Postprint of Research on Collaborative Routing Customization Problems in Fourth-Party Logistics

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Abstract

To address the high transportation cost issues faced by third-party logistics (3PL) providers, this paper proposes a multi-3PL collaborative customized routing problem from the perspective of fourth-party logistics (4PL) providers. For model solving of this problem, which requires simultaneous consideration of both routing characteristics and 3PL provider features, a hybrid particle swarm optimization algorithm based on k-shortest paths (K-PSO) is designed. In the experimental analysis, the effectiveness of the algorithm is demonstrated through computational results of simulation examples under varying numbers of nodes and different quantities of 3PL providers, comparing the K-PSO algorithm with genetic algorithms and enumeration algorithms. Finally, by varying the transfer costs of 3PL providers, the advantages of 4PL collaborative transportation are illustrated.

Full Text

Preamble

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Research on 4PL Collaborative Routing Customization Problem

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Abstract

To address the high transportation cost problem faced by third-party logistics (3PL) suppliers, this paper proposes a multi-3PL collaborative routing customization problem from the perspective of fourth-party logistics (4PL) suppliers. Given that solving this problem requires simultaneous consideration of both route characteristics and 3PL supplier features, a hybrid Particle Swarm Optimization algorithm based on K-shortest paths (K-PSO) is designed. Experimental analysis demonstrates the algorithm' s effectiveness through computational comparisons with genetic algorithms and enumeration algorithms across simulation cases with varying numbers of nodes and 3PL suppliers. Finally, by altering the transfer costs of 3PL suppliers, the advantages of 4PL collaborative transportation are illustrated.

Keywords: collaborative transportation; particle swarm optimization; fourth-party logistics; k-shortest path algorithm

0 Introduction

The Fourth-Party Logistics (4PL) Collaborative Routing Customization Problem (4PLCRCP) refers to the scenario where a single Third-Party Logistics (3PL) supplier struggles to complete or would incur excessive costs to fulfill a transportation task assigned by a customer, prompting the 4PL supplier to leverage its information resources to coordinate multiple 3PL suppliers in jointly customizing a transportation solution for the client.

Research on collaborative logistics centers on the holistic planning, allocation, acquisition, and integrated optimization of network resources [1]. For the 4PLCRCP, 4PL suppliers must not only coordinate multiple logistics branches but also undertake the task of selecting appropriate 3PL suppliers for these branches. Previous studies have treated 3PL suppliers between any two nodes as independent entities [2]. However, in actual transportation operations, many 3PL providers have extensive business scopes and only exhibit disadvantages on specific route segments. Consequently, 4PL suppliers should utilize their information resources to select 3PL suppliers for customers, thereby creating more advantageous distribution plans.

In the 4PLCRCP, the incorporation of collaborative mechanisms requires 4PL suppliers to consider the specific conditions at each transfer node. Numerous scholars have investigated solution methods for 4PL problems [2-5]. Nevertheless, the 4PLCRCP not only involves finding constrained shortest paths in a multigraph but also necessitates calculating transfer costs and times at transshipment nodes. While theoretically feasible, enumerating all paths using a simple graph would result in an enormous solution space. Therefore, this paper first employs the K-shortest path algorithm to identify the top K shortest paths in a simple graph, then utilizes the particle swarm optimization algorithm to select suppliers along these paths. This approach enhances both algorithmic efficiency and effectiveness.

Based on the above analysis, this paper establishes a mathematical model for the 4PLCRCP that simultaneously considers 3PL supplier stopover and switching costs within the 4PL collaborative transportation framework. A hybrid particle swarm optimization algorithm based on the K-shortest path algorithm (K-PSO) is designed. Experimental analysis demonstrates the effectiveness of the K-PSO algorithm through computational experiments on instances with varying numbers of nodes and 3PL suppliers, as well as comparative analysis with genetic algorithms and enumeration algorithms. Finally, computational results under different transfer costs indicate that compared to the transportation mode where customers use only a single 3PL supplier, the 4PL collaborative transportation mode not only increases the ratio of on-time task completion but also yields cost savings for customers.

1.1 Problem Description

Assume a 4PL supplier intends to undertake a transportation task from supply point to destination point , where represents transshipment nodes. The network consists of 3PL suppliers. The 4PL can assign tasks based on the transportation scope of each 3PL supplier. Each 3PL supplier incurs specific time and cost requirements during transportation and when passing through transshipment nodes. If the 4PL utilizes different 3PL suppliers on adjacent path segments, additional time and costs for switching 3PL providers are incurred (with origin and destination nodes considered as switching nodes). Treating the 3PL suppliers in the aforementioned problem as edges with indices (where denotes the node set and the edge set), we obtain the 4PLCRCP transportation network multigraph .

1.2 Mathematical Model

The objective of this paper is to identify a cost-optimal shortest path that satisfies all constraints. Under path , the model must simultaneously account for 3PL suppliers, transshipment nodes, and the time and costs associated with switching 3PL providers. Based on the above description, the established model is as follows:

In the above model, Equation (1) represents the objective function, denoting the total expenditure comprising transportation, transshipment node stopover, and switching costs. Equation (2) ensures that the arrival time at the destination does not exceed the customer' s required timeframe. Equation (3) enforces flow balance. Equations (4) and (5) guarantee that the selected nodes form a valid path from origin to destination. Equation (6) indicates that if switching occurs at node , then node must be a transshipment point. Equations (7) and (8) specify the origin and destination nodes, respectively. Equation (9) defines , , and as binary (0-1) variables.

2.1 Main Steps

In the K-PSO algorithm, the solution process comprises two phases: initial solution generation and solution updating. In the first phase, the K-shortest path algorithm is employed to identify the top K shortest paths. Subsequently, the number of K-shortest paths is proportionally expanded according to the population size, and 3PL suppliers along these paths are randomly generated while fitness values are calculated. In the second phase, the results from the first phase serve as the initial population, and the PSO algorithm is utilized to select 3PL suppliers along the paths. For each generation, the average fitness values of the previous generation' s K-shortest paths are sorted in ascending order, and the roulette wheel method [6] is applied to determine the allocation of individuals to each K-shortest path. Based on the above description, the main algorithmic steps are as follows:

a) Apply the K-shortest path algorithm to identify the top K shortest paths. Determine the K value based on these results. After proportionally expanding the population size, initialize the 3PL suppliers along the paths and calculate their fitness values.

b) Allocate the number of individuals for each K-shortest path within the population using the roulette wheel method based on the average fitness values of the K-shortest paths.

c) Employ the PSO algorithm to determine the 3PL suppliers along the paths and compute their fitness values.

d) For each distinct K-shortest path, check whether a better solution exists. If yes, update the best solution for that K-shortest path; otherwise, retain the current solution.

e) Check if the maximum iteration count has been reached. If yes, proceed to Step 6; otherwise, return to Step 2.

f) Upon algorithm termination, compare the best solutions across all K-shortest paths and output the optimal solution.

2.2 Encoding Structure and Initial Solution

Based on the problem characteristics, the solution encoding structure consists of two components: the node set along the path . Here, represents the th node along the path, and indicates whether to switch 3PL suppliers at node when passing through it, i.e., the th 3PL supplier.

During the initial solution generation phase, the node set along the path is obtained via the K-shortest path algorithm. The number of node sets is proportionally expanded to match the population size, and the edge set of the solution is constructed by randomly generating 3PL suppliers, thereby forming the initial population of solutions.

2.3 Solution Updating

In the solution updating phase, the velocity and position update formulas of the PSO algorithm [6] are first employed to calculate the values (0 or 1) of 3PL suppliers along the path, followed by the application of the roulette wheel method to determine the final 3PL selection. The specific procedure is as follows:

Assume the position of the th particle: , where denotes the population size. The velocity and position update formulas for the th particle are used to compute the 0-1 values for the 3PL from to based on generated from Equation (10) and Equation (11). The fitness values of paths when the 3PL value equals 1 are calculated separately and sorted in ascending order. Setting parameter yields the rank-based evaluation function:

The selection process is based on the roulette wheel method. According to evaluation function (13), the roulette wheel is spun, and the final selected 3PL supplier is determined using Equation (12).

The genetic algorithm (GA) designed in reference [2] and the enumeration algorithm (EM) were improved and applied to solve the aforementioned test cases. Assuming each case was run 50 times, the results are presented in Table 1 .

2.4 Fitness Function

When solving for K-shortest paths using the K-shortest path algorithm, time constraints of the paths are not considered. This paper incorporates time constraints as penalty values into the objective function, thereby forming the fitness function expressed in Equation (14).

where is the penalty coefficient. Figure 1 [Figure 1: see original paper] shows the convergence curve of the K-PSO algorithm for 8 nodes.

3.1 Experimental Data

Tailored to the characteristics of the 4PLCRCP, we assume that the nodes in network node set V are randomly generated within a 100$×$100 range. NO represents the number of adjacent nodes that may have edges connected to node . D is the adjacency matrix (where D(i, j)=r indicates that there are r edges between and). d(i, j).cost(ii) and d(i, j).time(ii) denote the cost and time attributes of the ii-th edge (ii=1,⋯,r) from node to node , respectively. The experimental data is generated through the following three stages:

a) Generate nodes connected to node . If |j-i| $\leq$ NO, randomly generate an integer t1 between 1 and NO. If t1 $>$ NO-1, set no edge between and , i.e., D(i, j)=0; otherwise, assume r edges connect to , i.e., D(i, j)=r.

b) Generate cost and time attributes for edges (3PL suppliers). If D(i, j) $\neq$ 0, randomly generate a real number t2 between 0 and 1. When t2 $>$ 0.2, the transportation cost for the ii-th edge from to is set as a random integer between 1 and 15, i.e., d(i,j).cost(ii)=rand(1,15); the transportation time for the ii-th edge from to is set as a random integer between 1 and 10, i.e., d(i,j).time(ii)=rand(1,10). When t2 $\leq$ 0.2 or for other nodes, d(i,j).time(ii)=|i-j|/d(i,j).cost(ii). When t2⋯the cost and time for the 3PL supplier are set to infinity.

c) Generate cost and time attributes for nodes. The transshipment and transfer costs for node are assigned random integers between 2 and 12; the transshipment and transfer times for node are assigned random integers between 4 and 14.

Fig. 1 Convergence curve of the 8-node K-PSO algorithm

Table 1 shows the comparison results. In Table 1, "-" indicates that the corresponding information does not exist in that algorithm. For EM, when n=8, the total computation time is 79 seconds, which matches the results obtained by K-PSO and GA. When n=30, EM cannot obtain the optimal solution within a reasonable time. K-PSO outperforms GA in terms of mean best solution and standard deviation. Moreover, GA' s population size is significantly larger than that of K-PSO. This phenomenon occurs because the collaborative mechanism makes it difficult for GA to account for each transshipment point, rendering its computational stability dependent on population size. When n=50 and n=100, the differences between the two algorithms become more pronounced in terms of deviation, worst solution, and mean values. Therefore, Table 1 demonstrates that although K-PSO consumes some time computing K-shortest paths, its average solution quality surpasses that of GA.

Table 1 The comparison of the K-PSO with GA and EM algorithm

3.2 Results Analysis

Assume a 4PL supplier intends to undertake a transportation task from node to node . The data is generated with NO=3 as described in Section 3.1. The algorithm is implemented using Matlab 7.0 on a Core2 2.83GHz PC. After extensive experimentation, the following parameter settings are found to be reasonable:

K=3, PS=5, GEN=20, c1=c2=2, =0.5, =0.8, =0.5. Assuming T=26 days, the optimal solution obtained is [1, 3, 6, 8] [1, 5, 5]. This indicates that when the decision-maker (4PL) needs to transport goods from node 1 to node 8 within 26 days, 3PL suppliers numbered 1, 5, and 5 are assigned to handle transportation from node 1 to 3, node 3 to 6, and node 6 to 8, respectively. This transportation process takes a total of 25 days and costs 157.7.

Figure 1 illustrates the convergence behavior of the K-PSO algorithm when n=8. To strengthen the credibility of the algorithm for solving 4PLCRCP, test cases are randomly generated with NO=5, n=30; NO=8, n=50; and NO=8, n=100. **Figure 2** [**Figure 2: see original paper**] presents a comparison of deviations calculated by GA and K-PSO when n=30, NO=5, and r=1, 5, 10, 15, 20.

When r=1, there is only one 3PL between any two points, transforming the 4PLCRCP into a constrained shortest path problem. As the number of 3PLs increases, the deviations of both algorithms grow. However, when r=10, 15, and 20, the solution deviation of K-PSO actually decreases to some extent. This occurs because the increased number of 3PLs expands the selection space for the K-PSO algorithm, whereas GA' s solution capability weakens as the number of 3PLs grows.

3.3 Problem Analysis

In the 4PLCRCP, the 4PL' s decision outcomes are intricately linked not only to the transportation time and costs of 3PL suppliers but also to the conversion costs at nodes. **Table 2** presents a comparison between the 4PL collaborative mode and single 3PL supplier transportation when n=30. In collaborative mode, when···the conversion cost of 3PL suppliers is zero, transforming the 4PLCRCP into the 4PLRP problem [2].

As conversion costs increase, the 4PL tends to utilize the same 3PL supplier whenever possible. Concurrently, as transshipment time increases, the transportation plan also changes accordingly. Table 2 reveals that under time constraints, transportation costs remain identical for the same conversion costs across different conversion times. However, as conversion time increases, such as···, the 4PL becomes unable to complete tasks on schedule, leading to significantly higher total transportation costs. Due to the limited business scope of

3PL suppliers, only 3PL suppliers 1, 2, and 5 can independently complete partial tasks in the n=30 test case. Using them for standalone transportation eliminates conversion costs but may increase total transportation expenses. An analysis of the number of completed tasks under different conversion costs in Table 2 (**Figure 3 [Figure 3: see original paper]**) and the cost increase magnitude compared to collaborative transportation (**Figure 4 [Figure 4: see original paper]**) demonstrates that the collaborative transportation mode not only reduces costs but also significantly outperforms the single 3PL supplier approach in terms of task completion count (Figure 3) and costs when completing tasks (Figure 4).

Fig. 2 The deviation under the different 3PL quantities

Table 2 The influence of the conversion cost on optimal solution under different transportation modes

Fig. 3 The 4PL' s task completion under different transportation modes
Fig. 4 Cost increase magnitude for 3PL suppliers 1, 2, and 5 under different transfer costs

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4 Conclusion

The Fourth-Party Logistics Collaborative Routing Customization Problem (4PLCRCP) represents a complex class of optimization problems. This paper establishes a mathematical model for the 4PLCRCP that incorporates transshipment costs and designs a K-shortest path-based particle swarm optimization algorithm (K-PSO). The effectiveness of K-PSO is validated through comparisons with GA and enumeration algorithms. Furthermore, experimental results demonstrate that if a 4PL can effectively integrate multiple 3PL suppliers, it can achieve the objectives of consolidating advantageous 3PL resources and reducing costs even when conversion fees are charged at transshipment nodes.

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Note: Figure translations are in progress. See original paper for figures.