Research on Logistics Distribution Route Optimization Based on Hyper-Heuristic Algorithm

Zongwei Li[a,1], Jianing Chen[a,2*], Kai Qiao[a,3], Yanhui Zhang[b,4]

[a]School of Economics and Management, Shanghai Institute of Technology,Shanghai, China
[b]School of business, East China University of Science and Technology,Shanghai, China
E-mail:lzw0118@163.com[1]
chappyjn@163.com[2*]
216121141@mail.sit.edu.cn[3]
yanhui415@163.com[4]

Abstract. In the rapid development of the Internet economy, the ability to get close to the end customer, share distribution costs equally, and shorten delivery times are becoming increasingly important. This paper proposes a practical, efficient, stable, and innovative approach for optimizing distribution routes. To develop a better delivery scheme, the hyper-heuristic algorithm was applied to establish a mathematical model that incorporated the objectives of lowest cost, maximum load rate, and maximum delivery order, while considering the constraints of load capacity and the number of customers served.

Keywords: Logistics distribution; Route planning; Hyper-heuristic algorithm

1 INTRODUCTION

In recent years, urban roads have become more complex, which poses a great challenge to logistics service providers. Efficient logistics route planning has become an important way for merchants to maintain customers [1]. Distribution route planning is the core part of logistics distribution [2]. It is true that many enterprises pay close attention to the planning of distribution routes, but the actual result is not ideal, primarily as a result of four factors. (1) It cannot be delivered in time [3]; (2) High empty load rate [4]; (3) The optimization effect of the algorithm is poor [5]; (4) The single objective distribution model is difficult to meet the actual demand [6]. In order to resolve the above issues, this study first identifies the pain points and difficulties experienced by logistics service providers in providing logistics services. This is done through online surveys and offline visits. The model construction and algorithm selection process are then improved and innovated by analyzing and comparing the relevant route optimization algorithms.

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2 Model

In this paper, the mathematical model with the shortest path, maximum load factor and maximum delivery order as the optimization objectives is established as follows: (Due to space constraints, the constraints of the model are not presented in this paper)

$$\min \sum_{k=1}^{K} \sum_{i=0}^{I} \sum_{\substack{j=0 \\ j \neq i}}^{I} d_{ij} x_{ij}^{k} \tag{1}$$

$$\max \sum_{k=1}^{K} \sum_{i=0}^{I} \sum_{\substack{j=0 \\ j \neq i}}^{I} \frac{q_j x_{ij}^{k}}{L_k} \tag{2}$$

$$\max \sum_{k=1}^{K} \sum_{i=0}^{I} \sum_{\substack{j=0 \\ j \neq i}}^{I} q_j x_{ij}^{k} \tag{3}$$

Equation (1) represents the objective function of calculating the drivable shortest path. Equation (2) represents the objective function of maximizing the load factor. Equation (3) represents the objective function of maximizing delivery orders.

I: The total number of customer demand points, where the customer distribution point is represented by i (or j), i,j = 0,1,2,... ,I(where 0 indicates the distribution center);

k: indicates the vehicle k, k = 1,2,... K, where K represents the total number of vehicles in the distribution center;

d_{ij}: the distance between customer i and j;

q_i: the demand of customer i;

L_k: Weight of the vehicle k

3 Algorithms

3.1 Single objective hyper-heuristic algorithm based on genetic algorithm

Six low-level heuristic operators of four types were designed for the purpose of optimizing single objective problems, namely cross operation, mutation operation, ant colony operation, and hill climbing operation. Fig 1 shows the flow chart.

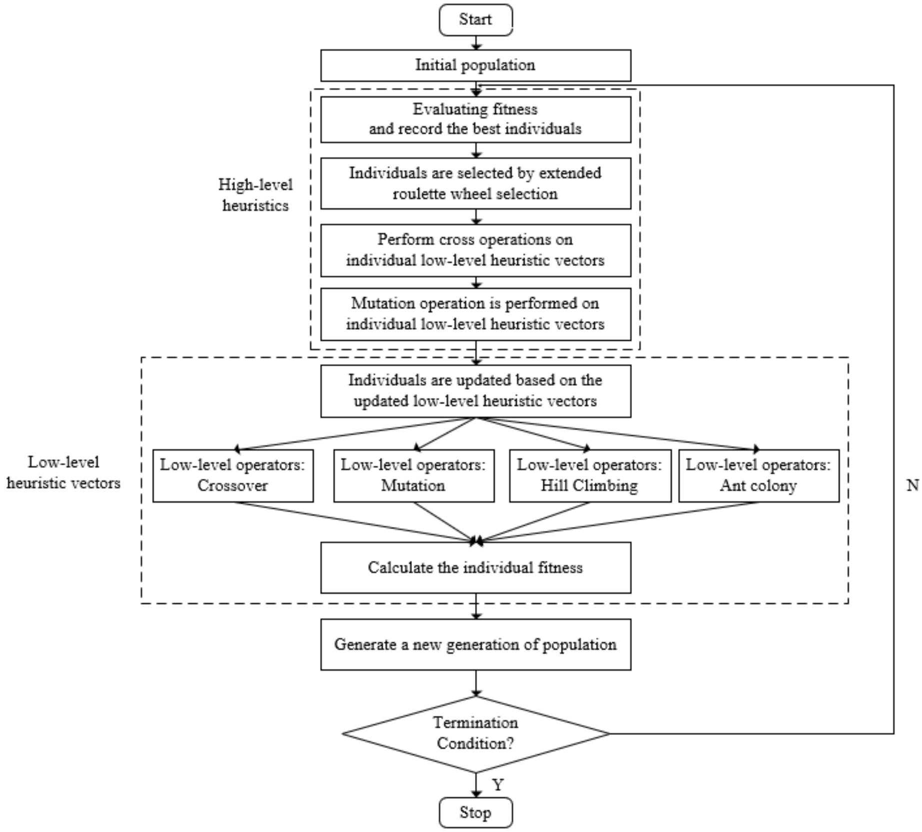

Fig. 1. Single objective hyper-heuristic algorithm based on genetic algorithm

3.2 Multi-objective hyper-heuristic algorithm based on NSGA-II

In the hyper-heuristic algorithm, the low-level heuristic algorithm acts as a bridge between the high-level heuristic algorithm and the solution domain. Aiming at the logistics distribution optimization problem, this paper designs six simple and efficient low-level heuristic operators of four types: cross operation, mutation operation, fusion operation, and local search. As shown in Fig 2, the flow chart illustrates the process.

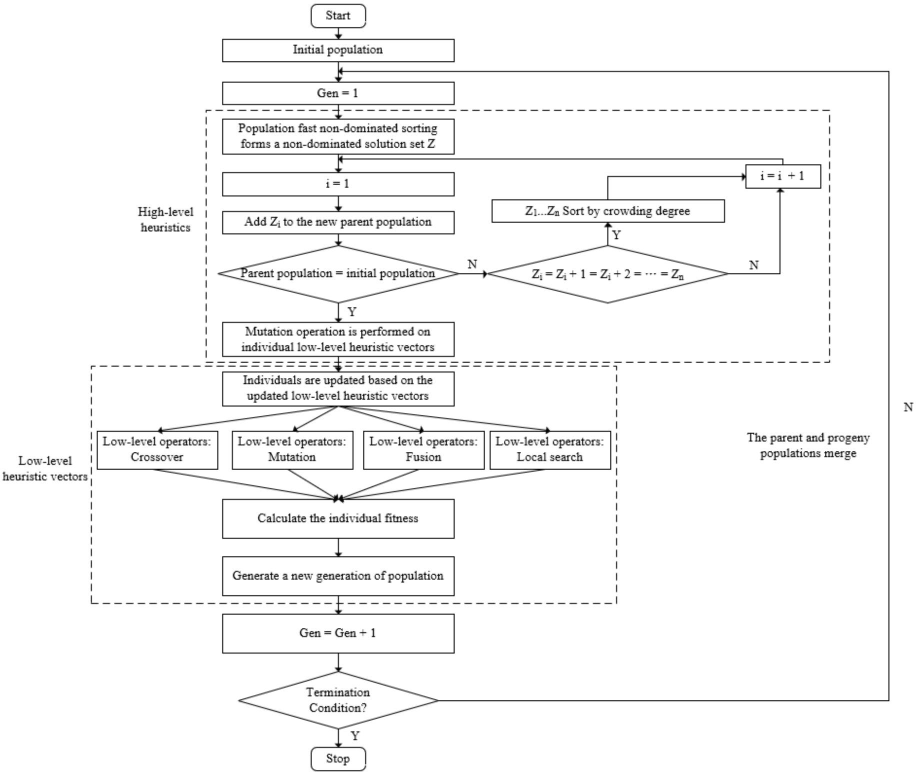

Fig. 2. Multi-objective hyper-heuristic algorithm based on NSGA-II

4 results

This paper randomly generates two sets of small-scale data, including ten customer points, one vehicle type, and two delivery vehicles, to evaluate the algorithm's performance comprehensively. Large-scale data includes fifty customer points, five vehicle types, and ten delivery vehicles. This paper sets the population size of each algorithm at 60, and the number of iterations at 100. Each data and algorithm are run 50 times on the same server to obtain the most accurate fitness value for each generation. As shown in Fig 3 and Fig 4, the hyper-heuristic algorithm based on the genetic algorithm has significant advantages over the other three algorithms, regardless of whether the data is small or large, and whether the optimal fitness value for each generation is high.

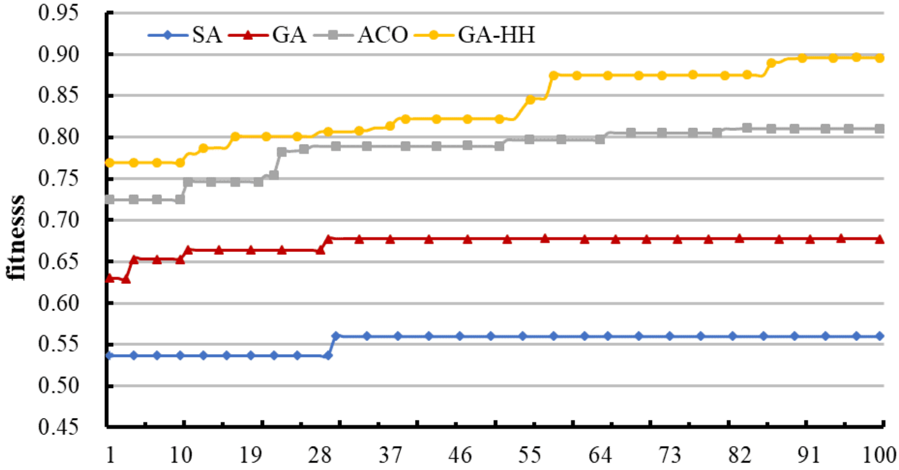

Fig. 3. Results of small-scale data operations

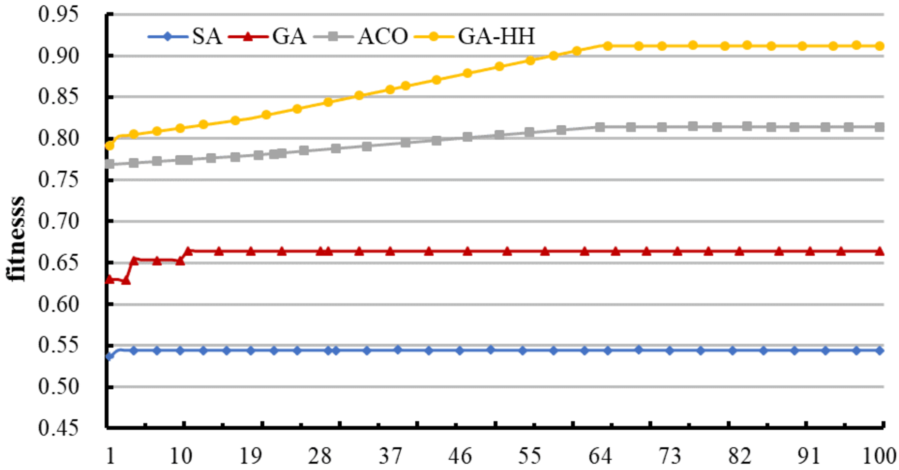

Fig. 4. Results of large-scale data operations

Several evaluation indexes of multi-objective evolutionary algorithms have been mentioned in papers related to multi-objective evolutionary algorithms [7-11], which can be categorized into three main categories: the indexes that evaluate the degree of convergence between the solved set and the real Pareto frontier; An index to evaluate the distribution of the solution set on the whole Pareto frontier, that is, the diversity index; The index that comprehensively considers the convergence and diversity of the solution set is the comprehensive index. To compare the pros and cons of each algorithm, this project uses Set Coverage (SC), Spacing-Metric (S-Metric), and Hyper-volume (HV). The SC index is a convergence index, which evaluates the convergence of different Pareto solutions. The greater the value of C(A,B), the better the convergence of the solution set of A. Otherwise, it shows that the convergence of solution B is better. S-Metric is a diversity metric used to evaluate Pareto solution set distribution uniformity. The smaller the S-Metric value, the better the uniformity and convergence of the solution set. HV is a comprehensive index. Calculating the total volume of different Pareto solution sets allows us to compare the comprehensive performance of different algorithms. The higher the HV value, the more similar the solution set is to the entire Pareto frontier.

To calculate the average value of the three evaluation indicators, each data set and algorithm was run 50 times on the server. Table 1 shows that the NSGA-II-based hyper-heuristic algorithm completely dominates both the NSGA-II algorithm and the MOEA/D algorithm in terms of the SC index.

Table 1. C-Metric results

	SC			
	C(NSGA-II-HH, NSGA-II)	C(NSGA-II, NSGA-II-HH)	C(NSGA-II-HH, MOEA/D)	C(MOEA/D, NSGA-II-HH)
small-scale data	1.000000	0.000000	1.000000	0.000000
Large-scale data	1.000000	0.000000	1.000000	0.000000

As a result of the calculation results of S-Metric and HV indicators, it can be concluded that the NSGA-II-based hyper-heuristic algorithm has a superior performance both in terms of uniformity and comprehensiveness as compared to NSGA-II and MOEA/D algorithms. The results are shown in Tables 2 and 3.

The above indicators indicate that the hyper-heuristic algorithm combined with a high-level heuristic strategy and a low-level heuristic operator performs more efficiently in solving path optimization problems.

Table 2. S-Metric results

	NSGA-II-HH	NSGA-II	MOEA/D
	S-Metric	S-Metric	S-Metric
small-scale data	0.498132337	0.623794615	0.749441635
Large-scale data	0.519843544	0.895184687	0.345891487

Table 3. HV results

	NSGA-II-HH	NSGA-II	MOEA/D
	HV	HV	HV
small-scale data	0.221190	0.138930	0.056250
Large-scale data	0.281970	0.049520	0.141800

5 conclusions

As the economy has developed and science and technology have advanced, modern logistics has evolved from traditional transport services to integrated logistics systems based on technology. Distribution and logistics organizations should arrange driving routes reasonably, increase the load factor, and reduce distribution costs. To optimize the distribution route, this paper proposes a multi-objective hyper-heuristic optimization algorithm combined with a single-objective hyper-heuristic optimization algorithm.

The project was developed using a variety of algorithms to optimize the path. The algorithms included multi-objective optimization algorithms such as NSGA-II-based hyper-heuristic algorithms, MOEA/D algorithms, NSGA-II algorithms, and single-objective optimization algorithms. This project utilizes NSGA-II-based multi-objective hyper-heuristic optimization algorithm along with genetic algorithm-derived single-objective hyper-heuristic optimization algorithm as innovative algorithms. Various distribution and vehicle parameters can be customized according to the requirements of the user. The system will call the optimization model based on user-defined data. By using the multi-objective hyper-heuristic optimization algorithm, the most efficient path can be found with the minimum cost, maximum delivery order, and maximum load rate. Additionally, the objective function can be selected according to the preferences of the user. After a linear weighted summation of the objective function, it can plan the path with the most appropriate value using the hyper-heuristic optimization algorithm. As a result of the two optimal solutions, enterprise managers can make more informed decisions.

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