Daily Imaging Scheduling of an Earth Observation Satellite

Wei-Cheng Lin, Da-Yin Liao, *Member, IEEE*, Chung-Yang Liu, and Yong-Yao Lee

***Abstract*—This paper presents the development of a daily imaging scheduling system for a low-orbit, earth observation satellite. The daily imaging scheduling problem of satellite considers various imaging requests with different reward opportunities, changeover efforts between two consecutive imaging tasks, cloud-coverage effects, and the availability of the spacecraft resource. It belongs to a class of single-machine scheduling problems with salient features of sequence-dependent setup, job assembly, and the constraint of operating time windows. The scheduling problem is formulated as an integer-programming problem, which is NP-hard in computational complexity. Lagrangian relaxation and linear search techniques are adopted to solve this problem. In order to demonstrate the efficiency and effectiveness of our solution methodology, a Tabu search-based algorithm is implemented, which is modified from the algorithm in Vasquez and Hao, 2001. Numerical results indicate that the approach is very effective to generate a near-optimal, feasible schedule for the imaging operations of the satellite. It is efficient in applications to the real problems. The Lagrangian-relaxation approach is superior to the Tabu search one in both optimality and computation time.**

***Index Terms*—Earth observation satellite, Lagrangian relaxation, satellite scheduling.**

I. Introduction

THIS research develops an imaging scheduling system for the low-orbit earth observation satellite, ROCSAT-II [16]. ROCSAT-II sails in an earth-centered inertial coordination system with the sun-synchronized orbital pattern, passing through Taiwan twice a day. The mission of the satellite is to achieve near real-time remote sensing of the ocean and landmass in the vicinity of Taiwan. Each day, ROCSAT-II takes three to four strips of images in approximately 10 min when it traverses the island of Taiwan. In order to take images on a specific area effectively, information or commands should be sent to the satellite first to maneuver the spacecraft position and posture. It takes time and power to maneuver the satellite from its previous position to the desired aspect angle for a new imaging operation. The maneuvering time and power depend on the positions and postures of these two consecutive imaging operations. To take the image of an area, the solution of the spacecraft position and posture is not unique. There are some preferences for the possible combination of positions and postures. They are represented in a form of "window of opportunity," specified by the suitability function [15]. Even though ROCSAT-II is in the correct orbital position, the conditions may not be conductive to qualify the imaging data due to weather conditions. The problem becomes to generate an imaging schedule, while considering the priority of imaging requests, the cloud coverage, the spacecraft resource availability, such as power, the imaging data storage space, and the physical limitation of camera turning angles. To fulfill an imaging request, it may involve more than one imaging operation.

This satellite daily imaging scheduling problem belongs to a class of single-machine scheduling problems featured by sequence-dependent setup effects, job-assembly characteristics, and time-window constraints, which is NP-hard in the computational complexity [12]. For problems of such a high complexity, dynamic programming and exhaustive search techniques are either too time-consuming or impractical for optimal solutions. Rule-based or heuristics approaches can reduce the computation time drastically. However, the resultant optimality is not guaranteed. For such a large-scaled, time-critical scheduling problem, it is important, but difficult, to generate a dedicated schedule within limited computation time.

The study of scheduling problems with sequence-dependent setups has gathered lots of attentions for years [6], [12]. However, most researchers either neglect the setup times or simplify the problems by assuming sequence-independent setup times or combining setup time with the processing time. To tackle real single-machine problem with sequence-dependent setup, some researchers adopt a global search approach, such as dynamic programming or branch-and-bound for small-scaled problems, while some of them develop heuristics [12]. Ovacik and Uzsoy [10] present a family of rolling horizon heuristics to minimize maximum lateness of schedules for a single machine with sequence-dependent setup times. They decompose the scheduling problem into many subproblems and solve these subproblems to the optimal by a branch-and-bound algorithm. Local search approaches, such as simulated annealing, Tabu search, genetic algorithm, and neural network, have been used for such a problem, but are still very limited to be applied into real problems [1]. The convergence of simulated annealing methods is typically in the complexity of exponential time. There is only little theoretical knowledge for designing the search process with Tabu search. A genetic algorithm depends heavily on the initial condition setting. Although neural networks may speed up the computational

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time, they require much time in training. The performance is still questionable of neural network techniques to optimization problems. All these methods cannot guarantee the optimality of solutions within a polynomial computational time. Lagrangian relaxation methods [4], [8] have been designed to solve scheduling problems of realistic sizes because it is powerful for a separable optimization problem. Coupling constraints are relaxed by using Lagrangian multipliers and the original problem can thus be decomposed into several easily solvable subproblems.

Hall and Magazine [3] describe a machine-scheduling model for the space mission planning problem, which is similar to the longest path problem with time windows and is NP-hard. They adopt greedy algorithms and dynamic programming technique to solve the problem. Agnese *et al.* [2] deal with the daily photograph-scheduling problem of an earth observation satellite system like SPOT [18]. This problem can be viewed as a valued constraint-satisfaction problem, which can be solved by exact methods, like the depth first branch-and-bound or pseudodynamic search, or by approximate methods like greedy search or Tabu search. Vasquez and Hao [14] formulate the daily photograph-scheduling problem of SPOT [18] as a generalized version of the knapsack model. They propose a Tabu search algorithm to determine which photographs to be taken. Lemaitre *et al.* [9] consider the problem of managing the new generation of agile earth observing satellites. A simplified version of the problem is studied and solved by four proposed algorithms: a greedy algorithm, a dynamic programming algorithm, a constraint programming approach, and a local search method. Wolfe and Sorensen [15] define and use the "window-constrained packing" problem to model ASA's earth observation system domain scheduling problem. They propose three algorithms: a dispatch algorithm, a look-ahead algorithm, and a genetic algorithm, which can only be applied to a limited and static part of the problem. LANDSAT-7 [17] is the newest member of the LANDSAT family of earth observation satellites. Porter and Gasch [13] propose an image scheduler for LANDSAT-7, which uses a multipass-scheduling algorithm. Their scheduling algorithm employs rules based on optimistic resource allocation and look-behind preemption to adjust past decisions based on current knowledge. This algorithm is a linear finite deterministic model. The image scheduler is not an optimal scheduler because it fails to execute full backtracking to find the most cost-effective path solution.

Instead of pursuit for the optimal solutions, in this paper, a mathematical programming approach is adopted to generate a near-optimal satellite imaging schedule within allowable computation time. The daily imaging scheduling problem is first formulated as an integer-programming problem. Lagrangian relaxation is used to decompose the problem into separable subproblems. Given a set of Lagrangian multipliers, each subproblem is then solved by a linear search method. A dual function is formed to optimize the Lagrangian multipliers by a subgradient method [5]. Based on the dual solutions, a feasibility adjustment heuristic algorithm is then developed to find a near-optimal and feasible solution.

The remainder of this paper is organized as follows. Section II describes the mathematical formulation to the satellite daily imaging scheduling problem. Solution methodology and the development of a feasibility-adjustment heuristic are described in Section III. Section IV conducts the numerical experiments to demonstrate the ability of the proposed approach in applications to ROCSAT-II daily imaging scheduling problems. In order to demonstrate the efficiency and effectiveness of the approach, in this section, a Tabu search algorithm is implemented and modified from the one in [14]. In Section V, concluding remarks are made with some future research directions.

II. Problem Formulation

A task is defined as a basic imaging operation unit. Since an imaging request may demand more than one task, a job (an imaging order) is defined as the collection of all the tasks from which a request can thus be fulfilled. Some assumptions are made as follows:

Assumptions:

1) A task only belongs to a job.
2) The satellite only can process one task at time.
3) All jobs are released and given at the beginning of the scheduling-time horizon.
4) There are N distinct areas covered by cloud during the scheduling-time horizon.

Some notations are defined for modeling the satellite daily imaging scheduling problem.

Notations:

T	scheduling time horizon;
t	time period index, $t = 1, \ldots, T$;
$\boldsymbol{J}$	set of requested imaging jobs;
j	job index, $j = 1, \ldots, J$, where $J = \lvert\boldsymbol{J}\rvert$;
$\boldsymbol{I}_j$	set of imaging tasks in job j;
$\boldsymbol{I}$	collection of all tasks, $\boldsymbol{I} = \bigcup_{j\in\boldsymbol{J}} \boldsymbol{I}_j$;
i,k	task index, $i, k = 1, \ldots, I$, where $I = \lvert I\rvert$;
p_i	processing time of task i;
C_{ki}	unit setup cost from processing tasks k to i;
s_{ki}	setup time from processing tasks k to i;
M	images storage capacity of Solid State Recorder;
D	available power at the beginning of time horizon;
m_i	imaging mode of task i, $m_i \in \{\text{Panchromatic (PAN), Multispectral(MS), PAN + MS}\}$;
q_i	image size of task i;
u_i	power required for processing task i;
v_{ki}	power required for setup from processing tasks k to i;
$[w_i^b, w_i^e]$	opportunity window of task i, w_i^b and w_i^e are the beginning time and end time of time frame available for processing task i, respectively;
$\Gamma_i(t)$	suitability of task i at time t;
A_j	penalty of the incompleteness of job j, $A_j \geq 0$;
B_i	suitability benefit of task i, $B_i \geq 0$;
N	number of cloud coverage areas;
$[w_n^b, w_n^e]$	the nth cloud coverage area, $n = 1, \ldots, N$, w_n^b and w_n^e are the beginning time and end time during the satellite's traversing over the nth cloud coverage area.

Decision Variables:

b_i	the initial processing time of task i;

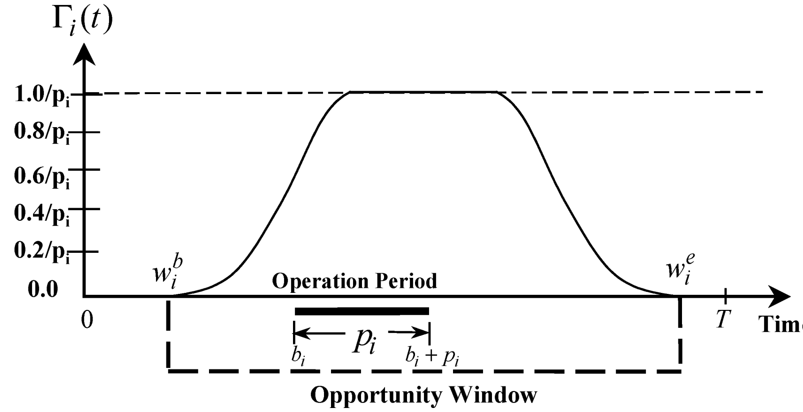

Fig. 1. An example of suitability function $\Gamma_i(t)$.

α_{it} a step function indicating the processing status of task i at time t;

β_j a binary variable indicating the completion of job j;

γ_{kit} a step function indicating the setup status of from processing tasks k to i at time t.

Assume that the initial state of the satellite is setup to a dummy task, 0, where, $s_{0i} = 0$, $C_{0i} = 0$, and $v_{0i} = 0, \forall i \in I$. There is one and only one task that can be setup from task 0.

Initial Setup Constraint:

$$\sum_{t=1}^{T}\sum_{i=1}^{I}\gamma_{0it} = 1. \tag{1}$$

An imaging operation cannot commence its processing before completing its setup, which gives

Setup Constraints:

$$\alpha_{it} = \sum_{\substack{k=0\\k\neq i}}^{I}\gamma_{ki(t-s_{ki})}, \quad \forall i, t. \tag{2}$$

There is only one camera equipped with the satellite. At any time, there is at most one task being processed or setup on the satellite, that is

Machine Capacity Constraints:

$$\sum_{i=1}^{I}\left[\alpha_{it} - \alpha_{i(t-p_i)}\right] + \sum_{i=1}^{I}\sum_{\substack{k=0\\k\neq i}}^{I}\left[\gamma_{kit} - \gamma_{ki(t-s_{ki})}\right] \leq 1, \quad \forall t. \tag{3}$$

The acquired images are firstly stored on board until they can be downloaded to a ground station. As the total storage memory on board is limited, this may impose constraints on the selection of images as well as their scheduling. The stored images should be less than the available storage capacity. As the storage size of an image is related to its imaging mode, we have

Storage Capacity Constraint:

$$\sum_{i=1}^{I}\sum_{t=1}^{T} q_i\left[\alpha_{it} - \alpha_{i(t-p_i)}\right] \leq M. \tag{4}$$

The total power consumption of imaging and setup operations should be less than the available power of the spacecraft, D.

Power Consumption Constraint:

$$\sum_{i=1}^{I}\sum_{t=1}^{T}u_i\left[\alpha_{it}-\alpha_{i(t-p_i)}\right]+\sum_{i=1}^{I}\sum_{\substack{k=0\\k\neq i}}^{I}\sum_{t=1}^{T}v_{ki}\left[\gamma_{kit}-\gamma_{ki(t-s_{ki})}\right]\leq D. \tag{5}$$

The mission of ROCSAT-II is to acquire substantially cloud-free images. It is accomplished by employing the cloud-coverage prediction data sets from the weather forecast data of Center Weather Bureau (CWB). Any task is assumed invalid if its imaging area is covered by cloud.

Windows of Cloud Coverage:

$$b_i \notin \left[w_n^b - p_i, w_n^e\right], \quad \forall i, n = 1, \ldots, N. \tag{6}$$

As the variables α, β, and γ are all binary values of either 0's or 1's, the following binary constraints should be satisfied:

Binary Constraints:

$$\alpha_{it} = \begin{cases} 1, \forall t \leq b_i; \\ 0, \forall t < b_i; \end{cases} \forall i, \forall t \tag{7.1}$$

$$\beta_j = \begin{cases} 0, \text{if } \alpha_{i(T-p_i+1)} = 1, \quad \forall i \in \mathbf{I}_j; \\ 1, \text{otherwise}; \end{cases} \forall j \tag{7.2}$$

$$\gamma_{kit} = \begin{cases} 1, \forall t \geq b_i - s_{ki}; \\ 0, \text{otherwise}; \end{cases} \forall k, \forall i, \forall t. \tag{7.3}$$

For an imaging task, it may result in different image quality when the spacecraft is at different traverse locations due to satellite dynamics and its aspect angle to the target. A suitability function $\Gamma_i(\mathrm{t})$, $0 \leq t \leq T$ is defined to indicate the suitability of executing task i over the time horizon. An example of the suitability function is shown in Fig. 1 [15], where the operation period is the satellite imaging period for task i.

Our satellite daily imaging scheduling problem is to schedule imaging operations that minimize the weighted number of incomplete jobs and the total setup costs and maximize the total suitability benefits of all the tasks while satisfying all constraints. Mathematically, it is formulated as $(\mathbf{P})$

$$(\mathbf{P}) \quad \min_{\gamma} \sum_{j=1}^{J} A_j\beta_j + \sum_{i=1}^{I}\sum_{\substack{k=0\\k\neq i}}^{I}\sum_{t=1}^{T} C_{ki}\left[\gamma_{kit} - \gamma_{ki(t-s_{ki})}\right] - \sum_{i=1}^{I}\sum_{t=1}^{T} B_i\Gamma_i(t)\left[\alpha_{it} - \alpha_{i(t-p_i)}\right]$$
subject to constraints $(1) - (7)$.

III. Lagrangian Relaxation Solution Methodology

The scheduling problem $(\mathbf{P})$ formulated in Section II is an integer linear programming problem of NP-hard computational complexity [11]. As $\sum_{j=1}^{J} A_j\beta_j$ is the only coupling term among jobs in $(\mathbf{P})$, we derive the following theorem to replace it so that the objective function in $(\mathbf{P})$ becomes separable to tasks.

For any $i \in \boldsymbol{I}_j$, let $\overline{A}_i = A_j$ and $\bar{I}_i = |\boldsymbol{I}_j|$. We then have the following two lemmas.

Lemma 1: $\sum_{j=1}^{J} A_j = \sum_{i=1}^{I}(\overline{A}_i/\bar{I}_i)$.

Proof: As a task only belongs to a job, then

$$\sum_{i=1}^{I}\frac{\overline{A}_i}{\bar{I}_i} = \sum_{j=1}^{J}\sum_{i\in\boldsymbol{I}_j}\frac{\overline{A}_i}{\bar{I}_i} = \sum_{j=1}^{J}\sum_{i\in\boldsymbol{I}_j}\frac{A_j}{|\boldsymbol{I}_j|} = \sum_{j=1}^{J}\frac{A_j}{|\boldsymbol{I}_j|}\sum_{i\in\boldsymbol{I}_j}(1) = \sum_{j=1}^{J}\frac{A_j}{|\boldsymbol{I}_j|}|\boldsymbol{I}_j| = \sum_{j=1}^{J} A_j.$$

∎

Lemma 2: $\beta_j \geq 1 - (1/|\boldsymbol{I}_j|)\sum_{i\in\boldsymbol{I}_j}\alpha_{i(T-p_i+1)}, \forall j$.

Proof: From the definition of β_j, the equation is derived

$$\beta_j = 1 - \left\lfloor \frac{1}{|\boldsymbol{I}_j|}\sum_{i\in\boldsymbol{I}_j}\alpha_{i(T-p_i+1)}\right\rfloor$$

where $x - 1 < \lfloor x\rfloor \leq x, \forall x \in R$. We have

$$\frac{1}{|\boldsymbol{I}_j|}\sum_{i\in\boldsymbol{I}_j}\alpha_{i(T-p_i+1)} - 1 < \left\lfloor \frac{1}{|\boldsymbol{I}_j|}\sum_{i\in\boldsymbol{I}_j}\alpha_{i(T-p_i+1)}\right\rfloor \leq \frac{1}{|\boldsymbol{I}_j|}\sum_{i\in\boldsymbol{I}_j}\alpha_{i(T-p_i+1)}.$$

Therefore,

$$\beta_j \geq 1 - \frac{1}{|\boldsymbol{I}_j|}\sum_{i\in\boldsymbol{I}_j}\alpha_{i(T-p_i+1)}, \quad \forall j.$$

∎

From lemmas 1 and 2, the following theorem is derived to provides a lower bound to $\sum_{j=1}^{J} A_j\beta_j$.

Theorem 1: $\sum_{j=1}^{J} A_j\beta_j \geq \sum_{i=1}^{I}(\overline{A}_i/\bar{I}_i)[1 - \alpha_{i(T-p_i+1)}]$.

Proof: From lemmas 1 and 2,

$$\begin{aligned}\sum_{j=1}^{J} A_j\beta_j &\geq \sum_{j=1}^{J} A_j\left(1 - \frac{1}{|\boldsymbol{I}_j|}\sum_{i\in\boldsymbol{I}_j}\alpha_{i(T-p_i+1)}\right)\\ &= \sum_{j=1}^{J} A_j - \sum_{j=1}^{J} A_j\sum_{i\in\boldsymbol{I}_j}\left(\frac{1}{|\mathbf{I}_j|}\right)\alpha_{i(T-p_i+1)}\\ &= \sum_{i=1}^{I}\left(\frac{\overline{A}_i}{\bar{I}_i}\right) - \sum_{j=1}^{J}\sum_{i\in\boldsymbol{I}_j}\left(\frac{\overline{A}_i}{\bar{I}_i}\right)\alpha_{i(T-p_i+1)}\\ &= \sum_{i=1}^{I}\left(\frac{\overline{A}_i}{\bar{I}_i}\right) - \sum_{i=1}^{I}\left(\frac{\overline{A}_i}{\bar{I}_i}\right)\alpha_{i(T-p_i+1)}\\ &= \sum_{i=1}^{I}\left(\frac{\bar{A}_i}{\bar{I}_i}\right)\left[1 - \alpha_{i(T-p_i+1)}\right]\end{aligned}$$

∎

From Theorem 1, a new mathematical program is defined as $(\mathbf{P}')$. Note that solutions to $(\mathbf{P}')$ provide a lower bound to those of $(\mathbf{P})$. Instead of solving the coupled problem $(\mathbf{P}')$ directly, we adopt the Lagrangian relaxation approach to solve problem $(\mathbf{P}')$ which is separable among tasks after relaxing the coupling constraints (1), (3), (4), and (5). Solution development is then detailed as follows:

$$(\mathbf{P}') \quad \min_{\gamma}\sum_{i=1}^{I}\left(\frac{\overline{A}_i}{\bar{I}_i}\right)[1 - \alpha_i(T - p_i + 1)] + \sum_{i=1}^{I}\sum_{\substack{k=0\\k\neq i}}^{I}\sum_{t=1}^{T} C_{ki}\left[\gamma_{kit} - \gamma_{ki(t-s_{ki})}\right] - \sum_{i=1}^{I}\sum_{t=1}^{T} B_i\Gamma_i(t)\left[\alpha_{it} - \alpha_{i(t-p_i)}\right]$$
subject to constraints $(1) - (7)$.

A. Lagrangian Relaxation Decomposition and Subproblem Solutions

Let $\xi \in R$, $\{\lambda_t \geq 0, \forall t\}$, $\pi \geq 0$, and $\eta \geq 0$ be the associated Lagrange multipliers to constraints (1), (3), (4) and (5), respectively. Define a Lagrangian function $\Phi(\xi, \lambda, \pi, \eta)$ is developed for problem $(\mathbf{P}')$ as

$$\Phi(\xi, \lambda, \pi, \eta) = \sum_{i=1}^{I}\Phi_i(\xi, \lambda, \pi, \eta) + \sum_{i=1}^{I}\left(\frac{\overline{A}_i}{\bar{I}_i}\right) - \xi - \sum_{t=1}^{T}\lambda_t - \pi M - \eta D$$

where $\Phi_i(\xi, \lambda, \pi, \eta), \forall i \in I$ represents the Lagrangian function of task-level subproblem.

The dual problem $(\mathbf{D})$ to $(\mathbf{P}')$ after Lagrangian relaxation is formed and problem $(\mathbf{P}')$ has been decomposed into I task-level subproblems. Each task-level subproblem $(\mathbf{P}_i')$ is also defined.

As for a given task, say i, there is only one solution to $\gamma_{kit} = 1$, for some k and t. Therefore, a linear search method is adopted to find the solution of $(\mathbf{P}_i')$, which yields $O(IT)$ of computational time.

B. Dual Solutions

To solve the dual problem $(\mathbf{D})$, Lagrange multipliers are iteratively updated by subgradient (SG) method [5], which is commonly adopted to solve the scheduling problem of realistic sizes [8].

Since problem $(\mathbf{P}')$ is an integer linea-programming problem, there usually exists a gap between the primal and dual optimal costs. The schedule obtained from solving $(\mathbf{D})$ may be infeasible to problem $(\mathbf{P}')$ [8]. In practice, the solution process of the dual problem may be terminated before the optimal solution is achieved due to limited computation time allowed. A heuristic is then developed to adjust the dual solutions to a feasible schedule of $(\mathbf{P}')$.

C. Feasibility Adjustment Method

Theoretically, due to the binary decision variables involved, the dual solutions may still result in an infeasible schedule. Some of the constraints (1), (3), (4), and (5) may not be satisfied. A heuristic algorithm is further developed to adjust the dual solution to a near-optimal, feasible schedule.

The heuristic algorithm checks the violations on relaxed constraints from $t = 1$ to T. If there exists any violation at time t, those tasks whose removals result in the lowest cost are removed from the schedule first. The removals of tasks continue until all the violations of constraints are resolved. Each removed task is then inserted into the schedule in a greedy way, while not causing any new constraint violation.

The insertion step continues until there are no more removed tasks that can be scheduled. Note that there are still chances that some tasks cannot be scheduled within the finite scheduling-time horizon. That is, the heuristic algorithm may still generate an infeasible schedule even after the feasibility adjustment steps

$$
\begin{aligned}
&\Phi_i(\xi, \lambda, \pi, \eta)\\
&\quad = \sum_{t=1}^{T-p_i} \{-B_i[\Gamma_i(t) - \Gamma_i(t+p_i)] + \lambda_t - \lambda_{t+p_i}\}\alpha_{it}\\
&\qquad + \sum_{t=T-p_i+1}^{T} [-B_i\Gamma_i(t) + \lambda_t + \pi q_i + \eta u_i]\alpha_{it}\\
&\qquad - \frac{\overline{A}_i}{\overline{I}_i}\alpha_i(T-p_i+1) + \sum_{\substack{k=0\\k\neq i}}^{I}\sum_{t=1}^{T-s_{ki}}(\lambda_t - \lambda_{t+s_{ki}})\gamma_{kit}\\
&\qquad + \sum_{\substack{k=0\\k\neq i}}^{I}\sum_{t=T-s_{ki}+1}^{T}(C_{ki} + \lambda_t + \eta v_{ki})\gamma_{kit} + \xi\gamma_{0iT}.
\end{aligned}
$$

$$
\begin{aligned}
(\mathbf{D})\quad &\max_{\xi,\lambda,\pi,\eta}\left\{\min_{\gamma}\Phi(\xi,\lambda,\pi,\eta)\right\}\\
&\equiv \max_{\xi,\lambda,\pi,\eta}\left\{\sum_{i=1}^{I}\min_{\gamma_{kit}}\Phi_i(\xi,\lambda,\pi,\eta) + \sum_{i=1}^{I}\left(\frac{\overline{A}_i}{\overline{I}_i}\right)\right.\\
&\qquad\left. -\xi - \sum_{t=1}^{T}\lambda_t - \pi M - \eta D\right\}
\end{aligned}
$$

subject to

$$\xi \in R \tag{8}$$

$$\lambda_t \geq 0, \quad \forall t, \text{ and } \pi \geq 0, \quad \eta \geq 0. \tag{9}$$

$$
\begin{aligned}
(P_i')\quad &\min_{\gamma_{kit}}\Phi_i(\xi,\lambda,\pi,\eta)\\
&= \min_{\gamma_{kit}}\left\{\sum_{t=1}^{T-p_i}\{-B_i[\Gamma_i(t) - \Gamma_i(t+p_i)]\right.\\
&\qquad + \lambda_t - \lambda_{t+p_i}\}\alpha_{it}\\
&\quad + \sum_{t=T-p_i+1}^{T}[-B_i\Gamma_i(t) + \lambda_t\\
&\qquad + \pi q_i + \eta u_i]\alpha_{it}\\
&\quad - \frac{\overline{A}_i}{\overline{I}_i}\alpha_{i(T-p_i+1)}\\
&\quad + \sum_{k=0,k\neq i}^{I}\sum_{t=1}^{T-s_{ki}}(\lambda_t - \lambda_{t+s_{ki}})\gamma_{kit}\\
&\quad + \sum_{k=0,k\neq i}^{I}\sum_{t=T-s_{ki}+1}^{T}(C_{ki} + \lambda_t + \eta v_{ki})\\
&\quad \left.\times\gamma_{kit} + \xi\gamma_{0iT}\right\}
\end{aligned}
$$

subject to constraints (2), (6) and (7).

The heuristic algorithm for constructing a good satellite imaging schedule is listed as follows. Once a schedule is obtained, the corresponding cost of the objective function is set as an upper bound on the optimal cost, while the dual cost serves as a lower bound. The difference between the optimal cost and the lower bound is known as the duality gap, which provides a measure of the optimality of the resultant schedule; the smaller the gap, the closer the feasible schedule to the optimal.

Heuristic Algorithm for Constructing A Good Feasible Satellite Imaging Schedule

Step 0: // Initialization

0.1 initialize schedule $\boldsymbol{S}$ with the dual problem solution $(\xi^*, \lambda^*, \pi^*, \eta^*)$

0.2 $\boldsymbol{R} \leftarrow \varnothing$. // initialize the set for removed tasks to be empty

Step 1: // Resolve the violations on constraints

for $t \leftarrow 1$ **to** T

while there are any constraint violations at time t

1.1 remove task $i^* = \arg\max_{r_{kit}} \Phi_i(\xi^*, \lambda^*, \pi^*, \eta^*)$ from $\boldsymbol{S}$

1.2 $\boldsymbol{R} \leftarrow \boldsymbol{R}\bigcup\{i^*\}$

// end of **while**

1.3 adjust setup relationship among the remaining tasks in $\boldsymbol{S}$

// end of **for**

Step 2: // Reschedule the removed tasks

2.1 Let $\boldsymbol{S^C}$ be the available imaging capacity after excluding $\boldsymbol{S}$

TABLE I
TEST DATA OF A TOY EXAMPLE

Job No.	Task No.	Penalty	Suitability	Imaging Periods (p_i)	Setup Time and Cost (s_{ki}, C_{ki})		
					Task 1	Task 2	Task 3
1	1	40	15	2	(0, 0)	(1, 1)	(2, 2)
2	2	25	20	1	(1, 1)	(0, 0)	(1, 0.5)
2	3	25	10	1	(2, 2)	(1, 0.5)	(0, 0)

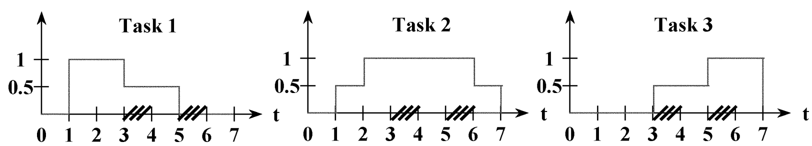

Fig. 2. Suitability function and cloud coverage of the toy example.

2.2 $Infeasible \leftarrow FALSE$
while $((\boldsymbol{R} \neq \emptyset)$ **and** $(Infeasible = FALSE))$
2.3 find $i^* \in \boldsymbol{R}$, $i^* = \arg \max_{n_{kit}} \Phi_i(\xi^*, \lambda^*, \pi^*, \eta^*)$ with $\boldsymbol{S^C}$
if $(i^* \neq NILL)$
then do 2.4 insert i^* into $\boldsymbol{S}$ by the linear search method
else do 2.5 **output error** "the schedule is infeasible"
2.6 $Infeasible \leftarrow TRUE$
// end of **if**
2.7 update the available capacity of $\boldsymbol{S^C}$
// end of **while**

IV. NUMERICAL EXPERIMENTS

Numerical experimentation is conducted to assess the feasibility, optimality, and features of the proposed satellite daily imaging scheduling algorithm. Features of job assembly, setup operation effects, cloud coverage, and opportunity windows are considered in the test cases. The algorithm is first applied to a toy example whose optimal schedule can be obtained from the exhaustive search method. The algorithm is then tested with a projected ROCSAT-II daily imaging scenario to demonstrate its applicability to the realistic problem. A Tabu-search algorithm is implemented to compare with our proposed algorithm. Algorithmic properties of both computational efficiency and optimality are further explored with respect to problem dimensions, setup effects, and time-window constraints as well.

A. Test of a Toy Example

A simple test case is considered with only two jobs. Job 1 has only one imaging task, while job 2 has two. All the test data of these two jobs are shown in Table I. The suitability function for each task is illustrated in Fig. 2, respectively. The cloud coverages (in dashed slots) are shown in the figure as well.

It takes 0.00076 s for our algorithm to generate a daily imaging schedule as shown in the Gantt chart of Fig. 3. This is also the optimal schedule obtained by the exhaustive search on the entire solution space. The resultant feasible cost is

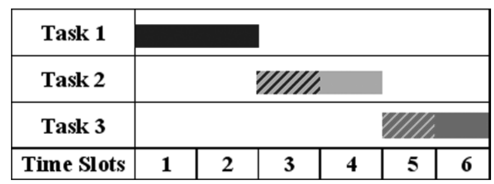

Fig. 3. Optimal solution of the toy example.

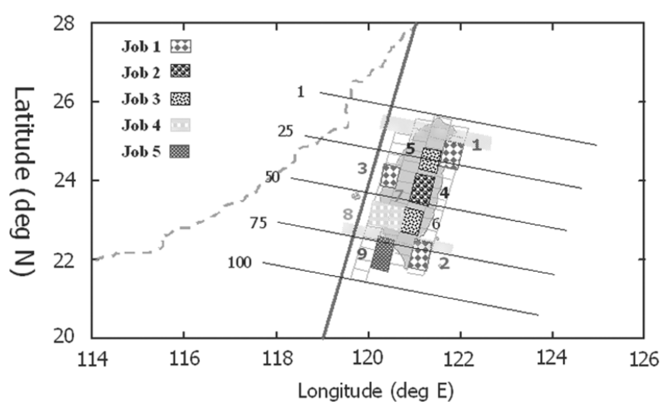

Fig. 4. Projected case of five jobs and nine tasks in 100 time periods (source: NSPO).

-58.5, while the dual cost is -59. The duality gap is defined as (feasible cost—dual cost)/dual cost $\times$ 100%, is 0.847%.

B. ROCSAT-II Daily Imaging Scheduling

Consider a test scenario of the daily imaging scheduling problem of ROCSAT-II. As shown in Fig. 4, there are five imaging jobs, Jobs 1∼5, which are composed of nine tasks. These five imaging jobs consider the conditions of widespread tasks (Job 1), large-area tasks (Job 2), separate-but-in-a-same-strip tasks (Job 3), cross-stripped tasks (Job 4), and consecutive tasks (Job 5), respectively. The time window of each task is determined by the geographical limitation of the task. The setup time between any two tasks is proportional to their geographical distance, and the setup cost is twice the value of the corresponding setup time. The parameters and coefficients of the cost functions are listed in Table II. The scheduling time horizon is of 100 time periods. Two cloud

TABLE II
DATA OF FIVE JOBS AND NINE TASKS IN 100 TIME PERIODS

Job No.	Task No.	A_j	Suitability B_i	Suitability Window	Imaging Time (p_i) Light	Heavy	Over	Setup Time (s_{ki})* 1	2	3	4	5	6	7	8	9
1	1	30	35	[1, 36]	7	8	9	0	4	3	2	1	3	4	5	5
1	2	30	35	[66, 101]	7	8	9	4	0	5	3	4	2	3	4	1
1	3	30	35	[21, 56]	7	8	9	3	5	0	1	2	3	2	1	3
2	4	60	30	[20, 60]	12	12	16	2	3	1	0	1	1	2	3	3
3	5	40	35	[10, 45]	6	8	9	1	4	2	1	0	2	3	4	4
3	6	40	35	[40, 85]	6	8	9	3	2	3	1	2	0	0	1	2
4	7	40	35	[40, 85]	6	8	9	4	3	2	2	3	0	0	0	1
4	8	40	35	[40, 85]	6	8	9	5	4	1	3	4	1	0	0	2
5	9	100	40	[57, 97]	10	12	14	5	1	3	3	4	2	1	2	0

*: setup cost = $2.0 \times s_{ki}$

TABLE III
EXPERIMENT RESULTS OF FIVE JOBS AND NINE TASKS IN 100 TIME PERIODS

Test Case	Scheduled Time: Setup Time	Scheduled Time: Imaging Time	Dual Cost	Primal Cost	Duality Gap	PSTC	CPU Time (in seconds)
Light	7	67	–311.682	–306.0	1.827%	9.46%	0.4465
Heavy	7	80	–310.806	–304.8	1.954%	8.05%	0.4935
Overloaded	9	77	–300.850	**infeasible**	N/A	N/A	0.5345

TABLE IV
SCHEDULE OF FIVE JOBS AND NINE TASKS IN 100 TIME PERIODS

Light Load									
Task no.	1	2	3	4	5	6	7	8	9
Imaging Period	[2, 8]	[92, 98]	[38, 44]	[25, 36]	[15, 20]	[66, 71]	[74, 79]	[56, 61]	[81, 90]
Task Setup from	0	9	4	5	1	8	6	3	7
Setup Period	0	[91, 91]	[37, 37]	[24, 24]	[14, 14]	[65, 65]	X	[55, 55]	[80, 80]
Heavy Load									
Task no.	1	2	3	4	5	6	7	8	9
Imaging Period	[2, 9]	[87, 94]	[37, 44]	[24, 35]	[15, 22]	[56, 63]	[64, 71]	[47, 54]	[74, 85]
Task Setup from	0	9	4	5	1	8	6	3	7
Setup Period	0	[86, 86]	[36, 36]	[23, 23]	[14, 14]	[55, 55]	X	[46, 46]	[73, 73]

X: without setup

coverage areas are assumed with totally four time periods of invalid imaging operations.

Define imaging loading as the ratio of total processing times over the scheduling horizon. Three test cases of light, heavy, and overloaded imaging loads are designed. The required imaging time is 67 for the lightloaded case, 80 for the heavyloaded case, and 93 for the overloaded one.

Numerical results of these three test cases are summarized in Table III. The resultant schedules for the cases of light and heavy loadings are listed in Table IV. The duality gaps in both cases of light and heavy loadings are less than 2%, which can be considered near optimal. No feasible schedule is obtained for the overloaded case. In addition to the duality gaps, the performance measure of percentage of setup time consumption (PSTC) [7] is adopted to study the significance of setup time effects on the overall scheduling problem. PSTC is defined as the percentage of total setup time against the total available machine time. From Table III, the PSTCs are less than 10% in both the light and heavy cases.

In order to demonstrate the efficiency and effectiveness of our approach, we implement a Tabu-search algorithm, which is modified from the one in [14]. As the Tabu-search algorithm in

TABLE V
COMPARATIVE RESULTS OF LAGRANGIAN RELAXATION AND TABU ALGORITHM

Problem	Lagrangian Relaxation		Tabu Algorithm	
	Primal Cost	CPU Time (seconds)	Primal Cost	CPU Time (seconds)
Toy Example	-58.5	0.0008	-58.5	0.0014
Light Load	–306.0	0.4465	-146.1	1.1670
Heavy Load	–304.8	0.4935	-208.8	0.8655

[14] only selects the photographs to be taken, we modify the algorithm with a greedy procedure to determine the beginning imaging time for each imaging task. Table V shows the comparison results of both our proposed algorithm and the Tabu-search method. Note that the Lagrange relaxation approach is better than the Tabu-search approach in both the performances of optimality and computation time.

C. Algorithmic Features

In order to further explore the algorithmic features of our satellite daily imaging scheduling algorithm, 40 test cases are designed and simulated. All the test data are based on a realistic problem (case 5 in Table VI) as their baseline data set. The baseline problem considers 25 imaging jobs $(J = 25)$ with 100 tasks $(I = 100)$ to be scheduled within a time frame of 600 s $(T = 600)$ when the satellite traverses the vicinity of the target area. The setup time and cost between any two consecutive tasks are randomly generated with mean setup time and variance to be one second, respectively. For each imaging task, its opportunity window, suitability function, and imaging mode are all randomly generated. The imaging size and power consumption factors of each task are assumed to be identical. They are 1 for PAN, 1.5 for MS, and 2 for PAN+MS. The power required to setup from task k to task i, is set to be $v_{ki} = 1.0 \times s_{ki}$, $\forall\, k, i$. For all cases, their corresponding coefficients in the objective function are set to $A_j = 150, \forall\, j$, $B_i = 15, \forall\, i$, and $C_{ki} = 2.0 \times s_{ki}, \forall\, k, i$.

There are five factors considered as the influences to the algorithmic performance of optimality as well as the computational time. They are

1) number of jobs;
2) number of tasks;
3) scheduling time horizon;
4) setup times;
5) duration of time windows.

Test cases of 40 scenarios are designed to investigate their effects. Each test case is simulated with ten scenarios randomly. The loading of each test case is set to 0.667. Simulation results are summarized in Table VI.

The results of Group I indicate that there are no significant differences in optimality for different numbers of jobs. Also, the number of jobs has no impact on the computational time. We, therefore, conclude that the number of jobs has no direct impacts on both the optimality and the computational time.

Group II in Table VI is designed to test the effect of the number of tasks, as well as the scheduling-time horizon on the system performance. The optimality becomes worse as the increase either in the number of tasks or in the scheduling time horizon. Compared to the effects from the scheduling horizon, the number of tasks is much more critical to the optimality and computation time.

In order to study the setup effects on the satellite scheduling algorithm, five test cases are designed in Table VII. Results indicate that both the duality gap and PSTC become worse as the increase of setup times. However, the computational times are almost without changes.

The effects due to different lengths of time windows are designed and studied in Group IV of Table VI. Fig. 5 shows the simulation results on duality gap and PSTC against different lengths of time windows. Note that both the average and the variance of the two performance measures do not change very much for the window sizes that larger than 100 s; while they become worse when the lengths of time windows decrease. For an imaging task, as the size of its time window constrains the feasible region for the possible imaging operations; the smaller the window size, the more restricted time slot for an imaging task. Similar phenomena also can be found in [15], where Wolfe and Sorensen consider the "window-constrained packing" in modeling the EOS scheduling problem. As those in Group III, the impact of computational times is not significant in Group IV.

In summary, most of the CPU times spent in the regular cases (in the same size of the baseline problem) are less than 300 s. The duality gaps in most of the test cases are less than 10%. Therefore, it is concluded that this daily imaging scheduling algorithm is quite efficient for realistic applications to provide a near-optimal imaging schedule to the earth observation satellite. Also, note that it takes most of the time for the scheduling algorithm to iteratively solve for subproblems and then update the Lagrange multipliers. For each iteration, there are totally I subproblems to be solved and it takes $O(IT)$ to solve each subproblem. As the effort in updating Lagrange multipliers is relatively small, the computational time of this algorithm can be approximately equal to $O(NI^2T)$, where N is the total number of iterations to update the Lagrange multipliers. That is, for a fixed number of iterations, the computational time of the scheduling algorithm is proportional to $O(I^2T)$. The computational time is dominated by the number of tasks, I.

Note that there could be several possibilities for the combination of tasks and their processing time to form a job. Fig. 6 depicts the simulation results of cases 5, 25, 26, 27, and 28,

TABLE VI
SIMULATION RESULTS OF 40 TEST CASES

Case	Group	Dimension Factor			Loads	Effects		Performance Index (Average)		
		J	I	T	Imaging (p_i)	Setup	Time Window	CPU	D.G.	PSTC
1	I	1	100	600	4	50%	$25\times p_i$	251.1	0.26	13.27
2		5	100	600	4	50%	$25\times p_i$	248.6	9.96	8.08
3		10	100	600	4	50%	$25\times p_i$	250.5	8.89	6.93
4		20	100	600	4	50%	$25\times p_i$	250.6	7.55	6.64
5		25	100	600	4	50%	$25\times p_i$	249.5	7.52	5.91
6		50	100	600	4	50%	$25\times p_i$	251.5	6.38	5.58
7		100	100	600	4	50%	$25\times p_i$	254.1	8.61	6.43
8	II	25	25	600	16	50%	$25\times p_i$	60.4	6.28	1.48
9		25	50	600	8	50%	$25\times p_i$	115.2	6.94	3.16
10		25	100	600	4	50%	$25\times p_i$	246.3	6.61	6.29
11		25	200	600	2	50%	$25\times p_i$	579.3	9.26	9.85
12		25	400	600	1	50%	$25\times p_i$	1587	15.48	13.30
13		25	100	150	1	50%	$25\times p_i$	25.7	4.29	11.41
14		25	100	300	2	50%	$25\times p_i$	74.2	5.84	9.36
15		25	100	450	3	50%	$25\times p_i$	148.1	6.62	7.563
16		25	100	750	5	50%	$25\times p_i$	366.9	6.34	4.99
17		25	100	900	6	50%	$25\times p_i$	510.7	6.59	4.15
18		25	25	150	4	50%	$25\times p_i$	4.6	6.02	5.65
19		25	50	300	4	50%	$25\times p_i$	33	5.64	4.95
20		25	75	450	4	50%	$25\times p_i$	105	6.09	5.89
21		25	125	750	4	50%	$25\times p_i$	482.4	8.12	6.79
22		25	150	900	4	50%	$25\times p_i$	810.1	7.89	6.48
23		25	175	1050	4	50%	$25\times p_i$	1290.8	9.41	6.52
24		25	200	1200	4	50%	$25\times p_i$	1905.9	10.2	6.75
25		25	100	600	1	50%	$25\times p_i$	99.5	9.17	29.23
26		25	100	600	2	50%	$25\times p_i$	144.1	7.63	14.74
27		25	100	600	3	50%	$25\times p_i$	194.7	6	8.58
28		25	100	600	5	50%	$25\times p_i$	296.3	13.27	4
29	III	25	100	600	4	0%	$25\times p_i$	238.6	0.32	0
30		25	100	600	4	25%	$25\times p_i$	242.9	1.3	1.84
31		25	100	600	4	75%	$25\times p_i$	255.1	13.98	11.8
32		25	100	600	4	100%	$25\times p_i$	260.89	18.54	22.48
33	IV	25	100	600	4	50%	$1\times p_i$	159.6	49.04	6.43
34		25	100	600	4	50%	$5\times p_i$	224	30.26	8.64
35		25	100	600	4	50%	$10\times p_i$	229.3	19.46	9.12
36		25	100	600	4	50%	$50\times p_i$	264.8	2.66	3.05
37		25	100	600	4	50%	$75\times p_i$	273.4	3.84	3.48
38		25	100	600	4	50%	$100\times p_i$	285.8	5.7	4.65
39		25	100	600	4	50%	$125\times p_i$	294.9	4.58	3.17
40		25	100	600	4	50%	$150\times p_i$	234.3	6.72	5.99

CPU: CPU Time (in seconds), D.G.: Duality Gap (%), PSTC: Percentage of Setup Time Consumption (%)

TABLE VII
FIVE TEST CASES FOR DIFFERENT SETUP SETTINGS

Case No.	Setup Time (s_{ki}) Distribution (%)			Mean	Variance
	$s_{ki}=0$	$s_{ki}=1$	$s_{ki}=2$		
Case 29	100	0	0	0.0	0.0
Case 30	75	25	0	0.25	0.1875
Case 10	50	25	25	0.75	0.6875
Case 31	25	50	25	1.0	0.5
Case 32	0	50	50	1.5	0.25

on the optimality against various imaging times of tasks, which indicates that the setting of an imaging period between 3 and 4 s is good for the optimality. It is therefore suggested to separate a job into tasks in equally lengths of 3–4 imaging seconds to achieve good optimality

V. CONCLUSION

This paper presents the development of a daily imaging scheduling system of an earth observation satellite, ROCSAT-II.

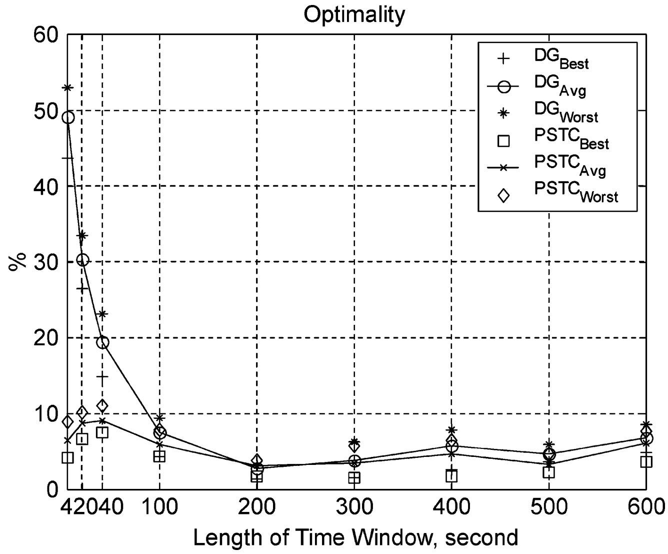

Fig. 5. Optimality versus length of time window.

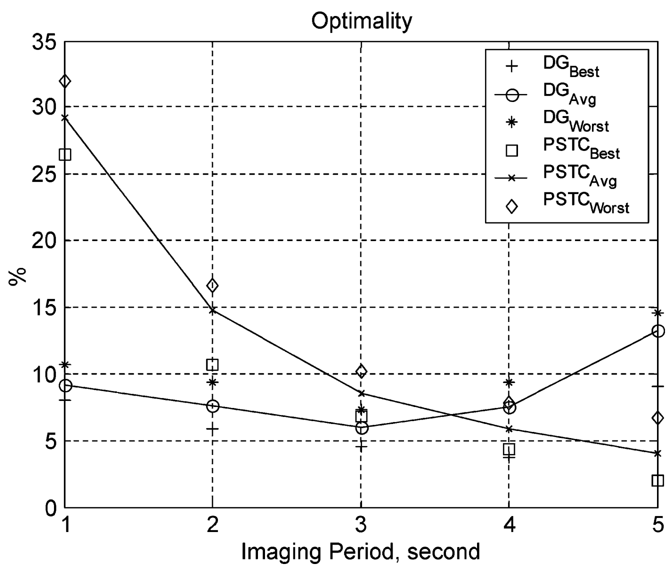

Fig. 6. Optimality versus imaging periods.

The daily imaging scheduling problem of the satellite belongs to single-machine scheduling problems with salient features of sequence-dependent setup, job-assembly, and constrained operating time windows. It is formulated into an integer programming problem. We utilize Lagrangian relaxation to decompose the scheduling problem into independent subproblems, each of which can be easily solved by the efficient linear-search method. A heuristic algorithm is developed to generate a good, feasible schedule. In order to compare the efficiency and effectiveness of the proposed solution methodology, a Tabu-search algorithm is implemented. Numerical results indicate that the approach is very effective to generate a near-optimal, feasible schedule for the imaging operations of the satellite. It is efficient in applications to the real problems. The proposed solution methodology has been implemented and is to be integrated as a part of the planning and scheduling system in ROCSAT-II before the satellite launches in 2004.

Future research may extend the algorithm to include realistic issues such as seasonal refreshment and coordination between multiple satellites. On the other hand, the developed algorithm deals with the scheduling problem assuming no machine failure and exclusions of imaging with cloud coverage. Extensions to this research may handle these stochastic issues.

The values of setup times are predetermined in this paper. The calculation of setup times is not straightforward and depends on the position, posture and angle of the spacecraft during its traverse around the earth. That is, the setup time depends not only on the consecutive tasks but also on the states when the satellite is to execute the task. Future researches may include the development of methodology for the efficient calculation of setup times to complete the development of an effective scheduler for image acquisitions in ROCSAT-II.

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REFERENCES

[1] E. Aarts and J. K. Lenstra, *Local Search in Combinatorial Optimization*. New York: Wiley, 1997.
[2] J. C. Agnèse, N. Bataille, D. Blumstein, E. Bensana, and G. Verfaillie, "Exact and approximate methods for the daily management of a remote sensing satellite," in *Proc. 5th Workshop Artif. Intell. Knowledge-Based Syst. Space, ESTEC*, Noordwijk, The Netherlands, Oct., 10–12 1995.
[3] N. G. Hall and M. J. Magazine, "Maximizing the value of a space mission," *Eur. J. Oper. Res.*, vol. 78, pp. 224–241, 1994.
[4] D. J. Hoitomt, P. B. Luh, E. Max, and K. R. Pattipati, "Scheduling job with simple precedence constraints on parallel machines," *Control Syst. Mag.*, vol. 10, no. 2, pp. 34–40, 1990.
[5] M. Held, P. Wolfe, and H. Crowder, "Validation and subgradient optimization," *Math. Program.*, vol. 6, pp. 62–88, 1974.
[6] S. C. Kim and P. M. Bobrowski, "Impact of sequence dependent setup time on job shop scheduling performance," *Int. J. Prod. Res.*, vol. 32, no. 7, pp. 1503–1520, 1994.
[7] C. Y. Liu and S. C. Chang, "Scheduling flexible flow shops with sequence dependent setup effects," *IEEE Trans. Robot. Autom.*, vol. 16, no. 4, pp. 408–419, Apr. 2000.
[8] P. B. Luh and D. J. Hoitomt, "Scheduling of manufacturing systems using the Lagrangian relaxation technique," *IEEE Trans. Autom. Control*, vol. 38, no. 7, pp. 1066–1079, Jul. 1993.
[9] M. Lemaitre, G. Verfaillie, F. Jouhaud, J.-M. Lachiver, and N. Bataille, "Selecting and scheduling observations of agile satellites," *Aerospace Sci. Technol.*, vol. 6, pp. 367–381, 2002.
[10] I. M. Ovacik and R. Uzsoy, "Rolling horizon algorithms for a single machine dynamic scheduling problem with sequence dependent setup times," *Int. J. Prod. Res.*, vol. 32, no. 6, pp. 1243–1263, 1994.
[11] C. H. Papadimitriou and K. Steiglitz, *Combinatorial Optimization: Algorithms and Complexity*. Englewood Cliffs, NJ: Prentice-Hall, 1982.
[12] M. Pinedo, *Scheduling Theory, Algorithms, and Systems—2nd Edition*. Englewood Cliffs, NJ: Prentice-Hall, 2002.
[13] W. Potter and J. Gasch, A Photo Album of Earth: Scheduling LANSDAT 7 Mission Daily Activities, NASA, 2001.
[14] M. Vasquez and J.-K. Hao, "A logic-constrained knapsack formulation and a Tabu algorithm for the daily photograph scheduling of an earth observation satellite," *Computat. Optim. Applicat.*, vol. 20, no. 2, pp. 137–157, 2001.
[15] W. J. Wolfe and S. E. Sorensen, "Three scheduling algorithms applied to the earth observing systems domain," *Manage. Sci. INFORMS*, vol. 46, no. 1, pp. 148–168, 2000.
[16] National Space Programs Office. [Online]. Available: http://www.nspo.gov.tw/
[17] LANDSAT 7. [Online]. Available: http://landsat.gsfc.nasa.gov/
[18] Spot Image Spot 5. [Online]. Available: http://www.spotimage.fr/home/system/future/spot5/welcome.htm

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