

# A Real-world-Like Evolutionary Algorithm on the Cloud-Computing Environment

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**Abstract**—This paper develops a multiobjective evolutionary algorithm on the cloud computing environment to help planners solve multiobjective problems more efficiently and effectively. The cloud environment is emulated as a virtualized biological world with several isolated regions. The main population initially continues evolutionary processes as the most widely-known evolutionary algorithms. To yield both exploration and exploitation, two processes, such as migration and interaction, are deployed. In the process of migration, local optimal solutions can migrate to form new populations so that the search space can be expanded. To overcome the disadvantages in isolated evolutionary algorithms, the individuals in different populations will interact stochastically in the interaction process. Taking the advantage of cloud computing environment, planners can take less effort on deploying both computation power and storage space. Instead, the planners can focus on the design of encoding, crossover, and mutation. Also, it can further applied in various complicated applications more practically.

**Keywords**—Evolutionary Computation, Cloud Computing

## I. INTRODUCTION

Emergency logistic is extremely important, when natural disasters, such as tornadoes, typhoons, tsunamis, earthquakes, and fire terror happen more frequently. When natural disaster occurs, most of these places will require a large quantity of resources, such as food, water, medical supplies, tents and clothes. However, these damages may destroy roads too. Under the circumstances, some places will be isolated. How to deliver required resources to these places as soon as possible becomes tedious.

Traditionally, the emergency logistic can be categorized as several aspects. Some researches focus on road reconstruction. Some cluster-based researches focus on finding clustering node. Also, some researches focus on routing selection. In general, the problem can be viewed as one type of vehicle routing problem (VRP). Since the VRP can be further categorized as VRP with pickup and delivering, VRP with LIFO, VRP with time windows (VRPTW), and capacitate VRP without or with time windows (CVRP or CVRPTW), the factors of the vehicle routing problems are time limitation, capacities, and path selection.

Assume there is a group of commodities, the emergency logistic problem is to find out the vehicles and the routes to deliver the supplies.

The feature of natural disasters is emergency. Natural disasters will cause the broken of transportation infrastructure, water and power supplies. Also, the natural disasters will cause the damages of lives, shortages of materials, broken of houses. When these damages occur, the rescuing processes should complete the tasks within the golden 72 hours. Furthermore, some diseases will occur after natural disasters.

In government and non-government organizations, there are usually problems of unfair allocation and unsuitable vehicles for rescuing. Therefore, if there exist some mechanisms to integrate and allocate the information about rescuing resources when disasters occur, the rescuing process would be more efficient and effective.

The emergency logistics planning has been studied for a long time and very beneficial to human being in real life. All of the problems are somewhat different from each case that mapped into different environment, population distribution, transportation network, relief needs and geography situation. These factors mentioned before make it hard to compare with each other. From the definition of San Diego State University, the logistics section of the emergency plan contains the service providing of food, facilities, human resource, and transportation. From the related definition above, this paper aims at providing the service at the same time. Those problems are usually mixed with many subproblems such as emergency rescue under the limited 72 hours for the experience of human physical ultimate, combining the VRP (Vehicle Routing Problem) [1]-[3] to dispatch emergency resource, limited capacity, the PDP (pickup-delivery problem) with different depots or destinations, time window constraints, that all make the problem even more complex. Based on the subproblems mentioned above, the research has several similar objectives such as saving time, lower economical cost, sending relief, saving lives, etc. Also, there are many types of solutions such as dynamic integer linear programming [4]-[10], Dijkstra algorithm [11]-[13], metaheuristic algorithms as ant colony and genetic algorithms [11], [13]-[17], immune intelligence [18], greedy method [19], game theory [20], fuzzy multi-objective program [4], [16], [21]-[23], etc.

After the happening of a disaster, many processes need to be prepared and organized. Before the step of logistics planning, some literature try to find the best station to restore relief that locate near by the disaster area [24] or predict the amount of demand [4], [22]; In [23] Chen and Tzeng try to repair the broken transportation network to send relief. While

into the step of logistics planning, In [4] and [5] they try to find the best route path to distribute relief and some paper tries to both objectives of finding the route path and evacuating wounded people. In the following paragraph, we present a brief review of the related literature.

Typically, VRP indicates a closed route and with once visit constraint. According to the model presented by Özdamar et al. [5], generates sets of “broken” routes and vehicles that do not need to return to depots. In addition, a distribution optimal model is constructed that not only commodity demand is known at the current date but also future requirement can be forecasted. This study proposed two sub-problems by relaxing the vehicle capacity constraints: (a) P1 involves the commodities flow variables and (b) P2 contains the integer vehicle flow variables. These two problems were considered by using Lagrangean Relaxation Method, which is a relaxation technique to treat constraints as objectives and achieve the desired tolerance of user. Later years, Yi and Özdamar [10] proposed an integrated capacitated location-routing model (LRP) with a multi-depot network flow based routing formulation for coordinating logistics support and evacuation operations. Özdamar and Yi [19] applied the greedy neighborhood search method to build path, and compared to the mixed-integer-programming solver CPLEX 7.5 with the nodes number from 20 to 80.

Cheng and Lu [25] used a framework of emergency logistics response model to make an operational analysis of the bottlenecks of the emergency logistics system, and put the key measures to achieve effective operation.

For the minimum total distance and time limit constraint, some assist systems had been designed. Chang et al. [24] formulated decision program by applying geographic information system software to help locate each rescue resource storehouses, estimate rescue demand points and required amount of rescue equipment, and then develop the scenario. The program also uses a sample average approximation method to satisfy the expected objectives that considering:

- 1) the structure of rescue organizations,
- 2) locations of rescue resource storehouses,
- 3) allocations of rescue resources under capacity restrictions, and
- 4) the selection of rescue demand points and equipment according to distributions of rescue resources.

Chiu and Chang [7] developed a cell transmission model based on linear-programming method. This model tries to solve simultaneous mobile mobilization destination, traffic assignment, and departure schedule for multi-priority groups (SEDTS-MPG) in response to a no-notice disaster.

Yi and Kumar [17] proposed researches related to emergency relief operations with ant colony optimization algorithms. In the researches, ants that have been treated as vehicles use the pheromone trail of probability strategy to update to a well route path. There were 28 randomly generated test problems have been tested and compared to MIP solver ILOG CPLEX 7.5 [6]. Kanoh and Hara [13] designed the hybrid genetic algorithm and Dijkstra algorithm to use three

objectives of route length, travel time, and ease of driving to choose a favourite route from the Pareto-optimal set. In the last, it was compared to the SOGA method.

Sheu [4] made trend prediction and completed a full-scale emergency schedule and divided the system into five phases such as Time-varying relief demand forecast, Grouping the affected areas, Determination of distribution priority, Group-based relief distribution, and Dynamic relief supply.

By using the hybrid fuzzy clustering-optimization method, the system groups affected area and recursively uses multiobjective dynamic linear programming models to achieve co-distribution relief under several limitations. A simulation scenario of 24 demand nodes, 3 rescue centers, and 6 supply nodes has been addressed in the experiment and compared to the existed results. In 2010, Sheu [22] extended the survey of relief-demand forecasting, affected-area grouping, and identified the urgency of demand dynamically. In the numerical experiment adopt the Nantou County to compare the simulated accumulated fatalities, casualties, and relief demand forecasted information with historical data.

Traditionally, the exact amount of resources is difficult to estimate. When the disaster is urgent, it is very critical to decide the distribution of rescuing resources. Decision centers cannot predict the amount of dispatching how many rescuing vehicles to resolve.

In [26] and [27], the problems of aircraft routing and airline crew pairing are solved using multiobjective genetic algorithms. However, as mentioned above, the number of aircrafts or airline crews should be given before the solution process. Motivated from [28], we would like to propose a multiobjective genetic algorithm with dynamic length. In other words, planners can obtain exact number of the resource, such as vehicles, aircrafts, aircrews, etc without pre-assigning a fixed value.

The remainder of this paper is organized as follows. Section II presents the problem formulation. Section III describes the proposed methods. Experimental results are shown in Section IV, and the conclusions are given in the last section.

## II. PROBLEM STATEMENT

When disasters occur, suppose the rescuing processes are held by an emergency center, or a rescuing center, the two main goals are to rescue the injured persons and deliver the relief materials. Here, we focus on the process of relief materials delivering. In general, there are several stages in relief materials delivering, such as information gathering, relief planning, rescuing resource gathering, and rescuing process.

Suppose there are multiple disaster points (DPs) and one supply point. All disaster points firstly issue their demand amount of relief materials. Then, all relief materials are collected in one supply point (SP) for delivering to the disaster points.

As shown in Figure 1, the supply and disaster points are represented in white and gray circles, respectively. The arrows are rescuing routes. There are three vehicles, denoted as  $v_1$ ,  $v_2$ , and  $v_3$  take responsibilities to carry and deliver relief materials

to all disaster points.

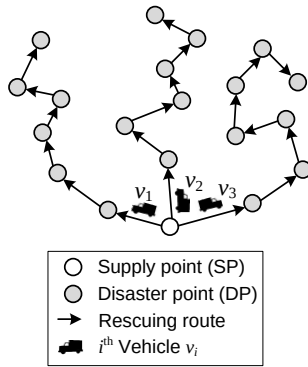


Figure 1. Concepts of emergency logistic problem

When considering the whole rescuing process, the available number of vehicles, the demand amount of relief materials should be considered. Hence, the highlighted problem here is to determine the exact number and the routing schedule of all vehicles from the supply point to all disaster points within their limited time periods. The notation is listed in Table 1.

TABLE 1. NOTATION TABLE

| Notation     | Meaning                                                              |
|--------------|----------------------------------------------------------------------|
| $\alpha$     | number of vehicles                                                   |
| $\beta$      | number of duties                                                     |
| $\gamma$     | number of disaster points                                            |
| $\delta$     | maximal number of duties assigned to each vehicle                    |
| $\mathbf{V}$ | set of vehicles                                                      |
| $v_i$        | the $i^{\text{th}}$ vehicle, where $1 \leq i \leq \alpha$            |
| $vid_i$      | identifier of the $i^{\text{th}}$ vehicle                            |
| $capt_i$     | maximal capacity of the $i^{\text{th}}$ vehicle                      |
| $\mathbf{P}$ | set of disaster points or demand points                              |
| $p_i$        | the $i^{\text{th}}$ disaster point, where $1 \leq i \leq \gamma$     |
| $pid_i$      | identifier of the $i^{\text{th}}$ point                              |
| $x_i$        | geographical position on the x-axis                                  |
| $y_i$        | geographical position on the y-axis                                  |
| $\mathbf{D}$ | set of duties for delivering goods                                   |
| $d_i$        | the $i^{\text{th}}$ duty for delivering goods, $1 \leq i \leq \beta$ |
| $did_i$      | identifier of the $i^{\text{th}}$ duty                               |
| $wt_i$       | weight of the $i^{\text{th}}$ duty                                   |
| $dest_i$     | issue point or destination of the $i^{\text{th}}$ duty               |
| $expt_i$     | expiration or expectation time of the $i^{\text{th}}$ duty           |
| $rcvt_i$     | practical receiving time of the $i^{\text{th}}$ commodity            |

Consider there are  $\gamma$  disaster points, or demand points, the set of the disaster points  $\mathbf{P}$  can be denoted as  $\mathbf{P}=\{p_i | 1 \leq i \leq \gamma\}$ . Each disaster point  $p_i$  has its associated information, such as identifier  $pid_i$ , geographical position on the x-axis (longitude) and on the y-position (latitude), denoted as  $x_i$ , and  $y_i$ , respectively.

Also, the disaster points can issue their demand amount of relief materials. Then, the supply points will collect relief materials according to the demands. Each issue can be viewed as a duty of delivering commodities or goods. Suppose there

are  $\beta$  duties, each element  $g_i$  in the set  $\mathbf{D}=\{d_i | 1 \leq i \leq \beta\}$  represents a duty. Various information associated with the  $i^{\text{th}}$  duty are identifier  $did_i$ , weight (or amount) of the  $i^{\text{th}}$  commodity  $weight_i$ , demand point or destination point  $dest_i$ , expiration or expectation time  $expt_i$ . Also, we use another information  $rcvt_i$  to represent the practical receiving time of  $dest_i$  for later use.

Furthermore, suppose the set of  $\alpha$  vehicles, denoted as  $\mathbf{V}=\{v_i | 1 \leq i \leq \alpha\}$ . All these vehicles are departed from the supply point to deliver relief materials to demand points. Various information associated with the  $i^{\text{th}}$  vehicle  $v_i$  are identifier  $vid_i$  and capacity  $capt_i$ .

The distance between two disaster points  $p_i$  and  $p_j$  can be denoted as  $dist(p_i, p_j)$ . Since the terrain factors may affect the practical distance among points, the value of  $dist(p_i, p_j)$  can either be the practical length of the that connects  $p_i$  and  $p_j$ , or just the Euclidean distance if the points reside on the same surface.

Since the goal of emergency logistic is to deliver materials to disaster points within their expectation time, a routing schedule of the vehicles is used. Each routing schedule can be represented as a two-dimensional matrix  $\mathbf{S}$  with  $\alpha \times \delta$  elements, as shown in equation (1).

$$\mathbf{S} = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,\delta-1} & s_{1,\delta} \\ s_{2,1} & \ddots & & & s_{2,\delta} \\ \vdots & & s_{i,j} & & \vdots \\ s_{\alpha-1,1} & & & \ddots & s_{\alpha-1,\delta} \\ s_{\alpha,1} & s_{\alpha,2} & \cdots & s_{\alpha,\delta-1} & s_{\alpha,\delta} \end{bmatrix} \quad (1)$$

where  $s_{i,j}$  represents the  $j^{\text{th}}$  point assigned to the  $i^{\text{th}}$  vehicle and  $s_{i,j} \in \mathbf{G}$ . The value of  $\delta$  represents the maximal number of duties assigned to each vehicle.

There are several objectives to be considered and minimized in this problem. The first objective can be denoted as time objective. Since the relief materials should be delivered within their time period, the successful delivering can be evaluated by the following equation.

$$f_1(\mathbf{S}) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\delta} x_{i,j}^{(1)} \quad (2)$$

where  $x_{i,j}^{(1)} = \begin{cases} 0 & \text{if } rcvt_{i,j} \leq expt_{i,j} \\ rcvt_{i,j} - expt_{i,j} & \text{otherwise} \end{cases}$

The second objective can be denoted as capacity objective. Due to limited capacities of all vehicles, the amounts assigned to the vehicles should not exceed the given capacities. This can be evaluated by equation (3).

$$f_2(\mathbf{S}) = \sum_{i=1}^{\alpha} x_i^{(2)} \quad (3)$$

where  $x_i^{(2)} = \begin{cases} 0 & \text{if } capt_i \geq \sigma_i \\ \sigma_i - capt_i & \text{otherwise} \end{cases}$

and  $\sigma_i = \sum_{j=1}^{\delta} wt_{i,j}$ .

The third objective is denoted as the number of vehicles objective. In fact, the main goal is to estimate the minimal number of vehicles that can satisfy the demands issued by all disaster points. To evaluate the number of vehicles, equation (4) is used.

$$f_3(\mathbf{S}) = \alpha \quad (4)$$

Since all three objective described here are all small-the-best objectives, the objective function of the emergency problem is

$$\begin{aligned} &\text{Minimize } f_i(\mathbf{S}), (1 \leq i \leq 3) \\ &\text{s.t. } \mathbf{s}_{i,j} \in \text{valid } \mathbf{S} \end{aligned} \quad (5)$$

Since the emergency logistic problem is a multiobjective problem with multiple conflicting objectives, the rank dominance is adopted here. For the sake of convenience, we define  $\Lambda(f_1, f_2, f_3)$  as the vector of objective values of solution  $\mathbf{S}$ , where  $f_1, f_2$ , and  $f_3$  represent the time, capacity, and number of vehicle objectives.

Suppose two routing schedules  $\mathbf{S}_a$  and  $\mathbf{S}_b$  has solution vectors  $\Lambda_a(f_1^{(a)}, f_2^{(a)}, f_3^{(a)})$  and  $\Lambda_b(f_1^{(b)}, f_2^{(b)}, f_3^{(b)})$ . For the small-the-best problem,  $\mathbf{S}_a$  dominates  $\mathbf{S}_b$ , if and only if

- 1)  $\forall (f_i^{(a)} \leq f_i^{(b)})$ , and
  - 2)  $\exists i$  such that  $(f_i^{(a)} < f_i^{(b)})$
- where  $1 \leq i \leq 3$ .

### III. PROBLEM STATEMENT

To solve the emergency logistic problem, we use a multiobjective genetic algorithm. The chromosome encoding, crossover, mutation operators are described as follows.

#### A. Chromosome Encoding

In this paper, we propose a way to represent variable number of vehicles. In addition to normal genes, we adopt some separators to make each chromosome be divided into several sections. In other words, to solve the problem of unable to estimate the number of exact vehicles, a dynamical adjusting way should be used.

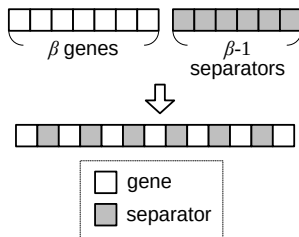


Figure 2. Chromosome encoding

Since the number of initial vehicles is very difficult to assign, suppose there are  $\beta$  duties, the proposed algorithm firstly append  $(\beta-1)$  dummies, denoted as separators.

As shown in Figure 2, the  $\beta$  duties and  $\beta-1$  dummies can form a total  $\beta+(\beta-1) = 2\beta-1$  chromosome. The lower part of Figure 3 is an example form of chromosome. The number of vehicles used in one chromosome can be viewed as the number of sectors in a chromosome separated by the separators.

Figure 3 demonstrates some samples of chromosome representation. Suppose there are 7 duties with  $7-1=6$  separators, due to different arrangement the 7 chromosomes can represent from one to seven sets by counting the number of groups formed by white cubes.

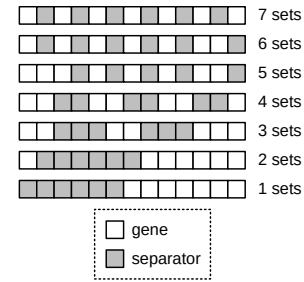


Figure 3. Samples of encoding schemes and their related number of sets

#### B. Crossover

In this paper, the partial mapped crossover (PMX) and the reciprocal mutation operators are adopted.

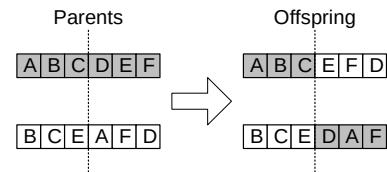


Figure 4. Partial-mapped crossover

Figure 4 demonstrates the partial-mapped crossover operator. First, one cut-point is chosen to make both parents into two separated parts, as shown in the left-hand side of Figure 5. The genes in the left of both parents are kept to form both offspring. On the other aspect, the right part of the offspring are formed according to the mapping list, i.e. to make each gene exists once.

#### C. Mutation

As shown in Figure 6, two genes are selected and exchanged randomly. If two duties assigned to different vehicles are exchanged, the routing schedule will be updated without modifying the number of vehicles. On the other aspect, if one duty exchanges with one separator, the number of vehicles may be changed.

The flowchart of multiobjective genetic algorithm is shown in Figure 6. The algorithm acquires related data about disaster points, demand amount of relief materials, and vehicles. As mentioned above, suppose there are  $\beta$  duties, the chromosome length will be  $\beta + \beta - 1 = 2\beta - 1$ .

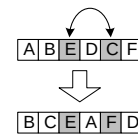


Figure 5. Reciprocal mutation

In the stage of routing schedule mapping and evaluation, all initialized individuals are evaluated by the objective functions. Also, these individuals are assigned using the rank dominance method described in Section II.

Here, we use the tournament selection operator, which choose the better one as the parent from two randomly selected parents.

The algorithm then enter and continue the evolution process, including selection, crossover, and mutation. When the number of generations reaches the demand threshold, the algorithm stops and obtains the result.

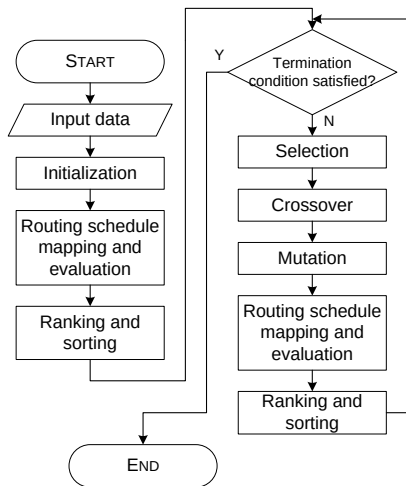


**Figure 6.** Flowchart of multiobjective genetic algorithm

#### IV. EXPERIMENTS

In this section, the experiments are conducted. As shown in Table 2, the columns of  $pid_i$ ,  $x_i$ , and  $y_i$  are identifiers, positions on x and y axes, respectively with 50 disaster points. The first point with  $pid_i$  equals 1 represents the supply point.

For the sake of computation convenience, the distance between two points  $p_i$  and  $p_j$  are the Euclidean distance calculated by the following equation

$$dist(p_i, p_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{6}$$

Table 3 lists the duty information issued by the disaster points. As mentioned above, since the first point with  $did_i$  equals to 1 is the supply point, there is no duty issued from the first point.

**TABLE 2.** INFORMATION OF 50 DISASTER POINTS

| $pid_i$ | $x_i$ | $y_i$ | $pid_i$ | $x_i$ | $y_i$ |
|---------|-------|-------|---------|-------|-------|
| 1       | 11    | 89    | 26      | 17    | 99    |
| 2       | 83    | 67    | 27      | 96    | 72    |
| 3       | 88    | 5     | 28      | 24    | 20    |
| 4       | 77    | 98    | 29      | 3     | 2     |
| 5       | 90    | 73    | 30      | 90    | 4     |
| 6       | 10    | 44    | 31      | 84    | 41    |
| 7       | 68    | 98    | 32      | 24    | 95    |
| 8       | 3     | 12    | 33      | 91    | 37    |
| 9       | 93    | 90    | 34      | 48    | 89    |
| 10      | 87    | 87    | 35      | 77    | 26    |
| 11      | 91    | 20    | 36      | 46    | 47    |
| 12      | 44    | 31    | 37      | 37    | 90    |
| 13      | 100   | 21    | 38      | 83    | 26    |
| 14      | 85    | 20    | 39      | 51    | 35    |
| 15      | 53    | 26    | 40      | 33    | 3     |
| 16      | 51    | 40    | 41      | 14    | 6     |
| 17      | 56    | 17    | 42      | 54    | 34    |

|    |    |    |    |    |    |
|----|----|----|----|----|----|
| 18 | 43 | 16 | 43 | 77 | 26 |
| 19 | 28 | 43 | 44 | 21 | 59 |
| 20 | 98 | 5  | 45 | 88 | 74 |
| 21 | 81 | 10 | 46 | 0  | 11 |
| 22 | 95 | 8  | 47 | 56 | 81 |
| 23 | 93 | 48 | 48 | 52 | 29 |
| 24 | 70 | 63 | 49 | 80 | 60 |
| 25 | 79 | 66 | 50 | 80 | 21 |

**TABLE 3.** DUTY INFORMATION

| $did_i$ | $wt_i$ | $expt_i$ | $did_i$ | $wt_i$ | $expt_i$ |
|---------|--------|----------|---------|--------|----------|
| 2       | 15     | 5        | 26      | 17     | 16       |
| 2       | 8      | 3        | 27      | 16     | 9        |
| 3       | 5      | 18       | 27      | 18     | 5        |
| 3       | 16     | 18       | 28      | 9      | 7        |
| 4       | 12     | 4        | 28      | 2      | 16       |
| 4       | 12     | 17       | 29      | 4      | 18       |
| 5       | 17     | 3        | 29      | 12     | 16       |
| 5       | 16     | 18       | 30      | 13     | 19       |
| 6       | 10     | 9        | 30      | 6      | 4        |
| 6       | 9      | 15       | 31      | 15     | 14       |
| 7       | 5      | 15       | 31      | 9      | 6        |
| 7       | 14     | 19       | 32      | 12     | 1        |
| 8       | 16     | 16       | 32      | 12     | 6        |
| 8       | 7      | 19       | 33      | 7      | 17       |
| 9       | 9      | 17       | 33      | 15     | 18       |
| 9       | 4      | 9        | 34      | 20     | 20       |
| 10      | 16     | 10       | 34      | 4      | 5        |
| 10      | 17     | 12       | 35      | 10     | 14       |
| 11      | 8      | 17       | 35      | 19     | 5        |
| 11      | 7      | 15       | 36      | 7      | 9        |
| 12      | 10     | 19       | 36      | 14     | 18       |
| 12      | 13     | 5        | 37      | 13     | 10       |
| 13      | 1      | 10       | 37      | 5      | 4        |
| 13      | 7      | 0        | 38      | 12     | 11       |
| 14      | 9      | 10       | 38      | 15     | 15       |
| 14      | 10     | 2        | 39      | 15     | 1        |
| 15      | 16     | 3        | 39      | 13     | 1        |
| 15      | 11     | 19       | 40      | 16     | 2        |
| 16      | 13     | 19       | 40      | 15     | 6        |
| 16      | 5      | 8        | 41      | 5      | 4        |
| 17      | 5      | 6        | 41      | 14     | 3        |
| 17      | 10     | 12       | 42      | 17     | 20       |
| 18      | 5      | 3        | 42      | 19     | 20       |
| 18      | 6      | 11       | 43      | 6      | 14       |
| 19      | 7      | 17       | 43      | 2      | 14       |
| 19      | 14     | 7        | 44      | 11     | 10       |
| 20      | 9      | 12       | 44      | 8      | 7        |
| 20      | 10     | 19       | 45      | 3      | 13       |
| 21      | 11     | 6        | 45      | 13     | 14       |
| 21      | 3      | 8        | 46      | 11     | 3        |
| 22      | 13     | 16       | 46      | 12     | 9        |
| 22      | 8      | 7        | 47      | 19     | 8        |
| 23      | 3      | 12       | 47      | 3      | 15       |

|    |    |    |    |    |    |
|----|----|----|----|----|----|
| 23 | 7  | 14 | 48 | 10 | 9  |
| 24 | 18 | 9  | 48 | 6  | 8  |
| 24 | 2  | 19 | 49 | 16 | 19 |
| 25 | 6  | 19 | 49 | 9  | 9  |
| 25 | 13 | 19 | 50 | 18 | 11 |
| 26 | 9  | 18 | 50 | 3  | 8  |

The parameters population size, number of generations, crossover probability, and mutation probability are given in Table 4.

**TABLE 4.** PARAMETERS OF EXPERIMENTS

| Parameters            | Values |
|-----------------------|--------|
| Population size       | 100    |
| Number of generations | 1000   |
| Crossover probability | 1.0    |
| Mutation probability  | 0.01   |

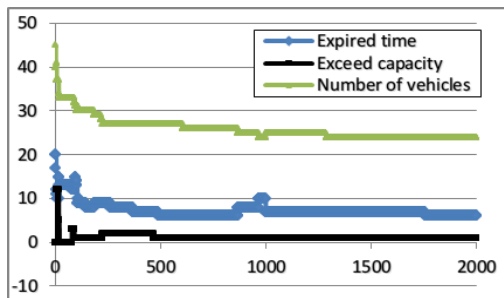


**Figure 7.** Convergence of all objectives

According to the experimental results shown in Figure 7, as the iteration increases, the three objective values of expired time, exceeded capacity, and the number of vehicles can be reduced. However, since the objects are conflicting, the number of vehicles cannot be decreased to zero.

## V. CONCLUSIONS AND FUTURE WORK

In this paper, we develop a multiobjective dynamic length genetic algorithm to solve the emergency logistic problem. The proposed method can generate optimized routing schedules with minimal number of rescuing vehicles. Via the proposed method, the whole rescuing process can be more efficiently and effectively.

In the future, we would enhance the proposed method to solve the emergency logistic problem with heterogeneous type of vehicles. Also, the proposed algorithm will be applied to emergency logistic problems with more complicated constraints.

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