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# Solving Vehicle Routing Problem in the Logistics Distribution Based on Immune Genetic Algorithm

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# Solving Vehicle Routing Problem in the Logistics Distribution Based on Immune Genetic Algorithm

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**Abstract:** In logistic transport industry, individual demands and diversity requirements are matters in transport operation; this paper focused on solving vehicle routing problem (VRP) by using the immune genetic algorithm (IGA). In this algorithm, firstly, establish the mathematical model of VRP. Secondly, design the IGA of which use natural number coding method to encode antibodies; apply R continuous method to calculate the affinity between antibodies; use the roulette wheel selection method to select good individuals; adopt partial matching method to improve the crossover operation; use simple inversion mutation method for mutation operation. Finally, example analysis proves that using the IGA can find out the optimal path quickly and efficiently.

Keywords: model, immune genetic algorithm, vrp, example analysis

## 1. INTRODUCTION

In today's era of electronic commerce, the global logistics industry has a new development trend. The core aim of modern logistics service is meeting the needs of customers with the minimum comprehensive cost. And in many factors of reducing the logistics cost, the proportion of distribution costs is particularly prominent. Thus, vehicle routing optimization is still a hot research topic in the field of logistics.

Currently, the research methods of VRP mainly include accurate algorithm, heuristic algorithm and intelligent optimization algorithms. Such as, Chunyu Ren and Shiwei Li [1] have designed a new genetic algorithm to solve the VRP. Baozhen Yao [2] has found the optimal path of VRP, quickly and efficiently, with the improved particle swarm algorithm; Ulrich Derigs [3] has applied hybrid heuristic algorithm to solve the complicated nonlinear VRP, Jianru Zheng [4] has introduced the improved particle swarm optimization algorithm in detail, simulated the VRP and found out the optimal path; In matlab environment, using the genetic algorithm is proposed by Xiuhong Guo [5] for VRP with optimal solutions, effectively reduce the transportation cost of distribution. Huayu Shi [6] has proposed the improved ant colony algorithm to shorten the total distance of vehicle distribution, optimized the logistics distribution vehicle routing, and reduced the transportation cost. According to the mathematical model of logistics distribution VRP and specific feature, Xiangli Ma and Huizhen Zhang [7] has designed bat algorithm for solving VRP problems, and verified the effectiveness and feasibility of the bat algorithm for solving VRP through simulation examples and comparison with particle swarm optimization (PSO) algorithm. In vehicle routing problem, however, IGA is used rarely. In the design of IGA, the calculation of the affinity between antibody and antibody is often the way of information entropy, which makes the computation complexity increase. So, in this paper, in the matlab environment, IGA is designed with R continuous method to calculate the affinity of antibodies that the calculation process is simplified, and compared with genetic algorithm, the immune genetic algorithm is proved to be able to solve the VRP, quickly and efficiently, by the example analysis.

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## 2. MATHEMATICAL MODEL OF VRP IN LOGISTICS DISTRIBUTION

In logistics distribution, the objective of VRP is to arrange several vehicles to a lot of customers from the distribution center and return to the common distribution center without exceeding the capacity of each vehicle at minimum cost. Each customer's geographical position and demand and the loading capacity of every vehicle must be certain. It requires a reasonable planning of vehicle routing so that the total transport distance is the shortest, and that meets the following conditions:

(1)The sum of customers' demands on the each path is less than the capacity of a vehicle;

(2)The total distance of each distribution path is less than the maximum transport distance of a vehicle;

(3)Meet the needs of each customer, and each customer's demands can only be distributed by a vehicle;

(4)The amount of transport is proportional to the cost;

(5)The number of vehicles in the distribution center, the capacity and the maximum transport distance of each vehicle, the number of customers, the demands of each customer and the transportation distance between the distribution center with the customers are all known constants.

VRP mathematical model [5] [8] of logistics distribution is established by reference [5] and [8] and taking the constraints and optimization of VRP in the logistics distribution into account.

Hypothesis that there are $k$ vehicles in the distribution center, the loading capacity of vehicle $k$ is $Q_k$ ( $k = 1, 2, ..., K$ ), and the maximum transport distance of a distribution is $D_k$ , need to deliver to $L$ customers, customer $i's$ demand amount is $q_i$ ( $i = 1, 2, ..., L$ ), the linear distance from customer $i$ to customer $j$ is $d_{ij}$ , the distance from the distribution center to customer $j$ is $d_{0j}$ ( $i, j = 1, 2, ..., L$ ); Hypothesis that the number of customers distributed by vehicle $k$ is $n_k$ ( $n_k = 0$ shows the vehicle $k$ is not involved in distribution), $R_k$ shows the customers' aggregation in path $k$ , and the element $r_{ki}$ shows the sequence of customer $r_{ki}$ is $i$ in path $k$ , which does not include the distribution center. Hypothesis that $r_{k0} = 0$ shows the distribution center, then the VRP model can be established as follows:

$$\text{Min } Z = \sum_{k=1}^{K} \left[ \sum_{i=1}^{n_k} d_{r_{k(i-1)} r_{ki}} + d_{r_{kn_k} r_{k0}} * sign(n_k) \right] \tag{1}$$

Constraints:

$$s.t. \quad \sum_{i=1}^{n_k} q_{r_{ki}} \le Q_k \tag{2}$$

$$\sum_{i=1}^{n_k} d_{r_{k(i-1)} r_{ki}} + d_{r_{kn_k} r_{k0}} * sign(n_k) \le D_k \tag{3}$$

$$0 \le n_k \le L \tag{4}$$

$$\sum_{k=1}^{K} n_k = L \tag{5}$$

$$R_k = \left\{ r_{ki} \middle| r_{ki} \in \{1, 2, 3, ..., L\}, i = 1, 2, 3, ...n_k \right\} \tag{6}$$

$$R_{k1} \cap R_{k2} = \varnothing \qquad \forall k1 \ne k2 \tag{7}$$

$$sign(n_k) = \begin{cases} 1, & n_k \ge 1 \\ 0, & other \end{cases} \tag{8}$$

In the above VRP mathematical model of logistics distribution, formula (1) is the objective function; formula (2) shows the sum of customers' demands on the each distribution path is less than the loading capacity of a vehicle; formula (3) shows the total distance of each distribution path is less than the maximum transport distance of a vehicle; formula (4) shows the number of customers in each path is less than the total number of customers; formula (5) shows each customer obtains the distribution; formula (6) is the set of customers in each path; formula (7) ensures that each customer's demands can only be fulfilled once by one vehicle; formula (8) shows if the number of customers distributed by vehicle $k$ is more than 1, the vehicle $k$ takes part in the distribution and $sign(n_k) = 1$, or the vehicle $k$ does not take part in the distribution and $sign(n_k) = 0$.

## 3. SOLVING VRP WITH IMMUNE GENETIC ALGRITHM

### 3.1 Introduction of immune genetic algorithm

Immune genetic algorithm is a kind of improved genetic algorithm based on biological immune system, which antigen corresponds to the objective function for solving practical problems, and the antibody corresponds to the solution of actual problem. This algorithm is a new optimization combination method which is based on the genetic algorithm and the learning, adaptability and memory function and other characteristics of the biological immune system. This algorithm finds a broader space for complex problems.

### 3.2 Immune genetic algorithm for VRP in logistics distribution

Immune genetic algorithm flow chart [9] is shown in figure 1.

Specific methods and steps of immune genetic algorithm:

(1)Antibody-encoding

According to the characteristics of logistics distribution VRP, this paper uses a simple natural number coding method to encode antibody. First, generate the non repetition natural number 1,2,…,M,M+1,…,M+K-1 which 0 denotes the distribution center, 1,2,…,M denote customers and K denotes the total number of vehicles, then permutate the M+K-1 numbers randomly to form an individual. For example, if there are 2 vehicles to 8 customers for delivery, it generates the natural number1,2,…,9 which 9 denotes the distribution center and permutates the 9 numbers to form a logistics distribution path. The individual 126398547 represents there are 2 distribution paths which one is 0-1-2-6-3-9 (0) and the other is 9 (0)-8-5-4-7-0.

(2)Generation of initial population

If the memory is not empty, the initial antibody population is selected from the memory database, otherwise, it will be generated by the feasible solution space. Antibody memory function is an important characteristic of immune optimization algorithm, and the system can keep some better individuals after solving a problem. When each generation of antibody updates, the optimal m antibodies are retained in the memory database and compared with the existing antibodies in its memory, then replace the poor antibodies.

(3)Fitness calculation of antibody.

If the distribution path corresponding to the antibody $v$ is feasible, the fitness value of the antibody $v$ is $F_v = 1/Z_v$, otherwise the fitness value is $F_v = 1/(Z_v + \alpha)$, $\alpha$ which is overweight value is 4000 in this paper.

(4)Immune operation

① Selection operation: Adopt the roulette wheel selection method to select antibody. The selected probability of antibody $v$ is expectation reproduction rate calculated by the formula (12).

② Crossover operation: In this paper, a partial matching method (PMX) is used for crossover operation. Randomly select two chromosomes in father generation. Take father (2 4 5 3 8 7 1 6) and father (8 5 1 2 7 6 3 4) for example: first, select two crossing points randomly, then the numbers between the two points are crossed, and the other numbers are replaced by the matching number or the copy. In this example, assuming the position of the first crossing point is 4, and the position of the second crossing point is 6, then 3, 8, 7 are selected in the father 1 and 2, 7, 6 are selected in the father 2, so 3 matches with 2, 8 matches with 7, 7 matches with 6. The matching process is shown in figure 2.

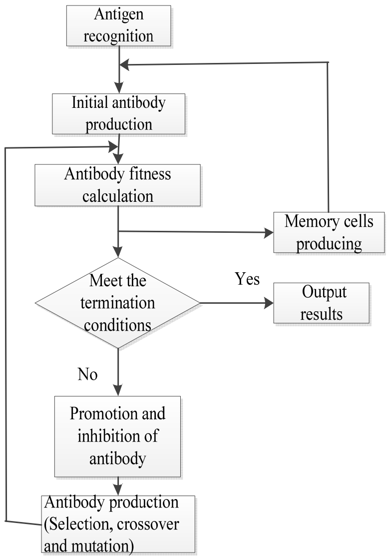


**Figure 1. Immune optimization algorithm flow**

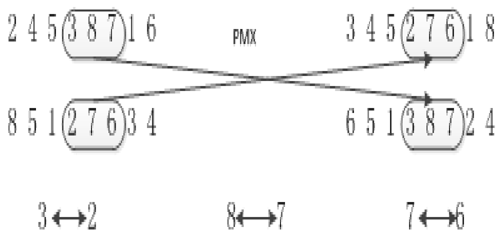


**Figure 2. PMX crossover operation**

③ Mutation operation [10]: Use simple inversion mutation method for mutation operation in this paper. Firstly, select a mutated individual according to the mutation probability. Secondly, select a string of genes from the mutated individual , then put the string of genes inversion. For example, if a mutated individual is 12345678 and the selected genes are 3,4,5, then this individual is 12543678 after mutation operation.

(5)The diversity of the solution

① Affinity between antibody and antigen

The recognition degree of antibody to antigen is expressed by the affinity between antibody and antigen. In this paper, for the logistics distribution vehicle routing optimization model, the fitness function $F_v$ of antibody $v$ is regarded as the affinity function $A_v$

$$A_v = \frac{1}{Z_v} \tag{9}$$

$Z_v$ is objective function.

② Affinity between antibody and antibody

The affinity between antibody and antibody is reflected by the similarity between antibodies. In this paper, the affinity between antibody and antibody is calculated by R continuous method which R is the threshold for the affinity determination.

If the same numbers are more than R in two encoded individuals, then it means the two antibodies are almost the same, otherwise it means the two antibodies are not the same. In this paper, antibodies are encoded without considering sorting and the affinity between antibody and antibody is calculated by deformed R continuous method.

$$S_{v,s} = \frac{k_{v,s}}{L} \tag{10}$$

$k_{v,s}$ is the same number between antibody $v$ and antibody $s$ ; $L$ is the length of antibody. For example, if the antibody $v$ is [3,7,15,21,6,11] and the antibody $s$ is [10,8,14,26,6,3], then there are two same values, so the affinity $S_{v,s}$ between antibody $v$ and antibody $s$ is 0.33.

③ Antibody concentration

The antibody concentration $C_v$ is the proportion of similar antibodies in the population.

$$C_v = \frac{1}{N}\sum_{i\in N} S_{v,s} \tag{11}$$

$N$ is the total number of antibody. $S_{v,s} = \begin{cases} 1, & S_{v,s} > T \\ 0, & else \end{cases}$; In this paper, $T$ which is a preset threshold is 0.9.

④ Expectation reproduction probability

In population, the expectation reproduction probability of each individual is decided by the affinity $A_v$ between antibody and antigen and the concentration $C_v$ of antibody.

$$p = \alpha \frac{Z_v}{\sum Z_v} + (1-\alpha)\frac{C_v}{\sum C_v} \tag{12}$$

In this paper, $\alpha$ which is constant is 0.95.

The formula (12) shows that the higher the affinity, the higher the expectation reproduction probability and the higher the concentration, the lower the expectation reproduction probability. This is not only to promote the high affinity antibodies, but also inhibit the high concentrations antibodies, so as to ensure the diversity of antibodies.

## 4. EXAMPLE ANALYSIS

There are 8 customers and a distribution center. The demand of customer $i$ is $q_i$（$i$=1,2,…,8）which the unit is t. There are 2 vehicles to participate in the distribution in distribution center. The maximum driving distance of each vehicle which the loading capacity is 9t is 45km in each distribution. The distance between the distribution center and every customer, the distance between customers, the demand of every customer are shown in table 1 which customer 0 expresses the distribution center. The following simulation experiment parameters [8] are used.

**Table 1. The distance and the demand information of customers**

| $d_{ij}$ | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 4 | 6 | 7.5 | 9 | 20 | 10 | 16 | 8 |
| 1 | 4 | 0 | 6.5 | 4 | 10 | 5 | 7.5 | 11 | 10 |
| 2 | 6 | 6.5 | 0 | 7.5 | 10 | 10 | 7.5 | 7.5 | 7.5 |
| 3 | 7.5 | 4 | 7.5 | 0 | 10 | 5 | 9 | 9 | 15 |
| 4 | 9 | 10 | 10 | 10 | 0 | 10 | 7.5 | 7.5 | 10 |
| 5 | 20 | 5 | 10 | 5 | 10 | 0 | 7 | 9 | 7.5 |
| 6 | 10 | 7.5 | 7.5 | 9 | 7.5 | 7 | 0 | 7 | 10 |
| 7 | 16 | 11 | 7.5 | 9 | 7.5 | 9 | 7 | 0 | 10 |
| 8 | 8 | 10 | 7.5 | 15 | 10 | 7.5 | 10 | 10 | 0 |
| $q_i$ | | 1 | 2 | 1 | 2 | 1 | 4 | 2 | 2 |

The population size is 50, the encoding length is 9, the crossover probability is 0.95, the mutation probability is 0.05, and the diversity evaluation parameter is 0.95.

When the evolution algebra is 20, 50 and 100 respectively, the results of the GA and IGA are shown in table 2, table 3 and table 4. And the convergences of the solution are shown in figure 3, figure 4, figure 5, figure 6, figure 7 and figure 8.

(1)When the evolution algebra is 20, the results of the GA and IGA are shown in table 2, which the number

0 expresses the distribution center. The optimal solution, the worst solution, the average solution with IGA are all better than with GA, and the number of occurrence of optimal solution with IGA is more than with GA. From figure 3 and figure 4, it can be seen that the IGA is earlier than the GA to converge to the optimal solution.

**Table 2. Results of genetic algorithm and immune genetic algorithm**

| | Optimal results | The worst results | Average results | The number of optimal results | Logistics distribution plan |
|---|---|---|---|---|---|
| GA | 70.5 | 82 | 74.6 | 2 | 03561082740 |
| IGA | 69.5 | 70 | 69.75 | 10 | 02731046580 |

Logistics distribution plan of GA: vehicle1: 0-3-5-6-1-0, vehicle2: 0-8-2-7-4-0.

Logistics distribution plan of IGA: vehicle1: 0-2-7-3-1-0, vehicle2: 0-4-6-5-8-0.

(2)When the evolution algebra is 50, the results of the GA and IGA are shown in table 3, which the number 0 expresses the distribution center. Although it is shown the GA is earlier than the IGA to converge to the optimal solution in figure 5 and figure 6, the optimal solution, the worst solution, the average solution with IGA are all better than with GA, and the number of occurrences of optimal solution with IGA is more than with GA.

**Table 3. Results of genetic algorithm and immune genetic algorithm**

| | Optimal results | The worst results | Average results | The number of optimal results | Logistics distribution plan |
|---|---|---|---|---|---|
| GA | 69.5 | 72 | 70.38 | 4 | 01356047280 |
| IGA | 68 | 71 | 68.54 | 25 | 01356804720 |

Logistics distribution plan of GA: vehicle1: 0-1-3-5-6-0, vehicle2: 0-4-7-2-8-0.

Logistics distribution plan of IGA: vehicle1: 0-1-3-5-6-8-0, vehicle2: 0-4-7-2-0.

(3)When the evolution algebra is 100, the results of the GA and IGA are shown in table 4, which the number 0 expresses the distribution center. Although the optimal solution of IGA is the same as GA, the number of occurrences of optimal solution with IGA is more than the number of occurrences of optimal solution with GA and the worst solution, the average solution with IGA are all better than with GA, and it is shown that the IGA is earlier than the GA to converge to the optimal solution in figure 7 and figure 8.

**Table 4. Results of genetic algorithm and immune genetic algorithm**

| | Optimal results | The worst results | Average results | The number of optimal results | Logistics distribution plan |
|---|---|---|---|---|---|
| GA | 67.5 | 79 | 69.205 | 69 | 02853104760 |
| IGA | 67.5 | 68.5 | 67.565 | 91 | 02853106740 |

Logistics distribution plan of GA: vehicle1: 0-2-8-5-3-1-0, vehicle2: 0-4-7-6-0.

Logistics distribution plan of IGA: vehicle1: 0-2-8-5-3-1-0, vehicle2: 0-6-7-4-0.

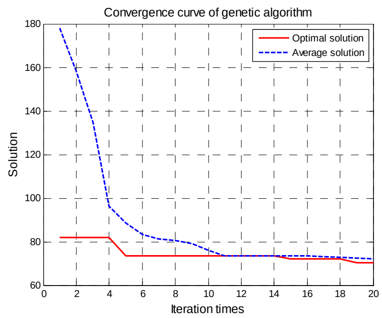


**Figure 3. Convergence curve of GA**

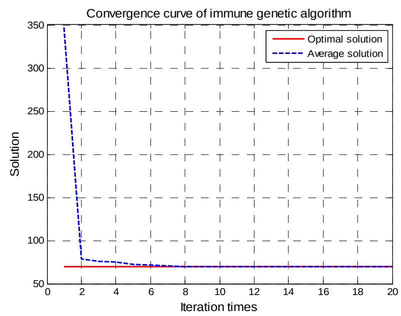


**Figure 4. Convergence curve of IGA**

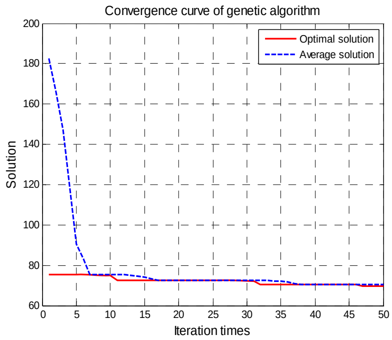


Figure 5. Convergence curve of GA

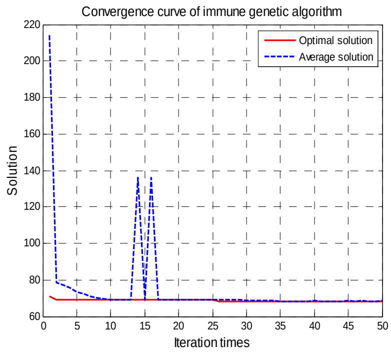


Figure 6. Convergence curve of IGA

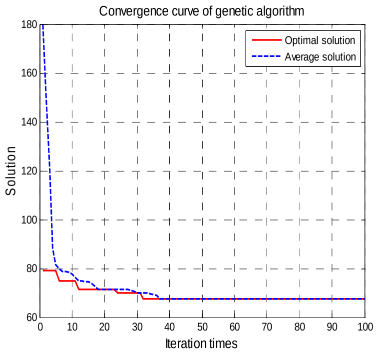


Figure 7. Convergence curve of GA

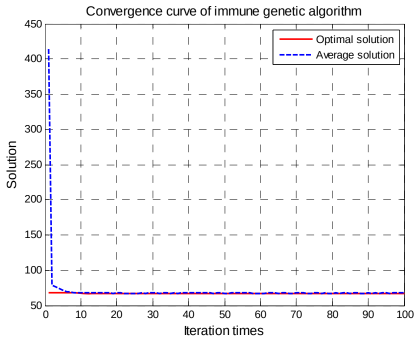


Figure 8. Convergence curve of IGA

From table 2, table 3 and table 4, it can be seen whatever the evolution algebra is, the optimal solution, the worst solution, the average solution with IGA are all better than with GA, and the number of occurrence of optimal solution with IGA is more than with GA. It is shown that the IGA is earlier than the GA to converge to the optimal solution in figure 3 and figure 4, figure 7 and figure 8. So IGA is superior to GA in vehicle routing problem.

## 5. CONCLUSIONS

Based on example analysis, the IGA is more quickly and efficiently than the GA to find the optimal solution that is the optimal path of logistics distribution, thus the total distance of logistics distribution is shortened, and the transportation cost is saved. At the same time, compared with the GA, the IGA has the following characteristics: it can maintain the diversity of antibodies and improve local search ability; it has the function of immune memory and self-adjustment and can accelerate the search speed, improve the global search ability, and avoid falling into local solution. Thus, it is more practical significance and value to reduce operating cost and improve economic benefit.

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