Research on Multi-objective Optimization Algorithm and Path Planning in Logistics Engineering

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Abstract. This paper explores the potential and limitations of multi-objective optimization algorithm in solving complex logistics path planning problems, and provides scientific and efficient decision support for logistics enterprises. Firstly, this paper introduces the multi-objective of logistics distribution path planning, including minimizing transportation cost, minimizing transportation time and optimizing resource utilization, and establishes the corresponding mathematical model. Then, how to apply NSGA-II algorithm to solve the problem of logistics distribution path planning is expounded in detail, including the specific steps and core ideas of the algorithm. Through the case study of S logistics company, the application effect of multi-objective optimization algorithm in actual logistics distribution path planning is demonstrated. The results show that the optimized scheme has significantly improved in transportation cost, transportation time and vehicle load utilization rate, which verifies the effectiveness and feasibility of the algorithm. This study not only provides a new solution for logistics distribution path planning, but also provides theoretical basis and practical guidance for improving the overall performance of logistics system.

Keywords: Multi-objective optimization, path planning, logistics engineering, NSGA-II.

1. Introduction

Under the background of global economic integration and the vigorous development of e-commerce, the efficiency and effectiveness of logistics industry, as a bridge connecting production and consumption, are directly related to the competitiveness of enterprises and the satisfaction of consumers. With the increasing diversification of market demand and the increasing demand of consumers for delivery speed, how to effectively reduce logistics costs and shorten delivery time while ensuring service quality has become a key issue in the field of logistics engineering.

Traditional logistics path planning often focuses on the optimization of a single goal, such as the pursuit of the lowest transportation cost or the fastest response time, but in the real world, logistics distribution system is a complex multi-dimensional decision-making problem, involving cost, time, customer satisfaction, environmental protection and other conflicting goals [1-2]. Therefore, exploring and applying multi-objective optimization algorithm to realize the comprehensive optimization of logistics path planning has become an important way to improve the overall performance of logistics system.

This study focuses on multi-objective optimization algorithm and path planning in logistics engineering, aiming at revealing the potential and limitations of multi-objective optimization algorithm in solving complex logistics path planning problems through theoretical analysis and empirical research, and providing scientific and efficient decision support for logistics enterprises.

2. Application of multi-objective optimization algorithm in logistics distribution path planning

2.1. Modeling of logistics distribution path planning

Logistics distribution path planning is one of the core issues in logistics engineering, and its goal is to optimize transportation costs, transportation time and resource utilization by reasonably arranging vehicle routes under the premise of meeting customer needs [3-4]. Consider a logistics distribution system consisting of a distribution center, multiple customer points and multiple vehicles

[5]. The distribution center has a certain number of vehicles, and each vehicle has a fixed load capacity and running speed. Customers have their own demand for goods and time window requirements. The goal is to plan the driving route of each car, so as to meet the needs of all customers and realize the comprehensive optimization of transportation cost, transportation time and resource utilization [6-7].

In order to fully reflect the multi-objective of logistics distribution path planning, the following three objective functions are set:

(1) Minimization of transportation cost

Transportation costs mainly include vehicle running costs and fixed costs (such as vehicle depreciation, maintenance, etc.). Let the driving cost of vehicle k from point i to point j be c_{ij}^k, then the total transportation cost Z_1 can be expressed as:

$$Z_1 = \sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} c_{ij}^k \cdot x_{ij}^k \tag{1}$$

Where x_{ij}^k is a decision variable, indicating whether the vehicle k travels from point i to point j (1 means yes, 0 means no); K is the total number of vehicles; N is the total number of customer points (0 means distribution center).

(2) Minimization of transportation time

Transportation time is mainly composed of vehicle driving time and loading and unloading time. Let the driving time of vehicle k from point i to point j be t_{ij}^k, and the loading and unloading time at point j be s_j, then the total transportation time Z_2 can be expressed as:

$$Z_2 = \sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} \left(t_{ij}^k + s_j\right) \cdot x_{ij}^k \tag{2}$$

(3) Optimization of resource utilization

Resource utilization mainly refers to the load utilization rate and mileage utilization rate of vehicles. Let the load capacity of vehicle k be Q_k, and the cargo transportation volume from point i to point j be q_{ij}, then the vehicle load utilization rate Z_3 can be expressed as:

$$Z_3 = \frac{\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} q_{ij} \cdot x_{ij}^k}{\sum_{k=1}^{K} Q_k} \tag{3}$$

In order to ensure the feasibility and effectiveness of the solution, a series of constraints need to be set:

Each customer point can only be visited once by one car:

$$\sum_{k=1}^{K}\sum_{i=0}^{N} x_{ij}^k = 1, \forall j = 1,2,\cdots,N \tag{4}$$

Vehicle load limit:

$$\sum_{i=0}^{N}\sum_{j=0}^{N} q_{ij} \cdot x_{ij}^k \le Q_k, \forall k = 1,2,\cdots,K \tag{5}$$

In the distribution planning, it is necessary to ensure that vehicles comply with a series of constraints when serving customers, including the time window constraint, that is, vehicles must arrive within the time window specified by customers; The journey of each vehicle must start from the distribution center and return to the distribution center after completing the task; In addition, other limiting factors in actual operation need to be considered, such as the maximum driving speed and maximum driving distance of vehicles.

2.2. Multi-objective optimization algorithm solution

In the path planning of logistics distribution, it is necessary to consider many conflicting objectives such as transportation cost, transportation time and resource utilization at the same time, so it is suitable to use multi-objective optimization algorithm to solve it. As a classic and efficient multi-objective optimization algorithm, NSGA-II is widely used in such problems. This paper will introduce in detail how to apply NSGA-II algorithm to solve the problem of logistics distribution path planning, and give the specific solution steps.

NSGA-II algorithm is a multi-objective optimization method based on genetic algorithm, which searches for the optimal solution set of the problem by simulating natural selection and genetic mechanism [8-9]. The core ideas of the algorithm include: non-dominated sorting, congestion calculation and elite retention strategy. Non-dominated sorting is used to stratify individuals in the population according to their advantages and disadvantages; The calculation of crowding degree is used to maintain the diversity of population; The elite retention strategy ensures that outstanding individuals are not lost.

The specific application steps of NSGA-II algorithm in logistics distribution path planning are shown in Figure 1, and the contents are described as follows:

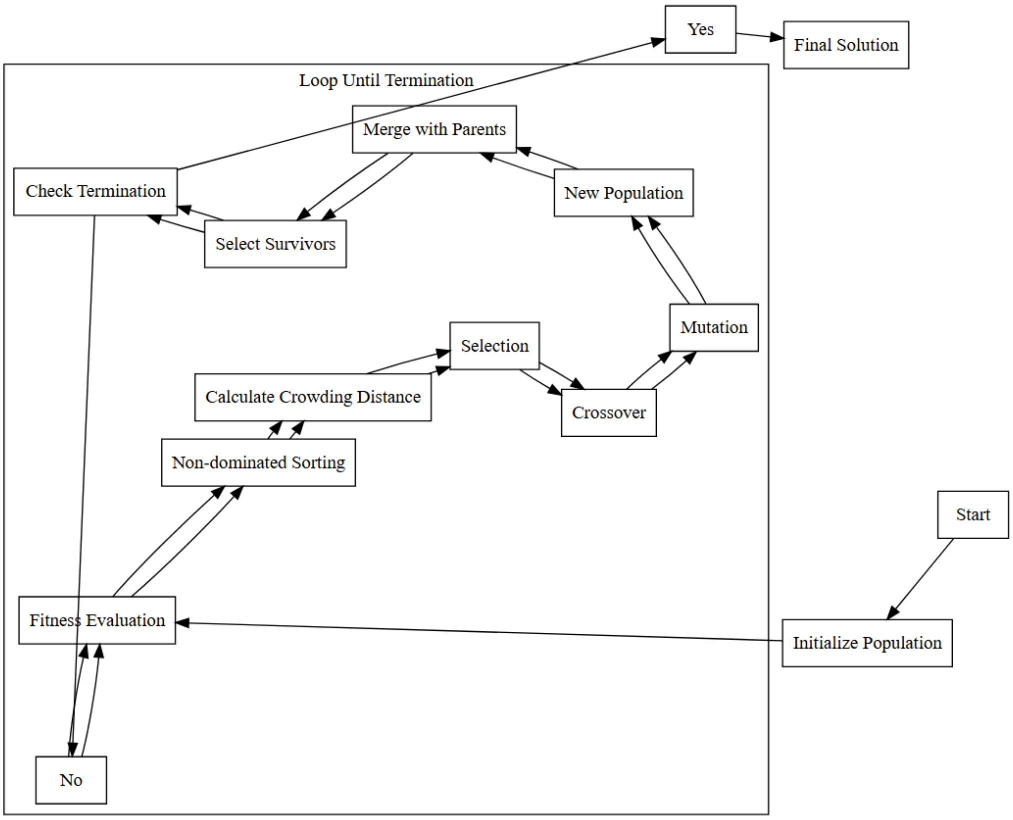

Figure 1. Application steps of NSGA-II algorithm

Step 1: Binary code is used to represent the solution of logistics distribution path planning problem, and an initial population is randomly generated, and each individual represents a possible vehicle routing scheme.

Step 2: For each individual, calculate its corresponding objective function value (Z1, Z2, Z3). These values will be used as the fitness of the individual.

Step 3: According to the fitness value of individuals, the whole population is sorted in a non-dominated way. The population is divided into multiple levels, and each level contains a group of non-dominant individuals (that is, no better individuals can be found in the current level).

Step 4: In each level, calculate the crowding degree of individuals. Crowding reflects the density of other individuals around an individual and is used to maintain the diversity of the population.

Step 5: According to the non-dominant ranking and congestion information, select outstanding individuals to enter the next generation. Perform crossover operation on the selected individuals, and the crossover operation adopts single-point crossover to generate new solutions. The crossover individuals are mutated to increase the diversity of the population. The mutation operation adopts random mutation.

Step 6: Combine the outstanding individuals in the parent with the offspring to form a new population. If the new population size exceeds the preset value, it will be cut according to the non-dominant sorting and congestion information.

Step 7: Set a maximum number of iterations as the termination condition. When the termination condition is reached, the algorithm stops running and outputs the final solution set.

Step 8: Decode the final solution set to obtain the specific vehicle driving route scheme. Analyze the performance indexes of the solution set, such as transportation cost, transportation time, resource utilization rate, etc., and choose the best scheme to implement.

3. Case study

3.1. Case background and algorithm application

S Logistics Company is an enterprise focusing on logistics distribution in the city, with multiple distribution centers and a large number of customer points. With the continuous expansion of business, the company is facing increasingly complex logistics distribution path planning problems. In order to reduce the cost, improve the distribution efficiency and meet the time requirements of customers, the company decided to use multi-objective optimization algorithm to plan the logistics distribution path.

The order details within one month are extracted from the order management system, including location, order quantity and delivery time, and the average driving time of each road section is determined by GPS and historical records. Statistics of transportation costs including fixed and variable costs. Clean to remove abnormal records, convert addresses to latitude and longitude for easy calculation, and aggregate orders by time and region to improve efficiency. Furthermore, in the analysis stage, the time and space distribution of orders are evaluated, traffic peaks and hot spots are identified, and the traffic conditions and transportation costs of road sections are analyzed in order to identify congestion and control costs.

The logistics distribution path planning problem is modeled as a multi-objective optimization problem, and the objective functions include minimizing transportation cost, minimizing transportation time and maximizing vehicle load utilization. Specifically, the transportation cost is quantified by calculating the total distance of each distribution route multiplied by the cost per unit distance; The transportation time is estimated based on the estimated driving speed and traffic conditions of each section; The vehicle load utilization ratio refers to the ratio of the actual load weight to the maximum carrying capacity of the vehicle.

The parameter setting is based on data analysis and practical experience. The population size is set at 100 to ensure the diversity of solution space, the number of iterations is 500 to promote the convergence of the algorithm to a better solution, the crossover probability is 0.8 to promote gene exchange, and the mutation probability is 0.1 to maintain population stability and introduce new mutation. The selection mechanism adopts roulette to select the next generation of individuals, and the elite retention strategy is implemented to ensure that the optimal solution is passed on to the next generation.

3.2. Result analysis

Observing the change of objective function value in the iterative process of the algorithm, it is found that the transportation cost and transportation time gradually decrease with the iteration. It can be seen from Figure 2 that with the increase of iteration times, the transportation cost shows an obvious downward trend. This shows that the algorithm effectively reduces the total distance of distribution routes or chooses a path with lower cost in the optimization process. The transportation time also decreases with the increase of iterations, which shows that the algorithm considers the driving speed and traffic conditions when optimizing the route, which makes the delivery time shorter. It shows that the algorithm effectively optimizes the distribution route, reduces the cost and time, and improves the efficiency of vehicle use.

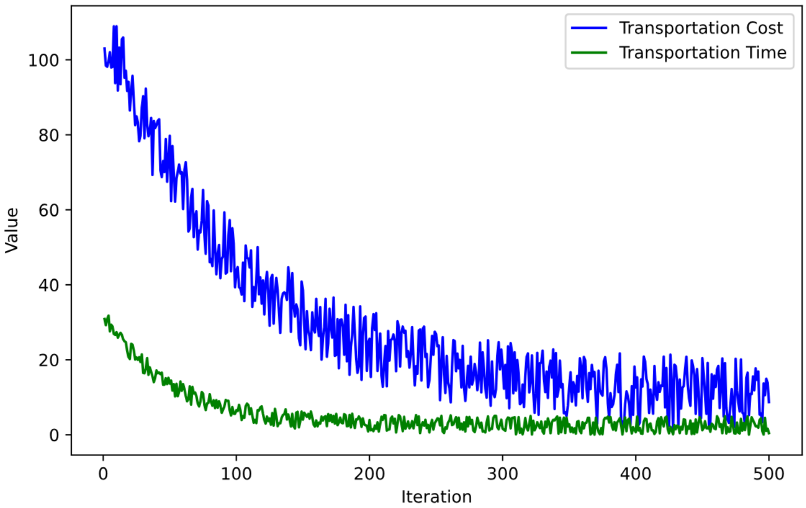

Figure 2. The change of objective function value in the iterative process of the algorithm

The Pareto optimal solution set is shown in Figure 3. The wide distribution of points in the solution set indicates that there are many solutions, and there are different trade-offs among transportation cost, time and vehicle load utilization rate, and the cost is positively correlated with time, while the change of load utilization rate reflects the influence of order quantity and vehicle capacity. Because there is no obvious single optimal solution, the actual logistics decision-making needs to choose the most suitable scheme according to the specific needs, while Pareto optimal solution set shows the balance between multiple objectives and helps to find a comprehensive optimization solution.

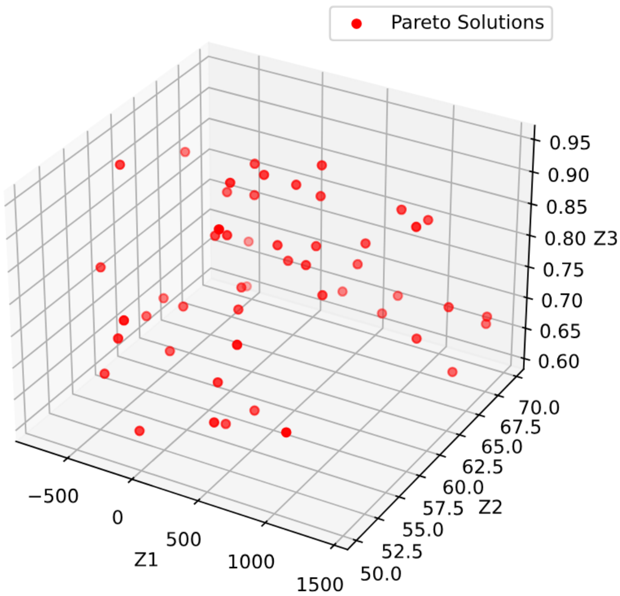

Figure 3. Pareto optimal solution set

As can be seen from Table 1, the optimization measures have achieved remarkable results in reducing transportation costs and transportation time. Specifically, the transportation cost is reduced from 120.50 before optimization to 108.30 after optimization, which is about 10.2% lower. The transportation time is also reduced from 65.20 minutes before optimization to 58.40 minutes, a decrease of about 10.5%. In addition, the vehicle load utilization rate increased from 0.75 before optimization to 0.85 after optimization, an increase of about 13.3%. This shows that the optimization scheme not only improves the distribution efficiency and reduces the cost, but also improves the use efficiency of vehicles. Generally speaking, optimization measures have a positive impact on improving the overall performance of logistics distribution.

Table 1. Comparison of indexes before and after optimization

index	Before optimization	After the optimization
Transportation cost (Z1)	120.50	108.30
Transport time (Z2)	65.20	58.40
Vehicle load utilization ratio (Z3)	0.75	0.85

Through this case study, the multi-objective optimization algorithm is successfully applied to the logistics distribution path planning of S Logistics Company. Through data analysis and algorithm optimization, a set of Pareto optimal solutions is obtained, and the optimal scheme is selected for implementation. The actual test results show that the optimized scheme has significantly improved in transportation cost, transportation time and vehicle load utilization rate, which verifies the effectiveness and feasibility of the algorithm. In the future, we will continue to explore more advanced algorithms and technologies to further improve the efficiency and benefit of logistics distribution.

4. Conclusion

Through in-depth discussion on the application of multi-objective optimization algorithm in logistics engineering path planning, this study reveals its great potential and limitations in solving complex logistics distribution problems. The research shows that the use of efficient multi-objective optimization algorithms such as NSGA-II can significantly improve the overall performance of the logistics system, and achieve the balance of minimizing transportation costs, minimizing transportation time and optimizing resource utilization. Case analysis shows that the application of this algorithm can effectively reduce the transportation cost and time, improve the vehicle utilization rate, and then enhance the market competitiveness and customer satisfaction of enterprises. In addition, Pareto optimal solution set provides a variety of trade-off schemes for decision makers, which is helpful to choose the most suitable distribution strategy according to specific needs. Although positive results have been achieved, more advanced algorithms and technologies need to be explored in future research to further optimize the efficiency and benefit of logistics distribution.

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