A Constraint Programming Approach for the Multi-Satellite Imaging Scheduling Problem with Variable Observation Durations

Margarida Caleiras
Dept. of Mechanical Engineering
CEMMPRE, University of Coimbra
Coimbra, Portugal
0009-0008-4815-7265

Samuel Moniz
Dept. of Mechanical Engineering
CEMMPRE, University of Coimbra
Coimbra, Portugal
0000-0002-7813-4514

Paulo Jorge Nascimento
Dept. of Mechanical Engineering
CEMMPRE, University of Coimbra
Coimbra, Portugal
0000-0003-4139-1100

***Abstract*—The new generation of active imaging agile Earth observation satellites (AEOS) offers unprecedented imaging flexibility through variable observation durations and multiple pointing directions. These capabilities make the AEOS imaging scheduling problem (AEOS-ISP) substantially harder, and no exact method has been proposed so far. This work presents the first exact Constraint Programming formulation for the multi-satellite AEOS-ISP, considering active imaging, multiple imaging directions, and sequence-dependent transition times. Experiments on a newly generated benchmark show that the model solves small to medium sized instances to proven optimality within very short times, and is competitive with non-exact approaches.**

***Index Terms*—active imaging agile Earth observation satellites, imaging scheduling, constraint programming**

I. Introduction

Earth observation satellites (EOS) acquire images of ground targets in response to customer requests, supporting time-critical applications such as disaster management, climate monitoring, and defense [1]. As constellations grow in size and agility, the EOS imaging scheduling problem (ISP), coordinating multiple satellites under limited visibility, maneuvering, and sequencing constraints, becomes a highly constrained, NP-hard combinatorial problem demanding fast and reliable decisions [2], [3].

Satellites can be classified as non-agile, semi-agile (SEOS), or agile (AEOS). Unlike SEOS, which acquire strips parallel to the satellite orbit by orbital motion (i.e., the sensor images targets passively as the satellite moves along its orbit, without maneuvers during the observation), AEOS image in arbitrary directions and maneuver while imaging [4], [5]. This capability, known as active imaging, substantially increases the number of visibility opportunities and turns the duration of each observation from a fixed value into an optimization decision, sharply enlarging the search space.

This research is sponsored by national funds through FCT – Fundação para a Ciência e a Tecnologia, under projects UID/00285/2025 and LA/P/0112/2020, and by the European Union under Next Generation EU, through the Portuguese Republic's Recovery and Resilience Plan, within project PRODUTECH R3.

Existing work mostly considers the SEOS-ISP, with both exact and non-exact methods having been proposed. However, these methods do not extend to the AEOS-ISP, as they assume fixed imaging durations and directions. Research on the AEOS-ISP considering active imaging capabilities is at an early stage and relies exclusively on non-exact methods [4]–[7], with no exact approach proposed to date. We address this gap with the first exact Constraint Programming (CP) formulation for the AEOS-ISP, considering variable observation durations, multiple imaging directions, and sequence-dependent transition times. Our model can be directly applied to both SEOS-ISP and AEOS-ISP scenarios, supporting different target types and mission configurations. We further introduce a new benchmark and the first comparison against a state-of-the-art non-exact method [8].

Compared to previous exact methods developed for the SEOS-ISP, our model accounts for: (1) variable-length observation windows, allowing imaging durations to vary for the same target; (2) multiple imaging directions, making the pointing direction a decision variable; and (3) sequence-dependent transition times, which capture satellite maneuvers between consecutive observations.

II. Problem Description

Let us consider a constellation of satellites $\mathbf{I} = \{1, \dots, I\}$ and a set of observation targets $\mathbf{N} = \{1, \dots, N\}$. Targets are decomposed into a set of strips $\mathbf{J} = \{1, \dots, J\}$, each considered as an individual observation task and associated with a priority weight w_j. Each strip must be observed continuously in one of two imaging directions, orbital (l=0) or opposite-orbital (l=1). Each satellite completes several orbits $k \in \mathbf{K}_i$ within a 24 h horizon, generating visible time windows (VTW) vw_{ijkl} for strip j on orbit k in direction l. Each strip can only be observed in one of the corresponding VTWs.

Because AEOS maneuver during observations, the processing time of each strip p_{ijkl} is a decision variable, bounded below by the satellite's maximum angular velocity and above by the VTW duration. Each observation is defined by its imaging angles, so maneuvering between consecutive observations

TABLE I
SUMMARY OF RESULTS PER INSTANCE CONFIGURATION.

Strips	No. interval variables	No. constraints	Gap (%)	Time (s)
17–36	353	29	0	0.02
50	736	54	0	0.05
70–95	1074	80	0	0.33
66–96	934	81	0	0.97
109–148	1865	134	0	3.92
113–169	1688	141	0.8	2164.35*
169–201	2329	191	3.36	2524.99*

*TL reached on some of the instances.

requires a sequence-dependent transition time $\Delta_{(ijkl),(ij'k'l')}$. VTWs and transition times are computed before scheduling, becoming input parameters of the problem. The goal of the AEOS-ISP is to decide which satellite observes which strips, on which orbit, and in which direction, so as to maximize the total priority weight of the observed strips.

III. Constraint Programming Model

The model uses IBM ILOG CP Optimizer, whose interval and sequence variables are tailored to scheduling [9]. For each VTW we define an optional interval variable X_{ijkl}, representing the time interval during which strip j is observed by satellite i in VTW vw_{ijkl}. We also define an optional interval variable Y_j to denote the interval of time during which strip j is observed, and a sequence variable S_i to describe the order of the strips assigned to satellite i. The CP formulation can be stated as follows:

$$\max \quad \sum_{j \in \mathbf{J}} w_j \times \mathit{presenceOf}(Y_j) \tag{1}$$

s.t.

$$\mathit{alternative}\Big(Y_j,\ \{\, X_{ijkl} \mid i \in \mathbf{I}, k \in \mathbf{K}_i, l \in \{0,1\} \,\}\Big), \forall j \in \mathbf{J} \tag{2}$$

$$\mathit{noOverlap}\Big(S_i,\ \Delta_{(ijkl),(ij'k'l')}\Big), \forall i \in \mathbf{I} \tag{3}$$

The objective (1) is to maximize the number of observed strips according to their priority weights. The scheduling constraints rely on the CP Optimizer global constraints *alternative* and *noOverlap*. Constraints (2) assign each observed strip to exactly one VTW, while constraints (3) define the observation sequence of each satellite, guaranteeing that only one strip is observed at a time and embedding the transition times between consecutive observations.

IV. Computational Study

As no standard AEOS benchmark exists, we generated instances by adapting SEOS datasets [1], [10], [11], using a four-satellite constellation over a 24 h horizon and different numbers and types of targets. We defined seven different configurations, each with ten instances. The model was solved with CP Optimizer 22.1.1 (DOcplex) on a MacBook Pro (Apple M3, 16 GB RAM), with a 1 h time limit (TL).

Table I summarizes the average results across our instances, reporting the number of strips, the average numbers of interval variables and constraints, and the average optimality gaps and run times. For the smaller instances (the first five configurations), the model consistently proves optimality within just a few seconds. For the larger instances (the last two configurations), although optimality cannot be proven for all instances within the imposed time limit, the model still obtains feasible solutions with small average optimality gaps.

Compared with the non-exact method of [8], our model is competitive in solution quality and significantly faster. On instances of comparable size and complexity, even without proving optimality within the imposed time limit, our model reaches feasible solutions with gaps below 1% in only 10 s, whereas [8] requires on the order of 10^3 s to attain comparable solutions.

V. Conclusions

This work presents the first exact CP formulation for the AEOS-ISP, considering variable imaging durations, multiple imaging directions, and sequence-dependent transition times. Our model proves optimality for small to medium instances within very short times and is competitive with non-exact methods while providing explicit optimality bounds. Future work will improve scalability and add energy and memory constraints.

References

[1] X. Chen, G. Reinelt, G. Dai, and A. Spitz, "A mixed integer linear programming model for multi-satellite scheduling," *European Journal of Operational Research*, vol. 275, no. 2, pp. 694–707, 2019.

[2] X. Wang, G. Wu, L. Xing, and W. Pedrycz, "Agile Earth observation satellite scheduling over 20 years: Formulations, methods, and future directions," *IEEE Systems Journal*, vol. 15, no. 3, pp. 3881–3892, 2021.

[3] M. Lemaître, G. Verfaillie, F. Jouhaud, J.-M. Lachiver, and N. Bataille, "Selecting and scheduling observations of agile satellites," *Aerospace Science and Technology*, vol. 6, no. 5, pp. 367–381, 2002.

[4] Z. Chang, Y. Chen, W. Yang, and Z. Zhou, "Mission planning problem for optical video satellite imaging with variable image duration: A greedy algorithm based on heuristic knowledge," *Advances in Space Research*, vol. 66, pp. 2597–2609, 2020. [Online]. Available: https://api.semanticscholar.org/CorpusID:224946921

[5] Z. Lu, X. Shen, D. Li, Y. Chen, and D. Li, "A mission planning modeling method of multipoint target imaging within a single pass for super-agile Earth observation satellite," *IEEE Systems Journal*, vol. 16, no. 2, pp. 1921–1932, 2022.

[6] Z. Lu, X. Shen, D. Li, and Y. Chen, "Integrated imaging mission planning modeling method for multi-type targets for super-agile Earth observation satellite," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 15, pp. 4156–4169, 2022.

[7] M. Wang, Z. Zhou, Z. Chang, E. Chen, and R. Li, "Deep reinforcement learning for agile earth observation satellites scheduling problem with variable image duration," *Applied Soft Computing*, vol. 169, p. 112575, 1 2025.

[8] Z. Lu, X. Shen, D. Li, D. Li, Y. Chen, and S. Shen, "Multiple super-agile satellite collaborative mission planning for area target imaging," *Int. J. Appl. Earth Obs. Geoinformation*, vol. 117, p. 103211, 2023.

[9] IBM Corporation, *IBM ILOG CPLEX Optimization Studio — CP Optimizer User's Manual*, 2024.

[10] P. Wang, G. Reinelt, P. Gao, and Y. Tan, "A model, a heuristic and a decision support system to solve the scheduling problem of an Earth observing satellite constellation," *Computers & Industrial Engineering*, vol. 61, pp. 322–335, 2011.

[11] X. Liu, G. Laporte, Y. Chen, and R. He, "An adaptive large neighborhood search metaheuristic for agile satellite scheduling with time-dependent transition time," *Computers & Operations Research*, vol. 86, pp. 41–53, 2017.