

MASTERING EFFICIENCY: OPTIMIZING LOGISTICS DISTRIBUTION CENTER LOCATIONS WITH PARTICLE SWARM OPTIMIZATION

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Abstract:

In an era marked by the relentless advancement of the transportation industry, logistics distribution centers have evolved into pivotal hubs for the turnover, sorting, storage, warehousing, and distribution processing of commodities. These centers represent integral components of the entire logistics chain, linking directly with terminal sales customers. They span procurement, warehousing, transportation, and information services, collectively forming a cohesive business model designed to meet the precise logistics experience expectations of customers. Moreover, they serve as the linchpins that overcome temporal and spatial constraints inherent in the intricate flow of goods. The strategic positioning of logistics distribution centers assumes paramount significance in determining the profitability of logistics companies. A miscalculation in this regard can unleash a series of detrimental repercussions, consuming substantial human and material resources during subsequent logistics activities. Consequently, the meticulous selection of logistics center locations forms the crux of decision-making processes for logistics distribution centers. In light of the imperative task of determining the optimal location for logistics distribution centers, this paper introduces a novel approach. Specifically, we propose a logistics distribution center planning method designed around the utilization of the particle swarm optimization algorithm. This innovative approach aims to enhance both the efficiency and accuracy of identifying the optimal location for distribution centers. By harnessing the computational prowess of this algorithm, we endeavor to propel the logistics industry into an era of enhanced precision, cost-effectiveness, and customer satisfaction.

Keywords: Logistics Distribution Centers, Location Planning, Particle Swarm Optimization, Logistics Efficiency, Strategic Decision-Making

1. Introduction

With the continuous development of the transportation industry, the logistics distribution center has gradually become the base for commodity turnover, sorting, storage, warehousing and distribution processing, including the entire logistics chain in contact with terminal sales customers, including procurement, warehousing, transportation and information as an integrated business model to ensure that the goods distribution can achieve the logistics experience services required by customers, and overcome the time and space barriers in the process of goods circulation [1]. The location of logistics distribution center is the most important strategic condition to determine whether the logistics company can make profits. The negative impact caused by improper location will consume a lot of manpower and material resources in the later logistics activities. Therefore, in the decision-making process of logistics distribution centers, a systematic and comprehensive analysis of the location of logistics centers is the core part of determining the future development of logistics companies [2]. Therefore, based on the analysis of the logistics distribution center location planning problem, this paper proposes a logistics distribution center planning method design based on particle swarm optimization algorithm to improve the efficiency and accuracy of finding the best location for the distribution center location problem [3].

2. Particle swarm algorithm improvement

This paper draws on the idea of this improved algorithm and proposes a new particle swarm algorithm by analyzing the operation mechanism of the particle swarm algorithm^[4].

If the algorithm falls into a local optimum, changing the individual extremes P_{id} and the global extremes P_{gd} can change the direction of the particles, so that the particles may find new individual and global extremes^[5]. The learning factors $C1$ and $C2$ play an important role in the genetic individual optimization and global optimization, the larger the $C1$, the more influenced by the individual optimum and vice versa, and the larger the $C2$, the more influenced by the global optimum and vice versa.^[6] This paper designs an adaptive particle swarm algorithm that dynamically adjusts the learning factor, i.e., by adjusting the learning factor of the particles to accommodate the individual and global extremes with a certain probability of variation, in order to improve the ability of the PSO algorithm to jump out of the local optimal solution, and the specific optimization formula is shown below.

$$\alpha - i \\ C1' = \quad (1)$$

$$\frac{T}{\beta - i} \\ C2' = \quad (2)$$

Where $C1'$ and $C2'$ represent the adjusted learning factors, α and β represent the dynamic parameters, and T represents the mutation rate. If the algorithm falls into a local optimum, it is necessary to add a little perturbation to the operation mechanism of the particle swarm algorithm, i.e., to combine the distinguished person retention strategy of the genetic algorithm by first retaining a few best particles and letting them iterate, while mutating the other particles with a certain probability P_m .

Then the new position of the mutated particle is taken as the position of the next generation of that particle, and the mutated particle then enters other regions for searching, so the particle has the possibility to discover new individual extremes and global extremes. In this paper, we propose that when the algorithm falls into a local optimum, the mutation operation is performed with a certain probability for the extreme value, and the mutation timing is related to the evolutionary state of the particle population, gives the definition of the population fitness variance below.

Definition 1: Let the number of particles in the particle swarm be m , f_i is the fitness value of the z th particle, f_{avg} is the current average fitness value of all particles, and σ^2 is the population fitness variance of the particle swarm, then the fitness variance is calculated as shown below.

$$\frac{(f_i - f_{avg})^2}{m} \\ \sigma^2 = \sum \quad (3)$$

Where f is the calibration factor, the population fitness variance reflects the "convergence" of all particles. σ^2 The larger the value of, the more the swarm tends to the random search phase, and vice versa, the more the swarm tends to global convergence. It can be seen that if the value of σ^2 is small and the global optimum produced by the algorithm deviates from the theoretical optimum of the problem, then the algorithm falls into a local optimum. Therefore, when the algorithm falls into a local optimum, the position of the i th particle should be mutated with a certain probability, and the formula for calculating the mutation probability P_m is shown below.

$$\frac{2}{\gamma \sigma^2} \leq f(ab) \leq \mu \\ P_m = \quad (4) \\ 0, \text{others}$$

Where, γ is the convergence accuracy $f(ab)$ is the adaptation value of gb and μ is the theoretical optimal value. The improvement of the particle swarm algorithm can be completed by the above steps to improve the optimization finding accuracy and provide help for the subsequent method of selecting the location of logistics delivery center.

3. Mathematical model construction for logistics delivery center site selection

The location of the logistics delivery center proposed in this paper mainly involves the connection problem between the supply and demand points.

In order to minimize the sum of construction cost, operation cost and transportation cost of goods distribution, the objective function expression of the mathematical model of logistics distribution center site selection is shown below.

$$\min Q = \sum_{i=1}^n \sum_{j=1}^n h_{ij} a_{ij} c_{ij} + \sum_{j=1}^n \sum_{k=1}^n b_{jk} d_{jk} + (f_j + v_j + u_j) \sum_{j=1}^n h_j \quad (5)$$

Where the first term on the right side of the equal sign represents the cost of transportation from the upstream supply point to the distribution center, and the second term is the cost of transportation from the distribution center to the downstream demand point; the third term is the fixed construction cost and variable operation cost of the distribution center. In equation (5), i represents the upstream supply point serial number, j represents the serial number of the alternative distribution center; k represents the serial number of the downstream demand point, and a_{ij} represents the annual cargo transportation volume from the supply point to the distribution center. c_{ij} denotes the unit transportation cost from supply point to distribution center. b_{jk} denotes the annual cargo transportation volume from distribution center j to demand point k . d_{jk} denotes the unit transportation cost from distribution center j to demand point k . f_j denotes the fixed cost per unit transportation volume of distribution center, v_j denotes the variable cost per unit transportation volume of distribution center, u_j denotes the annual maximum arrival volume of distribution center, h_j denotes the two-dimensional variable whether the alternative distribution center J is selected or not, 0 means not selected, 1 means selected.

After constructing the mathematical model of logistics distribution center site selection, it needs to be constrained, specifically the upper limit of goods shipped from the upstream supply point needs to be constrained so that it cannot exceed the maximum supply capacity of the supply point, the specific constraint expression is shown below.

$$\sum_{j=1}^n h_j a_{ij} \leq S_i \quad (6)$$

Where S_i represents the annual supply of goods from the upstream supply point. In addition to this it is also necessary to constrain the demand at the downstream demand point, the specific constraint expression is shown below.

$$\sum_{j=1}^n h_j b_{jk} \leq D_k \quad (7)$$

Where, D_k represents the annual cargo demand at the downstream demand point. The location of the logistics delivery center can be achieved by constraining the objective function through the above steps. According to the above model, the improved particle swarm optimization algorithm is used to solve, and the optimal solution is the best location.

4. Testing and Analysis

In order to prove the effectiveness of the logistics distribution center location method based on particle swarm optimization proposed in this paper, experimental tests are carried out. In this experiment, the logistics distribution point location method based on genetic algorithm and the logistics center location method based on cuckoo algorithm are selected as the experimental control group to carry out comparative experiments.

Table 1: Load values and positions

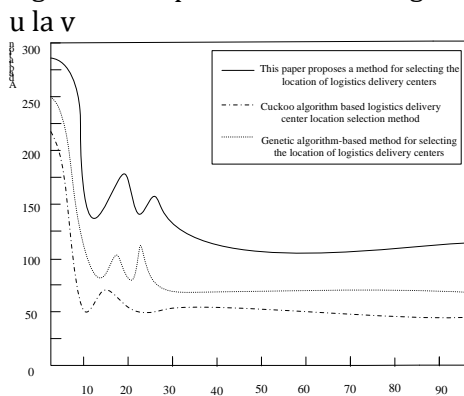
Load number	Load value	Coordinate value
1	42.3	(7.09,2.94)
2	25.6	(0.46,2.56)
3	58.4	(3.35,3.58)
4	41.3	(9.17,1.08)
5	39.8	(6.46,1.40)
6	50.4	(4.08,2.67)
7	37.8	(2.06,1.35)
8	40.5	(1.28,2.34)

The population size of the improved particle swarm algorithm is set to 150, the crossover probability is 0.7, the number of iterations is 100, the acceleration factor is 1.49, and the inertia weight is set to a random value between [0, 0.5]. Before running the logistics delivery center siting algorithm, the latitude and longitude of geographic information are first converted according to Gaussian projection to obtain the right angle coordinates of each load point, and the load point locations and specific load values are shown in Table 1.

The siting method proposed in this paper and two conventional siting methods are used for siting logistics delivery centers to compare the change in the value of the fitness function of the algorithm.

4.1 Analysis of test results

The evaluation index chosen in this paper is the algorithm's optimization-seeking ability, and the specific measure is the fitness value of the algorithm under different iterations, the higher the fitness value, the stronger the algorithm's optimization-seeking ability, and the specific experimental results are shown in Figure 1.



Number of iterations

Figure 1: Comparison of algorithm convergence

According to the above experimental results, it can be seen that the values of the fitness functions of the algorithms differ for different algorithms in siting logistics delivery centers with different numbers of iterations. The numerical comparison clearly shows that the two conventional logistics delivery center siting algorithms have significantly lower fitness function values, and the fitness function values are below 100 after the algorithms are stabilized. The proposed particle swarm algorithm-based logistics delivery center siting method has a significantly higher fitness function value of nearly 150 after the number of iterations stabilizes, which shows that the logistics delivery center siting algorithm constructed by this paper has higher convergence characteristics and its performance is better than the two conventional algorithms.

5. Conclusion

This study proposes a design of logistics distribution center location method based on particle swarm optimization. This method optimizes the algorithm, effectively avoids the possibility of falling into local optimization when solving,

and improving the convergence accuracy of the algorithm. The experimental results show that the improved particle swarm algorithm proposed in this paper has better results compared with other methods when used to solve the logistics distribution center location optimization problem, and the algorithm can quickly and accurately find the best logistics distribution center for the demand point.

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