A Multi-Objective Imaging Scheduling Approach for Earth Observing Satellites

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ABSTRACT

EOSs (Earth Observing Satellites) circle the earth to take shots which are requested by customers. To make replete use of resources of EOSs, it is required to deal with the problem of united imaging scheduling of EOSs in a given scheduling horizon, which is a complicated multi-objective combinatorial optimization problem. In this paper, we construct a mathematical model for the problem by abstracting imaging constraints of different EOSs. Then we propose a novel multi-objective EOSs imaging scheduling method, which is based on the Strength Pareto Evolutionary Algorithm 2. The special encoding technique and imaging constraint control are applied to guarantee feasibility of solutions. The approach is tested upon four real application problems of CBERS EOSs series. From the results, it is confirmed that the proposed approach is effective in solving multi-objective EOSs imaging scheduling problems.

Categories and Subject Descriptors

J.2 [**Physical Sciences and Engineering**]: Aerospace

General Terms

Algorithms, Experimentation

Keywords

Imaging scheduling, Multi-objective evolutionary, Constraint satisfaction

1. INTRODUCTION

Earth Observing Satellites (EOSs) circle the globe collecting images through imaging sensors, which has become an important means for earth reconnaissance and resources researches. Today, countries all over the world are actively developing EOSs and corresponding techniques. Although the number of EOSs are continuously increasing, yet it is not enough to satisfy the requirements for remote sensing data. Therefore the limited resources of EOSs become extremely valuable. To make replete use of the EOSs imaging resources and get maximum benefit, it is expected to conduct and control the EOSs as a whole; here, EOSs denotes the satellites which take on the same set of observation requests. As the key process of EOSs conducting and controlling, imaging scheduling is to decide which imaging requests to be shot, when to shot and the data transmission state of EOSs.

EOSs imaging scheduling is a complicated problem with a number of important constraints, such as imaging requests, satellite solid state recorder (SSR), data transmission etc. For further details, see [6], [12] [16]. And with the development of satellite techniques, many mathematic models and methods have been proposed to solve the actual problem. Sherwood *et al.* use ASPEN, a general purpose scheduling system, to automate NASA EO-1 satellite [14]. Potter and Gasch describe a clever algorithm for scheduling the Landsat 7 satellite featuring greedy search forward in time with fixup to free resources for high priority images [13]. Bensana *et al.* view this problem as a value constraint-satisfaction problem, and use exact methods like Depth First Branch and Bound or Russian Dolls search and approximate methods like Greedy Search or Tabu search to solve the problem in the framework of the SPOT5 satellite [1]. Michel and Hao deal with the daily photograph-scheduling problem as a knapsack problem which is solved by a Tabu search algorithm [15]. Harrison *et al.* abstract the imaging model of optical or radar based Earth observing satellite, and propose a enumerate search to solve the imaging scheduling problem of small scale [8]. Muraoka *et al.* adopt Greedy Search to decide which requests to shot [11]. Wei-Cheng Lin *et al.* define problem formulation of ROCSAT-II, and adopte the mathematical programming method to generate a near-optimal EOS schedule [10]. However, all these works only consider one EOS and a single objective. As the number of EOSs increases, we are expected to schedule more than one EOS and find the most cost-effective solution.

There are few approaches considering the multiple satellites, Frank *et al.* adopt constraint-based interval (CBI) framework to represent the resources of EOSs and propose a heuristic for guiding this search procedure based on a general notion of contention for resources, but does not consider the conflicting requests and considers resources are independent [3]. Wolfe and Sorensen define and use the window-constrained packing problem to model earth observation system domain scheduling problem. They propose three algorithms: a dispatch algorithm, a look-ahead algorithm, and a genetic algorithm . In the research, the genetic algorithm generates the best solutions [17]. Lamaitre *et al.* research the problem of scheduling the set of photographs for Agile Earth Observing Satellites, find that constraint programming is more flexible while local search performs better [9]. Al.Globus et al. combine the optimal objectives into a weighted sum, and use three methods, simulated annealing, improved hill climbing, genetic algorithm on two EOSs fleet [7]. Also few multi-objective method that have been proposed, Gabrel and Vanderpooten propose digraph without circuits to formulate imaging scheduling of SPOT5, then generate the efficient paths and select one of a satisfactory path by a multiple criteria interactive procedure [4]. Zhang *et al.* adopt the labeling correcting method to find the multi-objective effective sequence of imaging request, as an exact method, it can generate all the true optimal Pareto solutions of small scale problem[18].

To find the most cost-effective solutions of EOSs imaging scheduling, in this paper, EOSs imaging scheduling is firstly formulated as a multi-objective integer-programming problem, then a multi-objective evolutional algorithm, based on Strength Pareto Evolutionary Algorithm 2 (SPEA2)[19], is proposed; we propose a new coding method in which the ground stations are considered as special imaging requests with the different transmission state(detail discussed in section 2), and some special measures have been proposed to handle imaging constraints. The approach is tested on real data set and the result analysis is carried out.

2. PROBLEM FORMULATION

As EOS orbit in low earth space, the imaging belts are regions on the ground with axis of the substar tracks (Figure. 1). EOS flies with a high speed when taking shots; therefore there is a rigid time-limited imaging window for each request. Because of the restriction of attitude control and available power of EOS etc, it is impossible to shoot all pending imaging requests in one scheduling period. So it is required to decide which imaging requests to shot. All kinds of impacts are expected to be considered synthetically: importance of request, SSR cost, power consumption, weather and sunshine condition of request. However, these factors are usually conflictive. Thus it is very hard to maximize the quality of the shots, and minimize the cost of the EOSs resources at the same time.

When there is more than one EOS, the orbit design of each EOS may be different, therefore the image belts of them will be overlapped (Figure. 2). Usually the overlapped

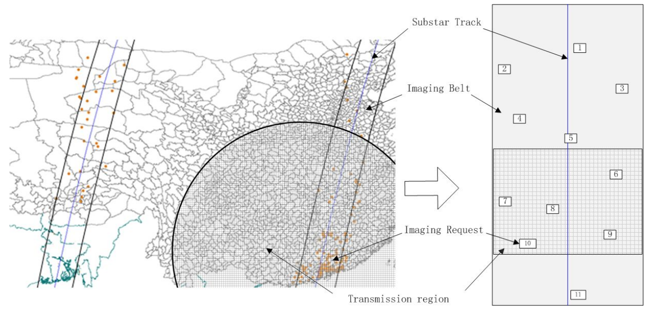

Figure 1: The grey belts denote areas that the EOS can shoot, the black blocks denote imaging requests. And the mesh region denotes the period of data transmission

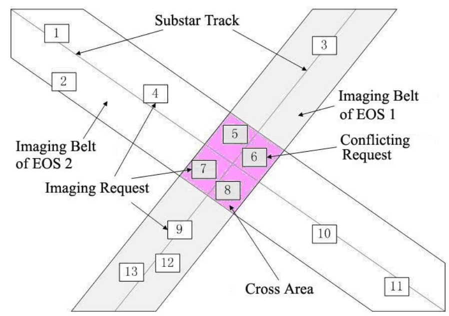

Figure 2: Conflicting imaging requests

areas are hot regions where imaging requests gather. The requests in the overlapped area, which are called the conflicting requests, may be shot by different EOSs. If we consider the imaging scheduling problem of these EOSs respectively, one conflicting request in the this area may be assigned to all the EOSs that can shoot it. To avoid the repetition of the same data acquisition, which may brings large waste of EOSs system resources(of low quality about 20%-30% [7]), it is required to schedule the EOSs as a whole. Certainly, sometimes it is required to shoot the requests repeatedly, as refer to some other reason such as requests demand, plan arranging, etc; here we do not take this condition into account.

As EOSs pass over the ground station (Figure. 1), there are two states of data transmission: playback transmission and real-time transmission. The playback transmission transmits the data from SSR(solid state recorder) to ground station, in this moment, the EOS can't shoot; and in the real-time transmission state, the payload of EOS takes image and then transmits the image to ground station immediately. These two states can not coexist. Here we think the ground stations have been assigned to corresponding EOS. As the state of the data transmission impacts the SSR cost, we should select the appropriate state of each ground station in the scheduling process.

According to the viewpoint of [16], CBERS EOSs in the paper are called non-agile optical EOSs. The imaging window of each request are relatively fixed. So the main work of the scheduling process is to select the requests, determine the imaging time for each selected request and select the state of data transmission. In order to get optimal imaging plans and make replete use of the valuable EOSs resources, we evaluate the solutions of imaging scheduling by multi-objectives criteria .

The scheduling period considered here does not exceed 24 hours. According to the characteristics of each EOS, we suppose:

1. All the pending imaging requests should be ordered before scheduling, during the scheduling period any new imaging request will be ignored;
2. At any moment, for one EOS, only one imaging request can be shot;
3. One EOS does not revisit the same imaging request in one scheduling period;
4. Each imaging request corresponds to a point target. If there is a large scale regional request exists, it will be divided into several point requests before scheduling;
5. Action of one shot is atomic, Thus, in case a request begins to be shot, it must be finished;
6. When EOSs pass over a ground station, there is only one data transmission state.

As image scheduling must satisfy the complicated constraints of EOSs, basing on the hypotheses above, Several notations are defined.

Notations :

S- set of all EOSs,

α, β- identifier of satellite; $\alpha, \beta \in \{1, 2, \ldots \mathrm{S}\}, \mathrm{S} = |S|$;

U- set of transmission requests, $U = \{-\mathrm{U}, \ldots -2, -1\}$, $\mathrm{U} = |U|$, though ground stations have been assigned to corresponding EOS, we should choose the state of each transmission request;

P- set of total pending imaging requests, $P = \{1, \ldots \mathrm{P}\}$, $\mathrm{P} = |P|$, here we suppose the set has been sorted by the beginning time of each request;

i, k- identifier of imaging request, here, the transmission requests are considered as special imaging requests with corresponding properties, and the values of these special requests are negative. $i, k \in U \cup P$; two dummy requests: 0 and $P+1$ denote the beginning and ending of the scheduling period;

I_α- set of pending imaging requests of EOS α, $0, P+1 \in I_\alpha$, $\bigcup I_\alpha \subseteq U \cup P$;

tml_α- minimal action time of EOS α to take one shot;

$b_{\alpha i}$- the beginning time of imaging request i to EOS α when it is shot separately, for transmission requests, it is the entering time of EOS α;

$e_{\alpha i}$- the ending time of imaging request i to EOS α when it is shot separately, for transmission requests, it is the leaving time of EOS α

$l_{\alpha i}$- slewing angle of EOS α for imaging request i, the angle of transmission request is zero;

M_α- SSR capacity of EOS α, which has been converted to imaging time span

E_α- power of EOS α;

Δ_α- average skip speed of EOS α;

v_α- power consumption of EOS α, caused by skipping unit angle;

z_α- power consumption of EOS α, caused by one shot action;

ω_i- importance level of imaging request i, $\omega_i = 1, 2, 3$, the higher the level the more important the request is, and the values of transmission request is zero

$A_{\alpha i}$- sun altitude level of imaging request i at $b_{\alpha i}$, Here we quantize the sun altitude as follows: $0^\circ \sim 25^\circ$ is level 1, $25^\circ \sim 60^\circ$ is level 2, $60^\circ \sim 90^\circ$ is level 3; the higher the level the better the sunshine condition is, the value is 90° to transmission request

R_i- required sun altitude level of imaging request i, the value is zero to transmission request;

$C_{\alpha i}$- cloudage level of imaging request i at the time of shooting, which is provided by correlative meteorology in weather situation; Here we quantize the cloudage into 9 levels: 1∼9, the higher the level the worse the cloudage condition is, the value is zero to transmission request;

W_i- required cloudage level of imaging request i, the value of transmission request is 9;

Decision Variables :

$\tau_{\alpha i}$- decision variable, $i \in P$, if $\tau_{\alpha i} = 1$, then the pending request i will be shot by EOS α, $\tau_{\alpha i} = 0$ denotes the contrary; (in general, if$i \in U$ $\tau_{\alpha i} = 1$)

$\theta_{\alpha i}$- decision variable, $i \in U$, 1 denotes playback state, 0 denotes real-time state;

$Span_{\alpha j}$- time span variable: real imaging time span of imaging requests set j of EOS α, here $j \subseteq P \cup U$, for single imaging request $j = \{i\}$, $Span_{\alpha j} = [b_{\alpha i}, e_{\alpha i}]$ shortened as $Span_{\alpha i}$; and $Span_{\alpha j} \cup Span_{\alpha m}$ denotes the merge of imaging time span of requests set j and m. Considering the minimal action time limit of take one photograph of EOS α, $Span_{\alpha j} \cup Span_{\alpha m}$ may not equal the simple sum of $Span_{\alpha j}$ and $Span_{\alpha m}$;

$TC_{Span_{\alpha j}}$- step function: denotes the time length of time span variable $Span_{\alpha j}$, the unit is second;

$\sigma_{\alpha ik}$- step variable, 1 denotes the request k, will be shot after the shooting of i finished, 0 denotes the contrary. here $i, k \in I_\alpha$;

$\Gamma_{\alpha ik}$- step variable, 1 denotes that the imaging process of EOS α of request i and request k overlap, 0 denotes the contrary. here $i, k \in I_\alpha \cap P$;

N_α- step variable, the number of shoot action, $N_\alpha = \sum\limits_{i \in I_\alpha} (\tau_{\alpha i} - \bigcup\limits_{k \in I_\alpha} \tau_{\alpha k} \tau_{\alpha i} \Gamma_{\alpha ki}), \alpha \in \{1, 2, \ldots \mathrm{S}\}$;

Then the constraints of imaging scheduling are as follows;(here,with out special explain, $\alpha \in \{1, 2, \ldots \mathrm{S}\}$)

(1) Dummy requests 0 and P+1 are the beginning request and ending request of imaging scheduling list of each EOS, which should satisfy the following constraints:

$\sigma_{\alpha 0 i} = 1$, $i \in I_\alpha \cap \mathrm{P}$,

$\sigma_{\alpha i \mathrm{P}+1} = 1$, $i \in I_\alpha \cap \mathrm{P}$,
$\Gamma_{\alpha 0i} = \Gamma_{\alpha i\mathrm{P}+1} = 0$, $i \in I_\alpha \cap \mathrm{P}$,
$l_{\alpha 0} = l_{\alpha \mathrm{P}+1} = 0$, $\tau_{\alpha 0} = \tau_{\alpha \mathrm{P}+1} = 1$,
$TC_{Span_{\alpha 0}} = TC_{Span_{\alpha \mathrm{P}+1}} = 0$;

(2) The binary variable $\sigma_{\alpha ik}$ should satisfy the following constraints($b_{\alpha i} \le b_{\alpha k}$):

- if $b_{\alpha k} \le e_{\alpha i}$, then $\sigma_{\alpha ik} = \begin{cases} 1, l_{\alpha i} = l_{\alpha k}; \\ 0, \text{others}; \end{cases}$,
- if $b_{\alpha k} > e_{\alpha i}$, then $\sigma_{\alpha ik} = \begin{cases} 1, \frac{|l_{\alpha i} - l_{\alpha k}|}{b_{\alpha k} - e_{\alpha i}} \le \Delta_\alpha; \\ 0, \text{others}; \end{cases}$ $i, k \in I_\alpha \cap P$,

and

- if $i \in I_\alpha \cap U$ or $k \in I_\alpha \cap U$, then $\sigma_{\alpha ik} = 0$;

(3) The binary variable $\Gamma_{\alpha ik}$ should satisfy the following constraints:
$\Gamma_{\alpha ik} = \begin{cases} 1, Span_{\alpha i} \cap Span_{\alpha k} \neq \emptyset \text{ and } l_{\alpha i} = l_{\alpha k}; \\ 0, others; \end{cases}$
$i, k \in I_\alpha \cap P$, and $\Gamma_{\alpha ik} = 0$,$i \in I_\alpha \cap U$ or $k \in I_\alpha \cap U$;

(4) As one EOS in the paper only can process one imaging request at any time, the imaging request sequence should satisfy the following constraints:

$$\sum_{\substack{k \in I_\alpha \\ k \neq i}} \tau_{\alpha i}\tau_{\alpha k}\sigma_{\alpha ik} - \sum_{\substack{k \in I_\alpha \\ k \neq i}} \tau_{\alpha i}\tau_{\alpha k}\sigma_{\alpha ki} = \begin{cases} 1, i = 0 \\ -1, i = P+1 \\ 0, others \end{cases},$$

$i \in I_\alpha, i, k \neq 0, \mathrm{P}+1$;

(5) Sun altitude constraint and cloudage constraint for requests:
$\tau_{\alpha i} A_{\alpha i} \ge R_i$;
$\tau_{\alpha i} C_{\alpha i} \ge W_i$;

(6) The capacity of SSR is limited, so the imaging list ought to satisfy the constraint of memory capacity. It is an important constraints of EOSs scheduling problem. As the imaging process of different requests in the request sequence might overlap, for convenience, we define an additional operation to denote the merging of the imaging action of these overlapped requests. ($b_{\alpha i} < b_{\alpha k}$),

- if $i, k \in I_\alpha \cap P$, then $Span_{\alpha i} \cup Span_{\alpha k}$ means the merge of them; (because there are minimal action time limit, and the $TC_{Span_{\alpha i} \cup Span_{\alpha k}}$ may not equal the sum of $TC_{Span_{\alpha i}}$ and $TC_{Span_{\alpha k}}$);
- if $i \in I_\alpha \cap U$, $\theta_{\alpha i} = 0$ and $b_{\alpha i} < b_{\alpha k}, e_{\alpha k} < e_{\alpha i}$, then $Span_{\alpha i} \cup Span_{\alpha k} = Span_{\alpha i}$ and $TC_{Span_{\alpha i}} = 0$;
- if $k \in I_\alpha \cap U$, $\theta_{\alpha k} = 1$, then $TC_{Span_{\alpha i} \cup Span_{\alpha k}} = max(TC_{Span_{\alpha i}} - TC_{Span_{\alpha k}}, 0)$;

The constraint of SSR capacity can be described as:
$TC_{Span_{\alpha i}} \ge tml_\alpha$ and $\forall k \in I_\alpha$, $0 \le TC_{Span_{\alpha K'}} \le M_\alpha$,
here, $Span_{\alpha K'} = \bigcup_{\substack{i=0, \\ i \in I_\alpha}}^{k} \tau_{\alpha i} Span_{\alpha i}$;

(7) Power is necessary for image shooting and skip. According to the characteristic of EOSs, these imaging actions should satisfy power constraint of each EOS:

$$\sum_{i \in I_\alpha} \sum_{\substack{k \in I_\alpha \\ k \neq i}} \tau_{\alpha i}\tau_{\alpha k}\sigma_{\alpha ik} v_\alpha |l_{\alpha i} - l_{\alpha k}| + \sum_{i \in I_\alpha} N_\alpha z_\alpha \le E_\alpha;$$

Constraints (1), (2) and (5) are only referable to imaging requests, therefore they can be processed before scheduling, here we mainly consider the constraints (3), (4), (6) and (7).

All results of the imaging scheduling problem of EOSs are subsets of the requests which will be taken by the EOSs during the scheduling period T. As mentioned above, we hope the results are of maximal importance level and minimal resources costing at the same time. So in the condition of multi satellites, we define the objective functions of imaging scheduling as follows:

Objective function for importance of imaging requests:

$$f_1 = \min \sum_{i=1}^{\mathrm{P}} \left(\prod_{\alpha=1}^{\mathrm{S}} (1 - \tau_{\alpha i})\right)\omega_i \qquad \text{(I)}$$

Objective function for resources consumption:

$$f_2 = \min \sum_{\alpha=1}^{\mathrm{S}} \Big(\sum_{i \in I_\alpha} \sum_{\substack{k \in I_\alpha, \\ k \neq i}} \tau_{\alpha i}\tau_{\alpha k}\sigma_{\alpha ik} v_\alpha |l_{\alpha i} - l_{\alpha k}| + N_\alpha z_\alpha + TC_{Span_{\alpha I'}} \Big), \qquad \text{(II)}$$
here, $TC_{Span_{\alpha I'}} = \bigcup_{i \in I_\alpha} \tau_{\alpha i} Span_{\alpha i}$

subject to constraints (1)∼(7).

3. IMAGING SCHEDULING ALGORITHM

In practice, imaging requests are ordered by different customs, thus the problem scale of the imaging scheduling varies a lot. Usually the process of imaging scheduling has very rigid time restriction; to generate the solutions in the given time, we propose a novel EOSs imaging scheduling algorithm.

Generally speaking, an easy method to solve a multi-objective problem is to convert it to a single-objective problem according to the preference information of the objectives. However it is very difficult here to get the preference information of the objectives with our problem [17], [2]. Therefore we will generate the Pareto solutions of the imaging scheduling problem, which help to bring the final imaging plan.

According to our model, if we only consider imaging scheduling of one EOS and objective Function $f(I)$, the problem, in some conditions, can be converted to a optimization problem of longest weight-constrained path, which is known to be NP-hard problem in according to the complexity theory[5], however our problem is more complex. To find the most cost-effective solution, we propose a multi-objective EOSs imaging scheduling algorithm , which is based on Strength Pareto Evolutionary Algorithm 2(SPEA2)[19]. In the algorithm, we design corresponding genetic operator to evolve the population and handle constraints of EOSs.

3.1 The Concept of SPEA2

SPEA2 uses a regular population and an archive. It adopts the mechanism of elitist archiving which is realized by fitness assignment and selection strategy, and through truncation operation it keeps the archive size and the diversity of the Pareto solutions. The processes of SPEA2 are as follows [19]:

Step 1: Initialization : Set t = 0, Generate an initial population P_0 and create the empty archive (external set) $A_0 = \emptyset$

Step 2: Fitness assignment : Calculate fitness values of individuals in P_t and A_t.

Step 3: Environmental selection : Copy all non-dominated individuals in P_t and A_t to A_{t+1}. If size of At+1 exceeds N then reduce A_{t+1} by means of the truncation operator, otherwise if size of A_{t+1} is less than N then fill A_{t+1} with dominated individuals in P_t and A_t.

Step 4: Termination : If $t \geq T$(T is the maximum number of generations) or another stopping criterion is satisfied then set A (non-dominated set) to the set of the non-dominated individuals in A_{t+1}. Stop.

Step 5: Mating selection : Perform binary tournament selection with replacement on A_{t+1} to fill the mating pool.

Step 6: Variation : Apply recombination and mutation operators to the mating pool and set P_{t+1} to the resulting population. $t = t + 1$ and go to Step 2.

The fitness assignment is a two-stage procedure. Firstly, each individual i in the archive A_t and the population P_t is assigned a strength value $Q(i)$, representing the number of solutions it dominates. Secondly, the raw fitness $R(i)$ of an individual i is determined by the strengths $Q(i)$ of its dominators in both archive and population. Additional density information $D(i)$ is used to discriminate the individuals which have identical raw fitness values. The density information technique proposed in [19] is an adaptation of the $k-th$ nearest neighbor method. Thus, the fitness of an individual i is defined by: $F(i) = R(i) + D(i)$.

During environmental selection, the first step is to copy all non-dominated individuals to the archive of the next generation: $A_{t+1} = \{i \,|i \in P_t + A_t \wedge F(i) < 1\}$, If the non-dominated front fits exactly into the archive ($|A_{t+1}| = N$) the environmental selection step is completed. Otherwise, if the archive is too small, This can be implemented by sorting the dominated individuals of $P_t + A_t$ according to the fitness values and copy the first $N - |A_{t+1}|$ individuals. if the number of the non-dominated individuals of $P_t + A_t$ exceeds N, an archive truncation procedure will be invoked, the detailed process see [19].

3.2 Design of Genetic Operators

The genetic operators determine the state transfer, which is important to the evolution of the population and constraints satisfaction. To present EOSs imaging scheduling problem effectively and avoid generating overmany infeasible solutions, the components of our method: problem coding and crossover,mutation operators are described in the following section.

3.2.1 Problem Coding

Each I_α is a permutation list of imaging requests, we use $|I_\alpha|$-length 0-1 coding to present imaging request lists of EOS α, each binary sequence is called a chromosome segment. The $|S|$ segments form the chromosome (Figure. 3). Obviously the imaging constraints of each EOS I_α are restricted in corresponding chromosome segments. And the total length of the chromosome is $\sum_{\alpha=1}^{S} |I_\alpha|$. Here the transmission requests are considered as special imaging requests, the difference is that the transmission requests would effect the imaging requests in their transmission region, the details see constraint (6).

3.2.2 Crossover and Mutation Operators

Considering (1)~(7) constraints, if we adopt simple crossover and variation operation , too many infeasible solution will be generated; therefore we propose new crossover ,mutation and constraint satisfaction operators considering the constraints of imaging scheduling, which do the crossover, mutation and modifying constraints estimation simultaneously. In this way, it guarantees each solution generated is feasible.

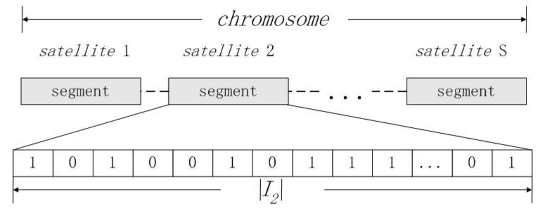

Figure 3: coding of problem, one bit denotes one request.

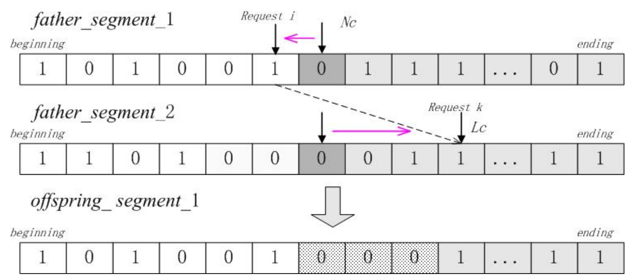

Figure 4: The first two chromosomes denote the father individuals. The crossover point is the gene i. The grey panes denote the genes that are exchanged in the crossover operation.

Select two individual from the mating pool. Because the imaging constraints are related to one EOS, the crossover and mutation operators will be finished upon the corresponding chromosome segment. As an example, we only the consider chromosome segment of EOS α. Suppose the chromosome segments are *father_segment_1* and *father_segment_2*, for illustration, as follows:

1. Randomly select a crossover point Nc and a mutation point Nm from integer interval $(1, |I_\alpha|)$, $1 \leq Nc, Nm \leq |I_\alpha|$;

2. Crossover operation:

Suppose crossover point Nc of *father_segment_1* represents request i;

• If i is a transmission request, then give up it and select another crossover point Nc, until the Nc an represents imaging request;

• If $\tau_{\alpha i} = 0$, then find the first request before point Nc, whose $\tau_{\alpha i} = 1$ and ;

And then, find out the first imaging request k which makes $\tau_{\alpha k}\sigma_{\alpha ik} = 1$ in *father_segment_2* as the crossover point Lc, (crossover point Lc of *father_segment_2* represents imaging request k); replace the chromosome section after Lc of *father_segment_1* with that of *father_segment_2* and set zero to the chromosome section of *father_segment_1* between Nc and Lc, but leave the genes that denote transmission requests unchanged (Figure. 4).

3. Mutation operation:

According to a certain probability, reverse all the gene values after mutation point Nm to generate $offspring\_segment$ (if the gene denotes a transmission request, reverse its θ value). Then if the $offspring\_segment$ satisfies constraints (4), save it for further operation, otherwise give up it.

4. Constraints satisfaction adjustment:

Apparently, both crossover and variation can assure that the results satisfy constraint (4). However, if the results of above operations may not satisfy constraint (6) and (7), we

INPUT:

set of imaging requests P,

set of EOSs S,

planning period T and other relevant parameters,

scale of population P_1 and the 2nd population P_2: V_1 and V_2,

generation number of evolution N,

crossover probability G_c, variation probability G_m;

OUTPUT:

imaging scheduling sequence P^*;

begin

② $n \leftarrow 0$, create the initial population P_1^0 by greedy thought, and $P_2^0, P^*, P_m^0 \leftarrow \varnothing$;

③ assign fitness for individuals in P_1^n, P_2^n;

④ refresh the 2nd population P_2^{n+1} according to the fitness of individuals in P_1^n, P_2^n;

⑤ **if** the scale of the 2nd population P_2^{n+1} is larger than V_2, then call the truncation function;
else select dominant solutions with high fitness to fill the 2nd population;

⑥ **if** $n > N$ or other stopping criterion is satisfied, then $P^* \leftarrow P_2^{n+1}$;
else $P_m^n \leftarrow matingSelect(P_2^{n+1})$;

⑦ genetic operation based on imaging constraint:
crossover operation of chromosome segment: $P_m^n \leftarrow cross(P_m^n)$;
variation operation of chromosome segment: $P_m^n \leftarrow mutate(P_m^n)$;

⑦ **if** the result of genetic operation can't satisfy the other imaging constraints, then do the constraints adjustment: $P_m^n \leftarrow cs(P_m^n)$;
else $P_1^{n+1} \leftarrow P_m^n$;

⑧ $n \leftarrow n+1$;

⑨ **go to** ②;

end

Figure 5: Main steps of the Multi-Objective EOSs Imaging Scheduling Algorithm

design a simple adjustment operation without impacting the satisfaction of constraint (4): According to the value of ω_i, randomly select an imaging request i by roulette method, and then delete it. Repeat the operation until the results can satisfy all the imaging constraints. From this operation, it guarantees that the results are all feasible individuals.

4. EXPERIMENTS

To test the effectiveness and efficiency of multi-objective EOSs imaging scheduling algorithm, considering most imaging constraints of CBERS series EOSs , we carried out some experiments upon real imaging requests data. Here were four typical imaging scenarios, the numbers of their imaging requests were 39, 102, 389 and 1338. And there were 4 transmission requests at most. Shown as Table. 1, The first column (PH) is ID of the imaging scenario. The second (NR) is the number of imaging requests. The third column (NS) is the number of satellites. The forth (CNR) is the number of conflicting requests in the imaging scenario. The fifth (GS) is the number of ground station requests in the imaging scenario. . The seventh column is the sum important values of all pending requests in the imaging scenario. The last three columns are numbers of requests with different importance.

The plan period was 8:00 to 20:00 of a certain day. The $b_{\alpha i}, e_{\alpha i}, l_{\alpha i}, A_{\alpha i}$ of imaging requests were calculated by other

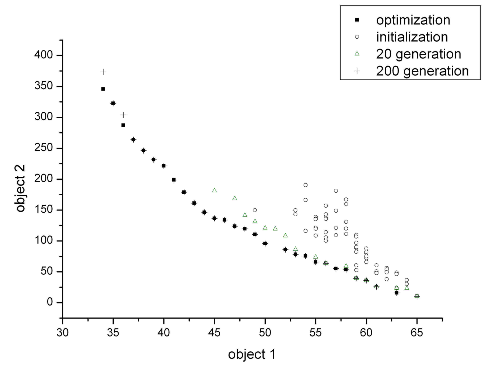

Figure 6: The approximate Pareto optimal solutions of PH75 on different generations and the true optimal Pareto set generated by exact method.

pre-scheduling programs. In real application, $C_{\alpha i}$ information is provided by correlative meteorology institution; while in the experiments, the values of $C_{\alpha i}$ were generated randomly. The parameters of the algorithm were: population size of 100; external archive size of 50; the crossover probability is 0.8; the mutation probability is 0.06; The tests were carried out on a compatible PC with 2.9 GHz Core2, 2 Gb of RAM, Windows XP and a Visual C++ compiler. The time restriction of our experiments was 5400 seconds. To all the four problem scales, our algorithm can satisfy the restriction of running time.

Here, to improve the efficiency of the algorithm, the initialization population was produced by selecting the first imaging request randomly and expanding the imaging sequence according to the importance of imaging requests.

Each experiment of these problems found a set of Pareto-optimal(or approximate Pareto-optimal) solutions considering two objectives, object I: importance of imaging requests, object II: resources consumption(see section 2). The solutions shown in figures produced conflicting scenarios of the objective functions(the middle results are also shown in the figures.). In general, there is no solution which is optimal with respect to both objectives. Nevertheless, the results can help the planner to analyze and evaluate the solutions by other criteria. At last, the planner will select one of these solutions as the final plan of EOSs imaging scheduling, then generate the action statements according to the plan to control the EOSs.

To analyze the validity of our algorithm, we compared the results of our algorithm with the true optimal Pareto sets of PH75, PH193, PH198. These true optimal Pareto sets were generated by the dynamic programming method [18] (In the scheduling restriction time, this method can only solves small scale problems). However, as a large scale problem, the true optimal Pareto set of PH227 was still unknown.

The results of PH75, PH198 in a single simulation run are shown as the Figure. 6, Figure. 7. From the Figures, we can see, in these two problems, the algorithm can find the true optimal Pareto front quickly. As the cardinality of the true optimal Pareto set of PH75 is 29, the algorithm can generate most solutions of the true optimal Pareto set within only 200 generations. To PH198, the cardinality of the true optimal

Table 1: Data of four scenarios

PH	NR	NS	CNR	GS	Total VofR	Unimportant	General	Important
75	39	1	0	0	67	18	14	7
193	102	2	5	1	208	34	29	39
198	389	1	0	1	658	171	167	51
227*	1338	3	149	4	2265	579	591	168

* the true optimal Pareto set is still unknown

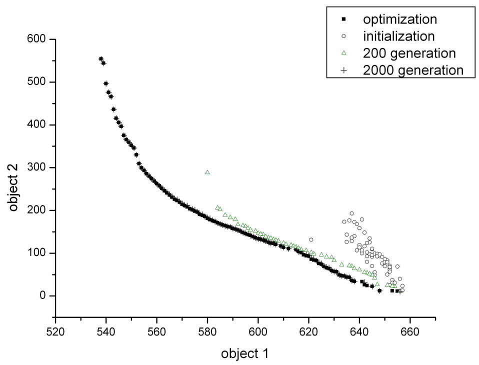

Figure 7: The approximate Pareto optimal solutions of PH198 on different generations and the true optimal Pareto set generated by exact method.

Pareto set is 124. The solutions of our algorithm are almost in the optimal Pareto set after 2000 generations Figure. 7.

As the problem of PH193 contains two-EOS, to generate the optimal Pareto set, it need to consider all possibilities of the selection of the conflicting imaging requests, which cost much more time than generating the approximate Pareto optimal by our algorithm.

The problem of PH227 is the only one in our experiments whose true optimal Pareto set is unknown. We give the solutions of 10000 generations. From Figure. 9, our algorithm can generate the the approximate Pareto optimal solutions with well diversified. And we find that the gradients of the Pareto front increases. When the value of object 1 is less than 1950, the object 2 increases rapidly. That is to say, a little improvement of the imaging requests importance will cause an excessive increase of EOSs resources cost.

From the figures, we can see that these feasible solutions are distributing well-proportioned, but non-linear. In practice, a plan which the EOSs shoot few imaging request or cost much EOSs resources is neither we expect. So, in general, the middle of the Pareto set, where the front are convex, denotes the better efficiency. From the Figure. 6, Figure. 7, Figure. 8, we can see that our algorithm can fleetly find these solutions which are in the middle of the optimal Pareto front.

5. CONCLUSIONS

The multi-objective EOSs imaging scheduling is a complex problem. It must satisfy the constrains of EOSs imaging payload. Considering these constraints, it is difficult to converge to the true optimal Pareto set and to diversify the solutions. And the conflicting requests and the data transmissions also increase the complexity of imaging scheduling.

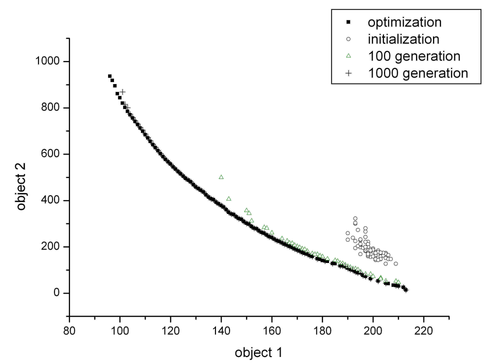

Figure 8: The approximate Pareto optimal solutions of PH193 on different generations and the true optimal Pareto set generated by exact algorithm.

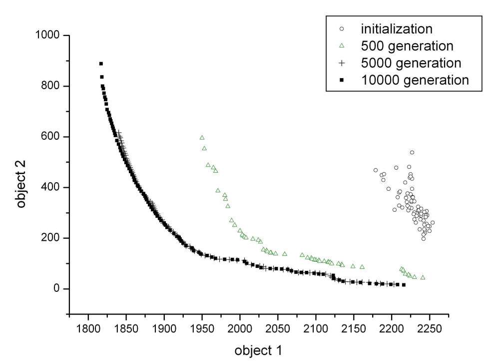

Figure 9: The approximate Pareto optimal solutions of PH227 on different generations .

Moreover, in some condition, we should generate the results of imaging scheduling in stated time. So it is intensively necessary to use an efficient algorithm to tackling these difficulties. In this paper we proposed a novel approach to resolve the problem of EOSs imaging scheduling.

We formulate the imaging scheduling of EOSs as an multi-objective integer-programming problem. As evolutionary algorithms are ideal candidates to solving problems with more than one objective, on the basis of the model, we propose the imaging scheduling algorithm basing on SPEA2. The approach has been tested on problems of different sizes. From the results, comparing with the true optimal Pareto set, we can see that the proposed algorithm is able to find the optimal Pareto set on small scale problems; and it can find the approximate Pareto optimal solutions of large scale problem in the stated time, despite the complexity of these problems.

In practice, the solutions, in term of multi-objective, will provide more information available to help the planner to compare and select the final imaging plan. In this view, it can be said that the proposed approach is successful in tackling the imaging scheduling problem of EOSs.

6. ACKNOWLEDGMENTS

This research is supported in part by the National High Technology Research and Development Program of China under Grant No.2006AA701316 and National Natural Science Foundation of China under Grant No.60604035.

7. REFERENCES

[1] E. Bensana, G. Verfaillie, J. Agnese, N. Bataille, and D. Blumstein. Exact and inexact methods for the daily management of an earth observing satellite. In *Proceedings of 4th International Symposium on Space Mission Operations and Ground Data Systems*, Munich, Germany, September.

[2] K. Deb. *Multi-objective optimization using evolutionary algorithms*. John Wiley and Sons, New York, USA, 2001.

[3] J. Frank, A. Jonsson, R. Morris, and D. Smith. Planning and scheduling for fleets of earth observing satellites. In *Proceedings of the 6th International Symposium on Artificial Intelligence, Robotics, Automation and Space 2002*, Montreal, Canada, June 2002.

[4] V. Gabrel and D. Vanderpooten. Enumeration and interactive selection of efficient paths in a multiple criteria graph for scheduling an earth observing satellite. *European Journal of Operational Research*, 139:533–542, 2002.

[5] M. R. Garey and D. S. Johnson. *Computers and Intractablility: A Guide to the Theory of NP-Completeness*. W.H.Freeman, San Francisco, USA, 1979.

[6] A. Globus, J. Crawford, J. Lohn, and A. Pryor. A comparison of techniques for scheduling earth observing satellites. In *Proceedings of the 16th Conference on the Innovative Applications of Artificial Intelligence*, San Jose, USA.

[7] A. Globus, J. Crawford, J. Lohn, and A. Pryor. Scheduling earth observing satellites with evolutionary algorithm. In *Proceedings of the International Conference on Space Mission Challenges for Information Technology (SMC-IT)*, Pasadena, USA, July 2003.

[8] S. Harrison, M. Price, and M. Philpott. Task scheduling for satellite based imagery. In *Proceedings of the Eighteenth Workshop of the UK Planning and Scheduling Special Interest Group*, pages 64–78, University of Salford, UK.

[9] M. Lemaitre, G. Verfaillie, F. Jouhaud, J. M. Lachiver, and N. Bataille. How to manage the new generation of agile earth observation satellites. In *Proceedings of of the 6th International Conference on Space Operations*, Toulouse, France, June 2000.

[10] W. C. Lin, D. Y. Liao, C. Y. Liu, and Y. Y. Lee. Daily imaging scheduling of an earth observation satellite. *IEEE Transaction on Systems, Man, and Cybernetics part A: system and humans*, 35(2):213–223, March 2005.

[11] H. Muraoka, R. H. Cohen, T. Ohno, and N. Doi. Aster observing scheduling algorithms. In *Proceedings of the 5th International Conference on Space Operations*, Tokyo, Japan, June 1998.

[12] P. Potin. End-to-end planning approach for earth observation mission exploitation. In *Proceedings of the 5th International Conference on Space Operations*, Tokyo, Japan, June 1998.

[13] W. Potter and J. Gasch. A photo album of earth: Scheduling landsat 7 mission daily activities. In *Proceedings of the 5th International Conference on Space Operations*, Tokyo, Japan, June 1998.

[14] R. Sherwood, A. Govindjee, D. Yan, G. Rabideau, S. Chien, and A. Fukunaga. Using aspen to automate eo-1 activity planning. In *Proceedings of the 1998 IEEE Aerospace Conference*, Colorado, USA, March 1998.

[15] M. Vasquez and J. K. Hao. Upper bounds for the spot 5 daily photograph scheduling problem. *Journal of Combinatorial Optimization*, 7:87–103, 2003.

[16] G. Verfaillie and M. Lemaitre. Tutorial on planning activities for earth watching and observation satellites and constellations: from off-line ground planning to on-line on-board planning. In *Proceedings of International Conference on Automated Planning and Scheduling (ICAPS2006)*, English Lake District, UK, June 2006.

[17] W. J. Wolfe and S. E. Sorensen. Three scheduling algorithms applied to the earth observing systems domain. *Management Science*, 46(1):148–168, January 2000.

[18] F. Zhang, J. Wang, J. Li, and N. Jing. Multicriteria optimal imaging scheduling based on time ordered acyclic directed graph. *Journal of National University of Defense Technology*, 27(6):61–66, November 2005.

[19] E. Zitzler, M. Laumanns, and L. Thiele. Spea2: Improving the strength pareto evolutionary algorithm. *Swiss Federal Institute of Technology (ETH), Zurich, Switzerland. Technical report TIK-Report*, 103, May 2001.