Research Article

Multi-Depot Pickup and Delivery Problem with Resource Sharing

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Resource sharing (RS) integrated into the optimization of multi-depot pickup and delivery problem (MDPDP) can greatly reduce the logistics operating cost and required transportation resources by reconfiguring the logistics network. This study formulates and solves an MDPDP with RS (MDPDPRS). First, a bi-objective mathematical programming model that minimizes the logistics cost and the number of vehicles is constructed, in which vehicles are allowed to be used multiple times by one or multiple logistics facilities. Second, a two-stage hybrid algorithm composed of a k -means clustering algorithm, a Clark-Wright (CW) algorithm, and a nondominated sorting genetic algorithm II (NSGA-II) is designed. The k -means algorithm is adopted in the first stage to reallocate customers to logistics facilities according to the Manhattan distance between them, by which the computational complexity of solving the MDPDPRS is reduced. In the second stage, CW and NSGA-II are adopted jointly to optimize the vehicle routes and find the Pareto optimal solutions. CW algorithm is used to select the initial solution, which can increase the speed of finding the optimal solution during NSGA-II. Fast nondominated sorting operator and elite strategy selection operator are utilized to maintain the diversity of solutions in NSGA-II. Third, benchmark tests are conducted to verify the performance and effectiveness of the proposed two-stage hybrid algorithm, and numerical results prove that the proposed methodology outperforms the standard NSGA-II and multi-objective particle swarm optimization algorithm. Finally, optimization results of a real-world logistics network from Chongqing confirm the applicability of the mathematical model and the designed solution algorithm. Solving the MDPDPRS provides a management tool for logistics enterprises to improve resource configuration and optimize logistics operation efficiency.

1. Introduction

With the advancement of information technology and Internet of Things, the logistics industry is playing an increasingly important role in the development of modern businesses [1, 2]. However, national and local governments worldwide are focusing on the environmental impacts of logistics and the efficient use of resources [3, 4]. In a logistics network, customers send out a series of requests for delivery and pickup services, and logistics service providers (LSPs) design service plans and arrange vehicles for these requests to deliver or pickup goods [5, 6]. Efficient logistics service plan can improve the operation efficiency of LSPs and resource utilization [7, 8]. Therefore, making an effective logistics service plan with resource sharing (RS) is essential,

which not only helps to reduce the operating cost for logistics facilities but also promotes the development of green logistics and provides better logistics services for consumers [9, 10].

In this study, a multi-depot pickup and delivery problem with RS (MDPDPRS) combines components from three subproblems: multi-depot vehicle routing problem (MDVRP) with pickups and deliveries (MDVRPPD), MDVRP with pickups and deliveries and time windows (MDVRPPDTW), and RS [11–13]. However, one of the difficult challenges in solving this problem is how to handle pickup and delivery activities among multiple depots through RS [14, 15]. In the traditional MDVRPPD, each vehicle performs only one type of activity in the service route, which may be delivering or picking up goods [16–18].

In addition, the traditional MDVRPPDTW and single-depot vehicle routing problem with pickups and deliveries mostly only consider the optimization of logistics operational costs [19, 20]. Therefore, MDPDPRS focuses on how to support and achieve the efficient utilization of transportation resources with RS strategy, and optimizes the logistics network.

With regard to RS, it is often jointly adopted with collaboration or cooperation between LSPs to optimize the logistics networks with multiple depots [21, 22]. RS strategy supports the sharing of customer information and transport resources to improve the resource configuration among logistics facilities to optimize the logistics network [23, 24]. Here, the sharing of customer information is often enabled by customer clustering, whereas the sharing of transportation resources is related to the use of shared transportation equipment [25, 26].

As for MDVRPPD, it is a crucial logistics issue with extensive applications, especially in reverse logistics [27]. Three basic types of vehicle routing problems exist in reverse logistics [28]. The first type is the vehicle routing problem with mixed deliveries and pickups, which involves customers with delivery demands, pickup demands, and delivery and pickup demands [29]. Vehicle routing problem with simultaneous delivery and pickup is the second type, which requires all customers to have both delivery and pickup demands [30]. The third type is the common MDVRPPD, which includes delivery and pickup customers in the logistics network [19, 31–33]. In this study, the consideration of customer service time windows makes MDVRPPD realistic.

In this study, the MDPDPRS can be formulated into a bi-objective mathematical model to minimize the total logistics operating cost and number of vehicles [32, 34]. On the basis of the multi-depot and RS properties of MDPDPRS, a two-stage hybrid algorithm is proposed to find the Pareto optimal solution. In the first stage, a k -means algorithm is adopted to reconfigure resources through customer clustering; thus, the MDVRPPDTW is simplified for solving [35]. The second stage focuses on finding the Pareto optimal solution for the bi-objective optimization problem [23, 36]. The Clarke-Wright (CW) algorithm, which is good at constructing the initial solution of vehicle routes, and the nondominated sorting genetic algorithm (NSGA-II), which is known for its capability of finding the Pareto solution, are adopted to optimize the vehicle routing in the second stage [33, 37, 38].

The remainder of this study is arranged as follows. Section 2 reviews the relevant literature. Section 3 elaborates the specifics of the MDPDPRS. Section 4 explains the bi-objective mathematical model for the MDPDPRS. Section 5 presents the designed methodology for solving the MDPDPRS. Section 6 analyzes the performance and application of the proposed model formulation and solution algorithm in a real-world case study compatible to the MDPDPRS. Finally, Section 7 summarizes the conclusions and discusses potential future research.

2. Literature Review

MDPDPRS is mainly related to the MDVRPPD, MDVRPPDTW, and RS strategy [18, 36]. MDVRPPD and

MDVRPPDTW are the extension problems of MDVRP and MDVRPTW with respect to the logistics service type of customer demands, responsively [39, 40]. In the widely studied MDVRP and MDVRPTW, the service types of customers are either deliveries or pickups [16, 33, 41]. However, in a real-world logistics network with multiple depots, customers with distribution and pickup demands often exist simultaneously and the service time windows are the additional characteristics of customers; this issue is abbreviated by scholars as MDVRPPD [11, 13]. Therefore, MDVRPPD and MDVRPPDTW have begun to attract the attention of scholars, and the difference between the two issues is mainly whether customers' service time window feature is considered [42, 43]. In the MDVRPPDTW, the optimization of vehicle routes focuses on the confirmation of customers' service time windows and the integration of vehicles' delivery and pickup activities, which are suitable with the factors that LSPs must consider if optimizing vehicle routes [44, 45]. The adoption of RS into the optimization of logistics network is also a current trend [12]. Thus, the MDPDPRS in this study integrates vehicles' distribution and pickup arrangement with the RS strategy to optimize the MDVRPPDTW.

In contrast to the MDVRP, the MDVRPPD studies customers with delivery and pickup demands [35, 42]. The MDVRPPDTW is an extension of MDVRPPD, which considers the characteristics of customer service time windows [46, 47]. Many scholars have studied MDVRPPD and MDVRPPDTW considering diverse aspects and proposed different mathematical models and algorithms [30, 48]. In terms of models, many of the proposed mathematical models reflect the characteristics of their problem studied by different constraints, including capacity, time windows, and priority constraints [29, 49]. Ropke et al. [50] established a standard three-index model based on the characteristics of customer time window and designed an accurate algorithm to solve it. Gribkovskaia et al. [19] studied the vehicle routing problem with deliveries and pickups considering the number of times a customer has been visited and proposed a mixed integer linear programming model. Chen et al. [31] established a comprehensive mathematical model to minimize the transportation costs for unpaired vehicle routing problem with deliveries and pickups in a multi-factory production network. Conversely, hybrid heuristics algorithms (e.g., genetic algorithm and adaptive large neighborhood search algorithm) and exact algorithms based on column generation are commonly designed to solve MDVRPPD and MDVRPPDTW [50–52]. The proposed model and solution methodology in the above studies provide abundant reference for solving the basic MDVRPPD and MDVRPPDTW. However, few studies have optimized MDVRPPDTW with RS strategy [32, 34].

Customer clustering analysis is a research aspect that groups customers based on their characteristics (e.g., location and time window), and common clustering algorithms include k -means clustering, parallel clustering, and fuzzy-based customer clustering [53–56]. In comparison with other customer clustering algorithms, k -means clustering is widely adopted to solve vehicle routing problems [57, 58].

Xu et al.[59] proposed an enhanced ant colony algorithm based on k -means clustering to solve dynamic vehicle routing problems and achieved good optimization results. Hakim et al.[60] designed a cluster-based method to solve a vehicle routing problem with limited vehicle capacity, and their calculation results proved the effectiveness of that method. Mourelo Ferrandez et al.[61] reduced the calculation difficulty of truck-drone in tandem delivery network by k -means clustering algorithm. Wang et al.[35] proposed a hybrid heuristic algorithm based on three-dimensional k -means clustering and improved reference point NSGA-II to solve the multi-objective optimization model. Therefore, cluster analysis can simplify the difficulty of solving vehicle routing problem [62, 63].

At present, the construction of multi-objective optimization model and multi-objective optimization algorithm is the research hotspot of finding the Pareto solution of vehicle routing problems, and scholars have designed different algorithms [38, 64]. NSGA-II and multi-objective particle swarm optimization (MOPSO) algorithm are two common multi-objective algorithms [65, 66]. NSGA-II adopts a reference point strategy to maintain population diversity [67]. Srivastava et al. [68] proposed a NSGA-II to solve the multi-objective optimization model for MDVRPTW and verified that the method is superior to the latest method of that problem through a real-world case study. Maadanpour Safari et al.[69] adopted NSGA-II, multi-objective simulated annealing (MOSA), and MOPSO to optimize the proposed three-objective mathematical function and concluded that NSGA-II was superior to MOSA according to the results of their examples. Shafiei Nikabadi et al. [70] formed a multi-objective model for the route selection of freight fleet, optimized it with NSGA-II and MOPSO, and considered that MOPSO was superior to NSGA-II. Therefore, NSGA-II and MOPSO are two commonly typical multi-objective optimization algorithms that can find Pareto solutions [71].

Many scholars have adopted the cooperation and RS strategy to optimize the multicenter logistics network [11, 17, 24]. Zhang et al. [15] believed that in the collaborative e-commerce truck carrier, participants can share transportation resources and customer demands to maximize the total profit of the whole alliance and improve vehicle utilization. Wang et al. [14] adopted the cooperation strategy to optimize the MDVRPPDTW with minimization of the operating cost of the transportation network and the total number of vehicles. Deng et al. [21] allowed the capabilities of the logistics facility, the vehicle resources, and the customer information to be shared through RS strategies, and they proved that this strategy can improve the utilization of logistics resources. In the study of Nourinejad et al. [72], vehicles can be used multiple times to reduce fleet size by extending vehicle reservation time. Li et al. [73] adopted the resource-sharing strategy to significantly optimize the logistics network and maximized the utilization of resources. Therefore, the adoption of RS strategy not only helps optimize the logistics costs but also improves the utilization of resources to protect the environment [22, 74].

In summary, the existing literature has provided rich reference materials about MDVRPPD, MDVRPPDTW, and

RS, including model formulations and solution algorithms. However, the existing literature related to MDPDPRS has the following limitations. (1) Few studies on MDPDPRS have considered RS, MDVRPPD, and MDVRPPDTW. (2) The fact that a vehicle can be used multiple times on a working day is insufficiently considered in the proposed mathematical models. (3) Most of the proposed solution algorithms in the existing literature only address how to solve MDVRP, MDVRPPD, and MDVRPPDTW, and RS has not been incorporated into the designed algorithms. (4) Most of the existing literature focuses on raising problems and designing algorithms but neglects testing the proposed methods with practical cases.

In consideration of the aforementioned shortcomings, the main contributions of this study to MDPDPRS are as follows: (1) Characteristics of RS, MDVRPPD, and MDVRPPDTW are comprehensively incorporated to enrich the research on MDPDPRS. (2) On the basis of RS, this study proposes and tests that vehicles can be used multiple times and that customer information can be shared to save the transportation resources of logistics networks, which are considered in the proposed mathematical model. (3) A two-stage algorithm is designed to combine RS with vehicle routing optimization to optimize the logistics network. (4) Benchmark and real-world cases are utilized to test and verify the performance and applicability of the proposed model and solution algorithm in this study.

3. Problem Statement

RS is an effective strategy that can optimize logistics operation costs and resource allocation in a multicenter logistics network with pickups and deliveries [21, 35]. In this study, the logistics network consists of multiple distribution centers (DCs), multiple pickup centers (PCs), and multiple customers. The logistics network before and after optimization with RS, which is composed of DC1, DC2, DC3, PC1, PC2, and 52 customers (marked C1, C2, ..., C52), is shown in Figure 1. The numerical number near the line represents the time distance between two elements (including facilities and customers).

In Figure 1(a), the unreasonable arrangement of vehicle routes and the nonsharing of resources are the main reasons for the higher operating costs of the logistics network. First, staggered driving and long-distance service are the two most significant unreasonable arrangements, and they cause additional travel costs. Second, vehicles that violate customers' time windows often occur. Arriving early and arriving late are generating penalty costs. Finally, the nonsharing of resources between facilities results in the capacity of facilities and transportation resources being left unused. For example, the vehicle no longer works after returning from C2 to DC1 in the service route DC1 $\rightarrow$ C25 $\rightarrow$ C6 $\rightarrow$ C1 $\rightarrow$ C2 $\rightarrow$ DC1.

In Figure 1(b), the logistics network is optimized through the sharing of customers and transportation resources among facilities. First, the reallocation of customers between facilities facilitates the rearrangement of vehicles, which can avoid staggering and long-distance service.

(a)

FIGURE 1: Continued.

FIGURE 1: Logistics network optimization diagram of MDPDPRS. (a) Initial logistics network before resource sharing. (b) Optimized logistics network with resource sharing.

Second, vehicle resources can be better configured through sharing among multiple facilities. For example, V1 is used by DC3 and DC1. V2 and V3 have also implemented distribution and pickup services. The repeated use of vehicles prevents resources from being idle. Finally, the situation of vehicle violating the customers' time window is avoided.

To clearly demonstrate the discounts that RS brings to logistics network optimization, six indicators are counted, namely, total travel cost (TTC), total penalty cost (TPC), total maintenance cost (TMC), total fixed cost (TFC), number of vehicles (NV), and total operating cost (TOC), which are listed in Table 1. The unit time travel cost using a vehicle can be set to \$10/h, and the unit time penalty cost for waiting or late can be set to \$20/h, and the maintenance cost using a vehicle in a working period can be defined as \$100, and the fixed cost of a facility being used in a working period can be set to \$200.

In Table 1, the gap of TOC and NV in the initial and optimized logistics network is \$1880 and 7, respectively,

which are highly significant. Before optimization, TTC (\$1500), TPC (\$440), and TMC (\$1400) are the main elements that cause additional logistics costs. In the optimized logistics network, the penalty costs are avoided, and the reduction in the number of vehicles also reduces the maintenance costs with RS. In addition, the travel costs of vehicles are also greatly reduced. Therefore, RS is an effective strategy for optimizing the logistics network of the MDPDPRS.

4. Mathematical Model for MDPDPRS

4.1. Assumptions and Notations. Some necessary assumptions can ensure the usability of the mathematical model [75] and those assumptions are listed as follows [14, 30, 36, 42, 49, 50].

Assumption 1. In a working period, the demand and coordination of customers are stable and known.

Assumption 2. Centralized transportation among logistics facilities is performed by trucks.

Assumption 3. The vehicles can be used multiple times by the same or different logistics facilities.

The relevant notations and their descriptions are listed in Table 2.

4.2. Mathematical Model. A bi-objective mathematical model that minimizes the logistics operational costs (Equation (1)) and the number of vehicles (Equation (2)) is formed to solve the MDPDPRS. In Equation (1), the logistics operation cost is composed of four parts, which are marked by the TTC (Equation (3)), TPC (Equation (4)), TMC (Equation (5)), and TFC (Equation (6)). In Equation (2), $\sum_{c \in S_F} \sum_{h \in C_U} x_{vch}$ represents the shared times of vehicle v .

$$\text{Min TOC} = \text{TTC} + \text{TPC} + \text{TMC} + \text{TFC}, \quad (1)$$

$$\text{Min TNV} = \sum_{v \in V} \min \left\{ \sum_{c \in S_F} \sum_{h \in C_U} x_{vch}, 1 \right\}, \quad (2)$$

$$\begin{aligned} \text{TTC} = & T \times \sum_{v \in V} \sum_{c \in C_U \cup S_F} \sum_{h \in C_U \cup S_F} x_{vch} \times d_{ch} \times f_v \times P_v \\ & + T \times \sum_{b \in B} \sum_{o \in S_F} \sum_{w \in S_F} \sum_{f \in S_F} x_{bowf} \times d_{wf} \times f_b \times P_b, \end{aligned} \quad (3)$$

$$\begin{aligned} \text{TPC} = & T \times \sum_{v \in V} \sum_{c \in C_U} \sum_{f \in S_F} \sum_{k \in R_v} x_{vcfk} \\ & \times (P_E \times \max\{E_c - A_{vck}, 0\} + P_L \times \max\{A_{vck} - L_c, 0\}), \end{aligned} \quad (4)$$

$$\text{TMC} = \sum_{v \in V} \frac{M_v}{W} \min\{R_v, 1\} + \sum_{b \in B} \sum_{o \in S_F} \sum_{w=0} \sum_{f \in S_F} \frac{M_b}{W} \times x_{bowf}, \quad (5)$$

$$\text{TFC} = \sum_{f \in S_F} \frac{z_f \times I_f}{W}. \quad (6)$$

Subject to

$$\sum_{v \in V} \sum_{f \in S_F} \sum_{k \in R_v} x_{vcfk} = 1, \quad \forall c \in C_U, \quad (7)$$

$$R_v = \sum_{c \in S_F} \sum_{h \in C_U} x_{vch}, \quad \forall v \in V, \quad (8)$$

$$\sum_{f \in S_F} x_{vcfk} = 1, \quad \forall v \in V, k \in R_v, c \in C_U, \quad (9)$$

$$\sum_{h \in C_U} x_{vch} - \sum_{h \in C_U} x_{vhc} = 0, \quad \forall v \in V, c \in C_U, \quad (10)$$

$$\sum_{c \in S_F} \sum_{h \in C_U} x_{vch} = \sum_{h \in C_U} \sum_{n \in S_F} x_{vhn}, \quad \forall v \in V, \quad (11)$$

$$\sum_{w=0, f \in S_F \setminus \{o\}} x_{bowf} = \sum_{w=0, f \in S_F \setminus \{o\}} x_{bowf}, \quad \forall b \in B, o \in S_F, \quad (12)$$

$$\sum_{w \in S_F} x_{bowf} - \sum_{w \in S_F} x_{bowf} = 0, \quad \forall b \in B, o, f \in S_F, \quad (13)$$

$$\sum_{c \in C_D} x_{vcfk} \times Q_c^D \leq C_v, \quad \forall v \in V, f \in S_F, k \in R_v, \quad (14)$$

$$\sum_{c \in C_p} x_{vcfk} \times Q_c^P \leq C_v, \quad \forall v \in V, f \in S_F, k \in R_v, \quad (15)$$

$$\sum_{f \in S_F} x_{bof} \cdot Q_{of} \leq C_b, \quad \forall b \in B, o \in S_F, \quad (16)$$

$$Q_{of} = \sum_{c \in C_D} x_{cof} \times Q_c^D, \quad \forall o, f \in D, \quad (17)$$

$$Q_{of} = \sum_{c \in C_p} x_{cfo} \times Q_c^P, \quad \forall o, f \in P, \quad (18)$$

$$\sum_{v \in V} \sum_{c \in C_D} \sum_{k \in R_v} x_{vcfk} \times Q_c^D \leq C_f, \quad \forall f \in S_D, \quad (19)$$

$$\sum_{v \in V} \sum_{c \in C_p} \sum_{k \in R_v} x_{vcfk} \times Q_c^P \leq C_f, \quad \forall f \in S_P, \quad (20)$$

$$E_f \leq G_{vfk} \leq L_f, \quad \forall v \in V, c \in S_F, k \in R_v, \quad (21)$$

$$A_{vck} + t_{cf} \leq G_{vf(k+1)}, \quad \forall v \in V, c, f \in S_F, k \in R_v, \quad (22)$$

$$E_c \leq A_{vck} \leq L_c, \quad \forall v \in V, c \in S_F \cup C_U, k \in R_v, \quad (23)$$

$$E_h \times x_{vch} \leq (A_{vck} + t_{ch}) \times x_{vch} \leq L_h \times x_{vch}, \quad \forall v \in V, c \in C_U, h \in C_U \cup S_F, k \in R_v, \quad (24)$$

$$\sum_{c, h \in S_F \cup C_U} x_{vch} \times t_{ch} \leq T_v, \quad \forall v \in V, \quad (25)$$

$$\begin{aligned} \sum_{c, h \in C_U, r \neq h} x_{vcfk} \times x_{vch} &= \sum_{c \in C_U} x_{vcfk} - 1, \\ \forall v \in V, f \in S_F, k \in R_v, \end{aligned} \quad (26)$$

$$\sum_{f, w \in S_D \setminus \{o\}} x_{bowf} \leq \sum_{f \in S_D \setminus \{o\}} x_{bof} - 1, \quad \forall b \in B, o \in S_D, \quad (27)$$

$$\sum_{f, w \in S_P \setminus \{o\}} x_{bowf} \leq \sum_{f \in S_P \setminus \{o\}} x_{bof} - 1, \quad \forall b \in B, o \in S_P, \quad (28)$$

$$x_{vcfk} = \{0, 1\}, \quad \forall v \in V, c \in C_U, f \in S_F, k \in R_v, \quad (29)$$

TABLE 1: Comparison of MDPDRS before and after optimization.

	TTC (\$)	TPC (\$)	TMC (\$)	TFC (\$)	NV	TOC (\$)	NV	Gap TOC (\$)
Initial	1500	440	1400	1000	14	4340		
Optimized	760	0	700	1000	7	2460	7	1880

TABLE 2: Notations and description.

Set	Description
S_D	Set of DCs, the total number of DCs is N_D
S_P	Set of PCs, the total number of PCs is N_P
S_F	Set of DCs and PCs, $S_F = S_D \cup S_P$
C_D	Set of delivery customers
C_P	Set of pickup customers
C_U	Set of all customers, $U = C_D \cup C_P$
V	Set of vehicles, the total number of vehicles is N_V
B	Set of trucks, the total number of trucks is N_B
Parameters	
Q_c^D	Delivery demand of customer c , $c \in C_D$
Q_c^P	Pickup demand of customer c , $c \in C_P$
$[E_o, L_c]$	Service time window of customer or logistics facility c , $c \in C_U \cup S_F$
d_{ch}	Travel distance between customer or facility c and customer h , $c, h \in C_U \cup S_F$
t_{ch}	Travel time of a vehicle driving from customer or facility c to customer h , $c, h \in C_U \cup S_F$
P_E	Waiting penalty coefficient of arriving earliness (unit: dollars/unit time)
P_L	Tardiness penalty coefficient of arriving delay (unit: dollars/unit time)
W	Number of working periods in a year
T	Number of working days in a working period
T_v	Maximum travel time of vehicle v , $v \in V$
T_b	Maximum travel time of truck b , $b \in B$
f_v	Fuel consumption rate of vehicle v per km (unit: gallon/miles)
f_b	Fuel consumption rate of truck b per km (unit: gallon/miles)
P_v	Gasoline price (unit: dollars/gallon)
P_b	Gasoline price (unit: dollars/gallon)
C_v	Capacity of vehicle v , $v \in V$
C_b	Capacity of truck b , $b \in B$
C_f	Capacity of facility f , $f \in S_F$
M_v	Annual maintenance cost of vehicle v , $v \in V$
M_b	Annual maintenance cost of truck b , $b \in B$
I_f	Annual fixed cost of facility f , $f \in S_F$
R_v	The total service route number of vehicle v , $v \in V$
G_{vfk}	The departure time of vehicle v from facility f in the k th service route, $v \in V$, $f \in S_F$, $k \in R_v$
A_{vck}	The arriving time of vehicle v at customer or facility c in the k th service route, $v \in V$, $c \in C_U \cup S_F$, $k \in R_v$
Q_{of}	The number of transported goods from facility o to f , $o, f \in S_F$
Variables	
x_{vcfk}	$x_{vcfk} = 1$ if customer c is served by vehicle v departing from DC or PC f in the k th service route of vehicle v ; otherwise, $x_{vcfk} = 0$, $v \in V$, $c \in C_U$, $f \in S_F$, $k \in v$
x_{cof}	$x_{cof} = 1$ if the facility providing logistics service for customer c is changed from facility o to f ; otherwise, $x_{cof} = 0$, $c \in C_U$, $o, f \in S_F$
x_{vch}	$x_{vch} = 1$ if vehicle v travels directly from facility o or customer c to h ; otherwise, $x_{vch} = 0$, $v \in V$, $c, h \in S_F \cup C_U$
x_{bof}	$x_{bof} = 1$, if the goods transported from facility o to f is carried by truck k ; otherwise, $x_{bof} = 0$, $b \in B$, $o, f \in S_F$
x_{bowf}	$x_{bowf} = 1$, if truck k departs from facility o and travels directly from facility w to f ; otherwise, $x_{bowf} = 0$, $b \in B$, $o, w, f \in S_F$
z_f	$z_f = 1$ if facility f agrees to share resource, otherwise, $z_f = 0$, $f \in S_F$.

$$x_{cof} = \{0, 1\}, \quad \forall c \in C_U, o, f \in S_F, \quad (30)$$

$$x_{vch} = \{0, 1\}, \quad \forall v \in V, c, h \in C_U \cup S_F, \quad (31)$$

$$x_{bof} = \{0, 1\}, \quad \forall b \in B, o, f \in S_F, \quad (32)$$

$$x_{bowf} = \{0, 1\}, \quad \forall b \in B, o, w, f \in S_F, \quad (33)$$

$$z_f = \{0, 1\}, \quad \forall f \in S_F. \quad (34)$$

Constraint (7) ensures that each customer is served once. Constraint (8) counts the shared times of vehicle v . Constraints (9)–(11) ensure that flow conservation is achieved on each customer. Constraints (12) and (13) are the flow balance constraints of the truck. Constraints (14)–(16) ensure that the loading quantity of each vehicle and each truck cannot

exceed their capabilities. Constraints (17) and (18) count the quantity of transshipment goods between logistics facilities. Constraints (19) and (20) guarantee that the total service quantity of each facility does not exceed its capacity. Constraints (21) and (22) require that the departure time and return time of each vehicle must meet the service time window of its served facility. Constraints (23) and (24) ensure that each vehicle must provide services for customers within the customers' service time window. Constraint (25) requires that the total working time of each vehicle does not exceed its maximum working time. Constraints (26)–(28) are used to eliminate the sub-tours of each vehicle and truck. The constraints of relevant binary variables are listed in Constraints (29)–(34).

5. Solution Methodology for MDPDPRS

MDVRPTW and MDVRPPDTW are typical NP-hard problems [12, 18, 41]. Multi-objective optimization algorithm and two-stage algorithm are often designed in combination to solve MDVRPPDTW [14, 23, 36]. Here, a two-stage algorithm with customer clustering first and then vehicle routing optimization is designed to solve MDPDPRS. This two-stage hybrid algorithm is composed of k -means, CW, and NSGA-II algorithms, and named KCW-NSGA-II. In the first stage of KCW-NSGA-II, customers and resources are reconstructed by the k -means clustering algorithm [57, 58]. The main purpose of the second stage is to optimize vehicle routes and find the Pareto optimal solution. The CW algorithm is adopted to construct the initial solution for NSGA-II [33, 37, 64, 65, 67].

The designed algorithm flow is illustrated in Figure 2. Here, Gen is the current number of iterations; $MaxGen$ is the maximum number of iterations; r is the number of iterations of the current internal re-optimization mechanism, which is between clustering and vehicle routing optimization; and $MaxR$ is its maximum number of iterations.

In Figure 2, the two-stage characteristics of customer clustering first and vehicle routing optimization later are clearly demonstrated. First, a k -means customer clustering mechanism based on Manhattan distance is designed. The clustering results are checked, updated, and saved after finishing the reallocation of all customers. Second, the CW algorithm is adopted to design the initial population and initial feasible solution, which accelerates the speed and possibility of NSGA-II algorithm to find the Pareto optimal solution. Third, the elite strategy and genetic operation of NSGA-II are used to iteratively optimize the generated initial solution to find the Pareto optimal solution, which is mainly embodied in the change of Gen . Fourth, a regulatory re-optimization mechanism between customer clustering and vehicle routing optimization is set up to maintain gene stability during genetic operation, and this mechanism is implemented by the re-updating of r . Finally, if Gen is updated to $MaxGen$, then the iterative optimization of the algorithm is finished and the found Pareto optimal solution is outputted.

5.1. K-Means Clustering Algorithm. Customer clustering is an important measure to reduce the complexity of solving MDVRPPDTW [36]. K -means algorithm is widely used to

solve MDVRPTW due to its simplicity and efficiency [14, 21]. The k -means clustering pseudocode based on Manhattan distance is listed in Algorithm 1.

5.2. CW Algorithm. A common and effective way to construct the initial solution of VRP is the CW savings algorithm, which is actually a greedy heuristic algorithm [33, 37, 76]. The service time windows of customers and the capacity of vehicles are the main constraints to construct the initial solution [77, 78]. The pseudocode of the CW algorithm designed in this study is listed in Algorithm 2.

5.3. NSGA-II. NSGA-II is a multi-objective optimization algorithm based on GA, which searches the Pareto optimal solution for multi-objective optimization [38, 64, 68]. Fast nondominated sorting operator, individual crowding distance operator, and elite strategy selection operator are the three key designs of NSGA-II [33, 65]. Here, we suppose that the population is P and n individuals exist, and the individual objective function value of individual i is x_i .

5.3.1. Fast Nondominated Sorting Operator. The key design of NSGA-II is to find the Pareto optimal solution. To enhance the possibility of finding the Pareto solution, the fast nondominated sorting operator stratifies the population P according to the quality of individual solutions [33, 64, 65, 67]. This method is a cyclic process of grading based on population fitness. Here, the nondominated solution set and the rank value assigned to the individual are the two indicators for fast nondominated sorting. Assume that F_i represents the nondominated solution set, and i_r represents the rank value of individual i . Then, the pseudocode of the fast nondominated sort operator is shown in Algorithm 3.

5.3.2. Crowding Distance and Its Comparison Principle. The crowding distance is designed to drive the population to converge to the Pareto optimal solution and maintain the diversity of the population, which is mainly for individuals in the same nondominant layer [38, 64, 68]. We assume that n individuals exist in the nondominant level of S_F , and the objective function value of individual i is x_i . Then, the crowding distance is calculated as

$$L(i) = \begin{cases} \infty, & i = 1 \text{ or } i = n, \\ |x_{i-1} - x_{i+1}|, & i = 2, 3, \dots, n-1. \end{cases} \quad (35)$$

In Equation (35), $|x_{i-1} - x_{i+1}|$ represents the sum of the distance between individuals $i-1$ and $i+1$ in each direction of the objective function. Here, the objective function values of individuals need to be sorted before calculating the crowding distance. If the rank values of individuals i and j are i_r and j_r , then the crowding distance is $L(i)$ and $L(j)$, respectively. The individual crowding comparison strategy based on crowding distance and nondominated ranking results is as follows.

FIGURE 2: Algorithm flowchart of MDPDPRS.

Input: The datasets, including logistics facility and customer information, such as the coordination, time windows, and demands

Output: The clustering results

- (1) **Step 1:** Select k objects as the initial clustering center
- (2) **Step 2:** Calculate the Manhattan distance between each customer and each clustering center
- (3) **Step 3:** (Re-)Assign each customer to their closest clustering center
- (4) **Step 4:** If some customers need to be adjusted among the clustering results, then enter **Step 3**; otherwise, go to **Step 5**
- (5) **Step 5:** Update the clustering centers
- (6) **Step 6:** Output the clustering results

ALGORITHM 1: Procedure of k -means algorithm.

- (1) If $i_r > j_r$, then individual i is the best one. If $i_r < j_r$, then individual j is the best one.
- (2) If $i_r = j_r$, then the individual with the most crowded distance is the better one.

5.3.3. Elite Strategy Selection Operator. To prevent the Pareto optimal solution from being lost in the iteration process, an elite strategy selection operator is designed, which selects the optimal solution by nondominated sorting and crowding distance between the parent and offspring populations. Suppose that the current iteration is t and the parent population is P_t , the offspring population is Q_t , and R_t is composed by P_t and Q_t . First, a fast nondominated sorting is performed for R_t , and the crowding distance is then calculated. On the basis of the crowding distance and the nondominated layer, N individuals with high-quality solution is selected to form a new population P_{t+1} .

6. Empirical Analyses

6.1. Algorithm Comparison. The standard NSGA-II, GA-PSO, and MOPSO are adopted for comparison to verify the applicability and effectiveness of the proposed KCW-NSGA-II algorithm in solving MDPDRS [38, 64–66, 68, 79]. The benchmark dataset C-mdvprtw (consisting of instances of 20 groups) is utilized for the test, which is mainly obtained from the website. Networking and emerging optimization and their related characteristics are listed in Table 3. To meet the characteristics of the research object in this study, depots are regarded as logistics facilities, and customers are divided into two types, that is, those with distribution demands and those with pickup demands.

In Table 3, the number of customers and logistics facilities in each instance is different. The first instance comprises four facilities and 48 customers, whereas Instance 10 includes six facilities and 288 customers. In addition, the loading capacity of vehicle used in each instance is differentiated.

Relevant parameters are properly unified to mitigate their effects on algorithm performance. These parameters are set as follows [38, 64–66, 68, 79]: (1) parameters about GA: population size $popsiz = 200$, selection possibility $sp = 0.6$, crossover possibility $cp = 0.9$, mutation possibility $mp = 0.2$; (2) parameters about PSO: $popsiz = 200$, inertia weight $iw = 0.85$, the personal learning confidences $pc = 2$, and social learning confidence $gc = 3$; and (3) other relevant parameters: maximum number of generation $genmax = 1200$ and velocity of vehicle $v = 5$. The costs, number of vehicles (NV), and computation time (CT) are calculated to verify the performance of the algorithms and the numerical results are listed in Table 4.

The numerical results shown in Table 4 demonstrate that the proposed algorithm KCW-NSGA-II performs better than the other three algorithms. First, the average cost of the four algorithms is \$2584, \$2944, \$2746, and \$3025, respectively. By contrast, the costs and the number of vehicles optimized by KCW-NSGA-II are the most economical

solution compared with the other three algorithms in each instance. Second, the value of t -test also shows that the KCW-NSGA-II is significantly different from the other three algorithms. In addition, the proposed algorithm can obtain the optimal solution quickly. Therefore, the proposed algorithm KCW-NSGA-II outperforms the other three algorithms. Moreover, this algorithm can be adjusted to address problems such as VRPMDP, VRPSDP, and PVRP.

6.2. Data Source and Relevant Parameter Setting. As an inland international logistics hub and an open highland, Chongqing is a new first-tier city in China. Therefore, as our numerical experiments, the logistics network adopted from Chongqing is appropriate to verify the applicability of this study. Six logistics facilities (i.e., DC1, DC2, DC3, PC1, PC2, and PC3) and 220 customers are the main elements of this real-world logistics network. The information and characteristics of these elements are listed in Table 5, and the spatial allocation information is plotted in Figure 3.

In Table 5, the number of customers served by the six logistics facilities is 27, 36, 39, 46, 31, and 41, respectively. In Figure 3, an obvious feature is that the customer allocation of each facility is relatively dispersed. The service area edge of each facility is not a clear division. In Table 6, the initial vehicle routes for the logistics network are shown, including the specific information of each service route.

In Table 6, the total number of vehicles used in the initial logistics network is 33, and the number of vehicles used at each facility is 5, 6, 6, 6, 4, and 6, respectively. In addition, some vehicles return to their origin early, such as V9, V10, V17, and V18, indicating that these vehicle resources are underutilized. The service vehicle routes of DC1 and the 27 customers it serves in the logistics network are shown in Figure 4.

In Figure 4, the service routes of V3, V4, and V5 are relatively complex. V5 performs delivery services for customers C23, C22, C6, C16, C2, and C5. However, these customers may be closer to DC3 on the basis of the perspective of spatial distribution. Therefore, optimizing this logistics network is necessary. The values of the relevant parameters used in this real-world case study are shown in Table 7 [38, 64, 65, 68].

6.3. Optimization Results. Clustering customers to optimize resource allocation is the first step in optimizing the logistics network. The customer clustering results of this logistics network by k -means algorithm are shown in Figure 5.

In Figure 5, the service relationship between customers and facilities is optimized by clustering. Each customer is covered by the logistics facility that is located close to that customer. On the whole, the service area of each logistics facility has been obviously allocated. For example, C23, C22, C6, C16, and C2 are served by DC1 before clustering; however, they are also served by DC3. Statistical analysis of customers whose service relationship has changed like those five customers is the key to handle centralized transportation. The details of the amount of goods transferred among facilities are shown in Figure 6.

Input: The datasets of customer and facility information including location, time window, demand, and other relevant parameters

Output: The initial feasible solution

- (1) **Step 1:** Mark the initial distance saving values with numbers 1, 2, 3, ..., (n-1)
- (2) **Step 2:** Assign vehicles to each customer
- (3) **Step 3:** Calculate the distance savings of new vehicle routes, which are formed by any two routes
- (4) **Step 4:** Sort the distance savings in descending order
- (5) **Step 5:** If new vehicle routes meet the time window and capacity constraints, then go directly to **Step 6**; otherwise set $n=n+1$ and return to **Step 5**
- (6) **Step 6:** Generate a new vehicle route with two vehicle routes whose distance savings are maximum
- (7) **Step 7:** Update the distance savings value through the fusion of vehicle routes
- (8) **Step 8:** Generate new vehicle route with two vehicle routes whose distance savings are maximum
- (9) **Step 9:** $n = 1$
- (10) **Step 10:** If new vehicle routes meet the time window and capacity constraints, then go directly to **Step 11**; otherwise, return to **Step 7**
- (11) **Step 11:** $n = n+1$
- (12) **Step 12:** Generate new vehicle route with two vehicle routes whose distance savings are maximum
- (13) **Step 13:** If there exists a route that serves only one, then go back to **Step 7**; otherwise enter **Step 14**
- (14) **Step 14:** Output the service route of each vehicle

ALGORITHM 2: Procedure of CW algorithm.

Input: Initial population P

Output: The nondominated sorting results of population P

- (1) **Step 1:** Setting $PP=P$, $rank=1$, $F=1$
- (2) **Step 2:** for $F=1:n$
- (3) **Step 3:** for $i=1:n$
- (4) **Step 4:** for $j=1:n$ & $j \neq i$
- (5) **Step 5:** Compare the solution quality of x_i and x_j , and determine the dominant and nondominant relationships of i and j .
End
- (6) **Step 6:** If x_i is superior to all x_j , then the individual i is considered to be a nondominant individual, and the nondominant ranking value of i is $rank$
End
- (7) **Step 7:** The nondominant individuals found in the above steps constitute set S_F , which is regarded as the F -level nondominant layer of the population P
- (8) **Step 8:** $PP=PP \setminus S_F$, $i_r=i_r+1$
- (9) **Step 9:** If PP is an empty set, then enter **Step 10**, otherwise continuous this cycle
- (10) **Step 10:** Stratify population P
- (11) **Step 11:** End

ALGORITHM 3: Procedure of the fast nondominated sorting operator.

In Figure 6, the amount of goods shipped from DC1 to DC2 is zero; thus, the initial customers of DC1 are not allocated to DC2 with clustering. The amount of goods transported from DC2 to DC1 is 170, which indicates that the service relationship of some customers has changed from DC2 to DC1. Here, the spatial distance between DC1 and DC2 is 33.07 km. The centralized transportation service routes of the truck are listed in Table 8.

In Table 8, T1 and T2 serve three routes. At the end of each service route, the trucks should return to their origin. The activity of T1 occurs early on each workday, and that of T2 occurs late on each workday. Table 9 shows the optimized vehicle service routes.

In Table 9, the number of vehicles used jointly by the six logistics facilities is 12. Some of the vehicles are used multiple times within and between the facilities. For example, V1 performs the route DC1 $\rightarrow$ C86 $\rightarrow$ C13

$\rightarrow$ C20 $\rightarrow$ C11 $\rightarrow$ C4 $\rightarrow$ C12 $\rightarrow$ C7 $\rightarrow$ C5 $\rightarrow$ C1 $\rightarrow$ C25 $\rightarrow$ C3 $\rightarrow$ C8 $\rightarrow$ DC1 and the route DC3 $\rightarrow$ C73 $\rightarrow$ C97 $\rightarrow$ C42 $\rightarrow$ C2 $\rightarrow$ C82 $\rightarrow$ C29 $\rightarrow$ C16 $\rightarrow$ C40 $\rightarrow$ DC3, which occur in DC1 and DC3, respectively. V10 provides service for PC2 and PC3 successively. V2, V4, and V6 are shared in DC1, DC2, and DC3, respectively.

To clarify the effect of the proposed model and algorithm, the gap of the cost and the number of vehicles in the initial and optimized logistics network are counted and listed in Table 10. Here, the TOC of the logistics facility includes the TTC, TFC, TPC, and TMC. Centralized transportation is a special project generated by the sharing of customer information and transportation resources among facilities. Therefore, the costs of centralized transportation should be jointly borne by all the facilities participating in the sharing. Similarly, given that

TABLE 3: Characteristics of benchmark datasets.

Instance	Datasets	Maximum loading capacity	Number of depots		Number of customers	
			DCs	PCs	Delivery demands	Pickup demands
1	C-mdvrptw-pr01	200	2	2	24	24
2	C-mdvrptw-pr02	195	2	2	48	48
3	C-mdvrptw-pr03	190	2	2	72	72
4	C-mdvrptw-pr04	185	2	2	96	96
5	C-mdvrptw-pr05	180	2	2	120	120
6	C-mdvrptw-pr06	175	2	2	144	144
7	C-mdvrptw-pr07	200	3	3	36	36
8	C-mdvrptw-pr08	190	3	3	72	72
9	C-mdvrptw-pr09	180	3	3	108	108
10	C-mdvrptw-pr10	170	3	3	144	144
11	C-mdvrptw-pr11	200	2	2	24	24
12	C-mdvrptw-pr12	195	2	2	48	48
13	C-mdvrptw-pr13	190	2	2	72	72
14	C-mdvrptw-pr14	185	2	2	96	96
15	C-mdvrptw-pr15	180	2	2	120	120
16	C-mdvrptw-pr16	175	2	2	144	144
17	C-mdvrptw-pr17	200	3	3	36	36
18	C-mdvrptw-pr18	190	3	3	72	72
19	C-mdvrptw-pr19	180	3	3	108	108
20	C-mdvrptw-pr20	170	3	3	144	144

TABLE 4: Comparison results of the four algorithms.

Instance	KCW-NSGA-II			NSGA-II			GA-PSO			MOPSO		
	Cost	NV	CT	Cost	NV	CT	Cost	NV	CT	Cost	NV	CT
1	1033	4	71	1178	4	77	1298	5	82	1593	5	98
2	1787	8	72	1724	9	91	2172	10	93	2115	8	119
3	2742	17	110	3121	18	133	2879	18	103	3309	18	127
4	3216	20	129	4027	21	146	3371	21	171	3579	21	184
5	3693	18	181	3827	22	239	3835	22	217	4121	30	264
6	3569	15	306	3671	23	290	4008	24	301	4577	33	298
7	1687	7	85	2386	9	83	1767	8	97	2044	14	79
8	2093	12	95	2394	13	141	2181	12	114	2361	12	147
9	2614	19	218	4010	22	210	2653	20	203	3167	30	240
10	3123	24	258	3355	24	311	3277	25	277	3459	29	325
11	1118	4	77	1405	5	74	1190	6	85	1754	11	101
12	2068	10	94	2692	11	96	2394	11	88	2135	11	114
13	2570	18	97	2655	18	103	2690	22	119	3282	28	99
14	3028	21	162	3564	24	186	3108	23	162	3620	25	172
15	3709	22	209	4117	26	240	3812	27	241	4272	33	248
16	3993	25	262	4072	25	305	4154	28	301	4366	34	339
17	1578	7	69	1763	7	87	1665	7	65	1652	7	126
18	2324	12	66	2428	12	110	2430	14	109	2635	19	166
19	2440	20	212	2790	21	206	2493	22	202	3029	22	241
20	3295	23	186	3692	25	316	3546	25	213	3421	26	309
Average	2584	15	148	2944	17	172	2746	18	162	3025	21	190
<i>t</i> -test				-13.95	-3.73	-3.29	-6.44	-4.76	-3.41	-8.60	-4.84	-5.31
<i>p</i> -value				9.8E-12	7.2E-04	1.9E-03	1.8E-06	6.8E-05	1.5E-03	2.8E-08	5.7E-05	2.0E-05

the vehicle is shared and some vehicles are used multiple times, the maintenance of the vehicles should be co-paid by all facilities.

In Table 10, the fixed costs of each facility are stable, which are \$315, \$427, \$533, \$578, \$612, and \$590, respectively. Reducing the travel, penalty, and maintenance costs is the main objective of optimizing the logistics operating cost. The TOC of

the initial logistics network is \$25473, whereas the optimized TOC is \$16614, which indicates that the logistics network is significantly improved. Transportation resources are greatly saved, as the number of vehicles before and after optimization is 33 and 14, respectively. The gap of TTC before and after optimization is shown in Figure 7, which can directly prove the optimization effect of vehicle routes.

TABLE 5: Characteristics of the logistics network.

Symbol	Description	Number of served customers	Mark of customers
DC1 and its customers	27	C1 - C27
DC2 and its customers	36	C28 - C63
DC3 and its customers	39	C64 - C102
PC1 and its customers	46	C103 - C148
PC2 and its customers	31	C149 - C179
PC3 and its customers	41	C180 - C220

FIGURE 3: Spatial distribution of DCs, PCs, and their customers.

TABLE 6: Distribution routes of DCs and pickup routes of PCs in the initial logistics network.

Facility	Vehicle	Departure time	Arriving time	Route
DC1	V1	162	689	DC1→C19→C1→C17→DC1
	V2	0	906	DC1→C13→C7→C20→C12→DC1
	V3	159	619	DC1→C8→C25→C11→C3→C4→C10→DC1
	V4	33	730	DC1→C27→C24→C21→C9→C26→C14→C15→C18→DC1
	V5	0	924	DC1→C23→C22→C6→C16→C2→C5→DC1
DC2	V6	0	1037	DC2→C42→C45→C48→C34→C35→C50→C54→DC2
	V7	30	1016	DC2→C58→C39→C41→C47→C37→C30→C43→C40→DC2
	V8	0	1014	DC2→C46→C61→C28→C59→C36→C32→C62→C52→C60→DC2
	V9	0	319	DC2→C63→C51→C49→DC2
	V10	35	823	DC2→C56→C55→C38→C53→DC2
	V11	10	1196	DC2→C31→C33→C44→C29→C57→DC2

TABLE 6: Continued.

Facility	Vehicle	Departure time	Arriving time	Route
DC3	V12	121	1002	DC3→C83→C98→C95→C77→C73→C93→C75→DC3
	V13	92	831	DC3→C79→C89→C92→C69→C101→C90→C68→DC3
	V14	109	1176	DC3→C86→C99→C78→C82→C100→C64→DC3
	V15	0	865	DC3→C102→C81→C85→C76→C70→C80→C97→C88→DC3
	V16	0	936	DC3→C74→C67→C84→C87→C71→C72→C91→C65→C96→DC3
	V17	0	295	DC3→C94→C66→DC3
PC1	V18	0	353	PC1→C114→C145→C119→PC1
	V19	19	891	PC1→C117→C125→C121→C120→C130→C113→C128→C111→C118→PC1
	V20	4	992	PC1→C115→C144→C116→C123→C140→C122→C106→C139→C124→PC1
	V21	95	1103	PC1→C135→C104→C136→C103→C147→C142→C141→C143→C112→PC1
	V22	138	951	PC1→C148→C133→C146→C107→C131→C137→C138→PC1
	V23	0	1055	PC1→C134→C132→C105→C127→C129→C126→C110→C109→C108→PC1
PC2	V24	0	883	PC2→C165→C162→C153→C151→C170→C168→C158→PC2
	V25	37	1067	PC2→C149→C179→C174→C176→C169→C166→C159→0
	V26	0	1115	PC2→C156→C172→C167→C157→C155→C152→C163→C150→PC2
	V27	18	819	PC2→C171→C178→C160→C161→C164→C177→C154→C173→C175→PC2
PC3	V28	202	1031	PC3→C192→C201→C182→C184→PC3
	V29	127	918	PC3→C220→C183→C193→C214→C207→C217→C205→C202→C180→PC3
	V30	0	720	PC3→C206→C211→C209→C212→C200→C215→C196→PC3
	V31	23	1121	PC3→C191→C185→C187→C188→C216→C199→PC3
	V32	217	674	PC3→C181→C213→C219→C203→C195→C210→PC3
	V33	66	918	PC3→C204→C198→C194→C197→C186→C208→C218→C190→C189→PC3

FIGURE 4: Initial vehicle service routes of DC1.

In Figure 7, the initial TTC of DC1, DC2, DC3, PC1, PC2, and PC3 is \$2210, \$3581, \$3730, \$4900, \$3067, and \$3506, respectively. The optimized TTC of each facility is \$2047, \$1738, \$1134, \$2064, \$2025, and \$2361, respectively. The

difference of TTC before and after optimization is relatively obvious. Although the transportation cost generated by the centralized transportation is \$1651, the logistics network is still significantly optimized on the whole.

TABLE 7: Relevant parameter setting.

Parameter	Numerical value	Parameter	Numerical value
P_E	\$35 per hour	C_b	1000
P_L	\$35 per hour	C_f	2000
W	52	M_v	\$13000
T	7	M_b	\$20000
T_v	10 hour	$[I_{DC1}, I_{DC2}, I_{DC3}, I_{PC1}, I_{PC2}, I_{PC3}]$	$[\$315, \$427, \$533, \$578, \$612, \$590]$
T_b	15 hour	Population size	300
f_v	0.363 gallon per miles	Maximum generations	1000
f_b	0.566 gallon per miles	Crossover probability	0.8
P_v	\$6.18 per gallon	Mutation probability	0.2
P_b	\$6.18 per gallon	Travel speed of vehicle	40
C_v	200	Travel speed of truck	60

(a)
FIGURE 5: Continued.

FIGURE 5: Customer clustering results with k-means algorithm. (a) Customer clustering results with DCs as cluster centers. (b) Customer clustering results with PCs as cluster centers.

FIGURE 6: Description of transmissions and distances among facilities.

TABLE 8: Optimized truck routes of centralized transportation.

Truck	Service routes
T1	DC1 → DC2 → DC1
	DC2 → DC3 → DC1 → DC2
	DC3 → DC2 → DC1 → DC3
T2	PC1 → PC2 → PC3 → PC1
	PC2 → PC3 → PC1 → PC2
	PC3 → PC2 → PC1 → PC3

6.4. Analysis and Discussion. The optimization of the logistics network is divided into four cases based on the RS strategy to analyze the influence of RS on the optimization

of the logistics network. In Case 1, customer information and transportation resources are privately owned by each logistics facility. In Case 2, RS is adopted by DCs (i.e., DC1, DC2, and DC3). Correspondingly, in Case 3, the members participating in RS are PCs (i.e., PC1, PC2, and PC3). In Case 4, all six facilities receive the RS strategy. Transportation resources can be used jointly by DCs and PCs in Case 4. Table 11 and Figure 8 show the numerical optimization results of the logistics network in the four scenarios.

In Table 11 and Figure 8, Case 4 outperforms Cases 2 and 3 in most aspects. First, the TOC of Cases 2 and 3 is \$17038 and \$16977, respectively, which are larger than

TABLE 9: Vehicle distribution and pickup sharing routes in the optimized logistics network.

Vehicle	Facility	Departure time	Arriving time	Origin	Destination	Vehicle distribution and pickup sharing routes
V1		200	602	DC1	DC3	C86→C13→C20→C11→C4→C12→C7→C5→C1→C25→C3→C8
V2		107	427	DC1	DC1	C24→C79→C39→C27→C89→C74→C51→C14→C9→C92
V2	DC1	577	1102	DC1	DC1	C17→C90→C101→C78→C30→C18→C65→C35→C96→C75→C50→C54→C57
V3		0	773	DC1	DC1	C63→C21→C45→C19→C26→C69→C37→C15→C10→C68
V4		0	420	DC2	DC2	C46→C31→C102→C61→C33→C56→C85→C66→C81→C76→C32
V5		491	1007	DC2	DC2	C62→C52→C80→C70→C99→C88→C53→C100→C43→C64→C60
V5	DC2	65	526	DC2	DC2	C49→C58→C94→C28→C36→C59→C41→C47→C38→C44
V1		672	938	DC3	DC3	C73→C97→C42→C2→C82→C29→C16→C40
V6		121	433	DC3	DC3	C83→C22→C6→C84→C67→C48→C87→C55→C23
V6		450	712	DC3	DC3	C98→C95→C77→C34→C71→C72→C93→C91
V7		69	556	PC1	PC1	C119→C115→C198→C130→C194→C161→C186→C128→C116
V7		640	1089	PC1	PC1	C122→C134→C140→C131→C139→C137→C118→C138→C109→C218→C110→C108→C124
V8		91	351	PC1	PC1	C145→C135→C104→C172→C126→C144→C204→C125
V8	PC1	393	906	PC1	PC1	C113→C148→C146→C133→C152→C107→C200→C215→C208→C106→C202
V9		37	571	PC2	PC2	C219→C220→C103→C213→C206→C174→C192→C169→C173→C175→C184
V9		592	1104	PC2	PC2	C149→C165→C162→C179→C196→C207→C212→C195→C189→C203→C201→C182→C166→C159
V10		0	630	PC2	PC3	C114→C211→C156→C120→C176→C209→C197→C177→C164→C154→C127→C129→C111
V10	PC2	692	997	PC3	PC3	C141→C188→C143→C163→C150→C216→C190→C112
V11		24	306	PC3	PC3	C117→C191→C180→C132→C160→C171→C183→C155
V11		355	843	PC3	PC3	C167→C136→C153→C142→C147→C187→C185→C123→C205→C170
V12	PC3	49	170	PC3	PC3	C121→C105→C178→C217
V12		192	928	PC3	PC3	C181→C157→C193→C151→C214→C210→C168→C158→C199

TABLE 10: Comparison before and after optimization.

Facility	Initial TOC				NV	Optimized TOC				NV	Gap	
	TTC	TFC	TPC	TMC		TTC	TFC	TPC	TMC		TOC	NV
DC1	2210	315	27	179	5	2047	315	0				
DC2	3581	427	55	214	6	1738	427	0				
DC3	3730	533	44	214	6	1134	533	0	429	12	8859	19
PC1	4900	578	65	214	6	2064	578	0				
PC2	3067	612	22	143	4	2025	612	0				
PC3	3506	590	33	214	6	2361	590	0				
Centralized transportation	–	–	–	–	–	1651	–	0	110	2		
Total			25473		33		16614			14	–	–

FIGURE 7: Comparison results of TTC before and after optimization.

TABLE 11: Comparison results of the four cases.

Cases	TTC (\$)	TPC (\$)	TFC (\$)	NV	TMC (\$)	TOC (\$)	NV	Gap	
								TTC (\$)	TOC (\$)
Case 1	20994	246	3055	33	1178	25473			
Case 2	17038	120	3055	23	841	21053	10	3956	4420
Case 3	16977	126	3055	24	876	21034	9	4017	4439
Case 4	13020	0	3055	14	539	16614	19	7974	8859

\$13020 in Case 4. Second, the number of vehicles and the TMCs of Scenario 4 is 14 and \$539, respectively, which indicates that Case 4 is more conducive to saving resources. Finally, the gap of TOC between Cases 4 and 1 is \$8859. Therefore, if the six logistics facilities adopt RS simultaneously, then the logistics costs can be optimized better and the transportation resources can be saved considerably.

6.5. Management Insights. In this study, the RS strategy optimizes the logistics network significantly by reallocating customers, including the logistics operation costs and the

number of vehicles. Therefore, the management insights obtained in this study are as follows:

- (1) In a multi-depot, large-scale logistics network with pickups and deliveries, customer information, facility capacity, and transportation resources can be shared to amplify resource utilization by introducing RS strategies. RS is not only conducive to the operation of logistics facilities, including the use of logistics costs and transport resources, but also conducive for providing customers with more convenient logistics services. In a logistics network with vehicle sharing, vehicles are used multiple times within and between facilities to avoid idle

FIGURE 8: Comparison results of TTC, TC, TMC, and NV in the four cases.

vehicle resources. In addition, the sharing of customer information helps facilities provide logistics services to customers with higher quality. Therefore, participating actively in RS is remarkably necessary for LSPs.

- (2) From the perspective of local traffic management departments and environmental departments, the optimization of the logistics network through RS not only reduces transportation resources but also relieves the local traffic pressure. In addition, the efficient use of resources promotes the development of green environment. Therefore, local government departments can actively support and give incentive policies to promote RS among local logistics facilities to optimize the logistics network and ease the traffic environment. Moreover, the effective sharing mechanism in the multicenter logistics network with pickups and deliveries can enhance the efficient operation of the logistics system and promote the green and sustainable development of the local intelligent logistics system. Therefore, the introduction of RS can promote the construction and development of local smart and green urban logistics with the incentive of departments and the active participation of facilities.

7. Conclusions

This study handles the MDPDPRS, which optimizes the logistics network by sharing customer and transportation resources. The reconfiguration of resources and customers improve the operating efficiency of the logistics network. The main contributions of this study include the following aspects. First, the MDPDPRS is modeled as a bi-objective mathematical model to optimize the total logistics operating cost and number of vehicles. Second, a two-stage hybrid algorithm is designed to solve the MDPDPRS, which

contains the k -means, CW, and NSGA-II algorithms. Third, the application of the proposed mathematical model and methodology are improved by the numerical result of a real-world case study and benchmark.

In view of the shared transportation resources and customers' information, a two-stage algorithm is designed, which initially clusters customers to reconfigure the resources and then optimizes the vehicle routes. On the one hand, k -means algorithm, which clusters customers based on Manhattan distance, helps reduce the difficulty of solving MDPDPRS and enables vehicle resources to be used in a centralized manner multiple times. On the other hand, the combination of CW and NSGA-II algorithms improves the global searching capability and the speed of the algorithm in finding the Pareto optimal solutions.

The numerical results of a real-word case study, which is obtained in Chongqing, China, is discussed and analyzed to improve the application and performance of the designed mathematical model and methodology in solving practical problems similar to the MDPDPRS. The gap of the logistics operating costs and number of vehicles before and after the optimization are \$8859 and 19, respectively, which verify the effectiveness of the model and methodology proposed in this study. In addition, the algorithm comparison results of benchmarks (from C-mdivrptw datasets) verify that the proposed KCW-NSGA-II algorithm is superior to the standard NSGA-II, GA-PSO, and MOPSO. The results of numerical discussion on the four cases in which different RS strategies are adopted prove that RS is helpful to optimize logistics costs and save transportation resources.

In this study, the bi-objective mathematical model and methodology of MDPDPRS are designed, which provide references for the reconfiguration of resources and the optimization of logistics operation costs. In view of the limitations of the current study and the dynamic development of the logistics industry, further research can be considered from the following aspects. (1) The dynamic change in customer demands and customer satisfaction are the two aspects that the realistic LSPs focus on, and these aspects can be added into the study of MDPDPRS. (2) Constructing a dynamic mathematical programming model and designing an exact algorithm to find the exact solution of MDPDPRS are worthy of research. (3) Exploring the approaches to realize RS in a large logistics network and the means to reduce the effect of logistics transportation on the environment can be considered in the study of MDPDPRS. (4) Considering the cost sharing mechanism under the RS mechanism to promote the formation of collaboration and maintain its stability can enrich the study of MDPDPRS.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they do not have any conflicts of interest.

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