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An Improved Genetic Algorithm for Task Scheduling of Electro-magnetic Detection Satellite with Uncertain Detecting Duration

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***Abstract*—Electro-magnetic Detection Satellite(EDS) is an important branch of Earth Observation Satellites (EOSs). It has been widely applied in industry and military areas. The detecting duration of EDS is different from imagery satellites, for it is an imprecise parameter because of the uncertain electro-magnetic environment within space surrounding targets. This factor makes the task scheduling for EDS becoming a complex combinatorial optimization problem. With consideration of this special property, we used fuzzy set and possibility theory to model imprecise parameters, other physical constraints, like on-board energy and transition time between different working patterns and sensor's rebooting, were also taken into account in the model. We presented an improved genetic algorithm to solve this problem by introducing new method of elitist and parents selection. The model and the algorithm have been tested by five experiments derived from STK's satellite database.**

***Index Terms*—Genetic algorithm, Electro-magnetic Detection Satellite, Task scheduling, Uncertain, Detecting duration,**

I. INTRODUCTION

EDS follows high earth orbit to collect signals within the space around its swath by on-board high sensitive sensor. The on-board signal processing device is responsible for picking up and transferring useful signals to ground station. To take full advantage of this precious resource, the united task scheduling of EDSs in a given scheduling horizon becomes the key process in the whole conducting and controlling procedure. Similar with general EOS's task scheduling, we need to make decisions on which requests to execute, which access time window (ATW) to choose, and when to start an action. When EDS flies over target areas, the detecting duration is depended on the electro-magnetic environment of the space surrounding target area, like signal density and other characteristics of electronic signals, these properties could be different even if sensor passes over the same target area. In real EDS system, the detecting duration is decided by on-board intelligent equipment referring to the real-time electron-magnetic condition, so, the detecting duration is an imprecise parameter when making schedule for EDS. But the bound of this duration could be given: the shortest limitation must no less than the shortest working time span of the sensor which executes this detection, the right bound will be given according to the range of ATW, and also the most possible value which could be derived from statistics of daily data. During the process of making scheule for EDS, we must pay attention to the request of coverage in time domain and space domain, other common physical constraints also have been taken into account at the same time.

Most scientific literatures on planning and scheduling for space considered imaging and SAR (Synthetic Aperture Rader) satellites, only Hao Chen et al [1] first described the scheduling problem for EDS and solved it with hybrid GA (Genetic Algorithm), in their work, the detecting duration was considered as a certain variable; Potter and Gasch described an algorithm for scheduling the Land-sat 7 [2], Michel and Hao deal with this problem as a knapsack problem which was solved by a Tabu search algorithm [3]. Frank et al. adapted constrained-based interval (CBI) framework to represent the resources of EOS and proposed a heuristic algorithm for guiding its search procedure based on a general contention for resources, but without consideration of the conflicting requests [4], Wolfe and Sorensen defined and used the window constrained packing problem to model earth observation system domain scheduling problem. They proposed three algorithms: a dispatch algorithm, a look-ahead algorithm, and a genetic algorithm. In their research, the genetic algorithm generates the best solutions [5]. All the existing method in the EOS scheduling field can not well solve the EDS scheduling because of its special and uncertain properties.

From the other perspective, the deterministic scheduling model and algorithm for JSSP (Job Shop Scheduling Problem) have been extended to the stochastic case, mainly on models with processing times which are random variables with specified probability distributions [6]. However, probabilistic characteristics of processing times and other scheduling parameters are often not available in manufacturing environments. That is the reason why standard stochastic methods based on probability are not appropriate to use. Fuzzy sets and fuzzy logic have been increasingly used to capture and process imprecise and uncertain information within scheduling procedure[7,8]. For example, Chanas et al. considered minimization of maximum lateness of jobs in a single machine scheduling problem [9] and minimization of maximal expected value of the fuzzy tardiness and minimization of the expected value of maximal fuzzy tardiness in a two-single machine scheduling problem [10]. Itoh et al. [11] represented the execution times and due dates as fuzzy sets to minimize the number of tardy jobs. Carole Fayad et al [12] developed shifting bottleneck heuristic and genetic algorithm for JSSP with imprecise processing time, this algorithm was applied in a British press company. Even these works make a great contribution to the task scheduling problem with uncertain parameters, they can't be used in EDS scheduling domain directly unless after practical improvement.

II. PROBLEM DESCRIPTION

In the EDS system, each EDS equips with high sensitive signal receiver and circles the globe in large elliptical orbit. When EDS flies through certain target area, the on-board sensor sets up and runs on a well-configured working pattern to collect electro-magnetic signals, the detecting time span is controlled by on-board decision support sub-system according to the real-time electro-magnetic condition in vicinity of the target, this time span is also constrained by the shortest working period of a on-board sensor and also the length of certain ATW, there is an time interval needed for releasing before sensor's shutting down. When a detection request is being performed, many constrains also have to be considered in other aspects, like enough on-board energy, working pattern and so on. Because of the amount of requests is on a larege scale and the limited EDS resource, this problem is categorized into the over-subscribed combinatory optimization problem with imprecise parameter, our work focus on how to select a subset in request set and make a stable schedule for this subset to satisfy all constraints and generate the optimal or near-optimal benefit, stable here means that the schedule could keep the feasible status under perturbations caused by uncertain real time detecting duration, without frequent revision or changing of original schedule during execution.

The set of EDS is denoted by $\mathtt{M}$, each EDS is identified by r, with following physical properties respectively: set up time $\mathtt{St_r}$, releasing time $\mathtt{Rt_r}$, the shortest working period $\mathtt{tml_r}$, the maximum continuous working duration $\mathtt{MaxDur_r}$, and the time needed for transition from working pattern m to n is $\mathtt{Pts_{mnr}}$, EDS r has initial on-board energy $\mathtt{E_r}$, one second detecting causes a energy consumption of $\mathtt{z_r}$, the energy charging rate of the solar panel on EDS is $\varphi_\mathtt{r}$. All detecting requests are submitted from the users set $\mathtt{J}$; a single user is j, request i submitted by user j is noted by req_{ij}, all requests submitted by user j share the same priority weight value ω_j, request req_{ij} has imprecise detecting duration p_{ij}, due date d_{ij} and completion time C_{ij}. $\mathtt{P_0}$ is the set of all pending requests that haven't been allocated yet, $\mathtt{P_r}$ is the pending requests queue of EDS r, and $\mathtt{P_r} \subseteq \mathtt{P_0}, \bigcup_{r\in \mathtt{M}} \mathtt{P}_r = \mathtt{P_0}$; b_{ijr} is the current possible earliest starting time of req_{ij} on EDS r when it separately executed, corresponding end time is e_{ijr}. If the pending request req_{ij} will be executed by satellite r, the decision variable τ_{ijr} values 1, 0 on the contrary; and if req_{ij} could be finished before its due date, that is $C_{ij} - d_{ij} < 0, \rho_{ij} = 1$, otherwise 0; if req_{ij} will be executed by EDS r using working pattern u, variable δ_{ijur} equals 1; decision variable $\sigma_{iji'j'r}$ denotes that request i' (submitted by j') will be executed after the finish of req_{ij} on EDSr, further more, if EDS r does not need to release and re-boot the on-board sensor, decision variable $\varsigma_{iji'j'}$ will be instanced by 1, if not by 0; on the condition that the covering swath of request i's overlap i''s swath, $\Gamma_{iji'j'}$ values 1. To evaluate the working burden of EDS r , we use step variable $\mathtt{N}_r$ represent the count of actions did by EDS r and wt_r for its total idle running time during its running period.

III. PROBLEM FORMULATION

For further solving process of this problem, we need to construct the mathematical model first, in which all imprecise parameters, constraints and optimal objectives are included.

A. Model with imprecise parameters

As the detecting duration is an imprecise parameter, consequently, completion time of each signal acquisition process becomes uncertain too. As a matter of fact, users also want to express their preference of the completion time of requests within a certain range, not a fixed time point generally. This model should fulfill these acquirements. Here, we used fuzzy sets to model these imprecise parameters. Related definitions and conceptions of fuzzy set could be found in literature[12].

We use possibility theory incorporated with fuzzy sets to depict the possibility of imprecise values. The result shows that it is a convenient way to express uncertainty. With this theory it is possible to take uncertainty associated with the occurrence of events into account explicitly. The estimation of detecting time of each access duration is obtained with the consideration of physical properties of satellite's orbit and sensors, and the possible value of due date could also be acquired from users' acquirement. Triplet fuzzy set $(p^1_{ij}, p^2_{ij}, p^3_{ij})$ [12] represents imprecise detecting time of req_{ij} , the possibility distribution of it is a tri-angle, where p^1_{ij} and p^3_{ij} are lower and upper bounds of detecting time while p^2_{ij} is so called modal point; trapezoidal fuzzy set (d^1_{ij}, d^2_{ij}) denotes for due date of req_{ij}, where d^1_{ij} is the crisp due date and the upper bound of the trapezoidal d^2_{ij} exceed d^1_{ij} by 1/10, the possibility distribution of these two are as Figure 1 and 2 show below.

Because the work schedule of each EDS is closely related to its running time line, basic arithmetical operations upon uncertain values can't be avoided, so uncertain operators, including addition (SUM), abstraction (MINUS) are needed here. Addition and abstraction of two fuzzy numbers $\tilde{A}(a_1, a_2, a_3)$ and $\tilde{B}(b_1, b_2, b_3)$ are defined as below:

$$\mathtt{SUM}(\tilde{A}, \tilde{B}) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{1}$$

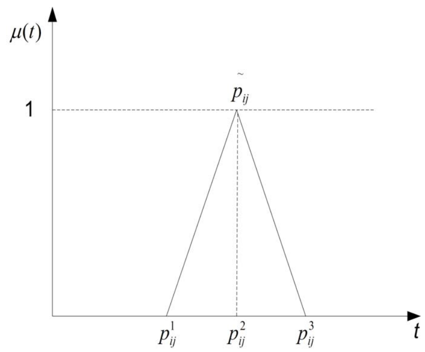

Fig. 1. Possibility distribution of detecting time

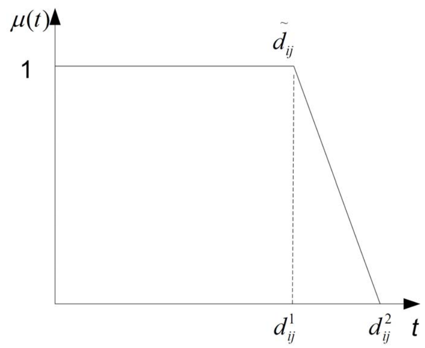

Fig. 2. possibility distribution of due date

$$\texttt{MINUS}(\tilde{A}, \tilde{B}) = (a_1 - b_3, a_2 - b_2, a_3 - b_1) \quad (2)$$

B. The mathematical description of constraints

The same as previous research works on task scheduling for multi-EOS, when making a schedule for EDS; we also need to let the final schedul conforms to operational constraints like limited on-board energy and sufficient transition time between different working statuses. Here, we considered four kinds of constraints, listed as follows.

1) Work status transition constraints on one EDS: For each EDS, a time interval with length of

$$\Delta t = b_{i'j'r} - e_{ijr} \quad (3)$$

is reserved for working pattern transition between two conjunctive requests req_{ij} and $req_{i'j'}$; there is only one situation could happen when $\Delta t < 0$, it happens when the cover swath of req_{ij} and $req_{i'j'}$ is intersected, so $\Gamma_{iji'j'r} = 1$, and their sensor working pattern must be identical, that is $\delta_{ijur} = \delta_{i'j'ur} = 1$.

$$\begin{cases} \tau_{ijr} = \tau_{i'j'r} = \sigma_{iji'j'r} = 1 \rightarrow \\ \varsigma_{iji'j'r} = \Gamma_{iji'j'} = \delta_{ijur} = \delta_{i'j'ur} = 1; b_{i'j'r} < e_{ijr} \\ others; b_{i'j'r} \geq e_{ijr} \\ j, j' \in \texttt{J}, r \in \texttt{M} \end{cases} \quad (4)$$

$$\varsigma_{iji'j'r} = \begin{cases} 1, \texttt{St}_r + \texttt{Rt}_r + \texttt{Pts}_{uvr} \geq \Delta t \geq \texttt{Pts}_{uvr} \\ 0, \Delta t > \texttt{Pts}_{uvr} + \texttt{St}_r + \texttt{Rt}_r \end{cases} \quad (5)$$
$$\Delta t = b_{i'j'r} - e_{ijr}, \delta_{ijur} = \delta_{i'j'vr} = 1, r \in M, j, j' \in J$$

2) Maximum continuous working time without releasing: For each EDS r, the on-board sensor has the maximum workload in a certain continuous period, which is known as $\texttt{MaxDur}_r$. In the mathematical expression below, m, n represents req_{ij} and $req_{i'j'}$ seperately, they are detection requests allocated to EDS r. The accumulated working duration between m and n must shorter than the summit continuous working period.

$$\prod_{m}^{n-1} (1 - \varsigma_{iji'j'r})\sigma_{iji'j'r} = 1 \rightarrow e_{i'j'r} - b_{ijr} < \texttt{MaxDur}_r \quad (6)$$
$$\forall m, n \in \{1, 2, \cdots, \texttt{N}_r\}, r \in \texttt{M}$$

3) Available on-board energy: Before a detecting action can be executed, there must be enough energy on board to finish the coming job. Because there are 8 hours available charging time for solar panel on-board in each scheduling horizon, so all the energy consumed in a scheduling period should not exceed the summit value of on-board energy.

$$\texttt{N}_r \cdot \texttt{z}_r \leq \texttt{E}_r + 8\varphi_r, r \in \texttt{M} \quad (7)$$

4) One request at a time: Since the on-board sensor could only detect one target at a time, the following constraint must be fulfilled, it means each action on EDS r can have only one precede and follow-up action, except for the beginning and ending dummy action 0 and P+1.

$$\alpha = \sum_{j,j' \in \texttt{J}, r \in \texttt{M}} \tau_{ijr}\tau_{i'j'r}\sigma_{iji'j'r} - \sum_{j,j' \in \texttt{J}, r \in \texttt{M}} \tau_{ijr}\tau_{i'j'r}\sigma_{iji'j'r} \quad (8)$$

$$\alpha = \begin{cases} 1, i = 0 \\ -1, i = \texttt{P} + 1 \\ 0, others \end{cases} \quad (9)$$
$$\forall req_{ij}, req_{i'j'} \in \texttt{P}_r$$

As completion time is an imprecise parameter, it's hard to define the satisfaction level for every user; we use satisfaction degree $SD(\tilde{C_{ij}})$ to stand for satisfaction level, and define it as Fig.3 illustrates, $\mu_{\tilde{c_{ij}}}(t)$, $\mu_{\tilde{d_{ij}}}(t)$ are membership functions of fuzzy set $\tilde{C_{ij}}$ and $\tilde{d_{ij}}$ respectively. First, to denote the possibility of a fuzzy set event occurring within the fuzzy set, we use the area of intersection portion to measure the completion time $\tilde{C_{ij}}$ that completed before the due date.

$$SD(\tilde{C_{ij}}) = \frac{(\texttt{area}\tilde{C_{ij}} \cap \tilde{d_{ij}})}{\tilde{C_{ij}}} \quad (10)$$

The satisfaction degree of a single user is the summation of all the satisfaction degree of requests he/she submitted:

$$\texttt{SD}_j = \sum_{i=1} SD(\tilde{C_{ij}}) \quad (11)$$

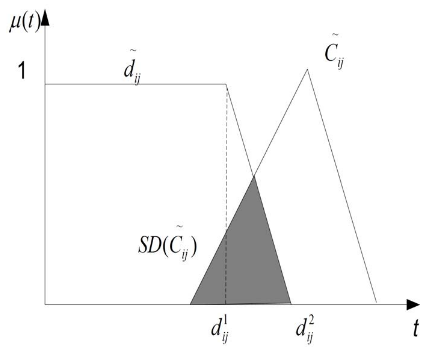

Fig. 3. Satisfy degree of completion time using area of intersection

C. Optimal objectives

First, we want requests with higher priority weight value be included in our final schedule, so the first objective function is to maximum the total weight of scheduled requests.

$$\texttt{max}(\sum_{j\in\texttt{J}}\rho_{ij}\omega_{ij}) \tag{12}$$

On the other hand, the final schedule should satisfy all users as much as possible; so, the second objective is to maximize total satisfaction degree.

$$\texttt{max}(\sum_{j\in\texttt{J}}SD_j\rho_{ij}\omega_{ij}) \tag{13}$$

IV. THE IMPROVED GENETIC ALGORITHM FOR MULI-EDS SCHEDULING

The task scheduling problem for multi-EOS is well known as a NP-hard problem in current literatures; however, our problem is even more complex because of the consideration of imprecise parameters. The efficiency of utilization of Genetic Algorithm (GA) in multi-EOS task scheduling has been proved by Globus et al [13] and algorithms comparison work has been done by AFSCN [14], they also listed some flaws of GA, such as populations may converge to a set of very similar chromosomes which are hard to discriminate from each other, this situation will lead to the phenomena of local and short-sight optimization easily. To find the most cost-effective solution, regarding to the characteristic of EDS task scheduling, we used GA in this paper with improvement in aspects mentioned above, including the implementation of tournament selecting procedure in elitist chromosome selection, we also improved the naive parents selection mechanism by total randomness.

A. Design of Genetic Algorithm

1) The generation of initial population pool: The trip of searching for optimal solutions starts from the initial populations pool, we used constructive algorithm with back tracking strategy to generate initial populations. For each detecting activity on EDS s, a time instant is recorded, it is the possible earliest time when this action could start, and we call this time instant "decision time", noted by dt_s . Assuming that the scale of initial populations is T, which means iterative process repeats T times. In each iteration, an EDS is selected randomly if its decision time earlier than the scheduling horizon and its request queue is not empty, we call it current active EDS s, picking up its earliest request q in $\texttt{P}_s$, if its priority higher than 'LOW' we put it into schedule, if its weight equals to 'LOW', check q's feasibility, take it if it is feasible, otherwise dispose it, at the end, update decision time for s and request queue of all EDSs, and then start a new iteration.

```
<1>while population size < T
    <2>While active EDS is not empty
        <3>Randomly select an active EDS s whose
        request queue is not empty and decision time is not exceed scheduling
        horizon, select q at the beginning of the queue
        <4>if priority(q) > LOW
            <5>Take(q)
        <6>else
            <7>if feasible(q)
                <8>Take(q)
            <9>else
                <10>Delete current ATW of q in q's ATW list
        <11>Update request queue and decision time for every EDS
        <12> population size increased by one
```

Fig. 4. Main procedure of constructive algorithm for initial solutions

The function "$Take(q)$" adds request q into schedule of EDS s, in this process, back tracking will be used to cancel previous choices whenever the available resources are not enough to satisfy request q with high or medium priority, the plan is scanned in reverse chronological order and the last selected requests with lower priority are temporarily deleted, until the available resources become sufficient. Then scan the plan forward again and re-insert the temporarily deleted request if and only if doing this does not conflict with the request that triggered the latest back tracking. Function $feasible(q)$ is used to checking whether request q with low priority can be executed under current sensor state, it needs to check all the constraints we considered in this problem. If q is feasible, it will be taken, otherwise, we moving q to next available AOW.
The current decision time of a satellite s, $dt_s$is calculated by adding detecting time span on previous decision time, so, dt_s is an imprecise parameter with tri-angular possibility distribution too. When judging whether decision time exceeds the end of the scheduling horizon, its right boundary value will be used, which is dt_{s3}.

2) Coding method: We deployed 0-1 code to present requests of EDS s, at each locus, if the request has been taken in the final schedule, it values 1, otherwise 0. The binary permutation of s is called a chromosome segment. All segments combine together to form a chromosome, as figure 5 shows.

3) Genetic operators: The cross-over and mutation operations were both used here, and all operations must be manipulated upon the corresponding chromosome segment

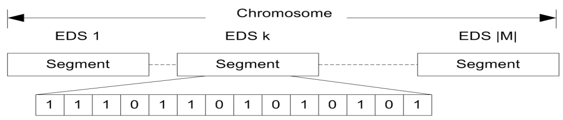

Fig. 5. Coding method

in two parents, because all constraints and ATWs are related to certain EDS. Firstly, the parent $father_1$ is selected out by tournament selection. In this process a chromosome list is defined by randomly permuting their index numbers $1, \cdots, \mathtt{M}$. Successive groups of T chromosomes are then taken from this list and compared, the one with the highest fitness value being chosen as a parent. This parent is then mated with another chosen purely at random. The selection probability is directly proportional to the fitness of the individuals. For the selection of multiple cross-over points, to avoid the parent chromosomes converge to such an extent that crossover has little effect; we embed XOR operator between two parents. Only positions whose outcomes are 1 in the XOR string will be considered as crossover points. The mutation operator accords to a certain probability, reverse all the gene values after mutation point N_m to generate offspring segment, if the offspring segment satisfies all constraints, save it for further operation, otherwise give it up.

$$p[k] = \frac{k}{M(2M+1)} \tag{14}$$

Here, $[k]$ is the kth chromosome when chromosomes are ranked in ascending order according to fitness value. This distribution gives a sensible selective pressure, in that the best ($[2M]$) will have a chance of 2/$(2M+1)$ of being selected, roughly twice of the median, whose chance of selection is 1/2M.

V. EXPERIMENTS

We generated targets corresponding to all signal collecting requests stochastically to simulate the EDS task scheduling problem in real condition. A reference scenario was defined with 4 characteristics:
(1)Four EDSs are in use.
(2)The scheduling horizon is 12 hours.
(3)The requests arrive at the rate of 100 every 12hours.
(4)Requests are spread at the surface of all over the world.

Beside this original scenario (we denoted it by SC1), all these four characteristics were altered, one at a time, to generate the other four alternative scenarios which denoted by SC2, SC3,SC4 and SC5.
(5)Two EDSs are in use.
(6)The scheduling horizon is 24hours.
(7)The requests arrive at the rate of 300 every 24hours.
(8)Requests are uniformly generated on the Earth surface with latitude between 60 degrees South and 60 degrees North.

The orbital parameters of EDS are taken from the satellite database of STK, the imprecise detecting time is supposed to be given, and in this experiment, detecting time triplet is generated stochastically within the range of each access time window.

In order to prove the efficiency and effectiveness of this approach, we used other two genetic algorithm to compare with our algorithms at the same time. The different strategies used in these algorithms are shown in the table1 as follows. The experiments are carried on a laptop with Centrino dual 1.8GHz,1 GB RAM, running on Windows Xp operating system, all algorithms are coded with C++ in Visual studio 2005. The results of experiments are shown as follows.

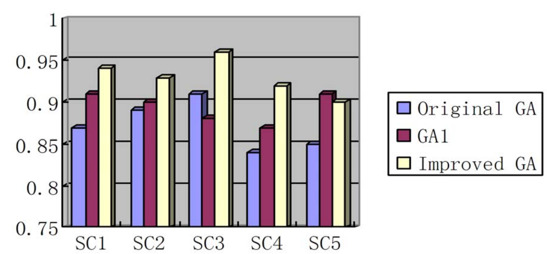

Fig. 6. Comparison of partition of requests in final schedule

Figure 6 shows the partition of requests that are included in the final schedule. From SC1 to SC4, the improved genetic algorithm has a better performance, more requests are scheduled, except in SC5, the reason is that the requests concentrate in a narrow region on the global surface, no enough AOW can be use.

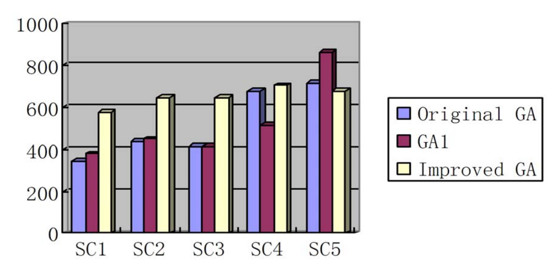

Fig. 7. Comparison of computation time

Figure 7 shows the computation time of each algorithm for five scenarios. As the improved genetic algorithm used special selection mechanism in both elitist and parents selection, so it takes more time than other two, but acceptable. The original genetic algorithm used the shortest computational

TABLE I
DIFFERENCES BETWEEN 3 ALGORITHMS USED IN EXPERIMENTS

Strategies	Original GA	GA1	Improved GA
Elitist selection	Objective value	probable selection	probable selection
Parent selection	randomly	randomly	tournament selection
Cross-over	Single point	multi-point	multi-point

time, because its selections are total random.

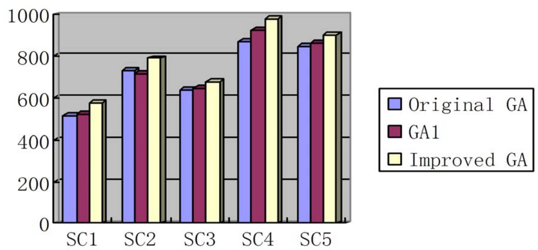

Fig. 8. Comparison of near-optimal generation

Figure 8 shows the near optimal generation (NOG) in each scenario,The NOG is the generation (iterative times) when the algorithm finds the near optimal solution. The NOG reflects the convergence speed of the algorithm. The results show that SC2, SC4 has higher NOG value, that because when the scale of problem increases, the solution domain and the constraints to be handled increase sharply.

VI. CONCLUSION

The task scheduling of EDS with uncertain detecting time is a complex combinatorial problem. When tackle with these imprecise parameters, we also have to consider all physical and operational constraints, and for more practical using, computation time is anticipated in a certain range. It is imperative necessary to use a tractable algorithm to fulfill these needs. In this paper, we proposed and used an improved genetic algorithm to deal with such problem.

We formulated this problem to a multi-objective constrained model, the issue of imprecise parameter is solved with fuzzy set and possibility theory. On the basis of this model, we proposed a constructive algorithm to get the initial populations pool, as the basis of our improved genetic algorithm. In the main procedure of our algorithm, the original genetic algorithm has been improved in following aspects: we did not use the objective value as the fitness value in elitist selection, but using probable selection instead; The parents in cross-over operation is chosen by tournament selection. This approach has been tested by simulative scenarios which using satellite data from database of STK, and targets' information were generated randomly. The results show that our algorithm is efficient to solve this problem.

Our future work will consider to add uncertain data volume into account, to make this approach more practical. On the other hand, lots of work need to do to deal with some stochastic occasions, like resource failure and emergent new request.

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