Dynamic Resource Scheduling in Emergency Environment

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Abstract: Nowadays, emergency accidents could happen at any time. The accidents occur unpredictably and the accidents requirements are diversely. The accidents happen in a dynamic environment and the resource should be cooperative to solve the accidents. Most methods are focusing on minimizing the casualties and property losses in a static environment. However, they are lack in considering the dynamic and unpredictable event handling. In this paper, we propose a representative environmental model in representation of emergency and dynamic resource allocation model, and an adaptive mathematical model based on Genetic Algorithm (GA) to generate an optimal set of solution domain. The experimental results show that the proposed algorithm can get a set of better candidate solutions.

Keywords: Cooperative allocation, dynamic resource scheduling, adaptive genetic algorithm.

1 Introduction

Emergency accidents, man-made incident or natural disasters, such as earthquake, floods, car accidents and so on, which usually happened unpredictably. Researches show that large-scale disasters have frequent occurrence probability [Gad-el-Hak (2008)]. In metropolitan regions, the occurred emergency accidents caused by the flow of population, operation error and careless driving, are usually called as incidents, such as fire, conflicts, terrorism, etc. [Haddow and Bullock (2013)]. These incidents usually have the following characters: (1) Most incidents are unpredictable, which makes the pre-allocation unrealizable; (2) It is easy to find out that the unsatisfied requirements are various, which indicates that multiply resource departments have to cooperate to solve the incidents; (3) A limited time for the resource allocation and the transportation to satisfy the demand of the incidents is existing; (4) The incident environment is dynamic, which represents that not all the resource departments are able to provide resources required for the incident as time goes on.

At present, emergency accidents have gained more and more attention. In order to solve accidents in a timely and effective manner, the emergency management (EM) came into being. In most urban or country areas, the scheduling processes are manually, which is inefficient and not intelligent. The execution function of each emergency departments are distributed and the location of the emergency service providers are scattered in various places, which makes it difficult to integrate multiple departments to cooperate together. For the unpredicted incident, it is difficult to foresee the actual demand of each incident.

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For example, when a fire breaks out, it usually calls for multiple disaster relief resources to address the incident, such as fire engines, police cars, ambulances, etc. The quantity of the rescue resources and the resource provider point are still needed to be discussed to make an efficient plan. In general, emergency management is mainly made up by four stages: mitigation, preparedness, response, and recovery [Galindo and Batta (2013)]. In mitigation stage, reducing potential risk of construction of a disaster and plans designed to setup to pre-arrange. Then select and construct the locations of supply points to reserve emergency resource to prepare for the allocation.

With the increase number of the events, it is no doubt that the research in searching complexity space, dynamic and changing space of solution set and the innovation way of resource scheduling to find an optimal solution for money and time have been done. For example, the traditional scheduling algorithms such as random assignment and equally distribution are used for some simple cases. However, the dynamic environment for multiply resource cooperative allocation is still a weak point in the research field.

To overcome the modeling problem in dynamic environment, this paper proposed a brand new model to represent the specific condition of the incidents and resources. To overcome the computing problem, an adaptive computing approach based on genetic algorithm was proposed to solve the dynamic model. By using this dynamic model to deploy environment variables, the incidents can be organized to a reasonable mathematical model. In the mathematical model, the calculation equation contains two main characters: 1) The number of required resources allocated from different resource locations, 2) The location chosen to provide the resources. For each character, the unit cost and the transportation cost of resources will be calculated. Then, we bring the concept of adaptation into the genetic algorithm to help solving the problem with dynamic and indeterminate requirements of the different emergency resource.

2 Related work

Generally, most emergency resource allocation approaches are focusing on each stage of the resource allocation, in Caunhye et al. [Caunhye, Zhang, Li et al. (2016)], focus on the original single model of location planning and route value selection and designed a two-stage location path planning model to minimize the overall disaster relief cost and the weighted sum of the worst case of total corresponding events. In Zhou et al. [Zhou, Liu, Zhang et al. (2017)], designed a model with two goals based on the uncertainty of the availability of the road. The first goal is to reduce the demand satisfaction of the affected points and the second goal is to minimize the waste of time selected to the damaged road during the scheduling process. Cavdur et al. [Cavdur, Kose-Kucuk and Sebatli (2016)] also proposed a two-stage random process based on the allocation of temporary facilities for temporary disasters in short-term disaster relief operations to minimize the total transport distance and the total number of cooperative facilities. In the above approaches, it is clear that they calculated the quantity allocation of resources and the selection of resource points as two different models. In Mohamadi et al. [Mohamadi and Yaghoubi (2017)], a bi-objective stochastic optimization model was developed for location of transfer points and medical supplies distribution centers.

Apart from environment models, algorithms to solve these mathematical models are also a major focus in our work. Some researches focus on resource allocation approaches from centralization to decentralization. For example, the approaches proposed by Chou et al. [Chou, Tsai, Chen et al. (2014)], Widener et al. [Hawe, Coates, Wilson et al. (2015); Widener, Horner et al. (2015)] were designed to optimize the resource allocation for large-scale emergency events with global information. In Zhang et al. [Zhang, Zhang, Ren et al. (2016)], Zhang et al. proposed a distributed resource allocation method based on multi-agent, which used the domain transmission theory to deal with emergencies, and effectively solved the problem of deploying the corresponding planning arrangement in the absence of appropriate resources with global information by considering the time severity level. In Liu et al. [Liu, Zeng, Duan et al. (2014)], Liu et al. proposed a method based on E-net, which is a formal model based on Petri Net for emergency response process constrained by resources and uncertain duration. In Belciug et al. [Belciug and Gorunescu (2015)], Belciug et al. used genetic algorithms to optimize bed management and medical resource utilization. In Su et al. [Su, Zhang, Liu et al. (2016)], Su et al. proposed a heuristic to repair infeasible encodings based on differential evolution from traditional one-dimensional real-number encoding to two-dimensional integer vector encoding. A coefficient to measure fairness was selected and a bi-objective heuristic particle swarm optimization algorithm to search the Pareto frontier in Hu et al. [Hu, Liu and Hua (2016)]. In Luscombe et al. [Luscombe and Kozan (2016)], dispatch heuristics, disjunctive graph methods and meta-heuristic search was used to provide fast solutions respond to unscheduled tasks. In He et al. [He, Zheng and Peeta (2015)], a mixed integer linear program model was proposed to represent transportation evacuation planning on large-scale networks and Benders decomposition algorithm was adopted to solve an optimal solution. In Othman et al. [Othman, Zgaya, Dotoli et al. (2017)], a multi-agent-based architecture for the management of Emergency Supply Chains and a decision support system based on communicating agents was proposed to solve resource allocation process. In Chen et al. [Chen, Tadikamalla, Shang et al. (2017)], an improved differential evolution was proposed to solve a bi-level programming model which represents delivering relief supplies to victims of natural disasters. In Zhan et al. [Zhan and Liu (2016)], the Bayesian updating framework was employed to focus on the trade-off between demand forecast accuracy and relief allocation efficiency.

To our best knowledge, although all these approaches can perform a good result in resource allocation, they are lack of the ability to allocate the resource in dynamic environment. In reality, cooperative resource allocation in dynamic environment is still a problem need to be solved. Especially the algorithm ought to have the ability to calculate the dynamic variables. In order to propose a reasonable solution to resource scheduling problems in dynamic environments, the main contributions of this paper are shown below.

- The dynamic environment is analyzed and both task model and resource model were designed to satisfy the real condition. Based on the models, the objective function was designed to calculate the total cost, which can represent the Evaluation effect of algorithm.
- In order to solve the problem that algorithm cannot calculate the dynamic number of variables and the range of variables. Adaptive encoding based on genetic algorithm is

proposed to fit the dynamic changing dimension. In the progress of the algorithm, the change of the variables is also designed to represents both the number allocated and the location that is chosen to provide the resource.

3 Problem definition and mathematical model

In this Section, we introduce the model of the dynamic emergency environment, and the proposed mathematical model that is put forward to address the model.

3.1 Problem definition

In the urban and country areas, there exists multiply emergency resource management departments, which performs different emergency management functions. For example, the fire department mainly deals with the fire disaster, the police station handles the social situation, and the hospital mainly solves the task of treating the wounded. Based on the analysis above, emergency management departments are defined as emergency resource providers and the attributes of these departments are described below.

Definition 1 (*resource*): $resource$={$type$, $rloc$, num, te}, where $type$ represents the type of the performed function of the emergency resource. $rloc$ represents the location of emergency departments. num represents the number of each type of the emergency departments. te represents the transportation efficiency of each emergency resource departments.

At the same time, when it come up with emergency incidents, it usually requires the collaboration between multiple emergency resource departments and a fast response and scheduling time. For convenience of explanation, we definition the emergency incidents as events. The definition is described below:

Table 1: Resource parameters

Input parameters	Description
n	Number of emergency resource types
d_i	The i-th type of emergency resource department. $i \in [1, n]$
$L\_r_i = [lr_1^i, \dots, lr_s^i]$	The locations of the i -th type of emergency resource departments
lr_p^i	The p-th location of d_i. $p \in [1, s]$
$N_i = [n_1^i, \dots, n_s^i]$	The amount of emergency resources owned by d_i
n_p^i	The original amount of the emergency resources owned in lr_p^i $p \in [1, s]$
$V = [v_1, \dots, v_n]$	The resource transportation velocity of d_i
v_i	The i-th emergency resource transportation velocity

Definition 2 (*event*): $event$={elo, rty, $rnum$, sev, $time$, $state$}, where elo represents the event's location. rty represents the emergency resource that the event requires. $rnum$ represents the amount of resource that is required in the event. sev represents the severity of the event, which is on behalf of the priority for the scheduling queue. The explicit instructions are shown in the table below. $time$ represents the time that must be taken to solve the task. $state$ represent the event state, which is a sign to indicate whether the event is solved or not.

Table 2: Event parameters

Input parameters	Description
m	Number of emergency events for each episode
e_j	The j-th emergency event $j \in [1, m]$
$L\_e_j = [le_1^j, \dots, le_m^j]$	The locations where the events happened
le_q^j	The location of the q-th emergency event
$R_j = [r_1^j, \dots, r_n^j]$	The resources that required by the j-th emergency event
r_k^j	Amount of the k-th resource required by e_j. $k \in [1, n]$
$T_j = [t_1^j, \dots, t_m^j]$	The time that the emergency resource required for each event
t_h^j	Time required for the emergency events to address in e_j

Definition 3 ($\boldsymbol{variables}$): The decision variables mainly include the four parameters, $variables = \{H_i, h_p^i, x_{i,j}, C_{i,j}\}$, which is defined as below in Tab. 3.

Table 3: Decision variables

Decision variables	Description
$H_i = [h_1^i, \dots, h_s^i]$	The residual emergency resources owned by d_i. $i \in [1, n]$
h_p^i	Amount of the residual emergency resource in lr_p^i
$x_{i,j}$	The amount of the i-th resources that transported to e_j
$C_{i,j} = [C_1^{i,j}, \dots, C_p^{i,j}]$	The distance of the transportation from lr_p^i to le_q^j

Definition 4 ($\boldsymbol{cost}$): $cost = \{nuc, trancos\}$, which nuc represents the number cost of each resource and $trancos$ represents the cost that the resource is transported from the lr_p^i to le_q^j. The calculation coefficient is the basic cost parameters, which contains three units. And the detailed descriptions are shown in the following table.

Table 4: Cost parameters

Calculation coefficient	Description
$A = [\alpha_1, \dots, \alpha_n]$	The unit cost of the emergency resource
α_i	The unit cost of the i-th emergency resources
β	The transportation cost for emergency resources

Then in order to minimize the total money and time cost, the mathematical model for the emergency problem can be defined as below:

$$\min F_1 = \sum_j^m \sum_i^n \alpha_i * x_{i,j} + \beta * \sum DIS \quad (1)$$

$$s.t.\ r_k^j = \sum_i^n \sum_p^s x_{i,j,s}, , p \in [1,s], i \in [1,n], j \in [1,m], k \in [1,n]$$

$$0 \le x_{i,j,s} \le h_p^i$$

$$h_p^i = n_p^i - x_{i,j,p}$$

With the transportation from the i-th resource location to the j-th event location, the distance is calculated as follows:

$$DIS = \sum_j^m \sum_i^n C_{i,j} \quad (2)$$

Which $C_{i,j}$ can be calculated by lr_p^i and le_q^j.

Then, the time consumed on the transportation (F_2) can be calculated as:

$$F_2 = \sum_j^m \sum_i^n \frac{C_{i,j}}{v_i} \quad (3)$$

After executing the processing event, the resource that used in the event will be recycled to the original resource location.

$$h_p^{i\,\prime} = h_p^i + x_{i,j,p} \quad (4)$$

4 Adaptation genetic algorithm

In this Section, the adaptation method based on genetic algorithm is introduced, which is proposed to solve the resource allocation in dynamic environment.

4.1 Adaptation encoding in genetic algorithm

In the proposal approach, the Adaptation Encoding is based on genetic algorithm, which is applied to generate the optimal allocation result to solve the dynamic resource requirements. Generally, GA is a parallel and global optimization algorithm, which is based on three main steps: selection, crossover and mutation. We proposed the single-objective programming template based on multi-group competition evolution based on Genetic algorithm to solve our dynamic resource model.

In general, GA is supposed to solve the stable variables and objective function so as to find the optimal solution of the objective function. Thus GA is lack of solve the problem of dynamic coding in the emergency environment.

For each task in the emergency environment, the adaptation is mainly solving the characters of resource matching problem, including the resource type, resource number and the department selection. Therefore, the proposal approach called adaptation encoding in the population initialization process is put forward. Adaptation encoding maintains the ability of solving dynamic problem by extending dynamic adaptability. In each coding phase, real-coded genetic algorithm is used to match the variable length of rty and $rnum$ in each task, which can be calculated by a judgement function to satisfy the actual standard decimal length. Since decimal coding can definitional express the length of the order of magnitudes. Besides decimal coding is capable of dynamic expansion to deal with the different orders of magnitude. In general genetic algorithm, the length n is lack of the ability to adapt the variable length arguments and its ranges. In order to solve the problem, a prejudging model is introduced by extract the number and length of variables. For example, when an event requires three different resources and each resource contains different quantity available. At this time, the number of variables is three and each scope of constraint variable is constraints in each order of magnitude of space.

The dynamic encoding is proposed to satisfy the dynamic resource requirement for each task. In each task requirements of each resource, the length of the chromosome can be fitted the specific of the resource requirements r_n^j. In the population chromosome matrix, each line corresponds to a chromosome and also corresponds to an individual, which is shown as:

$$Chrom = \begin{pmatrix} g_{1,1} & g_{1,1} & g_{1,1} & \cdots & g_{1,1} \\ g_{1,1} & g_{1,2} & g_{1,3} & \cdots & g_{1,Lind} \\ g_{2,1} & g_{2,2} & g_{2,3} & \cdots & g_{2,Lind} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ g_{Nind,1} & g_{Nind,2} & g_{Nind,3} & \cdots & g_{Nind,Lind} \end{pmatrix}$$

And we generally used $Nind$ to name the number of individuals in the population and $Lind$ to name the length of the individual's chromosome. As the problem we solved is a real number problem, the $Chrom$ matrix is actual the matrix of the number of variables, which can be seen as:

$$Phen = \begin{pmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \cdots & x_{1,Lind} \\ x_{2,1} & x_{2,2} & x_{2,3} & \cdots & x_{2,Lind} \\ x_{3,1} & x_{3,2} & x_{3,3} & \cdots & x_{3,Lind} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{Nind,1} & x_{Nind,2} & x_{Nind,3} & \cdots & x_{Nind,Lind} \end{pmatrix}$$

For each variables $x_{i,j}$ in the matrix, the range of the variables is in the form of 2 rows and n columns to represent the length of the variables $x_{i,j}$ and their ranges in the algorithm progress. A range descriptor is used to describe the detailed range of each variables named $FieldDR$.

$$FieldDR = \begin{pmatrix} x_{1,lb} & \cdots & x_{n,lb} \\ x_{1,ub} & \cdots & x_{n,lb} \end{pmatrix}$$

Two parameters are the main factors in our work, which are the resource allocation cost α_i and the transportation cost for emergency resource β. There are two problems to confront in this problem. First, for each resource required in each event, we can define the slice of event as a task. Therefore, we need to satisfy the quantity demanded in the event. Second, with the distributional location of each type of resource, the resource location selection is related to the transportation cost.

There are two main goals in our model, one is the number that allocated from each type of resources and another is the resource location that chosen from multiple locations to minimize the resource transportation cost. Thus each chromosome represents an individual which contains of two main aspects: the number of resource allocated and the resource location chosen. For example, for each type of resource, if the i-th variable is allocated, the i-th location is chosen to provide the resource. And the equation can be seen as a discrete function:

$$y_i = \begin{cases} 1, & x_i > 0 \\ 0, & x_i = 0 \end{cases} \tag{5}$$

In the objective function calculation part, we take an objective matrix to represent function value that represented by each variables, which is named Objective Value($ObjV$). In the matrix each line represents one objective function value. In our model, the matrix is presented as a binary matrix as shown below:

$$ObjV = \begin{Bmatrix} f(x_{1,1}, x_{1,2}, \cdots x_{1,Nvar}) \\ f(x_{2,1}, x_{2,2}, \cdots x_{2,Nvar}) \\ f(x_{3,1}, x_{3,2}, \cdots x_{3,Nvar}) \\ \vdots \\ f(x_{Nind,1}, x_{Nind,2}, \cdots x_{Nind,Nvar}) \end{Bmatrix}$$

Then we build a trace tool to help the algorithm to record the best individual of each generation in the process of population evolution and after each calculation progress, the optimal result will be chosen from the tool. We designed the tool as a matrix to record the fitness of each generation of individuals, which can be seen below:

$$trace = \begin{pmatrix} a_1 & b_1 & c_1 & \cdots & \omega_1 \\ a_2 & b_2 & c_2 & \cdots & \omega_2 \\ a_3 & b_3 & c_3 & \cdots & \omega_3 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{MAXGEN} & b_{MAXGEN} & c_{MAXGEN} & \cdots & \omega_{MAXGEN} \end{pmatrix}$$

where the first row represents the optimal objective function value of $x_{i,1}$, and the second row represents the average objective function value of $x_{i,1}$.

After the setting of our algorithm model, the population competition mechanism is used. The solution to the dynamic problem and total number of evaluation is pre-set. In the whole independent search processes, each individual of each search needs to pay a certain evaluation cost. If the solution falls into a local optimum, the population would continue to iterate, which will result in a waste of evaluation cost. Thus we can re-initializing the competing failed population, and the search for the environment will find a better local optimal region. The steps of the competitive process can be shown below:

Algorithm 1: Multi-population competitive evolution

Input:

x_i: the value of variables in x_n

$Genenum$: the total number of evolutions of the algorithm

$FieldDR$: the individual range of x_i

$Fitnum$: total number of fitness calculation for each population

Output:

The optimal solution result

Step 1: Initial all the parameters.

Step 2: If the environment is changed, update dimension parameter i, and re-initialize all search population objective function value $ObjV$, and jump to Step 7.

Step 3: Perform mutation operations on n search populations.

Step 4: Perform crossover operations on n search populations.

Step 5: Perform selection operations on n search populations.

Step 6: Competition algorithm, each m times iteration, calculate the optimal individual objective function value of x_i , which are $f(best_1), f(best_2),\cdots, f(best_n)$, and keep the population corresponding to the optimal value. The other populations are reinitialized and the individual generation mechanism is performed on the next generation of the only remaining population.

Step 7: The number of iterations continues, if the total number of evaluations is reached, then the algorithm ends; otherwise, jump to Step 2.

5 Experiment

In this Section, experiment results are presented and the performance of the proposed adaptation genetic algorithm is analyzed. The experiment mainly focus on the performance of the algorithm and the time consume of each calculation progress. The experiment results settings and the figures can definitely show the efficiency and effectiveness of our algorithm. The algorithm is implemented using Spyder. All experiments are conducted on a LENOVO M4600 with AMD Redeon R7 350, CPU i5-6500 3.2 GHz and 8 GB memory.

5.1 Experiment settings

In order to effectively analyze the advantages of the proposed approach, we simulated the settings of our data based on real-world data. For each task, the type of the resource are set in [5,10], which can definitely represent real-world event happened. And for each number requirements of each type of resources are set in [10,20]. The transportation speed of each resource is set in [60,80] (km/h), where all the parameters are given a range so as to satisfied the algorithm to calculate.

In the genetic algorithm setting, the problem type was set as a real number problem, and the max generation was set as 50, the size of the population was set as 50, the number of sub-populations participating in the competitive process was set as 1. Besides, in the progress of the genetic algorithm, three main operator which are selection and crossover are set as tournament selection and two-point crossover with reducing agents, respectively. The crossing probability and reorganization probability are set as 0.9 and 0.3, respectively. Because the length and range of the variables are dynamic, we enhanced the population distribution in our code so as to find the optimal solution.

5.2 Experiment results and analysis

We test the algorithm in 1000 times. For each 10 times, the result shows that the adaptation genetic algorithm can adapted to the dynamic process of variable change.

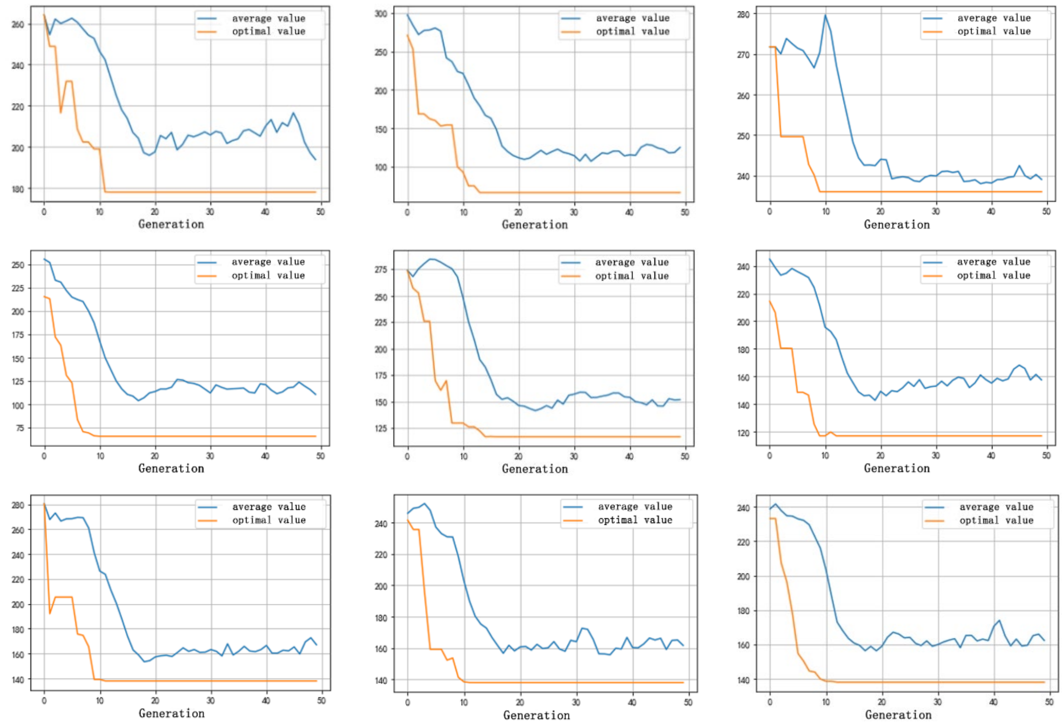

Figure 1: Results of adaptation genetic algorithm

In Fig. 1, the blue lines represent the average individual objective function value and the yellow lines represent the optimal individual objective function value. As can be seen in the figures, the average objective function value is generally falling because when the individuals are competing with each other, the bad population was abandon and they have to re-initialize to find the optimal solutions. However, there are still some rising trend in the results shown in the figure. At the same time, the orange lines record the optimal results of each generation so that the downward trend is very obvious. We can see that for each calculation progress, the optimal generation can always appear in 20 generations with no further decline. With the efficiency of the algorithm, we can find the optimal solution with more reliability.

At the same time, the time consume is also another investigation index. In our experiment in 1000 times, the average time consume of our algorithm is 18.25 s, and the time cost for every 10 times of our algorithm is show in the figure below.

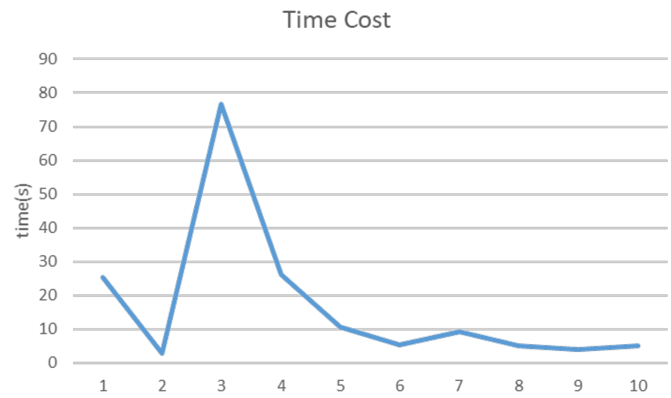

Figure 2: Time cost for each 10 times

We choose 10 times processes with distinct characteristics, the time cost was not stable because when the length and the ranges of the variables are changing, the calculating models are changing at the same time. When it comes to a large length and range of the variables, there will be like the peak value as shown in the Fig. 2, which will cost many times to calculate the optimal value.

6 Conclusion

In this paper, an adaptation genetic algorithm was proposed to handle the dynamic resource allocation in the emergency event. In order to efficiently solve the dynamic search domain in the changing requirements, the adaptation encoding was proposed to handle the problem. At the same time, the time cost was also a problem that we focused on. In the experiment results, we can see that the dynamic resource allocation can show a good result. However, the time cost is not stable and slightly spend time.

In the future, we will primarily focus on handling resource allocation in dynamic environment. We find that the oscillation of the experimental effect is mainly due to the variable number and the variation of the variable range. So how to minimize the effect of the changing of the variables is still our center of gravity. And how to minimize the time cost is also the main algorithm improvement direction.

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