Optimization Design of Multi-layer Logistics Network Based on Self-Adaptive Gene Expression Programming

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Abstract. In order to solve the multi-layer logistics network optimization problem of modern enterprises, a mixed integer programming model with minimum total cost is established by considering the inventory cost and transportation cost and the switching state of the transit logistics nodes. According to the characteristics of multi-layer logistics network optimization problem, the gene expression programming with the characteristics of multi-gene structure is adopted, and the self-adaptive evolution mechanism is introduced to dynamically adjust the genetic operator. A self-adaptive gene expression programming algorithm based on Prüfer coding (SA-GEP) is proposed to solve the model. The algorithm introduces the insertion operator based on the original genetic operator of gene expression programming. The experimental results show that compared with STD-GEP algorithm and EC algorithm, the optimization effect of SA-GEP algorithm is more significant, which greatly improves the performance of the algorithm, and verifies the feasibility of the model and the effectiveness of the algorithm.

Keywords: Gene expression programming · Logistics network · Self-adaptive mutation · Prüfer coding

1 Introduction

How to integrate and optimize the modern logistics network has always been one of the hot topics of enterprise development. In recent years, with the rapid development of the economy, the rise of global supply chain management and the development of e-commerce technology, enterprises are paying more and more attention to the construction and improvement of logistics networks. The integration and optimization of the logistics network structure has become the core to improve the efficiency of the supply chain [1]. Therefore, logistics must be networked to meet the needs of the development of the times [2].

The logistics network structure mainly consists of two components, nodes and paths. Logistics network optimization is the process of optimizing network nodes and all logistics paths in the supply chain [3]. With the improvement of the complexity of logistics network, there are multiple logistics centers to choose from in the process of

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product distribution in modern logistics, and each logistics center has many optional distribution centers, which makes the logistics network optimization problem become a typical NP-hard problem. It is difficult to solve this problem effectively by traditional methods.

For the optimization of logistics network, there are related research at home and abroad. Syarif et al. [4] and Xu Hang et al. [5] used the idea of spanning tree to propose a multi-stage logistics network optimization model based on the evolution algorithm of Prüfer number. Wang et al. [6] studied the problem of two-level logistics distribution area division with the goal of minimizing total cost, and proposed a hybrid algorithm based on extended particle swarm optimization and genetic algorithm (EPSO-GA). Cho SY et al. [7] considered a balanced allocation and vehicle path, proposed a two-stage solution method and established a multi-resource multi-objective mixed integer programming logistics network model. Li Bozhen et al. [8] considered the uncertainty of consumer demand, established a closed-loop logistics network stochastic programming model by stochastic programming method, and proposed a genetic algorithm based on new priority coding to solve the model. Liu Yanqiu et al. [9] aimed to minimize the overall cost, considered dynamically adjusting the node closure state, established an optimization model for describing multi-level distribution network design problems with capacity constraints, and proposed an improved simulated annealing algorithm to solve the model.

Based on the above analysis, considering the inventory cost and transportation cost as well as the switching state of the transit logistics node, this paper builds a mixed integer programming model for the cost optimization problem of the multi-layer logistics network, with the goal of minimizing the total cost generated by the operation logistics network. According to the characteristics of multi-layer logistics network, this paper adopts gene expression programming with the characteristics of multi-gene structure, and introduces self-adaptive evolution mechanism to dynamically adjust genetic operators. A self-adaptive gene expression programming algorithm is proposed to solve the model.

2 Problem Description and Model Construction

2.1 Problem Description

Most of the traditional logistics network models are two-tier logistics networks that are distributed between suppliers and their customers, which is also called simple logistics networks. With the development of China's economy, China's logistics industry is in a period of great development. This paper focuses on the node location problem and product allocation problem of complex multi-layer logistics network, which belongs to the location-allocation problem (LAP) of logistics network planning. The multi-tier logistics network includes supplier node, transit logistics node, and customer node. The multi-layer logistics network optimization problem studied in this paper can be described as: Several customers feed back the product demand to the supplier, and the supplier delivers the product to the corresponding customer without exceeding the maximum supply. During the delivery process, the product passes through one to several layers of transit logistics nodes and finally reaches the customer. Under the premise of meeting the customer's product demand, the cost incurred by the whole process is required to be the least.

2.2 Model Hypothesis

The logistics network optimization model studied in this paper is based on the following assumptions:

(1) Taking a certain type of product in a single cycle as the research object, regardless of environmental factors and social benefits;
(2) The logistics network consists of multiple suppliers, multi-tier transit logistics nodes and multiple customers;
(3) The number of suppliers and the number of customers are known, and the number of transit logistics nodes per layer is known;
(4) The maximum capacity and inventory cost of each transit logistics node (if the node is enabled, the fee is required) is known;
(5) The transportation cost per unit of product between each node of the adjacent logistics network layer is known;
(6) Cross-layer provisioning and horizontal supply between peer nodes are not considered.

2.3 Parameter Definition

K: the number of layers of the multi-layer logistics network (the first layer is the supplier, the Kth layer is the final customer, and the middle is the transit logistics node), K $\geq$ 3, k = 1, 2, 3,…, K;
M: number of supplier nodes, m = 1, 2, 3,…, M;
N: number of client nodes, n = 1, 2, 3,…, N;
W_k: the number of k-th layer logistics nodes (W_1 represents the number of supplier nodes when W = 1, i.e., W_1 = M; when k = K, W_k represents the number of client nodes, i.e., W_k = N);
$A_{k,i}$: the maximum processing capacity of the i-th node of the kth layer, i.e. the maximum capacity;
S_i: the maximum supply of products by the i-th supplier;
V_i: The demand for the i-th customer;
$C_{k,i}^{stock}$: inventory cost of the i-th logistics node of the kth layer;
$C_{k,i,j}^{trans}$: unit product transportation cost from the i-th node of the kth layer to the jth node of the k + 1th layer;
Decision variables:
$X_{k,i,j}$: number of product shipments from the i-th node to the j-th node of the kth layer;
$R_{k,i}$: the number of products passing through the i-th transit logistics node of the kth layer, k = 2, 3,… , K − 1;

$$Y_{k,i} = \begin{cases} 1, \text{Enable the i - th logistics node in the k - th layer} \\ 0, \quad \text{Other} \end{cases}$$

$$U_{k,i,j} = \begin{cases} 1, \text{The i - th node of the k - th layer sends the product to the jth node of the k + 1th layer} \\ 0, \quad \text{Other} \end{cases}$$

2.4 Mathematical Model Construction

The cost to be considered in the design of the multi-layer logistics network of this paper mainly includes inventory cost and transportation cost. Starting from the description and assumptions of the model, a mixed integer programming model with the primary goal of minimizing total cost is constructed to meet the needs of customers and reduce the operating costs of the enterprise as much as possible.

Objective function:

$$\text{Min } C^{total} = C^{stock} + C^{trans} \tag{1}$$

Where C^{total} represents the total cost, C^{stock} represents the inventory cost of the transit logistics node, and C^{trans} represents the transportation cost.

$$C^{stock} = \sum_{k=2}^{K-1} \sum_{i=1}^{W_k} C_{k,i}^{stock} \cdot Y_{k,i} \tag{2}$$

$$C^{trans} = \sum_{k=1}^{K-1} \sum_{i=1}^{W_k} \sum_{j=1}^{W_{k+1}} C_{k,i,j}^{trans} \cdot X_{k,i,j} \tag{3}$$

s.t.

$$\sum_{i=1}^{M} S_i \geq \sum_{i=1}^{N} V_i \tag{4}$$

$$\sum_{i=1}^{W_k} \sum_{j=1}^{W_{k+1}} X_{k,i,j} = \sum_{i=1}^{W_{k+1}} \sum_{j=1}^{W_{k+2}} X_{(k+1),i,j}, \quad \forall \text{k} = 1, 2, \ldots, \text{K} - 2 \tag{5}$$

$$R_{k,i} = \sum_{j=1}^{W_{k+1}} X_{k,i,j} \cdot U_{k,i,j}, \quad \forall \text{k} = 1, 2, \ldots, \text{K} - 1; \ \forall \text{i} = 1, 2, \ldots, W_k \tag{6}$$

$$R_{k,i} \leq A_{k,i} \cdot Y_{k,i}, \quad \forall \text{k} = 1, 2, \ldots, \text{K}; \ \forall \text{i} = 1, 2, \ldots, W_k \tag{7}$$

$$\sum_{i=1}^{W_k} \sum_{j=1}^{W_{k+1}} X_{k,i,j} = \sum_{i=1}^{N} V_i, \ \forall \text{k} = 1, 2, \ldots, \text{K} - 1 \tag{8}$$

$$\sum_{i=1}^{W_k} X_{k,i,j} \cdot U_{k,i,j} = V_i, \quad k = K - 1 \tag{9}$$

$$Y_{k,i}, U_{k,i,j} \in \{0, 1\} \tag{10}$$

$$S_i, V_i, A_{k,i}, X_{k,i,j}, R_{k,i}, C_{k,i}^{stock}, C_{k,i}^{stock} \geq 0, \quad \forall k, i, j \tag{11}$$

Among them, (4) stipulates that the total supply of the supplier must meet the total demand of all customers; (5) represents the flow conservation constraint of the nodes of different logistics layers; (6) represents the different logistics layers. The flow conservation constraint on the node ensures that the supply quantity of the product does not exceed the supply quantity; (7) represents the processing capacity limit of the logistics node, that is, the capacity limitation constraint; (8) and (9) stipulate that the supply quantity must satisfy the customer. The product demand ensures that the quantity of products delivered to the final customer node through the node is equal to the actual demand of the customer. (10) specifies the type of decision variable; (11) represents the non-negative constraint of the variable.

3 Self-Adaptive Gene Expression Programming Algorithm Based on Prüfer Coding

Gene Expression Programming (GEP) [12] is a new self-adaptive evolutionary algorithm based on natural selection and genetic mechanisms. It combines the advantages of genetic algorithm (GA) and genetic programming (GP) while overcoming the disadvantages of the two algorithms. Gene expression programming is characterized by the ability to separate genotypes from phenotypes and to solve complex problems with simple coding. The multi-layer logistics network problem studied in this paper is an NP-hard problem, which is difficult to solve with an accurate algorithm. It is more complicated than the traditional two-tier logistics network. This paper proposes a Self-Adaptive Gene Expression Programming Algorithm based on Prüfer Coding (SA-GEP). According to the multi-gene structure of GEP, in each chromosome, each gene can represent a simple logistics network in a multi-layer logistics network. Multiple simple logistics networks form a complete multi-layer logistics network, so a chromosome composed of multiple genes can represent a complete multi-layer logistics network, which is a major advantage of GEP in solving the logistics network optimization model.

3.1 Gene Coding and Decoding

When using the intelligent optimization algorithm to solve the multi-layer logistics network model, the coding method of the feasible solution is a key issue to be considered. Prüfer coding [10, 11] is an effective method for network coding. According to Cayley's theorem, in a complete graph with n vertices, there are n^{n-2} different label trees. Let the tree T be a label tree with n nodes whose node numbers are {1, 2,… , n}, which can be uniquely represented by an array of lengths n − 2 formed by natural numbers between 1 and n. This arrangement is usually called the Prüfer number. Please refer to literature [4, 5] for the decoding process of Prüfer for logistics network problems.

3.2 Fitness Function

This paper adopts the fitness function based on the objective function formula (1):

$$\text{Fitness} = \delta \cdot \frac{1}{C^{total} + 1} \tag{12}$$

Where C^{total} represents the total cost, δ is the fitness evaluation factor, and δ is a positive number.

3.3 Genetic Operation Design for Logistics Network

The basic genetic operators of GEP include selection, mutation, reversal, interpolation, root insertion, gene transformation, one-point recombination, two-point recombination and gene recombination [13]. The genetic operations designed for multi-layer logistics network optimization problems mainly include selection and copy operation, mutation operation, insertion operation, inversion operation and recombination operation.

(1) Selection and copy operations
The traditional GEP selection operator adopts the Roulette Wheel selection method. According to the fitness value, the individuals with better fitness values in the population are more likely to be selected and copied directly to the next generation to generate new populations. This paper adopts the combination strategy of roulette selection method and elite retention strategy. Firstly, N individuals are selected by roulette wheel selection method to perform a series of genetic operations to generate offspring, and then the parent population and the offspring population are combined to build a temporary population with a size of 2N, and then we carry out the elite retention strategy. By comparing the fitness value of the individual, select the N outstanding individuals with larger fitness values in the temporary population to form the next generation of new populations. The superior individuals in the population replace the poor individuals in the offspring population.

(2) Mutation operation
In view of the multi-layer logistics network optimization problem studied in this paper, the mutation operation first randomly selects a gene on the chromosome according to a certain mutation probability, and then generates a new individual by changing a certain node in the gene.

(3) Insertion operation
For the multi-layer logistics network optimization problem studied in this paper, each chromosome represents a complete multi-layer logistics network. Each gene in the chromosome corresponds to a simple logistics network. In a multi-layer

logistics network, one gene represents the adjacent two-layer logistics network. According to the requirements of Prüfer coding, the length of each gene in the chromosome is related to the number of nodes in the adjacent two-layer logistics network, and the position of each gene in the chromosome cannot be changed, otherwise the wrong result will be obtained, so gene insertion is not suitable for genetic operation of multi-layer logistics network. Since IS and RIS operations remove codes that exceed the length of the gene's head, this may affect the integrity and validity of the gene, and at the same time cause an imbalance in the Prüfer coding sequence. Therefore, this paper introduces a insertion operator [14], which randomly selects a substring from a gene, moves the substring to an arbitrary position of the gene according to a certain insertion probability. The substring of the insertion operation in the gene and its length is random.

(4) Inversion operation
In view of the multi-layer logistics network optimization problem studied in this paper, the inversion operation randomly selects a substring from the gene, and then inverts the characters in the substring in order, hat is to say, the center character of the substring is taken as the symmetry axis, and the symmetrical character positions are interchanged in order. The substring that is inverted in the gene and its length is random.

(5) Recombination operation
Recombination operation include one-point recombination, two-point recombination, and genetic recombination.

3.4 Self-Adaptive Operator Design

The mutation probability of the standard gene expression programming algorithm is usually a fixed constant when it performs mutation operation on individuals. This method of ignoring the individual's superiority and inferiority of the population limits the convergence speed of the algorithm to a certain extent. Therefore, this paper adopts the self-adaptive evolution mechanism to dynamically adjust the mutation probability according to the individual fitness value of the population, reduce the damage to the optimal individual, and improve the convergence speed of gene expression programming algorithm to a certain extent.

In the process of individual evolution, the self-adaptive adjustment formula of the mutation operator is as follows:

$$P_m = \begin{cases} P_1 - \frac{(P_1 - P_2)\cdot(f_{max} - f)}{f_{max} - f_{avg}} & ,f \geq f_{avg} \\ P_1 & ,f < f_{avg} \end{cases} \tag{13}$$

In (13), P_1 is the initial mutation probability, P_2 is the adjustment parameter, P_1 and P_2 are the constants in [0, 1], f_{max} is the maximum fitness value of the population, f_{avg} is the average fitness value of the population, and f is the fitness value of the individual which will be mutated. In the experiment of this paper, $P_1 = 0.3$ and $P_2 = 0.05$ were set.

3.5 Self-Adaptive Operator Design

The SA-GEP algorithm flow proposed in this paper is shown in the Fig. 1.

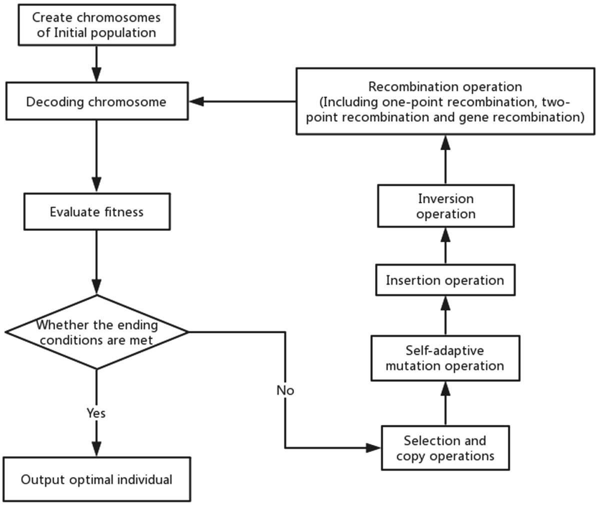

Fig. 1. Algorithm flow chart of SA-GEP.

4 Experimental Simulation and Analysis

4.1 Experimental Data and Algorithm Parameters

This section of the experiment considers the classic four-tier logistics network structure, namely, supplier (S), Logistics Center (LC), Distribution Center (DC), and Customer (C). Suppose a logistics network consists of 6 suppliers, 10 logistics centers, 15 distribution centers and 20 customers. The logistics center and distribution center belong to the transit logistics node mentioned in the model. Tables 1, 2, 3, 4, 5, 6 and 7 are experimental data of a four-layer logistics network, and Table 8 is an algorithm parameter description.

Table 1. Maximum supply of supplier (S)

	1	2	3	4	5	6
Supply	1251	1250	1531	1797	1267	1455

Table 2. Maximum capacity of logistics center (LC) and distribution center (DC)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
LC	928	955	955	757	815	998	985	846	785	918	–	–	–	–	–
DC	613	498	635	561	714	822	506	482	590	682	629	646	862	703	454

Table 3. Customer (C) product demand

	1	2	3	4	5	6	7	8	9	10
Demand	251	350	224	518	583	758	230	217	987	391

	11	12	13	14	15	16	17	18	19	20
Demand	313	198	535	261	514	222	206	482	490	482

Table 4. Inventory costs of logistics center (LC) and distribution center (DC)

	1	2	3	4	5	6	7	8	9	10
LC	1517	1828	1621	1298	1867	1751	1466	1371	1655	1889
DC	1040	1573	1042	1221	1508	1021	1205	1252	1382	1307

	11	12	13	14	15
LC	--	--	--	--	--
DC	1411	1427	1457	1265	1254

Table 5. Unit product transportation costs from supplier (S) to logistics center (LC)

S	LC									
	1	2	3	4	5	6	7	8	9	10
1	8	2	6	5	3	4	1	7	7	6
2	7	8	5	2	4	7	6	5	8	5
3	8	2	7	1	8	6	2	7	8	4
4	2	1	4	7	6	6	5	8	6	6
5	3	5	5	4	2	3	6	3	6	2
6	3	4	5	4	4	3	7	3	5	3

Table 6. Transportation costs per unit of product from the logistics center (LC) to the distribution center (DC)

LC	DC														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	5	4	7	5	8	4	4	2	6	2	1	5	6	7	8
2	2	1	3	6	7	9	4	2	4	3	7	3	5	5	6
3	5	5	4	3	5	8	4	7	9	8	5	4	4	5	6
4	1	4	5	7	2	7	5	5	4	2	4	7	6	4	1
5	7	4	3	6	5	4	4	3	2	5	4	6	4	7	6
6	5	7	3	5	4	3	8	7	5	2	5	1	6	3	4
7	7	2	6	3	8	4	3	6	1	2	3	6	7	3	7
8	5	4	4	1	5	9	6	5	7	3	4	7	9	5	1
9	4	5	7	5	4	8	2	4	5	2	1	5	4	7	4
10	8	6	5	6	2	7	9	8	8	5	7	9	5	7	4

Table 7. Unit Product transportation cost from distribution center (DC) to customer (C)

DC	C																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	1	6	4	7	5	6	7	5	5	1	1	8	4	4	7	9	4	6	6	2
2	2	9	6	4	6	5	7	5	6	5	2	7	5	4	6	7	4	4	5	2
3	7	7	2	2	3	1	1	7	5	8	1	7	6	4	7	7	5	4	3	1
4	4	5	3	3	2	1	2	5	7	5	8	7	5	4	5	6	5	2	3	4
5	2	4	6	6	3	5	4	7	9	9	1	6	3	9	1	3	7	1	2	4
6	7	4	9	3	6	8	1	6	7	1	1	6	7	8	5	1	1	1	8	4
7	1	7	5	8	1	7	6	4	7	7	8	2	4	9	3	6	9	4	4	7
8	9	4	7	2	5	1	8	2	6	9	6	2	1	6	5	4	8	3	8	1
9	1	5	8	2	5	7	5	2	4	5	3	3	6	2	6	6	7	6	9	7
10	8	2	4	9	3	6	9	4	4	7	6	8	2	8	4	3	3	6	2	6
11	2	4	6	6	3	5	4	7	9	9	4	5	9	9	7	9	5	8	3	2
12	1	6	7	5	1	6	7	8	5	1	7	8	1	8	1	8	6	3	2	2
13	4	6	5	7	5	6	5	2	7	5	5	7	5	2	4	5	4	6	1	8
14	3	8	4	3	6	1	2	3	6	7	8	1	7	6	4	7	7	8	2	4
15	5	5	4	5	9	9	3	2	6	4	3	3	1	2	3	3	4	9	7	3

4.2 Experimental Results and Analysis

In order to verify the effectiveness of the algorithm, this paper uses the SA-GEP algorithm, the standard GEP algorithm (STD-GEP) and the traditional evolutionary computation method (EC) of the literature [5] to carry out 100 experiments on the model, and each experiment output the optimal distribution scheme and optimal cost corresponding to the optimal individual in the population. Table 9 shows the performance indicators of the SA-GEP algorithm, the standard GEP algorithm, and the EC algorithm. Figure 2 shows the evolution of the population evolution process of the SA-GEP algorithm, the standard GEP algorithm, and the EC algorithm under the same evolutionary algebra.

It can be seen from Table 9 that the SA-GEP algorithm is better than the STD-GEP and EC algorithms in comparing the indicators related to the objective function of the model. It can be seen from Fig. 2 that in the initial stage of the algorithm (before the 50th generation), the convergence speed of the three algorithms is almost the same, but with the increase of the population evolution algebra, the EC algorithm is easy to fall into the local optimal solution. The self-adaptive operator of SA-GEP algorithm greatly improves the performance of the algorithm, and the optimal value obtained by solving the model is always better than the other two algorithms.

Table 8. Algorithm parameter setting and description

Parameter name	Parameter setting and description
Population size	100
Mutation probability	The initial probability is $P_1 = 0.3$, self-adaptive adjustment
Insertion probability	0.4
Inversion probability	0.4
One-point recombination probability	0.4
Two-point recombination probability	0.4
Genetic recombination probability	0.4
Fitness evaluation factor δ	10000
Maximum evolution algebra	1000
Number of genes	the number of logistics network layers is reduced by 1, i.e. $K - 1$

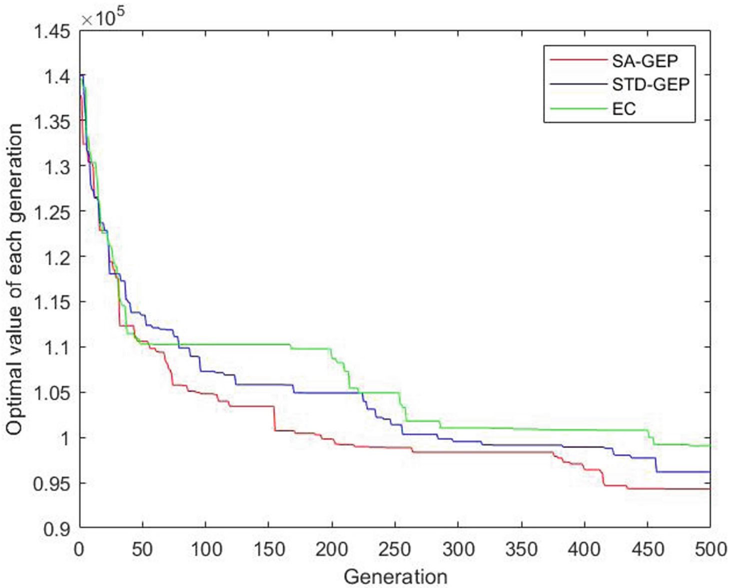

Fig. 2. Comparison of population evolution processes of SA-GEP, STD-GEP and EC under the same evolutionary algebra

Table 9. Comparison of performance indicators of SA-GEP algorithm, standard GEP algorithm and EC algorithm

Algorithm	Optimal cost	Worst cost	Average cost	Standard deviation	Average evolutionary algebra
SA-GEP	92898	108576	99966.01	2869.54	494.97
STD-GEP	97919	113759	104826.63	3582.15	455.70
EC	99819	115246	107659.62	3274.70	305.10

5 Conclusion

Logistics network optimization is the process of optimizing network nodes and all logistics paths in the supply chain. In this paper, a hybrid integer programming model with minimum total cost is constructed for the cost optimization problem of multi-layer logistics network. According to the characteristics of the model, the gene expression programming with the characteristics of multi-gene structure is adopted, and the self-adaptive evolution mechanism is introduced to dynamically adjust the genetic operator. A self-adaptive gene expression programming algorithm based on Prüfer coding is proposed to solve the model. Through experimental comparison and analysis, the optimization effect of SA-GEP algorithm is more significant than the other two algorithms, which verifies the feasibility of the model and the effectiveness of the algorithm.

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