A Fuzzy Chance-constraint Programming Model for a Home Health Care Routing Problem with Fuzzy Demand

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Abstract: Home Health Care (HHC) companies are widespread in European countries, and aim to serve patients at home to help them recover from illness and injury in a personal environment. Since transportation costs constitute one of the largest forms of expenditure in the Home Health Care industry, it is of great significance to research the optimization of the Home Health Care logistics. This paper considers the Home Health Care Routing Problem with Fuzzy Demand, which comes from the logistics practice of the home health care company. A fuzzy chance constraint programming model is proposed based on the fuzzy credibility theory, the hybrid genetic algorithm and stochastic simulation method are integrated to solve the proposed model. Firstly the uncertain constraints have been reduced to the deterministic ones, experimental results for the benchmark test problem show the good efficiency of the proposed algorithm. Then the proposed hybrid algorithm has been applied to solve the fuzzy model, the influence of the parameters to the objective function has been discussed. This research will help HHC companies to make appropriate decisions when arranging their vehicle routes.

1 INTRODUCTION

Home health care (HHC) is a growing medical service in France and other developed countries. This service is provided by the Home Health Care companies, which aim to serve the patients at home to help them recover from illness or injury in a personal environment(Liu et al., 2014). Each day, a HHC company carries out various logistics activities including the delivery of drugs or medical instruments from the a pharmacy to patients, and pickup the biological samples from patients' home to the laboratory (Liu et al., 2013). A large number of patients distributed in a town or village, a certain quantity of the drugs needed according to the recovery degree of them. For a HHC company, the transportation cost is one of the most important spendings in the company activities, so it is of great significance to optimize the vehicle routing problem in home health care companies.

According to a survey (Mankowska et al., 2014; Harris, 2015) of the home health care companies, the main operational process of the HHC can be summarized as 3 steps.

(1) The HHC company collects the information from the patients, this information may include: the name, address, sex, type of the illness, symptom and other related information;

(2) The HHC company plan to arrange the visited routes and assign nurses according to the information collected;

(3) The nurses are scheduled to visit the patients. Each nurse is assigned to a planned route, and he/she has to carry out all of the service-related activities for the route. This nurse will drive the vehicle to visit the patients one by one according to the designed route. In case of a lack of drugs, the nurse has to go back to the depot, load more drugs into the vehicle and continue to attend to the remaining patients until all the patients are attended to.

It is easy to find that the home health care routing optimization problem is closely related the Capacitated Vehicle Routing Problem (CVRP) which is one of the most classical combinatorial optimization problems (Eksioglu et al., 2009). CVRP is a basic model in supply chain, and it has been applied into many filed. However, our problem is neither like the classical VRP nor like the Open Vehicle Routing problem (OVRP); all the variations of VRP can be seen in the literature (Pillac et al., 2013; Toth and Vigo, 2014). In the classical VRP, each vehicle needs to return to the depot again, while in the OVRP, each vehicle does not return to the depot after servicing the last customer on

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a route, but may end at a different location.

Moreover, demand is one of the most important parameters in supply chain optimization. However in previous studies, most researchers have focused on the deterministic demand. While in the real world, it is usually very hard to determine the precise demands of customers and thus they are estimated from historical data. Given this aspect of VRPs, a consideration of stochastic vehicle routing problems (SVRP) and fuzzy vehicle routing problems (FVRP) may be useful (Wen and Iwamura, 2008). In the Vehicle Routing Problem with Stochastic Demand (Bianchi et al., 2006), the demand is a stochastic variable, which is decided by probability distribution parameters, but the parameters are often obtained from the historical data. However sometimes, we could not obtain enough historical data for the new customers or patients. Although stochastic models can cater for a variety of cases, they are not sufficient to describe many other situations, where the probability distribution of customers demands may be unknown or partially known (Wen and Iwamura, 2008). On the contrary, fuzzy language exists everywhere in the health care domain, such as a doctor may inform us “small penicillin”, or “you have a little fever ”. So, it is very appropriate to describe the non-deterministic demand in HHC domain using fuzzy variables.

This paper contributes to the home health care routing optimization with fuzzy demand in the following aspects: (1) a fuzzy chance constraint programing model is proposed based on the fuzzy credibility theory; (2) hybrid genetic algorithm and stochastic simulation are integrated to solve the proposed model; (3) Some experiments are carried out on the deterministic model to validate the efficiency of the proposed method, and then the heuristic method has been employed to solve the fuzzy model. The rest of this paper is organized as follows: in second section some necessary theory of credibility is introduced, then the home health care problem with fuzzy demand model is constructed, and a hybrid heuristic algorithm is proposed to solve the model, at last some experiments are presented to illustrate the algorithm.

2 SUPPLY CHAIN MODELING

2.1 The Description of Fuzzy Demand Constraints

Liu (Liu et al., 2003) recently developed credibility theory, which can be used to measure the chance of that a fuzzy chance occurs. The law of credibility in the theory of fuzzy sets plays a role similar to that played by the law of probability in measurement theory of the ordinary sets. In this section we will first introduce the credibility theory (Liu et al., 2003), because it is crucial to describe the fuzzy demand.

In the deterministic VRP, it is straightforward to describe the capacity constraints: the total demand of the whole route should not exceed the vehicle capacity. However, in the VRPFD, the capacity constraints become more complex than the deterministic ones for the uncertain demand. Now, we have to consider the relationship between the fuzzy demand and the capacity of the vehicle (Mousavi and Niaki, 2013).

For a vehicle, after serving the j th patient, the remaining capacity is changed and it becomes a fuzzy variable named $\widetilde{Q_j}$, where

$$\begin{aligned} \widetilde{Q_j} &= q - \sum_{i=1}^{j} \widetilde{d_i} \\ &= (q - \sum_{i=1}^{j} d_{3,i}, q - \sum_{i=1}^{j} d_{2,i}, q - \sum_{i=1}^{j} d_{1,i}) \\ &= (Q_{1,j}, Q_{2,j}, Q_{3,j}) \end{aligned}$$

In the deterministic model, if the remaining capacity of the vehicle is greater than a customer's demand, this vehicle has the chance to serve this customer. However, facing with a fuzzy variable of demand and remaining capacity, how can we make a decision that whether the vehicle should continue visiting the $(j+1)$th patient or go to the lab directly? It should be compared with the demand of the $(j+1)$ th patient, of course, which is also a fuzzy variable. Based the credibility we can derive equation (1) and equation (2) as follows:

$$\begin{aligned} Cr &= Cr\{\tilde{d}_{j+1} \leq \tilde{Q}_j\} \\ &= Cr\{(d_{1,j+1} - Q_{3,j}, d_{2,j+1} - Q_{2,k}, d_{3,k+1} - Q_{1,j}) \leq 0\}; \end{aligned} \tag{1}$$

$$\begin{aligned} Cr &= Cr\{\tilde{d}_{j+1} \leq \tilde{Q}_j\} \\ &= \begin{cases} 0, & d_{1,j+1} \geq Q_{3,j} \\ \dfrac{Q_{3,j} - d_{1,j+1}}{2(Q_{3,j} - d_{1,j+1} + d_{2,j+1} - Q_{2,j})}, & d_{1,j+1} \leq Q_{3,j}, d_{2,j+1} \geq Q_{2,j} \\ \dfrac{d_{3,j+1} - Q_{1,j} - 2(d_{2,j+1} - Q_{2,j})}{2(Q_{2,j} - d_{2,j+1} + d_{3,j+1} - Q_{1,j})}, & d_{2,j+1} \leq p_{2,j}, d_{3,j+1} \geq Q_{1,j} \\ 1 & d_{3,j+1} \leq Q_{1,j} \end{cases} \end{aligned} \tag{2}$$

There is no doubt that if the quantity of remaining drugs is very high, and the demand of the next patient is very low, then the chance of the vehicle of being able to provide the next patient's service becomes greater (Cao and Lai, 2010).

We will describe the preference index by Cr, which denotes the magnitude of our preference to drive the vehicle to the next patient after it has served the current patient according to formulation (2). Note that Cr $\in$[0, 1]. When $Cr = 0$, we declare that the vehicle does not have the capacity to serve the next patient and it should terminate service at the current patient and return to the depot to replenish drugs. When $Cr = 1$, we can be completely sure that the vehicle should serve the next patient. However, in most cases, Cr is neither 0 nor 1, but $Cr \in (0,1)$.

To describe Cr in a convenient way, let us introduce the dispatcher preference index DPI, where $DPI \in [0,1]$. Note that DPI expresses the dispatcher's attitude toward risk. When the dispatcher is not a risk-averse, he/she will choose lower values of parameter DPI, which indicates that the dispatcher prefers to use the vehicle available capacity as much as possible, although there is an increase in the number of cases in which the vehicle arrives at the next customer's home and is not able to carry out planned service due to small available capacity. On the other hand, when the dispatcher is a risk-averse, he will choose greater DPI, this may result in a less complete utilization of vehicle capacity along the planned routes and less additional distance to cover due to failures

2.2 Mathematical Model

In order to describe the supply chain by formulation, we give the assumption as follows.
(1)The vehicles are homogeneous.
(2)Each nurse responds for one route. In the process of delivery, if the remaining drugs is not enough for the patients, she must drive back and fill up the drugs, return to this patient, then she will continue visiting the remaining patients until all the patients she responds are served.
(3)Each vehicle starts from the depot, then visits and attends to patients, and terminates the journey at the laboratory.
(4)we assume that the drugs have their own volume, so the vehicle capacity must be taken into consideration. However, the samples are vials of blood, or temperature record sheets, which could be assumed to be negligible and will not be considered with respect to the capacity of the vehicle.
(5)In the process of delivery, the demand of the drugs is described by fuzzy triangle variable. Only if the nurse arrives the patient's home, can she know the exact quantity of the drugs.

Now, we give the mathematical notations as follows:
V: the set of the vehicles.
N: the set of the all the vertex in the graph, including the depot, patients,and laboratory.
$\tilde{d}_i = (d_{1,i}, d_{2,i}, d_{3,i})$: the fuzzy demand of the patient i;
C: the set of the patients.
$i, j = 0, 1, 2, \ldots, n+1$ is the index of the all the nodes in the graph. Especially 0 stands for the index of the depot, $n+1$ stands for the index of lab, and others are the patients.
$k = 1, 2, \ldots, K$ stands for the index of the vehicle.
q: the capacity of the vehicle.
p: the employee salary for every nurse in this task.
u_i: it is an artificial variable which is used to construct the sub-tour constraint.
f_1: the additional distance caused by failure route.

let us describe the mathematical model with the most common used 3-index method:

$$x_{ijk} = \begin{cases} 1 & \text{if the } k\text{th vehicle traveals from patient } i \text{ to patient } j; \\ 0 & \text{otherwise.} \end{cases}$$

The Home Health Care Routing Problem with Fuzzy Demand (HHCRPFD) model can be mathematically formulated as shown below:

$$\min f = \sum_{i \in V} p \sum_{i \in C} \sum_{j \in N} x_{ijk} + \sum_{k \in V} \sum_{i \in N} \sum_{j \in N} c_{ij} x_{ijk} + f_1 \quad (3)$$

subject to,

$$\sum_{k \in V} \sum_{j \in N} x_{ijk} = 1 \quad \forall i \in C \quad (4)$$

$$\mathrm{Cr}\Big(\sum_{i \in C} \tilde{d}_i \sum_{j \in N} x_{ijk} - q \geq 0\Big) \geq DPI \quad \forall k \in V \quad (5)$$

$$\sum_{j \in N} x_{0jk} = 1, \quad \forall k \in V \quad (6)$$

$$\sum_{i \in N} x_{ihk} - \sum_{j \in N} x_{hjk} = 0, \quad \forall h \in C, \forall k \in V \quad (7)$$

$$\sum_{i \in N} x_{i(n+1)k} = 1, \quad \forall k \in V \quad (8)$$

$$x_{ijk} \in \{0,1\}, \forall i, j \in N, \forall k \in V \quad (9)$$

$$u_i - u_j + q * \sum_{k=1}^{K} x_{ijk} \leq q - d_{1,j}, \forall i, j = 0, 1, \ldots, N+1, i \neq j; \quad (10)$$

The objective function (3) is to minimize the total cost which includes the nurse employee cost, planned transportation cost and the additional cost. The constraints (4) donate that each customer is visited once and only once, and constraints(5) mean that no vehicle is loaded with more than its capacity under the fuzzy credibility theory. The constraints (6) mean each vehicle starts from the depot. Constraints (7)mean that each vehicle visits the patient and then leaves the patient. Constraints (8) means that the vehicle ends at the laboratory. Constraints (9) make the decision-variable are binary. Constraints (10) are used to eliminate sub-tours.

Our problem is neither like the classical VRP nor like the Open Vehicle Routing problem (OVRP); all the variations of VRP can be seen in the literature (Pillac et al., 2013; Toth and Vigo, 2014). In the classical VRP, each vehicle needs to return to the depot again, while in the OVRP, each vehicle does not return to the depot after servicing the last customer on a route, but may end at a different location.

Remark 1: The mathematical is a typical Fuzzy Chance Constraint Programming(FCCP), which is a new branch in the uncertain programming. What's more, if we assume $d_{1,i} = d_{2,i} = d_{3,i}$, the fuzzy variable become a determinate variable, and the HHCRPFD is reduced to a vehicle routing problem. Considering that VRP has been proved to be the np-hard problem, so there is no wonder that our model is also a np-hard problem with fuzzy chance constraints.

Remark 2: If $d_{1,i} = d_{2,i} = d_{3,i}$, this problem becomes a deterministic model, and in this situation, the additional distance $f_1 = 0$.

3 HYBRID HEURISTIC ALGORITHM

As mentioned above, the proposed model is a NP-hard problem, which is difficult to solve by the exact method when the size of the problem becomes large. Here, we propose a hybrid heuristic algorithm (HHA) by integrating the stochastic simulation method and hybrid genetic algorithm. Generally speaking, in the first stage, we apply the route construction method to generate initial feasible solutions, then hybrid genetic algorithm is employed to improve the initial solution. To accelerate the convergence, elitism selection and local search are employed, while to make the solution escape from the local optima in advance, mutation operators and crossover operators are designed. Considering that our problem is an instance of Fuzzy Chance Constraint Programming (FCCP), Stochastic Simulation method is designed to evaluate the each solution candidate.

The detailed description of the HHA can are described in the rest part of this section.

3.1 Individual Representation

In our research, each individual stands for feasible solution, which is a vehicle routing arrangement. Here we use a List to encode an individual which contains a lot of routes. The process of the encoding and decoding can be seen in Figure 1. The strength of this encode method is that each individual does not need to be decoded and encoded alternately in the optimization process.

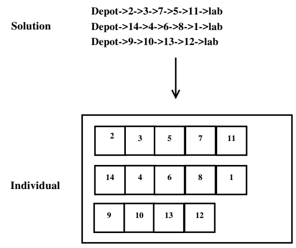

Figure 1: The representation of a individual.

3.2 Initial Population

The initial population are composed by two kinds, most of them are ordinary individuals which are generate randomly, the rest are high-quality ones which are obtained from the classical heuristic algorithm called insertion.

Insertion heuristic are widely used to quickly construct a feasible solution (Toth and Vigo, 2014). In each iteration, a node is selected among all the unvisited nodes, and then insert it in a right position which makes the new route feasible and least cost, while a insertion position couldn't be found, a new route is started. This insertion process repeated until all the nodes are visited. Figure 2 illustrates the insertion of the node k between i and j with the corresponding insertion cost $c_{ik} + c_{kj} - c_{ij}$.

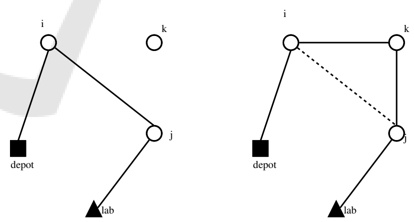

Figure 2: The brief description of the insert method.

3.3 Fitness Evaluation

As mentioned above, the demand of drugs for each patient is a triangular fuzzy number, so it cannot be directly considered as a deterministic one.

Regarding the simulation of the phases of the operation process of the HHC company and related works, we derive an approximate estimate about additional distances (f_1) due to route failures using a stochastic simulation algorithm. We summarize the stochastic simulation (Cao and Lai, 2010) as follows:

Step 1: For each patient, estimate the additional distance by simulating "actual" demand. The "actual" demands were generated by the following process:

(1) randomly generate a real number of x in the interval between the left and right boundaries of the triangular fuzzy number representing demand at the patient, and compute its membership u.

(2) generate a random number a, $a \in [0,1]$;

(3) compare a with u, if $a \leq u$, then "actual" demand at the patient is adopted as being equal to x; in the opposite case, if $a < u$, it is not accepted that demand at the patient equals x. In this case, random numbers x and a are generated again and again until random number x and a are found that satisfy relation $a \leq u$;

(4) check and repeat (1)–(3), and terminate the process when each patient has a simulation "actual" demand quantity.

Step 2: Move along the route designed by credibility theory and accumulate the amounts picked up and calculate the additional distance due to routes failure in terms of the "actual " demand..

Step 3: Repeat Step 1 and Step 2 for M times.

Step 4: Compute the average value of additional distance by M times simulation, and it is regarded as the additional distance f_1.

In the fuzzy demand model, the objective is to minimize the total cost, so the fitness value here we choose to use $f = \frac{1}{AD+PD}$. Specially, if $d_{1,i} = d_{2,i} = d_{3,i}$,this problem becomes a determinate model, and in this situation, the additional distance $f_1 = 0$, the fitness can be described as $f = \frac{1}{PD}$

3.4 Selection

In the evolution process, sometimes the good individuals may lost due to the crossover and mutation, which is not favorable to the convergence of fitness value. To overcome this drawback, we employ the famous elitism strategy in the selection operator.

Here we pick out the top 2% individuals as elite which are retained to the next generation directly without taking part in the crossover, mutation and local search operator.

3.5 Crossover

Crossover provides a chance to enhance the communication between different individuals, and aims to reproduce new offspring. Ombuki proposed a effective crossover operator named Best Cost Route Crossover (BCRC) (Ombuki et al., 2006), the main idea is to select nodes from one sub-route, and find a best position to reinsert them into the other individual one by one. We can call this operator as a global version of BCRC. Although his operator can perform well, it takes a long time to find the best position of whole the potential position. Inspired by his research, we proposed a local version of BCRC. we insert each node to the best position of a randomly selected route of the individual. It is obviously that the local version saves a lot of computing time.

The main steps of the crossover operator an be found in Figure 3.

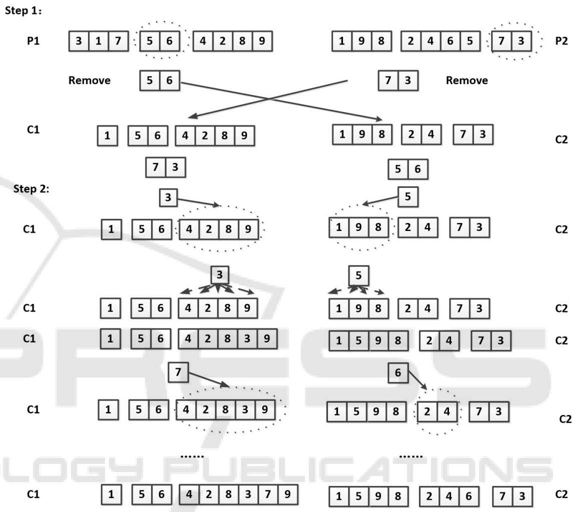

Figure 3: the crossover operator.

Specifically, for two individuals, the crossover is undertaken as follows:

Step 1: For each individual, a route is selected randomly. Before inserting the route into the other individual, the repeating nodes would be removed.

Step 2: The nodes selected from P1 (P2) are inserted in to P2 (P1) one by one. Be attention that, for the insertion of one node, one route is selected randomly. The length of this route is m, and the possible position for insertion is $m+1$, and this node is inserted to the best position. This insertion is undertake until all the selected nodes are inserted to the other individual. while a insertion position could not be found, a new route is started.

3.6 Mutation

Mutation is a divergence operation. It is intended to occasionally break one or more members of a population out of a local minimum space and potentially discover a better minimum space. The mutation operator is conducted by bring random, unrelated traits into the present population and increase the variance of the population. According to the characteristic of individuals, two simple mutation operators are introduced in our algorithm.

- inversion: two cut points are generated randomly, and all the nodes between them will be inversed.
- single-point mutation: two nodes are randomly generated, then they are swapped.

3.7 Local Search

In this paper, local search operator is employed to improve the fitness value of the individuals and obtain better solutions. The most commonly-used 2-opt method, or-opt method and their extension (Bräysy and Gendreau, 2005) are used to search the better solution.

Note that the local search operators are quite not the same with the mutation operator in two aspects: (1) the aim of the local search operator is to make an improvement of the solution, while the mutation is just to make the population diversified which aims to avoid the trapping into local optimal in advance. (2) The mutation operator is executed just once in one iteration, while the local search operators are executed many times, until a solution deemed optimal is found or a time bound is elapsed.

4 EXPERIMENTAL RESULTS

Because there was no one does the same work with us, so it can not compare our work with the exist work directly to validate the efficiency of the proposed Hybrid Heuristic Algorithm (HHA). Here, we firstly reduced our problem into the classical CVRP, experimental results are compared with the optimal results. After ensuring the algorithm is effective, we will use it to solve the proposed fuzzy model. Here we need to emphasize that the aim of our research is not to design a new and efficient algorithm to solve the classical CVRP, but just to design an efficient algorithm to solve the fuzzy model.

4.1 Experiments on Determinate Model

The fuzzy model is reduced to CVRP, if we assume the following 3 points: (1) the fuzzy variables reduce to the deterministic ones, namely $d_{i,1} = di,2 = d_{i,3}, i = 1,2,\ldots,N$; (2) the laboratory is in the same position with the depot. (3) the cost for each nurse is 0. In this situation, the fuzzy chance constraints become the deterministic ones, additional distance become 0.

Note that, when we apply the HHA to solve the deterministic model, for there is no chance constraints, the additional cost is 0. And in the process of fitness evaluation, stochastic simulation doesn't used.

Here we use one of the most famous benchmark instances called A series to test the proposed HHA. The instances and the optimal result can not be downloaded from the website http://neo.lcc.uma.es/vrp/vrp-instances/, and our computing results and the comparison can be found in Table 1.

Note that, in Table 1, NO means the ID of the instance,and the name of instance is composed in 3 parts: for example, the instance named "A-n60-k9", "A" means the instance is from A-series, "n60" means the size of the nodes is 60, and "k9" means that the number of expected used vehicle is 9. As results show, TD means the total distance (also called total cost in some literature), NV means the number of the used vehicles, CT means the computing time, and GAP means the percentage of the error between our result and the optimal result (Juan et al., 2010; MirHassani and Abolghasemi, 2011).

Table 1: Experimental results for the CVRP model.

	HGA			optimal result		GAP
No.	NV	TD	CT(s)	NV	TD	
A-n32-k5	5	787.20	10.54	5	784.00	0.41%
A-n33-k5	5	688.11	10.34	5	661.00	4.10%
A-n33-k6	6	745.80	9.56	6	742.00	0.51%
A-n34-k5	5	794.64	10.39	5	778.00	2.14%
A-n36-k5	5	819.93	11.34	5	799.00	2.62%
A-n37-k5	5	673.50	11.98	5	669.00	0.67%
A-n37-k6	6	961.68	19.77	6	949.00	1.34%
A-n38-k5	5	761.40	21.73	5	730.00	4.30%
A-n38-k5	5	845.00	19.84	5	822.00	2.80%
A-n45-k7	7	1216.56	20.47	7	1146.00	6.16%
A-n60-k9	9	1437.48	17.17	9	1408.00	2.09%
B-n31-k5	5	680.96	10.31	5	672.00	1.33%
B-n41-k6	6	875.31	11.02	6	829.00	5.59%
B-n50-k8	8	1373.56	12.09	8	1313.00	4.61%
B-n63-k10	10	1627.00	55.61	10	1537.00	5.86%
B-n78-k10	10	1305.00	66.50	10	1266.00	3.08%

We can conclude that: (1) the number of used vehicle in our results are quite the same with the expected number; (2) our result is quite close to the optimal solution; (3) our result arrives convergence in a reasonable time even for the big size instance, considering that CVRP is a NP-hard problem. So there is no doubt that the proposed hybrid algorithm have a good performance in solving the CVRP, and we will apply our heuristic algorithm to the fuzzy chance constraint programming in the next subsection.

4.2 Experiments on the Fuzzy Model

In this part, the experiments will be taken on the fuzzy model. Because there is no corresponding benchmark for this problem, we adopted the instance from the exited instance named A-n32-k5, which is a small size instance. The hybrid heuristic algorithm is encoded in Matlab 2015b; in the process of computing the fitness value, the stochastic simulation for every individual is 500 times.

The Value for the Dispatcher's Preference Index (DPI) varied with the interval of 0.1 to 1 with the step of 0.1. The computing results can be seen in Table 2 , Figure 4 and Figure 5.

Table 2: Experimental results for HHCRPFD model.

DPI	NV	TD	PD	AD
0.1	4	969.17	794.25	174.91
0.2	5	968.11	836.88	131.23
0.3	5	998.85	859.09	139.76
0.4	5	973.45	842.37	131.08
0.5	5	967.03	850.38	116.65
0.6	6	936.16	906.71	29.45
0.7	6	946.87	932.58	14.28
0.8	7	1063.27	1063.27	0.00
0.9	8	1163.66	1163.66	0.00
1	8	1203.94	1203.94	0.00

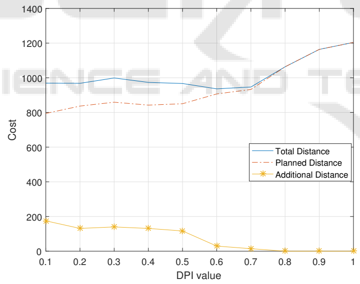

Figure 4: Cost changes for different *DPI* values.

We can find that, as *DPI* rose, the planned distance is increasing. While the additional distance is strictly decreasing as *DPI* value increases from 0 to 0.7. However, when $DPI \in [0.7, 1]$, the additional distance becomes 0, that means there's no failure route. The total distance is increasing, but not in a very strict tendency. We can also find that, with the *DPI* rose, the number of the needed nurses are increasing. It concludes that more used nurses can help to decrease the degree of the failure route.

As a consequence, lower values of parameter *DPI* express our desire to use vehicle capacity the best we can, so less nurses are needed. These values correspond to routes with shorter planned distances. On the other hand, lower values of parameter *DPI* increase the number of cases in which vehicles arrive

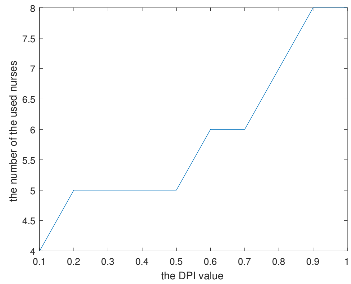

Figure 5: Number of the needed nurses changes for different *DPI* values.

at a customer and are unable to service it, thereby increasing the total additional distance they cover due to the "failure". Higher values of parameter *DPI* are characterized by less utilization of vehicle capacity along the planned routes and less additional distance to cover due to failures, so more nurses are needed. Therefore,when a HHC company makes decision on this scenes (instance), the selected dispatcher preference index should be 0.7 approximate.

5 CONCLUSIONS

Since transportation costs constitute one of the largest forms of expenditure in the Home Health Care industry, it is of great significance to research the optimization of the Home Health Care logistics. Based on a survey of the Home Health Care companies, the basic operational process illustrates that the demand for the required drugs for each patient is nondeterministic when the HHC company makes a decision to arrange the vehicle routing. In this paper, vehicle routing problem with fuzzy demand is considered, and a fuzzy chance constraint is constructed based on the fuzzy credibility theory. Stochastic simulation method and hybrid genetic algorithm are integrated to solve the proposed model.

In order to test the proposed model and algorithm, the fuzzy chance constraints were reduced to the deterministic ones. Hybrid heuristic algorithm were applied to solve the benchmark instances, results show that the proposed hybrid heuristic algorithm perform well. Then the algorithms are applied to the HHCRPFD, the best Dispatcher's Preference Index (DPI) is obtained, and the influence of the parameters to the objective functions are analyzed.

In the future, we will consider some other uncertain information in the routing optimization problem, such as stochastic traveling time, or fuzzy traveling time. Some other heuristic method like Simulated annealing (SA), Tabu search (TS), will also be integrated to solve the related problems.

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