81	1651.16	2.50E-01	0	95871.64	**98593.23**	1855.85	-1.04%	5.79
100-5MN	245285.53	248825.04	2377.51	6.80E-08	1	241460.64	246216.90	2963.41	1.66E-07	1	**232742.42**	**237326.32**	2970.13	3.75%	65.07
100-5MNb	199275.53	203008.44	2099.80	7.58E-06	1	**194126.95**	199344.23	2677.53	7.64E-02	0	194650.21	**197927.46**	2479.17	-0.27%	55.93
100-5N	217116.93	221845.32	2667.90	6.80E-08	1	211506.75	218118.78	3265.36	2.22E-07	1	**205301.90**	**209565.36**	2656.54	3.02%	63.64
100-5Nb	179401.81	180990.73	1164.72	6.80E-08	1	174159.89	176576.48	1645.07	2.00E-04	1	**169072.11**	**173159.19**	2715.07	3.01%	35.99
100-10MN	242397.25	248588.00	1997.02	9.17E-08	1	239145.95	242698.59	1948.84	2.30E-05	1	**232327.59**	**237626.07**	3307.04	2.93%	41.15
100-10MNb	206050.64	211679.16	2834.40	3.94E-07	1	198274.42	204291.00	3835.85	5.31E-02	0	**197286.26**	**202027.48**	3658.88	0.50%	53.97
100-10N	232741.76	236803.41	2725.57	6.80E-08	1	223683.96	228200.92	2030.69	1.66E-07	1	**217537.83**	**221508.40**	2407.12	2.83%	71.99
100-10Nb	182864.68	185594.60	1847.21	6.80E-08	1	175422.60	177666.94	1334.84	2.30E-05	1	**171635.80**	**174745.50**	1913.28	2.21%	40.33
200-10MN	436056.57	442240.86	2576.20	6.80E-08	1	428505.28	434422.94	3087.73	3.99E-06	1	**423022.18**	**428164.72**	2974.32	1.30%	605.06
200-10MNb	373812.22	377774.17	3027.83	6.80E-08	1	365507.64	370564.95	1773.14	2.56E-03	1	**362366.25**	**368348.01**	2328.34	0.87%	502.76
200-10N	398720.39	405364.84	3923.71	1.92E-07	1	395602.28	401424.73	3477.53	2.04E-05	1	**391229.27**	**395966.50**	2737.64	1.12%	760.81
200-10Nb	337105.68	342504.43	2803.28	6.80E-08	1	329054.91	333356.49	2900.21	2.04E-05	1	**321883.65**	**328339.64**	2755.43	2.23%	479.86
+/−/≈	**0/24/0**					**0/16/8**									

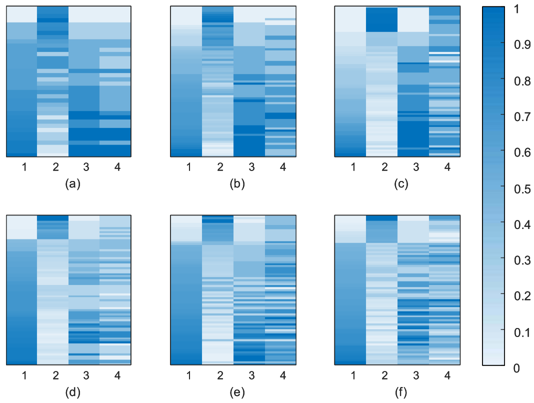

Fig. 7. The thermodynamic diagram of six instances from the Prodhon2E datasets. (a) 20-5-1b (b) 50-5-1b (c) 100-5-2 (d) 100-10-1b (e) 200-10-1 (f) 200-10-3.

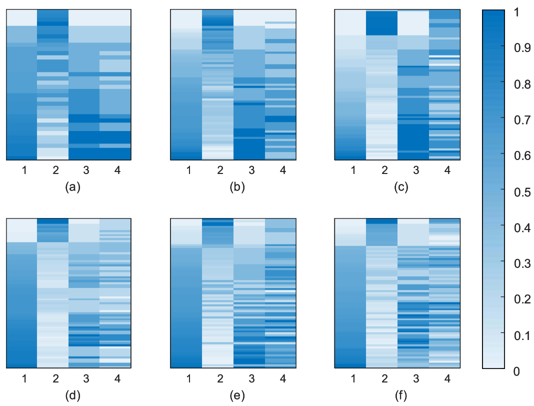

Fig. 8. The thermodynamic diagram of six instances from the Nguyen2E datasets. (a) 25-5MN (b) 50-5MNb (c) 50-10N (d) 100-5N (e) 100-10N (f) 200-10MN.

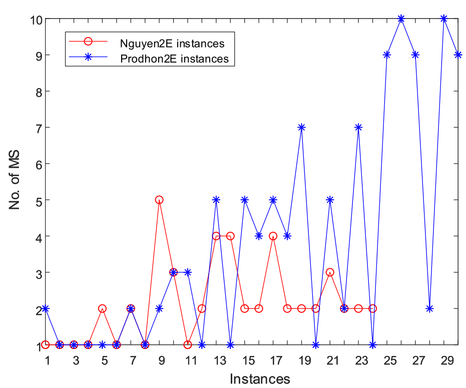

Fig. 9. The number of MS when each instance obtains the optimal cost.

As shown in Fig. 9, when the number of MS is 1, the Prodhon2E dataset achieves the most cost optimum value on 10 instances; when the number of MS is 2, the Nguyen2E dataset achieves the optimum value on 11 instances. Reasons for differences in the two datasets are related to the range of the dataset. Prodhon2E has a smaller coverage range, and the distance between customers is shorter. Therefore, the impact of the number of MS on the final cost is not obvious, while the Nguyen2E dataset has a large coverage and a long distance between customers, the number of MS has a great impact on the cost. The necessary number of MS settings is 1 or 2, which can achieve better results on most instances. To further explore the relationship between the number of MSs (f_3) and the cost, statistics of f_3 for each instance to obtain the optimal cost are shown in Fig. 9. As shown in Fig. 9, optimum cost values are obtained for the Prodhon2E dataset on 10 instances when $f_3 = 1$ while optimal cost values are obtained for the Nguyen2E dataset on 11 instances when $f_3 = 2$. Reasons for differences in the two datasets are related to the range of these datasets. Prodhon2E has a smaller coverage range and distances between customers are shorter. Therefore, the impact of the number of MSs on the final cost is not obvious. In contrast, the Nguyen2E dataset has a large coverage and long distances between customers, so the number of MSs has a great impact on the cost. The setting of the necessary number of MSs to be either 1 or 2 achieves good results on most instances.

VI. Conclusion

In this paper, we design a new two-echelon city dispatching model with mobile satellites, i.e. 2ECD-MS, of which the location changes according to demands of customers every day. Meanwhile, we propose a cluster-based VNS algorithm to determine locations of mobile satellites and dispatching routes of trucks and tricycles. Moreover, the 2ECD-MS is extended to the 2ECD-MS-TDD to allow trucks dispatching directly (TDD) for further cost reduction. Experimental results show that the 2ECD-MS significantly reduces the total cost against the model using fixed satellites by 3.5% while the 2ECD-MS-TDD further reduces the total cost against the 2ECD-MS significantly by 3.25% in 54 instances with different customer scales, geographical scope, and distribution types. These show the superiority of the proposed methods in cost reduction for city logistics in comparison to the traditional fixed model.

In future, there are several realistic factors should be considered to extend the 2ECD-MS model. For instance, a restriction on the number of vehicles being used can be added to further control the overall cost of the optimized result. Furthermore, the multi-objective two-echelon dispatching algorithm is scarce in existing literatures, the application of multi-objective optimization algorithm in two-echelon dispatching problem will be an important future direction of city logistics and deserves further studies.

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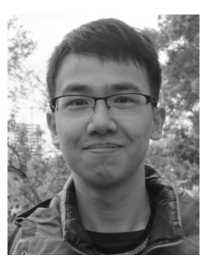

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