VEHICLE ROUTING AND SCHEDULING PROBLEMS RESEARCH BASED ON NANTIAN LOGISTICS COMPANY

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ABSTRACT

Modern logistics is the third important source in generating greater business profits for the enterprise apart from material cost reduction and labor productivity in product. Moreover, it is also the important way to reduce business operation cost and to enhance the market competitiveness of enterprises' products. Vehicle is one part of the most important business activities of logistics enterprises, and the vehicle routing problem (VRP) is the core issue that related to logistics distribution efficiency and cost control.

This paper is about VRP in the logistics company, and it is based on genetic algorithm (GA). GA is an algorithm with characteristics of global optimization and parallelism. It can make up the defects of the traditional optimization methods. The mathematical model of the VRP for GA and an improved genetic algorithm for the VRP is proposed in this paper. Author adopted the nature number sequence of coding method for VRP, the roulette wheel selection method for individual selection, and auto-adaptive probability system for different crossover probability and mutation probability according to the value of the individual fitness in the process of the crossover and the mutation. It improved the existing ability of the excellent individual, guaranteed the whole healthy of the evolution. This algorithm can find the best or nearly best solution for the vehicle routing problem effectively, which is proved by a number of numeration provided by this paper.

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ABBREVIATIONS

VRP	=	Vehicle routing problem
GA	=	Genetic algorithm
VSP	=	Vehicle scheduling problem
GAs	=	Genetic algorithms
SVRP	=	Stochastic vehicle routing problem
FVRP	=	Fuzzy vehicle routing problem
DVRP	=	Dynamic vehicle routing problem
TS	=	Taboo search
SA	=	Simulated annealing algorithm
NN	=	Neural network algorithm
EDAs	=	Estimation of distribution algorithms
ACO	=	Ant colony optimization
PSO	=	Particle swarm optimization
TSP	=	Traveling salesman problem
IGA	=	Improved genetic algorithm
CW pattern	=	Clarke and Wright pattern
FISAGA	=	Fitness-scaling adaptive genetic algorithm
CSP	=	Constrain satisfaction problem
VRPTW	=	Vehicle routing problem with time window
DC	=	Distribution center
Int pop size	=	Integral population size
NP problems	=	Non-deterministic polynomial problems

CHAPTER I

INTRODUCTION

Background

Vehicle is one part of the most important business activities of logistics enterprises, and the vehicle scheduling problem is the core issue that related to logistics distribution efficiency and cost control. Making vehicle scheduling carefully is so vital that whether company can reduce the cost, make quick response to customers' demands, improve service quality and gain more customers' satisfaction or not. Besides, to select the appropriate transportation vehicle routing can not only reduce the distribution scope, but also reduce fuel cost and vehicle consumption, and then it will improve the income of logistics, and it can bring benefits for the company.

So, next emergency problem is how to make a good vehicle scheduling. It is not difficult to choose because there are a number of methods to do vehicle schedule, you can choose suitable method according to the different conditions, such as customers' demanded goods, the distribution center sites and the traffic routes. General transportation can choose the directional car scheduling method, the loop scheduling method, the cross scheduling method and so on. On contrast, company can use linear programming methods to operate the vehicles, such as the shortest path method, the tabular method and the diagram method, while the transport task become heavy and the transportation network is complex (Chen, Y., Song, X., Han, X., and Wang, D. 2015).

Another problem needed to be concerned is the vehicle scheduling algorithm. In general, vehicle scheduling algorithm can be divided into exact algorithm (precise algorithm) and heuristic algorithm. Exact algorithm comprises branch and bound method, cutting plane method, network flow algorithm and dynamic programming algorithm. But the precise algorithm just can get the best solution when the problem scale is small. It is difficult to solve the problem when the real problem is of high complexity. And it is impossible to select classic exact algorithm to solve such large-scale vehicle scheduling problem with a large number of customers and the alternative vehicle routing solutions grow rapidly. So, choosing heuristic algorithm to solve this kind of problem has become an important research direction.

The heuristic algorithm includes initial solution, exchanging improved method and improved algorithm.

According to the problem of the relative importance of space and time characteristics, researcher (Raff, S., 1983) boiled vehicle routing problem down to Vehicle Routing Problem (VRP) and Vehicle Scheduling Problem (VSP). It is generally believed that regardless of the time request, only according to the space position to make arrangement called VRP; when considering time requirements, called VSP. In order to regulate the full text of the language, and also have not a conceptual confusion, this research unified problem to be VRP.

Vehicle Routing Problem (VRP) is an important content in the study of logistics management. Choosing the right vehicle routing can accelerate the speed of response to customer's requirement, improve the quality of service, enhance customer satisfaction of logistics, and decrease the cost of service operation. Most published research for the VRP has focused on the development of heuristics. Although the development of modern heuristics has led to considerable progress, the quest for improved performance continues. Genetic algorithms (GAs) have been used to handle many combinatorial problems, including certain type of vehicle routing problem. However, it has not yet made a great impact on the VRP as described here. This research focus to describe a GA that we have developed for the VRP, that we can know this approach can be competitive with other modern heuristic techniques in terms of solution time and quality. The generate problems of vehicle routing and scheduling in logistics enterprises and using genetic algorithm to optimize vehicle routing and scheduling problems will be showed in this research. But, the traditional GA optimization algorithm has a defect of premature convergence. Aiming at this issue, this research improves the standard genetic algorithm in terms of chromosome encoding, the adaptive operator mechanisms and dealing with these constraints. At last, improving the computational convergence and overcoming the premature phenomena to optimize VRP.

Problem Description

1. Vehicle Routing Problem

Usually, vehicle routing problem can be described as follows. Assuming that distribution center O deliveries goods with the most m cars for n demand points, the load of each vehicle is bi(i=1,2,3,…,B), the demand of each demand point is di(i=1,2,…,D), from demand point i to point j for shipping cost is Cij, from demand point i to distribution center O for shipping cost is Cio or Coi (i,j=1,2,…,n), the load capacity of vehicle can meet the demand of any arbitrary point. One sentence summary vehicle routing problem is how to arrange the vehicle routing and make the total transportation cost to be minimal under the condition of no overload and meeting the demand of each demand point.

2. Vehicle Routing Problems of Nantian Logistics

As identified by the business owner of Nantian logistics, the vehicle routing problems at Nantian logistic are:

2.1 Nantian can't forecast the customers' demand accurately because demands are stochastic. Although already has more than 50 collecting points Nantian can't forecast the demand comes from 12 cities in Guangxi province without any intelligent prediction software.

2.2 Nantian can't arrange vehicles well because of the first problem above. This so-called arrange vehicles well is to arrange right vehicle with the right volume at the right time and right place.

2.3 Transportation vehicle cost in some degrees will increase so the benefit space will be decrease on contrast. Because of the two reasons above Nantian has the unreasonable vehicle scheduling phenomenon that can't make full use of vehicle efficiently or use many vehicles for few demands.

Observation of the operation process at Nantian logistic company reveals that unreasonable vehicle scheduling phenomenon is the source of problem; to reduce the transportation vehicle cost and make vehicle routing efficiently through loading reasonable in the context of stochastic demand is the first task of Nantian logistics. For vehicle routing efficiency, a company must have an appropriate vehicle scheduling in order to meet their customer requirements. Therefore the genetic algorithm is applied, as it focuses on reducing all unreasonable activities.

Objectives of the Study

1. Find the best vehicle route(s) for Nantian Logistics

Viewing of the transportation problems of Nantian logistics enterprise, to improve and optimize the company's transportation routes and vehicle scheduling.

2. Cost minimization

Nantian Logistics can shorten the transport routes and shipping time through improvement and optimization. Finally, to save the transportation costs.

3. Gain more benefits for Nantian logistics.

Simultaneously, it will get more benefits for company because of the cost minimization.

Expected Output of the Study

An effective formulation of improved genetic algorithm for VRP will be output.

Based on the simply genetic algorithm (figure 1), this research got the improved genetic algorithm which shows in figure 2. These two figures will be covered later in this research.

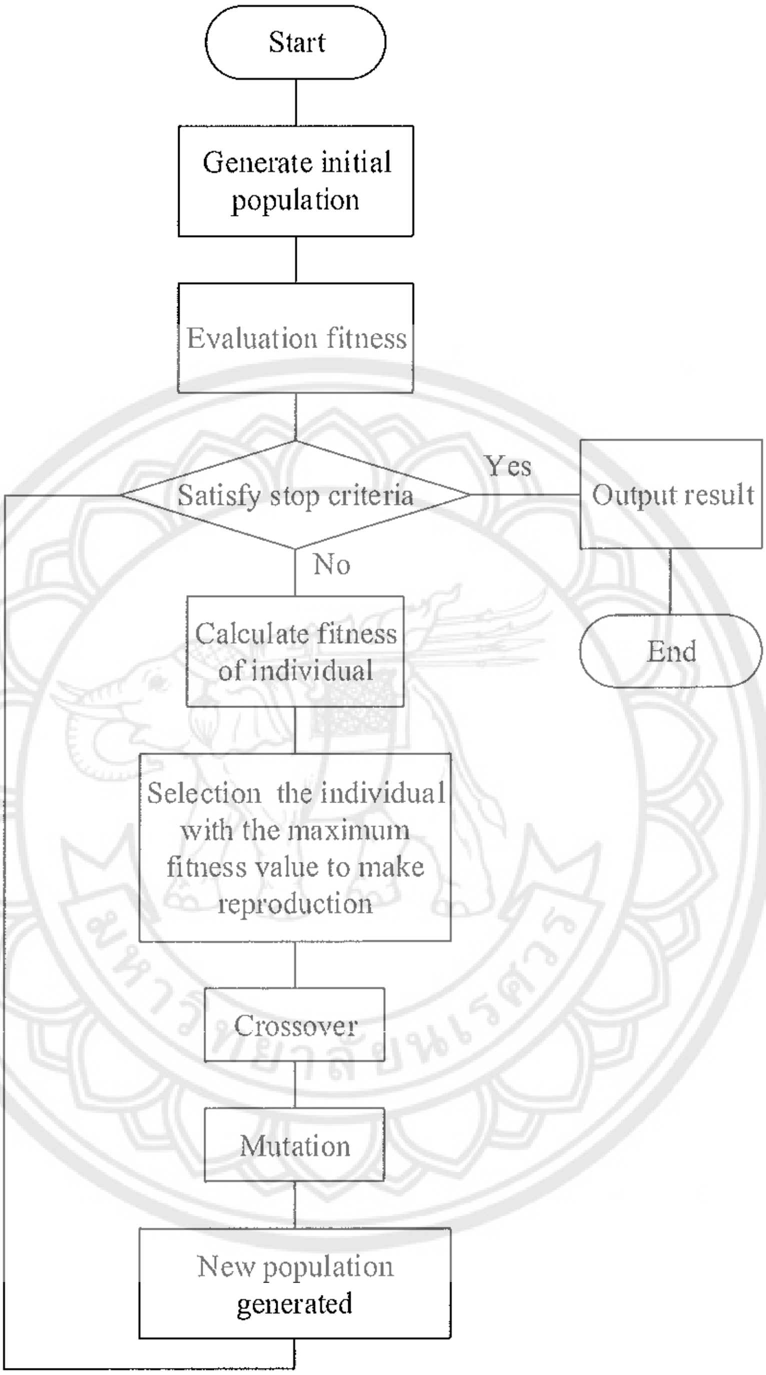

Figure 1 Simple Genetic Algorithm

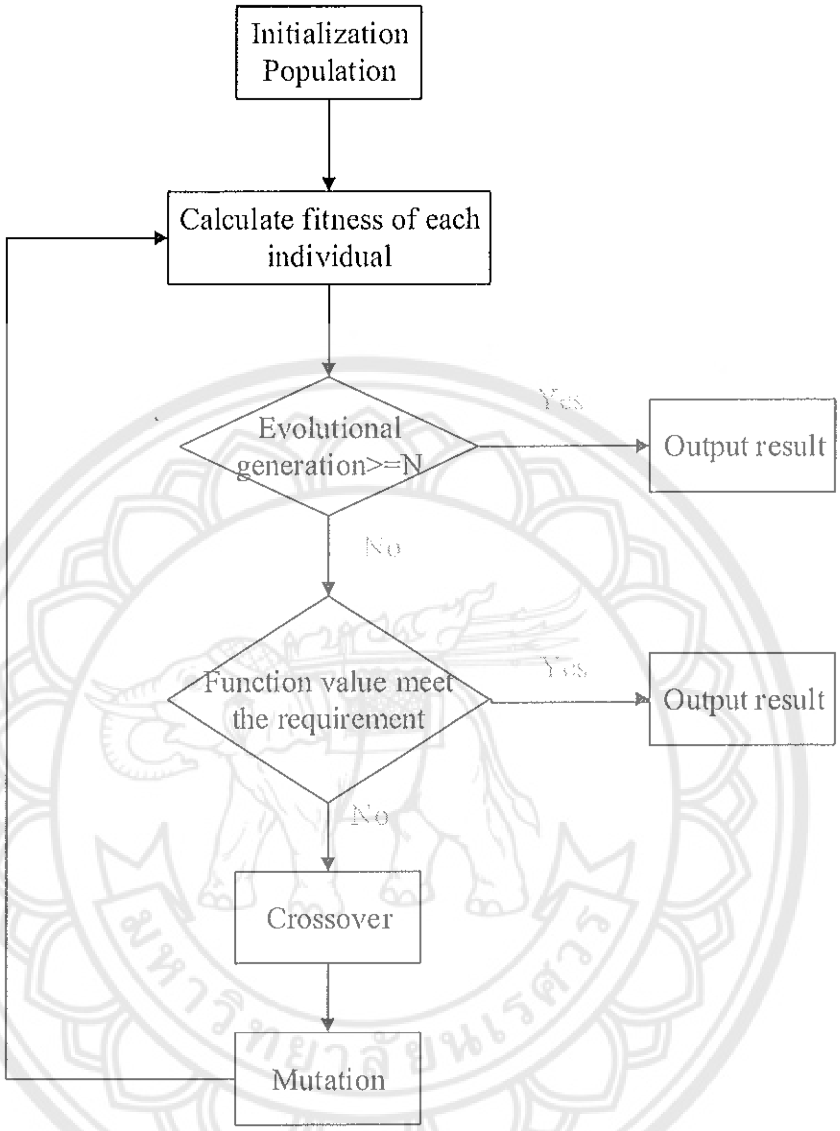

Figure 2 Improved Genetic Algorithm

Expected Outcomes

Although there are a lot of research literature about vehicle routing and vehicle scheduling problem, but the real apply theory to practice is still little. This research based on a real logistics company to do research work, has a certain practical significance and guiding significance.

Research Framework

This thesis is divided into five sections, and the details shows in Figure 3: Research Framework.

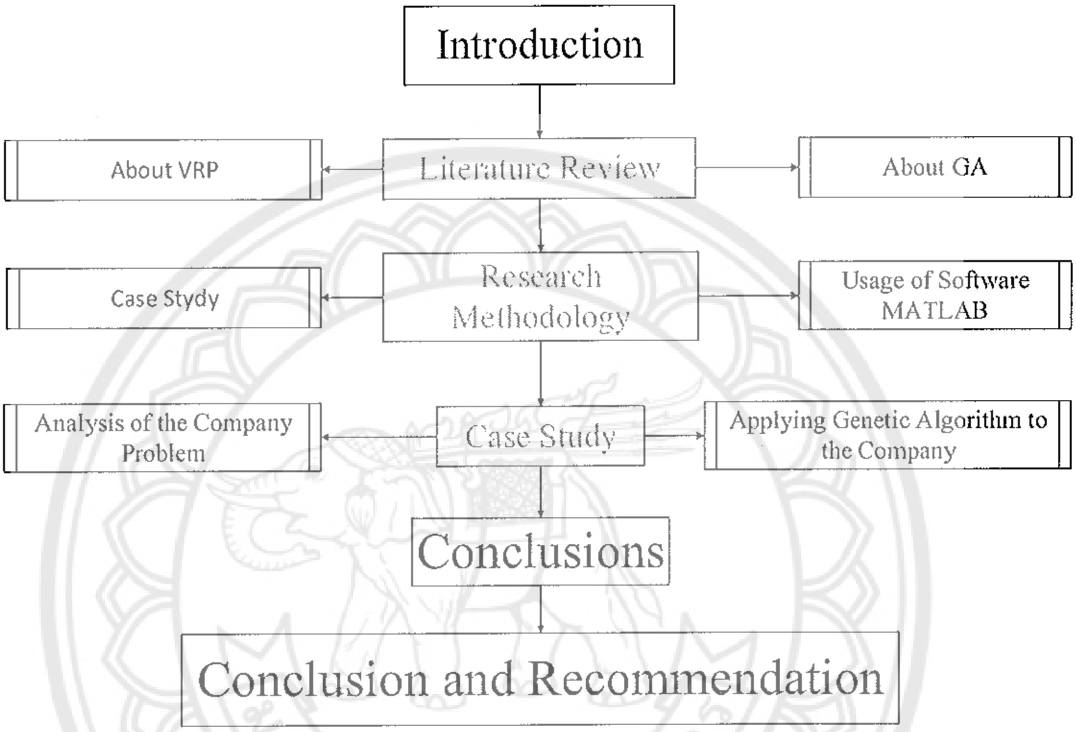

Figure 3 Research Framework

Chapter II briefly reviews the relevant studies in the field of vehicle routing problem, the algorithm of vehicle routing problem and genetic algorithm.

Chapter III is a description of the research methodology used in this study, which includes case analysis and computing application.

Chapter IV analyzes the company's vehicle routing problems and then applies genetic algorithm to the company. Meanwhile, the meaningful results will be also presented in this chapter.

Chapter V draws this thesis to a conclusion.

Chapter VI gives suggestions from this thesis and points out future research directions.

CHAPTER II

REVIEW OF RELATED LITERATURE AND RESEARCH

The research abut Vehicle Routing Problem is early and the literature is many by searching from Elsevier, Springer, Google scholar, and so on. And so does the research about Vehicle Routing Problem with Genetic Algorithm. But the research about Vehicle Routing Problem Use Genetic Algorithm in Logistics Company is rare. This paper selects the Web of Science, and set Vehicle routing problem as title, set Logistics Company and Genetic algorithm as subtitle, get 7 literatures. Set Vehicle routing problem and Genetic algorithm to be title, get 49 literatures. Set Vehicle routing problem and Logistics Company or all these three words to be title, the result is 0.

Nantian Logistics Profile and Information

Nantian Logistics was founded in 2001 with a registered capital of 3 million RMB, through the Nantian people's 15 years' hard working and the strong support of customers and the community, now company has developed into a strong and comprehensive logistics services company from original shipping department which only has 20 people.

At present, it has more than 1000 employees and more than 100 vehicles (including 9 dump trailers,16 big trucks, 26 small trucks, 75 van trucks, 8 commercial vehicles and 9 little cars); area of storage over 20,000 square meters; trading network covering the whole 12 cities of Guangxi province except Wuzhou city and Hezhou city. In Nanning city, Nantian has more than 40 collecting points, it has good city distribution network. Besides, it has built Liuzhou, Hechi, Bama and other more than 41 regional fine routes .Main transportation problems of Nantian logistics can be shown in figure as follow (Figure 4), it also summaries in the chapter 1.

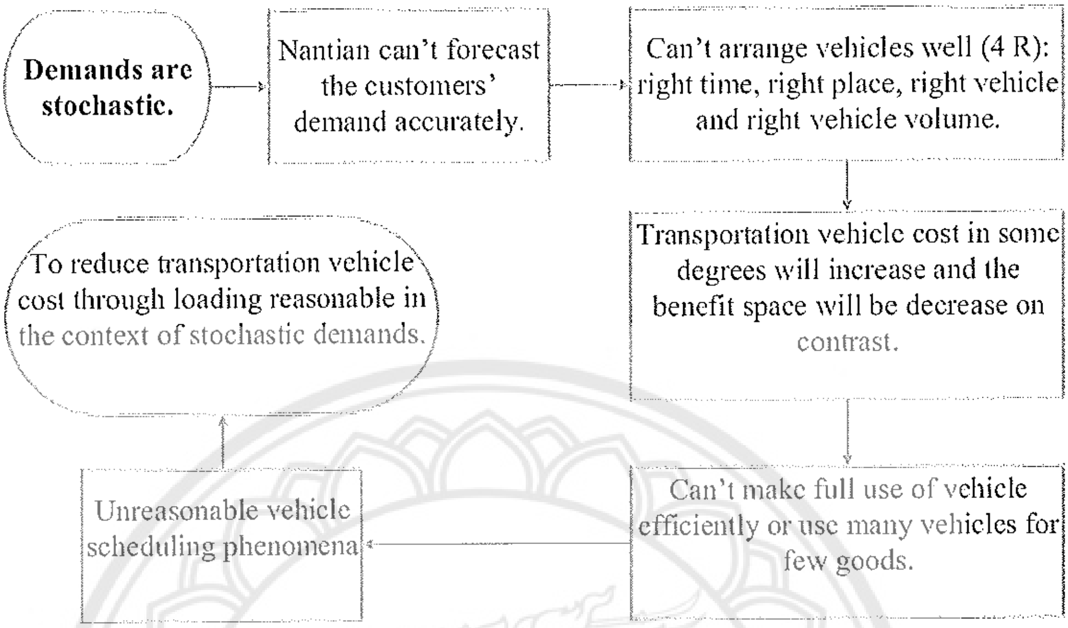

Figure 4 Main Transportation Problems of Nantian Logistics

Vehicle Routing Problem

The vehicle routing problem (VRP) consists of designing best delivery routes from a central depot to a set of geographically scattered customers, subject to various constraints, such as vehicle capacity, route length, time windows, precedence relations between customers, etc. (Li Jun and Guo Yaohuang, 2001).

The earliest study about VRP was done by Dantzig and Ramser (Dantzig, G.B. and Ramser, J.H., 1959). When they researched the project of gas transportation route optimization problem from Atlanta refineries to the gas station, VRP was proposed.

VRP including goods, vehicles, logistics center, customers, transportation network, constraints and objective function such constituent elements, according to these factors can be divided into different kinds of VRP (Lang Maoxiang, 2003). According to the characteristics of the known information to do classification, VRP has deterministic VRP and uncertainty VRP, the uncertainty of VRP can be further divided into stochastic VRP (SVRP), fuzzy VRP (FVRP) and dynamic VRP (DVRP).

Vehicle Routing Problem Algorithm

VRP, after being brought up, the study of VRP algorithm is the research emphasis and difficulty, and has proposed many algorithms for solving VRP. The algorithm mainly divided into two categories: precision algorithm and heuristic algorithm (Raff, S. 1983).

1. Precision Algorithm

Precise algorithm refers to can find out the best solution algorithm, it mainly aims at solving for the figure model and mathematical model of the VRP, calculation generally increases exponentially with the size of the problem, so, many precision algorithm used for smaller issues. Precision algorithm mainly includes three categories of direct tree search algorithm and dynamic programming method and the integer linear programming. Its typical algorithm has branch-bound algorithm (Laporte, G., Mercure, H., and Nobert, Y., 1986), K center tree algorithm (Christofides, N., Mingozzi, A., and Toth, P., 1981), Dynamic programming (Eilon, S., Watson Gandy, C. D. T., and Christofides, N., 1971), Set segmentation and column generation method (Balinski, M. L., and Quandt, R. E., 1964), three indices of vehicle flow equation method with capacity constraints and time window and free time of residence of VRP problems (Fisher, M. L., and Jaikumar, R., 1981), and the second subscript vehicle flow equation (Laporte, G., Nobert, Y., and Desrochers, M., 1985) etc..

2. Heuristic Algorithm

Heuristic algorithm is based on inductive reasoning and test analysis of the past experience to solve the problem, namely, by using some heuristics or test method. Heuristic algorithm for the analyst must use missile in perception and insight, seeking relationship and get inspired from the related research question and the basic model and the algorithm, to find suitable thinking and path for solving the problem.

When solving the small and medium-sized VRP, heuristic algorithm is disadvantaged on the accuracy when compared with the accurate algorithm. But in solving large-scale VRP, the heuristic algorithm can always find a satisfactory solution or feasible solution in the limited time. But this is difficult for precise algorithm to do so. Therefore, heuristic algorithm is more widely used in the practical application. The common heuristic algorithm has the following types in 40 ~ 70 s of the 20th century (Raff, S. 1983).

2.1 Clarke and Wright algorithm (saving algorithm)

2.2 K - opt algorithm

2.3 Sweep algorithm (scan algorithm)

2.4 Chrisofides Mingozzi - Toth two-phase algorithm.

After the 1970s, with the development of artificial intelligence technology, has produced a large number of excellent intelligent heuristic Algorithm, good results have been achieved in solving VRP problems, such as in the 70s ~ 90s of the 20th century the Genetic Algorithm (GA) and Taboo Search (TS), Simulated Annealing Algorithm (SA), Neural Network Algorithm (NN), etc., as well as in the 1990s to the early 21st century produced Estimation of Distribution Algorithms (EDAs), Ant Colony Algorithm (ACO) and Particle Swarm Optimization (PSO) Algorithm, etc.

Main Problems of Research on Vehicle Routing Problem

1. About the heuristic improvement study is not enough.
2. Research is not enough for the multi-objective vehicle routing problem.
3. Research on stochastic VRP (SVRP) was not enough.
4. Research on the application of VRP was not enough.

Uncertainty Vehicle Routing Problem

Before making the vehicle routing plan and the actual transportation process, not all of the objective conditions are invariable, it will always meet some uncertain factors, and the most common factor is the traffic congestion and vehicle malfunction. In many cases, data can't accurately obtain before supplying service, such as the customer's demand quantity, the number of customers, customer request service time, vehicle speed, etc. Researching the uncertainty of VRP problem has significance for guiding the actual operation of enterprise, so we need do further research of VRP problems with uncertain factors on the basis of traditional deterministic VRP theory and method.

Uncertainty VRP stems from the inadequacies of grasping information of path planner. According to the attribute information can be divided into accurate information, information subject to a certain probability distribution function, fuzzy information and real-time dynamic information four types, uncertainty VRP after corresponding to three types of information, namely stochastic VRP (SVRP), fuzzy VRP (FVRP) and dynamic VRP (DVRP).

1. Stochastic Vehicle Routing Problem (SVRP)

SVRP is characteristic of some elements of the information is not entirely sure while constructing vehicle routing, but can be obtained their statistical law from historical data or market research. Main research objects of SVRP including whether the customer point need service or not is random, the demand of customers order is random, driving time and constant service time are random three types (Crainic, T. G., Toulouse, M., and Gendreau, M, 1996). SVRP With stochastic demand is the study of the most wide problem at the earliest time, namely, customer demands obedience to a known probability distribution (Novoa, C., and Storer, R., 2009), the actual demand only can be determined when the vehicle arrives. After the vehicle reach to customers' point, if because of excess weight that can't service the customer, the car need to drive back to the garage and return the customers' point, or rescheduling other vehicles service the unfinished service tasks, the optimization goal is to minimize the expected vehicle cost. Sungur, et al. (2008) and Mendoza, et al. (2010) respectively study the robust genetic algorithm optimization method and culture GA algorithm of VRP with random demand. SVRP weight optimization method is proposed, Markov decision process model is established for each vehicle service, optimization strategy is given under the condition of the random demand (Secomandi and Margot, 2009). At the same time considering the maximum limited travel time for per vehicle studying the VRP with stochastic demand (Erera, et al., 2010).

In recent years, VRP problem with random customer also cause the attention of scholars. Tang and Miller-Hooks (2007) studied the TSP problem with random customers, to make classification of the requirements in accordance with customer group, and require vehicle passed through each customer group at least one time, customer request service at a certain probability, if the customers have no demand or demand is very low, the vehicle will skip the customers directly to next customer service group. Sorensen and Sevaux (2009) studied the SVRP problems with random customers point and random demand, they pointed out that the standard of the evaluation results including objective function, such as the mean, standard deviation and the worst case performance.

At present the study of random time factor is not a lot. Kenyon and Morton (2003) studied with stochastic travel time and random service duration problem, put forward to minimize the expected completion time and maximize the probability of completing the project by a pre-specified deadline these two kinds of model. Lecluyse, et al. (2009) in research VRP with time - dependent travel times, analyzed how to balance the trade-off the average of total vehicle travel time and variance of two rival goal. Sungur, et al. (2010) at the same time considering the stochastic customers and stochastic service duration, based on insertion heuristic and taboo search algorithm, this paper proposed a robust optimization method.

2. Fuzzy Vehicle Routing Problem (FVRP)

FVRP is the study of the customer descriptions information is not clear or is the enterprise to keep track of the uncertain information, mainly concentrated in the customer's demand, time Windows, vehicle travel time and in the service time of customers order.

VRP with fuzzy demand are widely studied in FVRP problem, this kind of problem, the demands of customers are assumed to be a known fuzzy number. Teodorovic and Pavkovic (1996) made the earliest studies the vehicle routing problem with fuzzy customer requirements, with the introduction of decision-makers preference, fuzzy rules are established on the basis of the intensity of preferences, using Sweep algorithm to optimize path selection. Teodorovic and Lucic (2007) using ant colony algorithm and combined with fuzzy simulation to solve the vehicle routing problem with fuzzy demand. Goncalves, et al. (2009) based on the theory of probability made further studies the fuzzy demand for vehicle routing problem with time Windows, by establishing the fuzzy chance compensation model, using fuzzy simulation and intelligent algorithm to solve problem.

3. Dynamic Vehicle Routing Problem (DVRP)

The development of modern communication technology enables enterprises to meet customers' demand for real-time distribution services. In the deterministic VRP, only need throughout the vehicle path planning in the beginning of each day, so planners can take a long time to get a high quality solution; but, in the DVRP, the customer request service is gradually over time, need service supplier in a very short period of time to dispatch vehicles arrival the new customer and make dynamic adjustment for distribution plan, thus put forward very high requirements for optimizing computing hardware and software. In recent years, with the society gradually increase demand for DVRP and the deepening of the academic research, scholars have mastered the basic characteristics and algorithms of the DVRP, and on the solving method and algorithm strategy has obtained certain achievement.

Bent and Van Hentenryck (2004) consider the dynamic vehicle routing problem with time windows that customer can request demand after the vehicle drive out, customer request time follows a certain probability distribution function; the optimization goal is to service most of the customers in the condition of the number of vehicles is certain. Haghani and Jung (2005) study the DVRP problem that vehicles' load is different, can take and delivery at the same time, and the vehicle speed is change, considering the traffic jam problem caused by traffic accidents has effect on vehicle scheduling. Coslovich, et al. (2006) put forward two phase insertion algorithm to solve dynamic dial to call the vehicle service problem (dynamic DARP). Hvattum, et al. (2006) applied historical information for the unknown demand of customers of dynamic VRP to give out its probability distribution, multi-stage stochastic programming model with correction and multi-stage heuristic algorithm was proposed, the results show that using the historical statistical information can effectively improve the quality of path planning.

Branchini, et al. (2009) studied the customers' demand and geographical location is DVRP problem with random soft time windows, we estimate in advance the use of the vehicle number, allow parking vehicles in some demand relatively concentrated areas, and require vehicle throughout the service area, and distribute priority scheduling the residual large load vehicle service new requirements, and put forward to solve the problem with an adaptive local search algorithm. Cortes, et al. (2009) give a hybrid adaptive predictive control method, takes into the random information in the future account in the real-time dynamic decision process. Beaudry, et al. (2010) proposed a two-stage strategy to solve problems of patients in the hospital transportation problem. Lorini, et al. (2011) studied the DVRP problems is more flexible, the paper allows vehicles to change direction while run between two customers, to give priority to service a new customer request.

More researches on DVRP refer review articles of Ghiani, et al. (2003), and Berbeglia, et al. (2010).

Main Problems of Research on Uncertainty Vehicle Routing Problem

Considering the time window factors and the introduction of uncertainty increases the complexity of VRP problems, this sort of question for study is not enough. In the VRP with fuzzy appointments and fuzzy time window, the existing literature are the average of customers' satisfaction as the purpose, without considering the distribution of customer satisfaction, so there are individual customer satisfaction to be low. VRP with stochastic time and fuzzy demand of existing research is generally based on the fuzzy or stochastic simulation method to optimize the mean of the objective function, but its algorithm is lack of flexibility. In view of the DVRP, many researches are the study of using real-time optimization algorithm of insert or batch of thought, did not consider the calculation of load and the urgency of the customer requirements.

VRP with uncertain factors not only need to consider one or more of the traditional VRP goals, but in the research of fuzzy appointments, VRP with fuzzy time window to consider customer satisfaction targets at the same time, most of existing literature use the method of linear weighted or penalty function method, transformed into single objective method is difficult to measure the quantitative relation among different dimensions. Therefore, we need to adopt the way of other multi-objective optimization (such as, Pareto optimization) to solve the problem of trade-offs amid multiple targets, and in this way to optimize VRP problem with uncertainty is still little.

Existing literature for the research of the VRP with uncertainty is to establish optimization model under uncertainty factors, preliminary optimization method and the real-time optimization algorithm, etc., many model ignores the real-time optimization scheduling strategy research, lacks the perspective of real-time dynamic of modeling and optimization.

Under the fuzzy demand, random time, and dynamic uncertain factors, estimate for the existing information is insufficient, can make the preliminary optimization of vehicle routing planning difficult to finish delivery task. Due to time window has the strict requirement of the delivery time, forcing scheduling algorithm should not only meet the requirements with rapid response, but also should have a certain ability to adapt to uncertainty factors. That is, in the volatile situation, also can fast effective dispatch vehicles driving, finish the delivery task.

Genetic Algorithm

In recent years, global convergence analysis of genetic algorithm has made breakthrough progress. Goldberg and Segrest (1987) firstly analyzed a very simple performance of genetic algorithm with Markov chain; Eiben, et al. (1990) proved an abstract global convergence of GA based on keeping the best individual with Markov chain; Fogel (1990) analyzed the asymptotic convergence of GA that has no mutation operator; Suzuki (1998) analyzed the convergence behavior of GA with the characteristics of the state transition matrix of Markov chain; Qi and Palmieri (1994) has carried on the strict mathematical analysis for floating-point coding genetic algorithm based on Markov chain, But the analysis is based on group infinity this hypothesis; Rudolph (1998) proved that the standard genetic algorithm convergence is less than the global best solution with homogeneous Markov chain, but the global convergence of GA will be improved with reserving the best individual selection mechanism. The genetic algorithm has fast convergence speed, and strong global optimization ability to avoid prematurity, and has a reasonable standard of downtime.

Genetic algorithm is an adaptive global random search method, which get inspiration and enlightenment from the law of the evolution. Due to the overall search strategy of genetic algorithm and optimized calculation does not depend on the characteristics of gradient information, so it has a very wide range of application scope, especially suitable for dealing with the complicated nonlinear problem that traditional search method can't solve.

1. The Characteristics of Genetic Algorithm

1.1 Genetic algorithm work on the code set of the problem parameter, rather than on the parameter itself. Processing object of genetic algorithm is chromosome. Therefore, it requires change the basic parameters of optimization problem into a fixed priority symbol of chromosome.

1.2 Genetic algorithm search from initial group, rather than search from a single point. Many traditional optimization methods are derived from searching the single point of space, to determine the next point through certain transformation rules. This kind of point to point search method firstly find may not be the best peak in multimodal optimization problems. But the optimization process of genetic algorithm begins with point set, and its initial population is randomly selected in the search space. So, the probability to achieve the best peak is greater than the probability of point to point method.

1.3 Genetic algorithm only uses the fitness function in the process of searching information, without derivative and other auxiliary information. For different types of optimization problems, traditional methods require different forms of auxiliary information, no any optimization methods is able to meet the requirements of all kinds of problems. Genetic algorithm abandons the use of the auxiliary information in optimization process, has extensive adaptability.

1.4 Genetic algorithm uses probability transformation rules to adjust the search direction, not certain rule. No unified relationship among the generation of groups. But using probability transformation rules does not mean that this kind of method belongs to the category of random algorithm, it just use random transform as a tool to adjust the searching process to tend to areas of continuous improvement of objective function.

1.5 Compared with traditional methods, the superiority of genetic algorithm mainly displays in: firstly, genetic algorithm has strong search ability and large probability to find the global best solution under the action of genetic operators; Secondly, because of its inherent parallelism, large-scale optimization problems can be effectively dealt with.

2. Steps of the Simple Genetic Algorithm

2.1 To structure chromosome that meet the constraint conditions. Genetic algorithm can't directly deal with the solution of the space, so it has to be said into the appropriate chromosome by coding. In practice, it has many chromosome coding methods, but chromosome encoding selection should meet the constraints of problems as much as possible, otherwise will affect the computational efficiency.

2.2 Randomly generate initial population. The initial population is a set of chromosomes at the start of searching, and its number should choose appropriately.

2.3 To calculate the fitness of each chromosome. Fitness is the sole indicator to reflect the good and bad level of chromosome. Genetic algorithm is to find the largest fitness of chromosomes.

2.4 To generate sub-population with the replication, crossover and mutation operator. These three operators are the basic operators of genetic algorithm, which replication embodies the evolution of nature, crossover embodies the thought of sexual reproduction, and mutation embodies the gene mutation in the evolutionary process.

2.5 To repeat step 2.3 and 2.4 until termination condition is satisfied.

Like this, to repeat step 2.3 to step 2.5 again and again, make the population evolution generation by generation. Finally, get the most adaptive individual fitness value and the best solution of the problem, the flow chart shown in figure 1 above.

Vehicle Routing Problems Solved by Genetic Algorithm

J. Lawrence is the first person who put the genetic algorithm into VRP research and made an effective result for VRP with time window. But traditional GA is a large range, coarse-grained optimization algorithm, Barnier combined it with constrain satisfaction problem (CSP) so as to reduce the search space and reduce the complexity of objective function and genetic constraints. Currently GA can already solve large-scale problems (LIU, Y. Z., and Xuan, H. Y., 2005).

Because of the advantage and disadvantage of genetic algorithm, the research on Vehicle Routing Problem with Genetic Algorithm becomes more and more popular.

Mockova, Denisa, Rybickova and Alena (2014) studied the application of genetic algorithm to vehicle routing problem, and use genetic algorithm in Mat lab, while results proved to be a better solution than the heuristic Clarke-Wright method. Lau, H. C. W., et al. (2010) studied the application of genetic algorithm to solve the multi-depot vehicle routing problem. Zhou Wei, et al. (2013) proposed a genetic algorithm for multi-objective vehicle routing problem. Tasan, A. Serdar and Gen, Mitsuo (2012) proposed a genetic algorithm to vehicle routing problem with simultaneous pick-up and deliveries. Ursani Ziauddin, et al. (2011) demonstrated that localized genetic algorithm is able to produce better solutions than most of the other heuristics on small scale problems of vehicle routing problems with time window. Ghoseiri, Keivan and Ghannadpour, Seyed Farid (2010) presented a goal programming and genetic algorithm for multi-objective vehicle routing problem with time windows.

Besides, due to the disadvantages of genetic algorithm, in recent years the research focuses on the improved genetic algorithm.

Li Peiqing, et al. (2015) used an improved genetic algorithm (IGA) for fruits and vegetables distribution in Jiangsu Province, and showed that the IGA is superior to the Group-based pattern, CW pattern and O-X type cross pattern. Nazif, Habibeh and Lee, Lai Soon (2012) optimized the crossover of genetic algorithm for capacitated vehicle routing problem. And Ting, CJ and Huang, CH (2005) also stated an improved genetic algorithm for VRPTW. Anbuuday asankar, S. P., et al. (2012) modified the genetic algorithm for vehicle routing problem, make GA be of more competitive than other heuristics.

Wang Shuihua, Lu Zeyuan and Wei Ling (2016) proposed a fitness-scaling adaptive genetic algorithm for solving the multiple depot vehicle routing problems, and showed the FISAGA is superior to the standard genetic algorithm. Antonio Cruz-Chavez, Marco, Martinez Oropeza and Alina (2016), Xu Shenghua, Liu Jiping and Zhang Fuhao (2015), they presented a combination of genetic algorithm and other methods or other facts for vehicle routing problems. Baker, BK and Ayechew, MA studied the genetic algorithm for VRP, pointed out the further study should focus on a hybrid of GA.

Mirabi and Mohammad (2015), Phuong Khanh Nguyen, Crainic, Teodor Gabriel, Toulous and Michel (2014), Liu Ran, Jiang Zhibin and Geng Na (2014), Osaba Eneko, et al. (2013), Vidal Thibaut, et al. (2013), Kuo, R.J.; Zulvia, Ferani E.; Suryadi and Kadarsah(2012), Lai Mingche, et al. (2012), Miao Lixin, et al. (2012), Wang Chung-Ho and Lu Jiuzhang (2009), Ho William, et al. (2008), Jeon, Geonwook; Leep, Herman R.; Shim and Jae Young (2007), Berger, J. and Barkaoui M (2004), Tan, KC; Lee, LH and Ou, K (2001), they introduced a hybrid genetic algorithm for different types of vehicle routing problems respectively.

How Does this Article Differ from those in Literature? And How Does it Contribute to the Field?

Most published research for the VRP focused on the development of heuristics. Although the development of modern heuristics has led to considerable progress, the quest for improved performance still continues. Genetic algorithm has been used to handle many combinatorial problems, including certain type of VRP. This study focuses to describe a GA that we have developed for the VRP, that we can know this approach can be competitive with other modern heuristic techniques in terms of solution time and quality. The generate problems of vehicle routing and scheduling in logistics enterprises and using the GA to optimize VRP will be shown in this study. But, the traditional GA has a defect of premature convergence. Aiming at this issue, this study improves the standard GA in terms of chromosome encoding, the adaptive operator mechanisms and dealing with its defect. At last, improving the computational convergence and overcoming the premature phenomena to optimize VRP.

The case study tries to solve vehicle routing problem existed in Nantian Logistics. After analyzing the problem in the company, proper method is adopted to reduce the transportation cost and increase benefit space. The method proposed in this case study, to some degree, can solve the problem of Nantian Logistics and be beneficial for other logistic company as well.

After finished this research and got prospective result, author feedback to Nantian's CEO also got good feedback. It proved again that improved genetic algorithm used in this research is of significance.

CHAPTER III

RESEARCH METHODOLOGY

This chapter presents the methodology of this research including research roadmap, research methods and design of improved genetic algorithm. The detail of each topic is described below.

Research Roadmap

The research method of this article, on the whole, is to do the literature research, algorithm design, model building, algorithm implementation, case application and evaluation, and finally with a discussion of the result. First, for the part of literature research, is to compare, conclude, make classification, and find out the similarities and differences among various methods, and then absorb useful methods and achievements; Second, do in-depth analysis for the relevant algorithm system, put forward a new improved method; Again, make reasonable assumptions, determine appropriate goals, correct the existing mature method for reference, build models, also make innovation and breakthrough in the modeling and algorithm. Finally, the paper puts forward the model and algorithm implementation through the simulation experiment and application instance to verify the effectiveness of the proposed algorithm and model.

In order to have more intuitive understanding for the research methods, the following (Figure 5) is the research roadmap.

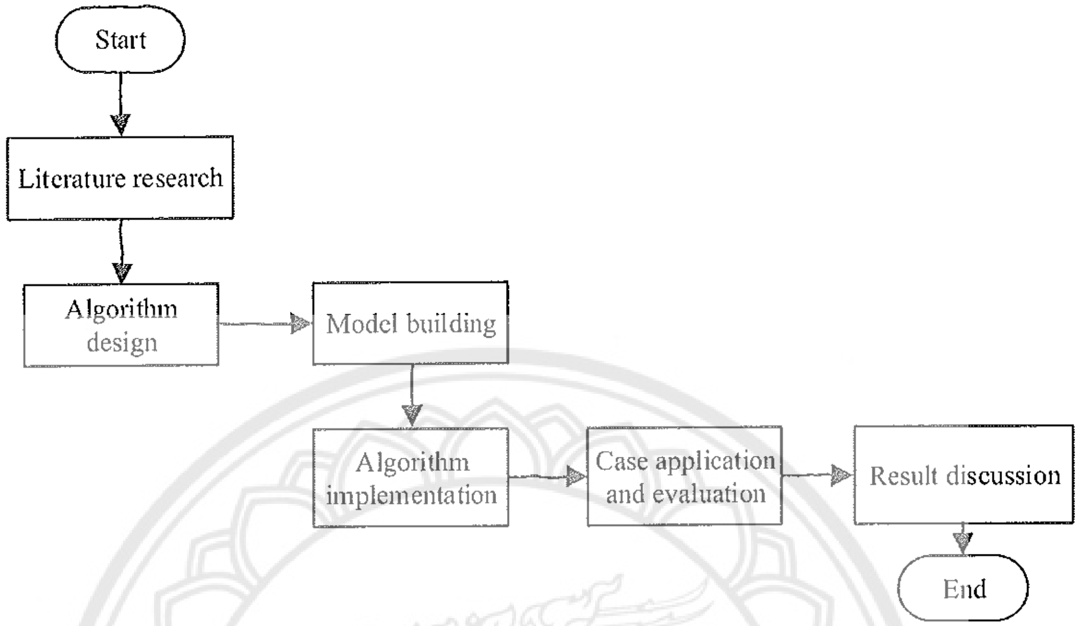

Figure 5 Research Roadmap

Research Methods

1. Mathematical Model

Here the mathematical model which combine the definition of VRP (Cordeau, Gendreau, Laporte, Potvin, & Semet, 2002) and the constraints of this paper is introduced.

To illustrate this, mathematical model is described as follow:

1.1 Variable

$$V_{ik} = \begin{cases} 1, & the\ kth\ vehicle\ service\ point \\ 0, & if\ not \end{cases} \qquad (i = 1,2,\dots,n; j = 1,2,\dots,m)$$

$$R_{ijk} = \begin{cases} 1, & the\ kth\ vehicle\ deliery\ goods\ from\ i\ to\ j \\ 0, & if\ not \end{cases}$$

$$i = j = 0,1,2,\dots,n; i \neq j; k = 1,2,\dots,m$$

1.2 Objective function

$$\min \sum_{k=1}^{m} \sum_{j=0}^{n} \sum_{i=0}^{m} C_{ij} R_{ijk} \qquad (1)$$

$$S.t \sum_{k=1}^{m} V_{ik} = 1, i = 1,2, \ldots, n \quad (2)$$

$$\sum_{j=1}^{n} R_{ojk} = 1, \sum_{j=1}^{n} R_{jok} = 1, \;\; k = 1,2, \ldots, m \quad (3)$$

$$\sum_{j=0}^{m} R_{ijk} = \sum_{j=0}^{m} R_{jik} = V_{ik}\,, i,j = 1,2, \ldots, m; k = 1,2, \ldots, m \quad (4)$$

$$\sum_{i=1}^{n} d_i V_{ik} \leq b_k, k = 1,2, \ldots, m \quad (5)$$

$$C_{ij} = C_{ji}, i,j = 1,2, \ldots, n \quad (6)$$

$$R_{ijk} \in \{0,1\}, i = j = 0,1,2, \ldots, n; k = 1,2, \ldots, m \quad (7)$$

$$V_{ik} = \{0,1\}, i = 1,2, \ldots, n; k = 1,2, \ldots, m \quad (8)$$

$$C_{ij} \geq 0, i,j = 0,1,2, \ldots, n \quad (9)$$

$$d_i > 0, i = 1,2, \ldots, n \quad (10)$$

$$b_k > 0, k = 1,2, \ldots, m \quad (11)$$

$$m > 0, n > 0 \quad (12)$$

Function (1) is cost minimization, (2) point i is serviced by vehicle k. (3) is vehicle delivery goods from distribution center and return distribution center, (4) every point is serviced by one vehicle, (5) there is no overload phenomenon, (6) the transportation cost between two point is equal. Function (7) (8) (9) (10) (11) (12) is other variations of this research.

In this paper, author did not take time window into consider.

2. Case Study

This study is based on case study to research the vehicle routing problem. Firstly, introduce the information and transportation problems of the participant (Nantian logistic company) to understand the detail of the case. And then carry out the implementation of genetic algorithm. Finally, do vehicle scheduling effectively and efficiently in Nantian.

3. Participant

Nantian logistic company is a transportation enterprise in Nanning, Guangxi, China, which has relatively mature logistics transportation system in Guangxi. The reason why to choose Nantian is that author study undergraduate course in Guangxi University and also has a chance to know this company. Although author now study graduate course in Naresuan University, Phistnulok, Thailand, for the language problem, to choose Nantian. In addition, the transportation problem of Nantian is match with the problem of this research.

4. Method of Data Collection

Data is obtained through observation and interview. Author has an on-the-spot investigation for the Nantian logistics company to talk with the manager and staff of company, and also with observation to understand the operation and vehicle routing of Nantian. Most of the data is obtained by interview manager of Nantian. It is of authority and persuasiveness.

5. Method of Data Analyzing

After get enough data information, the next step is to apply these data into model and algorithm. In this paper, to analyze data is coding first and then analyzing according to data with application software MATLAB.

The Improved Genetic Algorithm

1. The Overall Process of Design

In this paper, the detailed process of solution based on the design of genetic algorithm is shown in figure 2: (1) initial population is obtained by random function, and also with the first generation of the individuals; (2) calculate the fitness value of each individual; (3) record the largest individual fitness value, genetic code and function value of the most contemporary fitness; (4) determine whether the evolution generation meet the requirement, and then to stop counting and output result if meet requirement, otherwise to continue to evolve; (5) to choose the next generation of individuals with the roulette wheel method according to the fitness value; to cross individual according to the crossover probability; (6) after cross individuals, to mutate according to the mutation probability, eventually to form a new population, and then return step (2). The overall process design is shown in figure 2 above. To describe this improved genetic algorithm as follow:

1.1 Produce initial population by constructing individuals

Coding with natural number, that is, each individual (marked asi) is a full permutation of natural numbers from 1 to n, where each natural number corresponds to the demand number in distribution system. Randomly generated such int pop size (integral population size) individuals to be as the initial population. The order of each natural number in each individual is the actual delivery order of all transport vehicles, transport vehicles are running start and end of distribution center, where each vehicle start from the distribution center, and return to distribution center after finish distribution task. Novel crossover operator is introduced in the algorithm. Even cross with the same two individuals, it still can produce a new individual. This new crossover operator which can get rid of the requirement on the diversity of the population of traditional crossover operator, avoid the premature phenomenon at the same time, and reduce the possibility of result to be local best solution.

1.2 The calculation of fitness

Calculate corresponding feasible solution (the feasible vehicle routing and the required number of vehicles) for each individual respectively according to the demand of each point and vehicle loading capacity.

Specific operation is shown as follow: each individual, since the first gene which one didn't participate in the accumulation, to accumulate the corresponding distribution volume (di) of gene. If accumulation again it will be overloaded, it can be written as $\sum_{i=1}^{x} di \leq b$ (The load capacity of the vehicle is b). Record the first and the last gene of this circulation in the S-set, when x<m-1. If there is gene which not involved in accumulation in individual, enter it into the next cycle, otherwise, end program. If has already accumulated to the last individual gene, and no overload phenomenon, to add the first gene and the last gene of individual of this time cycle to S-set, and then over.

Such as individual i="1,2,3,4,5,6,7,8,9,10,11,12,13", the corresponding distribution amount of gene is "48,36,43,92,57,16,56,30,57,47,91,55,38", the vehicle load is 200. From the first gene "48" began to accumulate to the third gene "43", total distribution volume is 127 < 200, if accumulate the fourth gene "92" again, the total amount of distribution is 217 > 200, it is overload, gene "1" and "3" will be added into S, namely S={1, 3}, complete one cycle. After this cycle, followed by recycling, eventually get S= {1, 3, 4, 6, 7, 10, 11, 13}, then end. With individuals and their corresponding path start bit, the number of vehicles and the path of the vehicle can be obtained. from S can be concluded that needs 4 transportation vehicles, and the vehicle's running path will be "distribution center–point 1-2-3–distribution center; distribution center–demand 4-5-6–distribution center; distribution center - point 7-8-9-10 - distribution center; distribution center - point 11-12-13 - distribution center", respectively. The process of calculation can ensure that each individual is feasible solution and avoid infeasible solution in the running process of generation; it can save resources and improve the speed of calculation.

Adopted the fitness function fitness (i)=1/value (i), i =1, 2,..., pop size, in which, the value (i) is the total transportation cost of the i^{th} individual, pop size is population size. The calculation process of the value (i) : the first step, to accumulate the transport cost of the corresponding demand point of every two adjacent gene from left to right; the second step, to accumulate transportation cost between distribution center and various genes; the third step, make result sum for the former two steps; The fourth step, in the process of calculating start-stop path for their individual, remove the start bit gene and the last bit gene, to accumulate the transportation cost between the odd bit of remaining genes and its neighboring even bit. The fifth step, the calculation result of the third step minus the calculation result of the fourth step, is the value (i). Illustrate with the example of calculating in this paper. From above calculation can we get individual i = "1,2,3,4,5,6,7,8,9,10,11,12,13", and its corresponding start-stop path of each point S ={1,3,4,6,7,10,11,13 }. If transportation cost point to point is cij, then the value (i) = (c12 + c23 + c34 + c45 + c56 + c67 + c78 + c89 + c9, 10 + c10, 11 + c11, 12 + c12, 13) + (c10 + c30+ c40+c60+c70 + c10, 0 + c11, 0 + c13, 0) - (c34 + c67 + c10, 11). Thus get the fitness (i) = 1 / value (i).

1.3 The judgement of cycle stop

To determine whether reach to stop evolution condition, such as meet the requirement of the number of iteration, or the result meet certain requirement, if so, end the cycle and select the individual that has the largest fitness value and then output its corresponding path to be as the best solution of original problem; Otherwise, enter to the next step.

1.4 Choosing, crossover and mutation

With the roulette wheel selection method to choose the individual enter the next step of crossover and mutation.

In each generation population, with a certain crossover probability to cross and reorganize the individual, the crossover probability is adaptive probability, and its formula is as follows:

$$Pc = \begin{cases} Pavg - \dfrac{(Pavg - Pmax)(f - favg)}{fmax - favg}, & f \geq favg \\ Pavg, & f < favg \end{cases}$$

Pc is the crossover probability of individual i1 and i2 in the population;

Pavg is the basic crossover probability in the population;

Pmax is elite crossover probability used when the individual fitness value is bigger than average in the population;

f is the bigger individual fitness value between individual i1 and i2;

favg is average fitness value of the population;

fmax is the largest fitness value in the population.

In this way can effectively strengthen the genetic ability of excellent individual and protect it enter the next generation. For individual whose fitness value is lower than the average, to adopt the bigger crossover probability can increase the eliminate probability of the weak individual. But at the same time, it can ensure that the best individual will not possess complete dominance in the early evolutionary, and also reduce the probability of the emergence of local best solution.

Introduced a novel crossover algorithm at the same time, the biggest characteristic of the operator is that it still can produce new individuals when two parent individuals are same, so that it decreases the demand for community diversity, can effectively avoid “premature convergence” the disadvantage of traditional genetic algorithm, this is what ever crossover operator does not have. The crossover algorithm is different from the traditional genetic algorithm with the direct crossover in the process of crossover, but makes the cross section join in the front of the other individual, and then to remove the same genes between the original individual and the cross section one by one, finally will have the new individual that post-crossover. Crossover process is illustrated here. Two parent individuals i=j= "1,2,3,4,5,6,7,8,9,10,11,12, 13", randomly generated two intersection are 4 and 8, namely i=j="1, 2, 3, |4,5,6,7,8, | 9, 10, 11,12,13". Thus, for two individuals, their cross section is "4, 5, 6, 7, 8", then add "4, 5, 6, 7, 8" to the front of each individual, after get i=j= "4,5,6,7,8,1,2,3,4,5,6,7,8,9,10,11,12,13", to get rid of the same genes between original individual i=j= "1,2,3,4,5,6,7,8,9,10,11,12,13" and cross section "4, 5, 6, 7, 8" one by one, and the new individual is obtained i=j="4,5,6,7,8,1,2,3,9,10,11,12, 13". The operation method is the same for the second parent individual. Can be seen from the above example, even though the two parent individuals are the same, it still can produce a new individual to continue the iteration to find the best solution of the problem. It avoids the "premature convergence" phenomenon to some extent.

Mutation of species is of much less likely, so the mutation operation in the genetic algorithm is only a supplementary role. The mutation probability of every generation is adopted adaptive mutation probability to improve the individual mutation.

$$\mathrm{Pm} = \begin{cases} \mathrm{Pmavg} - \dfrac{(Pmavg - Pmmax)(fmmax - fm)}{fmmax - fmavg}, & \mathrm{fm} \geq \mathrm{fmavg} \\ \mathrm{pmavg}, & \mathrm{fm} < \mathrm{fmavg} \end{cases}$$

Pm is mutation probability of individual i1 in the population;

Pmavg is the basis mutation probability of population;

Pm max is elite mutation probability used when the individual fitness value is bigger than average value in the population;

fm is fitness value of individual i1;

fmavg is average fitness value of population;

fm max is the biggest individuals fitness value of population.

At the same time, adopt the reverse mutation for the individual of natural number coding. Specific process is as follows: randomly generated an individual temp= "1,2,3,4,5,6,7,8,13,12,11,10,9" and two mutation point 2 and 6, namely the temp= "1,|2,3,4,5,6|,7,8,13,12,11,10,9", to reverse the mutation section to get a new individual temp="1,|2,3,4,5,6|,7,8,13,12,11,10,9"→temp="1,|6,5,4,3,2|, 7,8,13,12,11,10,9". And then return to calculate fitness value.

1.5 Program design

It is unable to complete the evolution and computation of the genetic algorithm only by manual calculation. First of all, the amount of calculation of genetic algorithm is very large, it is determined not only by the genetic algorithm itself, but is determined by the characteristics of combination explosion and complexity of the specific operation of vehicle routing problem itself; Secondly, genetic algorithm needs a lot of random numbers to calculate in the process of calculation, random number that is obtained by artificial method cannot meet the needs of the genetic algorithm; Finally, the solution of the vehicle routing problem has its real economic significance, thus not only has requirement for the final result to be good and right, also asked that the calculation speed is faster. In terms of computing speed, compared with the artificial calculation, program calculation has obvious advantage.

In the process of design: (1) Produce initial population with the application of the random number, and the population size is limited to 50, that is, each generation population exists in relatively independent individual. (2) Calculate the fitness value of the individual, and then select the individual with the largest fitness value, change the fitness value as a function value, compare with target expectations, stop and output result if the function value is less than the target expectation, or continue. (3) Choose two individuals randomly and generate a range of random number between 0 and 1, used for comparing with crossover probability. Two individuals to carry out the cross, if this random number is lower than cross probability, otherwise do not cross. The location of the cross is random. (4) Choose one individual according to the fitness value size and the order from big to small, generate a random number between 0 and 1, used for comparing with mutation probability. To carry out the mutation, if this random number is lower than mutation probability, otherwise do not mutate. (5) To judge the evolution generation of process meets the requirement or not, and the set of this article is 100 generations. Stop evolving and output the best result if reach 100 generation, otherwise return to step (2).

CHAPTER IV

CASE STUDY

Simple theorctical analysis is not enough to prove the results' actual validity of this research, therefore, in this chapter, the author will use case study to do practical calculation, and test research results of this paper by comparing with the original method of case. Case is a logistics transportation company's actual business operation case, the data are derived from the specific operation practice, so it has strong persuasive.

Nantian logistic company was established in early 2001, which is given priority to storage and transport businces, and located at Qianlong logistic park of south China city in Nanning, Guangxi, China. In addition, its registered asset is 3 million RMB and its business scope is mainly in the Guangxi province. Its business has developed rapidly, and so does its assets. It is a strong and comprehensive logistics company in Guangxi province.

But on the transportation vehicle routing arrangement, Nantian still mainly relies on experience, and lacks of scientific and effective planning methods, so that its transportation cost is a little higher.

Analysis of the Company Problem

In this part, author will show two types of software application which can solve vehicle routing problems in Logistics Company with genetic algorithm. They are software VC++ and MATLAB.

Company got the cost of transport routes is 341 for a demand plan with saving matrix method, but through the genetic algorithm solution used in the Micro software VC++, we get the cost of transport routes is 209, which is proved in the paper published on the NIDA conference proceedings (it is shown in the appendix part), it is below the cost of the original plan. Thus it can be seen, the result to calculate with the method is better than the result to calculate with the company's method. Specific analysis is as follows:

Nantian logistics company now has 9 types of trucks with load capacity is 70 m^3, 60 m^3, 50 m^3, 43 m^3, 30 m^3, 16 m^3, 90 m^3, 120 m^3 and 140 m^3 respectively. Because of the complexity of vehicle capacity, this paper did not take it into consider.

One month, Nantian received orders for 11 customers whom come from 11 main cities in Guangxi, respectively. So it will deliver goods for 11 points. And company believes that the total transportation cost is related to the total kilometers of trucks. That is to say, the distance between two points is highly relevant with the total transportation cost. So the company decided to assign the delivery task of different customer to each truck, and design route for each truck, to reduce the total distance. To make the location of distribution center as the origin of coordinates, the position and demand of the 11 customers' are shown in the figure 6 and table 1 below.

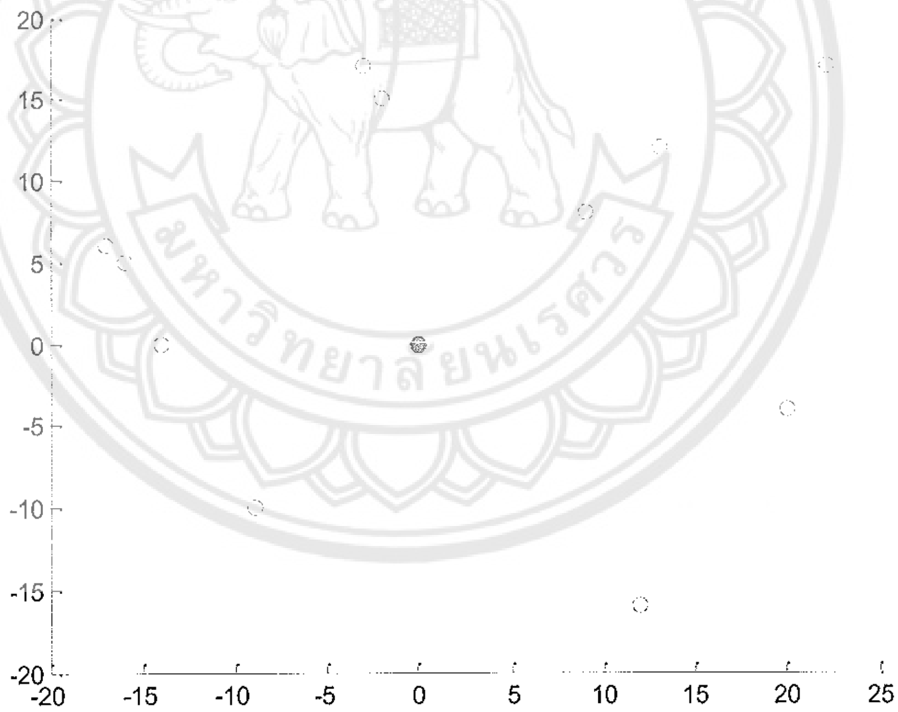

Figure 6 Scatter Plots of Customer Points

Set the distribution center Nanning to be the origin of coordinates and get this main picture.

Except the position of demand point, we also need to know the specific demand order of each point. So the next table 1 will show the detail.

Table 1 Coordinates and the Demands of Customers

		X	Y	Order size(m^3)		Total cost	
Distribution center		0	0	Jul.	Aug.	Jul.	Aug.
1	BH	-17	6	2577	2980	34550	42150
2	FCG	-14	0	1120	1050	/	/
3	QZ	-16	5	2576	2340	40950	36300
4	CZ	-9	-10	1850	2062	/	/
5	BS	12	-16	2358	2274	60700	56800
6	HC	20	-4	4476	3562	114470	101590
7	GL	22	17	2453	2644	68400	76850
8	LZ	13	12	4170	3834	119700	106900
9	LB	9	8	2170	2062	/	/
10	GG	-2	15	2170	2090	/	/
11	YL	-3	17	1779	2218	/	/

If we ignore the order size of customers and the load capacity of vehicles, only for routing selection has total $11! \times C_{10}^{3}$ kind of schemes. It is unable to complete tasks with the simple exhaustive method to find the shortest path. Besides, the problems will be more complex and the computation will be increased exponentially, if the order size of customers and the load capacity of vehicles the two constraints are to be considered.

Nantian got the solution with the saving matrix method; the best solution is shown in table 2. Its distance-square matrix is shown in table 3. The result of total scheduling is 341.

Table 2 Delivery Schedule of Nantian with the Saving Matrix Method

Truck	Capacity (m^3)	Travel journey	The length of the travel
1	70	DC-1-11-DC	53
2	60	DC-4-DC	26
3	50	DC-3-DC	34
4	43	DC-7-DC	56
5	30	DC-10-DC	30
6	16	DC-9-DC	24
7	90	DC-5-6-DC	54
8	120	DC-8-DC	36
9	140	DC-2-DC	28

Table 3 Distance-square Matrix for Delivering Goods of Nantian

	DC	C 1	C 2	C 3	C 4	C 5	C 6	C 7	C8	C 9	C 10	C 11
1	18	0										
2	14	7	0									
3	17	1	5	0								
4	13	18	11	17	0							
5	20	36	31	35	22	0						
6	20	38	34	37	30	14	0					
7	28	41	40	40	41	34	21	0				
8	18	31	30	30	31	28	17	9	0			
9	12	26	24	25	25	24	16	16	6	0		
10	15	19	19	17	26	34	29	24	15	13	0	
11	17	18	20	18	28	36	31	25	17	15	2	0

Appling Genetic Algorithm to the Company

To calculate with the genetic algorithm software VC++, the setting is as follows: encoding scheme uses the natural number sequence encoding; set population size to be 50, set the algebra of the evolution to be 100 generations; set the crossover probability Pavg = 0.95 and Pmax = 0.6, set the mutation probability Pmavg = 0.05, and Pmmax=0.01; selection method is the roulette wheel selection method; the judgment method of stopping is double judgment that can set the desired best result, such as set for 341, and once run to get the best value that is less than or equal to 341 to stop evolution and output result; at the same time can set evolution algebra, such as set for 100, so if there is no best value less than or equal to 341, the evolution to the 100th generation also stop evolving, and then output the best result in these 100 generations. According to the above settings to do calculation and will get the final solution, get the best path arrangement is 209, as shown in table 4.

Table 4 Best Path with Genetic Algorithm

Truck	Capacity (m^3)	Travel journey	The length of the travel
1	70	DC-9-7-DC	56
2	60	DC-5-DC	20
3	50	DC-3-1-DC	36
4	43	DC-10-DC	15
5	30	DC-11-DC	17
6	16	DC-4-DC	13
7	90	DC-2-DC	14
8	120	DC-6-DC	20
9	140	DC-8-DC	18

According to the data of table 1 and table 3, it can be proved that data of table 4 is feasible and reliable, and also proved that the method adopted is better than the saving matrix method adopted by the Nantian Company.

The best value judgment parameter for stopping judgment conditions in operation is set to be 341, the evolution algebra judgment parameter is set to be 100, other settings is unchanged. To run ten times, the result is shown in table 5.

Table 5 Ten Times Run Results Comparison

Time	1	2	3	4	5	6	7	8	9	10	Average	Unit
Result	209	258	277	209	209	307	275	209	265	341	255.9	R

In table 5, only the best value 307 of the sixth belongs to automatically stop that evolution algebra reach 100 generation in these 10 times' operations, the best values of the remaining nine times are not greater than 341 belong to automatically stop that the best values accord with condition. Moreover, the result of four times obtained the best value 209 among these 10 times, they are 1, 4, 5, 8 times, respectively. The average of these ten times is 255.9 and it is also lower than the best value 341 of the company.

Actually company has more than this 11 demand points. This paper will chose other 30 demand points to do research with software MATLAB. Company got the cost of transport routes of these 30 demand points is 25 with saving matrix method. The data is based on year in July and August. Specific analysis is as follows:

To make the location of distribution center as the origin of coordinates, the position of the demand points are shown in the figure 7 and the specific coordinate in table 6 below.

Figure 7 Scatter Plots

Table 6 Coordinates and Demands of Customers

Item	X	Y	Demands (m^3)
1	0	0	0
2	3	2	8
3	1	5	8.2
4	5	4	6
5	4	7	5.5
6	0	8	3
7	3	11	4.5
8	7	9	7.2
9	9	6	2.3
10	10	2	1.4
11	14	0	6.5
12	17	3	4.1

Table 6 Coordinates and Demands of Customers (Cont.)

Item	X	Y	Demands (m^3)
13	14	6	12.7
14	12	9	5.8
15	10	12	3.8
16	7	14	4.6
17	2	16	3.5
18	6	18	5.8
19	11	17	7.5
20	15	12	7.8
21	19	9	3.4
22	22	5	6.2
23	21	0	6.8
24	27	9	2.4
25	15	19	7.6
26	15	14	9.6
27	20	17	10
28	21	13	12
29	24	20	6
30	25	16	8.1
31	28	18	4.2

Note: The demand is demand of one day.

With the number of data points increasing, the distance-square matrix become complicated, so it will be not displayed here.

To calculate with the genetic algorithm in MATLAB, the setting is as follows: encoding scheme uses the natural number sequence encoding; set population size to be 30, set the algebra of the evolution to be 100 generations; set the crossover probability $P_c = 0.8$, set the mutation probability $P_m = 0.2$; selection method is the roulette wheel selection method; the judgment method of stopping is double judgment that can set the desired best result, such as set for 25, and once run to get the best value that is less than or equal to 25 to stop evolution and output result; at the same time can set evolution algebra, such as set for 100, so if there is no best value less than or equal to 25, the evolution to the 100th generation also stop evolving, and then output the best result in these 100 generations. According to the above settings to do calculation and will get the best path arrangement and the best cost.

The best value judgment parameter for stopping judgment conditions in operation is set to be 25, the evolution algebra judgment parameter is set to be 100, other settings is unchanged. To run ten times, the result is shown in table 7 and table 8.

Table 7 Ten Times Run Results Comparison (Path)

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

Table 8 Ten Times Run Results Comparison (Cost)

Time	1	2	3	4	5	Unit
Cost	1.6862e+04	1.6228e+04	1.5220e+04	1.4472e+04	1.4928e+04	RMB
Time	6	7	8	9	10	Unit
Cost	1.4408e+04	1.4080e+04	1.4724e+04	1.4276e+04	1.3390e+04	RMB

From table 7, we can see that the number of vehicle decreased from 2 to 1. It is also a way to make the total cost to be minimized.

In table 8, the best values of these ten times are not greater than 25 belong to automatically stop that the best values accord with condition. Moreover, the result of 10^{th} times obtained the best value 1.3390e+04 among these 10 times. The average of these ten times is also lower than the best value 25 of the company. It can do gap analysis with gap picture below.

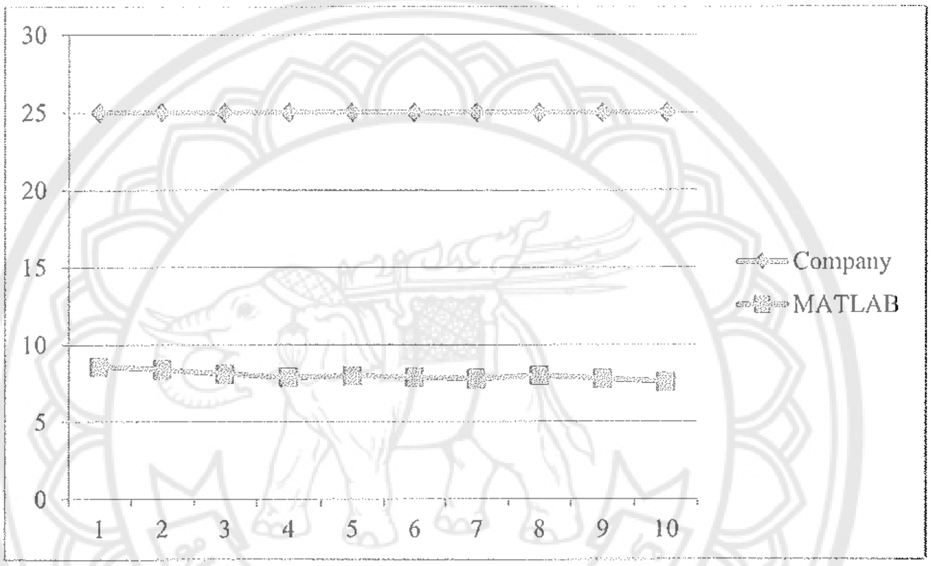

Figure 8 Gap Analysis of the Cost

According to the data of table 6, table 8 and figure8, it can be proved that data of table 7 is feasible and reliable, and also proved again that the method adopted of this paper is better than the saving matrix method adopted by the Nantian Company.

CHAPTER V

CONCLUSIONS

After applying genetic algorithm to analysis the vehicle routing problem of Nantian Logistics, this paper got the conclusions as follows:

1. This article has built up the mathematical model of vehicle routing problem through the systematic research for genetic algorithm, and then found out the solution of vehicle routing problem based on genetic algorithm. Through the case analysis, proved the solutions of this paper can solve the vehicle routing problem in logistics transportation. It proved that the solution of genetic algorithm is adopted in this paper the corresponding transportation cost is far less than the cost which is obtained by saving matrix method.

2. Genetic algorithm is a kind of calculation method which imitates the nature evolution. It has good convergence and operability on calculating the vehicle routing problem. Vehicle routing problem belongs to Non-Deterministic Polynomial (NP) problems in calculation, deducing from this can we believe that the genetic algorithm can also play a role of its advantages in other issues of NP computation.

3. Vehicle routing problem in logistics transportation related to the cost of transportation vehicle. Good vehicle transportation route plan can effectively reduce the transportation cost, improve the efficiency of transportation. This paper proves this point through case analysis.

CHAPTER VI

SUGGESTIONS AND FUTURE RESEARCH

Suggestions

From this thesis, author gave out the suggestions as follows:

1. Genetic algorithm also has its defects. Firstly is the uncontrollability of evolution, we can eliminate the individuals that are not applicable to our needs through the calculation of fitness in the process of evolution, but keep the excellent individuals, and finally the new individuals are obtained by crossover and mutation. That is very similar with the way of evolution of the nature. But genetic algorithm in the process of evolution, can't guarantee that the next generation must be better than the previous generation individuals, the whole trend of evolution is the volatility curves at the side of the best value. In this paper, in the process of case analysis, has make the population evolution ten thousand generations, and repeat 10 times, the best value of the best individual of the ten thousandth generation is local best value, not the global best value. Therefore, simply rely on natural evolution for the calculation of the best value is meaningless. Secondly, the initial generation of genetic algorithm has obviously impact on the whole population in the evolution of the individual, but individuals of the initial generation of the traditional genetic algorithm are obtained by adopting random numbers, it's more obvious for the uncontrollability of evolution of genetic algorithm. For the defects of genetic algorithm, we should change the defect the traditionally rely on random numbers to produce initial population with giving priority to population initialization to use genetic algorithm saving method. That is, combine the genetic algorithm and saving matrix method, to carry on the preliminary estimate with saving matrix method, and gets a local best solution or an approximate local best solution, and then the new individual is obtained through mutation. Different mutation positions and ways can get different individuals, and this part of individuals has obvious robustness than individuals that are obtained by randomly generated. At the same time, to get a population by mixed the random parts of individuals with the

mutation parts of individuals. Thus we can speed up the convergence of genetic algorithm.

2. Crossover and mutation is the essence and the focus of genetic algorithm. Through crossover and mutation can we get much better new individuals to promote the evolution of the whole population, but also can reduce the fitness values of excellent individuals after crossover and mutation, then appear the phenomenon that offspring is worse than parents. In this paper, the author with the way of adaptive evolution to adopt different crossover probability and mutation probability for individuals that have different fitness values, respectively. The crossover probability and mutation probability of individuals with bigger fitness value are reduced to give its proper protection. On the contrary, for individuals with lower fitness values, we should adopt larger crossover probability and mutation probability to get the new individuals. The fact proved that, using the adaptive evolutionary way, speed up the convergence speed of evolution.

3. This thesis has the limitation about the number of case study, the channels of collecting information and the number of constraints factors (such as, time window and capacity of vehicle). So it should extend the number of sample and take more constraints into consideration to do case study and application in order to get more meaningful result.

Future Research

The number of customers of the case is still small in this paper, so it has no obvious advantage to use saving genetic algorithm, even may also reduce the speed of the calculation, but it will show a clear advantage when calculating the complex problems what has more customers. Saving genetic algorithm is just a kind of thinking, we can also combine genetic algorithm with other algorithms, such as simulated annealing method and ant colony algorithm, etc. It can effectively improve the convergence speed of genetic algorithm and reduce the calculation time of the complicated problem to use hybrid algorithm.

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APPENDIX

APPENDIX A MORE INFORMATION ABOUT NANTIAN LOGISTICS

1. Nantian Logistics Park

1 Office building
2 Warehousing center
3 Distribution center
4 Parking area
5 Ecological plantations for staff
6 Dormitory building
7 Leisure park
8 Playgrounds
9 Car inspection and maintenance

Source: http://www.nt56.net/news_detail/newsId=133.html (Website of Nantian Logistics)

This logistics park has a total of 110mu (7.337 hectares) of area, 40000 square meters of warehousing area and 196 parking points. It is a comprehensive logistics ecological garden only for Nantian.

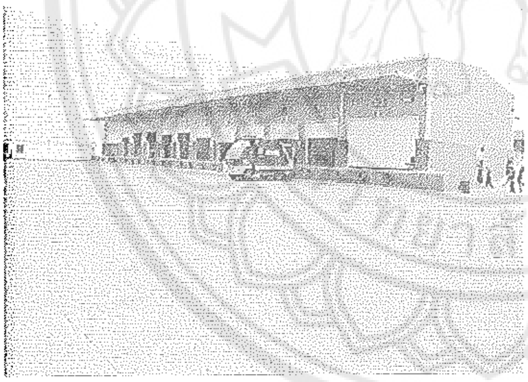
2. Nantian Headquarters

Source: Taken by Nantian manager

3. Warehousing area

Source: Taken by Nantian manager

4. Take and delivery area of goods



Source: Website of Nantian Logistics

5. Vehicle type of Nantian Logistics

5.1 Small truck

5.2 Big truck

5.3 Dump trailer

5.4 Little car

5.5 Commercial car

5.6 Van trucks

Source: Taken by Nantian manager

APPENDIX B SOFTWARE PROGRAM

1. GAVRP.m

```
% GAVRP    using Matlab
clear;clc
load matlab.mat
Sup_Parent=[3 6 7 17 18 5 8 16 19 15 26 25 4 27 29 2 9 14 20 28 30 31 13 22 21 24
11 12 23 10]-1;
G=100;% population size
Parent=rand(G,30);% random parent
for i=1:G
[m,n]=sort(Parent(i,:));
                                                  % initialization
Parent(i,:)=n;
end
Pc=0.8;% crossover probability
Pm=0.2;% mutation probability
species=[Sup_Parent;Parent];% population
children=[];% children
%fitness_value(4070,1)=0;% fitness value

g=input(' iteration of update');
for generation=1:g
Parent=species;%children become to be parent
children=[];%children
%crossover parent
[n m]=size(Parent);
% select=rand(1,n)<Pc;
% select=find(select==1);

                                                 %crossover
for i=1:n
    for j=i:n
        if i~=j & rand<Pc
            jiaocha
        end
    end
end

for i=1:n
    if rand<Pm
    parent=Parent(i,:);% mutation of individual
    X=floor(rand*30)+1;
    Y=floor(rand*30)+1;
    Z=parent(X);
    parent(X)=parent(Y);
```

```
parent(Y)=Z;
                                        %mutation
    children=[children;parent];
    end
end

% calculate fitness value of children
[m n]=size(children);
fitness_value_c=zeros(m,1);%fitness value of children
for i=1:m
    l1=1;
    for l2=1:n
        if sum(data(children(i,l1:l2),3))>25
            fitness_c
            l1=l2;
        end
        if l2==n
            l2=l2+1;
            fitness_c
        end

                                        %calculate fitness value
    end
end
%calculate fitness value of parent
[m n]=size(Parent);
fitness_value_P=zeros(m,1);%fitness value of parent
for i=1:m
    l1=1;
    for l2=1:n
        if sum(data(Parent(i,l1:l2),3))>25
            fitness_P
            l1=l2;
        end
        if l2==n
            l2=l2+1;
            fitness_P
        end
    end
end

%clean children out
[m n]=sort(fitness_value_c);
children=children(n(1:G),:);
fitness_value_c=fitness_value_c(n(1:G));
%clean parent out
[m n]=sort(fitness_value_P);
```

```
Parent=Parent(n(1:G),:);
fitness_value_P=fitness_value_P(n(1:G));
%clean population out
species=[children;Parent];
fitness_value=[fitness_value_c;fitness_value_P];
[m n]=sort(fitness_value);
species=species(n(1:G),:);
fitness_value=fitness_value(n(1:G));
                                                %update
end
species(1,:)%best path
fitness_value(1)%best cost
```

2. Fitness_P.m

```
  path=Parent(i,l1:l2-1);
  l=length(path);
  for k=1:l
        if k==1
              fitness_value_P(i)=fitness_value_P(i)+sum(data(path,3))*dis(1,path(1))*3;
        else
fitness_value_P(i)=fitness_value_P(i)+sum(data(path(k:l),3))*dis(path(k-1),path(k))*3
;
        end
  end
  fitness_value_P(i)=fitness_value_P(i)+dis(path(l),1)*2;
```

3. Fitness_c.m

```
  path=children(i,l1:l2-1);
  l=length(path);
  data(path,3);
  sum(data(path,3));
  for k=1:l
        if k==1
              fitness_value_c(i)=fitness_value_c(i)+sum(data(path,3))*dis(1,path(1))*3;
        else
fitness_value_c(i)=fitness_value_c(i)+sum(data(path(k:l),3))*dis(path(k-1),path(k))*3;
        end
  end
  fitness_value_c(i)=fitness_value_c(i)+dis(path(l),1)*2;
```

4. jiaocha

```
  %OX order crossover strategy
  P1=Parent(i,:);
  P2=Parent(j,:);
```

```
% choose point of contact to exchange middle part and repair gene
X=floor(rand*28)+2;
Y=floor(rand*28)+2;
if X<Y
    change1=P1(X:Y);
    change2=P2(X:Y);
    %P1(X:Y)=change2;
    %P2(X:Y)=change1;
    %begin to repair Order Crossover
    %1.gene list
    p1=[P1(Y+1:end),P1(1:X-1),change1];
    p2=[P2(Y+1:end),P2(1:X-1),change2];
    %2.1delete the existing gene P1
    for i=1:length(change2)
        p1(find(p1==change2(i)))=[];
    end
    %2.2delete the existing gene P2
    for i=1:length(change1)
        p2(find(p2==change1(i)))=[];
    end
    %3.1repair P1
    P1=[p1(30-Y+1:end),change2,p1(1:30-Y)];
    %3.1repair P2
    P2=[p2(30-Y+1:end),change1,p2(1:30-Y)];
else
    change1=P1(Y:X);
    change2=P2(Y:X);
    %P1(Y:X)=change2;
    %P2(Y:X)=change1;
    %begin to repair Order Crossover
    %1.gene list
    p1=[P1(X+1:end),P1(1:Y-1),change1];
    p2=[P2(X+1:end),P2(1:Y-1),change2];
    %2.1delete the existing gene P1
    for i=1:length(change2)
        p1(find(p1==change2(i)))=[];
    end
    %2.2delete the existing gene P2
    for i=1:length(change1)
        p2(find(p2==change1(i)))=[];
    end
    %3.1repair P1
    P1=[p1(30-X+1:end),change2,p1(1:30-X)];
    %3.1repair P2
    P2=[p2(30-X+1:end),change1,p2(1:30-X)];
end
%add to children
children=[children;P1;P2];
```

APPENDIX C PUBLISHED PROCEEDINGS

The author published e-proceedings on the International Conference for Case Studies 2016 (ICCS-2016). You can view the file from the following website link:

https://drive.google.com/open?id=0Bwi0zAduZqACVXlDVDE5UWZOV3c

BIOGRAPHY

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