A TIME-DIVISION DISTRIBUTION STRATEGY FOR THE TWO-ECHELON VEHICLE ROUTING PROBLEM WITH DEMAND BLOWOUT

MIN ZHANG\textsuperscript{1,2}

\textsuperscript{1}School of Mechanical Engineering
Southwest Jiaotong University
Chengdu 610031, China
\textsuperscript{2}Technology and Equipment of Rail Transit Operation and Maintenance Key Laboratory of Sichuan Province
Chengdu 610031, China

GUOWEN XIONG\textsuperscript{1}, SHANSHAN BAO\textsuperscript{1,2} AND CHAO MENG\textsuperscript{3,*}

\textsuperscript{1}School of Mechanical Engineering
Southwest Jiaotong University
Chengdu 610031, China
\textsuperscript{2}Avic Chengdu Aircraft Industrial (Group)Co., Ltd
Chengdu 610031, China
\textsuperscript{3}School of Marketing
University of Southern Mississippi
Hattiesburg, MS 39406, USA

(Communicated by Gerhard-Wilhelm Weber)

\begin{abstract}
Based on the rapid development of e-commerce, major promotional events and holidays can lead to explosive growth in market demand and place significant pressure on distribution systems. In this study, we considered a distribution system in which products are first transported to transfer satellites from a central depot and then delivered to customers from the transfer satellites. We modeled this distribution problem as a two-echelon vehicle routing problem with demand blowout (2E-VRPDB). We adopt a time-division distribution strategy to address massive delivery demand in two phases by offering incentives to customers who accept flexible delivery dates. We propose a hybrid fireworks algorithm (HFWA) to solve the 2E-VRPDB model. This model fuses an optimal cutting algorithm with an improved fireworks algorithm. To demonstrate the effectiveness and efficiency of the proposed HFWA, we conducted comparative analysis on a genetic algorithm and ant colony algorithm using a VRP example set. Finally, we applied the proposed model and HFWA to solve a distribution problem for the Jingdong Mall in Chengdu, China. The computational results demonstrate that the proposed approach can effectively reduce logistical costs and maintain a high service level.
\end{abstract}

\textit{2020 Mathematics Subject Classification.} Primary: 90B06, 62K05; Secondary: 68T37.

\textit{Key words and phrases.} Two-echelon vehicle routing problem, demand blowout, time-division distribution, hybrid fireworks algorithm.

The first author is supported by China Postdoctoral Science Foundation (No.2020M673279), National Natural Science Foundation of China (NSFC) (No.51675450), Sichuan Science and Technology Program (No.2020JDTD0012) and MOE (Ministry of Education in China) Project of Humanities and Social Sciences (No.18YJC630255).

* Corresponding author: Chao Meng.
1. Introduction. Based on the development of information and logistics technology, e-commerce has dramatically reshaped the retail industry. E-commerce companies regularly use various promotional strategies to increase sales and market shares. During special holidays and events, consumers tend to make large numbers of purchases based on deals and discounts offered by e-commerce companies [16]. For example, China’s online retail giant “Tmall,” which is Alibaba’s business-to-consumer platform, achieved 268.4 billion yuan (approximately $38.3 billion) in sales during its annual “Singles Day” shopping festival (“Double 11” on November 11) in 2019. As a result, approximately 1.3 billion packages were delivered to consumers in China [6]. Black Friday and Cyber Monday in the United States ([23], [8]), Boxing Day in the United Kingdom, and winter discount seasons in France are also examples of demand blowout in e-commerce. According to survey statistics, the numbers of package deliveries during holidays and major promotional sales can be up to three to four times the typical amount during off-peak periods, which inevitably leads to significant logistical pressure. Overloaded warehouses, insufficient delivery vehicles, and overwhelmed employees are common during demand blowouts. In this study, we focus on the distribution aspects of the demand blowout problem.

To alleviate logistical pressure stemming from holidays and promotional sales, the optimization of logistical distribution strategies has been proposed to improve distribution efficiency. [19] adopted pickup points and lockers to avoid delivery failures in the absence of a consignee. Crowdsourcing delivery is an emerging shared economy strategy and is considered to be effective tool for alleviating the problem of last-mile urban logistics. Some logistics service providers have considered supplementing their employees with temporary crowd workers to respond to demand increases after events like the Single’s Day shopping festival [9]. In addition to increasing logistics system capacity, using pricing tools to extend delivery windows is another way to mitigate logistical pressure. [5] proposed an e-commerce logistics congestion pricing model and used a pricing tool to alleviate logistical pressure. Amazon.com offers credit (e.g., a small discount for purchasing digital products at Amazon.com) to customers who accept longer delivery times.

Additionally, optimizing vehicle routes also plays a vital role in improving system capacity and delivery efficiency. Previous studies have mainly focused on the vehicle routing problem (VRP) to optimize vehicle driving routes in various applications. Recently, [26] studied the VRP for urban waste collection. [28] proposed a novel robust mixed-integer linear programming model (MILP) model to optimize the distribution of perishable products considering traffic conditions, fuel consumption, and uncertain demand. Most studies have focused on one-echelon VRP problems. However, for environmental protection purposes, major cities have implemented policies of restricting large vehicles within cities and multi-level logistics distribution using smaller vehicles for deliveries has emerged as necessary. Under such circumstances, it is necessary to investigate multi-echelon VRPs for distribution. A two-echelon VRP (2E-VRP) is a typical multi-echelon VRP that has been discussed in the operational research literature. There are multiple variants of the 2E-VRP. [15] proposed a simulation-based optimization approach for a 2E-VRP with stochastic demand. Recently, [27] developed a novel multi-objective MILP model for a two-echelon green capacitated VRP. [25] introduced the reliable pollution-routing problem with cross-dock selection, where products are processed and transported through at least one cross-dock. These models can also be applied to e-commerce
distribution applications. [13] studied a 2E-VRP with time windows and mobile satellites. [3] investigated the electric 2E-VRP as a prototypical problem. [2] introduced a two-echelon fixed-fleet heterogeneous VRP. [7] studied a two-echelon multiple-trip VRP with satellite synchronization. [10] studied a two-echelon multi-trip VRP with a dynamic satellite. However, these studies only optimized two-echelon vehicle routing. They did not consider a series of issues (e.g., warehouse overloading and delivery delay) caused by the emergence of demand blowouts. The 2E-VRP with demand blowout (2E-VRPDB) has not yet been fully investigated.

The 2E-VRP has been proven to be an NP-hard problem. Researchers have proposed several approaches to solving 2E-VRP models. Many exact algorithms have been proposed to solve the 2E-VRP ([1], [21], [14]). [12] developed a 2E-VRP mixed-integer nonlinear programming model and used an MILP model as a benchmark model. [14] used an MILP model for the 2E-VRP by considering varying real-time transshipment capacity. In addition to exact algorithms, heuristic algorithms have also been widely used in recent years. [4] proposed a hybrid metaheuristic algorithm based on the principle of enumerating local searches, damage, and repairs, and customized operators to optimize the selection of satellites. [7] proposed an adaptive large-neighborhood search algorithm to solve a second-level VRP under the constraints of time windows, synchronization, and multiple trips in urban logistics. [29] modeled the 2E-VRP to minimize driver wages, fuel consumption costs, and handling costs, and solved the problem using a variable neighborhood search algorithm combined with integer programming. [30] used a multiplayer game to analyze the mutual relationships among routing sub-problems to derive assignment preferences for satellites and customers. They introduced assignment preferences to provide solutions for the 2E-VRP. [11] studied a two-echelon capacitated electric VRP with battery swapping stations. They proposed a hybrid algorithm that combines column generation with an adaptive large-neighborhood search to solve this problem.

In this paper, we propose a hybrid fireworks algorithm (HFWA) to solve the 2E-VRPDB model by combining an optimal cutting algorithm (OCA) with an improved fireworks algorithm (IFWA). We consider an ant colony optimization (ACO) algorithm and genetic algorithm (GA) as benchmarks to evaluate the performance of the proposed HFWA. These meta-heuristics are also commonly used to solve VRPs. This study contributes to the literature in the following ways.

- A novel 2E-VRP is studied to address the logistical demand blowout problem during holiday seasons and major promotional events. A time-division distribution (TDD) strategy is adopted to mitigate demand pressure.
- The HFWA is proposed to solve the 2E-VRPDB problem by combining an OCA and IFWA.
- Comparative analysis considering a GA and ACO demonstrates that the proposed HFWA can obtain better solutions for the 2E-VRPDB problem.

The remainder of this paper is organized as follows. Section 2 presents an optimization model for the 2E-VRPDB. Section 3 describes the detailed procedures of the HFWA approach. A case study on the Jingdong Mall in Chengdu, China, is presented to validate the proposed approach in Section 4. Conclusions and future research are discussed in Section 5.

2. Problem description and model formulation. For major promotional activities (e.g., Double 11 and Black Friday), e-commerce and logistics companies face
tremendous pressure. Specifically, logistics companies face the 2E-VRP problem under demand blowout. The 2E-VRPDB, which is a variant of the classical 2E-VRP, can be solved in two steps.

The first step is to extend delivery windows via pricing tools and improve the capacity of distribution systems. We propose a TDD strategy under demand blowout conditions. For customers who can accept longer delivery times, e-commerce enterprises offer two delivery options: standard delivery (e.g., guaranteed three day delivery) and flexible delivery (e.g., guaranteed six day delivery). When customers are strict on delivery times, their packages belong to the standard delivery category and must be delivered first. For customers who are flexible with delivery times, the corresponding packages belong to the flexible delivery category and may be scheduled for delivery later than standard delivery packages. As compensation, customers who accept flexible delivery will receive a discount on their order. If the delivery time is beyond the flexible delivery time window, customers will be unsatisfied, so logistics companies should avoid this situation. Amazon.com has adopted a similar model for its prime members. If a customer does not receive a package within the specified time window, there will be a delay fee for the logistics company. Packages are classified into either standard or flexible delivery categories using the TDD strategy before entering the distribution system.

The second step is to model a two-echelon freight delivery system to obtain optimal routes. We consider a two-level distribution system in which cargo is distributed from a central depot (e.g., distribution center) to a set of transfer satellites (e.g., local delivery offices) via identical line-haul trucks at the first level. Each satellite then uses smaller trucks to make final deliveries at the second level [20]. The 2E-VRPDB problem is illustrated in Fig.1. The warehouse is numbered zero, the satellites are coded from S1 to S5, and the customers are numbered from 1 to 14. The solid line represents the first-level delivery route, the dotted lines represent the second-level routes, the blue color represents standard delivery vehicles and routes, and the pink color represents flexible delivery vehicle routes. Given customer demand and vehicle capacity information, the solutions to the 2E-VRPDB include the numbers of vehicles at both levels and the optimal vehicle routes.

The goal is to minimize the total distribution cost, which consists of the transportation cost and fixed cost of vehicles at both levels, staff salary, compensation for flexible deliveries, and penalties for delayed deliveries.

2.1. Model assumptions. According to the characteristics of two-echelon vehicle routing problem with demand blowout, the following assumptions are made.

- Customer delivery window selections are known.
- Flexible delivery can only start after standard delivery is complete.
- No backlog is allowed.
- First-level vehicles only transport cargo from the depot to satellites and second-level vehicles only deliver cargo from satellites to customers.
- Euclidean distance is used to calculate route distances between nodes.
- The demand at any customer point is less than the vehicle capacity.
- The demand on each route cannot exceed the vehicle capacity.
- Each customer’s demand is known and satisfied by a single delivery.
- Cargo can be delivered to customers ahead of schedule without penalties, but late deliveries incur penalties.
- Loading and unloading times are ignored.
2.2. Notations. The parameters and decision variables for our optimization model are listed in Tables 1 and 2, respectively.

**Table 1.** List of parameters and descriptions

| Sets and Parameters | Description |
|---------------------|-------------|
| $D$                 | Set of depots, $D=\{d_0\}$ |
| $S$                 | Set of satellites, $S=\{s_1, s_2, \ldots, s_{ns}\}$, and the total number is $ns$ |
| $C$                 | Set of customers, $C=\{c_1, c_2, \ldots, c_{nc}\}$, and the total number is $nc$ |
| $G$                 | Set of first-level delivery vehicles, $G=\{g_1, g_2, \ldots, g_{ng}\}$, and the total number is $ng$ |
| $H$                 | Set of second-level delivery vehicles, $H=\{h_1, h_2, \ldots, h_{nh}\}$, and the total number is $nh$ |
| $M$                 | A large enough number |
| $T_0$               | Working hours per day |
| $d_{ij}$            | The distance of the $(i, j)$ edge |
| $q_i$               | Demand of customer $c_i$ |
| $cap_1$             | The capacity of the first-level vehicle |
| $cap_2$             | The capacity of the second-level vehicle |
| $t_c$               | The deadline of customer $c$ |
| $b_1$               | Compensation per unit cargo for accepting flexible delivery |
| $b_2$               | Delay cost per delivery |
| $a_1$               | Fixed cost of the first-level delivery vehicle per delivery |
| $a_2$               | Fixed cost of the second-level delivery vehicle per delivery |
| $c_g$               | Unit distance cost of the first-level delivery vehicle per delivery |
| $c_h$               | Unit distance cost of the second-level delivery vehicle per delivery |
| $c_1$               | The labor cost of the first-level delivery vehicle per delivery |
| $c_2$               | The labor cost of the second-level delivery per delivery |
| $f_c$               | If customer $c$ chooses flexible delivery, $f_c = 1$; otherwise, $f_c = 0$ |
| $T_s$               | Time required to complete standard delivery |
Table 2. List of variables and descriptions

| Variables | Description |
|-----------|-------------|
| $x_{ijg}$ | First-level distribution vehicle $g$ travels the $(i,j)$ edge, $x_{ijg} \in \{0,1\}$; decision variable |
| $y_{ijg}$ | Second-level distribution vehicle $h$ travels the $(i,j)$ edge, $y_{ijg} \in \{0,1\}$; decision variable |
| $z_{cs}$ | Customer $c$ cargo comes from satellite $s$, $z_{cs} \in \{0,1\}$; decision variable |
| $w_{sg}$ | The actual load of first level vehicle $g$ to satellite $s$; decision variable |
| $l_s$ | The total demand of satellite $s$ |
| $t_{sg}$ | Time of first-level vehicle $g$ arriving at satellite $s$ |
| $t_{sh}$ | Time of arrival of second-level vehicle $h$ to satellite $s$ |
| $t_1$ | The longest time for the first-level vehicle to complete the distribution task |
| $time_c$ | The actual delivery time of the customer $c$ |
| $dt ime_c$ | The delay time for customer $c$ |
| $U_{tg}$ | Restrict the occurrence of sub-tour in the first-level vehicles |
| $U_{2h}$ | Restrict the occurrence of sub-tour in the second-level vehicles |
| $u_{sg}$ | Intermediate variable, no actual meaning |
| $u_{cp}$ | Intermediate variable, no actual meaning |

2.3. 2E-VRPDB models. Regular delivery model:

First, we formulate the 2E-VRPDB as a regular delivery model in which customers are served within their required time windows without considering the TDD strategy. Otherwise, penalty costs are incurred. This model is our benchmark and is defined as follows.

**Objective function**

$$
\text{Min} Z_1 = \sum_{i \in D} \sum_{j \in S} \sum_{g \in G} (a_1 + c_1) x_{ijg} + \sum_{i \in S} \sum_{j \in C} \sum_{h \in H} (a_2 + c_2) y_{ijh} + \sum_{i \in D \cup S} \sum_{j \in D \cup S} \sum_{g \in G} c_g d_{ij} x_{ijg} + \sum_{i \in S \cup C} \sum_{j \in S \cup C} \sum_{h \in H} c_h d_{ij} y_{ijh} + b_2 \sum_{i \in C} d_{time_i} 
$$

**s.t.**

$$
\sum_{i \in S \cup C} \sum_{j \in C} y_{ijh} = 1, \forall j \in C, i \neq j
$$

(2)

$$
\sum_{i \in D \cup S} x_{ijg} \geq 1, \forall j \in S, i \neq j
$$

(3)

$$
\sum_{s \in S} z_{cs} = 1, \forall c \in C
$$

(4)

$$
\sum_{i \in D} \sum_{j \in S} x_{ijg} = 1, \forall g \in G
$$

(5)
A strategy for the two-echelon vehicle routing problem

\[
\sum_{i \in S} \sum_{j \in C} y_{ijk} = 1, \forall k \in K
\]

(6)

\[
\sum_{j \in S} w_{ijg} \leq \text{cap}_1, \forall g \in G
\]

(7)

\[
\sum_{i \in S \cup C} \sum_{j \in C} y_{ijk} \leq \text{cap}_2, \forall h \in H
\]

(8)

\[
\sum_{j \in S} x_{ijg} = \sum_{j \in S} x_{ijg}, \forall i \in D, g \in G
\]

(9)

\[
\sum_{j \in S \cup C} \sum_{j \in C} y_{ijh} = \sum_{j \in S \cup C} \sum_{j \in C} x_{ijh}, \forall h \in H
\]

(10)

\[
l_s = \sum_{c \in C} z_{csq_c}, \forall s \in S
\]

(13)

\[
\sum_{g \in G} w_{sg} = l_s, \forall s \in S
\]

(14)

\[
U_{1ig} - U_{1jg} + Q_1 x_{ijg} \leq Q_1 - w_{ijg}, i \neq j, i, j \in S, g \in G
\]

(15)

\[
U_{2ih} - U_{2jh} + Q_1 y_{ijh} \leq Q_2 - q_i, i \neq j, i, j \in C, h \in H
\]

(16)

\[
t_{ig} + \frac{d_{ij}}{v_1} - M(1 - x_{ijg}) \leq t_{ijg}, \forall i, j \in D \cup S, g \in G
\]

(17)

\[
t_{ih} + \frac{d_{ij}}{v_2} - M(1 - y_{ijh}) \leq t_{ijh}, \forall i, j \in S \cup C, h \in H
\]

(18)

\[
t_1 \geq t_{sg}, \forall s \in S, g \in G
\]

(19)

\[
t_{sg} \geq t_1 - M(1 - u_{sg}), \forall s \in S, g \in G
\]

(20)

\[
\sum_{g \in G} u_{sg} \geq 1, \forall s \in S, g \in G
\]

(21)

\[
T_{0time_i} = \sum_{h \in H} t_{ih} + t_1, \forall i \in C
\]

(22)

\[
d_{time_i} \geq time_i - t_i, \forall i \in c
\]

(23)

\[
d_{time_i} \geq 0, \forall i \in c
\]

(24)

\[
time_i - t_i \geq d_{time} - M(1 - u_{ip}), \forall i \in c, p \in \{1, 2\}
\]

(25)

\[
\sum_{p \in \{1, 2\}} u_{ip} \geq 1, \forall i \in C
\]

(26)

Objective function (1) minimizes the total distribution cost of the regular delivery model, which consists of a fixed vehicle cost, labor cost, transportation cost at both levels, and late delivery penalties. Eqs. (2) to (22) are constraints. Constraint (2) ensures that each customer point can only be served once by a second-level delivery vehicle. Constraint (3) indicates that each satellite is served by a first-level vehicle at least once. Constraint (4) indicates that each customer is only served by one satellite. Constraint (5) ensures that each first-level vehicle can only complete one service route. Constraint (6) states that each second-level delivery vehicle can only complete one service route. Constraints (7) and (8) ensure that first-level and
second-level delivery vehicles are not overloaded, respectively. Constraint (9) ensures that each first-level vehicle returns to its depot. Constraint (10) ensures that the same first-level vehicle enters and leaves a satellite. Constraint (11) indicates that each second-level vehicle returns to its satellite. Constraint (12) indicates that the same second-level vehicle enters and leaves a satellite. Constraint (13) represents the total demand of the satellites. Constraint (14) ensures that each satellite receives sufficient cargo from a depot to meet customer demands. Constraint (15) ensures that there will be no sub-loops in the paths of first-level vehicles. Constraint (16) ensures that there will be no sub-loops in the paths of second-level vehicles. Constraint (17) defines the time required for a first-level vehicle to reach each satellite. Constraint (18) defines the time required for a second-level vehicle to reach a customer. Constraints (19) to (21) define the maximum time required for a first-level vehicle to complete a delivery. Constraint (22) defines the total time required to complete the distribution tasks for each customer. Constraints (23) to (26) define the delay times for each customer.

**TDD model:**
In the TDD strategy, additional compensation is given to customers who choose flexible delivery. Based on the regular delivery model, the TDD model was formulated as follows.

**Objective function**

\[
\text{Min} Z_2 = \sum_{i \in D} \sum_{j \in S} \sum_{g \in G} (a_1 + c_1)x_{ijg} + \sum_{i \in S} \sum_{j \in C} \sum_{h \in H} (a_2 + c_2)y_{ijh} + \\
\sum_{i \in D} \sum_{j \in S} \sum_{g \in G} c_g d_{ij} x_{ijg} + \sum_{i \in S} \sum_{j \in C} \sum_{h \in H} c_h d_{ij} y_{ijh} + \\
b_1 \sum_{i \in C} q_i f_i + b_2 \sum_{i \in C} \text{dtime}_i
\]

\[
\text{s.t.} \quad T_{0\text{time}} = \sum_{h \in H} t_{ih} + t_1 + T_S, \forall i \in C
\]

The objective function in Eq. (27) minimizes the total distribution cost, which includes a fixed vehicle cost, labor cost, transportation cost of two-level distribution routes, flexible delivery compensation, and delay penalty costs. The total time requested by the customer for completing the delivery task must be added to the standard delivery time. Constraint (28) replaces Constraint (22) in the regular delivery model and the remaining constraints are the same as those in the regular delivery model.

3. **HFWA solution approach.** The developed 2E-VRPDB model includes two interdependent VRPs. Considering the complexity of these problems, we propose the HFWA to solve the 2E-VRPDB. The proposed HFWA integrates an OCA and IFWA.

Considering the interdependence between the two levels of distribution networks, we optimize the routes for both levels in an integrated manner. Based on the TDD strategy, cargo is transported in two batches. First, a bottom-up approach is adopted to determine the second-level routes and obtain each satellite’s cargo volume. First-level routes are then planned. The OCA provides a reasonable initial second-level vehicle delivery route solution, which improves the computational efficiency of the next optimization process. The IFWA is then applied to optimize
the second-level delivery vehicle routes. The second-level routing solution can pro-
vide each satellite’s delivery volume as a basis for the first-level distribution routing
solution. Therefore, the IFWA can achieve global optimization by addressing the
coupling problem. The first-level delivery route is determined using Breuning’s sim-
ple insertion heuristic method [22]. If the demand of a satellite exceeds the capacity
of a single vehicle, then the depot must schedule multiple direct shipments to the
satellite until the remaining demand is less than the capacity of a first-level vehi-
cle. The remaining demand for all satellites is randomly inserted into the first-level
vehicle routes to generate a solution. This method can increase the diversity of
solutions.

3.1. Delivery route preprocessing using the OCA. To improve the efficiency
of the solution procedure, the OCA is used to obtain a reasonable initial solution
for the second-level vehicle routes as an initial population for the FWA and the
delivery volumes of satellites.

The principle of the OCA is to search for an optimal distribution scheme by
traversing all feasible schemes under the premise that a group of random customer
points is no greater than the maximum capacity of the delivery vehicles [17]. The
OCA produces a sequence using chromosome coding, which randomly arranges the
number of customer points. The pseudo-code for this algorithm is provided below.

In this pseudo-code, \( V_i \) is the number of second-level vehicles required for the
first \( i \) demand points in the population, \( L_{\text{Length}_i} \) is the shortest route distance, and
\( s_j \) records the corresponding satellite for customer \( c \). The cost is calculated based
on the objective function of the TDD model (Eq. (27)).

The OCA can acquire a better initial solution than the random generation
method. This initial solution includes the second-level vehicle delivery routes, the
satellites from which each vehicle are dispatched, the satellites from which each
customer point are assigned, and the demand of each satellite. Suppose there is
a two-echelon delivery system with one depot, three satellites, and 15 customers.
Satellite 1 serves customers 5, 6, 8, and 10 with one vehicle and the route is \{1, 10,
5, 8, 6, 1\}. Satellite 2 dispatches two vehicles for delivery with routes of \{2, 4, 11,
2\} and \{2, 14, 7, 10, 2\}. Satellite 3 dispatches two vehicles for delivery with routes
of \{3, 9, 13, 16, 3\} and \{3, 18, 15, 12, 3\}. The initial solution illustrated in Fig. 2
represents only the second-level delivery routes.

As shown in the initial solution in Fig. 2, the solution for the first-level vehicle
is generated from two routes of \{0,1,0\} and \{0,1,3,2,0\}. This indicates that the
Algorithm 1. Pseudo-code for the OCA

1: Length$\_0$ = 0; $V_0$ = 1;
2: for $i$ = 1 to $n_c$ do Length$\_i$ = $+\infty$, $V_i$ = $i$;
3: end for
4: load = 0; Cost = 0; Cost$\_k$ = 0;
5: for $i$ = 1 to $n_c$
6: load = load + $q(C_i)$
7: for $k$ = 1 to $n_s$
8: if $i$ = 1
9: Cost$\_k$ = $d(S_k, C_i)$ + $d(C_i, S_k)$;
10: else
11: Cost$\_k$ = Cost$\_k$ − $d(C_{j-1}, S_k)$ + $d(C_{j-1}, C_i)$ + $d(C_i, S_k)$;
12: end for
13: Costm = min {$Cost_k$ | $k$ $\in$ [1, $n_s$]}, Cost = Costm;
14: if (load $\leq$ $Q_2$)
15: if $V_i$ $>$ $V_{i-1}$
16: $V_i$ = $V_{i-1}$;
17: $s_i$ = $S_m$, Length$\_i$ = Length$\_{i-1}$ + Cost;
18: elseif ($V_i$ = $V_{i-1}$) and (Length$\_{i-1}$ + Cost $<$ Length$\_i$)
19: $s_i$ = $S_m$, Length$\_i$ = Length$\_{i-1}$ + Cost;
20: endif
21: else
22: for $k$ = 1 to $n_s$
23: Cost$\_k$ = $d(S_k, C_i)$ + $d(C_i, S_k)$;
24: end for
25: Costm = min {$Cost_k$ | $k$ $\in$ [1, $n_s$]}, Cost = Costm
26: $V_i$ = $V_{i-1}$ + 1;
27: $s_i$ = $S_m$, Length$\_i$ = Cost
28: end for

demand for satellite 1 is greater than the vehicle’s capacity, meaning multiple vehicles are required. The remaining demand for satellites 1, 2, and 3 can be served by one vehicle.

3.2. IFWA design. The FWA was inspired by the observation of the natural phenomenon of sparks from fireworks explosions [24]. This algorithm can generate an optimal solution by mimicking the fireworks explosion process and involving random factors from parallel search patterns during the search process [31]. The traditional FWA mainly solves continuous optimization problems and includes four components: an explosion operator, mutation operator, mapping rule, and selection strategy. In this paper, we propose an IFWA for the 2E-VRPDB. We discard the mapping rule because the discrete fireworks variation process does not exceed the problem domain. We retain the overall structure of the FWA and redesign the corresponding explosion operators and mutation operators. The following sections discuss the details of the IFWA.

3.2.1. Calculation of spark quantity. In this section, we present the steps for obtaining each firework’s fitness value and generating sparks in the IFWA. The smaller
the fitness value, the more sparks the fireworks will produce. The specific steps for generating sparks are defined as follows.

**Step 1.** Select fireworks randomly from the fireworks population as operation objects.

**Step 2.** Generate multiple sparks using the explosion operator, calculate their spark fitness values, and retain individuals with high fitness values.

**Step 3.** Determine whether the termination condition is satisfied. Stop searching if the condition is satisfied. Otherwise, return to step 1.

The number of sparks is calculated before performing the individual fireworks explosion operations. The number of sparks generated by firework \( i \) \((i = 1, 2, \ldots, n)\) is calculated as follows:

\[
S_i = \frac{m}{n} \frac{1}{\left(T_{\text{max}} - T_i + \varepsilon\right)^2} \sum_{i=1}^{n} \frac{1}{\left(T_{\text{max}} - T_i + \varepsilon\right)^2}
\]

(29)

In Eq. 29, \( S_i \) is the number of sparks produced by the \( i^{th} \) firework, \( m \) is the maximum number of sparks, \( T_{\text{max}} = \max\{T_i\} \), and \( \varepsilon \) is a very small constant. To limit the number of sparks, we define the following limit formula:

\[
S_i = \begin{cases} 
\text{round}(am), & S < am \\
\text{round}(bm), & S > bm \\
\text{round}(S_i), & \text{else}
\end{cases}, \ a < b < 1
\]

(30)

In Eq. 30, \( \text{round()} \) is a rounding function, and \( a \) and \( b \) are constants. The maximum number of sparks parameter \( m \) is set to 50 and \( n \) is set to five.

3.2.2. **Multi-operational explosion operator.** The explosion operator is an important component of the FWA for obtaining local and global solutions. However, random explosions for continuous optimization problems are not suitable for the discrete 2E-VRPDB. In this study, the explosion operator was redesigned to include two types of explosion operations (I and II).

Explosion operation I generates new sparks by changing the sequence of original fireworks individuals. The two types of explosion operations are described below.

(1) 2-opt: Randomly select two positions in a fireworks individual, perform a crossing operation, and generate a new solution. As shown in Fig. 3, we select a vehicle delivery route \( \{1, 5, 4, 3, 2\} \) and generate a new spark by changing the positions of customers 3 and 5. The order of the delivery route is then changed from \( \{1, 5, 4, 3, 2\} \) to \( \{1, 3, 4, 5, 2\} \).

(2) Exchange satellite: Randomly select a fireworks individual representing the delivery route for one vehicle and change the satellite selection for that fireworks individual. Assuming that the selected vehicle departs from satellite 1 to a customer, satellite 1 is replaced by satellite 2 in the new spark.

In explosion operation II, selected fireworks must operate and cross-reorganize using the best individuals in the existing firework sparks. Two modes of operation are described below.

(1) 2-opt*: The 2-opt operation for explosion operation II is presented in Fig. 4(a). Two intersection positions are randomly generated from the operation fireworks and optimal individual, and two new solutions are generated via cross-reorganization.
Fig. 3. Explosive operation I (2-opt)

Fig. 4. Explosive operation II

(2) Exchange: The detailed exchange operation for explosion operation II is presented in Fig. 4(b). Two exchange segments are generated from the operation fireworks and optimal individual, and then exchanged with each other. Repeated sections are rearranged to generate two new solutions.

If the new individuals generated by explosive operations I and II do not meet the vehicle capacity limit, then they will not be accepted new sparks will be regenerated. Explosive operations I and II are not greedy choices. The fitness values of new individuals are calculated after new solutions are generated and new individuals are accepted with a probability $p_a$. This mechanism avoids local optima. The probability $p_a$ is calculated as follows:

$$p_a = \exp(-\theta T_m/T_0)$$  \hspace{1cm} (31)

In Eq. 31, $T_m$ represents the changed delivery cost, $T_0$ represents the initial delivery cost, and $\theta$ is a control parameter with a value between one and two.
Explosive operation II is performed for local optimization to allow the proposed algorithm to jump out of local optimal solutions.

3.2.3. **Mutation operator 3-opt.** The new sparks generated by the mutation operator can increase the diversity of the fireworks population and enhance the local search ability of the algorithm. The 3-opt operation is performed on each firework to generate new sparks and calculate their fitness values. These processes can retain individuals with better fitness values and increase overall population diversity.

The mutation operator is based on the 3-opt mechanism, which modifies the positions of three customers in a firework. As shown in Fig. 5, the original delivery route \{1, 5, 4, 3, 2\} produces three intersections at customers 1, 4, and 2, which can produce two new individual routes of \{4, 5, 2, 3, 1\} and \{2, 5, 1, 3, 4\}.

![Figure 5. 3-opt operation](image)

3.2.4. **Individual update strategy.** For the fireworks generated by explosion operators and mutation operators, elite selection and roulette selection strategies are used to select the best fireworks individuals for the next generation.

The principle of the roulette strategy is explained below. Each individual in the population is represented by a sector and an individual’s fitness value determines the area of that sector. Individuals with higher fitness values have a higher chance of being selected.

To ensure that individuals with small fitness values have a chance of being selected for the next generation, the selection probability of firework \(x_i\) is defined as follows:

\[
p(x_i) = \frac{1}{\left(T_i - T_{\text{min}} + \varepsilon\right)^2} \sum_{i=1}^{n} \frac{1}{\left(T_i - T_{\text{min}} + \varepsilon\right)^2}
\]

In Eq. 32, \(T_{\text{min}} = \min\{T_i\}\) is the minimum fitness value and \(\varepsilon\) is a smoothing parameter.

Fig. 6 presents a flow chart for the proposed HFWA.

4. **Algorithm verification and case study.** In this section, a 2E-VRP standard calculation example is used to illustrate the effectiveness of the proposed HFWA algorithm. The distribution problem of the Jingdong Mall in the Jinmi District of the city of Chengdu, China, is considered as a case study. The computer used in our calculation experiments had an Intel (R) Core(TM) i3-6100 CPU running at 3.70 GHz, 4 GB of RAM, and the Windows 10 operating system.
4.1. **Algorithm verification.** To demonstrate the effectiveness of the HFWA for solving the 2E-VRP, we compare its solution and computational time to those of a GA, ACO, and other methods from the literature. After adjusting the parameters for the algorithm based on many experiments, an optimal set of parameters was obtained, as shown in Table 3. The test examples considered in this study were taken from a standard study set called “Set 2.” We considered three 2E-VRP examples called “En22-k4,” “E-n33-k4,” and “E-n51-k5.” The numbers of customers in each example are 22, 33, and 51, respectively. The data used in our experiments can be found at [https://www.univie.ac.at/prolog/research/TwoEVRP](https://www.univie.ac.at/prolog/research/TwoEVRP). In our experiments, the transfer satellite number, first-level vehicle capacity, and second-level vehicle number were consistent between all methods. Each test involved 1000 iterations and was performed 10 times. The results are listed in Table 4. to 7. and Fig. 7.

Table 4. to 7. reveals that the HFWA generates better solutions than the other two algorithms on most test cases and achieves optimality in all cases. The explosion operator in the HFWA enhances local optimization and increases the probability of obtaining an optimal solution. The GA only achieves the optimal solution once and the ACO fails to obtain the optimal solution in all cases. The gaps between the optimal values of ACO and the GA, and the HFWA increases with the scale of the examples. The gap between the HFWA and GA is smaller than that between the HFWA and ACO. The accuracy of the HFWA is greater than those of ACO and the GA in all test cases. Compared to the results of the methods proposed by [18] and [11], the proposed HFWA is superior in terms of solution quality and stability. In terms of computational time, the GA requires the most time, followed by the HFWA and ACO. The 10th testing case is a large-scale network with four transfer satellites. Therefore, the computational time of all algorithms increases significantly. The comparative results demonstrate that the HFWA provides excellent global and local search abilities. Although its computational time is not the shortest among the
### Table 3. Parameter settings

| Algorithm | Parameter                                      | Value     |
|-----------|------------------------------------------------|-----------|
| HFWA      | Fireworks population size                      | 5         |
|           | The number of explosion sparks                 | 2         |
|           | Upper limit of the number of explosion sparks  | 50        |
|           | Variation spark number                         | 2         |
|           | Number of iterations                           | 1000      |
| ACO       | Number of ants                                 | 50        |
|           | Pheromone heuristic factor                     | 1         |
|           | Fitness heuristic factor                       | 9         |
|           | Pheromone volatile factor                      | 0.1       |
|           | Constant coefficient                           | 1         |
|           | Number of iterations                           | 1000      |
| GA        | Population size                                | 50        |
|           | Cross factor                                   | 0.8       |
|           | Mutation factor                                | 0.2       |
|           | Number of iterations                           | 1000      |

![Optimal results of three algorithms](image)

**Figure 7.** Optimal results of three algorithms
Table 4. The optimization results of ACO algorithm

| No. | Standard test | n | Optimal solution (km) | Average solution (km) | Time (s) | GAP (%) |
|-----|---------------|---|-----------------------|-----------------------|----------|---------|
| 1   | Set2a_E-n22-k4-s6-17 | 22 | 422.93 | 422.93 | 50.7 | 1.40% | 417.07 |
| 2   | Set2a_E-n22-k4-s8-14 | 22 | 387.84 | 387.84 | 50.5 | 0.75% | 384.96 |
| 3   | Set2a_E-n22-k4-s9-19 | 22 | 479.05 | 484.18 | 49.1 | 1.80% | 470.6 |
| 4   | Set2a_E-n22-k4-s10-14 | 22 | 377.56 | 377.56 | 49.1 | 1.63% | 371.5 |
| 5   | Set2a_E-n33-k4-s1-9 | 33 | 753.75 | 768.28 | 74.9 | 3.23% | 730.16 |
| 6   | Set2a_E-n33-k4-s2-13 | 33 | 761.76 | 776.57 | 75 | 6.60% | 714.63 |
| 7   | Set2a_E-n33-k4-s3-17 | 33 | 745.38 | 759.23 | 74.9 | 5.36% | 707.48 |
| 8   | Set2a_E-n33-k4-s7-25 | 33 | 790.55 | 804.92 | 75 | 4.45% | 756.85 |
| 9   | Set2a_E-n33-k4-s14-22 | 33 | 797.87 | 802.72 | 75.7 | 2.42% | 779.05 |
| 10  | Set2b_E-n51-k5-s2-417-46 | 51 | 618.69 | 637.24 | 124.9 | 16.57% | 530.76 |
| 11  | Set2b_E-n51-k5-s2-17 | 51 | 665.23 | 684.06 | 120.8 | 11.34% | 597.49 |
| 12  | Set2b_E-n51-k5-s4-46 | 51 | 613.78 | 627.29 | 120.2 | 15.64% | 530.76 |

three tested algorithms, the HFWA is still suitable for solving large-scale 2E-VRPs in a reasonable timeframe.

4.2. Case data. The distribution problem of the Jingdong Mall in the Jinliu District of the city of Chengdu, China was selected as a case study. During the Double 11 period of 2018, the total number of packages to be delivered reached 460,000
Table 5. The optimization results of GA algorithm

| No. | Standard test | n  | Optimal (km) | Average (km) | Time (s) | GAP (%) | Optimal solution (km) |
|-----|---------------|----|--------------|--------------|----------|---------|-----------------------|
| 1   | Set2a_E-n22-k4-s6-17 | 22 | 417.07       | 438.04       | 472.4    | 0.00%   | 417.07                |
| 2   | Set2a_E-n22-k4-s8-14 | 22 | 387.84       | 399.37       | 468.9    | 0.75%   | 384.96                |
| 3   | Set2a_E-n22-k4-s9-19 | 22 | 475.62       | 492.41       | 474.9    | 1.07%   | 470.6                 |
| 4   | Set2a_E-n22-k4-s10-14 | 22 | 377.56       | 383.11       | 472.1    | 1.63%   | 371.5                 |
| 5   | Set2a_E-n33-k4-s1-9  | 33 | 730.16       | 764.25       | 502.2    | 0.00%   | 730.16                |
| 6   | Set2a_E-n33-k4-s2-13 | 33 | 725.04       | 747.5        | 484.6    | 1.46%   | 714.63                |
| 7   | Set2a_E-n33-k4-s3-17 | 33 | 732.37       | 760.82       | 488.5    | 3.52%   | 707.48                |
| 8   | Set2a_E-n33-k4-s7-25 | 33 | 763.58       | 790.26       | 491.8    | 0.89%   | 756.85                |
| 9   | Set2a_E-n33-k4-s14-22 | 33 | 782.04       | 792.21       | 510.7    | 0.38%   | 779.05                |
| 10  | Set2b_E-n51-k5-s2-417-46 | 51 | 599.66 | 631.44 | 860.2 | 12.98% | 530.76 |
| 11  | Set2b_E-n51-k5-s2-17 | 51 | 641.66       | 671.12       | 695.5    | 7.39%   | 597.49                |
| 12  | Set2b_E-n51-k5-s4-46 | 51 | 604.92       | 620.14       | 656.7    | 13.97%  | 530.76                |
### Table 6. The optimization results of HFWA algorithm

| No. | Standard test | n  | HFWA Optimal (km) | Average (km) | Time (s) | GAP (%) | Optimal solution (km) |
|-----|---------------|----|-------------------|--------------|----------|---------|-----------------------|
| 1   | Set2a_E-n22-k4-s6-17 | 22 | 417.07           | 417.07       | 103.7    | 0.00%   | 417.07                |
| 2   | Set2a_E-n22-k4-s8-14 | 22 | 384.96           | 386.69       | 106.2    | 0.00%   | 384.96                |
| 3   | Set2a_E-n22-k4-s9-19 | 22 | 470.6            | 472.84       | 107.1    | 0.00%   | 470.6                 |
| 4   | Set2a_E-n22-k4-s10-14 | 22 | 371.5            | 376.35       | 104.2    | 0.00%   | 371.5                 |
| 5   | Set2a_E-n33-k4-s1-9   | 33 | 730.16           | 734.76       | 188.9    | 0.00%   | 730.16                |
| 6   | Set2a_E-n33-k4-s2-13  | 33 | 714.63           | 724.6        | 191.1    | 0.00%   | 714.63                |
| 7   | Set2a_E-n33-k4-s3-17  | 33 | 707.48           | 712.08       | 192.1    | 0.00%   | 707.48                |
| 8   | Set2a_E-n33-k4-s7-25  | 33 | 756.85           | 765.18       | 192.1    | 0.00%   | 756.85                |
| 9   | Set2a_E-n33-k4-s14-22 | 33 | 779.05           | 781.95       | 194.7    | 0.00%   | 779.05                |
| 10  | Set2b_E-n51-k5-s2-4-17-46 | 51 | 530.76           | 557.82       | 593.6    | 0.00%   | 530.76                |
| 11  | Set2b_E-n51-k5-s2-17  | 51 | 597.49           | 622.8        | 490      | 0.00%   | 597.49                |
| 12  | Set2b_E-n51-k5-s4-46  | 51 | 530.76           | 549.47       | 499.2    | 0.00%   | 530.76                |

The total number of packages for the 50 self-pickup points was 8056. In this experiment, the delivery option (standard or flexible delivery) for each customer point was selected randomly. During the demand blowout period, the time for standard delivery was three days and the time for flexible delivery was six days. The demand and delivery times for each customer point are listed in Table 9.
Table 7. The results of existing literature

| No. | Standard test | n  | Optimal (km) | GPA (%) | Optimal (km) | GAP (%) | Optimal solution (km) |
|-----|---------------|----|--------------|---------|--------------|---------|----------------------|
| 1   | Set2a_E-n22-k4-s6-17 | 22 | 417.07       | 0.00%   | 417.07       | 0.00%   | 417.07               |
| 2   | Set2a_E-n22-k4-s8-14 | 22 | 384.96       | 0.00%   | 384.96       | 0.00%   | 384.96               |
| 3   | Set2a_E-n22-k4-s9-19 | 22 | 470.6        | 0.00%   | 470.6        | 0.00%   | 470.6                |
| 4   | Set2a_E-n22-k4-s10-14| 22 | 371.5        | 0.00%   | 371.5        | 0.00%   | 371.5                |
| 5   | Set2a_E-n33-k4-s1-9  | 33 | 743.22       | 1.79%   | 730.16       | 0.00%   | 730.16               |
| 6   | Set2a_E-n33-k4-s2-13 | 33 | 710.48       | -0.58%  | 714.63       | 0.00%   | 714.63               |
| 7   | Set2a_E-n33-k4-s3-17 | 33 | -            | -       | 707.48       | 0.00%   | 707.48               |
| 8   | Set2a_E-n33-k4-s7-25 | 33 | 756.85       | 0.00%   | 756.85       | 0.00%   | 756.85               |
| 9   | Set2a_E-n33-k4-s14-22| 33 | -            | -       | 779.05       | 0.00%   | 779.05               |
| 10  | Set2b_E-n51-k5-s2-417-46 | 51 | 577.16     | 8.74%   | 530.76       | 0.00%   | 530.76               |
| 11  | Set2b_E-n51-k5-s2-17 | 51 | -           | -       | 597.49       | 0.00%   | 597.49               |
| 12  | Set2b_E-n51-k5-s4-46 | 51 | -           | -       | 530.76       | 0.00%   | 530.76               |

Based on the data of the company’s existing delivery vehicle parameters, the number of first-level distribution vehicles was three, the maximum loading capacity of each vehicle was 2200 bags, the driving cost per unit distance was 2 yuan per kilometer, the fixed cost was 200 yuan per day, and the labor cost was 200 yuan per day. The number of secondary distribution vehicles was five, the maximum
Figure 8. Jindong distribution of self-pickup points in Jinniu District

Table 8. Distribution network node coordinates

| Node | X    | Y    | Node | X    | Y    | Node | X    | Y    |
|------|------|------|------|------|------|------|------|------|
| D    | 20639| 18019| 16   | 14533| 5098 | 34   | 13728| 8485 |
| S1   | 807  | 16768| 17   | 13623| 8242 | 35   | 12730| 4622 |
| S2   | 33084| 19137| 18   | 13573| 3064 | 36   | 12968| 4261 |
| 1    | 11066| 5223 | 19   | 15874| 7803 | 37   | 12611| 3804 |
| 2    | 10481| 7350 | 20   | 11212| 6558 | 38   | 15604| 5195 |
| 3    | 16356| 5406 | 21   | 13396| 3457 | 39   | 16340| 4248 |
| 4    | 14197| 6453 | 22   | 11813| 9258 | 40   | 15342| 6701 |
| 5    | 9591 | 5209 | 23   | 15606| 5339 | 41   | 12902| 3362 |
| 6    | 12664| 5236 | 24   | 17577| 5196 | 42   | 12149| 5210 |
| 7    | 10772| 5910 | 25   | 10496| 5801 | 43   | 13221| 5054 |
| 8    | 15321| 5178 | 26   | 17472| 3701 | 44   | 13451| 7415 |
| 9    | 15239| 5209 | 27   | 13839| 7873 | 45   | 15543| 7984 |
| 10   | 13556| 7147 | 28   | 16555| 8635 | 46   | 13025| 4248 |
| 11   | 16660| 4104 | 29   | 9347 | 6362 | 47   | 17460| 4241 |
| 12   | 12438| 3987 | 30   | 9547 | 8857 | 48   | 10895| 4818 |
| 13   | 13850| 6882 | 31   | 17942| 3752 | 49   | 13704| 10362|
| 14   | 15196| 8050 | 32   | 11042| 5921 | 50   | 12929| 4844 |
| 15   | 12864| 4804 | 33   | 11387| 5026 |      |      |      |

The load of each vehicle was 500 bags, the driving cost per unit distance was 1 yuan per kilometer, the fixed cost was 100 yuan per day, and the labor cost was 100 yuan per day. These data were used as the parameters for the TDD model (i.e., objective function and constraints). The parameters of the HFWA algorithm were set as follows. The initial flame group size was five, the upper limit of the number of explosive sparks was 50, the lower limit was two, the number of variable sparks was five, and the number of iterations was 1000.
Table 9. Demand and delivery time of customer points

| Node | Demand (packages) | Time (days) | Node | Demand (packages) | Time (days) | Node | Demand (packages) | Time (days) |
|------|-------------------|------------|------|-------------------|------------|------|-------------------|------------|
| 1    | 91                | 3          | 18   | 46                | 3          | 35   | 302               | 6          |
| 2    | 224               | 3          | 19   | 49                | 3          | 36   | 94                | 6          |
| 3    | 215               | 3          | 20   | 85                | 3          | 37   | 249               | 6          |
| 4    | 53                | 6          | 21   | 277               | 6          | 38   | 248               | 3          |
| 5    | 39                | 6          | 22   | 84                | 6          | 39   | 125               | 3          |
| 6    | 164               | 6          | 23   | 268               | 6          | 40   | 130               | 3          |
| 7    | 316               | 6          | 24   | 80                | 3          | 41   | 25                | 3          |
| 8    | 112               | 3          | 25   | 306               | 3          | 42   | 75                | 6          |
| 9    | 192               | 3          | 26   | 115               | 3          | 43   | 175               | 6          |
| 10   | 74                | 3          | 27   | 65                | 3          | 44   | 256               | 6          |
| 11   | 247               | 6          | 28   | 83                | 6          | 45   | 307               | 6          |
| 12   | 84                | 6          | 29   | 203               | 6          | 46   | 42                | 3          |
| 13   | 166               | 6          | 30   | 156               | 6          | 47   | 186               | 3          |
| 14   | 230               | 3          | 31   | 116               | 6          | 48   | 100               | 6          |
| 15   | 293               | 3          | 32   | 273               | 3          | 49   | 57                | 6          |
| 16   | 316               | 6          | 33   | 192               | 3          | 50   | 110               | 6          |
| 17   | 180               | 6          | 34   | 181               | 3          |      |                   |            |

4.3. Case solution. Based on the case data and algorithm parameters discussed above, the distribution costs for the regular delivery and TDD models were calculated. The computational results are listed in Tables 10. and 11. respectively. The average computational time for the particular case study and data set is 15 minutes. Regarding the vehicle number, S represents a first-level vehicle delivery under standard delivery and S* represents a first-level vehicle delivery under flexible delivery.

According to the results in Tables 10. and 11. , transfer satellite S1 was selected as the first-level delivery network for both the regular delivery and TDD models. According to the scope of this study, we only selected the self-pickup points in Jinniu District and transfer satellite S2 is far from the customer points. Therefore, the Jinniu District is only served by transfer satellite S1. In the regular delivery model, four first-level distribution vehicles and 21 second-level delivery vehicles are required. In the TDD model, five first-level delivery vehicles (two for standard delivery and three for flexible delivery) and 20 second-level vehicles (10 for standard delivery and 10 for flexible delivery) are required. In the TDD model, the standard delivery time must be satisfied. The number of vehicles in each level cannot be guaranteed to be minimized, but the service level is guaranteed. Additionally, the delivery completion time of the TDD model (i.e., six days) is one day less than that of the regular delivery model (i.e., seven days). The regular delivery model incurs compensation costs for deliveries made after more than three days. The TDD model does not incur any delay costs and only pays a small amount of compensation for flexible deliveries, resulting in a cost that is 92,541 yuan less than that of the regular delivery model. In terms of cost and delivery time, the TDD strategy can significantly improve efficiency and customer satisfaction.

4.4. Sensitivity analysis. In this section, we perform sensitivity analysis on the impact of the standard delivery time on costs. The results are listed in Table 12.
Table 10. Computational results for the regular delivery model

| Level                               | Vehicle NO. | Standard delivery vehicle route |
|-------------------------------------|-------------|---------------------------------|
| First-level vehicle delivery        | 1S          | D-S1-D                          |
|                                     | 2S          | D-S1-D                          |
|                                     | 3S          | D-S1-D                          |
|                                     | 4S          | D-S1-D                          |
| Second-level vehicle delivery       | 1           | S1-21-18-41-S1                  |
|                                     | 2           | S1-37-12-S1                     |
|                                     | 3           | S1-35-6-S1                      |
|                                     | 4           | S1-42-33-48-1-S1                |
|                                     | 5           | S1-32-20-S1                     |
|                                     | 6           | S1-25-5-S1                      |
|                                     | 7           | S1-29-2-S1                      |
|                                     | 8           | S1-30-22-49-34-S1               |
|                                     | 9           | S1-17-27-S1                     |
|                                     | 10          | S1-44-10-13-S1                  |
|                                     | 11          | S1-4-40-14-S1                   |
|                                     | 12          | S1-45-19-28-S1                  |
|                                     | 13          | S1-24-47-31-26-S1               |
|                                     | 14          | S1-11-39-S1                     |
|                                     | 15          | S1-3-23-S1                      |
|                                     | 16          | S1-38-8-S1                      |
|                                     | 17          | S1-7-S1                         |
|                                     | 18          | S1-9-S1                         |
|                                     | 19          | S1-16-43-S1                     |
|                                     | 20          | S1-50-15-36-S1                  |
|                                     | 21          | S1-46-S1                        |

Delivery time (days) 7
Delay cost (yuan) 32240
Compensation cost (yuan) 0
Total cost (yuan) 2159128

According to Table 12, the penalties and total cost decrease as the window of standard delivery time increases for the regular delivery model. In the TDD model, the compensation cost is related to the number of packages. When the standard delivery time is less than four days or the flexible delivery time is less than six days, there will be penalties. When the standard delivery time is three days and the flexible delivery time is greater than or equal to six days, no penalty is incurred and the total delivery cost is minimized. In summary, although both delivery options can incur compensation costs for customers, the TDD model can fully utilize customer flexibility and avoid late delivery penalties. In practice, unexpected late deliveries typically cause customer dissatisfaction. In this study, we quantified the value of these late penalties. However, the cost of dissatisfied customers cannot truly be
Table 11. Computational results for the TDD model

| Delivery method | Level | Vehicle NO. | TDD vehicle route |
|-----------------|-------|-------------|-------------------|
|                 |       | 1S         | D-S1-D            |
| First-level vehicle delivery | 2S     | D-S1-D     |                    |
| Standard delivery | 3     | S1-26-47-24-8-9-S1 |
|                  | 4     | S1-38-19-20-S1 |
|                  | 5     | S1-32-1-S1  |
| Second-level vehicle delivery | 6     | S1-2-25-S1  |
|                  | 7     | S1-33-41-18-S1 |
|                  | 8     | S1-46-15-S1 |
|                  | 9     | S1-10-27-S1 |
|                  | 10    | S1-39-S1   |
| Flexible delivery | 11    | S1-23-13-S1 |
|                  | 12    | S1-17-44-S1 |
|                  | 13    | S1-37-49-S1 |
| Second-level vehicle delivery | 14    | S1-22-31-11-S1 |
|                  | 15    | S1-16-43-S1 |
|                  | 16    | S1-6-37-12-S1 |
|                  | 17    | S1-21-36-S1 |
|                  | 18    | S1-35-48-S1 |
|                  | 19    | S1-7-5-S1  |
|                  | 20    | S1-29-30-S1 |

Delivery time (days) 6
Delay cost (yuan) 0
Compensation cost (yuan) 2239.5
Total cost (yuan) 1937381

Table 12. Delivery time sensitivity analysis

| Standard delivery time (day) | Penalty (yuan) | Standard delivery cost (yuan) | TDD second-level arrival time (day) | Penalty (yuan) | Compensation cost (yuan) | Total cost of delivery (yuan) |
|------------------------------|----------------|-------------------------------|-------------------------------------|----------------|-------------------------|-------------------------------|
| 2                            | 40300          | 1881455                       | 4                                  | 6250          | 2239.5                  | 1783100                       |
|                              |                |                               | 5                                  | 3750          | 2239.5                  | 1781518                       |
|                              |                |                               | 6                                  | 1250          | 2239.5                  | 1779718                       |
| 3                            | 32240          | 1868263                       | 4                                  | 5000          | 2239.5                  | 1782724                       |
|                              |                |                               | 5                                  | 2500          | 2239.5                  | 1779725                       |
|                              |                |                               | 6                                  | 0             | 2239.5                  | 1775722                       |
| 4                            | 24180          | 1862604                       | 5                                  | 2500          | 2239.5                  | 1779704                       |
|                              |                |                               | 6                                  | 0             | 2239.5                  | 1777541                       |
|                              |                |                               | 7                                  | 0             | 2239.5                  | 1777541                       |
quantified. Expected and compensated late deliveries do not typically cause significant dissatisfaction. Therefore, the TDD strategy is more suitable for addressing demand blowout issues during major promotional events.

5. Conclusions. Based on the rapid development of e-commerce, major promotional activities and holiday shopping have led to explosive growth in logistical demand and potential service failures. To address the logistical demand blowout issue, this study investigated a 2E-VRPDB. We integrated a TDD strategy and HFWA to solve the 2E-VRPDB. The proposed HFWA combines the OCA with the IFWA. Based on comparative analysis considering a GA and ACO, we demonstrated the effectiveness of the proposed HFWA. The proposed approach was applied to a case study of the Jingdong Mall in Chengdu. The results revealed that the proposed TDD strategy can reduce total logistical costs and can be adopted as a new decision support tool for e-commerce and logistics companies.

This study has several limitations. We assumed that depots have sufficient inventory and delivery vehicles, which may not be the case in some scenarios. We did not specify product types and only considered the number of packages as the demand. Additionally, same-day or express deliveries have been adopted by major e-commerce firms (e.g., Amazon.com), necessitating multiple deliveries on the same day. This type of delivery was not incorporated into our model. Therefore, we will consider these directions as future extensions.

Conflict of interests. The authors declare that there is no conflict of interests regarding the publication of this paper.

Data availability statement. All data generated or analyzed during the study are included in the submitted article or supplemental materials files.

Acknowledgments. This work is partially supported by China Postdoctoral Science Foundation (No.2020M673279), National Natural Science Foundation of China (NSFC) (No. 51675450), Sichuan Science and Technology Program (No. 2020JDTD 0012) and MOE (Ministry of Education in China) Project of Humanities and Social Sciences (No. 18YJC630255).

REFERENCES

[1] R. Baldacci, A. Mingozzi, R. Roberti and R. W. Clavo, An exact algorithm for the two-echelon capacitated vehicle routing problem, *Operations Research*, 61 (2013), 298–314.

[2] A. Bevilaqua, D. Bevilaqua and K. Yamanaka, Parallel island based Memetic Algorithm with Lin-Kernighan local search for a real-life Two-Echelon Heterogeneous Vehicle Routing Problem based on Brazilian wholesale companies, *Applied Soft Computing*, 76 (2019), 697–711.

[3] U. Breunig, R. Baldacci, R. F. Hartl and T. Vidal, The electric two-echelon vehicle routing problem, *Computers and Operations Research*, 103 (2019), 198–210.

[4] U. Breunig, V. Schmid, R. F. Hartl and T. Vidal, A large neighbourhood based heuristic for two-echelon routing problems, *Computers and Operations Research*, 76 (2016), 208–225.

[5] M.-C. Chen, P.-I. W and Y.-H. Hsu, An effective pricing model for the congestion alleviation of e-commerce logistics, *Computers and Industrial Engineering*, 129 (2019), 368–376.

[6] Double 11 constantly refreshes the imagination of Chinese market, *Global times*, November 12, 2019 (015).

[7] P. Grangier, M. Gendreau, F. Lehuédé and L.-M. Rousseau, An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization, *European Journal of Operational Research*, 254 (2016), 80–91.
[8] M. Guan, M. Cha, Y. Li, Y. Wang and J. Yu, Predicting time-bounded purchases during a mega shopping festival, 2019 IEEE International Conference on Big Data and Smart Computing (BigComp), (2019), 1–8.

[9] X. Guo, Y. L. Jaramillo, J. Bloemhof-Ruwaard and G. D. H. Claassen, On integrating crowdsourced delivery in last-mile logistics: A simulation study to quantify its feasibility, Journal of Cleaner Production, 241 (2019), 118365.

[10] P. He and J. Li, The two-echelon multi-trip vehicle routing problem with dynamic satellites for crop harvesting and transportation, Applied Soft Computing, 77 (2019), 387–398.

[11] W. Jie, J. Yang, M. Zhang and Y. Huang, The two-echelon capacitated electric vehicle routing problem with battery swapping stations: Formulation and efficient methodology, European Journal of Operational Research, 272 (2019), 879–904.

[12] H. Li, L. Zhang, T. Lv and X. Chang, The two-echelon time-constrained vehicle routing problem in linehaul-delivery systems, Transportation Research Part B: Methodological, 94 (2016), 169–188.

[13] H. Li, H. Wang, J. Chen and M. Bai, Two-echelon vehicle routing problem with time windows and mobile satellites, Transportation Research Part B: Methodological, 138 (2020), 179–201.

[14] H. Li, Y. Liu, X. Jian and Y. Lu, The two-echelon distribution system considering the real-time transshipment capacity varying, Transportation Research Part B: Methodological, 110 (2018), 239–260.

[15] R. Liu, L. Tao, Q. Hu and X. Xie, Simulation-based optimisation approach for the stochastic two-echelon logistics problem, International Journal of Production Research, 55 (2017), 187–201.

[16] T. Liu, Z. Luo, H. Qin and A. Lim, A branch-and-cut algorithm for the two-echelon capacitated vehicle routing problem with grouping constraints, European Journal of Operational Research, 266 (2018), 487–497.

[17] Z. Y. Ma, Y. B. Ling and J. Li, 2E-VRP Optimization Algorithm with Optimal Cutting and Full Path Matching Cross, Computer Engineering, 41 (2015), 279–285.

[18] M. Marinelli, A. Colovic and M. Dell’Orco, A novel Dynamic programming approach for Two-Echelon Capacitated Vehicle Routing Problem in City Logistics with Environmental considerations, Transportation Research Procedia, 30 (2018), 147–156.

[19] E. Morganti, L. Dablancg and F. Fortin, Final deliveries for online shopping: The deployment of pickup point networks in urban and suburban areas, Research in Transportation Business and Management, 11 (2014), 23–31.

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

[21] F. A. Santos, G. R. Mateus and A. S. D. Cunha, A branch-and-cut-and-price algorithm for the two-echelon capacitated vehicle routing problem, Transportation Science, 49 (2015), 355–368.

[22] M. Soysal, J. M. Bloemhof-Ruwaard and T. Bektas, The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations, International Journal of Production Economics, 164 (2015), 366–378.

[23] E. Swilley and R. E. Goldsmith, Black Friday and Cyber Monday: Understanding consumer intentions on two major shopping days, Journal of Retailing and Consumer Services, 20 (2013), 43–50.

[24] Y. Tan and Y. Zhu, Fireworks algorithm for optimization, International Conference in Swarm Intelligence, Berlin: Springer, 355–364.

[25] E. B. Tirkolaee, A. Goli, A. Faridinia, M. Soltani and G. W. Weber, Multi-objective optimization for the reliable pollution-routing problem with cross-dock selection using Pareto-based algorithms, Journal of Cleaner Production, 276 (2020), 122927.

[26] E. B. Tirkolaee, A. Goli, M. Pahelevan and R. M. Kordestanizadeh, A robust bi-objective multi-trip periodic capacitated arc routing problem for urban waste collection using a multi-objective invasive weed optimization, Waste Management and Research, 37 (2019), 1089–1101.

[27] E. B. Tirkolaee, S. Hadian and H. Golpra, A novel multi-objective model for two-echelon green routing problem of perishable products with intermediate depots, Journal of Industrial Engineering and Management Studies, 6 (2019), 196–213.

[28] E. B. Tirkolaee, S. Hadian, G.-W. Weber and I. Mahdavi, A robust green traffic-based routing problem for perishable products distribution, Computational Intelligence, 36 (2020), 80–101.
[29] K. Wang, S. Lan and Y. Zhao, A genetic-algorithm-based approach to the two-echelon capacitated vehicle routing problem with stochastic demands in logistics service, *Journal of the Operational Research Society*, **68** (2017), 1409–1421.

[30] X. M. Yan, Z. F. Hao, H. Huang, B Li and S. Jiang, Assignment-preference ant colony optimization for the two-echelon vehicle routing problem, *Indian Pulp and Paper Technical Association*, **30** (2018), 484–494.

[31] T. T. Zhang and Z. F. Liu, Fireworks algorithm for mean-VaR/CVaR models, *Physica A: Statistical Mechanics and its Applications*, **483** (2017), 1–8.

Received August 2020; 1st revision January 2021; 2nd revision March 2021.

E-mail address: zhangmin@swjtu.edu.cn
E-mail address: xgw9422@qq.com
E-mail address: 1099681647@qq.com
E-mail address: meng5656@gmail.com