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par

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The Vehicle Routing Problem Based on the Immune Algorithm

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Abstract

The Vehicle Routing Problem has been a popular research topic in logistics (Physical distribution) which is of much practical value. This thesis studies has the research technique toward vehicle routing problem and the advantage that the immune algorithm has over other algorithms. It also puts forward the method of solving vehicle routing problem by the immune algorithm. In the solution procedure, this thesis creates a new encoded model which can increase the operational efficiency of the algorithm presented by decreasing the encoding length. Through the design of immune memory data and the accelerating or restraining mechanism of the density between the antibodies, this algorithm enables the multiformity of the solution, avoids convergence to partial optimal solution and at the same time effectively avoids the optimal solution in the process of evolution. The experimental result shows that this algorithm is one effective algorithm solving the problem of vehicle routing which makes it possible to get the optimal solution fast.

Keywords: Vehicle Routing Problem, Algorithm, Immune Algorithm, Genetic Algorithm, Antigen, Antibody, Vaccine, Mutation.

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I wish to express my sincere gratitude to my research associate director, Prof. Fan-Jianhua who helps and guides me in my academic and professional success. This thesis would not be successful without my research supervisor, Prof. Yu-Changyun. He provides me with a substantial amount of help and suggestions throughout my work. Special thanks should be given to Prof. Paul for being a member of my thesis committee. I thank him especially for his key instruction at the opening stage of my thesis and the labor check at the final stage as well. I would also like to thank my classmate Wang Lei for his contributions, my friends and family who helped me with positive affirmation. Thanks to my parents for their unending support and love.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO THE VEHICLE ROUTING PROBLEM (VRP)

The vehicle routing problem has been one of the elementary problems in logistics ever since it was brought forward by Danting [12] in 1959. Because of its wide use and high economic value, it always attracts much attention from scholars at home and abroad.

The vehicle Routing Problem can be described as follows (see **Figure1.1**). Suppose there are M vehicles each of which has a capacity of Q and N customers who must be served from a certain depot. The goods each customer asks for and the distance between them are known in advance. The vehicles start from the depot, supply the customers and go back to the depot. It is required that the route of the vehicles should be arranged appropriately so that the least number of vehicles is used and the shortest distance is covered, and at the same time the following conditions must be satisfied.

(1) The total demand of any vehicle route must not exceed the capacity of the vehicle.

(2) Any given customer is served by one, and only one, vehicule.

(3) Customer delivery can not be split up

Practical applications of VRP(Vehicle routing problem) include logistic distribution, drawing up a bus route, delivery of mail and newspaper, arrangement of time schedule for aviation and railway and the collection of industrial waste[16].

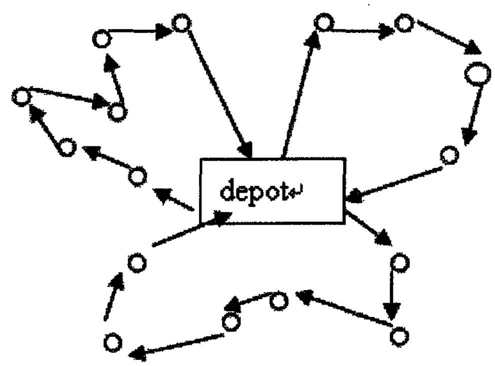

Figure1.1 VRP Abridged General View

1.2 THE IMPORTANCE OF VRP STUDY

Presently globalization, informatisation and unitisation are the developing direction of the logistics industry, and distribution becomes more important in the supply chain. With the characteristics of high frequency, small bulk, versatility and high efficiency in modern distribution, it will fulfill the 7R requirements (right product, right quality, right time, right place, right condition, right customer, right cost).

In many distribution systems, managers have to adopt an effective distributing strategy to increase service level and reduce cost. In the process of distribution transportation, because of the quantity of customers, the complexity of urban communication line, the problems of how to form a perfect line and how to make a collocation of the distribution and the distribution line effectively are the characteristics of distributing transportation as well as a task of great difficulty. Therefore, adopting a scientific and appropriate method to determine the distributing line has become an important way to enhance the benefit of distribution and actualize scientific distribution. So, designing the appropriate, effective vehicle routing program and trying to reduce the number of vehicles and the traveling distance have been very practical questions. One important problem that needs to be solved is the arrangement of the vehicle routing.

The study and application of VRP first originated from the public service occupations such as students' regular bus, bank delivery system, etc. With the development of electronic commerce and logistic distribution industry, VRP has become a problem whose solution urgently needed by commercial enterprises, post express industry and highway distribution.

Thus, VRP being a typical problem of combinational optimization, has become the most popular topic in operations research. Its problem modes have wide application. Studying high efficient intelligence heuristic for VRP has practical importance for enhancing distribution, intelligent communication, and transport movement control, and will render great social and economic benefit.

1.3 THE CONTENT

Meta heuristic has become one of the major approach to solve the VRP such as genetic algorithms, ant colony algorithms, simulated annealing algorithms, etc. The immune approach presents a great advantage over the mentioned ones. [35]. Developing the immune algorithms which simulate principle of immune system for engineering problem solving has become the rising research domain in computation intelligence. Therefore this thesis puts forward a method to solve VRP through the immune algorithm and proves its efficiency by experiment.

The main contents are as follows:

(1) This thesis presents the design of an appropriate encoding method for VRP. Traditional binary encoding has certain defects, while mostly in all the present documentation the encoding scheme is determined by the number of vehicles, and there are some disadvantages such as overlong code length, and complex operation. This paper presents an effective encoded mode to overcome the above shortcoming.

(2) This thesis also presents an efficient vaccine extraction strategy according to the characteristics of VRP. In vehicle routing, the distance between the clients has a direct influence on the traveling distance. So it is necessary to group together the clients close to one another, and supply them with the same vehicle so that the transportation cost can be cut down.

(3) This thesis presents an appropriate design to the memory library to speed up the convergence. In the process of algorithm running, the system can keep some antibodies of high quality after the update of every generation and then put them into the memory library, and replace some antibodies that have worse quality, avoiding the loss of optimal solutions in the evolution process.

(4) In order to search optimal solutions, this thesis employs an appropriate crossover operation and mutation operation. In order to keep the diversity of the antibodies, this thesis promotes the existence of antibodies which have a higher degree of matching with the antigen and at the same time, it also restrains the antibodies with excessive level of density.

(5) This thesis proves the efficiency of the algorithm with experiment and makes a comparison with genetic algorithms.

1.4 STRUCTURE

The remainder of the thesis is organized into the following chapters.

Chapter 2 introduces the actuality and research technique of VRP study, the principle theory of the immune algorithm, the research status of the immune algorithm and the comparison with other algorithm.

Chapter 3 studies the process of solving VRP and the idea and steps of algorithm through the immune algorithm detailedly, including the mathematical model for VRP, antibody encoding, antibody, crossover, mutation and memory library design.

Chapter 4 implements the algorithm through programming tool, verifies the availability of the algorithm and makes a comparison with genetic algorithms.

Chapter 5 draws the conclusion of the main work and experience. It also discusses prospects of future research and points out what needs to be improved in the future.

CHAPTER 2

OVERVIEW OF VRP AND IMMUNE ALGORITHM STUDY

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2.1 THE COMPLEXITY OF VRP CALCULATION

If an algorithm takes $O((n^k)$ time to solve a problem instance of size n in the worst condition where k is a constant, then the algorithm is a polynomial time algorithm. But not all problems have polynomial time algorithm, such as the classical travel salesman problem and 0/1 backpack problem. The currently existing algorithms for these problems are exponential time algorithms. Generally speaking, people consider problems that can be solved by a polynomial time algorithm as simple problems and those that can not be solved by it as hard ones. The computation time of exponential-time algorithms is increasing extremely rapidly as the problem size increases. When the problem scale is large, the practicability of an exponential-time algorithm decreases. As for these questions, though nobody has found polynomial time algorithms to solve these problems until now, still nobody has proved that these problem can not be solved by polynomial time algorithm either, thus these problem fall into the category of NP(Non-Deterministic Polynomial) Hard problems or NP absolute hard problem[6] .

For every travel salesman problem, if the distance between the customers is symmetric, the total amount of the feasible route is (n-1)!/2, and suppose the route comparison is the basic manipulation, there must be (n-1)!/2-1 times basic manipulation to get the absolute optimal solution. When n=20, a computer which operates 1 million times per second need 1929 years to find the optimal solution, so the travel salesman problem belongs to absolute NP hard problem. VRP can also be regarded as an absolute NP hard problem, and it is difficult to find the global optimal solution or satisfying solution,this problem deserves deeper research.[32]

2.2 RESEARCH METHODS OF VRP

For all these years, many scholars have been studying VRP. Scholars overseas began to study VRP as early as late 1950's. They brought forward savings methods to build the vehicles distribution route, and then put forward all kinds of solutions. With the development of logistic distribution industry in our country, research on VRP has also prospered in domestic.[34][23][30]The main research methods of VRP can be divided into exact algorithm, heuristic, and meta heuristic.[25]

2.2.1 Exact algorithm

The exact algorithm can be divided into branch and bound algorithm, direct tree search algorithm and dynamic programming algorithm.

1. Branch and bound algorithm.

Branch and bound algorithm was first introduced by Laporte[19] , which makes use of the relationship between VRP and its relaxation form m-TSP(Traveling salesman problem). According to the upper bound m_t of m given by Lenstra, m-TSP can be transfered into 1-TSP.

2. K-degree central tree and the related algorithm.

This algorithm was introduced by Christofides, etc [9] which give k-opt central tree relaxation to the m-TSP with fixed m,so it is necessary to know the lower bound of the number of vehicle needed. This mode is built through the angle of sides, starting from the k sides, the other two spots are depicted with 2 sides. By the Lagrange relaxing method, one constrained condition shall be eliminated and the original minimum problem is transformed to 3 sub-minimum problems which are easier to solve, and get the solution.

3. Dynamic programming.

Dynamic programming algorithm is originally introduced by Eilon et a1[10].It is applied at solving VRP with finite number of vehicles and uses recursion method to get the solution. In order to reduce the calculation time, it employs feasibility rule or relaxing course to reduce state computation. This method requires that the transform function is easy to compute, and at the same time the mapping scale should be small to get good lower bound.

Exact algorithm is based on a strict mathematic method. When problem scale is small, it is possible to get the optimum solution. But with the increase of customer number, the solution will increase exponentially. So, it has become an important orientation in solving VRP through heuristic.

2.2.2 Heuristic

The usual VRP heuristic is as follows:

1. Clarke - Wright saving algorithm

This is the earliest algorithm and was introduced by Clarke and Wright, for VRP with indefinite vehicles.[4] The algorithm at first creates the routes of same number as the number of the customers who need visiting. It calculates the travel cost saved after combining 2 routes randomly by $s_{ij}=c_{i1}+c_{1j}-c_{ij}$. After that, give the sequence according to the cost saved. Finally, according to the sequential outcome and the feasibility condition, the routes are combined until one can't find better solution. The time of this algorithm complexity is n^2logn, but it's hard to control the number of vehicle, thus the number of the vehicles needed may exceed that of vehicles available.

2. Sweep algorithm

This algorithm was originally introduced by Wren and Gillett[15] . It is necessary to calculate the polar coordinates of the spots which need to be visited, and give the sequence of them by angle. If the condition agrees with the feasibility condition, each point is merged into different sub-paths according to their angles. At last, optimize the sub-path using the TSP optimization algorithm.

3. Two phrase algorithm

Chrisofides and Mingozzi[8] brought forward two-stage algorithm to solve the constrained VRP and dynamic VRP. The problem solving process is comprised of two phases: on the first phase, initial solution will be generated according to the minimum route rule, then the sub-paths will be optimized with k-opt algorithm respectively; on the second phase, exchange spots within the sub-paths to save total travel cost, then optimize the sub-paths with k-opt algorithm This method is widely used in the study of VRP nowadays.

2.2.3 Meta heuristics

The application of meta-heuristics for VRP appears to be a new trend in 1990's. Some meta heuristics such as Ant Algorithm, Simulated Annealing,Tabu Search, Genetic Algorithm, have successfully solved some problems of VRP.

1.Simulated Annealing

Simulated Annealing, brought forward recently, is a meta heuristic imitating physical annealing process. With simple format, flexible application, high efficiency, and independence on initial solution, it has been applied in solving VRP[1] . The algorithm searches the solution space by imitating the annealing process of metallurgy. Under a certain original temperature, with the descending of the temperature parameter, it can search for target function's global optimal solution in the solution space combined with kick probability, namely, local optimal solution can jump out probabilistically and drive to global optimal solution at last.

2. Tabu Search

Tabu Search was used by Gendreau[14],etc, in solving VRP. Tabu Search is a searching method based on storage structure. Through the introduction of a flexible storage structure (tabu graph) and corresponding taboo rules, this algorithm tries to avoid circuity search, and at the same time remit some good estate tabooed by deprecating rules. Therefore, it enables diversified efficient search and implement global optimal solution.

3. Genetic Algorithm

Genetic Algorithm was first used in solving VRP by Lawrence[20] which can solve VRP with time window as well. The algorithm was first brought forward by Holland in

1975. This method starts with a random chromosome population. The chromosome with high degree of adaptability is selected to undergo crossover operation and mutation operation. The filial generation is different from the father generation, but it inherits some of the genetic factors of the father generation. The process ceases when some special generation is generated or the evolution is convergent.

4. Ant Algorithm

The idea of Ant Algorithm was originally introduced by Colorni in 1992. The inspiration came to him when seeing the phenomenon that ants can always find the optimal route when searching for food. The solution will be obtained by the cooperation of a set of artificial intelligence body called ants. Each ant exchanges information through pheromone scattered in the arc of the graph. Scholars such as Liu Zhishuo[26] put forward a self-adapting ant algorithm which can easily find the better solution and it also has high calculating efficiency.

In the above meta heuristics algorithms, tabu search is an artificial intelligence local search method whose solution is closest to the optimal solution while the operation time remains the longest. Simulated Annealing and ant algorithm have the advantage of high speed, and can give optimal solution to a certain degree. But both of them are only suitable for solving small-scale problems[36]. Standard Genetic Algorithm is easy trapped into the situation of getting local extremum solution and converging to the local optima prematurely[37].

2.3 IMMUNE ALGORITHM

2.3.1introduction

The idea of immune algorithm originated from the imitation of human immune system. Immune system is the basic defense system to resist bacterial virus and other pathogenic gene. Through a set of complicated mechanism, it gives a recombination of the gene and at the same time generates antibody to resist the antigen with the aim of annihilating the antigen. As the defensive system of mammal, immune system plays a vital part in animal's ordinary activity, therefore weakness in immune system will lead the human life to a dangerous situation. Simply speaking, the process of immune system annihilating virus can be depicted as follows: immunocyte identifies antigen, and the corresponding immunocyte is activated, then it clones itself and undergoes super mutation. Finally it annihilates antigen by excrete corresponding antibody. In order to defend human life, immune system must undergo pattern recognition to distinguish antigen from its own molecule and cell. Apart from recognition, the difference between immune system and other inferior biology defense system is that it can learn by itself and it has its own memory ability. Because of the above characteristics, the defense reaction of immune system to the same antigen is faster and stronger in the second time comparing with the first time.

Immune algorithm is a computational model which combines the characteristics of biology immune system and engineering practice. It imitates the immune system of biology, and has high global searching ability as well as great memorial ability. It imitates the immune system of human being. Inspired by human cell theory and network theory, it is able to actualize the function of adapting by itself and generating different antibodies which is similar to the immune system.[21][33]

2.3.2 Principle of immune algorithm

The basic flow of immune algorithm[31] is shown in **Figure 2.1**. In the algorithm, the antigen is actually the problem needed to be solved; it is usually called objective function. And the antibody is one of the solutions, which is usually called the optimized solution to the objective function.

To some extent, the flow of immune algorithm is similar to the one of genetic algorithm. Both of their individual's adaptive value needs to undergo the operation of calculating, selecting, crossover and mutation. But in the immune algorithm there have been added memory data, vaccine and restriction to the density of the antibody. These additions make it possible for the algorithm to convergent to the global optimal solution quickly, and at the same time, they also can avoid getting local optimal solution.

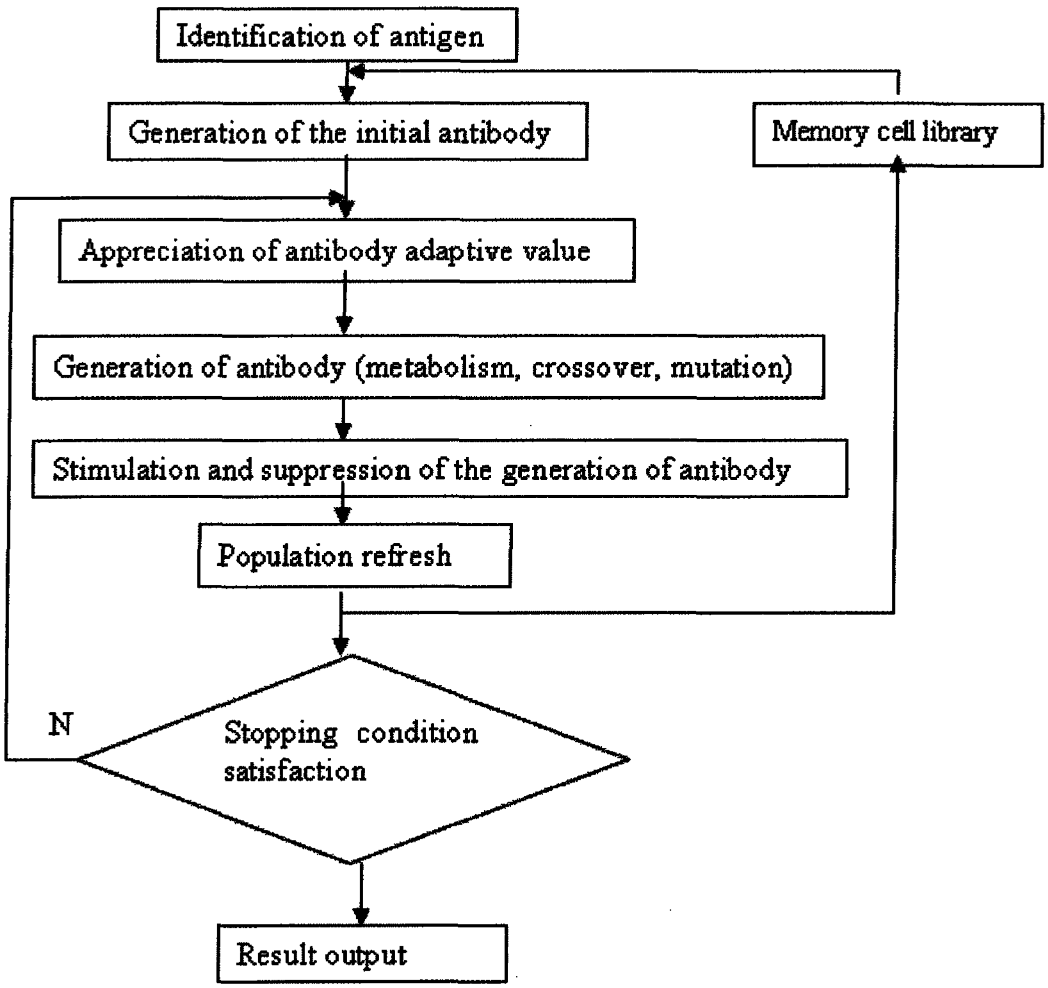

Figure 2.1 The flow chart of immune algorithm

Immune algorithm is a kind of multi-peak value search algorithm that simulates the variety recognition capability against bacteria of immune system. The detailed steps are as follows:

(1) Select appropriate expression and parameters (population scale, crossover rate, mutation rate, density threshold) according to the problem solving.

(2) Based on the memory element in the memory library, create initial solution population. If there is no corresponding memory element in memory library, then create it

randomly.

(3) Give comprehensive evaluation to each solution in the solution population synthetically, including adaptive value (affinity) between solution (antibody) and problem (antigen), semblance (affinity) between solutions.

(4) Perform incremental differentiation operation at solution population according to the overall evaluation of the solution for the generation of the new population.

(5) Estimate whether the pre-specified stopping condition is satisfied. If it is satisfied, terminate the process, and store the problem description and results into memory library, otherwise, repeat step 3 to step 5.

In the studying procedure, the essential element to the immune algorithm includes:

(1) The encoding form of the antibody

(2) The matching rule between antigen and antibody

(3) The evaluating method of antibody

(4) The creation of the new antibody and the formation rule of new population

(5) The design and application of memory library

Therefore whether an immune algorithm can convergent to the global optimal solution at a high speed depends greatly on the fulfillment of the above aspects.

2.3.3 Present State of the Research about immune algorithm

People have studied on the natural phenomenon like heredity and immune widely and deeply in the area of life sciences. In the 1960's, scientists such as Bagley, drawing lessons from the theories and concepts on genetics on the basis of analyzing and studying the former research, applied it to certain fields of engineering science successfully. In the middle of 1980's, professor Holland summarized and popularized former scholars' genetic concepts, and drew the common said Genetic Algorithm. Later on, Farme and other scientists created the dynamic mode of immune system originally basing on the immune network theory. They also discussed the relationship between immune system and other artificial intelligence method, which opened the door to the research on artificial immune system.[11]. However, the outcome of the study remained rare. It was not until December of 1996 that a special forum on immune system was celebrated in Japan for the first time, and the concept "artificial immune system" was first brought forward. After that, the study of artificial immune system prospered. D. Dasgupta (1997) and Ding Yongsheng (2000) considered the artificial immune system the hotspot in the research and application of artificial intelligence field. Thesis and research findings have increased yearly. In 1997 and 1998, both the international conference IEEE Systems and Man and Cybernetics discussed the topic, and later on founded the "artificial immune system and the application branch conference"

The above international academic activities make the study and application of artificial immune system more influential. The research findings have been widely used in automation, failure diagnosis, pattern recognition, image recognition, optimization design, machine learning, associative memory, network security, etc.[3][29][27]

Artificial Immune System (AIS) does not arise the same attention as what artificial neural net evolution algorithm did because of its complexity and because of the fact that people's knowledge about its original biology model remains in the state of deficiency.

Besides, the input in this area is not enough both in our country and abroad, its research and applicable achievement is comparatively small while the achievement applied in the field of VRP is even less.

2.3.4 The merits of immune algorithm

Immune algorithm shares the same merits with random optimization method (such as genetic algorithm and so on), but it also differs from the other random optimization methods. The difference between them is as follows:[13]

(1) The immune algorithm run on the basis of memory element and can guarantee to convergent to global optimal solution at a high speed.

(2) It owns the affinity calculating program which reflects the diversity of the real immune system.

(3) It can reflect the function of self-adjustment in the immune system through accelerating or restraining the creation of antibody.

The above characteristics make the immune algorithm has such additive optimization steps different from other algorithms:

(1) Calculating affinity

(2) Calculating expectation value

(3) Designing memory element

There are two forms for the affinity of immune algorithm: one denotes the relationship between antigen and antibody, namely, the matching degree between solution and objective; the other explains the relationship between antibodies. This particular characteristic ensures the diversity of immune algorithm. The function of the calculation of expectation value is to avoid the possibility of generating too many identical antibodies which are adaptive for the antigen (object). One set of memory element is used to keep one group of antibodies (candidate solution of optimization problem) to defend antigen. So on this basis, immune algorithm is able to convergent to global optimal solution quickly.

Because of the characteristics discussed above, and at the same time since the discussion about VRP in this paper is an NP absolute problem, so immune algorithm is adopted in this thesis to solve VRP

CHAPTER 3

IMPLEMENT OF VRP BASED ON IMMUNE ALGORITHM

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3.1 MATHEMATICAL MODEL OF VRP

The VRP can be described as follows:

n (1,2,…,n)customers must be served in a depot. Customer number k asks for goods of a quantity g_k (k=1, 2… m). Certain amount of vehicles is available to deliver goods. The traveling route with minimum cost which is able to satisfy the following conditions is requested:

(1) The customers should be served by only one vehicle;

(2) The total quantity of the demand from each customer along the vehicle route must not exceed the capacity of the vehicle;

(3) The demand of every customer must be satisfied.

Suppose a depot with vehicles amount to k has the capacity of serving L customers, and each vehicle has a capacity of g_k($k = 1,2,\ldots,K$), while the demand of each customer is d_i ($i=1,2,\ldots,L$) . The travel distance from customer i to customer j is c_{ij}(i=0, 1, … L-1, j=1, 2, … , L,when i is equal to 0, it stands for the depot, namely, the distance between the depot and each customer). n_k is the number of customers vehicle k supplied (if $n_k = 0$,vehicle k is not in use). The set R_k stands for route k and the element of r_{ki} means that customer r_{ki} is the number i in route k. $r_{k0} = 0$ is the depot, so the mathematical model of VRP is :

$$\text{Minimize} \quad \left(\sum_{k=1}^{K} \left(\sum_{i=1}^{n_k} C r_{k(i-1)} r_{ki} + C\, r_{k0} r_{kn_k} * \operatorname{sign}(n_k-1) \right) \right)$$

$$\text{s. t} \quad \sum_{i=1}^{n_k} d r_{ki} \leq g_k \qquad k=1, 2, \ldots K \tag{1}$$

$$0 \leq n_k \leq L \qquad k=1, 2, \ldots K \tag{2}$$

$$\sum_{k=1}^{K} n_k = L \tag{3}$$

$$R_k = \{ r_{ki} | \, r_{ki} \in \{1,2,\ldots,L\}, i=1,2,\ldots n_k \} \tag{4}$$

$$R_{k1} \cap R_{k2} = \Phi \quad \forall \; k_1 \neq k_2 \tag{5}$$

$$\operatorname{Sign}(n_k-1) = \begin{cases} 1 & n_k \geq 1 \\ 0 & \text{otherwise} \end{cases}$$

The inequation (1) above ensures that the total demand of any vehicle route must not exceed the capacity of the vehicle. Inequation (2) indicates that the number of customers on every route must not exceed the total number of the customers; equality (3) requires that every customer must be served; equality (4) denotes the route of each vehicle; equality (5) requires that each customer is supplied by exactly one vehicle.

3.2 THE BASIC STRUCTURE OF THE ALGORITHM

According to the above mathematical model, the objective function and all the constraints can be considered as the antigen, while the antibody is the optimal solution.

Figure 3.1 hows the structure of the immune algorithm for VRP. Every step of the implementation procedure will be depicted:

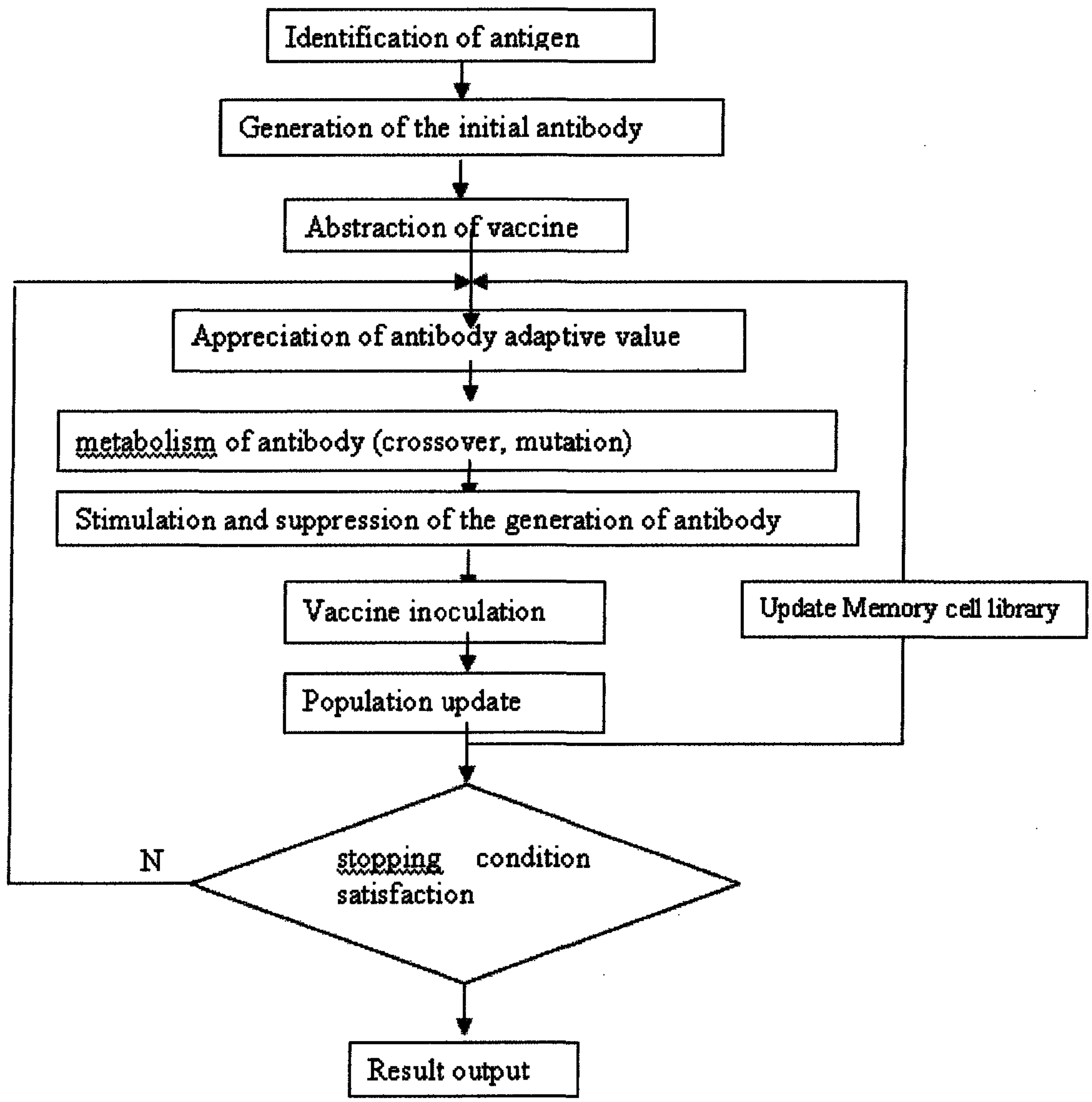


Figure 3.1 The structure of immune algorithm for VRP

3.3 CODING METHOD AND THE GENERATION OF INITIAL ANTIBODY

Presently, the encoding methods of the antibody include binary encoding, real number encoding, character encoding, gray coding and so on.

The antibody can be expressed as binary character string. Looking from the angle of biology, this is a kind of simplification. The identification of antigen and antibody is based on their matching relation. Character string denotes the gene coding of antigen and antibody. One big advantage of binary element string is that it is easy to be achieved. It can also be used to study how minor antibody identify antigen within a larger scale. But binary element string is not adaptive to the VRP discussed in this paper since the application of binary element string here will make the problem complicated. Therefore the integer encoding method is usually applied in solving this problem. The integer encoding forms widely used nowadays in literature are as follows:

3.3.1Encoding methods in literature

1.Jiang Dali and other scholars[17] put forward a theory which employ vector (s_1, s_2, …, s_l) to depict chromosome G. Among them, element (gene) s_j is a certain natural number which doesn't overlap with each other in the range of $[1,k\times L]$, (L is the number of customers,k is the number of vehicles) which expresses the relationship between customer $m=(s_j-[(s_j-1)/L]\times L)$and route $k=([(s_j-1)/L]+1)$ for the j time([ ]denotes integer, the latter ones obey the same denotation) . This determines whether customer m is served by vehicle m, and it also determines the order of customer m in route k is j.

for example: there is a chromosome encoding as follows ($L=8, k=2$):

1 2 4 7 8 16 15 9 10 13 12 5 6 14 3 11

$s_1 = 1$,determines the corresponding route $k= ([(s_j-1)/L]+1) = [(1-1)/8]+1=1$

the corresponding customer $m= (s_j-[(s_j-1)/L]\times L) =1-0=1$

$s_{16}=11$,determines the corresponding route $k= ([(s_j-1)/L]+1) = [(11-1)/8]+1=2$

the corresponding customer $m= (s_j-[(s_j-1)/L]\times L) =11-[(11-1)/8]\times 8=3$

There are altogether $L\times k$ relation between customers and routes when there are L customers and k vehicles, so each group of chromosome encode consists $L\times k$ genes. This forms a matrix with a capacity of k rows and L lines. The gene lies in the row that depicts which vehicle is needed and the line that depicts which customer to supply.

Though reflecting the essence of VRP, the calculating process of this method is difficult to understand. Therefore the encoding can be changed a little, coding from 0. Then the gene in the chromosome is an integer in the range from 0 to $k\times L-1$. The corresponding relation of route and customer are as follows:

$m= (s_j \bmod L) +1$

$k=[s_j / L]+1$

The number of the vehicles starts from 1, that's 1,2,…,k and the code of customers starts from 1, that's 1,2,…,L. The chromosome's suffix is also coded from 1.

2.Lang Maoxiang[18] brought forward a simple natural number encoding method.

Suppose 0 denotes depot, 1,2,...; L denotes each customer. Since there are vehicles reaching the amount of k in the depot, so there are k distribution routes existed at most. Every route originates and ends from the same depot. In order to indicate the vehicle distributing route in the encode, (K-1) dummy depots are adopted, which are represented by $L+1, L+2, \ldots L+K-1$respectively. These $L+K-1$ natural numbers $(1,2,\ldots,L+K-1)$ which do not overlap with each other will constitutes one individual, and this corresponds to one certain route plan.

For example: if a distribution problem has 7 demand spots and 3 vehicles, then the distribution route program can be represented by the random rank of 1,2,...,9 (8,9 is the distribution centre) .

For example: the distribution routes represented by individual 129638547 are described as follows:

Route 1 : 0 - 1 - 2 - 9 (0)

Route 2 : 9 (0) - 6 - 3 - 8 (0)

Route 3 : 8 (0) - 5 - 4 - 7 - 0,there are 3 distribution routes;

Routes corresponding to individual Route 573894216 are described as following:

Route 1 : 0 - 5 - 7 - 3 - 8 (0)

Route 2 : 9 (0) - 4 - 2 - 1 - 6 - 0,there are 2 distribution routes all together.

3.Li Jun and other scholars[22] put forward an encoding method. This method uses a chromosome code string with a length of $K + M + L$ which can be represented by $(0,n_1,n_2,\ldots,n_s,0,n_j,\ldots,n_k,0,\ldots,0,n_w,\ldots,n_q,0)$. Such chromosome code can be described as: vehicle 1 departs from depot , and after serving customer $n_1,n_2,\ldots,n_s$, it goes back to the depot. This is sub path 1. Vehicle 2 departs from the depot too, and after serving customer $n_j,\ldots,n_k$, it goes back to depot, that's sub path 2; After the m vehicles completed transportation in turn, there will be sub paths of the same number.

4.Another illustrative encoding method is to denotes the solution as a matrix of $m\times n$, in which row i denotes the way customer i is served while line j denotes vehicle of number j serves the customer of number j. It must be made sure that, the matrix is a 0 - 1 sparse matrix. Although the initial solution matrix is feasible to be used as the code of immune algorithm, the efficient in using the storage space of computer is quite low, so it is necessary to make the essential adjustment, and determine the appropriate encoding method based on initial matrix.

The initial matrix shall be compressed into a certain vector. The order of the elements of this vector corresponds to the situation customers are served, and the number of the elements are not 0 - 1, but 0 - m ,which is described as follows :

$V = (x_1,x_2,x_3,\ldots,x_n)$

$x_i =$ k,denotes that customer i is served by vehicle k

3.3.2 The encoding method proposed in this thesis

The above discussed encoding methods for VRP are all determined by the total amount of vehicles, so there are the problems that the code length is long and the space used is large. Frankly speaking, as for the requirement of the clients, it is impossible to determine whether all the vehicles are needed to serve them in advance, and usually, the cost increased by using one more vehicle always exceeds the cost saved by decreasing travel distance. So, minimum number of vehicles is always considered the initial goal, while the minimum travel cost is the second. The cost increased by using one more vehicle is bigger than that increased by the usage of other routes, so the purpose of this encoding method is to find an appropriate plan to minimize the travel distance under the presumption of decreasing the number of vehicles.

If the number of customers is m and the number of vehicles is k, then the natural numbers amount to number m which doesn't overlap with each other can be used to encode and it represented as the supply order. The numbers are in the range from 1 to m. n segments of the m natural numbers （$0<n<=k$） denotes customers supplied by n vehicles.

For example: there are 9 customers needed to be served, and 5 vehicles are available to do this job. Suppose the code generated is 129834657 which can denote every customer's precedence and route. Specifically speaking, a small segment of the encode, such as "129", indicates that a vehicle serves customer 1、customer 2、customer 9, but as for the question that how many vehicles are there or are needed, it highly depends on the capacity of the vehicle and the demand of the customers. In addition, different rank order will lead to different numbers of vehicles needed.

The generation of initial antibody is to make use of the random function to create population which is suit for the above encoding rule.

3.4 THE ABSTRACTION AND INOCULATION OF VACCINE

In the process of operation, analyzing the problem need to be solved (antigen) and abstract the most principle characteristic information from it. The information here is called vaccine. The vaccine shall be dealt with and transferred into a certain program to solve the problem. (the group of solutions based on this program are called antibody which are generated from such vaccine.) Choosing the right vaccine is highly meaningful to the efficiency of the algorithm.

1. Abstraction of the vaccine

According to the practical problem need to be solved, the strategy under consideration to abstract is comparing and choosing the customers nearest to each other. This is a selective encoding plan, namely, put customers adjacent together, and supply them with the same vehicle, so we can decrease the transport cost.

2. The injection of the vaccine

After the abstraction of the vaccine, the vaccine information will be studied to generate the code to reflect the basic characteristics of the problem and to put the relation of distance between the customers into the solution of the problem.

3.5 THE CALCULATION OF THE ANTIBODY ADAPTIVE VALUE

The adaptive value of the antibody is the affinity between antigen and antibody indicating the combination degree (matching degree) between antigen and antibody. It is actually the appraisal value corresponding to one of its solutions. For every antibody Ag, define the corresponding adaptive value $G = 1/F$, $F = \left(\sum_{k=1}^{K} \left(\sum_{i=1}^{n_k} C r_{k(i-1)} r_{ki} + C\ r_{k0} r_{kn_k} * \text{sign}(n_k-1) \right) \right)$. From the above equality, it is easy to see that the bigger G grows, the shorter the route will be, meaning that the closer the solution will turn to the optimal solution.

3.6 THE CROSSOVER OPERATION OF THE ANTIBODY

3.6.1 Usual chromosome crossover operation includes:

- Partial mapping crossover

As for the two parent chromosome P1 and P2, the implementation procedure of PMC(Partial mapping crossover) crossover algorithm[38]is as follows:

Informal procedure for parents P1 and P2:

1. Select and copy the random segment from P1
2. Look for the element in segment P2 which is not identical in the segment of P1 from the first crossover point
3. For each element i like this, look for the corresponding element j in P1
4. Put *i* into the position occupied by *j* in P2. j has already exist in the segment.
5. If the place occupied by *j* in P2 has already been filled in the offspring *k*, put *i* in the position occupied by *k* in P2
6. Having dealt with the elements from the crossover segment, the rest of the offspring can be filled from P2.

Informal procedure for parents P1 and P2:

Second child is created analogously

For example: **Figure 3.2** demonstrates the procedure of crossover operation on two segments:

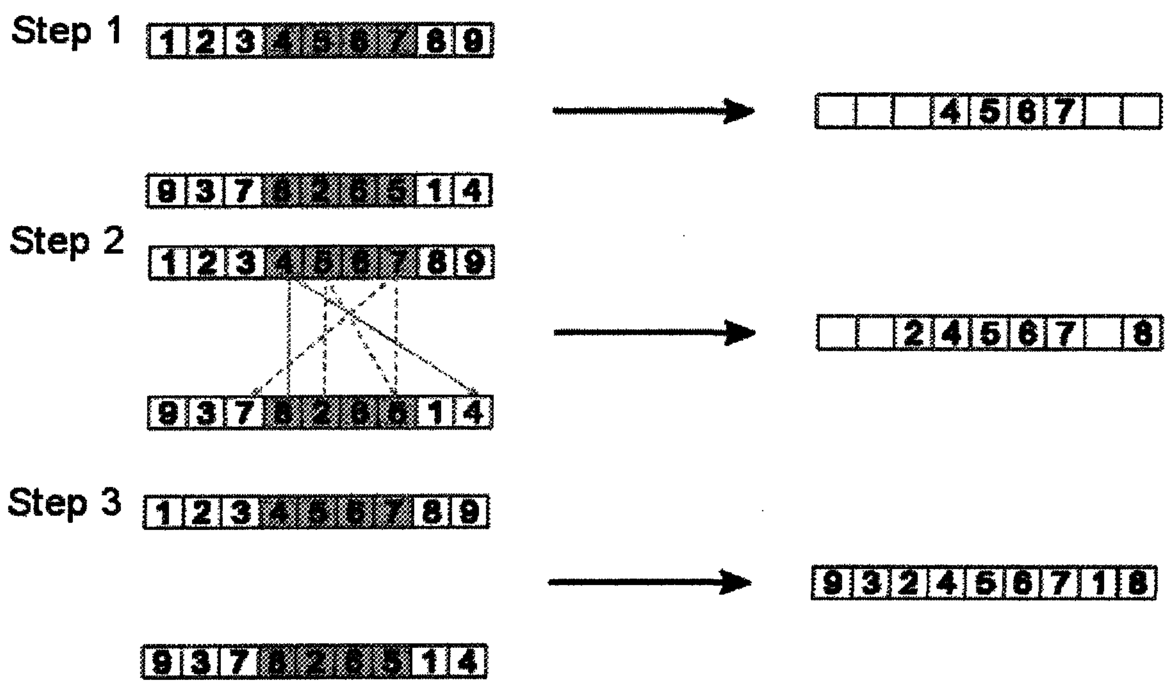


Figure 3.2 PMC crossover operation

•Sequential crossover operation

The implementation procedure steps are stated as follows[5]

(1) Pick up one mating area (mating pool) from the father individuals randomly. for instance: set two father individuals and mating area as A = 47 | 8563 | 921,B = 83 | 4691 |257 ;

(2) placing mating area B in front of A, and mating pool A in front of B, then: A'=4691 | 478563921,B'=8563 | 834691257 ;

(3) delete the repeated natural numbers in the self mating area in A',and B', then the two final individuals are : A"=469178532,B"=856349127.

Compared with other methods, even the two father individuals are identical this method to some extent can still generate mutation, which is useful to keep the variability of the population.

3.6.2 The crossover method used in this thesis

In this paper, an improved OX method[7] has been used in the crossover operation of the antibody. The implementation procedure is as follows:

First of all, two numbers working as the interlace point will be generated by random function. Exchange customer information between the insertion points in the two selected father antibody. After the exchange, for every new antibody delete in turn the elements out of the exchanging segment which overlap the elements in the segment, adding customer numbers that are not shown in the antibody, then finally two legal antibodies are newly formed.

For example: two numbers (3,5) will be generated as the insertion point :

P1 :(1 2 |3 4 5| 6 7 8 9)

P2 :(4 5 |2 1 7| 8 6 9 3)

Exchange the customer information between the insertion points of P1 and P2 , then :

O1 :(1 2 |2 1 7| 6 7 8 9)

O2 :(4 5 |3 4 5| 8 6 9 3)

For O1 and O2, delete in turn the elements out of the exchanging segment which overlap the elements in the segment, adding customer numbers that are not shown in the antibody, then finally two legal antibodies are formed.

O1 :(3 4 |2 1 7| 6 5 8 9)

O2 :(2 7 |3 4 5| 8 6 9 1)

3.7 THE MUTATION OPERATION OF THE ANTIBODY

In order to make the filial generation be capable of inheriting more genetic information of its father generation, this paper adopts an algorithm of evolution reversion operator mutation to enhance the algorithm's partial searching ability. It is highly demanded that the operators select two breakaway points randomly in the antibody gene strings to break the antibody gene strings on these two points ; then after reversing the gene segments between these two points, insert them into their initial positions to form the new gene strings. Finally, compare the new antibody with antibodies before the reversion. among them, the one with a high adaptive value will enter into the next generation。

For example: pick up two break points in the following antibodies

Reverse the gene strings between the break points, for example: 8 1 6 → 6 1 8. After the reversion, insert them into the initial position in the gene string to form a new gene string:

O :(2 3 4 7 | 6 1 8 | 5 9)

3.8 THE SIMULATION AND SUPPRESSION OF THE ANTIBODY

In the process of evaluation, in order to keep the variety of the antibody, avoid getting in to partial extreme optimal solution and represent the mutual stimulation and suppression between the antibodies, it is necessary to suppress the similar antibody and make the antibodies with different structures reproduce; therefore the global optimal solution can be located. The appraisal of the resemblance between antibodies can be calculated by their affinity

3.8.1 The calculation of the affinity

If there is the real number coordinate group $M=\langle m_1,m_2,\ldots,m_L\rangle, M \square S^L \subseteq R^L$. S denotes the morphological space, L denotes the number of dimension. Suppose antibody a and antibody b belong to M,and the affinity between a and b comes from their resemblance. The ordinary calculation mode for the affinity includes the distance between antibodies, the matching degree, etc.

1. Distance

The affinity between antibodies has a relationship with the distance between them, [2] like Euclidean distance,Manhattan distance, and Hamming distance, etc. The equality is presented as follows:

$$D=\sqrt{\sum_{i=1}^{L}(a_i-b_i)^2}$$

$$D=\sqrt{\sum_{i=1}^{L}|a_i-b_i|}$$

$$D=\sum_{i=1}^{L} x, \quad \begin{Bmatrix} x=1\,,\ ai\neq bi \\ x=0\,,\ ai=bi \end{Bmatrix}$$

The coordinate of the antibody shall be represented by $<a_1,a_2,\ldots,a_i>$and $<b_1,b_2,\ldots,b_i>$. The shorter the distance between two antibodies, the greater the affinity will be, namely, the more similar the two structures are. Under the circumstance, it is necessary to restrain the antibody to keep the variety of antibodies.

2. Bond strength

The bond strength between the antibodies is able to calculate their affinity.[28] the equality is:

$(Ab)_k=1/(1+t_k)$

$(Ab)_k$ denotes affinity between antibodies, t_k denotes their combination degree, $(Ab)_k$ is a number in the range o to 1.

3. Matching degree

For two character strings of the same length, if every character in them is identical with each other, it is called absolute match. Absolute match is very rare in immune system while partial match is more common, including the above discussed Hamming distance.

In 1994, Forrest put forward r-continuous bits matching rule, namely, for two character strings x and y, if there are at least r bits are identical then they are r-continuous bits matched. Given r=4,then for two character strings, if they have at least 4 bits identical at least, they match with each other, otherwise, they don't match. **Figure 3.3** exhibits this idea:

R=4

0 1 1 0 1 0 0 1 0 1

1 1 1 0 1 1 1 1 0 1

Match

0 1 0 0 1 1 0 1 0 0

1 1 1 0 1 1 1 1 0 1

Unmatch

Figure 3.3 Match under r-continuous bits matching rule

R-continuous bits matching rule is able to reflect the resemblance between the two character strings. if r is equal to 0,then it is absolute match; if r is equal to 1, then as long as 1 bit there is identical they will match with each other; if r equals to the length of character string,then only every element in the character string is identical can they match with each other.[24]

In order to decrease the calculation amount, according to the characteristics of the problem, the above Manhattan distance is used to be the appraisal index of affinity between antibodies in this paper. Define affinity between antibody a and antibody b as:

$$y_{v,w} = D = \sqrt{\sum_{i=1}^{L} | v_i - w_i |}$$

The density of every antibody Cv in the order group can be calculated according to the equality below, $y_{v,w}$ is the affinity between antibody v and antibody w:

$$Cv = 1 / \sum_{w=1}^{N} y_{v,w}$$

3.8.2 The colony select of antibody

The principle of clonal select is an algorithm that describes the basic reaction characteristic of the immune to the stimulation of antigen. In this thesis, it is possible to select and clone antibody according to its expected reproduction rate.

The expected reproduction rate of the antibody v is :

$$Ev=\sum_{w=1}^{N} y_{v,w} / \sum_{v=1}^{N} \sum_{w=1}^{N} y_{v,w}$$

Sequence every individual in each generation according to descending order (descending sort), then the filial individuals will be generated through roulette. At the same time, store the former antibodies which have the highest affinity into memory data until they get to number m. It ensures the variability of antibody and restrains its density since antibody with high affinity with antigen will be reproduced while antibody with high density will be repressed.

3.9 DESIGN THE MEMORY DATA

The introduction of the memory data is an important characteristic of immune algorithm. After obtaining the solution to every generation of the antibody, this system will keep the antibodies with higher quality, store them into the memory data base, and replace some antibodies of poor quality. It can avoid the possibility of losing the optimal solution in the procedure of crossover operation and mutation operation. Therefore the speed of convergence will be enhanced, and immune algorithm's self adapting ability can also be reflected.

3.10BREAK OFF CONDITION

In this thesis, the evolution number N was used to represent the termination of iteration. If the number is equal to N, then the algorithm terminates, and the solution with the highest adaptive value will be outputted. Otherwise, repeat the above process.

When outputting the optimal solution, it is necessary that the best antibody of generation N and the best antibody in the memory data base shall be compared with each other. If the objective function corresponding to the best antibody of generation N is bigger than that of the antibody in memory data base, then the best antibody of generation N shall be outputted as the ultimate solving route; otherwise, output the best antibody in memory data base as the ultimate solution.

CHAPTER 4

EMULATION EXPERIMENT AND THE RESULTS ANALYSIS

CHAPTER 4

EMULATION EXPERIMENT AND THE RESULTS ANALYSIS

4.1 INTRODUCTION

In order to prove the effectiveness of the algorithm, the algorithm is implemented by the tool of Visual Basic program in Windows XP operation system. The hardware configuration is Pentium IV 2.4G CPU and 256 M memory.

Many intelligent algorithms have been used to solve the VRP, such as tabu search, simulated annealing, genetic algorithm, and ant algorithm. Among them, because of better approach to optimal solution and less computation time needed, genetic algorithm has become the most widely used algorithm for VRP. But genetic algorithm can easily trap into local extremum solution and produce the "earliness and constringency" phenomenon. In this section, we compare the immune algorithm proposed in this thesis with the genetic algorithm with experiment data. The experiment related parameters and the generation of data are depicted as follows.

4.1.1 Experimental parameters

The interface of algorithm emulation experiment is shown in **Figure 4.1**:

The parameters in the emulation experiment are adjustable. The parameters involved in the experiment include:

1. Number of vehicles, means that the total number of vehicles available can be set to be any number according to the requirement

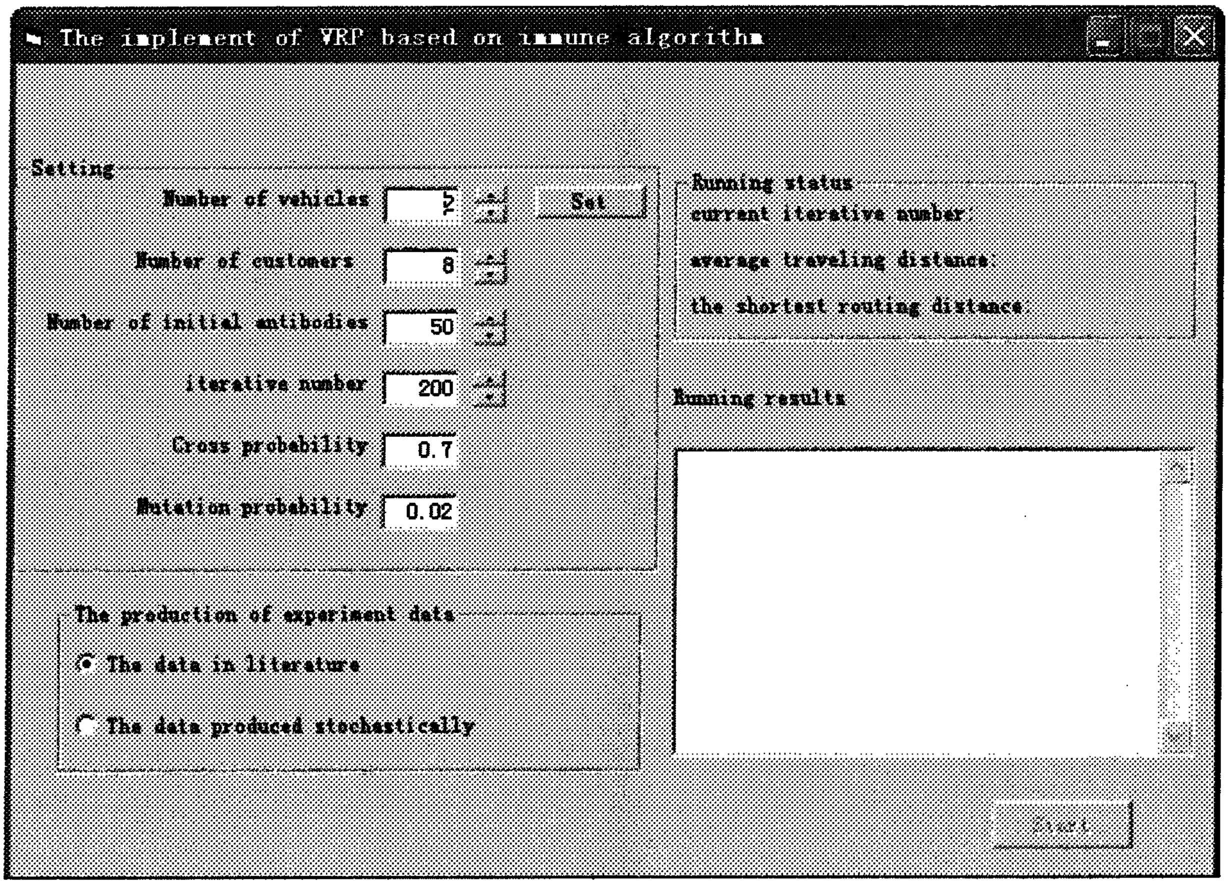


Figure 4.1 Experimental emulation interface

2. Number of customers: total number of customers need serving which can be set to be any number according to the requirement

3. The number of initial antibody: the number of the original population generated randomly which agrees with the coding rule can be set to be any number. The default quantity of population is 50.

4. Number of times of iteration: the algorithm loop execute need to be calculated

can be set to be any number. The default number of times of iteration is 200.

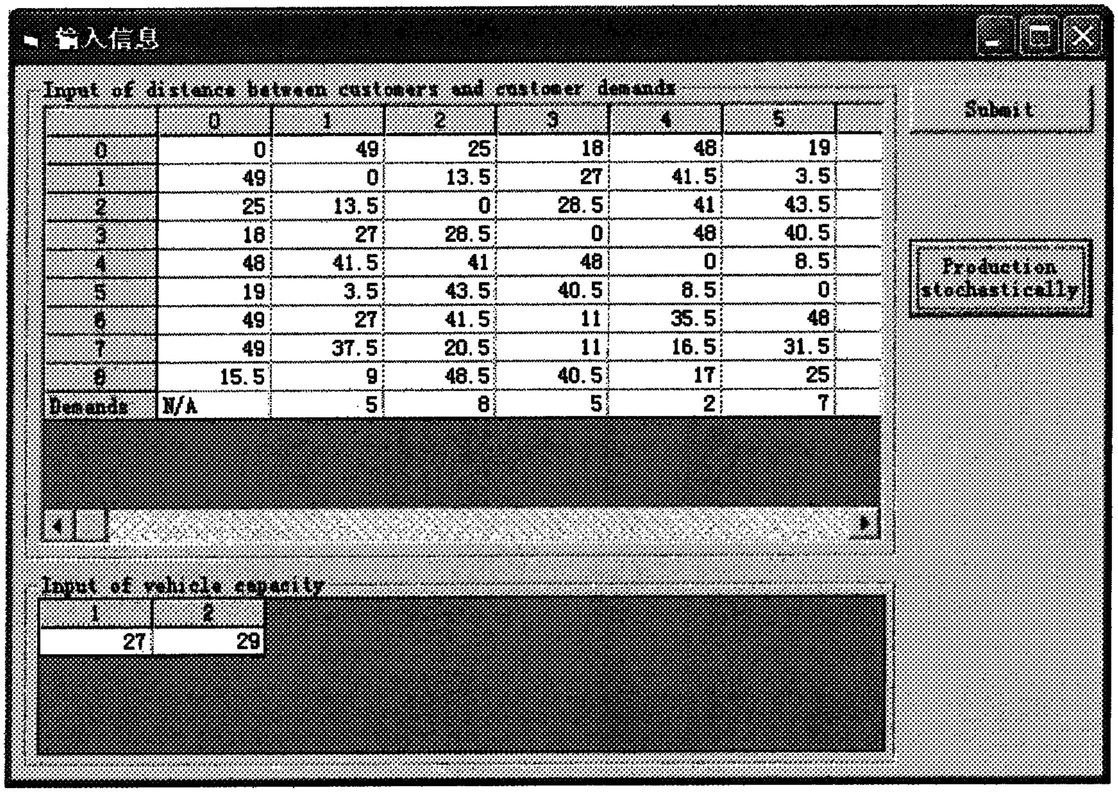
5. Crossover probability: the probability of antibody selected to undergo the crossover operation can be set to be any number. The default number is 0.7.

6. Mutation probability: the probability of mutation operation in every generation can be set to be any number. The default number is 0.02.

7. Memory data designation: the capacity of memory data is fixed. The number of antibody can be kept by the memory data is 10. When antibody in every generation updates, 5 antibodies of highest adaptive value shall be saved into the memory data. Every time when saving memories into the data, make sure that there are no identical antibodies in the memory data. If the memory data is full, remove 5 antibodies of poorest adaptive value.

4.1.2 The generation of the experimental data

The numerical data used in the simulation experiment include distance between customers, distance between customer and depot, demand of customers, capacity of vehicles. Among which the capacity of vehicles can be different. The experimental data can be obtained from two ways: one is from the literature. The other is generated randomly in a certain range. As what is shown in **Figure 4. 2** : the fixed amount of information can be obtained by clicking the random generation button or it can be inputted one by one by manually operation.



	0	1	2	3	4	5
0	0	49	25	18	48	19
1	49	0	13.5	27	41.5	3.5
2	25	13.5	0	28.5	41	43.5
3	18	27	28.5	0	48	40.5
4	48	41.5	41	48	0	8.5
5	19	3.5	43.5	40.5	8.5	0
6	49	27	41.5	11	35.5	48
7	49	37.5	20.5	11	16.5	31.5
8	15.5	9	48.5	40.5	17	25
Demands	N/A	5	8	5	2	7

1	2
27	29

Figure 4. 2 The generation of the experimental data

4.2 TEST AND MEASUREMENT OF DATA IN LITERATURE

First of all, test the performance of the algorithm through the data mentioned in the literature[17]. Suppose there is 1 depot and 8 customers, the distance between customers and the distance between depot and customers as well as the demand of each customer can be seen in **Table 4.1** Distance between customers and the demand of customers. Demand of all customers may not exactly occupy all the vehicles, so the total number of vehicles shall be a bigger number -10, and the capacity of the vehicle is 8.

Table 4.1 Distance between customers and the demand of customers

$C_{i,j}$	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
Customer demand		1	2	1	2	1	4	2	2

By using the coding method brought forward in this thesis, the encoding length is 8 bits which is 90 percent shorter than the encoding length ($8\times10=80$) in the documentation[17]And at the same time it makes possible to constrain to the optimal solution quickly. The population size in this paper is 50, and the evolution generation is 200. The probability of crossover and mutation are 0.7 and 0.02 respectively. After operating 10 times on the computer, the results can be shown in **Table 4.2**:

Table 4.2 The results after the operation of immune algorithm

Operation times	1	2	3	4	5	6	7	8	9	10
Route length	67.5	68.5	69.5	67.5	69	67.5	68.5	67.5	67.5	67.5
CPU Time(s)	5.78	5.64	5.52	6.01	6.12	5.62	5.57	5.65	5.74	5.60

It can be seen that most of the results of immune algorithm approach to the optimal solution (67.5), and the average route length is 68.05 and the average CPU time is 5.73 from **Table 4.2.**

After analyzing the data in **Table 4.3**, it can be seen that with the same data the average route length of genetic algorithm is 70.05 and the average CPU time is 5.2.

Table 4.3 Results after the operation of genetic algorithm

Operational times	1	2	3	4	5	6	7	8	9	10
Route length	71.5	68.5	69.5	73.5	69	67.5	68.5	67.5	67.5	67.5
CPU Time(s)	5.32	5.65	5.02	4.94	4.92	5.14	5.08	5.20	5.12	5.16

Obviously, it can be concluded that immune algorithm is superior to the genetic algorithm in global optimal solution search and need a little more CPU time than genetic algorithm. But it does not affect the running efficiency of immune algorithm and can be acceptable.

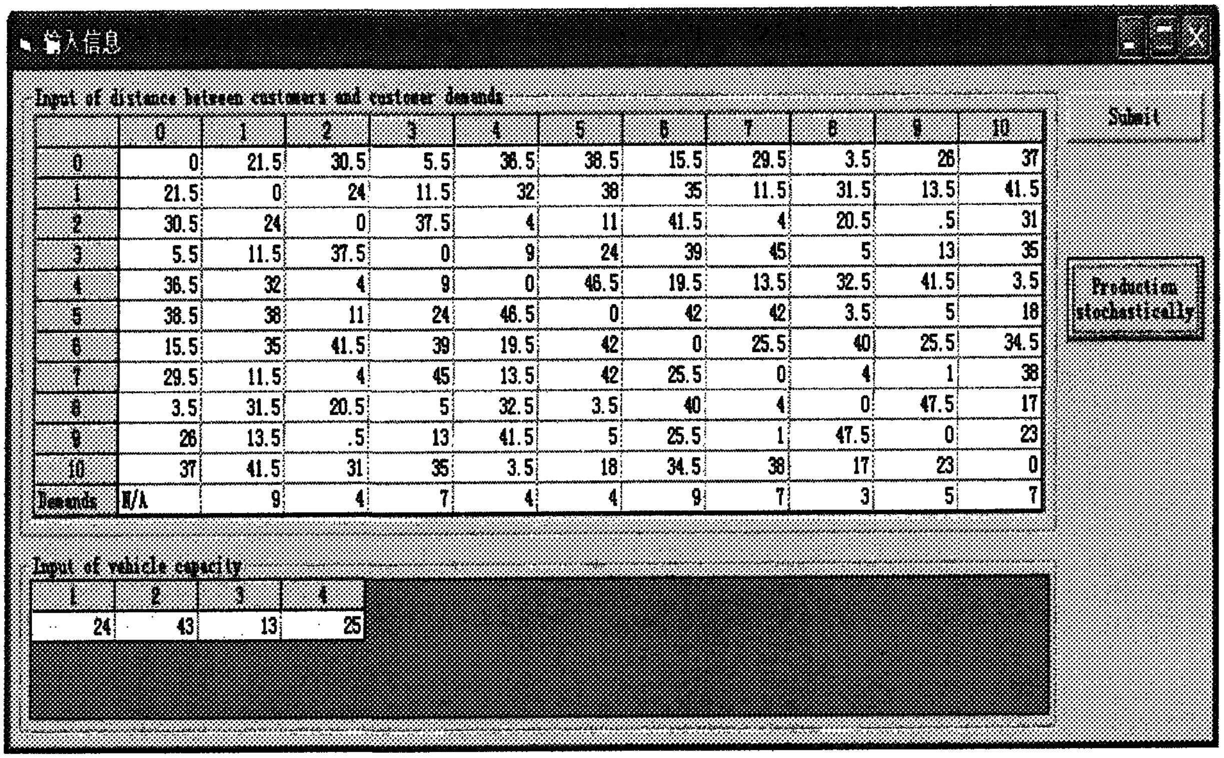
4.3 THE TEST OF RANDOM GENERATED DATA

Suppose the number of customers is 10, and there are 4 vehicles. The distance between customers, distance between customers and depot, the demand of customers and the capacity of each vehicle will be generated randomly. The generated data are shown in **Figure 4. 3**. The parameters operated in the algorithm are the same as 4.2. Operate ten times the randomly generated data. The best operating results are shown in **Figure 4. 4**, and the best route for algorithm operation is

0 - 1 - 6 - 0

0 - 8 - 10 - 4 - 7 - 2 - 5 - 9 - 3 - 0

If the total travel distance is 148, and the time for traveling is 6.25 seconds,the first and the second vehicle shall be used to supply customer. From the experiment results, it is easy to know that on the basis of using the least vehicles to serve customers, this algorithm minimizes the total travel cost. In addition, the biggest difference between this algorithm and the other ones is that the vehicle capacity in this algorithm can be different, while most of VRP algorithms suppose vehicles have the same capacity.



	0	1	2	3	4	5	6	7	8	9	10
0	0	21.5	30.5	5.5	36.5	38.5	15.5	29.5	3.5	26	37
1	21.5	0	24	11.5	32	38	35	11.5	31.5	13.5	41.5
2	30.5	24	0	37.5	4	11	41.5	4	20.5	.5	31
3	5.5	11.5	37.5	0	9	24	39	45	5	13	35
4	36.5	32	4	9	0	46.5	19.5	13.5	32.5	41.5	3.5
5	38.5	38	11	24	46.5	0	42	42	3.5	5	18
6	15.5	35	41.5	39	19.5	42	0	25.5	40	25.5	34.5
7	29.5	11.5	4	45	13.5	42	25.5	0	4	1	38
8	3.5	31.5	20.5	5	32.5	3.5	40	4	0	47.5	17
9	26	13.5	.5	13	41.5	5	25.5	1	47.5	0	23
10	37	41.5	31	35	3.5	18	34.5	38	17	23	0
Demands	N/A	9	4	7	4	4	9	7	3	5	7

1	2	3	4
24	43	13	25

Figure 4. 3 Randomly generated experimental data

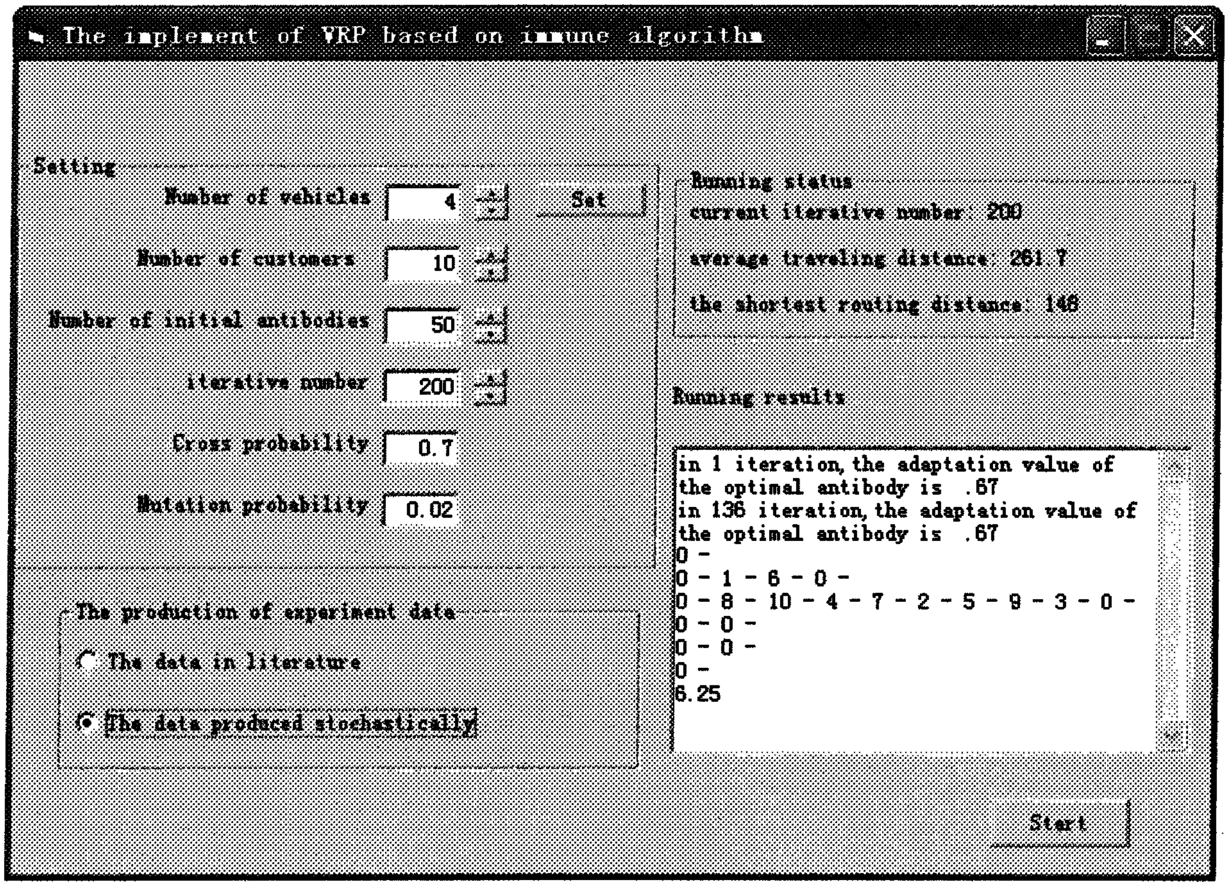


Figure 4. 4 The result of algorithm operation

CHAPTER 5

CONCLUSION

CHAPTER 5

CONCLUSION

In the distribution system, appropriate arrangement of the route is one of the most important ways to avoid the wasting of money and enhance the economic benefit. But because of the NP complexity of the problem, it is difficult to solve the problem with exact algorithm, so study on new heuristic algorithm becomes a main studying direction.

Combined with the engineering practice immune algorithm is a calculating model which abstracts and reflects characteristics of biology immune system. It imitates the biology immune process. Compared with other algorithms, it has better global searching ability and memory function. The research findings have been widely used in many areas.

After the analysis of VRP and the study on much reference documentation on immune algorithm, this paper put forward the idea of solving VRP with immune algorithm, and fulfilled the following work:

(1) According to the characteristics and the requirements of VRP, it brings forward an efficient integer coding method which doesn't depend on the total number of the vehicle. It can minimize the total traveling cost on the base of decreasing the vehicle number.

(2) Since the distance between customers has a direct influence on the traveling distance, an efficient vaccine abstraction strategy was put forward in this thesis. The customers live adjacent are put together in the encoding process and are served by the same

vehicle to decrease cost.

(3) Give a proper designation to the memory data, replace some antibodies of poor quality with some high quality antibodies from each generation and put them into the data. This can avoid losing optimal solutions in the evolution.

(4) In order to keep the variety of the antibody, this thesis brought forward an efficient method to calculate the expected reproduction rate of the antibody, which can restrain the antibody when its density is too high.

(5) The effectiveness of the algorithm has been proved through emulation experiment. It proves that this algorithm is able to avoid premature convergence phenomenon in immune algorithm and constrain to optimal solution at a high speed. Therefore it is an efficient way to solve VRP.

In the procedure of the study about VRP, because of the limitation of the energy and time, the author only studied on the area of VRP with limited capacity. Along with the development of logistic and distribution industry, there has been brought forward many questions put forward in the application of VRP. For example, VRP with time window (which means each customer needs special time to be served), VRP with back swing, VRP requiring dynamic service, etc. These topics may as well become the studying orientation for the future researches on VRP

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