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Research on the Optimization of Low-carbon Vehicle Routing with Time Window Based on Improved Genetic Algorithm

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Abstract: Under the background of green and low-carbon economy, the carbon emission factor is introduced into the distribution of cold chain logistics, and it is converted into the corresponding cost. A mathematical model of vehicle routing with the minimum comprehensive cost including vehicle fixed cost, transportation cost, refrigeration cost, penalty cost and carbon emission cost as the objective function is established. According to the characteristics of the model, an improved genetic algorithm is designed to solve the model. In the design of the algorithm, the evolutionary cycle is introduced, so that the hybrid operator of insert mutation and cycle crossover is carried out on the population in the evolutionary cycle to improve the diversity of the population and the local search ability. Matlab code is used to solve the established model, and the influence of carbon emission cost on the total cost is analyzed. It is concluded that if the government departments can give appropriate distribution compensation to enterprises, not only the total distribution cost of enterprises, but also the carbon emission can be reduced, and the win-win situation of economy and environment can be realized. Finally, the performance analysis of the algorithm shows that the algorithm designed is effective and feasible in this paper.

1. Introduction

Vehicle Routing Problem with Time Window (VRPTW) was first put forward by Savelsbergh in Literature [1]. Based on the vehicle routing problem (VRP), the requirement of time window for customers to receive distribution service is added, which is closer to life than VRP. According to the statistics of the International Energy Agency, 24.34% of carbon dioxide produced by burning fossil fuels in the world comes from transportation activities, while 74.4% of carbon dioxide produced by transportation activities comes from road transportation. Therefore, it is of great significance to study the vehicle routing problem to reduce carbon dioxide emissions and realize the sustainable development of green logistics and economy.

Vehicle routing problem is regarded as a NP hard problem, and many scholars have designed different algorithms to solve various types of vehicle routing problems. Kuo [2] considered fuel consumption and carbon emissions, and set up a vehicle routing model without time window with minimizing fuel consumption as the objective function, and designed simulated annealing algorithm to solve the established model. Xu et al. [3] combined genetic algorithm with particle swarm optimization to design a hybrid algorithm for solving vehicle routing problem with time window. Experiments show that the hybrid algorithm can improve the computational efficiency and avoid premature convergence and local minima. Nalepa et al. [4] proved the effectiveness and convergence of the proposed adaptive memory algorithm through experiments on the benchmark sets of famous Solomon, Gehring and Homberger. He et al. [5] designed the quantum ant colony algorithm, which combines quantum computing with ant colony algorithm, to solve the vehicle routing problem with time window. The simulation results show that this algorithm has good performance in solving VRPTW problem. Bachunlin et al. [6] established an optimization model of cold chain logistics joint distribution route considering time window, carbon emission cost and cargo loss cost, and designed an improved genetic algorithm to solve it. Tang et al. [7] designed an improved ant colony system algorithm to solve the established VRP problem considering carbon emission. The algorithm introduces chaotic disturbance mechanism when updating the ant pheromone on the path, and optimizes the heuristic factor, state transition probability, pheromone update and other links, thus improving the search efficiency of the optimal path. Zhu et al. [8] modeled the time-dependent green vehicle routing problem, designed a calculation method of vehicle travel time based on road segment division strategy, and proposed an improved ant colony algorithm to solve the established model. Ge et al. [9] studied the carbon emission vehicle routing problem with time window assignment, and designed a hybrid genetic-tabu search algorithm to solve the studied problem. Chen et al. [10] incorporated the spatio-temporal dynamics of vehicle speed into the research of vehicle routing problem considering carbon emissions, and designed a solution algorithm framework that first constructed the initial solution with the improved saving method, and then improved it with the variable neighborhood search algorithm.

To sum up, it can be seen that there are few cases of incorporating carbon emission costs into the cost function in the research of logistics distribution with time windows, and most of studies are focused on general logistics with less attention paid to the research of cold chain logistics. Therefore, combining with the low-carbon economy actively developing in current China, from the perspective of energy conservation and carbon emission reduction, this paper introduces carbon emission factors into the cold chain logistics distribution process, converts them into corresponding economic benefits, establishes an optimization model of cold chain logistics distribution routing with the lowest comprehensive cost, designs an improved genetic algorithm to solve the model, and gives a green cold chain logistics distribution vehicle routing planning scheme.

2. Model Construction

2.1. Problem Description

The vehicle routing problem refers to a distribution network composed of a distribution center and several customers in this paper. The location coordinates, the demand for goods, the expected time window and the acceptance time window of each customer point are all known. Several distribution vehicles start from the distribution center and serve the customers under the condition of meeting the vehicle load limit, so as to find the distribution routing with the lowest total distribution cost including vehicle fixed cost, transportation cost, refrigeration cost, penalty cost and carbon emission cost.

2.2. Description of Symbols and Parameters

The symbols and parameters involved in this paper are described as follows:

K : Number of vehicles owned by the distribution center; n : Number of customers ; C_1 : Fixed use cost of refrigerated trucks; C_2: Transportation cost per unit distance of refrigerated trucks; C_3: Refrigeration cost per unit time during transportation; $C_3^{'}$: Refrigeration cost per unit time during unloading; t_{ijk}: The driving time of the vehicle k from customer i to customer j; w_j: The unloading time when the vehicle k provides services to the customer j; $[ET_i, LT_i]$: The time window that the customer i expect to be served; t_{ik}: The time when the vehicle k arrives at the j-th customer; β_1: The waiting cost per unit time for the vehicle to arrive at the customer point in advance; β_2: Penalty cost per unit time for vehicles arriving late at the customer point; q_i: The demand of the i-th customer; Q:The maximum load capacity of the vehicle; S: The set of distribution customers of a vehicle; $|S|$: The number of vertices contained in the set S; Q_{ij}: The load capacity of the vehicle from the customer i to the customer j; ρ_0: Fuel consumption per unit distance when the load of the vehicle is 0; ρ^* : Fuel consumption when the vehicle's load capacity is the maximum Q; e_0: Coefficient value of carbon dioxide emissions; ω: The amount of carbon dioxide produced by a vehicle with a unit weight when driving a unit distance; d_{ij}: The distance from the customer i to the customer j; C_5: Environmental cost per unit of carbon dioxide emissions consumed (Yuan/kg).

Y_k: 0,1 variable. The value is 1 when the vehicle k is used, otherwise it is 0; X_{ijk}: 0,1 variable. The value is 1 when the vehicle k directly travels from the customer i to the customer j, otherwise it is 0; y_{jk} : 0,1 variable. The value is 1 when the vehicle k provides services to the customer j, otherwise it is 0.

2.3. Model Building

Under the background of low carbon, the mathematical model of cold chain logistics vehicle routing problem with the minimum total cost of distribution is described as follows:

Objective function:

$$\min Z = C_1\sum_{k=1}^{K}Y_k + C_2\sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{j=0}^{n}d_{ij}x_{ijk} + (C_3\sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{j=0}^{n}x_{ijk}t_{ijk} + C_3^{'}\sum_{k=1}^{K}\sum_{j=0}^{n}y_{jk}w_j) + \sum_{k=1}^{K}\sum_{i=0}^{n}\beta_1 \max\{ET_i - t_{ik}, 0\}$$
$$+\sum_{k=1}^{K}\sum_{i=0}^{n}\beta_2 \max\{t_{ik} - LT_i, 0\} + C_5\sum_{k=1}^{K}\sum_{i,j=0}^{n}x_{ijk}d_{ij}[e_0(\rho_0 + \frac{\rho^* \text{-} \rho_0}{Q}Q_{ij}) + \omega Q_{ij}] \quad (1)$$

Constraints:

$$\sum_{i=0}^{n} q_i y_{jk} \le Q \quad \forall k \quad (2)$$

$$\sum_{k=1}^{K} y_{ik} = 1 \quad \forall i \quad (3)$$

$$\sum_{i=0}^{n} x_{ijk} = y_{jk} \quad \forall j,k \quad (4)$$

$$\sum_{j=0}^{n} x_{ijk} = y_{ik} \quad \forall ,i \quad (5)$$

$$\sum_{i \in S} \sum_{j \in S} x_{ijk} \le |S| - 1 \quad k \in K \tag{6}$$

$$t_{jk} = t_{ik} + t_{ijk} \tag{7}$$

Among it: the cost in formula (1) is the fixed cost, transportation cost, refrigeration cost, penalty cost of being early, penalty cost of being late and carbon emission cost of the vehicle in turn; formula (2) is the constraint of the vehicle's carrying capacity; formula (3) ensures that each customer is only served by one car; formula (4) and formula (5) limit that only one car can provide services for any customer; formula (6) eliminates the sub-cycle; formula (7) indicates that the continuity of service between two customer nodes is maintained.

3. Improved Genetic Algorithm Design

The concept of Genetic Algorithms (GA) was first put forward by Holland in 1975. The basic principle of this algorithm is to imitate the evolutionary mechanism of "natural selection and survival of the fittest" in the biological world, encode the parameters of the problem into chromosomes, and exchange the information of chromosomes in the population by iterative operations such as selection, crossover and mutation, and finally generate chromosomes that meet the optimization goal, that is, the approximate optimal solution of the problem [11]. In this paper, based on the basic genetic algorithm, the coding mode, crossover operator and mutation operator are reset, and the established model is solved to improve the diversity of population acquisition, avoid falling into local convergence and improve the performance of the solution. The specific settings are as follows:

3.1. Coding Mode Setting

In view of the uncertainty of the number of assigned vehicles, the number of customers served by each vehicle and the order in which customers, natural number coding is adopted in the paper. The distribution center is coded as 0. For example, after decoding, a chromosome with a code of 0-1-8-4-0-3-2-6-0-7-5-9-0 means that the distribution center needs to dispatch three refrigerated trucks to deliver to nine customers, and the three distribution routes are 0-1-8-4-0, 0-3-2-6-0 and 0-7-5-9-0, respectively.

3.2. Setting of Crossover Operator

Crossover is the process of exchanging some structures of two parent individuals in some way to form two offspring chromosomes. In this paper, two-point crossover and cycle crossover are used to cross-recombine the newly generated population. The specific operation is as follows:

(1) Cycle crossover: Firstly, a cycle will be found according to the corresponding gene position of the parent chromosome. Secondly, the circulating gene is replicated to the offspring. Thirdly, the remaining genes are identified for the offspring, and the remaining genes outsides the parent chromosome cycle are used to fill with the original offspring. Finally, forming new descendants. For example: Firstly, parent chromosome 1: 2 7 5 6 4 8 9 1 3, parent chromosome 2: 4 3 6 8 9 7 1 2 5, find cycle 1: 2 4 9 1 2, cycle 2:4 2 1 9 4. Secondly, offspring chromosome 1: 2 * * * 4 * 9 1 *, offspring chromosome 2: 4 * * * 9 * 1 2 *. Thirdly, parent 1 remaining chromosome: * 3 6 8 * 7 * * 5, parent 2 remaining chromosome: * 7 5 6 * 8 * * 3. Finally, new offspring chromosome 1: 2 3 6 8 4 7 9 1 5; new offspring chromosome 2: 4 7 5 6 9 8 1 2 3.

(2) Two-point crossover: first, two chromosomes in the coding string are randomly selected as parents. Secondly, two random natural numbers r1 and r2 are generated. Finally, the gene fragments between the two parents chromosomes r1 to r2 are exchanged to obtain two offspring chromosomes, and the two obtained chromosomes are revised so that there is no conflict.

3.3. Setting of Mutation Operator

In this paper, a hybrid mutation operator is designed, which combines the reverse mutation operator, the insertion mutation operator and the exchange mutation operator to improve the diversity of population and avoid local convergence in the algorithm.

(1) Reverse mutation operator: Randomly select two reverse point positions in the coding string, and then insert substrings in these two reverse point positions into the original positions in reverse order. For example, if two reversal points are selected from 1 4 3 5| 7 6 2 9| 8 as the fourth and eighth positions, it will become 1 4 3 9| 2 6 7 5| 8 after reversal.

(2) Insert mutation operator: Randomly select two position points and insert the number of the first position point of the code string into the front of the second position in the code string. For example, if the first position point selected is the second position point, and the second posit- ion point is the sixth position point in 1 4 |3 5 7 6| 2 9 8, 1 3 5 7 4 6 2 9 8 will be obtained after insert mutation.

(3) Exchange mutation operator: Two points are randomly selected in the code string, and their positions are exchanged. For example, if the selected position points in 1 4 3| 9 2 6 7| 5 8 are the 3rd and 7th positions, 1 4 7| 9 2 6 3| 5 8 will obtain after exchange mutation.

3.4. Algorithm Solving Steps

To improve the local search performance of the algorithm and the diversity of the population, the catastrophic cycle is introduced in the algorithm design, and the population is greatly mutated. In each catastrophic cycle, the population is subjected to the mixed operation of insertion mutation and cyclic crossover. The specific steps are as follows:

Step 1: Initialize relevant parameters, code chromosomes according to the coding mode set in this paper, generate an initial population $p(0)$, and let gen = 1;

Step 2: Introduce a random number R. If $R<0.5$, perform exchange mutation on the chromos- ome, otherwise, perform reverse mutation on the chromosome;

Step 3: Carry out two-point crossover on the chromosomes to judge whether the catastrophic cycle is met. If it is met, perform insertion mutation and cyclic crossover on the chromosomes, and then decode the chromosomes, otherwise, directly decode the chromosomes, so that the route can be re-planned under the condition of meeting time window and load constraint. At the same time, calculate the individual fitness value and other constraint conditions;

Step 4: Calculate the total objective function value and the fitness value of individuals, and select better individuals from $p\ (gen)$ to form the next generation population $p\ (gen+1)$ according to roulette;

Step 5: If the termination condition is met, stop and output the optimal solution, otherwise, let $gen = gen+1$, and turn to step 2.

4. Experimental Setup and Result Analysis

4.1. Experimental Data and Parameter Setting

In this paper, the data in Literature [12] are adopted and adjusted appropriately according to the needs, in which the coordinates of the distribution center are X=35 *km*, Y=35 *km*, and the service time window is 5:00-17:30. The coordinates, time window, demand and service time of customers are shown in Table 1. It is assumed that the customer completes the distribution task by the 7t refrigerated truck of the same type, with conditions: its driving speed is 50 *km/h*, C_1 is 150 *yuan*, C_2 is 3 *yuan /km*, C_3 is 14 *yuan/h*, C_3' is 20 *yuan/h*, β_1 is 70 *yuan/h*, β_2 is 70 *yuan/h*, C_5 is 0.5 *yuan/kg.*CO_2, ρ^* is 0.337 *L/km*, ω is 0.0066/ *kg.km*, ρ_0 is 0.166*L/km*, and e_0 is 2.630 *kg/liter*.

Table 1: Demand of information of customers

NO	X coordinate /km	Ycoordinate /km	Specified time window	Acceptable time window	Demand (t/day)	Service time /min
1	29	21	7:00-9:00	5:30-11:00	1.5	20
2	35	53	7:30-9:30	7:00-11:30	0.5	10
3	15	25	6:00-8:00	5:30-10:30	1.5	20
4	15	50	6:30-9:00	6:00-11:00	1.5	20
5	55	40	7:00-9:00	6:30-10:00	2	25
6	45	40	7:00-9:00	6:30-10:20	2	25
7	50	20	7:20-9:00	7:00-11:30	1.8	22
8	60	27	7:30-9:00	7:00-12:00	1	15
9	40	10	7:00-9:30	6:40-11:30	1	15
10	50	5	7:00-9:40	6:30-11:40	1	15
11	40	45	8:30-10:30	8:00-12:30	1	15
12	55	60	8:30-10:00	7:00-12:00	0.5	10
13	40	65	7:30-9:30	7:00-12:30	0.5	10
14	60	50	7:30-9:30	7:00-12:00	1.5	20
15	65	40	7:50-9:30	7:20-11:30	2	25
16	50	30	7:20-9:40	6:40-11:30	1.5	20
17	55	10	7:00-8:40	6:40-11:30	1.5	20
18	25	50	7:50-9:50	7:00-12:00	0.5	10
19	25	60	6:30-8:30	6:00-11:30	2.5	30
20	15	20	7:50-9:50	7:00-12:00	1	15

4.2. Model Calculation Results and Analysis

According to the specific requirements of cold chain distribution, *Matlab*2017 is used to program the designed algorithm and realize the algorithm solving model. It is assumed that the population number N=100, the maximum iteration number *Maxgen* =500, the catastrophe cycle is 5, the crossover probability P_m=0.7, and the mutation probability P_c=0.05.

In the distribution process, the number of vehicles used is 4 regardless of carbon emissions (Fig.1 and Fig. 2). The convergence curves of the optimal value are shown in Fig. 3 and Fig. 4. From the curves in the figure, it can be seen that at the beginning of the algorithm's operation, the curve drops faster, indicating that the algorithm's optimization speed is faster. The optimal value gradually begins to converge as the curve changes moderate. When considering carbon emissions, it converges to the optimal solution of the problem for about 80 generations. When not considering carbon emissions, it converges to the optimal solution for about 50 generations.

When considering carbon emissions, its total distribution mileage is 374.6 *km*, the average full load rate is 93.9%, the total carbon emissions are 262.2 *kg* CO_2, the total carbon emissions cost is 125.4 *yuan*, and the total enterprise cost is 2391.3 *yuan* (Table 2). When carbon emissions are not considered, the total distribution mileage is 396.3 *km*, the average full load rate is 93.9%, and the total enterprise cost is 2,284.9 *yuan* (Table 3). The total distribution mileage is 21.7*km* higher than that when carbon emissions are considered, and the average full load rate remains unchanged. In the process of distribution, whether or not carbon emissions are considered, carbon emissions always exist. However, when carbon emissions are considered, the environmental cost is borne by the enterprise, and it is borne by the government when carbon emissions are not considered.

Through the above analysis, it can be concluded that, on the one hand, when enterprises consider carbon emissions, the total social cost can be reduced by 33.6 *yuan*, and the carbon emissions can be reduced by 17.7 *kg* carbon dioxide, which indicates that the carbon emissions cost has a significant impact on the cold chain distribution cost of enterprises. On the other hand, when enterprises do not take into account of carbon emissions, although the distribution cost paid by enterprises is reduced by 104.6 *yuan*, the government has to pay the carbon emission cost of 140 *yuan*, which is 14.6 *yuan* more than that when enterprises take into account of carbon emissions. Therefore, facing the increasingly severe environment, the government can implement carbon emission subsidy to encourage cold chain logistics enterprises to take the carbon emission cost into account in the distribution process, so as to achieve mutual benefit between enterprises and the government, reduce carbon emission, improve environmental pollution and realize green logistics.

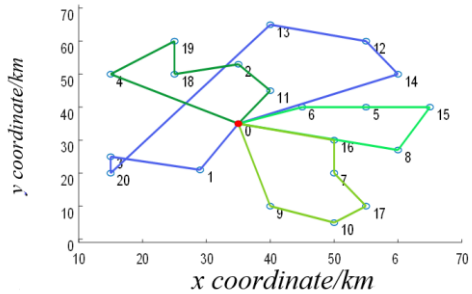

Figure 1: Optimal route Considering Carbon Emissions

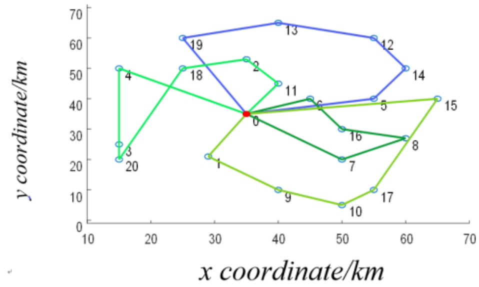

Figure 2: Optimal route without considering carbon emissions

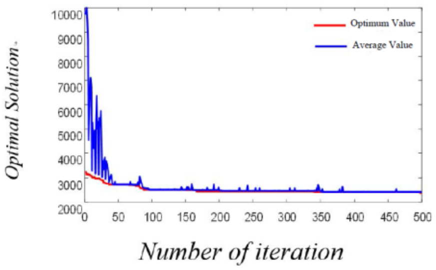

Figure 3: Convergence Curve of Optimal Value Considering Carbon Emissions

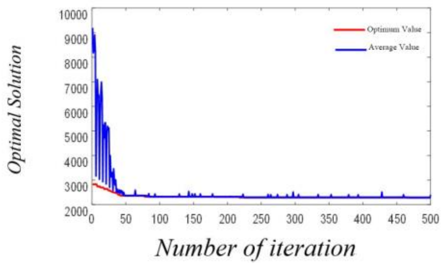

Figure 4: Convergence Curve of Optimal Value without Considering Carbon Emission

Table 2: Distribution parameters value Considering Carbon Emission

Vehicle routing scheme	Distribution mileage/*km*	load capacity/*t*	Carbon emission/*kg*
Scheme 1:0-1-3-20-13-12-14-0	142.4	6.5	93.4
Scheme 2:0-6-5-15-8-0	71.3	7	45.8
Scheme 3:0-4-19-18-2-11-0	80.2	6	57.1
Scheme 4:0-16-7-17-10-9-0	80.7	6.8	65.9
The total cost of distribution is 2391.3 *yuan*, and the total carbon emission is 262.2 *kg*.			

Table 3: Distribution parameters value without Considering Carbon Emission

Vehicle routing scheme	Distribution mileage/*km*	load capacity/*t*	Carbon emission/*kg*
Scheme 1:0-19-13-12-14-5-0	101.5	7	77.2
Scheme 2:0-4-3-20-18-2-11-0	117.6	6	82.6
Scheme 3:0-6-16-8-7-0	66.2	6.3	43.4
Scheme 4:0-1-9-10-17-15-0	111	7	76.7
The total cost of enterprise distribution is 2,284.9 *yuan*.			
The total social cost = total cost of enterprise distribution+carbon emission cost: 2,424.9 *yuan*.			
The total carbon emission is 279.9 *kg*.			

4.3. Algorithm Performance Analysis

Table 4: Experimental statistical results of different algorithms

Algorithm	Number of Vehicles	Optimal solution/yuan	Maximum deviation/%	Average deviation/%	Average running time/s
Basic genetic algorithm	4	2426.5	15.81	3.45	12.05
Basic ant colony algorithm	4	2415.2	13.42	3.21	13.35
Improved genetic algorithm	4	2391.3	10.23	3.05	8.23

To further verify the performance of the algorithm proposed in this paper, aimed at minimizing the total cost of the model and based on *Matlab* 2017 programming, the improved genetic algorithm proposed in this paper, the basic genetic algorithm and the basic ant colony algorithm are used for numerical experiments 20 times respectively, and the experimental statistical results are shown in Table 4. Among it, the maximum deviation = (worst solution-optimal solution)/optimal solution, and the average deviation = (average solution-optimal solution)/optimal solution. As can be seen from Table 4, the number of vehicles used by the three algorithms is 4, but the improved genetic algorithm has obvious advantages in the optimal solution and solution time, which shows that the algorithm designed is effective in solving the vehicle routing problem with time window in this paper.

5. Conclusion

In terms of the traditional cold chain logistics vehicle routing problem, this paper introduces time window and carbon emission factors, establishes a mathematical model of cold chain logistics vehicle routing with the lowest total cost including carbon emission cost, and designs an improved genetic algorithm to solve the established model. Numerical experiments verify the effectiveness and feasibility of the proposed algorithm for solving the vehicle routing problem with time window. The conclusions are as follows: (1) If enterprises take the carbon emission into account in the distribution process, they can not only reduce the total carbon emission of cold chain logistics distribution enterprises, but also reduce the environmental pollution as well as the total distribution cost. (2) The government gives appropriate carbon emission subsidies to enterprises and encourages distribution enterprises to save energy and reduce emissions, which is more conducive to achieving a win-win situation of the economy and the environment. (3) In this paper, the improved genetic algorithm proposed not only provides an effective tool for solving the vehicle routing problem with time window, but also broadens the method of genetic algorithm improvement.

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