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Improved Differential Evolution Algorithm for 4PL Supply Chain Network Design Considering the Customer Behavior

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Abstract. Fourth party logistics (4PL) supply chain network design problem considering the behavior of customer service satisfaction becomes more important in supply chain network design problem. It is NP-hard problem. Improved differential evolution (IDE) algorithm is applied to solve this problem in this paper. In order to handle the infeasible solution efficiently, a two-stage algorithm, the minimum cost flow incorporated with macro-micro adjustment embedded improved differential evolution (MMAMFC-IDE), is designed. The results of numerical experiments show that MMAMFC-IDE can get relatively better results compared with the minimum cost flow embedded improved differential evolution(MFC-IDE).

Keywords: Fourth party logistics, Supply Chain Network Design, service satisfaction, MMAMFC-IDE

1. Introduction

Under the current competitive business environment, companies put forward higher and higher requirements for the design of supply chains as well as the integration of logistics. In this situation, fourth party logistics(4PL), which has the ability to integrate supply chains resources and optimize supply chains, is gaining more and more attention. The concept of 4PL is an integrator that assembles the resources, capability, and technology of its own organization and other organizations to design, build, and run comprehensive supply chain solutions [1].

Compared with classical supply chain network design[2–4], the proposed 4PL supply chain network design needs to select one or more 3PL providers, and design flow allocation for selected 3PL providers from certain suppliers to potential DCs or retailers, and then to customers. From this perspective, most researches considered the three-echelon supply chain network. Several researchers enter the forest: Huang et al.[5] designed a 4PL network based on resilience, and a particle swarm optimization (PSO) method was presented to select 3PL providers and distribution centers (DCs); Jia et al.[6] considered dynamic environment with disruptions in a 4PL network, and a two-stage stochastic optimization model was formulated to solve the problem; and Li et al.[7] worked on providing satisfactory service to customers at a comparatively lower cost when disruptions strike through establishing a robust optimization model, and the artificial fish swarm algorithm (AFSA) and the genetic algorithm (GA) are combined to solve the problem.

The influence of service quality and behavioral intentions on customer satisfaction has attracted attention in field of transportation research[8]. Anantadjaya et al.[9] claimed the significance of supply chain management considering consumer behavior in improving the customer satisfaction level toward products and services. The supply chain network design is a major type of strategic decisions in the field of supply chain management. Hence, considering the customers' psychological behavior in the 4PL supply chain network design is becoming a meaningful new research direction. Yue et al.[10] designed the 4PL supply chain network, considering multi-customer psychological behavior by using prospect theory (PT), and solved the proposed problem with a particle swarm optimization (PSO) algorithm. Yu et al. [11] studied 4PL network design considering time satisfaction, establishing a programming model that takes into account network investment constraints and user demand constraints to maximize user time satisfaction. Wang et al. [12] studied the 4PL network design problem, which considers the psychological behavior of both suppliers and users. Based on PT, they developed a mixed-integer nonlinear programming model to characterize psychological behavior, maximize supplier and user satisfaction. Huang et al. [13] introduced the definitions of the psychological reference point and the service level for customers based on the PT, then they formulated a non-linear integer programming model, and an approximation linearization method is introduced to designed to solve 4PL supply chain network design problem considering customer psychological behavior. The problem proposed by Huang et al.[13] is NP-hard, so we design a two-stage algorithm based on improved differential evolution algorithm (IDE)[14] to solve large scale cases quickly.

In this paper, a two-stage algorithm, the minimum cost flow incorporated with macro-micro adjustment embedded improved differential evolution (MMAMFC-IDE), is proposed.

2. Problem description and formulation

In this section, the formulation of the supply chain network design problem considering customer satisfaction from a 4PL perspective is given based on the model of Huang et al. [13]. The main objective of the proposed model is to maximize the value function of customer satisfaction with cost constraint considering customer behavior, thereby selecting the corresponding sub-network.

Supply chain network design from 4PL perspective considering customer behavior can be defined as selecting sub-network for optimization in the potentially existing supply chain network including 3PL providers to make customers feel satisfied according customer preference with limited capital. A potential supply chain network including 3PL providers can be represented by a directed multi-graph. The nodes in the directed multi-graph correspond to suppliers, distribution centers(DCs) and customers. The arcs denote 3PL providers for transportation between two locations, as shown in Figure. 1.

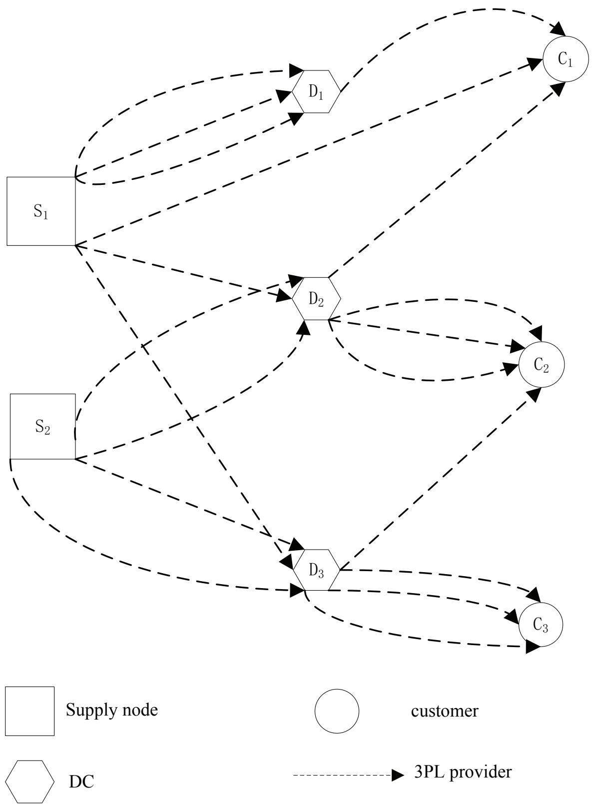

Fig. 1. 4PL supply chain network

A client of 4PL needs to supply goods for customers. He consults the 4PL service company to design a network, and requires it to try to satisfy the demands of customers within limited capital. The numbers, location and demands of customers are known. And the number, location and supply capability of suppliers are known, too. Each alternative DC has fixed constructive costs as well as storage costs for each per unit. And each alternative 3PL provider has fixed costs and shipping costs. In order to reflect customer satisfaction, customer service level is defined as the proportion between the supply which is obtained by customer and its actual demand[13]. In order to reflect psychological change of customer satisfaction, the value function of customer satisfaction is defined as polynomial function of difference between customer service level and reference position[13]. Supply chain network optimization problem from 4PL perspective, which considers about customer behavior, is how to design network to maximize total value function of customer satisfaction with limited capital and the satisfaction of relevant constraints. Whether the customer feels satisfied with the design mostly depends on the psychological standard of customer, so PT is used to address it.

For a given task in existing supply chain network including 3PL providers, 4PL needs to select nodes and edges in the potentially existing supply chain network including 3PL providers and computes the flow from supplier locations to customer locations, as the thick line shown in Fig.1. In order to formulate the problem, the notations used in this paper are introduced as follows.

Sets

S Set of supplier locations,
I Set of potential DC locations,
J Set of customer locations,
V Set of all nodes= $S \cup I \cup J$,
K_{gh} Set of potential 3PL providers between node $g \in V$ and node $h \in V$.

Parameters

F_s Maximum capacity at supplier location $s \in S$,
D_j Demand at customer location $j \in J$,
C_i Variable cost per unit processed at potential DC location $i \in I$,
Q_i The capacity processed at potential DC $i \in I$,
H_i Fixed cost of locating a potential DC at potential location $i \in I$,
C_{ghk} Unit cost of transportation between node $g \in V$ and node $h \in V$ by potential 3PL provider $k \in K_{gh}$,
Q_{ghk} The capacity of transportation between node $g \in V$ and node $h \in V$ by potential 3PL provider $k \in K_{gh}$,
h_{ghk} Fixed cost of potential 3PL provider $k \in K_{gh}$,
C_m Maximum investment provided by client,
G_{mj} Customer reference point of each customer $j \in J$.

Decision variables

$x_{ghk} \begin{cases} 1, \text{ if the potential 3PL provider } k \in K_{gh} \text{ is selected} \\ 0, \text{ otherwise} \end{cases}$,
$y_i \begin{cases} 1, \text{ if potential DC } i \in I \text{ is open} \\ 0, \text{ otherwise} \end{cases}$,
z_{ghk} Quantity transported from node $g \in V$ to node $h \in V$ by potential 3PL provider $k \in K_{gh}$.

With the notations above, the customer service level is formulated based on its definition.

$$G_j = \frac{\sum_{g \in V} \sum_{k \in K_{gj}} z_{gjk}}{D_j}, \forall j \in J \tag{1}$$

In economics, utility is the ability to satisfy people's desire, or the satisfaction of the consumer during their consumption of goods. According to the definition of value function of PT[15], the value function of customer satisfaction is formulated as follows:

$$B_j = \begin{cases} (G_j - G_{mj})^{\alpha} & (G_j \geq G_{mj}) \\ -\lambda(G_{mj} - G_j)^{\beta} & (G_j < G_{mj}) \end{cases}, \forall j \in J \tag{2}$$

where, α, $\beta(0 < \alpha \leq \beta < 1$) are the risk attitude coefficient, $\lambda(\lambda \geq 1$) is the loss aversion coefficient. If the customer service level is higher than the reference position G_m, then the increase of customer satisfaction will be more and more slow with the increase of customer service level, and the smaller the α is, the more slowly the speed of increase becomes. If the customer service level is lower than the reference position G_m, then the increase of customer satisfaction will be more and more quick with the increase of customer service level, and comparing the gain, the psychological change is more obvious. At the same time, the bigger the β is, the more quickly the speed of increase becomes.

The mathematical model for supply chain network design from 4PL perspective for maximization the sum of value function of customer satisfaction under the cost constraint can be constructed as follows:

$$\max \sum_{j \in J} B_j \tag{3}$$

s.t.

$$\sum_{g\in V}\sum_{h\in V}\sum_{k\in K_{ij}} h_{ghk}x_{ghk} + \sum_{i\in I} H_i y_i + \sum_{g\in V}\sum_{h\in V}\sum_{k\in K_{gh}} c_{ghk}z_{ghk} + \sum_{g\in V}\sum_{i\in I}\sum_{k\in K_{gi}} C_i z_{gik} \leq C_m \tag{4}$$

$$x_{ihk} \leq y_i, \forall i \in I, \forall h \in V, \forall k \in K_{ih} \tag{5}$$

$$x_{gik} \leq y_i, \forall i \in I, \forall g \in V, \forall k \in K_{gi} \tag{6}$$

$$\sum_{h\in V}\sum_{k\in K_{ih}} x_{ihk} \geq y_i, \forall i \in I \tag{7}$$

$$\sum_{g\in V}\sum_{k\in K_{gi}} x_{gik} \geq y_i, \forall i \in I \tag{8}$$

$$z_{ghk} \leq x_{ghk}q_{ghk}, \forall g \in V, \forall h \in V, \forall k \in K_{gh} \tag{9}$$

$$\sum_{h\in V}\sum_{k\in K_{ih}} z_{ihk} \leq y_i Q_i, \forall i \in I \tag{10}$$

$$\sum_{g\in V}\sum_{k\in K_{gj}} z_{gjk} \leq D_j, \forall j \in J \tag{11}$$

$$\sum_{h\in V}\sum_{k\in K_{sh}} z_{shk} \leq F_s, \forall s \in S \tag{12}$$

$$\sum_{h\in V}\sum_{k\in K_{ih}} z_{ihk} = \sum_{g\in V}\sum_{k\in K_{gi}} z_{gik}, \forall i \in I \tag{13}$$

$$z_{ghk} \geq 0, \forall g \in V, \forall h \in V, \forall k \in K_{gh} \tag{14}$$

$$z_{ghk} \in Z^n, \forall g \in V, \forall h \in V, \forall k \in K_{gh} \tag{15}$$

$$x_{ghk} \in \{0,1\}, \forall g \in V, \forall h \in V, \forall k \in K_{gh} \tag{16}$$

$$y_i \in \{0,1\}, \forall i \in I \tag{17}$$

In the formulation, Eq.(3) is the objective function, ie, maximize the total value function of customer satisfaction. Eq.(4) means the cost should not be more than the capital provided by client, and the cost includes the fixed cost(DC location and 3PL provider) and operational cost(storage and transportation) of network. Eq.(5) and (6) ensure that if the DC is not selected, then the 3PL provider which is adjacent to DC can't be selected also. Eq.(7) and (8) ensure that if the DC is selected, there is at least a flow through the location by 3PL providers. Eq.(9) states that the total amount shipped by 3PL provider can't exceed the its transport capacity. Eq.(10) states that the total amount shipped from DC can't exceed the its processed capacity. Eq.(11) says that the supply which is obtained by demand node can't exceed its actual demand. Eq.(12) says that the total amount shipped form supplier node can't exceed the its maximum throughput. Eq.(13) ensure that flow conservation constraint through DC. Eq.(14) and (15) are non-negativity integrality constraints. Eq.(16) and (17) are standard integrality constraints.

Huang et al. [13] has mathematically modeled the 4PL network design problem. Since it is NP-hard, we propose a meta-heuristic algorithm to solve the proposed problem in the following section.

3. MMA-IDE Algorithm

In this section, we provide MMA-IDE algorithm to solve the provided network design formulation. Designing supply chain network from 4PL perspective can be divided into two steps: selecting a sub-network with proper DCs and 3PL providers and calculating the service level and cost of the selected sub-network, respectively. IDE with adaptive mutation factor and adaptive crossover factor is robust and easy to use, so it is developed to handle the sub-network selection problem; and in order to handle infeasible solutions efficiently, the MMA is incorporated into the minimum cost flow to assign flow with cost constraint. Specifically, the IDE is introduced in details in Subsection 3.1, and the MMA is described in Subsection 3.2. Then the MMA-IDE algorithm is designed as shown in Subsection 3.3.

3.1. Improved Differential Evolution Algorithm

The IDE algorithm with adaptive mutation factor and adaptive crossover factor is proposed to select a sub-network. IDE proposed by Alguliev[16], is an evolutionary algorithm based on group iteration. It is an effective and robust method for solving the problem when its objective function is nonlinear and non-differentiable, while the decision variables are multidimensional. Hence, IDE is applied to deal with the network design problem at the first stage. The major operating processes of the IDE, including encoding, initializing and repairing, designing fitness function, crossover, mutation, selection and termination criteria, will be described in details in the following subsections.

3.1.1 Encoding and decoding scheme The 4PL supply chain network is firstly represented by an adjacency matrix $A = (a_{v,w})_{v,w \in V(G)}$, where the element $a_{v,w} \in A$ represents the number of directed arcs connected from node v to node w. Then, the adjacency matrix can be represented by a nonzero vector $B^T = (b_1, b_2, \ldots, b_r)$ which is consist of all nonzero elements of $A = (a_{v,w})_{v,w \in V(G)}$ in a row-major order. Note that $b_l \in B^T, 1 \leq l \leq r$ means the l-th none-zero element in $A = (a_{v,w})_{v,w \in V(G)}$ in a row-major order, and r indicates the number of nonzero elements in the adjacency matrix A. After that, a r-digit vector $C^T = (c_1, c_2, \ldots, c_r)$ is designed to represent a group decision variables x_{ghk} for all $g \in V, h \in V, k \in K_{gh}$, where the integer value of $c_l \in C^T, 1 \leq l \leq r$ can be randomly generated, ranging from 0 to $2^{b_l} - 1$.

To identify corresponding 3PL provider(s), the generated value of $c_l \in C^T$ needs to be decoded. Specifically, for all $c_l \in C^T, 1 \leq l \leq r$, the value of c_l can be transformed into a binary code, reading from right to left , where 1 indicates that a corresponding 3PL provider is selected, and 0 means not.

An element in the r-digit vector C^T is mapping to a nonzero element of the adjacency matrix A in a row-major order. Then, according to the mapping relation, the nodes connected by selected 3PL provider(s) can be identified, and a group solution x_{ghk} for all $g \in V, h \in V, k \in K_{gh}$ can be reached.

3.1.2 Initial population generation and repairing Assume that the population size of an initial population is N, according to the encoding scheme introduced above, N r-digit vectors can be generated randomly. Then, for each generated r-digit vector, corresponding 3PL providers can be identified and the value of decision variables $x_{ghk}(g \in V, h \in V, k \in K_{gh})$ can be obtained; and if a DC location is incident with one or more selected 3PL provider(s), the DC should be selected. Then, the value of decision variables $y_i(i \in I)$ can be obtained. Note that the values of decision variables, $x_{ghk}(g \in V, h \in V, k \in K_{gh})$ and $y_i(i \in I)$, will satisfy the constraints (5), (6), (16) and (17) in formulation.

However, the obtained values of decision variables may violate the constraints (7) and (8) in formulation, indicating that either in-degree or out-degree exists for some certain DC location. In these situations, the initial population needs to be repaired before the conduction of further processes. Specifically, if there exists only in-degree(or out-degree) for the DC location $i \in I$, a node $g \in V$ can be randomly selected, which (i, g) leaves from $i \in I$ (or (g, i) enters $i \in I$); and if there exist m 3PL providers between node $g \in V$ and node $i \in I$, the value in the r-digit vector which is correspond to the decision variable $x_{gik_{gi}}(x_{igk_{ig}})$ need to be replaced by an integer value which is randomly generated from $[1, 2^m - 1]$. Then, the constraints (7) and (8) in formulation will be satisfied. Through the encoding, decoding and repairing processes, the initial 4PL supply chain sub-networks can be obtained.

3.1.3 Fitness Function In this research, the objective function is selected as the fitness function. After the selection of 4PL supply chain sub-networks, the commodity flow can be calculated by the minimum cost flow algorithm with MMA. Then, the objective function can be calculated. Thus, the fitness function is represented as:

$$f(x_{ghk}, y_i, z_{ghk}) = \sum_{j \in J} B_j(z_{ijk}) \tag{18}$$

where $g, h \in V, i \in I, k \in K_{gh}$. Note that $\sum_{j \in J} B_j(z_{ijk})$ is the objective function, which is a maximization problem.

3.1.4 Adaptive Mutation and Crossover Operation The mutation in this paper adopts the form of $DE/best/2/bin$[16], it is given as follows:

$$V_{i,t} = X_{best,t} + F(t)[(X_{r_1,t} - X_{r_2,t}) + (X_{r_3,t} - X_{r_4,t})] \tag{19}$$

where $V_{i,t}$ is the mutant vector. r_1, r_2, r_3, r_4 are random variables which represent indexes of different vectors in the population, and i is the index of current mutant vector. The values of r_1, r_2, r_3, r_4 and i are different from each other. $X_{best,t}$ is the vector with the best fitness value in the population at generation t (the optimal vector in population for the t-th generation). According to the encoding and decoding scheme in this research, the calculated solution of eq. (19) needs to be rounded.

The mutagenic factor F is related to the convergence speed and the diversity of a population. The adaptive dynamic adjustment strategy is adopted to set the value of F.

$$F(t) = (F_{max} - F_{min}) * \frac{NG - t}{NG} + F_{min} \tag{20}$$

where F_{max} is the maximized mutagenic factor and F_{min} is the minimized mutagenic factor. NG is the maximum number of iterations, and t is the current generation.

After that, the method of binomial crossover is adopted to generate trial vectors based on original vectors and mutant vectors. According to the method of binomial crossover, the trial vector can be determined through the comparison between the randomly generated vector and the crossover factor. Let the r-digit vector $V_{i,t} = (v_{i,t}^1, v_{i,t}^2, \cdots, v_{i,t}^r)$ be the i-th generated mutant vector and the r-digit vector $X_{i,t} = (x_{i,t}^1, x_{i,t}^2, \cdots, x_{i,t}^r)$ be the i-th original vector for the t-th generated population. Then, the randomly generated vector is represented as $Rand = (rand_1, rand_2, \cdots, rand_r)$, where $rand_j \in [0, 1], 1 \le j \le r$, and the value of element in trial vector $U_{i,t} = (u_{i,t}^1, u_{i,t}^2, \cdots, u_{i,t}^r)$ can be given as follows:

$$u_{i,t}^j = \begin{cases} v_{i,t}^j \; rand_j \le CR \text{ or } j = RN \\ x_{i,t}^j \; rand_j > CR \text{ and } j \ne RN \end{cases} \quad j = 1, 2, ..., r \tag{21}$$

where CR is the crossover factor. Note that the integer value $RN \in [1, r]$ is generated randomly to ensure that at least one element in trial vectors comes from the mutant vector.

In order to achieve a balance between global search and local search, the value of the crossover factor(CR) which can adjust adaptively is designed as follows:

$$CR(t) = CR_{min} + \frac{(CR_{max} - CR_{min})t}{NG} \tag{22}$$

where CR_{max} is the maximized crossover rate and CR_{min} is the minimized crossover rate. t and CR are positively correlated.

After mutation and crossover operations, the generated trail vectors may become infeasible solutions for the supply chain network design from a 4PL perspective. Hence, a repair for the generated solutions is required, referring to in 3.1.2.

3.1.5 Selection Mechanism After the mutation, crossover and repair operations, the "greedy strategy" [17] is adopted to select the better vector between $U_{i,t}$ and $X_{i,t}$ for the t-th generated population to generate the new individual for the $(t+1)$-th generated population.

$$X_{i,t+1} = \begin{cases} U_{i,t} \; f(U_{i,t}) > f(X_{i,t}) \\ X_{i,t} \; f(U_{i,t}) \le f(X_{i,t}) \end{cases} \quad i = 1, 2, ..., N \tag{23}$$

where $f(\bullet)$ is the fitness function. If $f(U_{i,t}) > f(X_{i,t})$, $U_{i,t}$ is better than $X_{i,t}$, and vice versa.

3.1.6 Termination Criteria After each selection process, the number of iteration increases by 1. The IDE Algorithm stops when the number of iteration reaches the limit of NG. The operation processes and termination criteria for the IDE Algorithm is as shown in Figure 2.

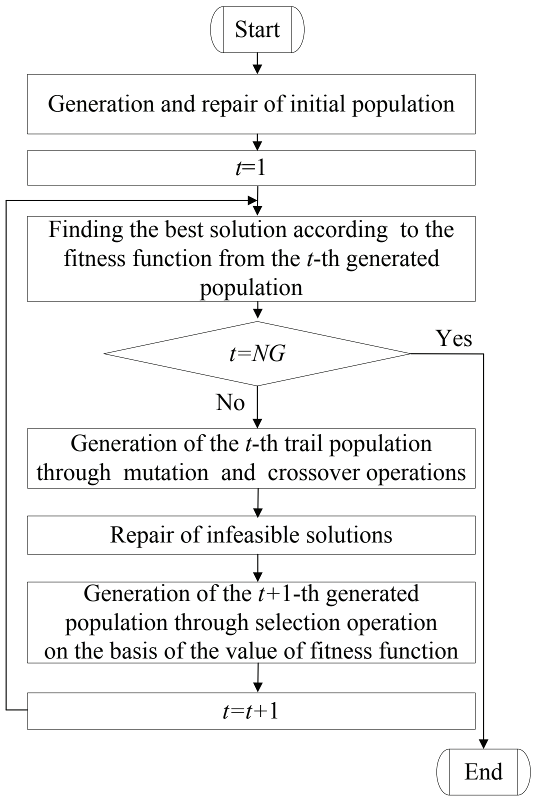

Fig. 2. The flow chart of the IDE algorithm

Until now, the first stage of the two-stage algorithm has been finished. Specifically, the IDE algorithm with adaptive mutation factor and adaptive crossover factor has been developed, and the sub-network has been identified through selecting proper DCs and 3PL providers in the supply chain network.

3.2. MMA mechanism

Based on the identified sub-network MMA mechanism is proposed to modify the minimum cost flow to maximize the value function of customer satisfaction as far as possible under cost constraint. The classical minimum cost flow problem [18] is to satisfy customer's demand completely when there are enough supply capacity and transportation capacity. The assigned flow based on the minimum cost flow algorithm will satisfy the constraints (9)-(15) of the supply chain network design. However, the flow may violate constraint (4) which means the total cost may exceed the given investment.

Hence, in this paper, considering limited investment, a repair strategy, MMA, is proposed to modify the minimum cost flow to satisfy customer's demand as far as possible. Note that, the total cost consists of the fixed cost and the variable cost. If the fixed cost is higher than the given investment, the flow is assigned to zero. Otherwise, the minimum cost flow is modified through the MMA mechanism:

- macro adjustment: when the difference between calculated total cost and the given investment is larger than a certain value, the demand for all customers reduces in a same proportion;
- micro adjustment: when the difference between calculated total cost and the given investment is smaller than or equal to a certain value, only one customer's demand decreases by a unit per time.

Then, the detailed steps of MMA are shown as follows:

Step 1: Compute the fixed cost $C_f = \sum_{g\in V}\sum_{h\in V}\sum_{k\in K_{gh}} h_{ghk}x_{ghk} + \sum_{i\in I} H_i y_i$ on the basis of the identified sub-network. If $C_f > C_m$, set $z_{ghk} = 0, \forall g \in V, h \in V, k \in K_{gh}$, then $G_j = 0$, $\forall j \in J$, stop; otherwise set $d_j = D_j, \forall j \in J$, go to *Step 2*. Note that C_f includes the fixed cost at potential DC locations and the fixed cost of potential 3PLs.

Step 2: Compute the flow $z_{ghk}, \forall g \in V, h \in V, k \in K_{gh}$ using minimum cost flow algorithm based on the demand $d_j, \forall j \in J$. Then set the variable cost $C_0 = \sum_{g\in V}\sum_{h\in V}\sum_{k\in K_{gh}} c_{ghk}z_{ghk} + \sum_{g\in V}\sum_{i\in I}\sum_{k\in K_{gi}} C_i z_{gik}$.

If the total cost $C = C_f + C_0 > C_m$, go to *Step 3*; otherwise set $G_j = \frac{\sum_{g \in V} \sum_{k \in K_{gj}} z_{gjk}}{D_j}, \forall j \in J$, stop. Note that C_0 includes the variable cost per unit at potential DC locations and the unit cost of transportation of potential 3PLs.

Step 3: If $(C - C_m) > \theta$, then set $d_j = \lceil \gamma d_j \rceil, \forall j \in J$, go to *Step 2*; otherwise go to *Step 4*.

Step 4: For ($j = 1; j \leq |J|;$ j++) , note that $|J|$ is the number of elements in the set J , do

$\{d_j = d_j - 1;$

Compute the flow $z_{ghk}, \forall g \in V, h \in V, k \in K_{gh}$ using minimum cost flow algorithm when the other customers' demand are stay still, and calculate the value of objective function $\sum_{j' \in J} B_{j'}$. Then set $E_j = \sum_{j' \in J} B_{j'}$;

$d_j = d_j + 1; \}$

Choose $j, \forall j \in J$ which makes the E_j is maximum among the customers which the demands are greater than or equal to one unit. Then, set $d_j = d_j - 1$, go to *Step 2*.

Note that Steps 1-2 check the stop criterion. Step 3 does the macro adjustment, adjusting the demand for all customers. Step 4 does the micro adjustment, adjusting the demand for only one customer.

3.3. Framework of the MMA-IDE Algorithm

According to the description above, the operation processes of MMA-IDE algorithm can be summarized as follows:

Step 1: Generate the initial population, repair infeasible solutions, and identify the sub-networks.

Step 2: Based on the identified sub-network, assign the flow using the minimum cost flow algorithm with MMA mechanism.

Step 3: Calculate the fitness function of the initial population.

Step 4: Perform the mutation operation to obtain the mutant population.

Step 5: Perform the crossover operation, get the trial population, and repair the infeasible solution to generate the sub-networks.

Step 6: Assign the flow through minimum cost flow algorithm with MMA based on the selected sub-networks of *Step 5*.

Step 7: Calculate the fitness function of the trial population.

Step 8: Perform the selection operation, that is, select the vector whose fitness function's value is better through comparison between the t-th generated original vector and the trial vector to generate the $t + 1$-th original vector, and the number of iteration increases by 1.

Step 9: If the maximum number of iteration is achieved, stop; otherwise, go to *step 4*.

Note that Step 1 initializes the network at the first stage. Step 2 assigns the flow on the basis of initial network at the second stage. Steps 3-5 improve the network at the first stage. Step 6 calculates the flow on the basis of the improved network at the second stage. Steps 7-8 perform the selection operation to obtain the original vector of the next generation at the first stage. Step 9 checks the stop criterion.

Figure 3 illustrates the process of MMA-IDE algorithm.

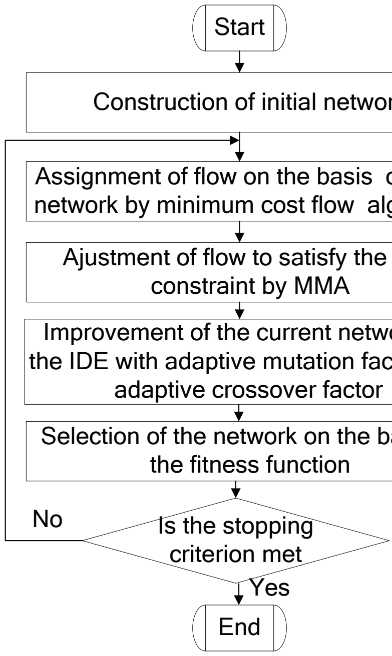

Fig. 3. The flow chart of the MMA-IDE algorithm

4. Numerical Experiments

In this section, numerical experiments are designed to analyze the performance of the algorithm and the significant of considering behavior. Numerical experiments and evaluation criteria for algorithms are given in subsection 4.1. The values of parameters for the algorithm are testified and identified based on samples in subsection 4.2. After that, the results for MMA-IDE and IDE which through adding a penalty factor to handle the infeasible solution are compared through experiments in subsection 4.3.

4.1. Experimental Design

Experiments with the 9-node, the 15-node and the 23-node are designed and testified in this subsection. When we calibrate our model, we follow [19] in setting $\alpha = \beta = 0.88$ and $\lambda = 2.25$. To simplify the calculation, the reference point for each customer G_{mj} is set to be 0.7. When the model is applied to the real problem, the value of G_{mj} can be identified according to customers' requirements through investigation. Then, the data is randomly generated for experiments, as shown in Table 1.

Table 1. Data for experiments

Data / numerical experiment	SN	UN	LN	KN	F	D	p	C_m
9-node	1	3	5	[0,2]	300	40,39,49,38,32	30	15000
15-node	3	4	8	[0,2]	600,400, 500	42,40,54,42,52, 56,41,47	60	27000
23-node	4	6	13	[0,3]	300,420, 630,540	41,41,42,43,56, 32,44,44,35,42, 45,33,50	143	30000

where SN is the number of suppliers, UN is the number of DCs, LN is the number of customers, KN is the number of 3PL providers between any two nodes, F is the capability of supply nodes, D provides each customer' demand, and p is the number of 3PL providers. The multi-Graph of the 9-node experiment is shown in Figure 4.

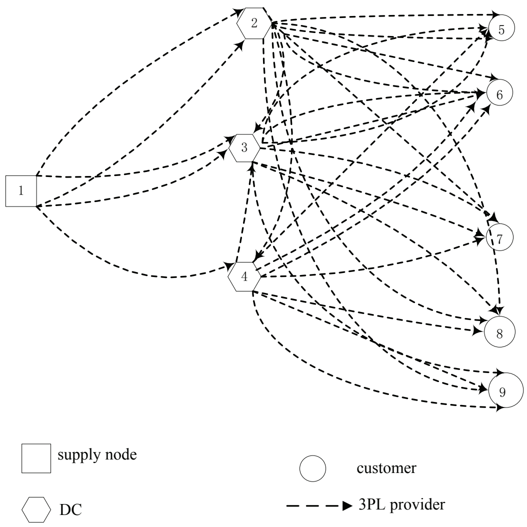

Fig. 4. Multi-graph of the 9-node experiment

The criteria used in parameters tuning are explained as follows: the best value that n runs (BS); the worst value that n runs (WS); the mean value that n runs (Mean), the standard deviation (S): S $= \sqrt{\frac{\sum_{i=1}^{n}(x_i-\overline{x})^2}{n-1}}$; and the fifth criterion is the average time that n runs (Time). In the next subsection, different combinations of parameters are analyzed to obtain reasonable calculation results.

4.2. Parameters Tuning

The IDE algorithm involves several parameters: the population size N, the mutagenic factor F_{max}, F_{min}, the cross factor CR_{max}, CR_{min}, and the maximum number of iterations NG. The parameters tuning for MMA algorithm contains two parameters θ and γ. In order to obtain reasonable combination of parameters for MMA-IDE algorithm, the parameters are adjusted through three numerical experiments with different sample sizes. The performance of the algorithm in the parameters adjustments are measured by "BS", "WS", "Mean", "S" and "Time". In the parameters turning, only one parameter is adjusted each time when values of the other parameters are fixed, and each adjustment of one parameter has 50 runs. The results of the parameters for the 9-node numerical experiment, the 15-node experiment and the 23-node experiment are identified and provided in Table 2, Table 3 and Table 4, respectively.

Table 2. The identified parameters for the 9-node experiment

NG	N	F_{max}	F_{min}	CR_{max}	CR_{min}	θ	γ
60	40	0.9	0.2	0.5	0.2	10000	0.5

Table 3. The identified parameters for the 15-node experiment

NG	N	F_{max}	F_{min}	CR_{max}	CR_{min}	θ	γ
80	40	0.9	0.2	0.5	0.2	22500	0.5

Through the comparison among the calculation results of the three numerical experiments, it can be found that the value of NG increases along with the increasing number of designed nodes. For example, The NG is 60 in the 9-node numerical experiment, 80 in the 15-node numerical experiment, and 100 in the 23-node numerical experiment.

Table 4. The identified parameters for the 23-node experiment

NG	N	F_{max}	F_{min}	CR_{max}	CR_{min}	θ	γ
100	40	0.9	0.2	0.5	0.2	54000	0.5

The value of the parameter θ can be affected by the following factors, including the maximum investment provided by the client (C_m), fixed cost at potential DC locations and the fixed cost of potential 3PLs (C_f) , the variable cost per unit at potential DC locations and the unit cost of transportation of potential 3PLs (C_0), and the size of the problem. Normally, the larger value of parameter θ we set, the more precise calculation results can we get, and the more running time we need. However, according to the proposed algorithm, the value of the parameter θ has a positive correlation with value of $C_f + C_o - C_m$. For example, if the value of $C_f + C_o - C_m$ is relatively smaller, the value of θ can also be set as a relatively smaller value. In this situation, the running time can be greatly deduced without losing of accuracy. Since variables C_f and C_0 cannot by identified, θ' is defined as $\theta' = C'_f + C'_0 - C_m$ based on the original network, where C'_f and C'_0 indicate the fixed cost and the variable cost for the original network, respectively. Because the original network gets the highest values of C_f and C_0, parameter θ is defined as $\theta = \delta\theta'$. From the above tables, the value of the θ of each experiment is about 0.5 times as much as the value of $C'_f + C'_0 - C_m$ for the original network.

4.3. Performance Analysis

In this subsection, a comparison is conducted on performance of proposed MMA-IDE algorithm and the IDE algorithm by using three numerical experiments.

In the IDE algorithm, the fitness function with penalty is set as follows:

$$f(x_{ijk}, y_i, z_{ijk}) = \sum_{j \in L} B_j(z_{ijk}) + w[C_m - C]^- \tag{24}$$

where $g, h \in V$, $i \in I$, $k \in K_{gh}$ and w is a penalty factor. $C = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K_{ij}} h_{ijk} x_{ijk} + \sum_{i \in U} H_i y_i + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K_{ij}} c_{ijk} z_{ijk} + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K_{ij}} C_j z_{ijk}$. The solution may violate constraint (4), so the cost is treated as a penalty in fitness function. $(\bullet)^-$ indicates that if the value in a bracket is negative, the value is taken, otherwise the value is 0. Note that $\sum_{j \in L} B_j(z_{ijk})$ is the objective function, which is a maximization problem.

Each of the designed numerical experiments is executed for $n = 20$ runs. Table 5 provides the calculation results for the above three numerical experiments by using the MMA-IDE and IDE algorithm.

Table 5. The calculation results for numerical experiments

numerical experiment	Algorithm	Evaluation Criterion				
		BS	WS	Mean	S	Time
9-node	MMA-IDE	0.807703	0.807703	0.807703	0	79.79
	IDE	0.0644404	-0.448634	-0.239074	0.134	75.26
15-node	MMA-IDE	1.25664	1.00165	1.2022265	0.0598	783.1
	IDE	-7.17948	-7.17948	-7.17948	0	811.3
23-node	MMA-IDE	0.78549	0.54429	0.651847	0.1227	11666
	IDE	-0.380366	-0.751546	-0.547641	0.195454	11040

From Table 5, it can be seen that the values of best value, the worst value and means by the proposed MMA-IDE are better than those obtained by IDE with similar running time. Through the running time is not an eye blink, the running time can be still accepted, because the problem of network design is a strategic problem. From the calculation results, the values of Mean obtained by the IDE algorithm indicate that the designed 4PL supply chain network can't reach the customer' reference point, while the MMA-IDE algorithm can obtain a better network, which can reach the customer's reference point. According to the values of S, it can be seen that the results calculated by the MMA-IDE algorithm has better stability than the IDE algorithm. Therefore, the MMA-IDE can achieve a better solution in the 4PL supply chain network design problem.

A 4PL supply chain network can be designed based on the calculation results. For example, Figure 5 illustrates the solution for the 9-node experiment. The supply which is obtained by each customer is 30, 30, 35, 29 and 32 respectively. The total cost is 14958, in which the fixed cost is 7487 and the variable cost is 7471.

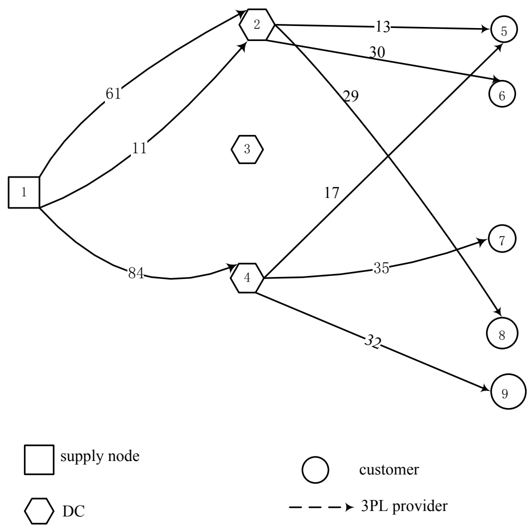

Fig. 5. The solution for the 9-node experiment

5. Conclusion

In this paper, in order to find the infeasible solutions for 4PL supply chain network design problem considering the behavior of customer service satisfaction more quickly, an MMA-IDE algorithm is designed to modify the minimum cost flow to satisfy customer's demand when the investment is limited. The framework of the MMA-IDE algorithm is proposed, based on which, a sub-network can be selected through IDE with the adaptive mutation factor and the adaptive crossover factor; then the cost feasible flow with maximized customer satisfaction can be calculated by the minimum cost flow algorithm with MMA mechanism. Note that the MMA mechanism is proposed to modify the flow to maximize the value function of customer satisfaction under cost constraint.

Three scale numerical experiments are carried out to test the performance of the MMA-IDE algorithm. The numerical experiments show that the MMA-IDE algorithm is effective to solve our problem. Compared with the IDE algorithm, MMA-IDE algorithm can get relatively better calculation results. This research offers a tool to solve 4PL network design problem considering the behavior of customer service satisfaction.

6. Conflict of Interest

The authors declare that there are no conflict of interests, we do not have any possible conflicts of interest.

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