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Large Scale Customer Points in Genetic Algorithms

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ABSTRACT

Aiming at the path optimization problem of pharmaceutical green logistics distribution, a green logistics path optimization model is designed considering constraints such as time window limitation and vehicle capacity, with the optimization objective of minimizing the sum of vehicle transportation cost, overtime cost and green cost, and the constructed model is solved by using genetic algorithm. The constructed model and designed algorithm are verified by actual distribution data. The example experiments show that the genetic algorithm has better solution quality, higher efficiency and more stable results in solving the vehicle path problem at large-scale customer locations. The research results not only expand the vehicle path problem, but also provide decision-making reference for the distribution optimization of related express logistics enterprises.

KEYWORDS

Genetic algorithm; Path optimization; Green logistics

1. INTRODUCTION

At major international conferences, countries around the world have put forward the concepts of low-carbon, environmental protection and green. In order to address climate change, the 2021 session of the National People's Congress made a solemn commitment to “strive to peak carbon dioxide emissions by 2030 and strive to achieve carbon neutrality by 2060”. Promoting carbon emissions to peak as early as possible is an important means for China to fulfill its commitment to make independent contributions and win the initiative in global climate governance, and it is also the core content and inherent requirement for China to build an ecological civilization and practice the concept of green development. The transportation industry is in a stage of rapid development, which is the main driving factor for the increase of energy consumption and carbon emissions in the coming decades, and is also the most likely industry that China will not be able to reach the peak of carbon emissions in 2030. Therefore, it is very important to realize the decarbonization of road transport and promote the coordination of road logistics and transportation development with ecological environment protection.

With the continuous development of logistics and distribution, in recent years, scholars at home and abroad have conducted extensive and in-depth research on time window setting, green distribution, and algorithm design. In terms of considering time windows, Yougang Xiao et al[1]proposed the green vehicle path problem with time windows for multiple distribution centers; Haoxiong Yang et al[2]investigated the delivery path optimization problem for takeout orders with time windows; Li et al[3]established a mixed integer linear programming model with time windows and vehicle capacity constraints for the fact that the delivery of products and services must be carried out at the same time. In terms of considering carbon emissions, Wenting Fang et al[4]transformed energy saving and emission reduction into green costs and incorporated them into the path optimization problem; Xiancheng Zhou et al[5]considered fuel consumption and carbon emission costs in a time-dependent green vehicle path model; Hsien-Lung Ge et al[6]introduced a new carbon emission trading mechanism to calculate the carbon emission costs; and Ferani E. Zulvia et al[7]proposed a green vehicle for perishable product path problem. In terms of algorithm design, Ehmke et al[8]constructed a time-dependent green vehicle path problem model and solved it using the LANTIME forbidden search algorithm; Liu G et al[9]used a simulated annealing algorithm to solve a green vehicle path problem model for co-distributing cold-chained commodities; and Poonthalir and Nadarajan et al[10]utilized a greedy variational operator and a time-varying acceleration coefficients of the particle swarm algorithm to solve the bi-objective fuel-efficient green vehicle path problem; Kang K. et al[11]proposed an improved ant colony algorithm combining the 2-opt local search mechanism and the push-bump-throw process to solve the multi-objective vehicle path problem optimization model;

In summary, the existing research results have laid a good foundation for the green logistics and distribution path optimization problem to be studied in this paper, but this paper does further optimization.

(1) Distribution data is more practical. The existing articles use Solomon's standard algorithms to simulate and analyze the constructed models and designed algorithms, while this paper selects the actual distribution data and a large amount of data, so it has a certain practical significance.

(2) Under the premise of maximizing the economic benefits of the enterprise, this paper incorporates the overtime penalty cost and green cost into the optimization objective function, which improves the timeliness of distribution and customer satisfaction, and at the same time, it also has significant results in terms of energy saving and emission reduction.

In summary, firstly, the relevant fixed parameters and carbon emission calculation formula are determined according to the actual situation; then, the conditions such as distribution time limitation and vehicle load constraints are considered, and the sum of vehicle transportation cost, overtime penalty cost and green cost is taken as the optimization objective, so as to establish a model of the green logistics and distribution path optimization problem, and solve it by using genetic algorithm. Finally, it is verified by the actual distribution data.

2. PROBLEM AND MODEL

2.1. Description of the Problem

For the distribution problem in this paper, the main assumptions are as follows:

(1) There is a distribution center and multiple customer points, and the distance between them is known.

(2) Factors such as traffic signals and traffic jams are taken into account, and the speed of the distribution vehicles is assumed to be constant.

(3) The demand for each customer point is randomly generated in a certain interval.

(4) The distribution center selects vehicles of the same model for distribution and each customer point is served by a vehicle.

(5) The total demand of customer points on a distribution path does not exceed the capacity of the vehicle.

(6) Each customer point can be served by only one vehicle and each customer point is served once.

2.2. Description of Symbols

The symbols and their meanings are shown in Table 1.

Table 1. Parameter Symbols Define the Table

symbol	connotation
d_{ij}	Indicates the shortest distance between customer points
q_{ij}	Indicates the load capacity of the vehicle from i to node j
t_{ij}	Indicates the time taken by the delivery vehicle from customer point i to customer point j
C_1	Indicates the transportation cost per kilometer
Q	Indicates the maximum capacity of each vehicle
T	Indicates the delivery time limit
P	Indicates the unit penalty cost
t_i	Indicates the time for the vehicle to reach the first customer point i
ϑ	Indicates the average speed of the vehicle
t_0	Indicates the moment when the vehicle departs from the distribution center
ω	Fixed Value Factor
α_i	Fixed value factor
β	Fixed value coefficient

2.3. Mathematical Modeling

2.3.1. Penalty cost calculation

In the reality of the transportation process, when the transportation road is not smooth such as encountering traffic congestion, traffic accidents, distribution vehicle accidents occur will lead to the distribution vehicle transportation time is too long, the arrival time exceeds the customer's requirements of the time window, so this paper sets up the overtime penalty cost, as shown in Equation (1).

$$P_T = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} \left[\left(T - t_{ij} \right), 0 \right] \tag{1}$$

2.3.2. Transportation cost calculation

The transportation cost in this paper only considers the variable cost, which is related to the distance traveled by the vehicle, as shown in Equation (2).

$$T_C = \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{M} C_1 d_{ij} \tag{2}$$

2.3.3. Carbon emission calculation

Vehicles in the process of traveling, the amount of fuel consumption and vehicle speed and load has an inevitable correlation[12], the vehicle in the process of traveling the carbon emissions mainly from fuel exhaust emissions, so the carbon emissions and the speed of the vehicle there is a close link. This paper refers to the relevant literature[13]to express the carbon emissions produced by the vehicle due to the change of speed as shown in Equation (3).

$$EC_{ij}^{1}=\left\{\alpha_0+\alpha_1\vartheta+\alpha_2\vartheta^3+\alpha_3\frac{1}{\vartheta^2}\right\}d_{ij} \tag{3}$$

At the same time, the vehicle load also affects the carbon emission of the vehicle in the process of traveling, and this paper refers to the relevant literature[14]to derive the relationship between the vehicle load and carbon emission as shown in Equation (4).

$$EC_{ij}^{2}=\beta d_{ij}q_{ij} \tag{4}$$

In summary, the distribution model and constraints are shown in Equation (5):

$$\begin{aligned}&\min W=T_C+P_T+EC\\&=\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{M}C_1d_{ij}+\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{M}P[(T-t_{ij}),0]+\\&\omega\{\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{M}\{\alpha_0+\alpha_1\vartheta+\alpha_2\vartheta^3+\alpha_3\frac{1}{\vartheta^2}\}d_{ij}+\sum_{i=0}^{N}\sum_{j=0}^{N}\sum_{k=1}^{M}\beta d_{ij}q_{ij}\}\end{aligned} \tag{5}$$

$$s.t.\ \sum_{k=1}^{M}y_{ki}=1(i=1,2,...,N) \tag{6}$$

$$\sum_{i=0}^{N}x_{ijk}=y_{kj}(j=1,2,...,N,k=1,2,...,M) \tag{7}$$

$$\sum_{j=0}^{N}x_{ijk}=y_{ki}(i=0,1,2,...,N,k=1,2,...,M) \tag{8}$$

$$\sum_{i=1}^{N}q_iy_{ki}\le Q \tag{9}$$

$$\sum_{i=1}^{N}x_{oik}=1(k=1,2,...M) \tag{10}$$

$$\sum_{j=1}^{N}x_{jok}=1(k=1,2,...,M) \tag{11}$$

Equation (6) indicates that drugs at customer points are delivered only by the vehicle and cannot be delivered in batches and by vehicles; Equation (7) and Equation (8) indicate that when the customer point and is on the vehicle's service route, it is served by the vehicle; Equation (9) indicates that the total demand for the customer point does not exceed the total capacity of the compartment; and Equation (10) and Equation (11) indicate that the vehicle departs from the distribution center, completes the distribution task, and then returns to the distribution center。

3. MODEL SOLVING ALGORITHM

For the model constructed in this paper, this paper proposes to use genetic algorithm to solve it. Genetic algorithms are relatively simple and applicable, and have been applied in many fields with remarkable success.

3.1. Chromosome Coding

In order to reduce the complexity of the program operation, this paper encodes the distribution center by using natural number notation, defines the distribution center with code 0, and sets the target customer point code as a non-repeating natural number

3.2. Generating Initial Solution

In this paper, the initial population is generated by random method, in the distribution path problem, a path can be generated randomly to ensure that the path starts from the distribution center, passes through each customer point once, and finally returns to the distribution center.

3.3. Adaptation Function

The objective function of this paper is to minimize the total cost cost, and the inverse of the objective function is used as the fitness function, indicating that the smaller the total cost cost is, the larger the fitness value is.

3.4. Selection Operator

Screening method on this paper through the roulette method. In this method, firstly, the corresponding fitness values of all individual chromosomes are obtained, secondly, the fitness values of all chromosomes are summed up to find the total sum, and finally, the former is divided by the latter to get the percentage of individual chromosomes in the overall sum, which is taken as the probability of entering the next generation in this selection process.

3.5. Crossover Operator

In this paper, single-point crossover is used to generate new populations, and its basic idea is to select a crossover point from two parent individuals, and then exchange the part behind the crossover point to generate new individuals. The specific steps are as follows:

(1) Selection of crossover point: first, randomly select a crossover point, which will determine the position of two parent individuals for crossover.

(2) Crossover operation: the parts of the two parent individuals behind the crossover point will be exchanged. In this way, the generated new individual will contain the front part of one parent individual and the back part of the other parent individual.

(3) Generate new individuals: after the crossover operation is completed, two new individuals are obtained, which are the results obtained from the crossover of the two parent individuals.

Single-point crossover is one of the simplest and most common crossover operations in genetic algorithms, which can effectively retain some good characteristics of the parent individuals and introduce a certain degree of variation, which contributes to the diversity and evolution of the population.

3.6. Variation Operator

The two-point variation operator is a variation operation in genetic algorithms, which selects two points of variation on an individual's chromosome instead of one, compared to the single-point variation operator. This introduces a greater degree of randomness and diversity in the individual and helps to avoid falling into local optimal solutions.

The specific steps are as follows:

(1) Selecting the mutant individual: one individual from the population is randomly selected as the object of mutation.

(2) Select mutation points: Among the selected individuals, two different positions are randomly selected as mutation points. These two positions correspond to two different genes on the chromosome of the individual.

(3) Mutation operation: Mutation operation is performed on the two selected mutation points. The specific operation can be to change the values of these two genes or to make appropriate changes according to the characteristics of the problem.

(4) Generate new individual: after the mutation operation is completed, a new individual is generated, which is similar to the original individual but slightly different.

The two-point variational operator introduces more degrees of variation relative to the single-point variational operator, which allows for better exploration of the solution space. However, when applying the two-point variational operator, it is also necessary to choose the variational probability carefully to balance the effects of local and global search.

3.7. Termination Conditions

Determine that the number of iterations has reached the set number of iterations, and if it has been satisfied, terminate the evolution and select the optimal chromosome.

4. CASE SIMULATION

4.1. Calculation Setup

In order to verify the validity of the model and algorithm, the actual distribution data are selected, and the scientific and effective distribution program is given through MATLAB programming.

The model parameters and algorithm parameters are set as shown in Table 2 and Table 3, which are programmed in Matlab and run on a desktop computer with Intel i8-15400, 3.8GHz CPU and 128GB memory, and the program running software is Matlab R2023b.

Table 2. Model Parameter Values

Model Parameters	Taking Values	Model Parameters	Taking Values
C_1	1.8RMB/km	α_1	-5.6
T	8h	α_2	0.0327
P	11RMB/h	α_3	26.067
ϑ	50km/h	β	0.0581
L	600	Q	10.1
ω	0.05	α_1	1.322

After repeated trials, the parameters of the improved genetic algorithm were set as shown in Table 3 below.

Table 3. Algorithm Parameter Values

Algorithm parameters	Meaning	Value
P_C	Probability of crossove	0.9
P_m	Probability of variation	0.05
Gen	Maximum number of iterations	500
$CustomerNum$	Population size	356

4.2. Analysis of Simulation Results of the Algorithm

4.2.1. Analysis of Simulation Results

In this paper, the simulation test on large-scale customer points, the algorithm runs 10 times, calculate the average value as a result of the run, the simulation results show that when the simulation data increases, the need for two vehicles to complete the distribution task and the loading capacity of the two vehicles were 9.97m3 and 8.08m3, the loading rate of 80% or more; the total cost of distribution of the two vehicles for 1203.40 yuan, of which the cost of carbon emissions is 464.86 yuan, the total mileage of the two vehicles is 423.18 kilometers; the number of customers served by the first vehicle is 197, the vehicle driving time is 5.76h, and the distribution path is as follows: 0→301→303→307→129→320→323→151→326→327→329→351→319→328→26→339→349→346→345→348→347→346
345→348→347→341→139→332→1→343→342→336→43→47→46→324→63→134→142→141→137→138→146→147→230→233→231→234→241→240→243→244→245→235→236→239→
285→287→288→289→155→153→291→237→208→259→257→261→252→255→269→265→264→256→82→263→260→253→224→276→277→274→271→272→275→354→278→280→282
→283→279→284→281→286→254→258→249→248→251→247→246→223→198→221→214→215→178→56→204→209→210→213→267→266→270→268→262→189→196→197→200→212→195→211→217→274→276→274→272→27275→354→278→280→282
171→180→353→187→184→185→186→194→352→190→191→192→193→188→273→55→31→109→199→182→181→174→216→176→163→165→164→305→306→183→316→314→315→
312→310→309→308→299→290→298→297→293→292→296→98→294→295→300→304→0.

The number of customers served by the second vehicle is 159, the vehicle traveling time is 4.84h, and the distribution path is: 0→321→322→340→338→344→330→325→44→10→45→331→333→16→17→15→13→14→7→8→9→11→12→5→6→40→39→41→3→2→4→136→
38→32→27→28→37→29→33→36→35→335→334→337→42→57→58→356→62→61→65→66→67→68→69→70→71→73→60→72→229→75→74→19→145→160→159→175→355→302→166→
227→152→148→242→149→150→144→143→135→140→133→131→132→126→130→78→77→80→85→92→84→86→88→87→90→93→94→91→183→99→97→95→96→123→120→121→122
→101→102→103→89→105→104→350→107→100→110→106→108→113→115→116→114→112→111→118→117→119→238→202→124→128→127→125→83→81→79→64→76→18→48
59→54→51→53→49→50→30→21→52→22→23→24→34→20→25→311→313→317→0.

The running time of each vehicle is no more than 11h, which indicates that the vehicle can complete all the distribution tasks within the specified time. Large-scale customer locations may require at least two vehicles to complete the distribution, but based on the optimization objectives and constraints in this paper, the solved results are optimal.

4.2.2. Comparison of Simulation results with Different Optimization Objectives Under Large-Scale Data

In order to verify whether the distribution scheme with the optimization objective of minimizing the total cost is optimal, we conducted a series of comparison experiments. In these experiments, we keep the other conditions of the algorithmic procedure unchanged, and verify the optimization objective by minimizing the carbon emission cost of all vehicles, minimizing the total driving distance, and disregarding the carbon emission cost, respectively. Ten simulation experiments were conducted using the genetic algorithm on the distribution data of all customer locations and the average value was taken as the final result, as shown in Table.

Table 4. Comparing Simulation Results with Different Optimization Objectives

Optimization Objective	Total cost/RMB	Carbon emission cost/RMB	Travel time/h		Distance traveled/km	Number of vehicles used/vehicle
Total distance traveled	1227.26	479.88	5.57	5.47	435.98	2
Carbon emission cost	1208.71	468.96	5.79	4.97	424.09	2
Without considering carbon emission	1213.36	470.51	5.71	5.00	425.99	2
Optimization objective of this paper	1203.40	464.86	5.70	4.62	423.18	2

As can be seen from Table 4:

(1) Validation of the effectiveness of different optimization objectives: through the study, it is found that the genetic algorithm can find the optimal solution no matter what the optimization objective is, which indicates that the algorithm has good versatility and effectiveness in solving the green vehicle path problem.

(2) Validation of total cost minimization: choosing to minimize the total cost as the optimization objective, the results show that the total cost, carbon emission cost, vehicle travel time and travel distance are all minimized, which proves the correctness and superiority of the model construction.

(3) Optimization results of carbon emission consideration: the total cost is significantly reduced after considering carbon emission, which indicates that the optimization objective can simultaneously satisfy the purpose of energy saving and emission reduction as well as the reduction of distribution cost, which reflects the practicality and diversity of the algorithm.

(4) Savings in the number of distribution vehicles: the number of distribution vehicles is the same under different optimization objectives, which indicates that the algorithm is able to effectively utilize the resources and reduce the waste of resources under the consideration of vehicle capacity limitation.

5. CONCLUSION

This study focuses on solving a key problem in green logistics: how to effectively plan distribution vehicle paths to reduce total cost. In today's society, green logistics has become a topic of great concern because it can not only improve the competitiveness of enterprises, but also reduce environmental pollution and promote sustainable development. However, to achieve green logistics, it is necessary to solve the optimization problem of distribution vehicle path planning, which not only involves the efficient distribution of goods, but also needs to take into account the aspects of cost and environmental impact.

In order to solve this problem, we chose genetic algorithm as the research method. Genetic algorithm is an optimization algorithm that simulates the process of biological evolution and searches for the optimal solution by simulating natural selection and genetic mechanisms. In our study, we use genetic algorithms to optimize delivery vehicle paths to make the total cost minimized. Through this method, we can find the most economical and environmentally friendly distribution solution taking into account various constraints.

To verify the effectiveness of our proposed method, we conducted experiments using real distribution data. The experimental results show that our genetic algorithm still exhibits superiority when dealing with large-scale customer locations, which means that our method is not only applicable to small-scale problems, but also to real large-scale distribution scenarios. This finding provides a solid theoretical foundation and practical guidance for our research, and provides useful references and lessons for practice in the field of green logistics.

Overall, the goal of this study is to reduce the total cost by optimizing the path of distribution vehicles, thus promoting the development of green logistics. By using genetic algorithm and verified by actual distribution data, we proved the effectiveness and feasibility of our method, which provides new ideas and methods for future research on the optimization problem of green logistics distribution paths.

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