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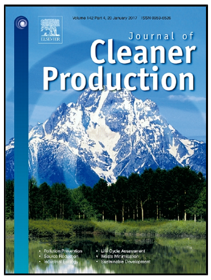

Profit Distribution in Collaborative Multiple Centers Vehicle Routing Problem

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Highlights:

- An integer programming model is established to minimize the total cost.
- A hierarchical hybrid approach is proposed to solve the model formulation.
- Improved Shapley value model with optimal sequential selection is proposed.
- The empirical results reveal that proposed approach outperforms other algorithms.

Profit Distribution in Collaborative Multiple Centers Vehicle Routing Problem

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ABSTRACT
A collaborative multiple-center vehicle routing problem (CMCVRP) is a multi-constraint combinatorial and game optimization issue containing both vehicle routing optimization and profit distribution procedures. The CMCVRP is generally used to study the logistics network structure adjustment from a non-optimal network structure to a collaborative multiple DCs network optimization structure. The optimization of CMCVR can effectively improve vehicle loading rate and reduce the crisscross transportation phenomenon. Designing a reasonable profit distribution mechanism is a critical step of CMCVR optimization. Collaboration can be organized through a negotiation process by a logistics service provider. This paper establishes an integer-programming model that contains transportation costs among distribution centers (DCs) and vehicle routing costs in each DC to minimize the total costs of CMCVRP. A multi-phase hybrid approach with clustering, dynamic programming, and heuristic algorithm is presented to solve the model formulation. The clustering procedure increases the likelihood that the solution will converge to an optimal value, between-route operations (relocate, 2-opt* exchange, and swap move) in the heuristic algorithm will improve the initial solution, and the within-route (dynamic programming) procedure will calculate a good feasible solution for each vehicle route. Both between- and within-route operations are recursively executed to find the best solution. Profit distribution plans are then established using the improved Shapley value model. Optimal sequential coalitions are selected based on strictly monotonic path, cost reduction model, and best strategy of sequential coalition selection in cooperative game theory. An empirical study in Chongqing, China suggests that the proposed approach outperforms other algorithms, and the best sequential coalition can be selected and adjusted to increase the negotiation power for network optimization of logistics distribution.

Keywords: Multiple-center vehicle routing optimization; Profit distribution; Integer-programming model; Multi-phase hybrid approach; Improved Shapley value model

1 Introduction

The traditional vehicle routing problem (VRP) seeks to find a set of routes that serve a series of customers (Allahyari et al. 2015). Each route can be performed by a single vehicle, which starts and returns to its own depot, and fulfills all customer requirements with minimized global transportation costs (Cordeau and Maischberger 2012; Fikar and Hirsch 2015). A collaborative multiple-center vehicle routing problem (CMCVRP) is the relaxed type of traditional VRP that is usually studied as a multiple-depot VRP (MDVRP) and a collaborative problem among multiple distribution centers (DCs). CMCVRP occurs when more than one DC is utilized in the network. Each vehicle departs from a DC to serve a series of customers by following a certain route plan and finally returns to the same DC. Each customer is reasonably assigned to its adjacent DC, where merged and transshipped goods are transported by a fleet of semitrailer trucks. Each customer should be also served by one vehicle on one occasion, whereas the loading of each vehicle should not exceed the vehicle capacity (Cattaruzza et al. 2014; Allahyari et al. 2015). Properly optimizing MCVR not only mitigates city-wide traffic congestion and alleviates negative environmental effects, but also reduces individual operating costs for profit maximization (Dai and Chen 2012).

Different from conventional MDVRP, CMCVRP incorporates the cooperation mechanism among depots and increases modeling difficulty. CMCVR optimization is achieved through the negotiation-facilitated collaboration among multiple participants. The ultimate objective is to minimize the total costs of MCVR optimization, including vehicle routing costs in each DC and transportation costs among DCs, which may involve a transformative process from an original, non-optimal network structure to an optimized one. This process is organized by a logistics service provider (LSP) that performs corresponding logistics operations and strategies for participants in logistics distribution networks (Zäpfel and Bögl 2008; Braekers et al. 2014). Third-party LSPs can perform logistics activities better, including transportation, warehousing, information system, and value-added service, all of which integrate transportation, storage, and information into the LSP market.

The mutually beneficial situation among different logistics companies can be achieved through outsourcing non-core logistics activities by LSPs. LSPs have the capability to persuade more participants to join the coalition and save more from an original non-optimal network structure to a newly optimized one in the logistics network optimization process. Determining a reasonable profit distribution strategy with collaboration among its participants is the critical issue during a negotiation and optimization procedure. The robustness of collaboration relies on the rationality of profit distribution. Conventional MCVRP studies neglect the collaboration mechanism in the optimization procedure and assume that any two depots are willing to share their customer resources, delivery facilities without costs and the need for third-party logistics; such an assumption is not true in reality, and a series of value-added services including warehousing, negotiation, and transportation require third-party logistics providers (i.e., LSPs) to manage certain costs.

Although the aforementioned collaboration mechanism widely exists in the MCVR optimization procedure, little research effort has been made to investigate the cooperative process, including profit distribution plans, strategies of sequential coalition selection, and so forth (Dai and Chen 2012), especially in the context of MCVRP. To fill this research gap, the current study proposes to incorporate the collaboration mechanism into traditional MCVRP as CMCVRP. Therefore, a hierarchical hybrid approach should be proposed to find near-optimal vehicle routes (Dondo and Cerdá 2007). To reduce the computational complexity of this problem and improve calculation accuracy, customer clustering procedure, dynamic programming procedure, and heuristic algorithm are consecutively applied. Next, a profit distribution strategy based on the Shapley value model (Shapley, 1953) is developed to study collaborative sequences and analyze the negotiation process.

The rest of this paper is organized as follows. Relevant studies are first discussed in Section 2, and CMCVRP is further illustrated. Model formulation with related definitions is developed in Section 4. The multi-phase hybrid approach, including clustering procedure, dynamic programming procedure, and heuristic algorithm, is proposed and described thoroughly in Section 5. An improved Shapley value model is then utilized to distribute gained profit among different logistics participants. To evaluate the effectiveness of the established model and proposed approach, a case study of allocating benefits in collaborative CMCVRP from Chongqing, China is presented in Section 6, followed by a thorough analysis with collaborative sequences and negotiation power. Finally, conclusions are summarized at the end of this paper.

2 Literature Review

With the advent of new technology such as electronic commerce, the collaboration among multiple participants in the large-scale logistics distribution network has become much easier. Collaboration among multiple participants reduces logistics costs, increases profits for large-scale industrial companies, and can benefit the overall economy. Given the potential importance that collaboration can provide, many researchers have begun studying different collaboration methods with the goal of maximizing the overall benefits such methods can provide. An innovative clustering approach is a critical issue used to alleviate computational complexity for the network optimization of large-scale logistics (Bosona and Gebresenbet 2011; Ng and Lam 2014; Wang et al. 2014a). Dondo and Cerdá (2007) developed a cluster-based three-phase optimization approach for routing problems of multi-depot heterogeneous fleet vehicles with time windows. This algorithm first groups customers into multiple clusters, and then assigns each cluster to a depot using mixed-integer linear programming (MILP) model. The third-phase approach allocates border and non-border customers to depots to construct solutions for globally optimized MDVRP. Miranda et al. (2009) proposed a collaborative e-work-based optimization approach, including fleet design and customer clustering decisions, to assist in the design problem of strategy logistics networks. Bosona and Gebresenbet (2011) studied the logistics network integration and cluster building of local food supply chain in Sweden, and found that most clusters can be integrated into food distribution channels and improve the delivery routes including time and distance. Yücenur and Demirel (2011) developed a genetic algorithm based on genetic clustering algorithm for the MDVRP solution process. Mehrjerdi and Nadizadeh (2013) proposed a greedy clustering method combined with stochastic simulation to study capacitated location-routing problems with fuzzy demands. Wang et al. (2014a) presented a fuzzy clustering algorithm to divide the customers into multiple clusters for further logistics network optimization. Tu et al. (2014) introduced a bi-level Voronoi diagram-based metaheuristic to solve large-scale MDVRP. The upper-level algorithm is used to assign customers to depots, and the lower level is used to reallocate customers among depots and rearrange them among routes from each depot to its neighbors.

Customer clustering can be considered an important step during the MCVR optimization procedure (Özdamar and Demir 2012; Ng and Lam 2014), while mathematical programming model and heuristic algorithms can be further improved to study CMCVRP within each DC and among DCs (Luo and Chen 2014). Ho et al. (2008) developed two hybrid genetic algorithms, including Clarke and Wright saving methods and nearest-neighbor heuristic algorithms, to deal with MDVRP. Tatarakis and Minis (2009) presented suitable dynamic programming algorithms to study vehicle routing problem with multiple depot returns. Dondo and Cerdá (2009) presented manageable MILP formulations and a hybrid local improvement algorithm for large-scale MDVRP with time windows. Bettinelli et al. (2011) established an integer linear programming model and proposed a branch-and-cut-and-price algorithm to study the routing problems of multi-depot heterogeneous vehicles with time windows. Kuo and Wang (2012) presented a variable neighborhood search method that is similar to the simulated annealing algorithm for solving MDVRP with loading costs. Ng and Lam (2014) proposed a supply network optimization model based on a functional clustering approach for reducing the transportation cost. Contardo and Martinelli (2014) modeled MDVRP with the constraints of capacity and route length as a vehicle-flow and set-partitioning formulation, and developed an exact multi-stage algorithm to solve the formulation. Allahyari et al. (2015) proposed a hybrid metaheuristic algorithm for routing problems of multi-depot covering tour vehicles. A brief comparative summary of relevant literature involving solution methods and objective functions of MDVRP is presented in Table 1.

In summary, the necessary definition of the abbreviations in Table 1 can be shown as follows:

MDVRPPD: Multiple Depot Vehicle Routing Problem with Pickups and Deliveries.

MDHVRPTW: Multiple Depot Heterogeneous Vehicle Routing Problem with Time Windows.

MPVRCSOO: Multiple Period Vehicle Routing and Crew Scheduling with Outsourcing Options.

BOMDLRP: Bi-Objective Multiple Depot Location Routing Problem.

FTMDCVRP: Full Truckloads Multiple Depot Capacitated Vehicle Routing Problem.

MDHVRPTW: Multiple Depot Heterogeneous Vehicle Routing Problem with Time Windows.

MDVRPLC: Multiple Depot Vehicle Routing Problem with Loading Cost.

CCPD: Carrier Collaboration in Pickup and Delivery.

GLNC: GLobal Network Configurations.

LSDRLP: Large Scale Disaster Relief Logistics Planning.

MTVRP: Multiple Trip Vehicle Routing Problem.

2E-LRPTW: Two-echelon Location Routing Problem with Time Windows.

MD-H-DARP: Heterogeneous Dial-A-Ride Problems with Multiple Depots.

VRPSDPSLTW: Vehicle Routing Problem: Simultaneous Deliveries and Pickups with Split Loads and Time Windows.

MDCTVRP: Multiple Depot Covering Tour Vehicle Routing Problem.

MAVRP: Multiple Attribute Vehicle Routing Problem.

Table 1. Comparative literature summary of relevant solution methods and objective functions of MDVRP

References in temporal order	Acronym of problem studied	Solution method	Objective function
Nagy and Salhi (2005)	MDVRPPD	Heuristic algorithm	Minimize total routing costs and computational times
Crevier et al. (2007)	MDVRP	Heuristic and tabu search method	Minimize total routing costs and computational times
Dondo and Cerdá (2007)	MDHVRPTW	Three-phase heuristic algorithm	Minimize overall service expenses
Ho et al. (2008)	MDVRP	Two hybrid genetic algorithms (HGAs)	Maximize delivery time spent among n depots
Zäpfel and Bögl (2008)	MPVRCSOO	Hybrid metaheuristic	Minimize total costs of all tours
Moghaddam et al. (2010)	BOMDLRP	Multi-objective scatter search algorithm	Maximize total demand services and minimize total costs
Liu et al. (2010b)	FTMDCVRP	Two-phase heuristic algorithm	Minimize empty vehicle movements
Bettinelli et al. (2011)	MDHVRPTW	Branch-and cut-and-price algorithm	Minimize the sum of vehicles fixed and routing costs
Kuo and Wang (2012)	MDVRPLC	Variable neighborhood search	Minimize total transportation costs
Dai and Chen (2012)	CCPD	Three-profit allocation mechanisms based on Shapley value	Maximize post-collaboration total profit of carrier alliance
Sheu and Lin (2012)	GLNC	Integer programming and hierarchical cluster analysis method	Minimize network configuration costs and maximize both operational profit and customer satisfaction
Özdamar and Demir (2012)	LSDRLP	A hierarchical cluster and route procedure approach	Minimize estimated total travel times and efficient vehicle utilization
Cattaruzza et al. (2014)	MTVRP	HGA	Minimize total travel times

Govindan et al. (2014)	2E-LRPTW	MHPV algorithm	Best designs in SSCN and minimize costs and environmental effects
Braekers et al. (2014)	MD-H-DARP	Exact branch-and-cut algorithm and deterministic annealing meta-heuristic	Minimize total routing costs
Wang et al. (2013)	VRPSDPSLTW	Hybrid heuristic algorithm	Minimize total travel costs, number of vehicles, and loading rate
Luo and Chen (2014)	MDVRP	Improved shuffled frog-leaping algorithm	Minimize total costs and computational times
Allahyari et al. (2015)	MDCTVRP	Hybrid metaheuristic algorithm	Minimize total routing and allocation costs
Dayarian et al. (2015)	MAVRP	Branch-and-price algorithm	Minimize total arc costs of route

Integrated transportation services among multiple depots should be also considered in the collaborative MDVRP, which usually appears in two-echelon VRP (Baldacci et al. 2013; Wang et al. 2015a). The cooperation process can be implemented between first- and second-level facilities (Hemmelmayr et al. 2012; Govindan et al. 2014; Ahmadizar et al. 2015). Other approaches, including collaboration model, centralized and decentralized approaches, were also used to solve the planning problems of collaborative logistics. Berger and Bierwirth (2010) developed two decentralized approaches to study problems of request reassignment in collaborative carrier networks. Hernández et al. (2011) developed a branch-and-cut algorithm to solve deterministic planning problems of dynamic single-carrier collaboration for less-than-truckload industry. Hemmelmayr et al. (2012) presented an adaptive large neighborhood search heuristic approach to solve the Two-Echelon Vehicle Routing Problem (2E-VRP). Hernández and Peeta (2014) presented a collaboration model to tackle carrier collaboration problems for less-than-truckload carriers. Wang et al. (2015a) proposed a hybrid particle swarm optimization-genetic algorithm for studying the two-echelon logistics distribution region partitioning problem. Ahmadizar et al. (2015) presented a hybrid genetic algorithm to optimize two-level vehicle routing with cross-docking in a three-echelon supply chain. Hafezalkotob and Makui (2015) developed a stochastic mathematical programming model for cooperative maximum-flow problems under uncertainty in logistics networks. Generally, the mathematical programming model based on MDVRP can be established with accurate and intelligent algorithms. However, only a few studies can be found to investigate collaborative strategy design among the same-level logistics facilities in the MDVRP context.

The MCVR optimization process usually contains vehicle routing optimization and the problem of collaborative strategy design (Govindan et al. 2014; Allahyari et al. 2015). The problem of collaborative strategy design belongs to the category of cooperative game theory, which can be used to analyze the cooperative behavior and benefit allocation relationship among participants (Frisk et al. 2010; Hellström et al. 2015). Krajewska et al. (2008) presented a feature combination of routing and scheduling problems and cooperative game theory. Shapley value methods were used to determine the fair allocation of cost reductions. Nagarajan and Sošić (2008) presents the game-theoretic analysis review and extensions of cooperation among supply chain agents.

Özener and Ergun (2008) developed a cost allocation mechanism based on cooperative game theory and proposed several cost allocation schemes to study the transportation network of collaborative logistics. Cruijssen et al. (2010) proposed a new procedure that outsources initiative to LSPs. The Shapley value method was utilized to allocate cost reduction, and a practical example was demonstrated to study collaboration and cost reduction allocation among participants. Frisk et al. (2010) presented a new cost allocation method based on Shapley value, nucleolus, separable and non-separable costs, shadow prices, and volume weights for collaborative forest transportation. Lozano et al. (2013) proposed a linear model to study the profit distribution process among different companies when their transportation requirements are merged. Hellström et al. (2015) proposed three cases from distributed energy ecosystems to study the collaboration mechanisms for business models around renewables and sustainability. However, the above studies suffer from the following issues: (1) MCVR optimization procedure rarely considers how to optimize vehicle routes and allocate benefits when goods between different depots are transshipped. (2) Transportation costs are usually not considered among multiple centers, whereas costs are an important factor during the MCVR optimization procedure. (3) Most studies focus on designing a profit distribution mechanism based on cooperative game theory and centralized and decentralized approaches, but ignore the interaction between vehicle routing optimization and profit distribution. Therefore, a reasonable profit distribution approach based on cooperative game theory should be properly designed for CMCVRP.

3 Problem Statements and Model Formulation

3.1 MCVRP

The MCVRP can be regarded as an extension of MDVRP. MCVRP optimization can be achieved through collaboration among multiple DCs, and the collaborative process can be organized by LSPs (Nagurney 2009; Manzini 2012; Wang et al. 2015b). MCVRP optimization can effectively improve vehicle loading rate, reduce crisscross transportation phenomenon, and enhance the efficiency of logistics network operation. In our study, CMCVRP contains multiple DCs and a large number of customers to be served. Figure 1 shows the structural change before and after MCVRP optimization. DCs are independent with each other before optimization. Through optimization, DCs can mutually cooperate for achieving the centralized transportation.

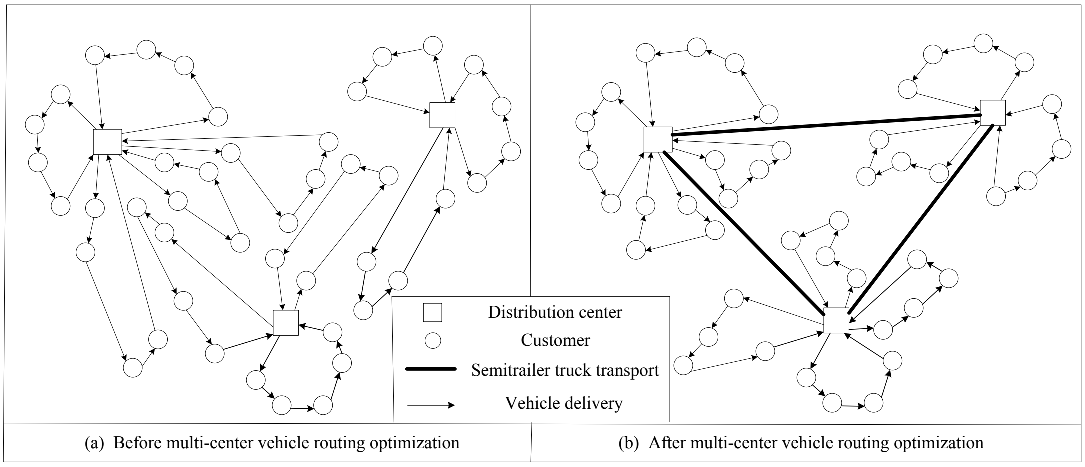

Fig. 1 Comparison Diagram of MCVRP Optimization

As shown in Fig. 1(a), a non-optimal network structure can be observed before MCVR optimization, where several DCs serve long-distance customers, even though these customers are fairly adjacent to other peer DCs due to customer loyalty and the conditions of market competition. Certain customers are more likely to receive logistics service from those previous DCs even though these DCs are far away from them. In addition, because of competition among multiple DCs, some later-established DCs can provide more favorable service (e.g., discount service, door-to-door service, etc.) to attract new customers, leading to long-distance and crisscross deliveries. Therefore, optimizing a non-optimal network structure is important.

To optimize this non-optimal network structure, the network structure adjustment through collaboration among multiple DCs is required. The generated benefit from the new optimized network structure must be also allocated fairly among the multiple DCs. Therefore, MCVRP is a three-part problem: 1) how to redesign the multiple-center network structure, 2) how to collaborate among multiple DCs, and 3) how to allocate the benefits among multiple DCs. These are both critical issues in the MCVRP optimization procedure.

As shown in Fig. 1(b), the adjusted network structure through collaboration among DCs, each customer is reasonably assigned to its adjacent DC. The merged and transshipped goods can be transported among DCs by a fleet of semitrailer trucks, and each DC can serve the adjacent customers by a fleet of vehicles. Therefore, MCVRP optimization can be regarded as a multi-constraint combinatorial and game optimization issue. MCVRP optimization aims to serve customers and minimize the total logistics costs of the entire network system. Three key research issues should be addressed: 1) redesign the non-optimal network structure, 2) select a collaborative mechanism, and 3) distribute the cost savings from a non-optimal to an optimal network. A three-stage procedure is proposed in this study. Multi-phase hybrid approach is initially developed to solve CMCVRP, an improved Shapley value model is utilized to split the gained profit based on cost savings as a result of the optimized logistic network through CMCVRP, and finally, a collaborative mechanism is presented with a real-world numerical experiment.

3.1.1 Related Definitions and Notations

Related notations and definitions (Li, et al. 2016) used in MCVR optimization formulation are listed in Table 2.

Table 2. Notations and definitions in CMCVRP

Symbol	Definition
I	Set of all DC sites; if $i, h \in I$, and h represents a DC that is different from i, then $h \neq i$
J	Set of customers; $j \in J$
K	Expresses vehicle set; $k \in K$, where K is a predetermined set based on the initial non-optimized logistic network
D_i	Delivery quantity of DC i within one working day
L_{ih}	Distance from DC i to h
L_{ij}	Distance between customers i and j; $i, j \in I \cup J$
q_j	Demand quantity of customer j; $j \in J$
B	Capacity of semitrailer truck
Q_v	Vehicle capacity
τ	Number of working periods
W	Number of days in one working period
C_v	Average fuel consumption per 100 miles of vehicle
C_s	Average fuel consumption per 100 miles of semitrailer truck
ρ	Gasoline price (USD/gallon)
A	Average annual maintenance costs of semitrailer truck
F_v	Average annual maintenance costs of vehicle
λ_i	Variable cost coefficient of each DC i
L	Maximum delivery distance
d_{ih}	Delivery quantity from DC i to h; a variable related to the change of decision variable z_{ijh}^{c}
z_{ij}	z_{ij}=1; customer j is served by DC i, otherwise set z_{ij}=0, $i \in I$, $j \in J$ in the the initial non-optimized logistic network
N_i	Number of vehicles for serving customers in DC i
G_i	Fixed costs (Unit: USD) of DC i in a working period; LSP covers the fixed costs when DC agrees to cooperate
P_i	Service costs (e.g., personnel, maintenance, etc.) of LSP for DC i when cooperation is achieved within one working period (Unit: USD)

In addition, several decision variables are listed in Table 3.

Table 3. Decision variables in CMCVRP

Decision variable	Definition
x_{ijk}	x_{ijk}=1; vehicle k travels directly from i to j ($i \in I \cup J, j \in J$); otherwise set x_{ijk}=0, $k \in K$
y_i	Coalition relation between DCs and LSP. If DC i agrees to cooperate in vehicle routing optimization, then set y_i=1; otherwise

	set y_i=0
z^c_{ijh}	Change of service relation from DC i to h, if customer j is served from DC i to DC h, then set $z^c_{ijh}=1$; otherwise set $z^c_{ijh}=0$, $i,h\in I$, $j\in J$
ϖ_k	$\varpi_k=1$; vehicle k serves the number of customers greater than 0; otherwise set $\varpi_k=0$, $k\in K$

3.2 Model Formulation

Model formulation is composed of T_1, T_2, and T_3 and can be described as follows.

T_1 is transportation and maintenance costs from DC i to h (if collaboration occurs) in a working period. It can be calculated as

$$T_1=\sum_{i,h\in I,h\neq i}\left(\frac{d_{ih}}{B}\times C_s\times\rho\times L_{ih}\times W+\frac{d_{ih}}{B}\times\frac{A}{\tau}\right)\tag{1}$$

T_2 is the sum of fixed, dispatching, and maintenance costs for assigned vehicles within a working period. It can be calculated as

$$T_2=\sum_{i\in I}[(1-y_i)G_i+y_iP_i+(\lambda_i\times D_i\times W)+(N_i\times\frac{F_v}{\tau})]\tag{2}$$

T_3 is the delivery costs for assigned vehicles within a working period and can be calculated as follows:

$$T_3=\sum_{i\in I\cup J}\sum_{j\in I\cup J}\sum_{k\in K}(L_{ij}\times x_{ijk}\times\varpi_k\times\rho\times C_v\times W)\tag{3}$$

The mathematical model can be expressed as follows:

$$T=\min T_1+T_2+T_3\tag{4}$$

Subject to

$$\sum_{k\in K}\sum_{i\in I\cup J}x_{ijk}=1,\ j\in J\tag{5}$$

$$\sum_{j\in J}(q_j\sum_{i\in I\cup J}x_{ijk})\leq Q_v,\ k\in K\tag{6}$$

$$\sum_{j\in I\cup J}x_{ijk}-\sum_{j\in I\cup J}x_{jik}=0,\ k\in K,\ i\in I\cup J\tag{7}$$

$$\sum_{i\in I}\sum_{j\in J}x_{ijk}\leq 1,\ k\in K\tag{8}$$

$$\sum_{u\in I\cup J}(x_{iuk}+x_{ujk})-z_{ij}\le 1\,,\ i\in I\,,\ j\in J\,,\ k\in K \tag{9}$$

$$L_{ij}\le L\,,\ i,j\in I\cup J \tag{10}$$

$$d_{ih}=\sum_{j\in J}z^{c}_{ijh}q_j\,,\ i,h\in I\,,\ j\in J \tag{11}$$

$$x_{ijk}=0,1\,,\ i\in I\cup J, j\in J\,,\ k\in K \tag{12}$$

$$y_i=0,1\,,\ i\in I \tag{13}$$

$$z^{c}_{ijh}=0,1\,,\ i,h\in I\,,\ j\in J \tag{14}$$

$$\varpi_k=0,1\,,\ k\in K \tag{15}$$

Model Equation (1) is used to calculate the transportation and maintenance costs from semitrailer trucks among DCs. Model Equation (2) is utilized to calculate the sum of fixed costs of DCs, service costs of cooperation process, and maintenance costs from vehicles. Model Equation (3) expresses the delivery costs for assigned vehicles. Objective Function (4) minimizes the total network costs. Constraint (5) ensures that each customer can be served by a single vehicle. Constraint (6) assures that the sum of customer demands for a single route does not exceed the delivery vehicle's capacity. Constraint (7) guarantees that flow conservation is achieved. Constraint (8) specifies that a vehicle starts only from one DC. In other words, the total number of trips that vehicle k travels directly from i to j ($i\in I, j\in J$) should be less than or equal to 1. Constraint (9) ensures that a customer can be served by DC only if there is a vehicle from DC serving the customer. Constraint (10) regulates that distance between i and j should not exceed the maximum delivery distance. Constraint (11) stipulates the delivery quantity from DC i to h, which is equal to the total change of customer quantities from DC i to h. Constraints (12), (13), (14), and (15) are binary decision variables.

4 Multi-phase Hybrid Approach Solving Procedure

As presented in Section 3.3, Objective Function (4) is different from the traditional MDVRP (multiple-center vehicle routing problem) objective function, because the cooperation process is considered in Model Equations (1), (2), and (3). That is, Model Equations (1), (2), and (3) demonstrate the calculation process for costs, including transportation, maintenance, and service, among DCs (Distribution Centers) from a non-optimal network structure to a collaborative multiple-center optimal network structure. Therefore, Objective (4) is used to calculate the total minimum costs of Model Equations (1), (2), and (3). Designing a reasonable approach to solve the above objective function is critical. During CMCVRP (collaborative multiple-center vehicle routing problem) optimization, some customers that were originally delivered to by one

DC may be assigned to another DC, which will lead to concentrated transportation services among DCs at the beginning of cooperation. The process is the prerequisite in the practical cooperation process, while traditional MDVRP models tend to ignore these costs.

An unreasonable distribution network structure is known in advance as well. Our approach aims to optimize the unreasonable network. Optimization is based on a three-step process with a multi-phase hybrid solution approach in an optimization framework (see Fig. 2). First, customer clusters in the heuristic clustering procedure can be generated. Then, an initial feasible solution is yield based on the dynamic programming method and the mathematical programming process. Next, a heuristic algorithm process is presented to further improve the initial solution, and a cycle operation is performed based on optimal mathematical model *T*. In the proposed multi-phase hybrid approach, the clustering procedure is presented to obtain customer clustering units based on Constraints (5)–(10) in Section 3.3, the dynamic programming method procedure can be used to obtain initial routes based on Constraints (5)–(9) in Section 3.3, and the heuristic algorithm procedure contains between-route operations (relocate, 2-opt* exchange, and swap move) and within-route operations (dynamic programming).

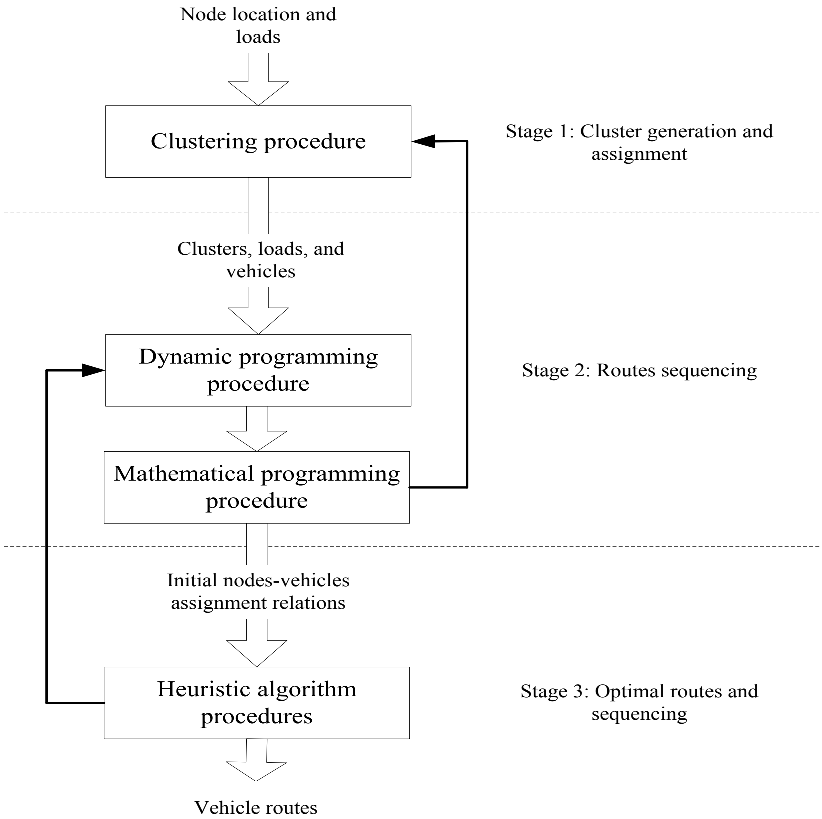

Fig. 2. Schematic of CMCVRP multi-phase hybrid approach

4.1 Clustering procedure

The clustering procedure is necessary to be performed prior to the initial route construction procedure, which is illustrated in this section. Several notations are introduced as follows: C is a cluster set, $C=\{C_k \mid k=1,2,\cdots,m\}$, and m is the total number of vehicles from DCs, $k \in K$; J' is the set of unvisited customers; and n is the number of DCs. The number of clusters is equal to the number of vehicles for each DC. Therefore, the initial number of clusters is a fixed value. The clustering procedure based on previous research (Mitra 2008; Özdamar and Demir 2012; Wang et al. 2014b) can be designed as follows:

Step 1: For each DC, set the first and last elements as DC in each cluster.
Step 2: Choose the second element in each cluster of each DC as the customer with the minimum distance to DC from the unvisited customers.
Step 3: Choose the third element in each cluster of each DC as the customer with the minimum sum of distances from the existing elements within the cluster.
Step 4: Obtain remaining elements with the minimum sum of distances from existing elements within each cluster. The clustering procedure ends when cumulative delivery demands exceed the vehicle capacity or all customers are assigned.
Step 5: Find those clusters whose delivery demands are less than half of the vehicle capacity and merge every two clusters into one.
Constraints (5)–(10) will be used to check the unqualified element inserting into clustering routes in each of the above steps. If the chosen element is unqualified, the next element will be chosen. Once clusters are formed, vehicle routing is scheduled within each cluster and cross-optimization is conducted among clusters. Customer clustering is a fundamental step for the procedure of initial route construction. Dynamic programming procedure is presented below to further enhance the procedure of initial solution seeking.

4.2 Dynamic programming procedure

Dynamic programming method (Boyer et al. 2011; Desai and Lim, 2013; Arokhlo et al. 2014) is used to adjust customer orders within each cluster gained from the above clustering procedure. Relevant notations can be predefined as follows. $V=\{V_k \mid k=1,2,\cdots,m\}$ is the set of customers in each cluster; $G=(V,E,H)$ is the urban road network; E is the set of edges of urban road network; H is the set of edge lengths of urban road network; Ψ is the visited customers before customer v_j; $v_j \in V_k$; $\Psi \subseteq V_k$; $|p_{ij}|$ is the shortest distance between customers v_i and v_j; v_0 is the DC in cluster; and f_α is the optimal index function of α^{th} stage. Suppose that cluster contains β customers, and then the dynamic programming procedure within an arbitrary cluster V_k is detailed below.

Step 1: Divide the procedure of dynamic programming optimization into β stages based on the number of customers in cluster.

Step 2: Select all state variables (v_j, Ψ), $v_j \in V_k$, where Ψ is the visited customers before v_j, $\Psi \subseteq V_k$.

Step 3: Find customer V_i, and calculate the route from customer v_i to v_j as follows: construct the optimal index function $f_\alpha(v_j, \Psi) = \min_{i \in \Psi}\{f_{\alpha-1}(v_i, \Psi / \{v_i\}) + | p_{ij} |\}$, $\alpha = 1, 2, \cdots, \beta$, where $\Psi / \{v_i\}$ is the set of customers excluding customer v_i; and $f_0(v_j, \varphi) = | p_{0j} |$, $j = 1, 2, \cdots, \beta$ is the boundary condition.

The initial routes can be obtained with the above dynamic programming procedure.

4.3 Heuristic algorithm to improve the initial solution

Heuristic algorithms are effective in solving MCVR (multiple-center vehicle routing) problems (Nagy and Salhi 2005; Lin and Kwok 2006; Liu et al. 2010b). Several local search approaches from heuristics algorithm are 2-opt* exchange, swap move, shift move, and relocate operator (Dondo and Cerdá 2007; Cordeau and Maischberger 2012; Tlili et al. 2014). The heuristic algorithm is illustrated as follows:

Step1: Calculate the initial solution based on dynamic programming method and record the total transportation costs. Set iteration number as $l = 1$.

Step 2: Randomly select one route from each DC, and then select two routes in turn from C_n^2 combinations. Repeat the relocate operator until no more improvement can be found over the best known solution within γ consecutive iterations.

Step 3: Repeat 2-opt* exchange procedure until no more improvement can be found over the best known solution within γ consecutive iterations.

Step 4: Perform (2, 0), (1, 1), (2, 1), and (2, 2) swap moves recursively until no more improvement can be found over the best known solution within γ consecutive iterations.

Step 5: Select two routes in turn from all possible combinations within each DC. Apply the relocate operator, 2-opt* exchange, and (2, 0), (1, 1), (2, 1), and (2, 2) swap moves recursively until no more improvement can be found over the best known solution within ξ consecutive iterations.

Step 6: Apply the dynamic programming procedure in each cluster within each DC and record the best total transportation costs. In set $l = l + 1$, determine whether l reaches maximum iteration number ρ^m; if not, return to Step 2. Otherwise, the heuristic

algorithm procedure will be terminated.
Constraints (5)–(10) will also be used to check unqualified routes in each of the above steps. In the above heuristic algorithm procedure, between-route operations (relocate, 2-opt* exchange, and swap move) can be also used to improve the sequence of visited customers between different routes. The within-route (dynamic programming) procedure is used to acquire the optimal solution in each route. In the heuristic algorithm procedure, if the updated total transportation costs are lower than the one in the previous iteration, then the adjusted route will be accepted; otherwise, the previous route will be kept. Both between-route and within-route operations are recursively executed until the best solution is found.

5 Improved Shapley Value Model and Application

When the vehicle routing optimization is achieved, each customer is adequately assigned to a vehicle, and an optimized route is generated. Consequently, LSP is required to estimate and allocate cost savings as a result of change in the distribution network structure. The improved Shapley value model is a unique solution to the costs and profit distribution problem.

5.1 Improved Shapley value model

Shapley value model is a part of cooperative game theory, which is utilized to analyze collaborative behavior in a negotiation process within a group of participants to set up a contract or cooperative plan of activities, including generated profit allocation (Krajewska et al. 2008; Nagarajan and Sošić 2008; Frisk et al. 2010). Allocating profit properly is critical to each participant of a logistics cooperation process (Liu et al. 2010a; Özener and Ergun 2013; Wang et al. 2015b).

Let N be a set of players (each player is a DC in the context of our study), and $2^N - 1$ can be expressed as the collection of all subsets of N, excluding null set. The elements of all subsets are called *coalitions*. N is the *grand coalition*, T is a coalition from set N, and all $T \subset N$. The Shapley value (Shapley 1953) model can be denoted by $\phi(N, v)$ and used to calculate the average marginal revenue of participants when they enter the coalition in a completely random order.

If sub-game (T, v) of coalition T is given by the restriction of v to $2^T - 1$, then marginal revenue is denoted by $v(S) - v(S - \{i\})$ for all $S \subset T$. The improved Shapley value model can be expressed as $\phi(T, v)$ and recalculated as follows:

$$\phi_i(T, v) = \sum_{T \subset S; i \in T} \left[(|S| - 1)!(|T| - |S|)! / |T|! \right] \left[v(S) - v(S - \{i\}) \right] \tag{16}$$

Four fairness properties are preferred in the improved Shapley value model. These properties are *efficiency*, *symmetry*, *dummy property*, and *monotonicity*, and are considered useful in profit distribution calculation (Shapley 1953; Cruijssen et al. 2010; Frisk et al. 2010). Efficiency assures that the total value of grand coalition is distributed among all participants. Symmetric means that if two arbitrary participants create the same marginal revenue to all coalitions, both participants should receive the same share of total value. Dummy property ensures that if a participant is a dummy player, this participant will not have any contribution to any joined coalitions, and allocated profit should be zero. Monotonicity establishes that if all participants' marginal contributions increase, profit will also increase. These four properties can guarantee the rationality and stability of profit distribution from a practical perspective.

5.2 Cost reductions

To study the cost reduction based on the improved Shapley value model, related notations are introduced as follows:

σ	LSP's synergy requirement
$C_0(i)$	Costs of player *i* without coalition
$C(T)$	Total costs in *T* by LSP
Γ	Set of possible sequential coalitions in grand coalition *N*
$\pi(i)$	Rank of player *i* in sequence π
$\eta(i,\pi,t)$	Cost reduction percentages to player *i* on step *t* along sequence π

To cover the extra overhead costs of collaboration service (i.e., warehousing, transportation management, negotiation, etc.) for participants in the synergy process, LSP needs a pre-determined percentage of profit as the synergy result. This share is called *synergy requirement* and is denoted as $\sigma \in [0,1]$. LSP will gain a higher prospected profit by setting a higher σ, while participants are more likely to accept cooperation by setting σ as a lower value. The value $v(T)$ of coalition *T* can be calculated by means of Formula (17).

$$v(T) = \begin{cases} (1-\sigma)\left(\sum_{i\in T} C_0(i) - C(T)\right) & if \sum_{i\in T} C_0(i) - C(T) \geq 0 \\ 0 & otherwise \end{cases} \tag{17}$$

where $C(T)$ are the total costs when transportation plans are executed with LSP in coalition *T*; and $C_0(i)$ are the costs when participant *i* performs individual transportation plan. In addition, whenever $\sum_{i\in T} C_0(i) < C(T)$ occurs, participants in *T* will not accept LSP's service, and $v(T)$ becomes zero in Formula (17). If *N* is the grand coalition, the possible sequential coalition set Γ contains $|N|!$ different combinations. The $\pi(i)$ is rank of player *i* in sequence π. Cost reduction percentages $\eta(i,\pi,t)$ can be calculated as follows:

$$\eta(i,\pi,t) = \phi_i\left(\bigcup_{\pi(\mu)\leq t,\mu\in N} \mu, v\right) \Big/ C_0(i)\,,\ t \geq \pi(i) \tag{18}$$

In Formula (18), the cost reduction percentages $\eta(i,\pi,t)$ can be used to explain the strictly monotonic path (SMP) (Cruijssen et al. 2010; Wang et al. 2015b). In game theory, if all $S,T,M \subseteq N$ satisfy the $S \subset T \subset N \setminus M$ condition, then $v(S \cup M) - v(S) < v(T \cup M) - v(T)$, which is called strictly convex. Suppose that (N,v) is strictly convex, it must satisfy a certain requirement, which is expressed as each $\pi \in \Gamma$ being an SMP. Based on the above assumption, we can further demonstrate the corresponding theorem and proof:

Theorem 1. (N,v) is strictly convex if, and only if, every $\pi \in \Gamma$ is an SMP.

Proof. Let (N,v) be strictly convex and consider two coalitions O and T. A single $j \in N \setminus T$ and $O = T \cup \{j\}$ occurs, and then for all $i \in T$:

$$
\begin{aligned}
\phi_i(T,v) &= \sum_{S\subset T, i\notin S} \frac{(|S|-1)!(|T|-|S|)!}{|T|!}(v(S)-v(S-\{i\})) \\
&= \sum_{S\subset T, i\notin S} \frac{(|T|+1)(|S|-1)!(|T|-|S|)!}{(|T|+1)!}\times(v(S)-v(S-\{i\})) \\
&= \sum_{S\subset T, i\notin S} \frac{[(|S|)+(|T|-|S|+1)](|S|-1)!(|T|-|S|)!}{(|T|+1)!} \\
&\quad \times(v(S)-v(S-\{i\})) \\
&= \sum_{S\subset T, i\notin S} \left[\frac{(|S|)(|S|-1)!(|T|-|S|)!}{(|T|+1)!}+\frac{(|T|-|S|+1)(|S|-1)!(|T|-|S|)!}{(|T|+1)!}\right] \\
&\quad \times(v(S)-v(S-\{i\})) \\
&= \sum_{S\subset T, i\notin S} \left[\frac{(|S|)!(|T|-|S|)!}{(|T|+1)!}+\frac{(|S|-1)!(|T|-|S|+1)!}{(|T|+1)!}\right] \\
&\quad \times(v(S)-v(S-\{i\})) \\
&= \sum_{S\subset T, i\notin S} \left[\frac{(|S|)!(|O|-1-|S|)!}{(|T|+1)!}+\frac{(|S|-1)!(|O|-|S|)!}{(|T|+1)!}\right] \\
&\quad \times(v(S)-v(S-\{i\})) \\
&= \sum_{S\subset T, i\notin S} \left[\frac{(|S|)!(|O|-1-|S|)!}{(|T|+1)!}\right]\times(v(S)-v(S-\{i\})) \\
&\quad + \sum_{S\subset T, i\notin S} \left[\frac{(|S|-1)!(|O|-1-(|S|-1))!}{(|T|+1)!}\right]\times(v(S)-v(S-\{i\})) \\
&< \sum_{S\subset T, i\notin S} \left[\frac{(|S|-1)!(|O|-1-(|S|-1))!}{(|T|+1)!}\right]\times(v(S)-v(S-\{i\})) \\
&\quad + \sum_{S\subset T, i\notin S} \left[\frac{(|S|)!(|O|-(|S|+1))!}{(|T|+1)!}\right]\times(v(S\cup\{j\})-v(S\cup\{j\}-\{i\})) \\
&= \sum_{S\subset O, i\notin S} \left[\frac{(|S|-1)!(|O|-|S|)!}{(|T|+1)!}\right]\times(v(S)-v(S-\{i\})) \\
&= \phi_i(O,v)
\end{aligned}
$$

Through the above proof procedure, the SMP can be considered as a sequence where cost reduction percentages for all committed participants are monotonically increasing as each participant joins the coalition. The selection process for choosing the best sequential coalition based on SMP is detailed as follows:

Step 1: Select diagonal values from the cost reduction percentage matrix in possible sequential coalitions based on SMP.

Step 2: Find the participant with the maximal lowest cost reduction percentage in selected diagonal values. If the cost reduction percentage is equal for all possible sequential coalitions, then find another participant with the maximal second lowest cost reduction percentage. The above procedure is iteratively executed until at least one participant can be found or all participants have been searched.

Step 3: The selected sequential coalition is chosen as the candidate for profit distribution strategy. If all participants have been searched, select any sequential coalition as candidate for profit distribution strategy.

6 Implementation and Analysis

6.1 Data source

An empirical study in Chongqing, China is utilized to evaluate the applicability of the proposed approach in MCVRP optimization. Chongiqng City, the municipality, is a critical transportation hub in southwest China. It is therefore selected as an ideal test location for this study. For each DC, the delivery demand data is provided by the local government. Four DC locations (D1, D2, D3, and D4) and 55 representative customers (C1, C2…C55) in Industry I are displayed in Fig. 3. The four DCs are independent from each other, meaning that collaborations exist among them. Customers in triangle are assigned to D1, circular customers are assigned to D2, solid x customers are assigned to D3, and square customers are assigned to D4. Three DC locations (D1, D2, and D3) and 44 representative customers (C1, C2…C44) in Industry Π are displayed in Fig. 4. Similarly, five DC locations (D1, D2, D3, D4, and D5) and 77 representative customers (C1, C2…C77) in Industry Ш are displayed in Fig. 5. Initial vehicle routes from the three industries are shown in Tables 6–8. According to Figs. 3–5 and Tables 6–8, significant overlapping regions of logistics services can be found in logistics distribution networks; therefore, the cooperation mechanism provided by LSP is necessary.

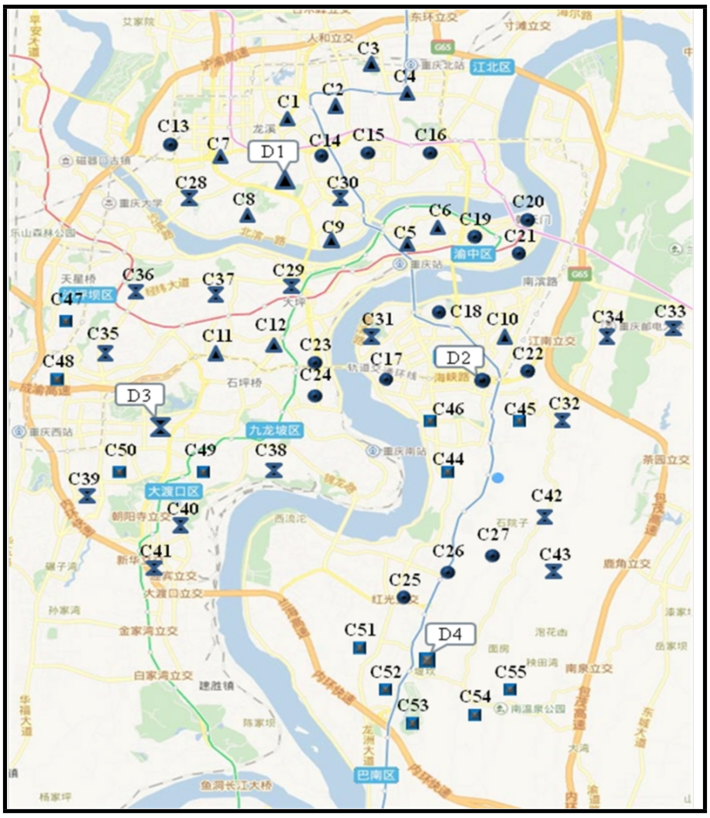

Fig. 3. Spatial distribution of logistics centers and customers in Industry I

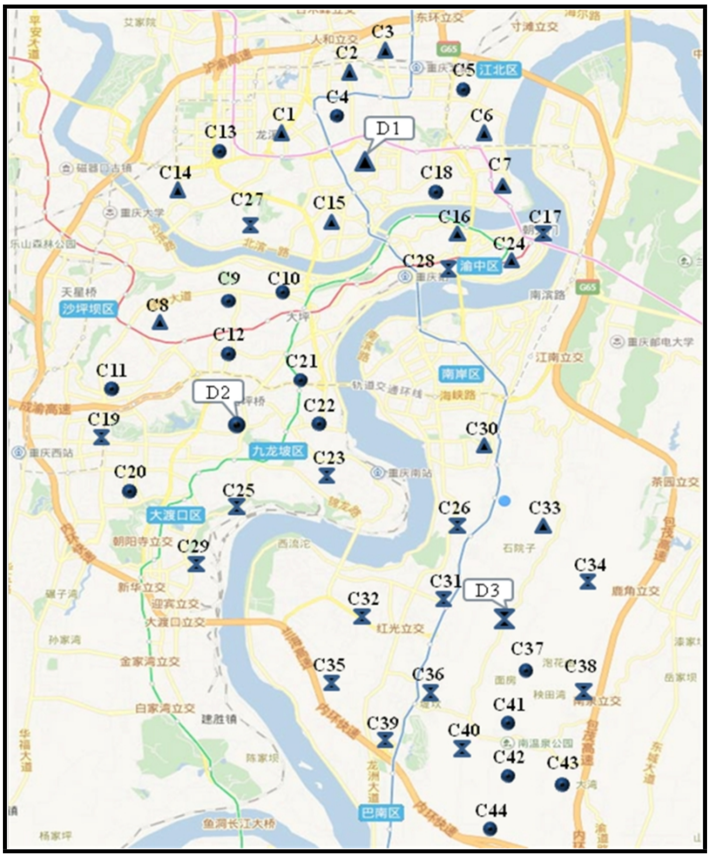

Fig. 4. Spatial distribution of logistics centers and customers in Industry Π

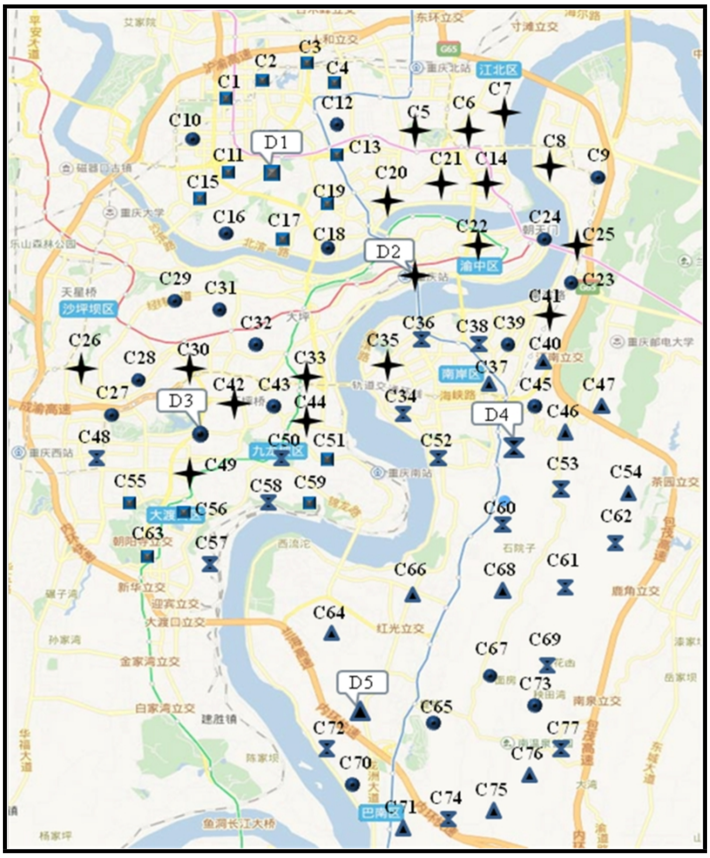

Fig. 5. Spatial distribution of logistics centers and customers in Industry Ш

Table 6. Initial vehicle routes from four DCs in Industry I

DC	Initial vehicle routes
D1	D1→C1→C2→C3→C4→C6→C5→D1 D1→C7→C11→C12→C8→C9→C10→D1
D2	D2→C17→C16→C15→C14→C13→D2 D2→C18→C19→C20→C21→C22→D2 D2→C23→C24→C25→C26→C27→D2
D3	D3→C30→C31→C32→C33→C34→D3 D3→C35→C36→C37→C28→C29→D3 D3→C39→C40→C41→C43→C42→C38→D3
D4	D4→C44→C45→C46→D4 D4→C50→C49→C48→C47→D4 D4→C51→C52→C53→C54→C55→D4

Table 7. Initial vehicle routes from four DCs in Industry Π

DC	Initial vehicle routes
D1	D1→C14→C1→C2→C3→D1 D1→C6→C7→C8→D1 D1→C15→C30→C33→C16→C24→D1
D2	D2→C20→C18→C5→C4→C13→D2 D2→C22→C21→C10→C12→C9→C11→D2 D2→C37→C41→C42→C44→C43→D2
D3	D3→C36→C32→C26→C31→D3 D3→C34→C29→C25→C23→D3 D3→C28→C17→C19→C27→D3 D3→C35→C39→C40→C38→D3

Table 8. Initial vehicle routes from four DCs in Industry Ш

DC	Initial vehicle routes
D1	D1→C1→C2→C3→C4→D1 D1→ C11→C15→C17→C19→C13→D1 D1→C51→C59→C56→C63→C55→D1
D2	D2→C14→C5→C6→C7→C8→D2 D2→C22→C21→C20→C35→C41→C25→D2 D2→C33→C44→C42→C30→C26→C49→D2
D3	D3→C16→C10→C12→C18→D3 D3→C27→C28→C29→C31→C32→C43→D3 D3→C45→C39→C23→C24→C9→D3 D3→C67→C65→C70→C73→D3
D4	D4→C52→C34→C36→C38→D4 D4→C53→C62→C61→C60→D4 D4→C50→C58→C57→C48→D4 D4→C69→C77→C74→C72→D4

D5	D5→C54→C46→C47→C40→C37→D5 D5→C76→C75→C71→C64→C66→C68→D5

To streamline calculation procedure, the delivery demand of each customer is converted into a standard roll pallet quantity. The DC characteristics in Industries I, П, and Ш contain the number of customers, period demand quantity, and graphic symbol, and are listed in Table 9.

Table 9. DC characteristics in Industries I, П, and Ш

DC		Number of customers	Periodic demand (roll pallets)	Customer symbol in Figs. 3–5
Industry I	D1	12	513	▲
	D2	15	672	●
	D3	16	722	⧗
	D4	12	568	■
Industry П	D1	12	542	▲
	D2	16	695	●
	D3	16	746	⧗
Industry Ш	D1	14	617	■
	D2	17	711	✦
	D3	19	856	●
	D4	16	682	⧗
	D5	11	528	▲

6.2. Relevant parameter setting of multi-phase hybrid approach and optimization results

In this empirical study, parameters for multi-phase hybrid approach are determined based on previous studies (Mitra 2008; Nagurney 2009; Özdamar and Demir 2012; Zhu et al. 2014). The parameter settings are given as follows:

1. Parameters are involved in data source and can be obtained in the initial routes for Industries I, П, and Ш:

a. Industy I: $m = 11$, $n = 4$, $N_1 = 2$, $N_2 = 3$, $N_3 = 3$, $N_4 = 3$;

b. Industry П: $m = 10$, $n = 3$, $N_1 = 3$, $N_2 = 3$, $N_3 = 4$;

c. Industry Ш: $m = 16$, $n = 5$, $N_1 = 3$, $N_2 = 3$, $N_3 = 4$, $N_4 = 4$, $N_5 = 2$;

d. β is equal to the number of customers in each route.

2. Several other parameters are involved in the model formulation: $B = 600$, $Q_v = 75$, $C_s = C_v = 3.2$, $U = 100$, $\tau = 52$, $W = 5$, $L = 65$, $\rho = 3.99$, $A = 4{,}800$, $F_v = 1600$, and $\lambda = 1.5$. For calculation and comparison convenience, fixed and service costs can

likewise be set as $G_1 = 605$, $G_2 = 874$, $G_3 = 936$, $G_4 = 802$, $G_5 = 756$, $P_1 = 645$, $P_2 = 586$, $P_3 = 602$, $P_4 = 563$, and $P_5 = 621$. These costs can be computed based on the different numbers of DCs within various industries.

3. Several parameters are involved in the algorithm configuration: $\gamma = 10$ is the maximum number of iterations in obtaining the best known solution without any improvement between two routes from different DCs, $\xi = 15$ denotes the maximum number of iterations in obtaining the best known solution without any improvement between two routes within each DC, and $\rho^m = 500$ is the maximum number of iterations in terminating the multi-phase hybrid approach.

The multi-phase hybrid approach is implemented to optimize the total costs for grand coalition based on empirical data in Industries I, П, and Ш. Good feasible routes are shown in Tables 10–12, and a comparison between initial and optimal total costs is presented in Figs. 6–8. Determining the costs and reducing the number of vehicles in three industries for grand coalition can be achieved because of three reasons: (1) The clustering procedure in multi-phase hybrid approach can help increase the possibility that the final solution converges with the optimal one. (2) Heuristic algorithm can significantly improve the initial solution. (3) Dynamic programming procedure obtains good feasible solution within each vehicle route.

Table 10. Good feasible vehicle routes for grand coalition from four DCs in Industry I

DC	Good feasible vehicle routes
D1	D1→C14→C1→C2→C15→C3→C4→C16→D1 D1→C30→C9→C29→C8→C28→C7→C13→D1
D2	D2→C18→C5→C6→C19→C20→C21→D2 D2→C22→C34→C33→C32→C45→D2 D2→C17→C31→C10→C44→C46→D2
D3	D3→C38→C24→C23→C12→C11→D3 D3→C48→C47→C35→C36→C37→D3 D3→C50→C39→C49→C40→C41→D3
D4	D4→C25→C26→C27→C42→C43→D4 D4→C51→C52→C53→C54→C55→D4

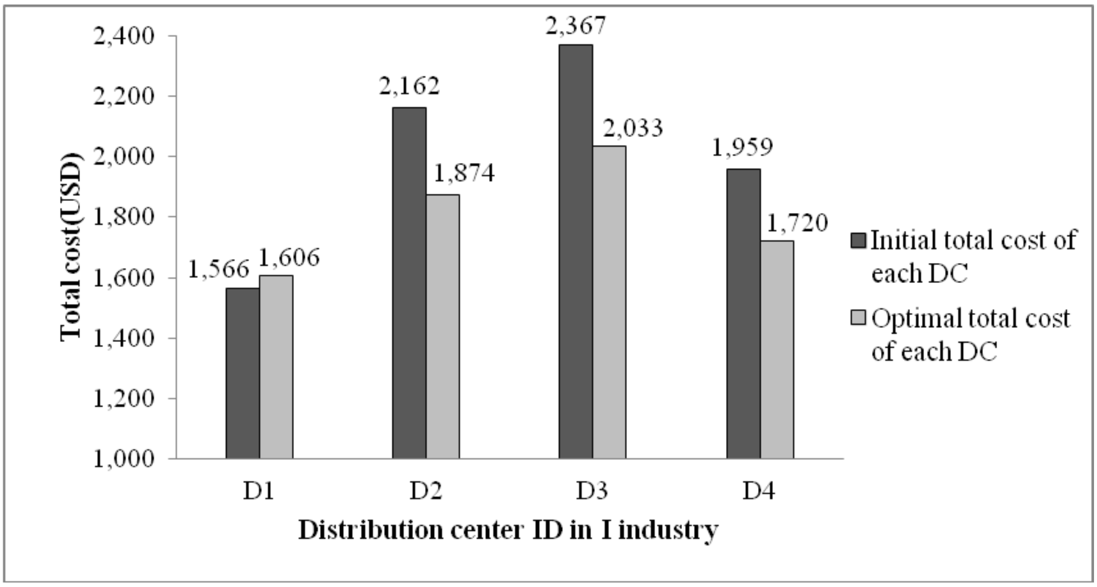

Fig. 6. Initial and good, feasible costs comparison diagram in Industry I

Table 11. Good feasible vehicle routes for grand coalition from three DCs in Industry Π

DC	Good feasible vehicle routes
D1	D1→C4→C1→C13→C14→C27→D1 D1→18→C7→C6→C5→C3→C2→D1 D1→C15→C16→C28→C24→C17→D1
D2	D2→C20→C29→C25→C23→C22→C21→D2 D2→C12→C10→C9→C8→C11→C19→D2
D3	D3→C35→C31→C32→C26→C30→D3 D3→C36→C37→C38→C34→C33→D3 D3→C39→C40→C42→C44→C43→C41→D3

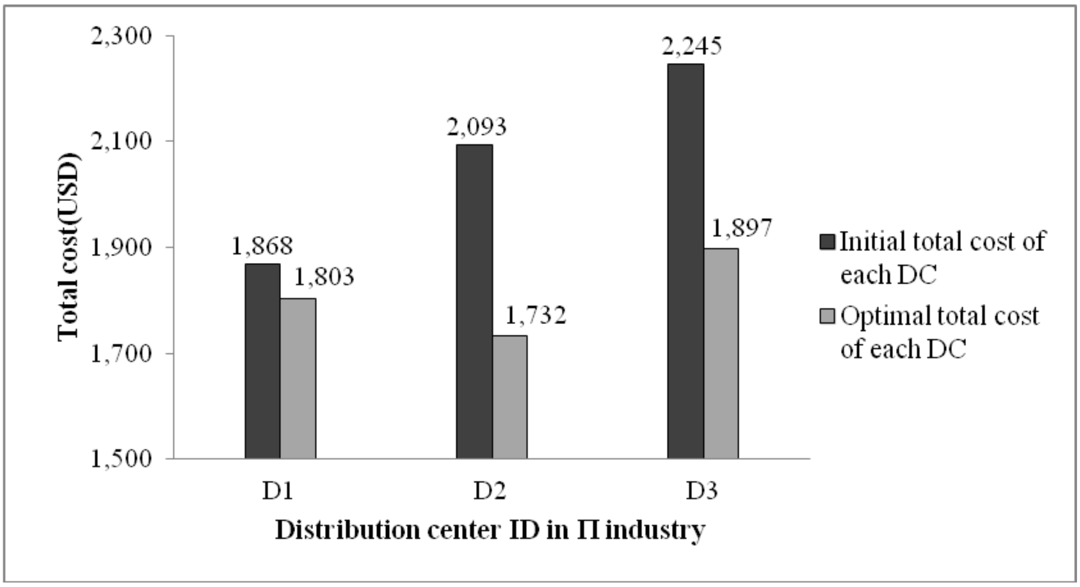

Fig. 7. Initial and good, feasible costs comparison diagram in Industry Π

Table 12. Good feasible vehicle routes for grand coalition from five DCs in Industry Ш

DC	Good feasible vehicle routes
D1	D1→C10→C1→C2→C3→C4→C12→C13→D1 D1→C11→C15→C16→C17→C18→C19→D1
D2	D2→C14→C6→C5→C7→C8→C9→D2 D2→C24→C25→C23→C22→C21→C20→D2
D3	D3→C27→C26→C28→C29→C31→C32→C30→D3 D3→C49→C56→C58→C57→C63→C55→C48→D3 D3→C42→C43→C33→C44→C51→C59→C50→D3
D4	D4→C37→C39→C38→C36→C35→C34→D4 D4→C53→C54→C62→C61→C60→C52→D4 D4→C45→C40→C41→C47→C46→D4
D5	D5→C65→C64→C66→C67→C68→C69→C73→D5 D5→C72→C70→C71→C74→C75→C76→C77→D5

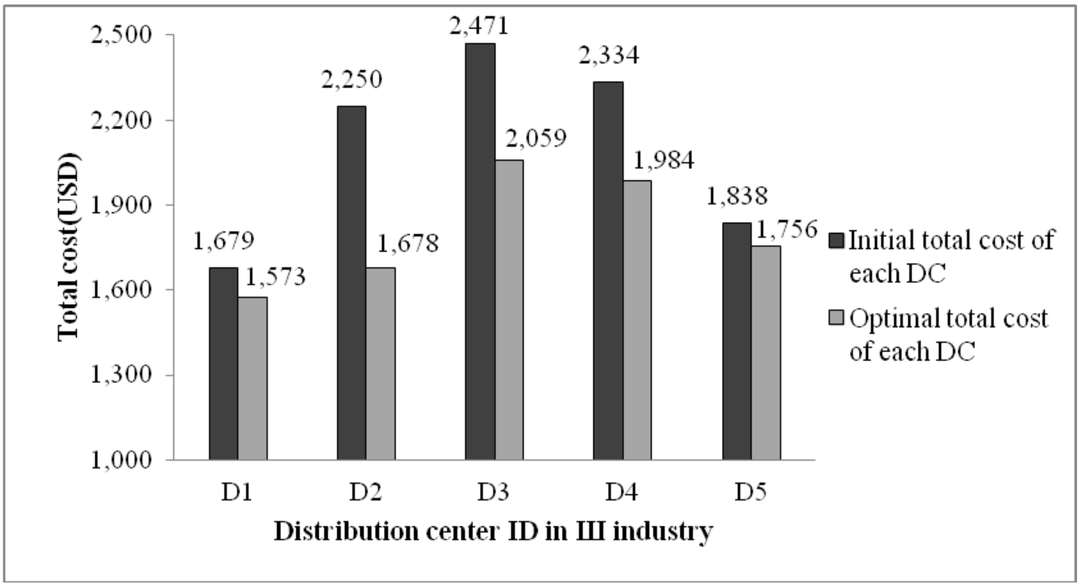

Fig. 8. Initial and good, feasible costs comparison diagram in Industry Ш.

For comparison purposes, HGA (Ho et al. 2008), ISFLA (Luo and Chen 2014), and BVDH (Tu at al. 2014) are also implemented and tested based on the same datasets and parameters from the above industries I, П, and Ш. The comparison results are shown in Table 13. The measures of effectiveness from the results contain the total cost and number of vehicles (TC expresses total costs (USD), and NV expresses number of vehicles).

Table 13. Comparison of proposed approach and three other algorithms in Industries I, П, and Ш

Industry no.		Initial solution		Proposed approach		HGA		ISFLA		BVDH	
		TC	NV	TC	NV	TC	NV	TC	NV	TC	NV
I	D1	1,566	2	1,606	2	1,675	2	1,649	2	1,606	2
	D2	2,162	3	1,874	3	1,931	3	1,902	3	1,874	3
	D3	2,367	3	2,033	3	2,153	3	2,102	3	2,078	3

	D4	1,959	3	1,720	2	1,846	3	1,755	3	1,720	2
П	D1	1,868	3	1,803	3	1,837	3	1,819	3	1,803	3
	D2	2,093	3	1,732	2	1,862	3	1,753	2	1,732	2
	D3	2,245	4	1,897	3	2,053	3	1,921	3	1,897	3
Ш	D1	1,679	3	1,573	2	1,605	2	1,573	2	1,573	2
	D2	2,250	3	1,678	2	1,824	3	1,678	2	1,716	3
	D3	2,471	4	2,059	3	2,189	4	2,113	4	2,084	3
	D4	2,334	4	1,984	3	2,191	3	2,114	3	2,035	3
	D5	1,838	2	1,756	2	1,792	2	1,779	2	1,756	2
Overall average		2,069	3.08	1,810	2.5	1,913	2.83	1,847	2.67	1,823	2.58

Based on the results in Table 13, the following findings can be summarized:

- In Industries I, П, and Ш, the total costs of each DC and each industry from the proposed approach decreased in comparison with those from other three algorithms. D4 costs in Industry Ш decreased from 2,191 USD with HGA to 1,984 USD with the proposed algorithm. In addition, the total costs of Industry Ш decreased from 9,601 USD with HGA to 9,050 USD with the proposed algorithm.
- The number of vehicles from the proposed approach is less than that from the other three algorithms.

To demonstrate the capability of optimizing large-scale logistics networks based on the proposed multi-phase hybrid approach, a comparative study with the BVDH algorithm on benchmark instances for MDVRP, including p08, pr02, pr03, pr05, pr06, pr07, and pr10 (more than 200 customers exist in p08, pr05, pr06, and pr10 benchmark instances), was undertaken. We found that the average solution from the proposed approach is closer to the average solution from the New Best Solution than that from BVDH.

Table 14. Comparison results on benchmark instances for large-scale MDVRP

Benchmark instances	Number of customers	New best solutions	Proposed multi-phase approach	BVDH
p08	249	4,420.95	4,452.37	4,536.82
pr02	96	1,288.37	1,288.37	1,288.37
pr03	144	1,782.58	1,782.58	1,851.65
pr05	240	2,343.66	2,343.66	2,456.38
pr06	288	2,675.16	2,702.23	2,862.19
pr07	72	1,085.61	1,085.61	1,120.32
pr10	288	2,811.49	2,828.56	3,127.39
Average	197	2,343.97	2,354.77	2,463.3

Compared with other models and algorithms, the proposed approach has the following merits:

- In Industries I, П, and Ш, the total travel cost and number of vehicles are significantly improved using the proposed approach. More realistic factors are introduced into the problem formulation; for example, transportation cost among DCs, maintenance cost for semitrailer trucks and vehicles, delivery cost for each DC, and so on. The proposed approach includes a multi-stage process with clustering, dynamic programming, and heuristic algorithm: Clustering can effectively reduce computational complexity; dynamic programming can acquire the optimal solution for each route; the heuristic algorithm combines both between-route operations and within-route operations, where dynamic programming is also integrated. The multi-stage process is iteratively executed and can reduce the conservativeness of the obtained result. Therefore, this strategy gains more benefits for logistics and transportation operators.

- The initial route construction is generated from the clustering procedure, followed by a dynamic programming procedure to further enhance the procedure of initial route solution seeking. The heuristic algorithm and the cycle operation process are presented to assist increase the possibility that the final solution converges to the known best solution. For example, the total costs in the pr02, pr03 and pr07 from Table 14 calculated from proposed approach are equal to the new best solutions.

- The heuristic algorithm contains between-route operations (relocate, exchange, 2-opt*, and swap move), within-route operations (dynamic programming). These operations can be used to improve the sequence of customers between different routes, and the within-route operations can obtain the optimal solution in each route. The between-route and within-route operations are applied interchangeably until the known good feasible solution is achieved.

6.3. Applications of Shapley value and cost reduction models

For calculation and presentation convenience, Industry I is selected for analysis. Fifteen non-empty coalitions are generated and served by LSP because four DCs exist in the logistics distribution network. The optimization results over a planning period from all non-empty coalitions are shown in Table 15.

Table 15. Comparison between initial and optimized networks over a planning period

S	Demand (roll pallets)	Total costs (USD) for initial network	Total costs (USD) for optimized network
{D1}	513	1,566	1,606
{D2}	672	2,162	1,874
{D3}	722	2,367	2,033
{D4}	568	1,959	1,720
{D1, D2}	1,185	3,728	3,338
{D1, D3}	1,235	3,933	3,455
{D1, D4}	1,081	3,525	3,332
{D2, D3}	1,394	4,529	3,786
{D2, D4}	1,240	4,121	3,497
{D3, D4}	1,290	4,326	3,527
{D1, D2, D3}	1,907	6,095	5,146

{D1, D2, D4}	1,753	5,687	4,967
{D1, D3, D4}	1,803	5,892	5,103
{D2, D3, D4}	1,962	6,488	5,290
{D1, D2, D3, D4}	2,475	8,054	6,535

Cost savings between initial and optimized network can be redistributed among different DCs using the improved Shapley value model. A previous discussion indicated that the Shapley value model can be used to study profit distribution among multiple participants. For practical purposes, the synergy requirement is set as $\sigma = 0.15$ in this study. Synergy requirement value is a key factor that reflects the negotiation process between LSP and coalition participants. The profit distributions for all non-empty coalitions are shown in Table 16 (Unit: USD).

Table 16. Profit distribution in MCVR optimization

T	$\sum_{i \in S} C_0(i)$	$C(T)$	$v(T)$	$\phi(T, v)$
{D1}	1,566	1,606	0	(0.0; ·; ·; ·)
{D2}	2,162	1,874	245	(·; 245; ·; ·)
{D3}	2,367	2,033	284	(·; ·; 284; ·)
{D4}	1,959	1,720	203	(·; ·; ·; 203)
{D1, D2}	3,728	3,338	332	(44; 288; ·; ·)
{D1, D3}	3,933	3,455	406	(61; ·; 345; ·)
{D1, D4}	3,525	3,332	164	(-20; ·; ·; 184)
{D2, D3}	4,529	3,786	632	(·; 297; 335; ·)
{D2, D4}	4,121	3,497	530	(·; 286; ·; 244)
{D3, D4}	4,326	3,527	679	(· ; ·; 380; 299)
{D1, D2, D3}	6,095	5,146	807	(93; 329; 385; ·)
{D1, D2, D4}	5,687	4,967	612	(35; 341; ·; 236)
{D1, D3, D4}	5,892	5,103	670	(11; ·; 410; 249)
{D2, D3, D4}	6,488	5,290	1,018	(·; 307; 401; 310)
{D1, D2, D3, D4}	8,054	6,535	1,519	(116; 469; 552; 382)

All possible profit distributions are shown in Table 16. Figure 9 shows the cost reduction percentages and all possible coalitional sequences. The figure shows that D2, D3, and D4 have positive reduction percentages in the last column, which means that D2, D3, and D4 can receive certain percentage cost savings if they agree to accept the cooperation service provided by LSP. LSP can also further optimize the logistics distribution network compared to the scenario when each DC serves its own customers individually. The third column of Fig. 9 shows that D1 and D4 can obtain -1.3% and 9.4% cost reduction percentage respectively in the coalition {D1, D4}. This finding indicates that DC D1 will receive a negative cost reduction percentage in collaboration with D4 served by LSP; under this circumstance, D1 will not accept the service provided by LSP.

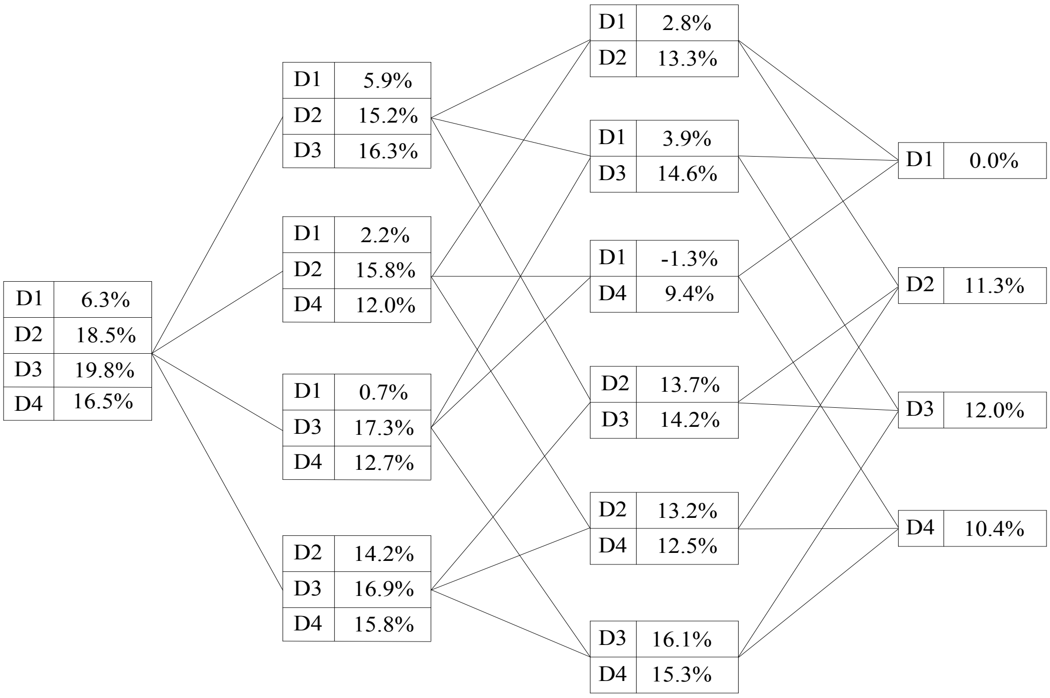

Fig. 9. Cost reduction percentages for all coalitions

6.4 Sequential coalition selection

Sequential coalition selection is necessary to analyze the impact of sequential coalition on profit distribution strategy. Equation (18) and SMP are used to select sequential coalitions for grand coalition establishment. These SMP-based sequential coalitions can be used to investigate the negotiation power for all participants by LSP. All possible sequential coalitions with cost reduction percentages are shown in Fig. 9. Sequential coalitions based on SMP can be further selected and are exhibited in Tables 17–20.

Table 17. Sequential coalitions starting from D1 D2, D3, and D4 for SMP-based grand coalition

Sequential coalitions starting from D1									
$\pi_1 = \{D1, D2, D3, D4\}$					$\pi_2 = \{D1, D3, D2, D4\}$				
Player *i*	D1	D2	D3	D4	Player *i*	D1	D3	D2	D4
$\eta(i,\pi,1)$	0.0%	-	-	-	$\eta(i,\pi,1)$	0.0%	-	-	-
$\eta(i,\pi,2)$	2.8%	13.3%	-	-	$\eta(i,\pi,2)$	3.9%	14.6%	-	-
$\eta(i,\pi,3)$	5.9%	15.2%	16.3%	-	$\eta(i,\pi,3)$	5.9%	16.3%	15.2%	-
$\eta(i,\pi,4)$	6.3%	18.5%	19.8%	16.5%	$\eta(i,\pi,4)$	6.3%	19.8%	18.5%	16.5%
Sequential coalitions starting from D2									
$\pi_1 = \{D2, D1, D3, D4\}$					$\pi_2 = \{D2, D3, D1, D4\}$				
Player *i*	D2	D1	D3	D4	Player *i*	D2	D3	D1	D4
$\eta(i,\pi,1)$	11.3%	-	-	-	$\eta(i,\pi,1)$	11.3%	-	-	-
$\eta(i,\pi,2)$	13.3%	2.8%	-	-	$\eta(i,\pi,2)$	13.7%	14.2%	-	-
$\eta(i,\pi,3)$	15.2%	5.9%	16.3%	-	$\eta(i,\pi,3)$	15.2%	16.3%	5.9%	-
$\eta(i,\pi,4)$	18.5%	6.3%	19.8%	16.5%	$\eta(i,\pi,4)$	18.5%	19.8%	6.3%	16.5%
$\pi_3 = \{D2, D3, D4, D1\}$					$\pi_4 = \{D2, D4, D3, D1\}$				

Player i	D2	D3	D4	D1	Player i	D2	D4	D3	D1
$\eta(i,\pi,1)$	11.3%	-	-	-	$\eta(i,\pi,1)$	11.3%	-	-	-
$\eta(i,\pi,2)$	13.7%	14.2%	-	-	$\eta(i,\pi,2)$	13.2%	12.5%	-	-
$\eta(i,\pi,3)$	14.2%	16.9%	15.8%	-	$\eta(i,\pi,3)$	14.2%	15.8%	16.9%	-
$\eta(i,\pi,4)$	18.5%	19.8%	16.5%	6.3%	$\eta(i,\pi,4)$	18.5%	16.5%	19.8%	6.3%
Sequential coalitions starting from D3									
$\pi_1=\{\mathrm{D3,D1,D2,D4}\}$					$\pi_2=\{\mathrm{D3,D2,D1,D4}\}$				
Player i	D3	D1	D2	D4	Player i	D3	D2	D1	D4
$\eta(i,\pi,1)$	12.0%	-	-	-	$\eta(i,\pi,1)$	12.0%	-	-	-
$\eta(i,\pi,2)$	14.6%	3.9%	-	-	$\eta(i,\pi,2)$	14.2%	13.7%	-	-
$\eta(i,\pi,3)$	16.3%	5.9%	15.2%	-	$\eta(i,\pi,3)$	16.3%	15.2%	5.9%	-
$\eta(i,\pi,4)$	19.8%	6.3%	18.5%	16.5%	$\eta(i,\pi,4)$	19.8%	18.5%	6.3%	16.5%
$\pi_3=\{\mathrm{D3,D2,D4,D1}\}$					$\pi_4=\{\mathrm{D3,D4,D2,D1}\}$				
Player i	D3	D2	D4	D1	Player i	D3	D4	D2	D1
$\eta(i,\pi,1)$	12.0%	-	-	-	$\eta(i,\pi,1)$	12.0%	-	-	-
$\eta(i,\pi,2)$	14.2%	13.7%	-	-	$\eta(i,\pi,2)$	16.1%	15.3%	-	-
$\eta(i,\pi,3)$	16.9%	14.2%	15.8%	-	$\eta(i,\pi,3)$	16.9%	15.8%	14.2%	-
$\eta(i,\pi,4)$	19.8%	18.5%	16.5%	6.3%	$\eta(i,\pi,4)$	19.8%	16.5%	18.5%	6.3%
Sequential coalitions starting from D4									
$\pi_1=\{\mathrm{D4,D2,D3,D1}\}$					$\pi_2=\{\mathrm{D4,D3,D2,D1}\}$				
Player i	D4	D2	D3	D1	Player i	D4	D3	D2	D1
$\eta(i,\pi,1)$	10.4%	-	-	-	$\eta(i,\pi,1)$	10.4%	-	-	-
$\eta(i,\pi,2)$	12.5%	13.2%	-	-	$\eta(i,\pi,2)$	15.3%	16.1%	-	-
$\eta(i,\pi,3)$	15.8%	14.2%	16.9%	-	$\eta(i,\pi,3)$	15.8%	16.9%	14.2%	-
$\eta(i,\pi,4)$	16.5%	18.5%	19.8%	6.3%	$\eta(i,\pi,4)$	16.5%	19.8%	18.5%	6.3%

Tables 10–13 demonstrate the cost reduction percentage based on SMP provided in Section 5.2. On the basis of the proposed approaches in Section 5.2, the best sequential coalitions from each table can be selected: $\pi=\{\mathrm{D1,D3,D2,D4}\}$ are sequential coalitions starting from D1; $\pi=\{\mathrm{D2,D3,D4,D1}\}$ are sequential coalitions starting from D2; $\pi=\{\mathrm{D3,D4,D2,D1}\}$ are sequential coalitions starting from D3; and $\pi=\{\mathrm{D4,D3,D2,D1}\}$ are sequential coalitions starting from D4. These sequential coalitions, along with their respective cost reduction percentages, are summarized in Table 18.

Table 18. Sequential coalitions for SMP-based grand coalition

$\pi_1=\{\mathrm{D1,D3,D2,D4}\}$					$\pi_2=\{\mathrm{D2,D3,D4,D1}\}$				
Player i	D1	D3	D2	D4	Player i	D2	D3	D4	D1
$\eta(i,\pi,1)$	0.0%	-	-	-	$\eta(i,\pi,1)$	11.3%	-	-	-
$\eta(i,\pi,2)$	3.9%	14.6%	-	-	$\eta(i,\pi,2)$	13.7%	14.2%	-	-
$\eta(i,\pi,3)$	5.9%	16.3%	15.2%	-	$\eta(i,\pi,3)$	14.2%	16.9%	15.8%	-

$\eta(i,\pi,4)$	6.3%	19.8%	18.5%	16.5%	$\eta(i,\pi,4)$	18.5%	19.8%	16.5%	6.3%
$\pi_3 = \{\mathrm{D3, D4, D2, D1}\}$					$\pi_4 = \{\mathrm{D4, D3, D2, D1}\}$				
Player *i*	D3	D4	D2	D1	Player *i*	D4	D3	D2	D1
$\eta(i,\pi,1)$	12.0%	-	-	-	$\eta(i,\pi,1)$	10.4%	-	-	-
$\eta(i,\pi,2)$	16.1%	15.3%	-	-	$\eta(i,\pi,2)$	15.3%	16.1%	-	-
$\eta(i,\pi,3)$	16.9%	15.8%	14.2%	-	$\eta(i,\pi,3)$	15.8%	16.9%	14.2%	-
$\eta(i,\pi,4)$	19.8%	16.5%	18.5%	6.3%	$\eta(i,\pi,4)$	16.5%	19.8%	18.5%	6.3%

All possible sequential coalitions for SMP-based grand coalition are illustrated in Table 18. The profit gain procedure for these four sequential coalitions is shown in Fig. 10. Applying the approach in Section 5.2 into Table 18 and Fig. 10 leads to the optimal sequential coalition as $\pi = \{\mathrm{D3, D4, D2, D1}\}$. The best cooperation strategy can be described as follows. D3 is first optimized by LSP and will obtain 12.0% cost reduction. Then, coalitions containing D3 and D4 are served by LSP with 16.1% and 15.3% cost reduction respectively, followed by D2. D3, D4, and D2 can respectively receive 16.9%, 15.8%, and 14.2% cost reduction. Finally, D1 joins the coalition, and the grand coalition is established. D3, D4, D2, and D1 can obtain 19.8%, 16.5%, 18.5%, and 6.3% cost reduction, respectively.

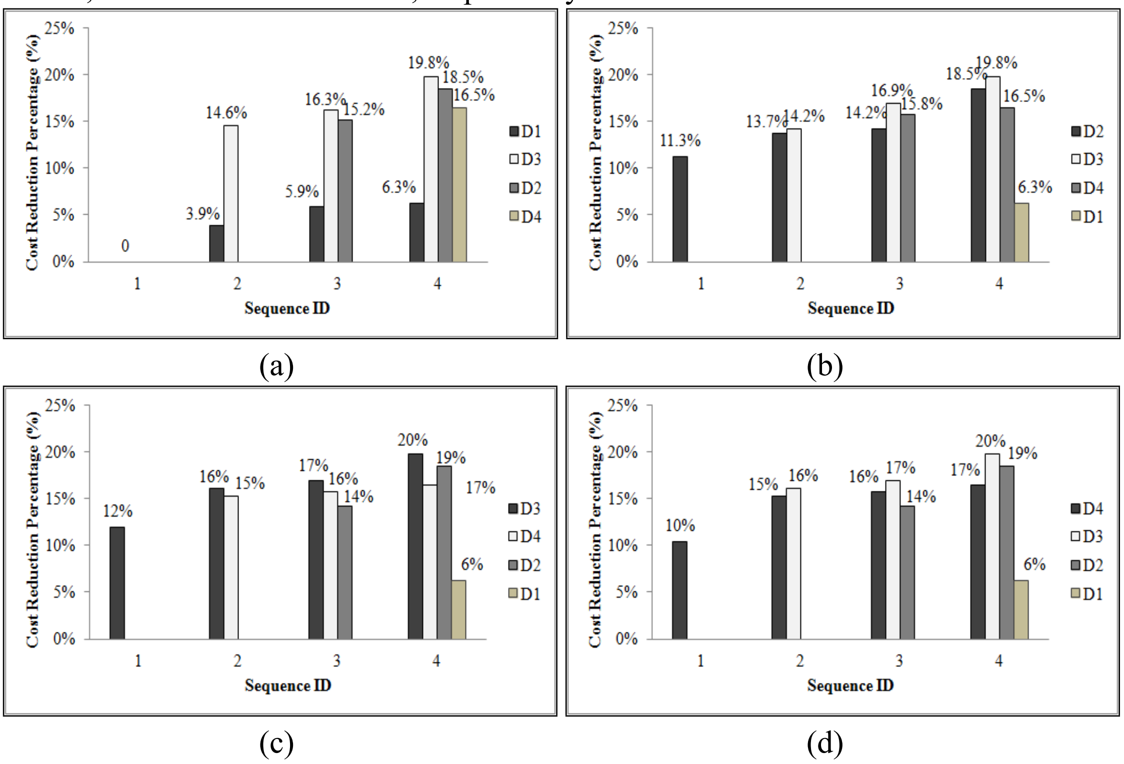

Fig. 10. Selected possible sequential coalitions for grand coalition: (a) starting from D1, (b) starting from D2, (c) starting from D3, and (d) starting from D4.

As shown in Fig. 10, cost reduction percentages increase for each DC when the coalition is updated for these four possible sequential coalitions based on SMP strategy. In practice, SMP strategy is attractive for participants because the percentages of monotonic cost reduction and the strategies of reasonable profit distribution will encourage logistics participants to cooperate with one another.

To verify the accuracy of optimal sequential coalition, the nucleolus, core center, and minmax core methods from cooperative game theory (Cruijssen et al. 2010; Lozano et al. 2013) are used for comparison and analysis in Table 19.

Table 19. Profit distribution according to improved Shapley value, nucleolus, core center, and minmax core

T	Shapley	Nucleolus	Core centre	Minmax core
{D1}	(0.0; · ; · ; ·)	(0.0; · ; · ; ·)	(0.0; · ; · ; ·)	(0.0; · ; · ; ·)
{D2}	(· ;245; · ; ·)	(· ;245; · ; ·)	(· ;245; · ; ·)	(· ;245; · ; ·)
{D3}	(· ; · ;284; ·)	(· ; · ;284; ·)	(· ; · ;284; ·)	(· ; · ;284; ·)
{D4}	(· ; · ; · ; 203)	(· ;· ; · ; 203)	(· ;· ; · ; 203)	(· ; · ; · ; 203)
{D1,D2}	(44;288; · ; ·)	(29;303; · ; ·)	(38;294; · ; ·)	(35;297; · ; ·)
{D1,D3}	(61; · ;345; ·)	(43; · ;363; ·)	(52; · ;354; ·)	(47; · ;359; ·)
{D1,D4}	(-20; · ; · ;184)	(-35; · ; · ;199)	(-25; · ; · ;189)	(-32; · ; · ; 196)
{D2,D3}	(· ;297;335; ·)	(· ;369;263; ·)	(· ;337;295; ·)	(· ;354;278; ·)
{D2,D4}	(· ;286; · ; 244)	(· ;373; · ; 157)	(· ;352; · ; 178)	(· ;365; · ; 165)
{D3,D4}	(· ; · ;380;299)	(· ; · ;409;270)	(· ; · ;394;285)	(· ; · ;401;278)
{D1,D2,D3}	(93;329;385; ·)	(88;306;413; ·)	(99;313;395; ·)	(90;309;408; ·)
{D1,D2,D4}	(35;341; · ;236)	(21;350; · ;241)	(30;343; · ;239)	(23;346; · ;243)
{D1,D3,D4}	(11; · ; 410 ;249)	(5; · ; 414 ;251)	(9; · ; 396 ;265)	(7; · ; 405 ;258)
{D2,D3,D4}	(· ;307;401;310)	(· ;237;445;336)	(· ;280;423;315)	(· ;258;439;321)
{D1,D2,D3,D4}	(116;469;552;382)	(83;302;624;510)	(104;331;591;493)	(94;307;603;515)

As shown in Table 19, sequential coalitions based on SMP from nucleolus, core center, and minmax core methods are further selected and exhibited in Table 20.

Table 20. Sequential coalitions from nucleolus, core center, and minmax core for grand coalition based on SMP

Sequential coalitions from nucleolus									
$\pi_1 = \{D3, D4, D2, D1\}$					$\pi_2 = \{D4, D3, D2, D1\}$				
Player *i*	D3	D4	D2	D1	Player *i*	D4	D3	D2	D1
$\eta(i,\pi,1)$	12.0%	-	-	-	$\eta(i,\pi,1)$	10.4%	-	-	-
$\eta(i,\pi,2)$	17.3%	13.8%	-	-	$\eta(i,\pi,2)$	13.8%	17.3%	-	-
$\eta(i,\pi,3)$	18.8%	17.2%	11.0%	-	$\eta(i,\pi,3)$	17.2%	18.8%	11.0%	-
$\eta(i,\pi,4)$	26.4%	26.0%	14.0%	5.3%	$\eta(i,\pi,4)$	26.0%	26.4%	14.0%	5.3%
Sequential coalitions from core center									
$\pi_1 = \{D2, D1, D3, D4\}$					$\pi_2 = \{D3, D4, D2, D1\}$				
Player *i*	D2	D1	D3	D4	Player *i*	D3	D4	D2	D1
$\eta(i,\pi,1)$	11.3%	-	-	-	$\eta(i,\pi,1)$	12.0%	-	-	-
$\eta(i,\pi,2)$	13.6%	2.4%	-	-	$\eta(i,\pi,2)$	16.6%	14.5%	-	-
$\eta(i,\pi,3)$	14.5%	6.3%	16.7%	-	$\eta(i,\pi,3)$	17.9%	16.1%	13.0%	-
$\eta(i,\pi,4)$	15.3%	6.6%	25.0%	25.2%	$\eta(i,\pi,4)$	25.0%	25.2%	15.3%	6.6%
$\pi_3 = \{D3, D1, D2, D4\}$					$\pi_4 = \{D4, D3, D2, D1\}$				

Player i	D3	D1	D2	D4	Player i	D4	D3	D2	D1
$\eta(i,\pi,1)$	12.0%	-	-	-	$\eta(i,\pi,1)$	10.4%	-	-	-
$\eta(i,\pi,2)$	15.0%	3.3%	-	-	$\eta(i,\pi,2)$	14.5%	16.6%	-	-
$\eta(i,\pi,3)$	16.7%	6.3%	14.5%	-	$\eta(i,\pi,3)$	16.1%	17.9%	13.0%	-
$\eta(i,\pi,4)$	25.0%	6.6%	15.3%	25.2%	$\eta(i,\pi,4)$	25.2%	25.0%	15.3%	6.6%
Sequential coalitions from minmax core									
$\pi_1 = \{\mathrm{D3}, \mathrm{D1}, \mathrm{D2}, \mathrm{D4}\}$					$\pi_2 = \{\mathrm{D3}, \mathrm{D4}, \mathrm{D2}, \mathrm{D1}\}$				
Player i	D3	D1	D2	D4	Player i	D3	D4	D2	D1
$\eta(i,\pi,1)$	12.0%	-	-	-	$\eta(i,\pi,1)$	12.0%	-	-	-
$\eta(i,\pi,2)$	15.2%	3.0%	-	-	$\eta(i,\pi,2)$	16.9%	14.2%	-	-
$\eta(i,\pi,3)$	17.2%	5.7%	14.3%	-	$\eta(i,\pi,3)$	18.5%	16.4%	11.9%	-
$\eta(i,\pi,4)$	25.5%	6.0%	14.2%	26.3%	$\eta(i,\pi,4)$	25.5%	26.3%	14.2%	6.0%
$\pi_3 = \{\mathrm{D4}, \mathrm{D3}, \mathrm{D2}, \mathrm{D1}\}$									
Player i	D4	D3	D2	D1					
$\eta(i,\pi,1)$	10.4%	-	-	-					
$\eta(i,\pi,2)$	14.2%	16.9%	-	-					
$\eta(i,\pi,3)$	16.4%	18.5%	11.9%	-					
$\eta(i,\pi,4)$	26.3%	25.5%	14.2%	6.0%					

As shown in Tables 19–20, applying the approach in Section 5.2 into Tables 19–20 leads to the optimal sequential coalition as $\pi = \{\mathrm{D3}, \mathrm{D4}, \mathrm{D2}, \mathrm{D1}\}$ for nucleolus, core center, and minmax core methods. The best cooperation strategy from the improved Shapley value model receives the same result compared with other cooperative-game-theory-based approaches. As more participants join the collaborative logistics network, a higher gain can be observed, which is known as the snowball effect (Frisk et al. 2010; Lozano et al. 2013). The radius of the snowball represents the algorithm stability and can be calculated as the difference between the maximum and minimum cost reduction percentages. A smaller radius means a more stable profit distribution scheme. As shown in Tables 19–20, radii for the four methods can be respectively computed as 13.5% for improved Shapley value model, 20.7% for nucleolus, 18.6% for core center, and 20.3% for minmax core. Evidence supports that the improved Shapley value model outperforms the other algorithms in terms of stability.

With synergy requirement set as $\sigma = 0.15$, the LSP can receive 15% of the total cost savings, equivalent to 228 USD per working period. The remaining profit is distributed among D1, D2, D3, and D4 based on the improved Shapley value model. D3 receives 469 USD cost savings and has the greatest cost reduction percentage because of customers' uneven geospatial distribution and high customer demand. Considering the proximities between DCs and customers, good transportation condition, and high service costs for D1, D1 receives the lowest cost reduction percentage.

LSP can adjust the synergy requirement σ to increase negotiation power for increased benefit. If several participants cannot accept the profit distribution plan based on a certain synergy requirement σ, then the LSP can decrease synergy requirement to enhance the cooperation opportunity. If a certain DC (e.g., D1) cannot achieve collaboration agreement regardless of what synergy requirement is provided by the LSP, then the optimal sequential coalition becomes $\pi = \{D3, D2, D4\}$ rather than $\pi = \{D3, D4, D2\}$. The optimal sequence can be recalculated and generated based on a similar calculation process in Section 5.3. Additional managerial insights can also be generated: (1) Monotonicity and additivity properties are not always existent in the coalition logistics network optimization procedure. (2) The heterogeneous behavior of participants will influence the robustness of the cooperative logistics network. (3) Key factors, such as the transaction cost and the complexity of managing the collaboration, can limit the formation of collaborative logistics network.

7. Conclusions

This paper studies the MCVR optimization and profit distribution problem, where vehicle routes among DCs can be optimized and adjusted from a global optimization perspective. The optimization process is organized by either LSP or existing participants in a logistics network. A multi-phase hybrid approach with clustering, dynamic programming, and heuristic algorithm is presented to optimize the multi-center network. A profit distribution method based on an improved Shapley value model is then proposed to distribute the gained profits among DCs. MCVRP optimization and profit distribution problems are interrelated, and LSP can organize the negotiation procedure to distribute cost savings from MCVRP optimization among DCs. Through the above procedures, robustness and reliability of large-scale logistics distribution network can be enhanced, and network complexity can be reduced.

The MCVRP optimization model is first constructed to optimize the total costs of non-empty coalition logistics network, followed by the multi-phase hybrid approach to solve the model. Then, profit distribution is calculated based on the improved Shapley value model among DCs from non-empty coalitions. Finally, cost reduction percentages and optimal sequential coalitions can be obtained based on the SMP theory, cost reduction model, and best sequential coalition selection strategy. The proposed approach is successfully applied to a multi-center distribution network in Chongqing City, China, and compared with other prevailing algorithms based on cooperative game theory. Results demonstrated that the proposed approach outperforms other algorithms, and the best sequential coalition can be selected. Moreover, the synergy requirement value can be adjusted to increase the negotiation power for logistics distribution network optimization.

To enhance the usability and depth of this study, further research should consider incorporating additional factors, such as products that require temperature control, customers' time windows, split loads, and simultaneous deliveries and pickups into logistics network design. These additional factors can be integrated into both MDVRP and profit distribution problems. The heterogeneity of synergy requirement values among participants should be also considered to enhance the robustness of logistics distribution network. Meanwhile, the approach can be also extended to solving other similar multiple centers pharmaceutical distribution problems for decision-makers.

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