Economic Management & Global Business Studies
World Scientific Reports
2023, Volume1, Issue1, 2023, Type: Articles

Research article

Research on environmental location routing problem based on an improved NSGA-II algorithm

Sophia Martin[1*]

1.University of Mississippi, School of Applied Sciences, United States

In order to solve the location routing problem (LRP) by means of energy saving and environmental protection, we propose a LRP optimization model with bi-objectives of minimizing the carbon emissions and the distribution costs. To address the shortcomings of traditional heuristics in solving large-scale LRPs with poor generality and low efficiency, an improved fast non-dominated ranking genetic algorithm (NSGA-II) is proposed and applied to the LRP optimization. In order to improve the convergence and optimization ability of the algorithm, an improved method of adaptive crossover operator and adaptive population size adjustment is introduced on the basis of the original method. With the benchmark test example solved, the algorithm is able to design an accurate, efficient and intelligent scheduling scheme for solving the established LRP model. Compared with the traditional heuristic algorithm in terms of the overall quality of the solution and the convergence efficiency of a single solution, the feasibility and effectiveness of the proposed method are verified.

Keywords: Location routing problem; logistics; carbon emission; bi - objective optimization; Improved NSGA-II

Statement: The data in this study can be provided without reservation by the corresponding author, also, the authors have no potential conflicts of interest.

1 Introduction

With the rapid development of the social economy and the improvement of the living standard of the residents, the whole human race is increasingly concerned about a series of environmental problems such as air pollution [1], energy saving and emission reduction gradually become the theme of the development of all walks of life [2-3]. Therefore, the logistics industry, as a major emitter of greenhouse gases [4], should vigorously carry out energy conservation and emission reduction, and is committed to achieving green logistics. Optimizing logistics scheduling to reduce CO_2 emissions is not only an energy saving and emission reduction measure, but also a cost reduction for enterprises to enhance their competitiveness in their own industries.

The main function of logistics distribution center is to gather and handle goods. It can be regarded as an entity engaged in large-scale and multifunctional logistics activities in enterprises, which makes it must have warehousing, packaging, transportation, information transmission, circulation and processing functions. The location of logistics distribution center is related to the cost, efficiency and service level of logistics distribution. Many studies have shown that goods spend more in the process of distribution, and the location of logistics distribution center has a great role in saving distribution costs and improving distribution efficiency and service quality. In the past few years, most companies involved in the logistics industry have established distribution centers. Before the emergence of new distribution centers, the functions of distribution centers were similar to those of operational logistics nodes. With the continuous development of the industry, part of the distribution centers only assumed the function of transfer stations, i.e., mainly responsible for the distribution of different modes and scales of transportation, while another part enhanced the function of "delivery" and later developed in the direction of "distribution". From the perspective of international logistics development, the development of logistics distribution center is not only the objective requirement of logistics rationalization, but also the result of modern social productivity development. Therefore, the establishment of logistics distribution centers should be based not only on the development needs of the logistics market but also on the rationalization of logistics. In terms of enterprises, how to find the optimal site selection plan is the important research problem to improve their logistics system.

To my best knowledge, the purpose of logistics distribution center site selection can be divided into three categories. Specifically, 1) Provide quality logistics services: quality logistics service is essential in the fierce market competition. As a professional logistics service facility, the logistics distribution center needs to meet the requirements of customers for small quantities, multiple types, high frequency and short delivery periods, and also to complete the delivery tasks in terms of quality and quantity, so as to gain competitive advantages with quality logistics service. 2) Reduce logistics costs: as a hub facility, logistics distribution center connects the production sector and consumers, and works as an institution that creates space value and time value. By centralizing logistics nodes to establish large logistics distribution centers, we can realize centralized inventory, scale procurement and cost saving. Collaborative distribution can also achieve the purpose of reducing transportation costs, construction fees, labor costs, land purchase fees, etc., which is conducive to reducing the total cost of logistics. 3) Focus on social benefits: logistics distribution center site selection should be from the perspective of the logistics system, so that it not only adapts to the regional logistics resources, regional distribution and demand distribution, but also to the local economic development requirements. At the same time, the site selection planning should also consider the environment and promote green logistics. In addition, it should also consider issues such as reducing unreasonable transportation such as over-distance transportation and convection transportation.

Logistics distribution center site selection has an important role in the overall logistics system. Whether it is the government planning the logistics system of the whole city, or the enterprise planning its own logistics operation network, it is inseparable from the scientific and reasonable analysis of logistics site selection. Since logistics distribution centers generally have a large scale of investment in construction, take up a lot of land in the city and should not be changed once built, it will have a long-term impact on society and enterprises, so a detailed demonstration is needed before choosing a site for the logistics distribution center. If the site selection fails, it may not only lead to lower profits because the company cannot meet the requirements of the demand point, but also have an impact on the overall social production and efficiency of commodity exchange.

As one of the most effective means of logistics site selection, the optimization problem of logistics scheduling broadly includes distribution center selection problem, cargo distribution problem, vehicle path problem, etc. As the core function of the logistics system, distribution is directly related to the customer, and the quality of the completion of the distribution function directly affects the customer's satisfaction of the whole logistics service. As the core part of distribution, the optimization for vehicle distribution routes is crucial to the overall logistics transportation speed, cost and efficiency.

Therefore, this paper innovatively uses an improved NSGA-II algorithm to solve the environmental LRP model. The remainder of this paper is organized as follows: Section 2 introduces the work related to the location routing problem solved by optimization algorithm; In Section 3, we develop an environmental LWR mathematical model and design an improved NSGA-II algorithm.; Section 4 presents the numerical experiments and the comparison of the results; Finally, some import findings are concluded in Section 5.

2 Related work

Recently, distribution network is the basis of logistics distribution system operation, and reasonable distribution center location and vehicle route planning play an important role in the effective operation of distribution system. The Location-Routing Problem integrates both the addressing problem and the vehicle path optimization problem, and various LRP problems and their extensions have been studied by many researchers.

The Location Routing Problem model takes into account both location and route optimization. The multi-objective LRP model also takes into account factors such as location and distribution costs, distribution time, and carbon emissions. The multi-objective LRP model is more valuable in practical applications, and the scheduling solutions obtained by using this model are more competitive in all aspects. Therefore, the multi-objective LRP model has been extensively studied and analyzed by scholars. Vahdani et al. [5] studied the efficient distribution of relief supplies and materials in post-earthquake relief operations by proposing a multi-objective mixed mathematical model with total cost and travel time as objectives. The multi-objective problem with service time constraints was studied by Nedjati et al. [6] To solve the distribution center replenishment as well as the siting problem for customers moving within a predetermined walking distance , a new bi-objective integer linear programming model is proposed , which minimizes the total weighted waiting time and the total amount of losses as the objective . Bozorgi-Amiri et al. [7] propose a multi-objective dynamic stochastic programming model for humanitarian relief logistics problems. The model proposes three objectives: the maximum shortage for all periods in the affected area, the total travel time, and the sum of pre- and post-disaster costs. Asgari et al. [8] propose a multi-objective model for waste location and routing problems considering various types of waste and multiple treatment technologies. The model includes three objective functions that maximize the demand of treatment facilities, minimize the various costs associated with the problem, and ultimately reduce the risk of transporting untreated materials. Considering the location of distribution centers and vehicle routing in the available traffic network, Wang et al. [9] constructed a nonlinear LRP model that minimizes travel time, total cost, and maximizes delivery reliability. In the most recent studies of LRP problems, when considering low carbon problems, many studies have mostly added low carbon as one of the constraints or as a penalty factor [10] to the objective function of the system cost, and it is difficult to avoid having a preference for one objective or setting the importance of different objectives in the optimization process. In this paper, the carbon emission minimization is taken as the second objective function and the system cost together constitute a dual objective model for optimization. There is no preference information for the target value in the optimization process.

With the increasing awareness of environmental protection, people are also beginning to notice the environmental pollution caused by CO_2 emissions in the logistics and distribution process. Green logistics and distribution system design is of great significance for the development of sustainable logistics. Currently, there are fewer studies on the environmental LRP problem. Govindan et al. [11] study the perishable two-level LRP problem with time windows in the food supply chain while minimizing cost and environmental impact. Tricoire et al [12] studied the urban hub LRP problem while optimizing the cost and CO_2 emissions. Dukkanci et al. [13] study the green LRP problem by developing a single-objective optimization model that minimizes the operating cost and emission cost and considers the time window constraint. In the study of the Green Vehicle Routing Problem (GVRP), existing studies have typically used fuel consumption models or methods that calculate traffic emissions and energy consumption to characterize the environmental factors that should be considered in VRP modeling. Kara et al. [14] first extended the Capacitated Vehicle Routing Problem to study the CVRP model for energy minimization and described it as an integer linear programming problem, which was solved using CPLEX. Raeesi et al. [15] investigated a multi-objective Pollution-Routing Problem (PRP) with a time window, assuming that carbon emissions are time- and load-dependent, with the objective functions of minimizing vehicle rental costs, minimizing total fuel consumption, and minimizing path time. Ashtineh et al. [16] investigated the VRP with alternative fuels by developing a mixed integer programming model with distance, load, speed and transmission ratio as the main factors affecting vehicle emissions, and their study evaluated the economic and environmental performance of alternative fuels in the VRP. Macrina et al. [17] incorporated speed, acceleration, deceleration, load and other factors into a comprehensive energy consumption model, studied the green VRP model of a hybrid fleet consisting of an electric vehicle and a traditional diesel locomotive, and designed an embedded large domain search heuristic algorithm.

Location - Routing Problem is the integration of FLP (Facility location problem) and VRP (Vehicle Routing Problem). FLP and VRP have a mutual influence on each other, and the classical LRP research literature demonstrates that the integration and optimization of the two can reduce system costs and promote scientific decision-making. Koç et al. [18] studied LRP in urban logistics by considering fuel consumption and CO2 emissions in the system cost and proposed a new adaptive large neighborhood search heuristic. Toro et al. [19] propose a new model for calculating GHG emissions from vehicle routes, investigating capacity-constrained LRPs that take into account environmental impacts. Their study shows that using more vehicles leads to greater fuel economy and thus reduced emissions, and that activating more vehicles on short routes and prioritizing high-demand customers can also reduce emissions.

Therefore, this paper innovatively uses an improved NSGA-II algorithm to solve the green LRP model and proposes a new adaptive crossover operator with adaptive population size adjustment; on the basis of solving the traditional LRP, the effect of carbon emission is considered. The proposed algorithm optimizes the scheduling scheme and applies heuristic rules to select the optimal scheduling path, and finally obtains a scientific and reasonable scheduling scheme.

3 The proposed model

In this section, the terms and concepts related to multi-objective optimization problems are first introduced; then we describe the green LRP problem in detail and model its mathematics; finally, we introduce an improved NSGA-II algorithm.

3.1 Multi-objective optimization problem

Multi-objective optimization problems are also known as multi-criteria optimization problems. Without loss of generality, a multi-objective optimization problem with n decision variables and m objective variables can be formulated as follows:

$$\begin{array}{ll} \min \ y = & F(x) = (f_1(x), f_2(x), \cdots, f_m(x))^{\mathrm{T}} \\ \mathrm{s.t.} & g_i(x) \leqslant 0, i = 1,2,\cdots,q \\ & h_j(x) = 0, j = 1,2,\cdots,p \end{array} \tag{1}$$

Where $x = (x_1, \cdots, x_n) \in X \subset R^n$ denotes a n-dimensional decision variable, X represents the n-dimensional decision space; $y = (y_1^1, \cdots, y_1^n) \in Y \subset R^m$ denotes a m-dimensional objective vector, and Y represents the objective space. Since there are m objectives for the optimization problem, the objective function F(x) defines m mapping functions from the decision space to the objective space. $g_i(x) \leqslant 0 (i = 1,2,\cdots,q)$ denotes q inequality constraints, while $h_j(x) = 0 (j = 1,2,\cdots,p)$ represents p equality constraints. Based on this, several important definitions are given below.

Definition 1. For $x \in X$, if x satisfies all the constraints in **Equation (1)** (i.e., $g_i(x) \leqslant 0, i = 1,2,\cdots,q$ and $h_j(x) = 0, j = 1,2,\cdots,p$),then x is said to be a **feasible solution**.

Definition 2. Suppose x_A , $x_B \in X$ are two feasible solutions of the multi-objective optimization problem shown in **Equation (1)**, then x_A dominates x_B (denoted as $x_A \succ x_B$)if and only if the following conditions are satisfied:

$$\begin{gathered}\forall i = 1,2,\cdots,m, f_i(x_A)\leqslant f_i(x_B) \wedge \exists \\ j = 1,2,\cdots,m, f_j(x_A) < f_j(x_B),\end{gathered} \tag{2}$$

Definition 3. A feasible solution x^* is referred to as a Pareto optimal solution (or non-dominated solution) if and only if the following conditions are satisfied:

$$\nexists\, x \in \mathrm{X}: x \succ x^* \tag{3}$$

3.2 Environmental LRP problem description and modeling

In the study of logistics and operational issues , most of them have taken into account the environmental impact of transport and the impact of the industrial environment on the cost of transport activities.

(a) Problem description

In this paper, we propose a new mathematical model for LRP that considers fuel consumption minimization. minimization. The problem is stated as follows.

Given a set of distribution centers M and customers C, the objective is to find the best distribution center and its path to the customer point, and each distribution center has set open cost C_m . There is a transportation cost C_f for transportation between each two customer points (i.e., (i,j) $i,j \in C$). Each customer $i \in C$ has a demand d_i , which can be delivered by only one vehicle. In total, there are K vehicles of capacity Q_K available. There is a depreciation cost C_d for each vehicle transported between every two customer points (i,j) $i,j \in C$. In the traditional LRP model, only one objective function is considered, i.e., minimizing the total operating cost, which includes the open cost C_m of the facility, the depreciation cost C_d of the vehicle and the transportation cost C_f between two customer points. The model in this paper includes a second objective function in addition to the operating cost, which takes into account the carbon emissions due to the fuel consumption in transportation. Ultimately, the LRP is optimized as a bi-objective problem.

(b) Description of symbols and variables

In this section, the relevant variables of the bi-objective LWR model based on operating costs and carbon emissions are described in Table 1.

Table 1 Description of symbols and variables

Symbol	Description
$M\{m \mid m = 1, \cdots, M\}$	Set of distribution centers
$C\{i \mid i = 1, \cdots, I\}$	Set of customer coordinates
$V\{k \mid k = 1, \cdots, K\}$	Set of vehicles in distribution centers
K_m	Vehicles belonging to distribution center m
$S\{M \cup C\}$	Set of distribution centers and customer points
d_i	Demand of customer i
y^{ij}	The total amount of goods loaded by vehicles going to Customer point j after leaving customer point i
C_d	Depreciation cost per unit vehicle
C_f	Cost per unit of fuel
C_m	Costs of opening distribution centers
D_{ij}	Distance from customer i to customer j
Q_k	Capacity of the vehicle K
Q_m	Capacity of distribution centers M
X_{ijk}	A binary decision variable with a value of 1 indicates that vehicle k travels from the distribution center i to the customer j
Z_m	Binary decision variable, a value of 1 means the distribution center is open

(c) Calculation of carbon emissions

There are many factors that affect fuel consumption and CO_2 emissions, such as loading rate, driving distance, driving speed and terrain slope. It is not realistic to quantitatively analyze all these factors, and we must make appropriate assumptions and simplifications.

There are different methods to calculate CO_2 emissions, and according to Kirby et al. [20], CO_2 emissions are proportional to fuel consumption. In this paper, **Equation (4)** is used to calculate fuel consumption and CO2 emissions.

$$F = G \times D \times (a \times L + b) \quad (4)$$

Where F denotes the fuel consumption of the transportation process; G represents the terrain slope factor; D is the distance traveled by the vehicle; L indicates the weight of the load; a and b are the fuel consumption parameters. Given a fuel conversion factor η, the CO_2 emissions can be expressed as $E_{co_2} = F \times \eta$.

(d) Construction of mathematical models

$$\min\ C_m \sum_{m\in M} Z_m + C_d \sum_{i\in S} \sum_{j\in S} \sum_{k\in K_m} D_{ij} X_{ijk} + C_f G \sum_{i\in S} \sum_{j\in S} \sum_{k\in K_m} D_{ij} X_{ijk} [a_{yij} + b]; \quad (5)$$

$$\min\ \gamma G \sum_{i\in S} \sum_{j\in S} \sum_{k\in K_m} D_{ij} X_{ijk} [a_{yij} + b] \quad (6)$$

$$s.t.\quad \sum_{i\in S} \sum_{j\in S} \sum_{k\in K_m} X_{ijk} = 1, \forall i \in C \quad (7)$$

$$\sum_{j\in C} X_{mjk} = 1, \forall m \in M, \forall k \in K_m \quad (8)$$

$$\sum_{i\in C} X_{imk} = 1, \forall m \in M, \forall k \in K_m \quad (9)$$

$$\sum_{m\in M} \sum_{j\in C} X_{mjk} \leqslant 1, \forall k \in V \quad (10)$$

$$\sum_{m\in M} \sum_{j\in C} X_{mjk} + \sum_{n\in M} \sum_{j\in C} X_{jnk} \leqslant 1, \forall k \in V \quad (11)$$

$$\sum_{i\in S} X_{ihk} - \sum_{j\in S} X_{hjk} = 0, \forall h \in C, k \in K_m \quad (12)$$

$$\sum_{k\in K_m} \sum_{i\in C} d_i \sum_{j\in S} X_{ijk} \leqslant Q_m Z_m, \forall m \in M \quad (13)$$

$$\sum_{i\in C} d_i \sum_{j\in S} X_{ijk} \leqslant Q_k, \forall k \in K_m \quad (14)$$

$$\sum_{i\in C} y_{ij} - \sum_{y_{jm}} = d_j, \forall j \in C \quad (15)$$

$$y_{ij} - (Q_k - d_i) X_{ijk} \leqslant 0, \forall i, j \in S, k \in K_m \quad (16)$$

$$y_{ij} - X_{ijk} d_j \geqslant 0, \forall i, j \in S, k \in K_m \quad (17)$$

$$\sum_{i\in s} \sum_{j\in s} X_{ijk} \leqslant |S| - 1, \forall k \in K_m \quad (18)$$

$$X_{ijk} \in \{0,1\}, \forall i, j \in S, k \in K_m \quad (19)$$

$$Z_m \in \{0,1\}, \forall m \in M \quad (20)$$

Equation (5) and (6) are objective functions. The former is the opening cost of distribution center plus vehicle depreciation cost plus fuel cost, and the latter is carbon dioxide emissions. Due to the consideration of multiple real-world constraints, we introduce many constraints in the environmental LRP model, which are described below. Equation (7) guarantees that each client is visited once; Eq. (8) and Eq. (9) show that the vehicle departs from the distribution center and must return to the original distribution center; Eq. (10) ensures that each transport vehicle's path departs from at most one distribution center; To ensure that the vehicles from any two distribution centers will not be on the same path, we set the constraint (11); Eq. (12) ensures that service workers must leave after visiting customers, and Equation (13) is a constraint to ensure that the total customer demand per distribution center visit is less than the capacity of the distribution center; In addition to the relevant constraints imposed on distribution centers, we have also imposed the following constraints on the vehicles. Equation (14) ensures that the load of the vehicle is not allowed to exceeding its load capacity, and the load of each vehicle have to meet the amount of customer demand in Equation (15); Equation (16) and (17) ensure a numerical relationship between X_{ijk} and y_{ij}, i.e., y_{ij} is a positive number when X_{ijk} = 1, otherwise y_{ij} is 0; Equation (18) is the subloop elimination constraint; Finally, Equation (19) and (20) are simple constraints on the decision variables.

3.3 The improved NSGA-II algorithm

(a) The standard NSGA-II algorithm

As one of the most classical algorithms in the field of multi-objective optimization, NSGA-II (Non-dominated Sorting Genetic Algorithm-II) is a powerful multi-objective optimization algorithm based on genetic algorithm [21]. The core modules of NSGA-II algorithm are fast non-dominated ranking and crowding calculation. The former stratifies the population according to the strength and weakness of the individuals and distributes them into several different frontiers, while the latter describes the dispersion degree of the individuals in the population to ensure diversity. The formula for calculating the crowding distance is as follows:

$$C_i = \sum_{k=1}^{m} \frac{|f_k^{i+1} - f_k^{i-1}|}{f_k^{max} - f_k^{min}} \tag{21}$$

where f_k^{i+1} denotes the value of individual $i+1$ on the k-th objective function, f_k^{max} represents the maximum value of all individuals on the k-th objective function, and f_k^{min} denotes the minimum value of all individuals on the k-th objective function. Through the validation of numerous studies, the comparisons of crowding are necessary to maintain the diversity of populations. For individuals in the same frontier, we should prefer those with less crowding to ensure the diversity of individuals. In addition, the NSGA-II algorithm is the first multi-objective optimization algorithm that proposes an elite strategy. Specifically, the parent population P_t and the offspring population Q_t are combined into a new population of size $2N$, and the top N individuals are selected into the population P_{t+1} by performing fast non-dominated sort order and crowding calculation. It is worth noting that additional judgments will be made by the crowding distance if the participation of all individuals of an identical frontier would result in exceeding the population limit.

(b) Adaptive Crossover Operators

In order to improve the convergence of this algorithm as well as the merit-seeking ability, an improvement method of adaptive crossover operator is proposed on the basis of the original method. Binary crossover is employed in the standard NSGA-II algorithm. The crossover operator is very convenient to implement, but the move space is insufficient and the algorithm has a small search space, which is easy to fall into local optimal solutions. Due to the deficiency of binary crossover operator, a new crossover operator is introduced, that is, normal distribution crossover operator. The normal distribution crossover operator has a large search range to satisfy the need for powerful search capability in the early stage of the algorithm. Therefore, a large proportion of the early populations in the iteration of the algorithm will use the normal distribution crossover operator. When the algorithm is in the late iteration, the individuals in the population are close to the optimal solution, and there is no need for a large search range at this time. Therefore, a large proportion of the population should be replaced with binary crossover operators to accelerate the convergence. Based on this idea, this section introduces a factor that can adaptively adjust the crossover degree of the algorithm according to the iterations, which increases the crossover degree of individuals in the early stage and decreases it appropriately in the later stage, and the update formula of the adaptive crossover operator is as follows:

$$x_1 = \frac{g}{2G}(M + \alpha N) + \frac{G-g}{2G}(M + \mathrm{beta} \times N) \tag{22}$$

$$x_2 = \frac{g}{2G}(M - \alpha N) + \frac{G-g}{2G}(M - \mathrm{beta} \times N) \tag{23}$$

$$x_3 = \frac{g}{2G}(M + \alpha N) + \frac{G-g}{2G}(M - \mathrm{beta} \times N) \tag{24}$$

$$\alpha = \frac{1}{1-\mathrm{e}^{(G-g)}} \tag{25}$$

Suppose P_1 and P_2 are the selected parent individuals for crossover, then $M = P_1 + P_2$, $N = P_1 - P_2$ denotes the crossover operation. g denotes the current number of iterations and G represents the total number of iterations of the algorithm. $beta$ is a normally distributed random variable.

(c) Adaptive regulation of population size

In the early stage of the algorithm, when a larger population is used, it can improve the optimization search range of the algorithm. In the later stage, the individuals in the iteration have basically converged to the optimal value, and fast convergence is required. Therefore, it is no longer necessary to have a large-scale population, and the convergence of the algorithm can be accelerated by reducing the population size appropriately at this time. Based on the above analysis, a judgment condition needs to be adapted to determine what is pre-algorithm and what is post-algorithm. Each m iteration of the algorithm can produce m optimal values, and the linear fitting method is used to find the slope of these m points. When the absolute value of the slope is less than a certain value, it indicates that the optimization process has been gradually stable, and the optimal solution is basically obtained. At this time, large-scale population is no longer needed. The specific judgment condition are formulated as follows:

$$\left|\frac{\mathrm{d}(f(x))}{\mathrm{d}x}\right|_m \leqslant \varepsilon \tag{26}$$

where $\left|\frac{\mathrm{d}(f(x))}{\mathrm{d}x}\right|_m$ indicates the absolute value of the slope of the m points taken, and ε denotes the criterion for judging the pre-late stage of the algorithm. The procedure of the improved NSGA-II algorithm is as follows:

1) Randomly generate an initial population P_0 of $2N$ individuals;

2) Perform adaptive crossover and mutation operations to generate new populations Q_t of number N;

3) Merge populations P_t and Q_t to obtain R_t and performing a fast non-dominated sort on the merged populations;

4) Calculate the crowding distance and use the elite strategy to select N individuals as the new the parent population P_t;

5) Determine whether the current iteration number g is not less than the maximum iteration number G. If it is satisfied, the iteration of the algorithm is terminated;

6) After the current number of iterations g has reached m, the m optimal values of m generations are selected for each iteration, and the judgment of Equation (26) is performed. If it is true, return to step 2), otherwise proceed to the next step.

7) N populations are randomly generated, and the number of $2N$ population P_r is generated by merging with the parent population P_{t+1}.

8) Perform a fast non-dominated sorting, elite strategy on the population P_r to find the optimal of N individuals and return to step 2). In summary, the flow chart of the improved NSGA-II algorithm is shown in **Fig. 1**.

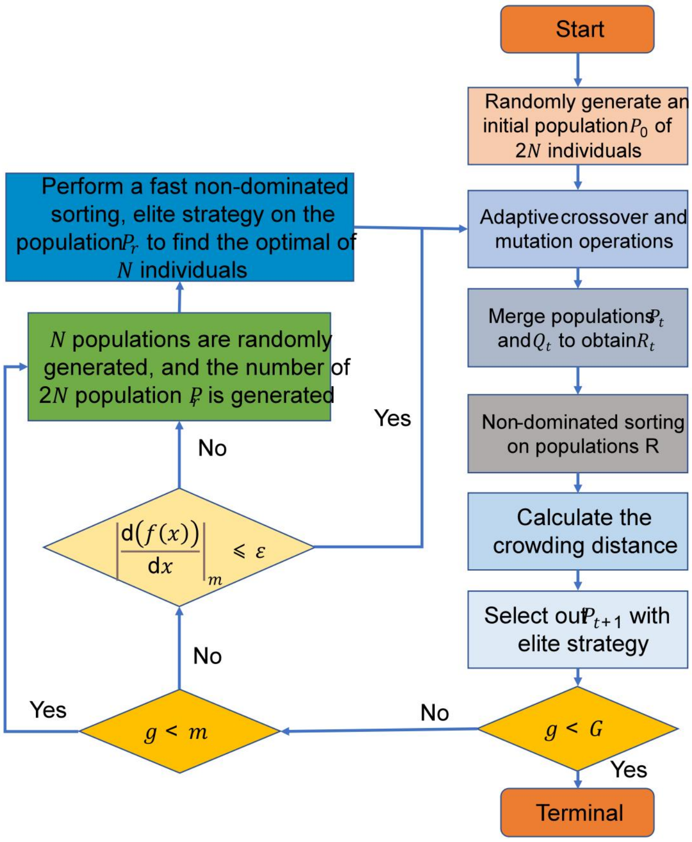


Fig.1. Algorithm flow chart of improved NSGA-II

4 Experiments and Analysis

4.1 Experimental environment and case study

In order to verify the feasibility and validity of the proposed model and algorithm, this paper takes the example of the Barreto benchmark test (refer to http://prodhonc.free.fr/Instances/instances_ us.html) as the object of calculation. In this paper Python 3.8 was used to program experiments on a computer with an Intel Core i5 processor, 4G RAM, and a 64-bit Windows operating system. In this section, the 'Christ100 × 10' test scenario of the Barreto benchmarking example (with 100 customer sites and 10 distribution centers) is selected for the experiments, and the results are presented in Table 2.

Table 2 Calculation results for the Christ100 × 10 example

Number of distribution centers	$f_1/\$$	f_2/kg	Distribution Center Costs/$	Transportation Costs/$	Fuel Costs/$
5	18367	7018.1	200	3309.8	14856.8
4	18403	6910.0	160	3390.9	14851.6
6	18693	6905.4	240	3534.5	14918.6
5	18837	6905.4	200	3544.5	15092.6
5	18907	6845.0	200	3634.3	14992.7
6	18987	6840.3	240	3655.0	15082.6
7	19023	6749.3	280	3612.8	15209.7

A detailed description of the Pareto frontier and the Pareto optimal solution for the Christ100 × 10 example is given in Table 2. As shown in **Fig. 2**, there are three types of solutions on the Pareto front for the Christ100× 10 test, that is, (1) the solution with the smallest objective function f_1 (total cost); (2) the solution with the smallest objective function f_2 (carbon emissions); and (3) the solution that is more compromising for the both objectives. Obviously, as the number of distribution centers increases, the cost of opening a distribution center also increases, and the corresponding total cost also increases. However, with the increase in the number of distribution centers, the carbon emissions will decrease accordingly. This is because the increase in the number of distribution centers will result in shorter distances for delivery vehicles, which will directly contribute to the reduction of carbon emissions. Ultimately, we offer 7 solutions with excellent performance. Depending on the degree of preference for total cost and carbon footprint, the appropriate solution can be selected.

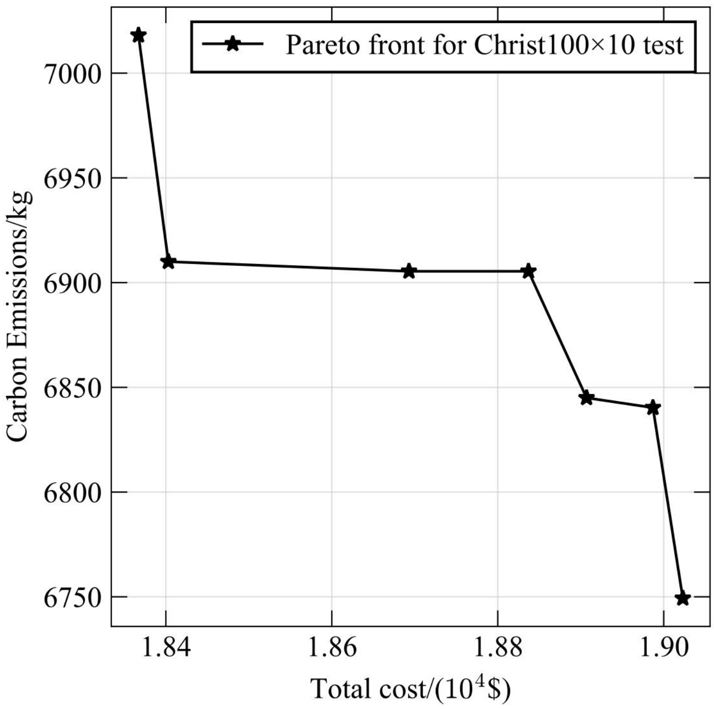


Fig.2. The pareto front for the Christ100 × 10 test

4.2 Comparison of Algorithms

In this section, NSGA-II, SPEA2 [22] and the improved NSGA-II algorithm of this paper are selected for comparison. Because NSGA-II and SPEA2 are two traditional heuristic algorithms with different frameworks, the operators cannot be unified. For the sake of fairness, we can only ensure that the population size, the number of iterations, and the cross-variance rate are consistent. The specific settings of the experimental parameters are shown in Table 3.

Table 3 Calculation results for the Christ100 × 10 example

Parameters	Setting values
Population size	100
Maximum of iterations	80
Crossover probability	0.88
Mutation probability	0.04

In this section, we choose the Christ100 × 10 test case, and use NSGA-II, SPEA2, and improved NSGA-II algorithms to solve the scheduling scheme, and compare the four scheduling schemes. As can be seen from **Fig. 3**, the Pareto fronts obtained using the improved NSGA-II algorithm completely dominate the Pareto fronts calculated by NSGA-II, SPEA2. This indicates that the scheduling solution obtained by the improved NSGA-II algorithm is less than the scheduling solution obtained by the other two algorithms in terms of both total cost and carbon emissions. This is because, traditional multi-objective algorithms use binary crossover operators, which are inefficient in solving large-scale LRP (complex NP-Hard problems). Through the comparison of the algorithms, it is demonstrated that the improved NSGA-II algorithm has significant advantages in solving large-scale LRP.

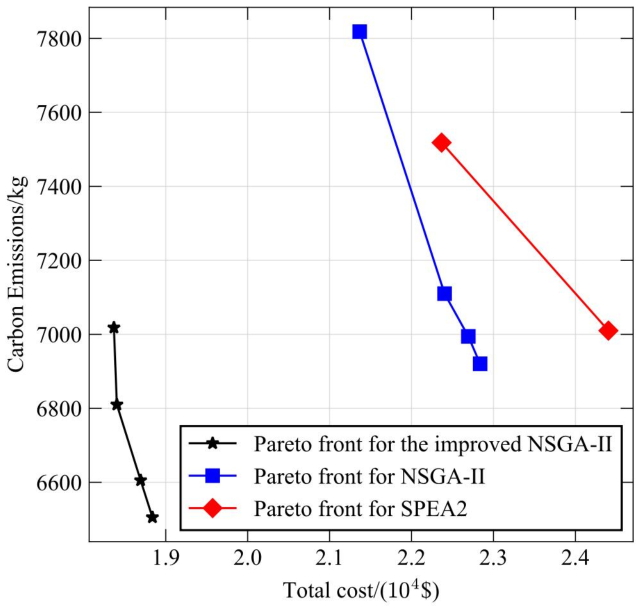
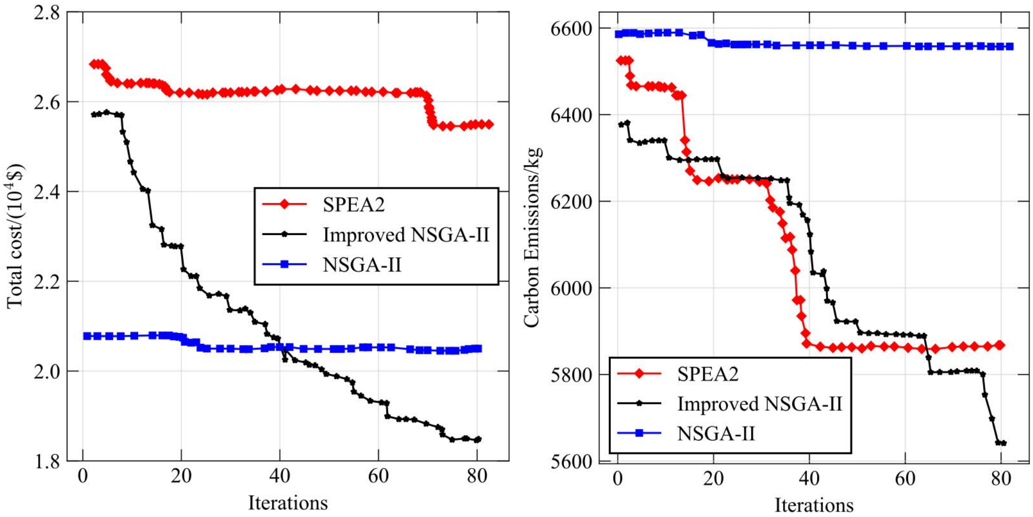


Fig.3. The pareto front for the Christ100 × 10 test

Then, we also compare and analyzes the convergence of single objective in the iterative process of dual objective optimization through the change of single objective value with the number of iterations. As shown in Fig. 4(a), the SPEA2 algorithm has the worst optimization effect and falls into partial convergence after about 30 iterations. In Fig. 4(b), we can also see similar results, i.e., the NSGA-II algorithm falls into a local optimum early in the iteration. In contrast, the improved NSGA-II algorithm in this paper has good optimization results in both iterations of the objective function, which proves that the algorithm has excellent search ability.



(a)

(b)

Fig.4. The pareto front for the Christ100 × 10 test

5 Conclusion

In this paper, we study the multi-objective optimization problem of environmental LRP by considering the objectives of distribution center opening, transportation, fuel cost and carbon emission, and establish a bi-objective model to minimize the total cost and carbon emission. Then, an improved NSGA-II optimization algorithm is proposed to optimize the distribution center location and logistics distribution scheduling scheme, and the optimal scheduling scheme is obtained. Then, we performed validation experiments using a test scenario named Christ100 × 10 in the Barreto benchmark instance. By comparing with NSGA-II and SPEA2 algorithms from Pareto front, total cost and carbon emission convergence, the optimization results and comparative analysis prove the effectiveness of the improved NSGA-II algorithm in this paper.

References

[1] Zhu J, Wong S L, Cakmak S. Nationally representative levels of selected volatile organic compounds in Canadian residential indoor air: population-based survey[J]. Environmental science & technology, 2013, 47(23): 13276-13283.

[2] Wang Q, Chen Y. Energy saving and emission reduction revolutionizing China's environmental protection[J]. Renewable and sustainable energy reviews, 2010, 14(1): 535-539.

[3] Wu H, Xue Y, Hao Y, et al. How does internet development affect energy-saving and emission reduction? Evidence from China[J]. Energy Economics, 2021, 103: 105577

[4] Dekker R, Bloemhof J, Mallidis I. Operations Research for green logistics–An overview of aspects, issues, contributions and challenges[J]. European journal of operational research, 2012, 219(3): 671-679.

[5] Vahdani B , Veysmoradi D , Noori F , et al. Two-stage multi-objective location-routing-inventory model for humanitarian logistics network design under uncertainty[J]. International Journal of Disaster Risk Reduction, 2017:S2212420917303059.

[6] Nedjati A , İzbirak, Gökhan, Arkat J . Bi-objective covering tour location routing problem with replenishment at intermediate depots: Formulation and Meta-heuristics[J]. Computers & Industrial Engineering, 2017, 110(aug.):191-206.

[7] Bozorgi-Amiri A , &, Khorsi M . a dynamic multi-objective location-routing model for relief logistic planning under uncertainty on demand, travel time, and cost parameters[J]. International Journal of Advanced Manufacturing Technology, 2016, 85(5-8):1633-1648.

[8] Asgari N , Rajabi M , Jamshidi M , et al. A memetic algorithm for a multi-objective obnoxious waste location-routing problem: a case study[J]. Annals of Operations Research, 2017, 250(2):1-30.

[9] Wang H , Du L , Ma S . Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake[J].

Transportation Research Part E: Logistics and Transportation Review, 2014.

[10] Xu M , Yu G , Zhou X , et al. Low-carbon vehicle scheduling problem and algorithm with minimum-comprehensive-cost[J]. Computer Integrated Manufacturing Systems, 2015, 21(7):1906-1914.

[11] Govindan K , Jafarian A , Khodaverdi R , et al. Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food[J]. International Journal of Production Economics, 2014, 152:9-28.

[12] Tricoire F , Parragh S N . Investing in logistics facilities today to reduce routing emissions tomorrow[J]. Transportation Research Part B Methodological, 2017, 103(sep.):56-67.

[13] Dukkanci O , Kara B Y , Bektas T . The green location-routing problem[J]. Computers & Operations Research, 2019, 105(MAY):187-202.

[14] İmdat Kara, Kara B Y , Yetis M K . Energy Minimizing Vehicle Routing Problem[C]// International Conference on Combinatorial Optimization & Applications. Springer, Berlin, Heidelberg, 2007.

[15] Raeesi R , Zografos K G . The multi-objective Steiner pollution-routing problem on congested urban road networks[J]. Transportation Research Part B: Methodological, 2019, 122:457-485.

[16] Ashtineh H , Pishvaee M S . Alternative Fuel Vehicle-Routing Problem: A life cycle analysis of transportation fuels[J]. Journal of Cleaner Production, 2019, 219(MAY 10):166-182.

[17] Gm A , Gl B , Fg A , et al. An energy-efficient green-vehicle routing problem with mixed vehicle fleet, partial battery recharging and time windows[J]. European Journal of Operational Research, 2019, 276(3):971-982.

[18] Bektas, Tolga, Jabali, et al. The impact of depot location, fleet composition and routing on emissions in city logistics[J]. Transportation research, Part B. Methodological, 2016, 84B(Feb.):81-102.

[19] Toro E M , Franco J F , Echeverri M G , et al. A Multi-Objective Model for the Green Capacitated Location-Routing Problem Considering

Environmental Impact[J]. Computers & Industrial Engineering, 2017:S0360835217302176.

[20] Lai M , Cao E . An improved differential evolution algorithm for vehicle routing problem with simultaneous pickups and deliveries and time windows[J]. Engineering Applications of Artificial Intelligence, 2010, 23(2):188-195.

[21] Deb K , Agrawal S , Pratap A , et al. A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II[C]// International Conference on Parallel Problem Solving from Nature. Springer, 2000.

[22] Zitzler E , Laumanns M , Thiele L . SPEA2: Improving the strength pareto evolutionary algorithm[J]. Technical Report Gloriastrasse, 2001.