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Improved Genetic Algorithm Based Cold Chain Logistics Path Planning with Time Window

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Abstract: To solve the problems of high distribution costs and unreasonable distribution paths of M cold chain company, a cold chain logistics path planning problem with a single distribution centre under a soft time window is proposed. The objective of optimization is to minimize the total costs incurred in the cold chain logistics distribution process and to improve efficiency through rational path planning. Based on the general vehicle path system, the conventional process of the traditional genetic algorithm is introduced, and improvements are made in the genetic selection, crossover and mutation links to design an improved genetic algorithm that introduces a migration strategy and improves the shortcomings of the traditional heritage algorithm that tends to converge prematurely. An empirical study is conducted to solve the optimal route for the problems existing in the current cold chain distribution status quo of Company M. The effectiveness and feasibility of the model and algorithm are confirmed to provide reference for the cold chain logistics and distribution industry.

1. Introduction

With the rapid development of the social economy and the continuous improvement of people's living standards, the quality of all kinds of food has been widely concerned, and people's demand for food preservation has gradually increased, and the cold chain logistics industry has developed rapidly as a result. Cold chain logistics is a combination of refrigeration technology and logistics transport, using refrigeration and insulation and other technical means to achieve the purpose of transporting goods at low temperatures or in different temperature environments. [1] Route planning is a key issue in the entire cold chain logistics process. Selecting the right route for distribution vehicles can reduce costs and improve the timeliness and quality of distribution services while achieving rapid customer satisfaction.

The vehicle path problem (VRP) was first proposed by Dantzig and Ramser [2] in 1959. Chen et al [3] used a non-linear mathematical model to investigate the problem of production scheduling and vehicle routing considering perishable food products with time windows. In studying the cold chain logistics path optimization problem, Fang Wenting et al [4] created a hybrid ant colony algorithm by combining the A* algorithm with the ant colony algorithm for the problem of slow convergence in the initial stage of the ant colony algorithm.Yao Yuanguo and He Shengyu [5] established a mathematical model for cold chain logistics distribution path optimization of agricultural products based on real-time road conditions and feeder points, and solved the model by ant colony algorithm.

Belhaiza et al [6] selected Pareto non-dominated solutions from a search space of a set of Nash equilibrium conditional solutions satisfying a multi-intelligence game theoretic model to optimize a multi-objective vehicle path problem with multiple time windows. Bai Qin Yang et al [7] took the implementation traffic in the road network into account when studying the cold chain logistics path optimization, and accurately portrayed and simulated a real distribution scenario. Li Juntao et al [8] investigated the fresh produce cold chain logistics vehicle problem by adaptive genetic simulated annealing algorithm on the basis of considering the congestion index. xiao et al [9] defined a new mixed integer linear model and proposed to reflect the impact of traffic on distribution using time period division. jesica et al [10] proposed a heuristic algorithm based on variable neighbourhood search to study the dynamic multi The problem of target vehicle paths was investigated by Jesica et al. Zhang Mingyu et al [11] used a simulated annealing algorithm to solve a mathematical model for profit-maximising mixed-pair delivery logistics optimisation to help solve the distribution optimisation of multi-species and multi-temperature products for supermarket chains. küçükoğlu et al [12] solved a model for vehicle path problems with return and time windows by a hybrid algorithm that included forbidden search and simulated annealing.

Based on the existing research, this paper establishes a cold chain logistics path optimisation model with the objective function of minimising the total cost of distribution, and improves the traditional genetic algorithm, using M Cold Chain Company as an example for empirical analysis, in order to enrich the research on cold chain logistics path optimisation.

2. Model construction and Algorithm Solving

2.1. Problem Description and Research Hypothesis

The cold chain logistics distribution studied in this paper, its distribution centre location, the location of the customer, the demand, demand time window is known, the goal is to meet the cold chain vehicle load constraints, customer satisfaction constraints, etc., so that the entire distribution process total cost is minimized, the ultimate goal of the problem is to determine a reasonable transportation route, where the distribution costs include: fixed costs, vehicle travel costs, time window penalty costs, refrigeration costs . The vehicle path optimization problem is an NP-hard problem, the main method to solve such problems is only algorithm, this paper uses improved genetic algorithm to solve the problem, with a strong global search capability.

The following conditions are assumed in this paper:

(1) A distribution centre where the location is known and where no stock-outs will occur at the distribution centre.

(2) Multiple customer points, all with known locations, demand and soft time windows for requested delivery.

(3) The delivery vehicle shall arrive at the customer's point within the time window specified by the customer. If it arrives after the time window, compensation shall be paid and charged to the penalty cost; if it arrives before the time window, it shall wait until the start of the time window.

(4) All distribution vehicles are the same type of refrigerated vehicles, and distribution centre vehicles are filled, all vehicles must not be overloaded.

(5) All distribution vehicles start and end at the distribution centre and return to the distribution centre as soon as the distribution is completed.

(6) Each customer point is served by one delivery vehicle, and each vehicle can provide delivery services to multiple customer points.

(7) Traffic conditions do not take into account special circumstances such as congestion, and all delivery vehicles travel at an even speed and at a known speed.

(8) Once a customer's needs are identified, they do not change.

2.2. Description of the Symbols

Let N be the set of distribution points that N= {0,1,2,...,n}. Where 0 is the distribution centre,1,2,...,n is the customer. Let K be the set of all distribution vehicles owned by the distribution centre, K={1,2,3,...,m}. The relevant variables and parameters of the model are expressed as follows:

V: Average speed of distribution vehicles

C_1: Distribution vehicle unit fixed cost

C_2: unit transportation cost

D_{ij}: distance between i and j

α : degree of deterioration of the box

R: heat transfer rate

ΔT : temperature difference between inside and outside of the box

β : coefficient of frequency of opening the door

v_k : volume of vehicle k refrigerated compartment

a, b: constant coefficients

C_4: cost per unit of carbon emissions

Q: maximum vehicle loading capacity

Q_0: vehicle deadweight

$[ET_i, LT_i]$: customer desire time window for delivery service

$[EET_i, LLT_i]$: Customer acceptable time window for delivery service

μ_1 : early arrival unit time penalty cost

μ_2 : Late arrival unit time penalty cost

t_i: time for delivery vehicle to arrive at customer i

q_i: the quantity demanded by customer i

Q_i: the load capacity of the vehicle when it leaves customer i

C_6: price per unit of product

t_{si}^k : The service time of vehicle k to customer i, i.e. the unloading time

T_{ijk}^t : the travel time of vehicle k on roadway ij at moment t when it enters roadway ij

y_k , x_{ijk} , x_{ik} : 0-1 variables

2.3. Cold Chain Logistics Distribution Path Planning Objective Function Construction

$$MinG = G_1 + G_2 + G_3 + G_4 \tag{1}$$

$$G_1 = \sum_{k=1}^{m} c_1 y_k \tag{2}$$

$$MinG_2 = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} c_2 d_{ij} x_{ijk} \tag{3}$$

$$MinG_3 = \mu_1 \sum_{i=0}^{n} \max\{ET_i - t_i, 0\} + \mu_2 \sum_{i=1}^{n} \max\{t_i - LT_i, 0\} \tag{4}$$

$$MinG_4 = c_5 \left[\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} T_{ijk}^t z_{ik} (1+\alpha) \bullet R \bullet \left(\sqrt{S_0 - S_i}\right) \bullet \Delta T + \sum_{k=1}^{m}\sum_{i=0}^{n} \beta\left(0.54 v_k + 3.22\right) \Delta T x_{ik} t_{si}^k \right] \tag{5}$$

Satisfy:

$$\sum_{k=1}^{m} x_{ik} = 1, k = 1, 2, 3, \ldots, m \tag{6}$$

$$\sum_{i=1}^{n} x_{ik} q_i \le Q, k = 1, 2, 3, \ldots, m \tag{7}$$

$$EET_i \le t_i \le LLT_i, i = 1, 2, 3, \ldots, n \tag{8}$$

$$\sum_{k=1}^{m} \sum_{i=1}^{n} x_{i0k} = \sum_{j=0}^{n} \sum_{k=1}^{m} x_{0jk} \tag{9}$$

Eq. (1) represents the target cost, i.e. the sum of fixed cost, vehicle travel cost, time window penalty cost and refrigeration cost is minimised; Eq. (2) represents fixed cost; Eq. (3) represents vehicle travel cost; Eq. (4) represents time window penalty cost; Eq. (5) represents refrigeration cost; Eq. (6) represents that each customer has one and only one refrigerated vehicle to serve him/her; Eq. (7) represents that the load of the transport vehicle must not exceed the rated load of the vehicle; Eq. (8) represents the time window requirement for customer collection; Eq. (9) represents that the distribution vehicle starts and ends at the distribution centre and returns to the distribution centre immediately after the delivery is completed.

3. Improved Genetic Algorithm Design

The genetic algorithm was proposed by Professor Holland of the University of Michigan in the United States and is based on the principle of "survival of the fittest" to optimise the objective function. It has the advantages of strong global search ability and wide range of applications, but has the drawbacks of easy premature convergence and falling into local optimum solutions.

3.1. General Process of Genetic Algorithms

The genetic algorithm consists of the following main steps:

(1) Selection: the ability to determine the number of individuals in the offspring of recombinant/crossover individuals and individuals. Any one individual has a probability of being selected, and this probability depends on the fitness and distribution of the population.

(2) Generation of the initial population: A number of initial strings are randomly generated, each constituting a chromosome (individual) and in encoded form, together forming a random initialised population. The content of the encoding varies with the solution of the problem.

(3) Initialising the population: selecting the better individuals from the population and generating the next generation of chromosomes with the other better individuals. Choose the genetic strategy, including the population size and the specific ways in which selection, crossover and mutation will occur, the probability of crossover and the probability of mutation.

(4) Calculation of the adaptation values of individuals in the population after decoding.

(5) Act on and co-evolve the offspring population by selection, crossover and mutation operators in the population.

(6) Determine whether the newly generated population can achieve the purpose or complete the expected number of iterations, and if unsatisfactory, repeat step (5) until the purpose is satisfied, or achieve the result by re-optimisation of the genetic strategy.

The exact process is shown in Figure 1:

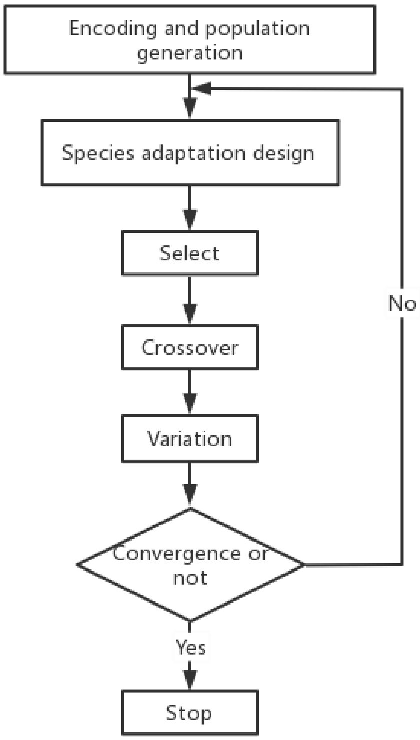

Figure 1: Genetic algorithm flow

3.2. Improved Genetic Algorithm Design

The solution steps of the improved genetic algorithm in this paper are as follows:

(1) Encoding and decoding. The solution sequence is reflected into the genetic space by parameter encoding; decoding is then applied to reflect the processed genetic space into the solution sequence.

(2) Relevant parameter settings. The fitness function is determined, including the population size, crossover and variation probabilities, and the maximum number of algorithm termination iterations.

(3) Initialisation of the population. A suitable number of initial solutions are randomly generated.

(4) Calculation of individual fitness values. The high fitness is inherited to the next generation, and the inverse of the total cost is set as the fitness function in this paper.

$$fitness(i) = \frac{1}{G_i}(i = 1, 2, ..., N, P) \tag{10}$$

(5) Selection. In this paper, the most commonly used roulette wheel selection method was chosen to screen chromosomes. At the same time, to avoid losing and destroying the best individuals in the previous generation population during crossover and mutation, an elite retention strategy was used to store the best individuals in the algorithm solution process. In this paper, individuals in the top 10% of the ranking of fitness values in the parent generation are retained and replaced by those in the bottom 10% of the ranking of fitness values in the subsequent offspring to avoid the loss of potential optimal solutions during the genetic operation.

(6) Crossover. Individuals in a population are randomly paired and each pair swaps some of their chromosomes with some probability (called crossover probability) following a rule to produce a new individual.

(7) Variation. The mutation operator is applied to the population to change the value of one or more genes with some probability for selected individuals.

(8) Reversal operation. After the mutation operation, each chromosome is reversed for each individual and the decision to retain the reversal is based on the magnitude of the fitness taken after the reversal.

(9) Migration operation. A threshold is set to determine whether the current algorithm has fallen into premature convergence, and if so, an "immigration strategy" is implemented to introduce external individuals to increase the population diversity and thus further enhance the population search ability. In order to solve the problem that genetic algorithms tend to fall into local optimum solutions, this paper uses the "migration strategy" to transplant some of the better individuals into the current reserved population, so as to increase the diversity of the existing population and thus improve the efficiency of the algorithm's search. When the genetic algorithm shows early convergence, it means that the fitness of the individuals in the current population is very similar, so we can determine whether the algorithm has fallen into early convergence based on the variance of the fitness of each population.

The genetic algorithm is a very early convergence. To facilitate the calculation, let

$$E = \frac{1}{N}\sum_{i=1}^{n}\left| f_i - f_{avg} \right| \tag{11}$$

where: f_i is the fitness of the i-th individual; f_{avg} is the average fitness of the population; and N is the population size. When E is less than a certain threshold, we consider that the current algorithm is converging prematurely, and we apply a "migration operation" to it.

(10) Go back to step 4 and recycle until the termination condition is met and the algorithm is jumped.

4. Empirical Analysis

4.1. Basic Data

Company M is a cold chain logistics company with a distribution centre and 30 customer points in city A. The information on Company M's customers is shown in Table 1, with serial number 0 being the distribution centre and 1-30 being the customer points. The company's cold chain vehicle distribution starts at 7:00 and ends before 21:00, i.e. the left time window of the distribution centre is 7:00 and the right time window is 21:00, and the distribution vehicle must return to the distribution centre before 21:00 on the same day. the distribution vehicle models owned by company M have uniform specifications, the maximum loading capacity of the distribution vehicle is 150kg, and the average speed of the distribution vehicle is 30km/h. the distribution path is based on The distribution path is based on the data provided by the example, and the genetic algorithm designed in this paper is used to solve it, so as to arrange the distribution path reasonably and reduce the distribution cost of the enterprise.

4.2. Analysis of Solution Results

Based on the above data, the thesis uses Matlab R2020a to simulate and solve the algorithm with a population size of 100, a number of iterations of 250, a crossover rate of 0.9 and a variance of 0.05.

Using the improved genetic algorithm to solve for the optimal total delivery distance of 590.68km for the example, it can be seen from Figure 2 and Table 2 that a total of 6 vehicles are used for this delivery and the 6 delivery routes are: 0→3→13→10→18→27→2→4→0; 0→22→23→26→15→0;

0→8→24→0;0→16→21→28→19→11→0;0→7→9→17→20→1→0;0→5→29→14→25→30→6→12→0.

Table 1: M Cold Chain Company Distribution Information Sheet

Serial number	X coordinate /km	Y coordinate /km	Demand /kg	Left time window	Right time window	Service time /min
0	37.2	40.8	0	7:00	21:00	0
1	38.9	48.9	36	17:00	17:30	15
2	54.8	33.4	33	14:00	15:10	15
3	47.7	26.3	3	8:00	9:30	15
4	87.4	56.3	26	16:00	16:30	15
5	34.5	28.9	14	7:20	8:00	15
6	13.7	38.5	10	15:00	15:40	15
7	34.3	77.3	37	10:40	11:20	15
8	34.2	29.8	30	10:40	11:30	15
9	33.8	87.3	9	12:50	13:40	15
10	67.4	37.4	5	12:00	12:30	15
11	28.9	42.1	32	13:30	14:20	15
12	34.5	36.7	13	15:00	16:10	15
13	68.3	17.5	16	8:30	9:30	15
14	21.3	24.6	23	10:40	12:00	15
15	43.5	37.2	31	12:40	13:40	15
16	33.9	43.3	30	9:00	9:50	15
17	33.2	54.4	9	14:10	15:00	15
18	67.3	27.6	34	12:20	13:30	15
19	14.2	56.2	32	11:40	12:20	15
20	35.1	51.6	52	14:10	15:20	15
21	33.7	44.2	15	10:30	11:20	15
22	57.4	78.1	40	9:10	10:30	15
23	51.3	60.2	28	11:20	12:10	15
24	32.2	15.9	73	12:20	13:40	15
25	14.3	21.6	13	11:30	12:30	15
26	54.3	43.2	33	12:30	13:50	15
27	66.8	25.3	25	13:40	14:20	15
28	21.4	67.3	27	11:20	12:20	15
29	24.2	35.6	43	9:50	11:30	15
30	22.5	28.4	16	12:20	14:00	15

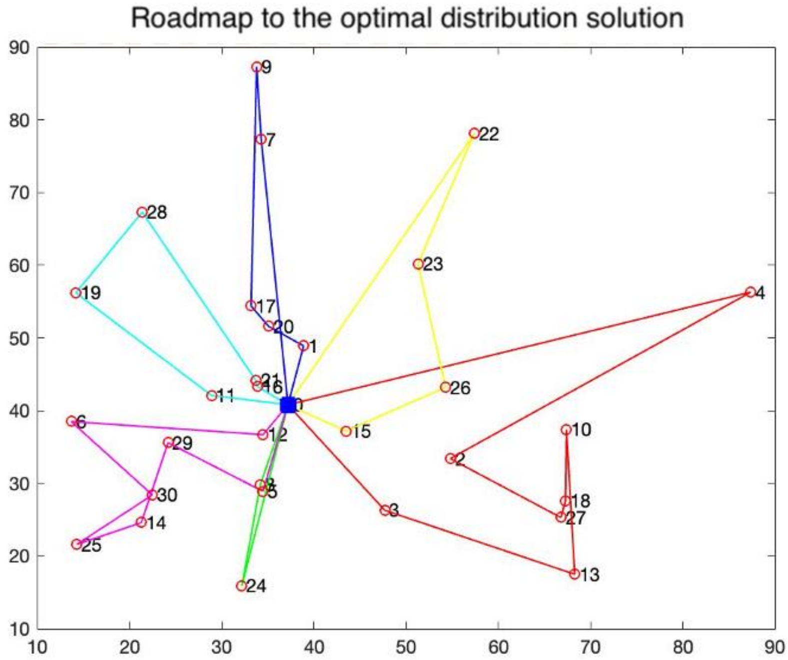

Figure 2: Roadmap to the optimal distribution solution

Table 2: Improved genetic algorithm for optimal distribution routes

	Route
1	0→3→13→10→18→27→2→4→0
2	0→22→23→26→15→0
3	0→8→24→0
4	0→16→21→28→19→11→0
5	0→7→9→17→20→1→0
6	0→5→29→14→25→30→6→12→0

The process of algorithm iteration can be seen through Figure 3, the improved genetic algorithm iterates to about 20 times and starts to converge. The cold chain logistics path planning can significantly save logistics costs, reasonably plan the path to reduce fuel consumption, and also provide more timely and convenient services for customers by saving vehicle delivery time.

5. Conclusion

The path planning model established in this paper belongs to the logistics supply scenario with a single distribution centre and a relatively intensive supply time, and can be applied to the vehicle path planning of small supermarkets, agricultural products supermarkets, etc. The optimized genetic algorithm has a better convergence speed in practical application and can provide better path selection. The effectiveness and feasibility of the model and algorithm are confirmed, which provides a reference for solving the related cold chain logistics distribution path planning problems.

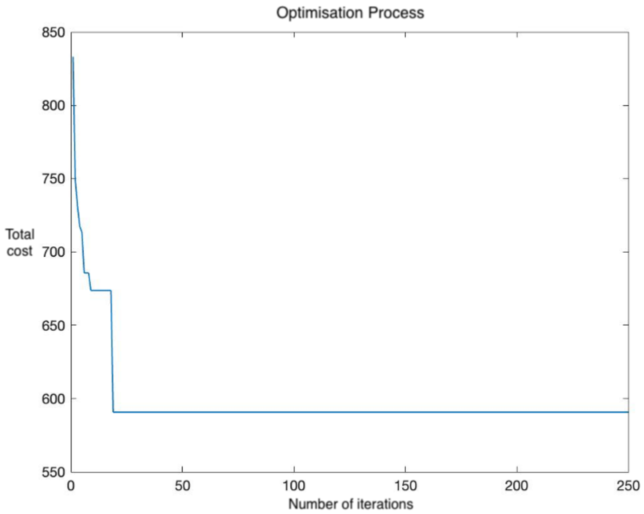

Figure 3: Improved genetic algorithm for solving iterative graphs

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