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Article

Integrated optimization of logistics routing problem considering chance preference

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Integrated optimization of logistics routing problem considering chance preference

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Abstract

Purpose – This study aims to examine the impact of the decision makers' risk preference on logistics routing problem, contributing to logistics behavior analysis and route integration optimization under uncertain environment. Due to the unexpected events and complex environment in modern logistics operations, the logistics process is full of uncertainty. Based on the chance function of satisfying the transportation time and cost requirements, this paper focuses on the fourth party logistics routing integrated optimization problem considering the chance preference of decision makers from the perspective of satisfaction.

Design/methodology/approach – This study used the quantitative method to investigate the relationship between route decision making and human behavior. The cumulative prospect theory is used to describe the loss, gain and utility function based on confidence levels. A mathematical model and an improved ant colony algorithm are employed to solve the problems. Numerical examples show the effectiveness of the proposed model and algorithm. **Findings** – The study's findings reveal that the dual-population improvement strategy enhances the algorithm's global search capability and the improved algorithm can solve the risk model quickly, verifying the effectiveness of the improvement method. Moreover, the decision-maker is more sensitive to losses, and the utility obtained when considering decision-makers' risk attitudes is greater than that obtained when the decision-maker exhibits risk neutrality.

Practical implications – In an uncertain environment, the logistics decision maker's risk preference directly affects decision making. Different parameter combinations in the proposed model could be set for decision-



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makers with different risk attitudes to fit their needs more accurately. This could help managers design effective transportation plans and improve service levels. In addition, the improved algorithm can solve the proposed problem quickly, stably and effectively, so as to help the decision maker to make the logistics path decision quickly according to the required confidence level.

Originality/value – Considering the uncertainty in logistics and the risk behavior of decision makers, this paper studies integrated routing problem from the perspective of opportunity preference. Based on the chance function of satisfying the transportation time and cost requirements, a fourth party logistics routing integrated optimization problem model considering the chance preference of decision makers is established. According to the characteristics of the problem, an improved dual-population and colony algorithm is designed to solve the proposed model. Numerical examples show the effectiveness the proposed methods.

Keywords Fourth party logistics, Routing optimization, Dependent-chance programming,

Ant colony algorithm, Risk attitude

Paper type Research paper

1. Introduction

With the rapid development of modern economy and e-commerce, the competition among modern enterprises is becoming more and more fierce (Tian *et al.*, 2022; Fu *et al.*, 2021a, b). As an important means of promoting enterprise industrial upgrading and enhancing core competitiveness, logistics has attracted widespread attention from various industries (Stodola, 2020; Goli *et al.*, 2022). At the same time, people's demands for logistics service levels have continued to increase (Qian *et al.*, 2021; Mehmann and Teuteberg, 2016), particularly in uncertain logistics services where stable and efficient delivery is one of the most effective ways for modern logistics companies to win customer recognition.

In order to improve logistics efficiency and core competitiveness of enterprises, most enterprises outsource logistics business to professional third-party logistics (3PL) providers. However, with the rapid development of modern logistics, customers' requirements for logistics service level are constantly increasing. Logistics decision is not only about accomplishing transportation tasks, but also resource sharing and ability integration among different subjects (Wang *et al.*, 2020, 2024). Traditional 3PL providers lack supply chain management capabilities, and the cooperation between 3PL providers is not deep enough, and complementary resources are not fully utilized, making it difficult to meet the current market demand for fierce competition (Zhang *et al.*, 2021). Therefore, the industry and academia are both focusing on fourth-party logistics (4PL) from a resource integration perspective (Gattorna, 1998; Yao, 2010). In recent years, 4PL companies and logistics enterprises formed and providing services based on the 4PL concept have gradually demonstrated their strong competitiveness and influence (Huang *et al.*, 2009).

The essential nature and core advantage of 4PL operation lie in its ability to integrate supply chain resources (Tao *et al.*, 2017). By cooperating with participants at various stages within the supply chain, 4PL can facilitate mutual promotion, alleviate the phenomenon of 3PL enterprises acting alone, vicious competition in developed areas and inadequate supply in underdeveloped areas, and effectively integrate and fully utilize social resources (Yin *et al.*, 2022). Many scholars at home and abroad have conducted research on issues related to 4PL, such as supplier evaluation problems (Krakovics *et al.*, 2008), 3PL supplier selection (Aguezzoul, 2014), contract design (Wang *et al.*, 2021; Huang *et al.*, 2019), scheduling (Liu *et al.*, 2014), network design (Wang *et al.*, 2021), routing problem (Zhang *et al.*, 2005) and so on.

Route planning is one of the core factors affecting the overall efficiency of logistics (Goli *et al.*, 2022; Wang *et al.*, 2023). The fourth party logistics routing optimization problem (4PLROP) is a critical issue in modern logistics optimization (Huang *et al.*, 2016). 4PL involves selecting appropriate transportation routes for shipping tasks while also selecting the 3PL suppliers who provide transportation services along that path, presenting a challenge to traditional routing problems. Some scholars have proposed simplifying 4PLROP by using a

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description method of a directed multigraph. Chen *et al.* (2003) described each edge in a directed multigraph as a 3PL supplier that provides transportation services along that path, providing a clear description of 4PLROP and quickly solving small-scale problems. Cui *et al.* (2013) integrated path selection and 3PL supplier selection into an undirected multigraph, also describing each edge in the graph as a 3PL supplier, and studied the more complex 4PLROP while considering issues such as transfer truck time and multitasking.

Most existing relevant research has focused on deterministic problems. However, due to factors such as weather, traffic, human error and various unexpected situations, logistics transportation processes have strong uncertainty (Huang *et al.*, 2015), which caused substantial losses in profits (Zhou *et al.*, 2023; Goli *et al.*, 2023a, b). Especially in long-distance delivery such as cross-border transportation, there are significant disturbances in logistics transportation time and cost due to geography, relevant systems and language reasons. Huang *et al.* (2013) assumed that the 4PL system had no historical data, so the distribution of 3PL supplier transportation time could be described as a fuzzy variable by relevant experts based on historical experience, and studied the 4PLROP with fuzzy processing time with the objective of minimizing total cost. However, in another scenario in logistics operations, logistics companies have some historical data, which can be used to estimate the probability or probability distribution of uncertain events using random variables. Moreover, with the rapid development of e-commerce and fierce competition in the logistics industry in recent years, traditional price competition between logistics companies has gradually shifted to competition based on customer service levels (Fu *et al.*, 2020, 2021a, b).

In an uncertain environment, decision-makers often hope to maximize the probability function of event realization (Liu, 1997), rather than absolute returns, and hope to achieve higher customer satisfaction while ensuring a certain return. In order to accurately describe and measure the characteristics of people's cognition, judgment and choice in uncertain situations, Simon (1955) proposed the theory of bounded rationality. On this basis, Tversky and Kahneman (1992) proposed the Prospect theory. Prospect theory applies psychological research to economics and provides an effective tool for human judgment and decision making under uncertain environment.

This study describes the transportation time and cost of 3PL suppliers as random variables and investigates the 4PLROP in an uncertain environment. As the scheme designer, 4PL hopes to minimize the probability of delay from the customer's perspective, while also minimizing the probability of exceeding cost expectations from the perspective of the participating 3PL suppliers. Therefore, depending on the risk attitude of the decision-maker, this study establishes a mathematical model for the Dependent-chance based 4PL Routing Optimization Problem (DP-4PLROP) by maximizing the total utility of the transportation time and cost opportunity functions, taking into account attitude towards opportunities. The proposed DP-4PLROP is an NP-hard problem, which is difficult to be solved by traditional algorithms. Intelligent optimization algorithm is one of the effective ways to solve large-scale complex optimization problems (Goli *et al.*, 2023b; Wang *et al.*, 2022). Based on the characteristics of the problem, ant colony algorithms and dual-population improved ant colony algorithms are designed to solve the model. The numerical examples demonstrate the rationality of the established model and the effectiveness of the proposed algorithm.

2. Problem description

Assuming a certain company (4PL) has undertaken a supply chain logistics path integration business, it is required to design a set of transportation plans for the client which will transport transportation tasks from the starting point of the supply chain to the destination node. Since 4PL is a logistics solution integrator, it is assumed that it has certain path information and some cooperating 3PL suppliers before the task starts. The transportation network information and alternative 3PL suppliers' information in the supply chain are known, and there may be multiple 3PL suppliers that can provide transportation services along each path. In order to describe the problem more clearly, supplier information and path information are integrated. The proposed DP-4PLROP can be described by a multi-graph with multiple attributes.

An undirected multigraph G(V, E) shown in Figure 1 is used to describe the proposed DP-4PLROP. V(|V| = n) is the set of nodes, representing cities, warehouses, processing plants and other facilities in the supply chain; E is the set of edges, each edge represents a candidate 3PL supplier who can undertake transportation tasks on that path, and there may be multiple edges between adjacent nodes. Both nodes and edges have cost and time attributes. Due to various uncertain factors in logistics transportation, the transportation time and cost of the 3PL supplier have a certain degree of disturbance, which is described as a random variable. The parameters and decision variables of the DP-4PLROP based on the description of the undirected multigraph are presented in Table 1.

Figure 1. Multi-graph of DP-4PLROP

ecision variables of the DP-4PLROP based on the description of the are presented in Table 1. (1) - (

Source(s): Authors' own work

Parameters

1 urumeters		
e _{ijk}	Represents the kth 3PL supplier (kth edge) between nodes v_i and $v_j, i, j \in (1,2,\cdots,n)$	
r _{ij}	Represents the number of 3PL suppliers (edges) between nodes v_i and v_j	
$\dot{T}_{ijk} + t_{ijk}$	Represents the time between nodes v_i and v_j for 3PL supplier e_{ijk} to complete the transportation task of this section. Where, T_{ijk} is constant and represents basic time; t_{ijk} is a random variable, representing the disturbance of time	
$C_{ijk}+c_{ijk} \\$	Represents the cost required by 3PL supplier e_{ijk} to complete this section of transportation task. Where C_{ijk} is constant, representing basic cost; c_{ijk} is a random variable representing the perturbation of cost	
T_i^\prime, C_i^\prime	Represents the time and cost required by the transportation task when it passes through node $v_{\rm i}, \ensuremath{respectively}$	
T_0, C_0	Respectively represents the decision-maker's requirements on the total time and total cost of the transportation task, that is, the total transportation time should not exceed T_0 and the total transportation cost should not exceed C_0	
α, β	The confidence level indicating the total time and total cost that meet the requirements separately, that is, in an uncertain environment, the probability that the total transportation time does not exceed T_0 and the probability that the total transportation cost is not greater than C_0	
R	It represents a path from the starting node $v_{\rm s}$ to the destination node $v_{\rm e}$ of a task	
Decision var	riable	
$e_{iik}(R)$	1 if $e_{ijk} \in \mathbb{R}$, 0 otherwise	
$y_i(\mathbf{R})$	1 if $v_i \in \mathbb{R}$, 0 otherwise	
Source(s):	: Authors' own work	N



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Table 1. Mathematical notation MSCRA 6,4

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Here, t_{ijk} and c_{ijk} respectively represent the disturbance of transportation time and cost of 3PL supplier e_{ijk} . For the purpose of exposition and necessary mathematical simplification, it is assumed that they follow normal distributions $N(0, \sigma_{ijk}^2)$ and $N(0, \overline{\sigma}_{ijk}^2)$, and are independent of each other [1]. It can be seen that R is the solution to the proposed problem. In the multi-graph, each R

It can be seen that R is the solution to the proposed problem. In the multi-graph, each R uniquely determines the path taken by the transportation task and the 3PL supplier who performs the transportation task on that path. The time and cost of R are represented by T(R) and C(R) respectively, then:

$$T(R) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{r_{ij}} (T_{ijk} + t_{ijk}) x_{ijk}(R) + \sum_{i=1}^{n} T'_{i} y_{i}(R),$$
(1)

$$C(R) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{r_{ij}} (C_{ijk} + c_{ijk}) x_{ijk}(R) + \sum_{i=1}^{n} C'_i y_i(R).$$
(2)

Therefore, T(R) and C(R) also follow normal distributions, that is

$$\begin{split} T(R) &\sim N \Bigg(\sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{r_{ij}} T_{ijk} x_{ijk}(R) + \sum_{i=1}^{n} T'_{i} y_{i}(R), \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{r_{ij}} \sigma_{ijk}^{2} x_{ijk}(R) \Bigg), \\ C(R) &\sim N \Bigg(\sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{r_{ij}} C_{ijk} x_{ijk}(R) + \sum_{i=1}^{n} C'_{i} y_{i}(R), \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{r_{ij}} \overline{\sigma}_{ijk}^{2} x_{ijk}(R) \Bigg). \end{split}$$

The problem to be solved in this paper is to provide customers with a transportation plan that transports transportation tasks from the starting node to the destination node under certain time and cost requirements. Due to the disturbance of transportation time and cost of 3PL suppliers, the plan meets the total time and total cost requirements with a certain confidence level, and maximizes the total utility of the confidence level while considering the decision maker's preference.

3. Problem formulation

For a given path R, its total time T(R) and total cost C(R) satisfy the confidence levels α and β (opportunity function) required by the customer, as shown in Eq. (3) and Eq. (4).

$$\alpha = \Pr\left\{\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{r_{ij}}(T_{ijk} + t_{ijk})x_{ijk}(R) + \sum_{i=1}^{n}T'_{i}y_{i}(R) \le T_{0}\right\}$$
(3)

$$\beta = \Pr\left\{\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{r_{ij}} (C_{ijk} + c_{ijk}) x_{ijk}(R) + \sum_{i=1}^{n} C'_{i} y_{i}(R) \le C_{0}\right\}$$
(4)

People often pay more attention to differences rather than absolute return values when making decisions (Tversky and Kahneman, 1992). Therefore, we first assume that the decision maker has expectations for the confidence levels of total time and total cost, which are the reference points α_0 and β_0 . For each alternative plan R, it represents a loss when the confidence level is below the reference point, and a gain when the confidence level is above the reference point. Thus, drawing on the value function description in cumulative prospect theory (CPT) (Tversky and Kahneman, 1992), the utility functions of total time and total cost can be defined as follows:

$$v(\alpha) = \begin{cases} (\alpha - \alpha_0)^{\gamma_1}, \text{ if } \alpha \ge \alpha_0 \\ -\lambda_1(\alpha_0 - \alpha)^{\gamma_1}, \text{ else} \end{cases}$$
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$$\mathbf{v}(\boldsymbol{\beta}) = \begin{cases} (\boldsymbol{\beta} - \boldsymbol{\beta}_0)^{\gamma_2}, \text{ if } \boldsymbol{\beta} \ge \boldsymbol{\beta}_0\\ -\lambda_2 (\boldsymbol{\beta}_0 - \boldsymbol{\beta})^{\gamma_2}, \text{ else} \end{cases}$$
(6)

Here, the parameters γ_1 and γ_2 represent the sensitivity of the decision maker to the confidence levels of time and cost, with larger values indicating greater sensitivity. Moreover, $0 < \gamma_1 < 1, 0 < \gamma_2 < 1$, which reflects the general characteristic of decreasing sensitivity of the decision maker. The parameters λ_1 and λ_2 are the relative sensitivity coefficients for gain and loss, with higher values indicating a stronger aversion to losses. In addition, the relative values of γ_1 , λ_1 and γ_2 , λ_2 can reflect the relative sensitivity of the decision maker to the confidence levels of time and cost.

In an uncertain environment, the mathematical model for DP-4PLROP can be established as follows:

$$\max\{\mathbf{V} = \mathbf{v}(\alpha) + \mathbf{v}(\beta)\}\tag{7}$$

s.t.

$$\mathbf{x}_{ijk}(\mathbf{R}) = \begin{cases} 1, \text{if } \mathbf{e}_{ijk} \in \mathbf{R} \\ 0, \text{else} \end{cases}$$
(8)

$$y_{i}(R) = \begin{cases} 1, \text{ if } v_{i} \in R\\ 0, \text{ else} \end{cases}$$
(9)

$$R = (v_s, \cdots, v_i, k, v_j, \cdots, v_e) \in G$$
(10)

Among them, formula (7) is the objective function, which represents maximizing the total utility of the confidence levels for time and cost. The confidence levels α and β are expressed in formulas (3) and (4), respectively, and the utility functions $v(\alpha)$ and $v(\beta)$ are expressed in formulas (5) and (6), respectively. Formulas (8) and (9) are the 0–1 decision variables of the model, which determine the selected 3PL provider for executing the task and the nodes passed through. Formula (10) indicates that the selected path is a route from the starting node to the destination node.

4. Algorithm design

4.1 Design idea

It can be seen that DP-4PLROP is an extension of the Constrained Shortest Path Problem (CSPP). CSPP is an NP-hard problem (Liu *et al.*, 2012), and therefore DP-4PLROP is also NP-hard, making it difficult to solve using traditional exact algorithms (Fu *et al.*, 2022; Tian *et al.*, 2023). The Ant Colony Algorithm (ACA) is an intelligent algorithm that mimics the behavior of ant colonies. It has high robustness, distributed computing and is easily combinable with other optimization methods, especially when solving shortest path problems such as VRP and TSP, showing unique advantages (Dorigo *et al.*, 1996). Considering the problem of premature convergence and stagnation in ACA during evolution, an Improved Ant Colony Algorithm (IACA) is designed by incorporating the idea of dual-population independent searching with periodic information exchange based on the characteristics of undirected multigraphs.

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(1) Coding mechanism

R is the solution to the problem, representing a path from the starting node v_s to the destination node v_e in a multi-graph. It includes a set of edges and a set of nodes. From the multigraph description, it can be seen that each edge e_{ijk} uniquely determines a pair of adjacent nodes v_i and v_j in R, that is, the set of edges in R can uniquely determine the set of nodes. Therefore, only the set of edges is encoded. Considering that the number of edges in each solution may vary, a variable-length encoding mechanism is designed. NP represents the population size, and the coding of the mth (m = 1, 2, \cdots , NP) ant can be represented as follows:

$$\mathbf{R}_{\mathrm{m}} = (\mathbf{e}_{\mathrm{sik}}, \cdots, \mathbf{e}_{\mathrm{jel}}) \in \mathbf{G}. \tag{11}$$

Here, e_{sik} represents the starting node v_s of R_m , e_{jel} represents the final destination node v_e . In order to ensure the connectivity of R_m , adjacent elements (edges) must pass through the same intermediate node, that is, the arrival node of the previous element and the entry node of the next element are the same.

(2) Transfer probability

During the transfer process of ant m, its direction is determined based on the information on all feasible edges and the path heuristic information. Let NG represent the maximum number of iterations, and allowed_m represent the set of all feasible edges for ant m at the current moment. Then, the calculation method for the transfer probability $p_{ijk}^m(Ng)$ of a certain edge e_{ijk} in the current feasible set at the $Ng(Ng = 1, 2, \dots, NG)$ iteration is as follows:

$$p_{ijk}^{m}(Ng) = \begin{cases} \frac{[\tau_{ijk}(Ng)]^{\omega}[\eta_{ijk}]^{\phi}}{\sum_{arccallowed_{m}} [\tau_{arc}(Ng)]^{\omega}[\eta_{arc}]^{\phi}}, arc \in allowed_{m}. \\ 0, else \end{cases}$$
(12)

Here, τ_{ijk} (Ng) represents the concentration of information pheromones on edge e_{ijk} in the Ng-th iteration, η_{ijk} represents the path heuristic information, where $\eta_{ijk} = 1/(T_{ijk} + C_{ijk})$. ω and φ respectively represent the pheromone heuristic factor and path heuristic factor, reflecting the relative importance of information pheromone concentration and path heuristic information.

(3) Pheromone updating strategy

At the beginning of algorithm execution, the same initial information pheromone concentration P_0 is assigned to each edge in the multi-graph. After every generation of ants completes the search, the pheromone concentration is updated using the following formula:

$$\tau_{ijk}(Ng + 1) = \rho \tau_{ijk}(Ng) + \Delta \tau_{ijk}$$
(13)

$$\Delta \tau_{ijk} = \begin{cases} \frac{\alpha + \beta + \theta \,\overline{\nabla}}{Q}, e_{ijk} \in \overline{R} \\ 0, else \end{cases}$$
(14)

Here, $\tau_{ijk}(Ng + 1)$ represents the concentration of information pheromones on edge e_{ijk} in the iteration of (Ng + 1), $\Delta \tau_{ijk}$ represents the increment of pheromone concentration, \overline{R}

represents the current optimal solution, \overline{v} represents the current optimal value and θ is a constant when $\overline{v} \ge 0$, but $\theta = 0$ when $\overline{v} < 0$.

(4) Maximum and minimum ant

As the algorithm iterates, it is possible for the concentration of information pheromones on certain paths in the multi-graph to continuously increase, while pheromones on other paths continuously evaporate. To avoid highly concentrated pheromone levels that cause all ants in the population to search the same path, leading to premature convergence to a local optimum, the concentration of pheromones on each edge is limited to a certain range. When $\tau_{ijk}(Ng) < \tau_{min}$, $\tau_{ijk}(Ng) = \tau_{min}$; when $\tau_{ijk}(Ng) > \tau_{max}$, $\tau_{ijk}(Ng) = \tau_{max}$.

(5) Repair strategy of illegal paths

During the ant search process, there may be a situation where the current feasible set allowed_m is empty, which means that there is no valid path to reach the destination node. In this case, it is necessary to repair the invalid path. The traditional method is for the ant to backtrack to the previous node and add the current path to the taboo list. However, this method consumes a lot of computational time due to the backtracking process. Therefore, according to the characteristics of the problem, the following method is designed for repairing invalid paths: for the current invalid path R_m , starting from its initial node, check whether the current node is directly connected to the destination node in the multi-graph. If it is, randomly select an edge between the node and the destination node and add it to the encoding; otherwise, the ant restarts the search.

4.3 IACA

ACA often shows unique advantages in solving routing problems (Dorigo *et al.*, 1996). However, premature convergence and stagnation often cause the algorithm to fail to obtain optimal solutions. To address this problem and solve the proposed model quickly and efficiently, a dual-population independent evolution approach is designed. In IACA, two populations evolve independently and regularly interact with each other, to prevent local convergent behavior of single-population search and improve the global search capability.

(1) The update method of pheromone for population A

In the multi-graph, each edge e_{ijk} has two types of pheromones, $\tau^A_{ijk}(Ng)$ and $\tau^B_{ijk}(Ng)$, which represent the pheromone concentration of populations A and B, respectively, in the Ng-th generation.

Population A uses the elite strategy to update pheromones, as shown in equations (13) and (14).

(2) The update method of pheromone for population B

In population B, pheromone is updated based on the fixed amount of pheromone left by each ant on the path it has passed through, and the update formula is as follows:

$$\tau^{\rm B}_{\rm iik}({\rm Ng}+1) = \rho \tau^{\rm B}_{\rm iik}({\rm Ng}) + \mu \Delta \overline{\tau}, \tag{15}$$

In which μ represents the number of ants passing through the edge e_{ijk} in the Ng-th generation, and $\Delta \overline{\tau}$ is the pheromone left by the ants as they pass by.

(3) Pheromone interaction

When the iteration number Ng is a multiple of M, the pheromone interaction between population A and population B is performed. The interaction method is as follows:

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$$\tau_{ijk}^{A'}(Ng) = \frac{\tau_{ijk}^{A}(Ng) + \tau_{ijk}^{B}(Ng)}{2}, \qquad (16)$$

$$\tau^{B'}_{ijk}(Ng) = \tau^{A}_{ijk}(Ng).$$
(17)

Where $\tau_{iik}^{A}(Ng)$ and $\tau_{iik}^{B}(Ng)$ are the pheromone concentrations of edge e_{ijk} before information exchange for population A and population B respectively. $\tau_{iik}^{A'}(Ng)$ and $\tau_{iik}^{B'}(Ng)$ are the pheromone concentrations after the information exchange.

(4) Replacement strategy of elite ants

Population A updates the path pheromone using an elite strategy. Therefore, for each generation of population A, a replacement strategy is used for the current best solution.

For each element e_{ijk} on the current best path, it is compared with the other $r_{ij} - 1$ edges between v_i and v_i. If a better solution is found, then the current best solution is updated.

(5) The flowchart of the IACA algorithm

The algorithm flowchart of IACA is shown in Figure 2.

5. Numerical experiments

To verify the rationality of the established model and the effectiveness of the algorithm, three instances of different scales, namely, a 7-node (E7), a 15-node (E15) and a 30-node (E30), are given in this section. Through specific examples, we will carry out comparative analysis from two aspects of the model and algorithm.

The investigated algorithms are coded with Microsoft Visual Studio and run on a Intel Core-2 Duo 3.0 GHz PC.

5.1 Example design

As is introduced previously in problem description, the proposed DP-4PLROP can be described by an undirected multi-graph with multiple attributes. The multi-graphs are generated randomly in a rectangle to represent examples (Chen et al., 2009; Huang et al., 2016). Detailed steps are shown below:

Step 1. Generate n-2 nodes (a total of n nodes including the source and destination) randomly in a $d \times d$ square area. (0,0) and (d,d) represent the source and destination, respectively.

Step 2. If the Euclidean distance between two nodes is less than or equal to Ds, edges exist between them.

Step 3. Generate a random number $r_{ii} \in [a_1, b_1]$ which represents the number of edges between two nodes.

Step 4. Randomly generate cost C_{ijk} and time T_{ijk} for each edge, where $C_{ijk} \in [a_2, b_2]$ and $C_{iik} \in [a_3, b_3].$

Step 5. Randomly generate cost C'_i and time T'_i for each node, where $C'_i \in [a_4, b_4]$ and $T'_i \in [a_5, b_5].$

To illustrate the ideas discussed above and compare more clearly, three examples of E7, E15 and E30 are generated. d = 1, and $Ds \in [0.5, 0.75]$. Based on these, other parameters are set as follows:





 $a_1 = 2, b_1 = 4, a_2 = 6, b_2 = 30, a_3 = 2, b_3 = 22, a_4 = 5, b_4 = 15, a_5 = 4, b_5 = 9.$

For example, the multi-graph of example E7 is shown in Figure 1.

5.2 Algorithm comparison MSCRA

To test the performance of the algorithm, relevant performance parameters are defined. The algorithm is executed 100 times. "Best" represents the objective function value of the best solution obtained in 100 runs, that is the best value. "Bad" represents the worst value, "Mean" represents the average value, "Msd" represents the standard deviation and "Time" represents the average time consumed by the algorithm to run once.

$$Msd = \sqrt{\frac{\sum_{i=1}^{N} (V_i - V_{mean})^2}{N - 1}},$$
(18)

Here, N = 100, V_i represents the value during the i-th execution of the algorithm, and V_{mean} represents the mean value of N executions.

Let $\sigma_{iik} = \sigma = 2.5$, $\overline{\sigma}_{iik} = \overline{\sigma} = 3.0$. The algorithm parameter values are all chosen from a set of parameter combinations that have been tested multiple times and shown to perform well. For example, in the E7 instance, the parameter combinations for ACA and IACA algorithms are:

$$\begin{split} P_0 &= 0.9, \rho = 0.9, \omega = 0.8, \phi = 1.0, Q = 5.0, \tau_{\min} = 0.1, \tau_{\max} = 2.0. \\ P_0 &= 0.8, \rho = 0.9, \omega = 0.8, \phi = 1.0, Q = 5.0, \tau_{\min} = 0.1, \tau_{\max} = 1.2, \theta = 1.0, \\ \Delta \overline{\tau} &= 0.01, M = 5 \end{split}$$

The comparison results between ACA and IACA for E7, E15 and E30 are shown in Table 2, where "Example" denotes three instances with different scales and Algorithm represents the two algorithms, ACA and IACA.

Table 2 shows that both algorithms are effective for the proposed problem especially for small and medium scale problems. Moreover, as the problem scale increases, IACA gradually exhibits advantages. When the problem scale is small, both ACA and IACA can obtain stable solutions in a short time. When the problem scale is large, IACA requires fewer iterations and search time than ACA, and the quality and stability of the solution obtained by IACA are higher. The dual-population IACA enhances the algorithm's global search capability, verifying the effectiveness of the improvement method.

5.3 Model comparison

This paper proposes a mathematical model considering decision-makers' risk attitudes. It can be seen that when $\lambda_1 = \lambda_2 = 1$, $\gamma_1 = \gamma_2 = 1$, the model reduces to the one that does not consider decision-makers' risk attitudes. In this case, the decision-maker behaves as riskneutral, and the proposed DP-4PLROP model will degenerate into a risk-neutral model.

	Example	Algorithm	NP	NG	Best	Bad	Mean	Msd	Time
	E7	ACA	100	10	0.4053	0.4053	0.4053	0	0.065s
	E7	IACA	20	10	0.4053	0.4053	0.4053	0	0.052s
	E15	ACA	150	15	0.3738	0.3738	0.3738	0	0.164s
	E15	IACA	50	10	0.3738	0.3738	0.3738	0	0.116s
Table 2	E30	ACA	400	90	-0.1518	-0.4081	-0.1672	0.0612	7.083s
Comparison of ACA	E30	IACA	200	50	-0.1518	-0.1518	-0.1518	0	4.737s
and IACA	Source(s)	Authors' own	work						

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6.4

To compare the two models and evaluate the impact of C_0 , T_0 , α_0 , β_0 on the results, firstly, we conduct a test using the E7 instance. The initial values for $T_0 = 65$, $C_0 = 85$, $\alpha_0 = 0.8$, $\beta_0 = 0.8$, and draw on the parameter settings of prospect theory for the general population, $\lambda_1 = \lambda_2 = 2.25$, $\gamma_1 = \gamma_2 = 0.88$ (Tversky and Kahneman, 1992). The test results are shown in Figures 3 and 4, where "Vu" denotes the results obtained by considering decision-makers' risk attitudes, and "Vn" denotes the results obtained when the decision-maker exhibits risk neutrality.

From Figure 3, it can be observed that as the requirements on total time and total cost decrease, that is as the values of C_0 and T_0 increase, the overall utility value increases continuously. Furthermore, since $0 < \gamma_1 < 1$ and $0 < \gamma_2 < 1$, when the overall utility is less than zero, the utility obtained when considering decision-makers' risk attitudes is less than that obtained when the decision-maker exhibits risk neutrality. It indicates that the decision maker is risk preference when facing losses; when the overall utility is greater than zero, the utility obtained when considering decision-makers' risk attitudes is greater than that obtained when the decision-maker exhibits risk neutrality. It indicates that the decision maker is risk averse when facing gains. Furthermore, as $\lambda_1 = \lambda_2 > 1$, when the utility is less than 0, the gap between Vu and Vn is larger, indicating that the decision-maker is more sensitive to losses.

The value of reference points is a key factor affecting overall utility and satisfaction. From Figure 4, it can also be seen that as the reference point (i.e. the decision-maker's requirement) increases, the overall utility decreases continuously. Moreover, since α and β always take values in the range (0, 1), the utility obtained when considering decision-makers' risk attitudes is greater than that obtained when the decision-maker exhibits risk neutrality.



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5.4 Effect of risk attitude coefficient on the results

In the above experiments, the utility function parameters $\lambda_1, \lambda_2, \gamma_1$ and γ_2 are set to values based on prospect theory for the general population (Tversky and Kahneman, 1992), that is $\lambda_1 = \lambda_2 = 2.25, \gamma_1 = \gamma_2 = 0.88$. In actual logistics operations, different customers and partners may have different risk attitudes, and the values of their risk attitude coefficients could vary significantly. Therefore, under the condition that other parameters remain unchanged, the influence of $\lambda_1, \lambda_2, \gamma_1$ and γ_2 on the results is tested separately. The test results are shown in Figures 5 and 6 when $T_0 = 55$, $C_0 = 85$, $\alpha_0 = 0.8$ and $\beta_0 = 0.8$.

The relative values of λ_1 and λ_2 represent the sensitivity relative coefficient of decisionmakers for cost and time respectively, and with higher values indicating a stronger aversion to losses. When λ_1 and λ_2 are less than 1, the decision-maker is more sensitive to gains. When λ_1 and λ_2 are greater than 1, the decision-maker is more sensitive to losses. As shown in Figure 5, as λ_1 and λ_2 gradually increase, the decision-maker becomes more sensitive to losses and the total utility value decreases. Moreover, since the solution's time confidence level α is slightly larger than the reference point (0.8), and the cost confidence level β is smaller than the reference point (0.8), the total utility is greater than zero when λ_1 or λ_2 is relatively small. However, as λ_1 or λ_2 increases, the total utility gradually becomes negative and decreases.

The parameters γ_1 and γ_2 are the exponents of the utility function, which reflect the convexity or concavity degree of the S-shaped curve. As shown in Figure 6, for the proposed problem, the total utility does not consistently increase or decrease with the increase of γ_1 or γ_2 . Taking γ_1 as an example, when $0.1 \le \gamma_1 \le 0.5$, the time confidence level $\alpha = 0.82 > 0.8$. Although the total utility is negative, the decision-maker perceives time as gain. As γ_1 gradually increases, the total utility decreases. When $0.6 \le \gamma_1 \le 1$, the selected path has



Figure 5. The effect of λ_1 and λ_2 on the results



Source(s): Authors' own work

 $\alpha = 0.76 < 0.8$. At this point, both time and cost are perceived as losses by the decision-maker. As γ_1 gradually increases, the total utility also increases.

To sum up, different parameter combinations could be set for different kinds of decisionmakers. Decision-makers' behavioral characteristics can be presented through risk parameters to fit their needs more accurately. To improve the overall utility of the decision scheme, decision makers should effectively identify customer risk preferences, estimate reference criteria and distinguish key factors such as cost and time. This could help 4PL design effective transportation plans and improve service levels.

6. Conclusions

In the complex environment, uncertainty is everywhere in the process of logistics operation. This study investigates the integrated routing optimization problem under uncertain environments. Considering the bounded rationality of decision makers in risk situations, utility function of prospect theory is introduced. The transportation time and cost of the 3PL supplier are described as random variables. Then, from the perspective of relevant opportunities, a mathematical model of 4PL routing optimization considering opportunity preference is established. The proposed DP-4PLROP is NP-hard. Therefore, on the basis of designing ACA for undirected multi-graph features, the IACA is designed to solve the model by incorporating the idea of dual-population independent searching with periodic information exchange. Numerical examples demonstrate the effectiveness of the descriptive approaches, the proposed models and the designed algorithms.

In an uncertain environment, the decision maker's risk preference directly affects decision making. In the proposed model, different parameter combinations can be set for decision-makers with different risk attitudes to fit their needs more accurately. The results show that risk behavior directly affects logistics route decision. Specifically, the decision-maker is more sensitive to losses, and the utility considering decision-makers' risk attitudes is greater than that the decision-maker exhibits risk neutrality. Furthermore, the dual-population improvement strategy enhances the algorithm's global search capability and the improved algorithm can solve the risk model quickly. This could help managers design effective transportation plans and improve service levels.

In the future, the work in this paper can be extended. This paper builds a model for routing integration optimization problem under risk conditions based on prospect theory, and some other classical behavior theories can also help to build the model, such as overconfidence theory and regret theory. In addition, more uncertain factors and different probability distributions may be considered. Moreover, the methods proposed in this paper can also be applied to other logistics integration optimization scenarios, such as cooperative optimization of trucks and drones, automatic vehicle scheduling problem, etc.

Note

1. T_{ijk} and C_{ijk} respectively represent the basic time and cost of the 3PL supplier. Therefore, assuming that their perturbations t_{ijk} and c_{ijk} have a mean of 0. Additionally, $t_{ijk}(i, j \in (1, 2, \cdots, n), k \in (1, 2, \cdots, r_{ij}))$ are mutually independent, as are $c_{ijk}(i, j \in (1, 2, \cdots, n), k \in (1, 2, \cdots, r_{ij}))$.

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