Fuzzy Information Based Vehicle Routing Problem with Improved Hybrid Intelligent Algorithm

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Abstract: Vehicle routing problem is one of the most popular supply chain management problems, which are at the heart of most decision support systems for real-life distribution problems. The traditional vehicle routing problem (VRP) is often constrained to some specific terms. But in actual situations, the procedure of the travel is full of uncertain elements (i.e. traffic jams et al.). In this paper, an improved hybrid intelligent genetic algorithm is designed to solve fuzzy information constrained VRP. The roulette heuristic algorithm is adopted to create the initial chromosomes with great efficiency. A numerical experiment is presented at the end of this paper to show the efficiency and effectiveness of the hybrid intelligent genetic algorithm under the given condition. Some critical parameters of this algorithm are discussed and some suggestions are proposed in the paper to guide the use of this model in practice.

1 INTRODUCTION

With the development of modern manufacturing technology, engineers and researchers begin to improve all technologies to increase efficiency and qualities of the manufacturing process. As an important part of this procedure, vehicle routing problem (VRP) plays a crucial role in it. VRP was proposed by Dantzing G, Ramser J in 1959 firstly (G.B.Dantzig et al., 1959). The traditional methods pay attention to the specific information (include the workstation information, travel time information and so on), this cannot describe the real problem precisely. After that the Stochastic demands and stochastic travel times were considered to simulate the case, F.Tillman proposed a model which has several depots (F. Tillman, 1969). These problems are called stochastic vehicle routing problems (SVRP). Stewart andGolden contributed to the problem too (Jr. Stewart, W.R. et al., 1983). Teodorovic and Pavkovic gave many models and algorithms to SVRP models (D.Teodorovic et al., 1992).

In real situation, we cannot describe the problems with those random variables either for there are not enough information for use to analyze. As a result, the fuzzy variables were adopted to simulate the actual situation. Teodorovic and Pavkovic used fuzzy programming to deal with the uncertain parameters (Teodorovic et al., 1996). In their model, fuzzy customer's demands were used to solve VRP problem with single central depot. All other information (travel time, cargo capacity et al.) is given certain. Lai et al, also contributed to this problem by a fuzzy model with possibility measure (K.K.Lai, B.Liu et al., 2003). Chen and Gen solve the problem with genetic algorithm under fuzzy due time to meet the multiple purposes including minimize the fleet size of vehicles, maximize the average grade of satisfaction over customers, minimize the total travel distance and total waiting time (Chen, R. et al., 1995). Zheng and Liu depicted the fuzzy information with triangular fuzzy number to describe the preferences of customers (Zheng, Y. et al., 2006). Zhang et al analyze the problem under the fuzzy customer's demands (Jianyong, Z. et al., 2004) and fuzzy travel time (ZHANG Jianyong et al., 2006). Cao et al discussed the problem with fuzzy customer's demands either (Cao Erbao et al., 2007).

All these papers mentioned above discussed about the one of many elements that affects the whole process. But as we all know, in the real delivering process, none of these elements show its influence respectively. Anyone factor interacts with others. So researches on the multiple fuzzy variables in VRP are totally necessary and important.

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2 MAIN FUZZY INFORMATION

2.1 Fuzzy Requirements

Fuzzy requirements mean that each workstation's cargo requirements are not certain. In modern workshop, the products in one workshop often need to be changed, such as agile manufacturing. In that case, different products may be manufactured in one machine to meet the different needs of customers. That demands the travel vehicle carry different raw materials to meet the need. After serving the previous stations, the vehicle needs to find out whether it has the ability to serve the next station. The a_i is the cargo demand of i_{th} workstation.

2.2 Fuzzy Travel Time

When the vehicle is on the way to the next station, there are plenty of uncertain elements (such as traffic jam, the speed of vehicle is not constant and so on) preventing the cargo to be delivered just on time. As a result, the fuzzy variables are used to describe the fuzzy travel time. The d_{ij} is the distance between the workstation i and j.

2.3 Fuzzy due Time

The actual reservation time will also be an uncertain element. The traditional time window use rectangle frame to depict the tolerance of the workstation. This cannot describe the preferences of each station. Chen and Gen (Chen R et al., 1996)brought forward the tolerance of interval time for workstation as triangular fuzzy window (TFW). The preferences of workstation were naturally represented by triangular fuzzy number (TFN) with respect to the grade of satisfaction for service time. Two windows are listed in figure 1. Where e_i and l_i is the earliest and latest tolerance of the workstation which is waiting to be served. The u_i means the grade of satisfaction is 1. The function $u_i\left(t_i\right)$ is used to represent the degree of satisfaction, which is zero when the arrival time falls out of [e_i ,l_i].

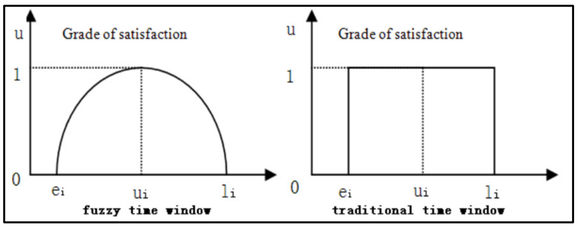

Figure 1: Contrast of fuzzy time window and traditional time window.

3 MODEL DESIGNING

In order to describe the problem, some parameters are introduced to help designing the model. We assume that,

- Each vehicle has a container with a physical capacity limitation and the total loading of each vehicle cannot exceed its capacity.
- A vehicle can only be assigned for only one route.
- A workstation will be visited by one and only one vehicle.
- Each vehicle begins at central depot and ends at it.

For the triangular fuzzy window

$$u_i=\begin{cases}0, t_i<e_i\\ \dfrac{t_i-e_i}{u_i-e_i}, e_i\le t_i\le u_i\\ \dfrac{l_i-t_i}{l_i-u_i}, u_i\le t_i\le l_i\\ 0, t_i\ge l_i\end{cases} \tag{1}$$

Auxiliary decision parameters

y_{ik} — $y_{ik}=1$ when workstation i is served by vehicle k, otherwise 0;

x_{ijk} — $x_{ijk}=1$ when vehicle k travels from workstation i to j, otherwise 0;

Optimal goals

$$\max\frac{1}{n}\sum_{i=1}^{n}u_i(t_i) \tag{2}$$

$$\min\sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n}d_{ij}x_{ijk} \tag{3}$$

S. T.

$$u_i(t_i) > 0, \forall i \tag{4}$$

$$\sum_{i=1}^{n} a_i y_{ik} \le C_k, \forall k \tag{5}$$

$$\sum_{k=1}^{m} y_{ik} = 1, \forall i \tag{6}$$

$$\sum_{i=1}^{n} x_{ijk} = y_{ik}, \forall i, k \tag{7}$$

$$\sum_{j=1}^{n} x_{ijk} = y_{ik}, \forall i, k \tag{8}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ijk} \le |S| - 1, \forall k \tag{9}$$

$$x_{ijk} = 0 \; or \; 1, \forall i, j, k \tag{10}$$

$$y_{ik} = 0 \; or \; 1, \forall i, k \tag{11}$$

$$t_i \ge 0, \forall i \tag{12}$$

y_{ik} and x_{ijk} are auxiliary decision parameters, C_k is cargo capacity of each vehicle. Objective (2) maximize the credibility of satisfaction over each workstation. Objective (3) minimize total travel cost of all vehicles. Constraint (4) ensures that each desired time is within the tolerable interval of time. Constraint (5) ensures each vehicle is assigned to serve the workstation without exceeding its freight restriction. Constraint (6) ensures that each workstation is served by one and only one vehicle. Constraints (7) and (8) ensures that each station connect to only one station traveled to itself and only one it will travel to, that means each station has two neighbor stations. Constraint (9) show the relationship between vehicles and workstations for each journey of each vehicle, that means each vehicle should start from central depot and end at this depot after finishing the journey. (10), (11) and (12) is auxiliary decision parameters constraint.

4 INTELLIGENT ALGORITHM DESIGNING

Hybrid intelligent algorithm was a kind of intelligent algorithm which was proposed by Baoding Liu (Liu Baoding et al., 2003)in 2003 for solving the problems under uncertain condition (including random and fuzzy). The main idea of this algorithm is to express uncertain information by using the characteristics of neural network and to search the approximate optimal solution by genetic algorithm (GA). Because the main function of optimization is GA, how to design GA directly affects the efficiency and precision of this algorithm.

4.1 Representation of Genetic Chromosomes

Assume workstations encoding in natural number from 1 to n, as a result, the chromosomes are designed as natural denote. $0, i_{j,} ......i_k, 0, i_m, ...i_n, 0, ..., 0, i_s, ...i_t, 0$ is one of the chromosome means that there are k vehicles in total, which carry the raw material. The symbol 0 represents the central depot, i_{sym} is the workstation that the specific vehicle serves.

4.2 RHA Algorithm

In this paper, the roulette heuristic algorithm (RHA) is adopted to generate the first population for the genetic algorithm. The steps are listed below:

Step 1: $\varphi(\xi)$ is the membership degree function. α is a credibility number. Workstation demand and transportation time can be drawn from $\xi^0 \in \left(\xi_{\inf(\alpha)}, \xi_{\sup(\alpha)}\right)$. The fuzzy due time window can be simplified into certain traditional time window which using ET_i and LT_i as up and down boundaries and satisfaction degree always equals 1.

Step 2: Select current all workstations at first. If there isn't any station satisfying the demands, select the distribution center as current node. Draw lines between the select node and other unselected stations. Erase those incompatible constraint lines. Use evaluation function which considers the distance as important weight to give a score to each existing line. If there is no line remains, this path is arranged over. Choose another vehicle to arrange again. At this time, we choose distribution center as current node, repeat what we have done above.

Step 3: If all remained lines with scores were available. Roulette selection is used to select the best line of all. After we getting a line by this method, delete others and decide the downstream station as the current node.

Step 4: If all of workstations have been arranged well, RHA method selection is finished. Otherwise go to step2 to repeat the loop.

Apparently, we can get one feasible chromosome after the RHA selection is used once. Repeat that method by n times, the number of n chromosomes can be created. These chromosomes can be used as initial population of the genetic algorithm. In this way of choosing the initial population of the algorithm, we can easily get some chromosomes that are closer to the shortest solution that we expect. The result of the demo can prove that the convergence iterations are less than ordinary methods.

4.3 Crossover Designing

Because of the specialty of the vehicle routing problem, traditional method of crossover cannot be used directly. In this paper, the PMX crossover (Li Renan et al., 2004) is adopted to solve the VRP problem.

Assume that A and B is two chromosomes of the initial population, the PMX choose a part of route from A randomly, then the part is hand over to its next generation A1. Find the same route in chromosome B, and then delete it. Arrange the rest parts of routes of B to A1. After that, we get a new chromosome of next generation. Repeat the same procedure to B and we can get B1 too. Do the procedure by crossover probability. All chromosomes of next generation are available.

4.4 Mutation Designing

In this paper, the reverse mutation (Zhang Jing et al., 2004) is adopted to mutate each chromosome. The main idea of this method is to reverse the part of the route of chromosomes. Certainly, this reverse should ensure that the new chromosome is better than the old one. Assume L13 represents the length of route between workstation 1 and 3, so do L28, L34, and L56. If L13 +L28< L12 +L38, then the exchange of 3 and 2 is valid.

After crossover and mutation, there may be unreasonable chromosomes. If the there is no central depot in head and tail position, or there are two neighborhood depots among the chromosomes, exchange any non-depot station to central depot randomly. Then check the feasibility of each chromosome.

4.5 General Hamming Similarity Degree

Standard genetic algorithm has two weak characters. One is local convergence and the other is lower efficiency in later evolution period. This paper proposes general hamming similarity degree to distinguish chromosomes from each other and establishes double-selection and double-mutation operations in the evolution period.

This paper proposes general hamming similarity degree, which refers to the concept of general hamming distance mentioned by Wang Jie et al (Wang Jie et al., 2008). The definition is listed below:

Definition 1: Generalized Hamming similarity GL_{ij} is the ratio of the number of the same routes between two chromosomes i and j to the number of routes which are less than the other one.

For instance, chromosome 015403206780 and 0320154060780 both concludes the same two routes 01540 and 0320. The first chromosome has the three routes which are less than the second one. According to the definition we mentioned before, the $GL_{ij} = 2/3$. If two different chromosomes have the same number of routes and all route have the same contents with each other, like 0123057068940 and 0570123068940, then $GL_{ij} = 1$.

It can be concluded that $GL_{ij} = 1$ only if the two chromosomes represent the same solution of the problem (Li Jinhang et al., 2009).

4.6 Improved Hybrid Intelligent Algorithm

Improved hybrid intelligent algorithm more efficient than traditional algorithm for it uses neural network to train an approximate function to help looking for the solution of problems, which refers to Baoding Liu et al. The steps of this algorithm are listed below:

Step 1: Use fuzzy simulation function to create input and output data for the following uncertain functions.

$$U_1 : x \to Pos\left\{ g_j(x,\xi) \le 0, j = 1,2,...,p \right\}$$

$$U_2 : x \to \min\left\{ \bar{f} \mid Pos\{ f(x,\xi) \ge \bar{f} \} \ge \beta \right\}$$

Step 2: According to the data generated by step 1, train a neural network to approximate to the uncertain functions.

Step 3: Create $\xi^0 \in \left\{ \xi_{\inf(\alpha)}, \xi_{\sup(\alpha)} \right\}$ randomly and use roulette heuristic algorithm to create initial population. Use the neural network mentioned above to check the feasibility of each chromosome.

Step 4: Mutate and intersect chromosomes by genetic algorithm with double-selection and double-mutation operations. In this process, general hamming similar degree is used to distinguish similar genes from each other to avoid inbreeding.

Step 5: Evaluate all chromosomes by neural network that has been prepared well.

Step 6: Evaluate the fitness of each chromosome according to their value.

Step 7: Select healthy chromosomes as the next generation under roulette wheel selection.

Step 8: Do not stop repeating step 4 and step 7 until the ultimate number of loops is reached.

Step 9: Find the best chromosome as the solution of the problem.

5 APPLICATIONS

Central depot to seven workstations (denote from 1 to 7). Each vehicle has a maximum load of 8 units. The freight volume of each workstation is listed below in Table 1. The travel time and cost between workstations is listed in Table 2 (the travel time is triangular fuzzy number, and the coefficient matrix is symmetric). Given that overload is not allowed and each workstation's cargo requirements are met, it's important and crucial to arrange a vehicle routing with a lowest total mileage.

Table 1: Reservation time and cargo demand of each workstation.

Position Number	1	2	3	4	5	6	7
Demand [unit]	(3,3.5,4)	(2.6,3,3.5)	(1.8,2,2.1)	(2.1,2.5,2.5)	(3.6,4,4.1)	(3,3.5,4)	(2.6,3,3.4)
Due time[min]	(30,40,43)	(50,70,80)	(90,110,117)	(45,50,67)	(66,80,100)	(85,100,110)	(120,150,160)

Table 2: Travel time and mileage between workstations.

Travel-time[s] / Distance[m]		Position Number							
		0	1	2	3	4	5	6	7
Position Number	0	0	(30,36,38)	(27,31,35)	(12,14,20)	(5,10,14)	(15,20,25)	(17,22,30)	(26,31,34)
	1	17	0	(30,30,30)	(21,22,28)	(20,28,30)	(30,50,65)	(50,58,64)	(35,41,50)
	2	29.22	22.09	0	(24,28,31)	(17,22,30)	(28,31,34)	(40,50,60)	(50,56,59)
	3	5.83	11.18	32.37	0	(9,10,11)	(24,31,41)	(30,36,40)	(23,27,32)
	4	26.4	7.07	18.38	31.18	0	(15,22,29)	(29,31,38)	(31,36,40)
	5	20.25	24.6	13	5	18.03	0	(19,22,28)	(45,51,60)
	6	5	31.54	6.32	24.44	19.85	19.1	0	(38,41,50)
	7	16.76	6	25.06	19	29.43	37	18.87	0

Algorithm parameters are configured as below. The first selection probability is set to 0.8, second probability is 0.8, local mutation probability is 0.1, global mutation probability is 0.2, population size is 40, Hamming similarity degree is not larger than 0.5, iterations is set to 200. For the fuzzy number's credibility, we set reservation time to 0.2, travel time to 0.8, workstation volume to 0.8.

Program the hybrid intelligent algorithm on PC, after 31 iterations, the best solution of the problem was found. The best chromosome is 067014025030. Decode the chromosome to the VRP problem, we get the following routes:

Routes 1: central depot→workstation 6→workstation 7→central depot

Routes 2: central depot→workstation 1→workstation 4→ central depot

Routes 3: central depot→workstation 2→workstation 5→ central depot

Routes 4: central depot→workstation 3→central depot

The total distance is 165.23.

Traditional genetic algorithm is also used to solve the problem for comparison. Initial population size is set to 40, selection probability is set to 0.8, crossover probability is set to 0.8, and mutation probability is set to 0.1. For the selection of fuzzy number's credibility, we set reservation time to 0.2, travel time to 0.8, and workstation volume to 0.8. This algorithm converges to the same result as the hybrid intelligent algorithm after 170 iterations.

In order to test and verify the solution of the problem, the same problem was programmed on MATLAB 7.0. The problem was solved by genetic algorithm tool and neural network tool in MATLAB, we got the same solution showed in figure 2. In figure 3, we find that the hybrid intelligent algorithm used in this paper got the best solution after 31 iterations, the traditional genetic algorithm found the same solution after 170 iterations. Besides that, the hybrid intelligent algorithm created a better chromosome which is 179.71, approaching the final solution which is 165.23. Because the traditional genetic algorithm creates the first population randomly, the best solution of the traditional algorithm is 195.71, which is larger than 179.71.

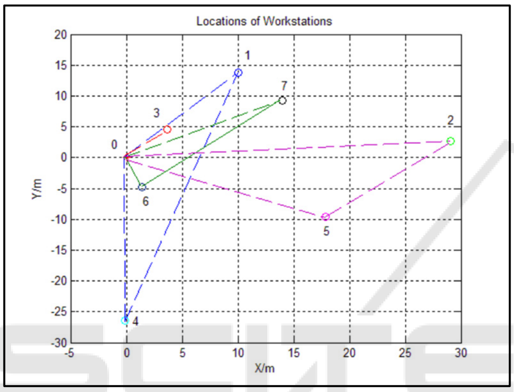

Figure 2: Result of MATLAB simulation.

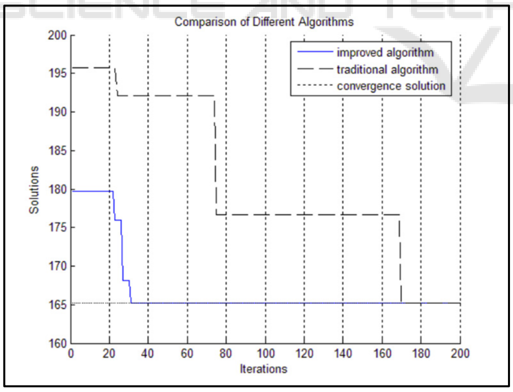

Figure 3: Comparison of different algorithms.

In this case, it can be concluded that the improved hybrid intelligent algorithm is more efficient than the traditional algorithm on the fuzzy VRP problem, and the convergence speed of improved algorithm is faster too.

6 RESULTS ANALYSIS AND CONCLUSIONS

In this model, there are three important fuzzy variables: credibility of fuzzy reservation time α_1, credibility of fuzzy travel timeα_2, and credibility of fuzzy cargo requirements α_3. In the following part, the selection of these variables will be introduced.

The parameters are listed bellow: population size is set to 40, the first and second selection probability are set to 0.8, both crossover probabilities are set to 0.8, local mutation probability is 0.1, global mutation probability is 0.2, Hamming similarity degree is not larger than 0.5, iterations is set to 200. The credibility of fuzzy travel time α_2 is set to 0.8, the fuzzy cargo requirements $\alpha_3\alpha_3$ is set to 0.8. The credibility of fuzzy reservation time α_1 is set to 0.2, 0.4, 0.6, 0.8, and 1.0 separately. The solution of the problem is showed in figure 4.

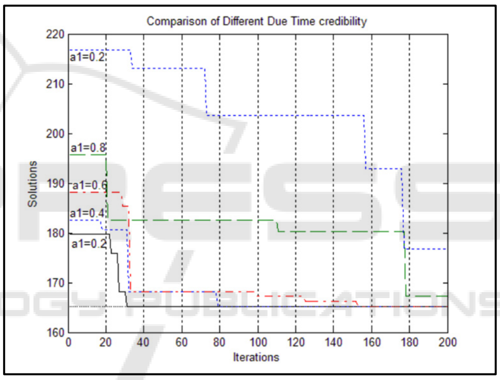

Figure 4: Comparison of different credibility of fuzzy due time.

As it's shown in figure 4, the value of credibility of fuzzy reservation time plays a significant part in the algorithm. Different values lead to different results. It can influence the best solution of first population and the convergence speed of the algorithm. The larger α_1 means workstations ask vehicles to deliver the goods in need much stricter. In other words, the larger credibility of fuzzy reservation time is, more narrower time window is. As a result, there are less feasibility solutions satisfying the requirements of workstations.

When the credibility is larger than 0.8, the algorithm converged to different solutions rather than the best solution we got. That means the vehicles can only satisfy the reservation time requirements whose credibility is smaller than 0.8.

Credibility of Fuzzy Travel time α_2 and Cargo Requirements α_3

Set population size to 40, the first and second selection probability are set to 0.8, both crossover probabilities are set to 0.8, local mutation probability is 0.1, global mutation probability is 0.2, Hamming similarity degree is not larger than 0.5, iterations is set to 200. The credibility of fuzzy due time $\alpha_1$is set to 0.8, the fuzzy cargo requirements α_3 is set to 0.8. The credibility of fuzzy travel time α_2 is set to 0.2, 0.4, 0.6, 0.8, and 1.0 separately. Then set the credibility of fuzzy travel time α_2 to 0.8, the credibility of fuzzy cargo requirements α_3 to 0.2, 0.4, 0.6, 0.8, and 1.0 separately. The results are listed in table 3.

Table 3: Comparison of results under different $\alpha_2$and α_3.

Credibility value		Initial solution	Convergence generation	Optimal solution
α_2 $\begin{pmatrix}\alpha_1=0.2\\ \alpha_3=0.8\end{pmatrix}$	0.2	179.71	180	165.23
	0.4	179.71	153	165.23
	0.6	182.6	98	165.23
	0.8	184.4	38	165.23
	1	195.71	42	165.23
α_3 $\begin{pmatrix}\alpha_1=0.2\\ \alpha_2=0.8\end{pmatrix}$	0.2	182.6	165	165.23
	0.4	195.71	123	165.23
	0.6	191.2	80	165.23
	0.8	194.85	39	165.23
	1	195.71	41	165.23

As the table shown, different values of credibility of fuzzy travel time and fuzzy cargo requirements have less influence on the solution of the VRP problem. The larger these two variables are, the more constant travel time and cargo requirements are. It leads to faster convergence of the algorithm.

The result shows that different variables play different roles in the algorithm. The changes of these variables can lead to different results. If we want to increase the grades of satisfaction, we should increase the credibility of fuzzy reservation time α_1. If the traffic condition and workstation's demands are more stable, values of α_2 and α_3 should be increased in order to speed up the convergence.

The fuzzy vehicle routing problem has several kinds of fuzzy information. Those uncertainties make the problem more complex and difficult to be solved. The improved hybrid intelligent algorithm shows its advantages over the traditional genetic algorithm. This can be used to associate decision makers to solve these problems more efficiently.

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