Multi-target Rural Vehicle Route Planning Model with Satisfaction Evaluation

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Abstract. According to the rural logistics distribution problem, a multi-target vehicle routing planning model with satisfaction evaluation is constructed. First, the basic assumptions and descriptions of the problem are given. The goal is to minimize the total mileage and the number of vehicle's departure times with a highest overall satisfaction. Considering the constraints of vehicle load, the delivery time of orders, customer satisfaction and so on, a multi-objective 0–1 nonlinear programming model is constructed, then an improved genetic algorithm is designed according to the characteristics of the model. Furthermore, with an example, the effectiveness of the improved genetic algorithm is illustrated. Then, an accurate algorithm is used to prove the illustration, and the result shows the improved genetic algorithm is effective in solving the problem.

Keywords: satisfaction evaluation · rural logistics · vehicle routing problem · genetic algorithm

1 Introduce

In the age of high-speed Internet, online shopping is constantly popularized in China, and drives the prosperity of the logistics industry. Now there is a very complete distribution system in cities, and its distribution capacity is much stronger than that in rural areas [12]. The logistics network is hard to extend, and rural logistics distribution has become an important and urgent problem. Nowadays the issue of rural logistics distribution [2] has attracted the attention of relevant scholars at home and abroad [3].

The existing research results on other types of vehicle routing planning problems can provide ideas. The vehicle route planning with load constraints is complex [5]. Annealing algorithm with crossover operators is proposed. The coal mines' material distribution problem [4] is aimed at minimizing transportation cost.

To maximize the utilization of logistics resources, a 3D customer clustering algorithm based on the spatial distribution balance of demand and customer service characteristics is proposed [10] to allocate customers, then optimize the pickup and delivery with taboo search hybrid genetic algorithm.

Additionally, most of the vehicle routing problems are solved by heuristic algorithms [11]. There is hybrid strategy algorithm combined with scanning algorithm, ant colony

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algorithm and path reconnect algorithm [1] and particle swarm algorithm with dynamic weights [9] to solve the vehicle path optimization problem.

At the same time, there are studies that do not use heuristic algorithms [7]. The VRP can be transformed into reinforcement learning problem optimized for different algorithm strategies for size and scale problems [8]. Branch cutting method is used to calculate the exact results considering the carbon emission constraint and the accompanying cost-effectiveness [6].

To make logistics enterprises can serve quickly with lower cost in rural areas. Based on the constraints of vehicle load, speed, time, and rural road conditions, etc., an optimization model is established to minimize the total mileage of vehicle routes, the number of vehicle's departure times and maximize customers' satisfaction. An improved genetic algorithm leads to a result evaluated by an accurate algorithm.

2 Problem Description

In this section, rural logistics distribution problem is firstly explained, and the reasonable assumptions are introduced, then the variables are described.

2.1 Assumptions

This paper abstracts the starting point of one town and the main destination villages into service nodes.

1) Assume that the vehicle is at uniform speed during delivery, and ignore the delivery time of the order when it arrives at the customer.
2) Assume the weight of the goods in the order is consistent, and the order quantity is taken as the dimension to measure the load.
3) Assume that orders from the same village will not be divided into multiple vehicles.
4) Assume that the vehicle will not return to the starting point after delivery.

2.2 Variable Description

To describe the problem, the following mathematical symbols and variables are listed:

$C = \{C_0, C_1, C_2 \cdots C_n\}$: set of n service nodes and 1 distribution center, $i = 1, 2 \cdots n$.

$V = \{V_1, V_2 \cdots V_m\}$: set of vehicles responsible for distribution, $k = 1, 2 \cdots m$. In addition, the vehicle type V_{s_u} is also used to replace V_k, and s_u is the vehicle type number, $u = 1, 2 \cdots w$. There are $V_k = \eta_1 V_{s_1} + \eta_2 V_{s_2} + \cdots + \eta_u V_{s_u} + \cdots + \eta_w V_{s_w}$ and $\sum_{u=1}^{w} \eta_u = 1$ to prove the relationship, η_u is 0 or 1.

$E = \left(e_{ij}\right)_{n\times n}$: The connectivity matrix between service nodes. E limits variables according to the case when introducing cases, and not directly reflects the body of the mathematical model.

q_i: number of orders required by the node i;

l^k: the load of the vehicle k;

v^k: the average driving speed of the vehicle k;
d_{ij}: the distance between nodes i and j;
t_{ij}^k: the time between the vehicle k passing through the adjacent nodes i and j;
a_i: the time when the node i accepts the delivery service, that is, the delivery time of the vehicle at the node;
r_{ij}: correcting coefficient about road condition;
λ_i: the satisfaction weight of the node i, is positively related with the demand;
β: the ideal time of delivery;
σ: maximum time limit for order delivery.

3 Model Construction and Solution

3.1 Model Construction

Two 0–1 variables x_{ij}^k and w_i^k are first introduced.

x_{ij}^k: 1 if v^k from i arrives j; otherwise 0. $\forall i = 0, 1 \ldots n, j = 1, 2 \ldots n, k = 1, 2 \ldots m$.

w_i^k: 1 if v^k stops at i; otherwise 0. $\forall i = 0, 1 \ldots n, k = 1, 2 \ldots m$.

The model objectives and constraints are considered as follows:

(1) Objectives

1) Minimum total mileage of the vehicle path:

$$\min \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=1}^{n} \sum\nolimits_{k=1}^{m} x_{ij}^k d_{ij} \tag{1}$$

2) Minimum number of vehicle's departure times:

$$\min \sum\nolimits_{i=1}^{n} \sum\nolimits_{k=1}^{m} x_{0i}^k \tag{2}$$

3) Maximum overall customer satisfaction:

$$\max \sum\nolimits_{i=1}^{n} \lambda_i \cdot T(a_i) \tag{3}$$

(2) Constraints

1) Vehicles are required to start from the distribution center and terminate the distribution at the end of the route. There is no repeated access to the same service node and return to the distribution center. Each service node is required to be visited and be accessed by only one vehicle.

Specifically, formula (4) means that service node j can only be reached from one service node, and can only be delivered to the service node by one vehicle:

$$\sum\nolimits_{i=0}^{n} \sum\nolimits_{k=1}^{m} x_{ij}^k = 1, \ \forall j = 1, 2 \ldots n \tag{4}$$

Formula (5) means that the service node i cannot be used as both distribution transit node and termination node, that is, there is a vehicle, or terminate distribution at any service node i, or reach another service node from any service node i:

$$\sum\nolimits_{j=1}^{n} \sum\nolimits_{k=1}^{m} \left(x_{ij}^k + w_i^k \right) = 1, \ \forall i = 1, 2 \ldots n \tag{5}$$

Further, formula (6) means that if any vehicle k is assigned a distribution task, it must start from the distribution center, as follows:

$$\left(1 - \sum\nolimits_{j=1}^{n} x_{0j}^{k}\right) \cdot \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=1}^{n} x_{ij}^{k} = 0,\ \forall k = 1, 2 \ldots m \tag{6}$$

$\sum\limits_{j=1}^{n} x_{0j}^{k} = 1$ represents the departure of vehicle k from the distribution center when assigned the distribution task; $\sum\limits_{i=0}^{n} \sum\limits_{j=0}^{n} x_{ij}^{k} = 0$ means that vehicle k does not participate in this delivery, and formula (6) stipulates that at least one is right. Vehicle k participating in the delivery must start from the distribution center, otherwise, vehicle k will not participate in this delivery.

2) The load constraints. The total order demand of each vehicle service node cannot exceed the vehicle load limit, is expressed as:

$$\sum\nolimits_{i=0}^{n} \sum\nolimits_{j=1}^{n} x_{ij}^{k} \cdot q_j \le l_k,\ \forall k = 1, 2 \ldots m \tag{7}$$

In addition, the principle of capacity saving needs to be considered:

$$l_k - \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=1}^{n} x_{ij}^{k} q_i \le l_{k'} - \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=1}^{n} x_{ij}^{k} q_i, \forall k, k' = 1, 2 \ldots m \tag{8}$$

3) Orders delivery time constraints. Considering the complexity of rural roads, the time of vehicles passing through the roads is affected not only by the speed, but also by the static road conditions:

$$t_{ij}^{k} = d_{ij} r_{ij} / v^{k},\ \forall i = 0, 1 \ldots n,\ j = 1, 2 \ldots n,\ i \ne j,\ k = 1, 2 \ldots m \tag{9}$$

In the real logistics distribution problems, the time of order delivery to reach the service node also has a certain timeliness. Since the distribution route of the vehicle starts from the distribution center, so:

$$a_0 = 0 \tag{10}$$

When the service time of the latest node is known, the service time of the next node to be accessed can be calculated as:

$$a_j = \sum\nolimits_{i=0}^{n} \sum\nolimits_{k=1}^{m} \left(t_{ij}^{k} + a_i\right) \cdot x_{ij}^{k},\ \forall j = 1, 2 \ldots n \tag{11}$$

The maximum time limit for order arrival is expressed as:

$$a_i \le \delta,\ \forall i = 1, 2 \ldots n \tag{12}$$

4) Satisfaction constraint on the time of order delivery. The smaller the time for the order to reach the service node, the higher the customer satisfaction of the service node. Let function $T(a_i)$ represent the satisfaction related to a_i:

$$T(a_i) = \begin{cases} 1 & 0 \le a_i < \beta \\ 2 \cdot \sqrt{\frac{a_i - \delta}{\beta - \delta}} - 1 & \beta \le a_i \le \delta \end{cases}, \ \forall i = 1, 2 \ldots n, \delta > \beta \tag{13}$$

5) Satisfaction weight constraint on the service node. The weight of each service node needs to be calculated first. The larger the order requirement for a service node, the heavier the node is:

$$\lambda_i = q_i / \sum_{i=1}^{n} q_i, \ \forall i = 1, 2 \ldots n \tag{14}$$

3.2 Improved Genetic Algorithm

The improved model-solving algorithm based on the genetic algorithm mainly includes six steps:

(1) Initial coding design

A segmentation operation was added after the initial coding to interpret the code as schemes.

First, the n service nodes are respectively coded as $1, 2 \cdots n$, and then a random sequence of codes from 1 to n was randomly selected to form a chromosome, in which each code contained in the chromosome could be called a gene locus.

For example, 6 villages $\{C_1, C_2, C_3, C_4, C_5, C_6\}$ are considered as service nodes, coding by 1 to 6, then a random arrangement among 6 nodes such as (3, 5, 4, 1, 2, 6) is selected as a chromosome, and "4" in the chromosome indicates the third gene locus.

Then considering the load limit of different types of vehicles, chromosome is segmented. The specific segmented operation can include:

Step 1: Select the vehicle model and a service order participating in the distribution;

Step 2: According to the load limit of different types of vehicles and the initial code segmented. A feasible solution is formed.

For example, it assumes that there are two types of delivery vehicles V_{s_1} and V_{s_2} with load limit l^{s_1} and l^{s_2}, and the order demands of the six service nodes are q_1, q_2, q_3, q_4, q_5 and q_6. If the vehicles are selected as V_{s_1} first and V_{s_2} later, with the inequality $q_3 + q_5 \le l^{s_1} \le q_4 + q_1 + q_2 + q_6 \le l^{s_2}$, the scheme can be determined as:

Route $0 \to 3 \to 5$ with V_{s_1}; route $0 \to 4 \to 1 \to 2 \to 6$ with V_{s_2}.

It should be noted that when the order of vehicles involved in delivery varies, even the same chromosome divided, schemes can be different.

Function building.

The objective value of each target is normalized to take the sum as the relative fitness. The larger the relative fitness is, the better the individual will be.

Specifically, h^w is an individual segmented from the same chromosome, w is the number of the individual in the population. z_u^w is the u-th target value of h^w. For a single target, the normalized target value of h^w is $\overline{z}_u^w = \frac{|z_u^w - z_u^{min}|}{z_u^{max} - z_u^{min}}$, where z_u^{max} and z_u^{min} represent the optimal and worst values of h^w. Then add different normalized target values up to get the relative fitness of h^w is $Z^w = \sum_{u=1}^{3} \overline{z}_u^w$.

(3) Selection policy

First, the optimal individuals are selected into the offspring, and then the roulette selection method is selected for individuals, these individuals through a certain probability of crossover and variation operation to obtain new individuals, forming the offspring population. The individual of the parental population is set as $\{h^1, h^2 \cdots h^N\}$. All the individuals in the parental population are arranged from the largest to the smallest according to the relative fitness Z^w, that is, $Z^{s(1)} \geq Z^{s(2)} \geq \cdots \geq Z^{s(N)}$, where $s(i) = w$ is a displacement on the serial number set $\{1, 2 \cdots N\}$ of the individual population.

Then, $h^{s(1)}$ is directly selected into the offspring population, and then for the remaining individual $\{h^{s(2)}, h^{s(3)} \cdots h^{s(N)}\}$, the relative fitness $Z^{s(i)}$ are used as the parameter for roulette, and the probability of individual $h^{s(i)}$ being selected is $r^{(i)} = \frac{Z^{s(i)}}{\sum_{x=2}^{N} Z^{s(i)}}$, $i = 2, 3 \cdots N$.

(4) Cross operation

For two crossed paternal chromosomes, the starting and ending points of genes are firstly selected, and the selected fragment of one chromosome is reserved as daughter chromosome, while the location of the genes not selected are left blank.These genes are then removed on another chromosome, and the remaining genes are sequentially extracted to fill in the blank of the left child chromosome, and the child chromosome is obtained. It should be noted that this crossover method will generate two chromosomes in offspring.

For example, chromosome $X(3, 5, 4, 1, 2, 6)$ and chromosome $Y(4, 6, 2, 5, 3, 1)$ are the paternal chromosomes. If the gene points 2 and 4 are selected, the fragment of chromosome X is obtained and the remained positions are left blank like (0, 5, 4, 1, 0, 0). After removing the genes on the fragment of chromosome Y, it becomes (0, 6, 2, 0, 3, 0). Then, 6,2 and 3 are filled in the fragment in sequence to obtain a daughter chromosome (6, 5, 4, 1, 2, 3). Another one (3, 6, 2, 5, 4, 1) can be obtained by swapping paternal chromosomes (4, 6, 2, 5, 3, 1) and (3, 5, 4, 1, 2, 6).

(5) Variant operation design

The mutation frequency is p_m, and a random selection and swap strategy is used, where two gene sites are selected on the chromosome and switched positions. If the

Table 1. Distance between the center and nodes (km)

	0	1	2	3	4	5	6	7	8	9
0		1	1.8	1.3	1.1	1.8	*M*	1.6	*M*	*M*
1	1		*M*	*M*	*M*	*M*	1	1.8	1.2	1.6
2	1.8	*M*		1.2	*M*	*M*	1.5	*M*	*M*	*M*
3	1.3	*M*	1.2		*M*	*M*	*M*	*M*	*M*	*M*
4	1.1	*M*	*M*	*M*		0.7	*M*	0.7	*M*	*M*
5	1.8	*M*	*M*	*M*	0.7		*M*	*M*	*M*	*M*
6	*M*	1	1.5	*M*	*M*	*M*		*M*	*M*	1
7	1.6	1.8	*M*	*M*	0.7	*M*	*M*		2	*M*
8	*M*	1.2	*M*	*M*	*M*	*M*	*M*	2		1.5
9	*M*	1.6	*M*	*M*	*M*	*M*	1	*M*	1.5	

new chromosome after mutation is different from any existing individuals in the offspring population, the individuals segmented will be added to the offspring population; otherwise, no subsequent more segmented operation is required.

(6) End condition

The best one remains in the population after o generations genetic iteration. "o" generally takes a larger number to ensure that the convergence result doesn't fall into a local optima.

4 Example Analysis

4.1 Example Background

There are 9 villages around P Town, D Community selected as background. Only D community has basically completed the urbanization and can accept large quantities of goods transfer. The other villages are decentralized and the rural roads are only for small vehicles. The consumption level and road conditions of each village are also different. A distribution center in D is responsible for arranging vehicles and routes for distribution to 9 villages to serve customers. The ideal time β for order delivery is 20 min and the maximum time limit δ is 1 h from the vehicle leaving the center. Two kinds of distribution vehicles: tricycle and van with different speed, load and rental cost respectively.

4.2 Basic Data

The distance between nodes unconnected is written by M. In calculating, it takes a value that obviously bigger than the real distance. And "10" is chosen (Tables 1 and 2).

Table 2. Road conditions between center and nodes

	0	1	2	3	4	5	6	7	8	9
0		1	1	1	1	1	0	1	0	0
1	1		0	0	0	0	1.1	1.1	1.3	3
2	1	0		1.4	0	0	1.1	0	0	0
3	1	0	1.4		0	0	0	0	0	0
4	1	0	0	0		1.4	0	1.2	0	0
5	1	0	0	0	1.4		0	0	0	0
6	0	1.1	1.1	0	0	0		0	0	1.1
7	1	1.1	0	0	1.2	0	0		1.2	0
8	0	1.3	0	0	0	0	0	1.2		1.2
9	0	3	0	0	0	0	1.1	0	1.2	

Table 3. Order demand for each service node

node	1	2	3	4	5	6	7	8	9
Demand	30	20	20	10	30	10	20	30	10

Table 4. Speed and load parameters of each vehicle type

vehicle type	Average speed (km / h)	Load (parts)
tricycle	15	50
van	20	80

The road conditions between nodes unconnected is recorded as "0", but still counted as "1" in the algorithm to avoid high fitness (Tables 3 and 4).

With the information provided, the algorithm takes $N = 100$, $p_c = 0.6$, $p_m = 0.2$, $o = 100$. The solution of distribution task is:

Vehicle 1 is a van, route $0 \rightarrow 5 \rightarrow 4 \rightarrow 7$;

Vehicle 2 is a van, route $0 \rightarrow 1 \rightarrow 8 \rightarrow 9$;

Vehicle 3 is a tricycle, route $0 \rightarrow 3 \rightarrow 2 \rightarrow 6$.

4.3 Analysis to the Effectiveness

As the results of classical genetic algorithm may fall into the local optimal, in order to determine the effectiveness of the proposed improved genetic algorithm, an accurate algorithm is designed for this example with few service nodes, simple parameters and low difficulty of calculating.

The accurate algorithm finds out all the legal schemes that meet the constraints by exhaustive method, and puts all legal schemes into the same group for comparison. The steps of the accurate algorithm are given:

Step 1. According to the connectivity between the distribution center and each service node in the example, there is $D(C_i) = \left\{ C_j \cdot \sum_{k=1}^{m} x_{ij}^k \right\}, i = 0, 1 \cdots n, j = 1, 2 \cdots n$, which represents the set of service nodes connected with C_i.

Step 2. Assign the route. After the nearest service node C_i, select node C_i in set $D(C_i)$ as the next node of the route and decide whether to terminate the route. The starting point of each route is C_0.

Step 3. Get a reasonable route under the condition of meeting the load and time constraints, and then extract all legal routes in the method of tree decision, and be included in the legal route set.

Step 4. Remove the route containing "nodes covered by the route in the current scheme" in the legal route set, and then select one of the remaining routes in the collection for the current scheme until the route in the scheme covers all service nodes. If all the routes in the collection have been eliminated, the current scheme is illegal.

Repeat Step 4 until all feasible schemes are exhaustive. The total mileage, total satisfaction and total vehicle's departure times target values of each scheme are added up to obtain the relative fitness.

Further, through the algorithm, 10 kinds of feasible schemes come. Based on the evaluation in 3.2, the optimal solution is:

Vehicle 1 is a van, route $0 \rightarrow 1 \rightarrow 8 \rightarrow 9$.

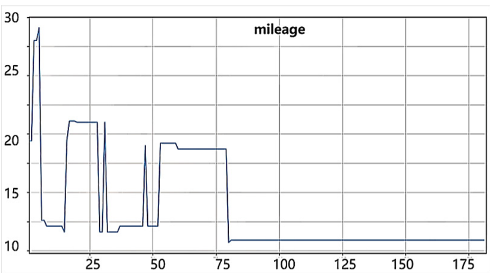
Vehicle 2 is a tricycle, route $0 \rightarrow 3 \rightarrow 2 \rightarrow 6$.

Vehicle 3 is a van, route $0 \rightarrow 5 \rightarrow 4 \rightarrow 7$.

It can be found the results of the two algorithm is equivalent, proving that the improved genetic algorithm brings the optimal solution in this case.

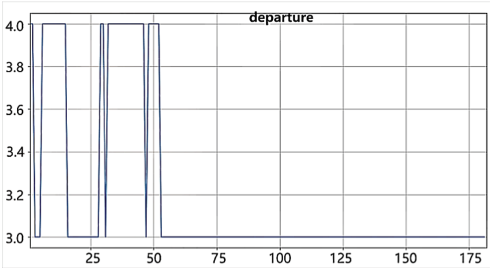
5 Results Analysis

The changes of each target for generations during the iterative process of the improved genetic algorithm are plotted as line diagrams shown in Fig. 1 including five figures.

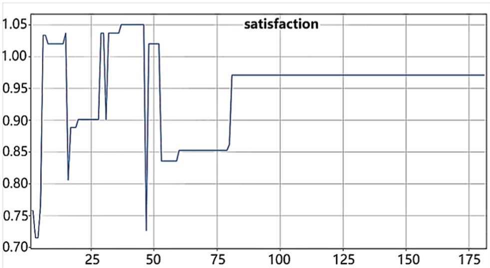


(a) Total mileage change chart

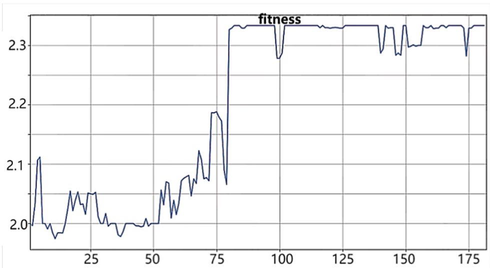
Fig. 1. Change plot of each target value of the successive optimal individual



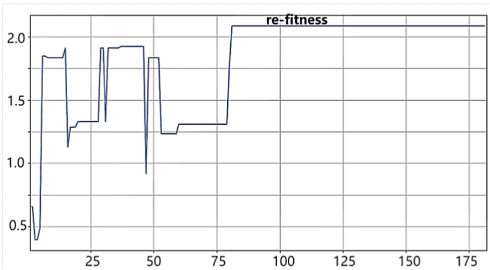
(b) departure times change chart



(c) customer satisfaction change chart



(d) fitness change chart



(e) Fitness change chart after re-normalization

Fig. 1. (*continued*)

Figure 1(a)–1(c) respectively show "the minimum total mileage", "the least departure times", "the maximum total customer satisfaction with weight" the target value of iterations. Figure 1(d) shows the relative fitness of the best individual in each generation. Figure 1(e) shows the relative fitness in the set of the best individuals among generations.

According to Fig. 1, conclusions are obtained:

1) The overall optimal solution after iteration is not necessarily optimal in a single goal, and the optimal solution is often the individual who is always close to the best in all dimensions.
2) The set of end condition avoids the deviation caused by "accidental variation" near the end condition. From Fig. 1(e), although an individual comes in a worse direction at about 50th iteration, after 80th iteration, it will be eliminated, and the population will eventually get a more stable one.

6 Conclusion

Compared with previous studies, the uniqueness of rural distribution is taken into account: (1) the static road conditions and limited adjacency, (2) the customer satisfaction associated with the arrival time to measure service quality.

This paper mainly measures cost by the mileage and vehicle's departure times. But in actual rural distribution, there may be more factors affecting the cost, such as vehicles renting and return cost. So the next step is to study the cost quantification of the distribution schemes based on the proposed multi-objective 0–1 nonlinear planning model.

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